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Hybrid deep learning and CNN-Isotonic Regression framework for accurate global mean sea level rise prediction using multi-source atmospheric and oceanic data

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ABSTRACT

Keeping track of Global Mean Sea Level (GMSL) over long periods is important for assessing coastal risk. However, deep learning models may produce predictions that exhibit short-term increases and decreases, potentially conflicting with expected long-term physical behavior. In this study, we propose a combined Convolutional Neural Network and Isotonic Regression framework, termed CNN-ISO, for modeling and forecasting annual GMSL changes over the period 1880–2024. The framework uses 11 predictors representing atmospheric, oceanic, and cryospheric conditions. To provide longer temporal sequences, the original 144 annual observations are linearly interpolated into 1728 monthly observations. Model evaluation follows a strict chronological split, with training data from 1880–1979, validation data from 1980–1999, and test data from 2000–2024. All preprocessing transformations and the isotonic mapping are fitted exclusively on the training set to prevent information leakage from later periods. On the unseen test period, CNN-ISO achieves $R^2 = 0.997$ with a 95% confidence interval of $[0.995, 0.999]$, together with an MAE of 0.56 mm and an RMSE of 0.72 mm. For comparison, linear regression achieves $R^2 = 0.982$. Although the predictive improvement over linear regression is relatively modest, CNN-ISO provides an additional constraint by producing monotonic out-of-sample projections, which is consistent with the assumed long-term behavior of GMSL. Under statistical trend extrapolation to 2050, CNN-ISO estimates a GMSL increase of 184.10 mm relative to the baseline. However, estimates vary substantially across models, with linear regression and LSTM producing 116.60 mm and 299.19 mm, respectively. These results should therefore be interpreted as trend-based statistical extrapolations rather than comprehensive climate projections, as the framework does not explicitly model ice-sheet dynamics, changes in ocean circulation, or future emission pathways. Nevertheless, the proposed approach provides a transparent framework for examining model uncertainty and may support early-stage coastal adaptation planning.

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1. Introduction

The rise of global mean sea level (GMSL) is a contemporary problem of climate change that finds proof in the level of destruction it has brought about to coastal ecosystems, human populations, and critical infrastructure. With increased greenhouse gases due to anthropogenic activities, global temperatures rise, causing seawater thermal expansion and melting of glaciers and polar ice caps. Such a phenomenon, combined with other meteorological conditions such as natural variability, adds to the burden of GMSL rise for researchers, policymakers, and urban planners alike (Mimura, 2013). Researchers have widely studied the impact of rising sea levels on coastal regions, emphasizing the susceptibility of these areas to flooding, erosion, and habitat loss (Cazenave and Llovel, 2009). According to Nicholls and Cazenave (2010), altitude is a multiplier for risks faced by low-lying coastal regions, enhanced even more by the fact that infrastructure and human densities are often at their peak. By contrast, Warrick and Oerlemans (Cazenave et al., 2014) provide an overarching overview of the physical mechanisms responsible for sea-level changes while elaborating on joint activities of thermal expansion, ice sheet dynamics, and ocean circulation patterns. The new framework solves the limitations which present studies face because it uses different environmental data sources and temporal data enrichment and multiple model optimization to predict GMSL.

Sea level change prediction is complex in a general way that is influenced by both atmospheric and oceanic dynamics making robust methods to integrate many influencing factors. Extensive use of traditional statistical methods fails to capture the nonlinear relations in the interaction of this complicated phenomenon (Makarynskyy et al., 2004). The machine learning paradigm has revolutionized many domains; thus, it opens the possibility to develop predictive models in a way that they may use large data for improving predictions and reliability. Studies such as Altunkaynak and Kartal (2019) and Shiri et al. (2011) show the worth of this approach in overcoming traditional methods' limitations fog GMSL prediction. Cazenave and Llovel (2009) present an extensive survey of sea level changes from ancient times to the modern age and associate their influences with the accelerating melting of polar ice sheets and glaciers. The authors also go a step ahead to show insight into regional variability, revealing some of the places most affected by sea level rise. Cazenave et al. (2014) further review global components of sea level change, thus refining prediction models based on satellite altimetry data and oceanographic measurements. The impacts of GMSL rise on society are undoubtedly overwhelming; coastal and island communities, in particular, are exposed to threats such as flooding, erosion, and habitat loss. For example, much of what Makarynskyy et al. (2004) have focused on relates to the risk of exposure to western Australian coastline infrastructure and the need for accurate predictions for impact mitigation. Mimura (2013) also elaborates on some of the wider societal and economic challenges associated with rising sea levels, underlining the urgency with which intervention strategies need to take place.

Applications of machine learning methods which include artificial neural networks (ANNs), Gaussian process (GP), and adaptive neuro-fuzzy inference system (ANFIS) have been successful in solving this problem. For example, short-term sea-level behavior has been predicted through ANNs, with application done by Makarynskyy et al. (2004), whereas island-specific predictions have been attempted by Ghorbani et al. with GP (Ghorbani et al., 2010). New techniques surpass the previous methods and models by adapting to nonlinearity and utilizing multiple datasets.

This study builds on these by adding neglected atmospheric and oceanic elements and fine-tuning data through hybrid feature engineering and training with modern cutting-edge machine learning techniques. Following wise ideas coming from previous works in Refs. Altunkaynak and Kartal (2021), Muslim et al. (2020), and Nicholls and Cazenave (2010) we plan to develop a holistic framework for GMSL prediction, with this project positively influencing scientific knowledge on sea level movement besides providing tools to deal with or plan infrastructure for possible climate change.

Historical data has validated the proposed model's abilities to capture the complex underlying interactions and make reliable predictions. According to Lai et al. the incorporation of climatic parameters in the study enhances the performance of the model, which is the principle behind the proposed methodology (Lai et al., 2019). This preliminary study will go a long way in informing decisions made by vulnerable stakeholders in such areas as regards the impacts of climate change. In conclusion, tackling the problem with GMSL rise demands new techniques that are both data-driven and very much understand the atmospheric-oceanic functioning. This research actually provides the basis for this attempt as a contribution to better sustainability and resilience.

For the rest of the paper, the literature review is presented in Section 1.4. The methodology is described in Section 2, followed by the results in Section 3. The conclusion is provided in Section 4.

1.1. Research gap and motivation

Despite significant advancements in sea-level prediction, several critical gaps remain in the existing literature:

1. **Limited integration of multivariate drivers:** Almost all past research works used only a few predictor variables at a time in their analysis; specifically, either the variable of temperature or historical data of sea level (Elneel et al., 2024; Hassan et al., 2021). Such an approach fails to take into consideration the dependencies between atmospheric (CO_2, CH_4, N_2O), oceanic (sea surface temperature, ENSO), and cryospheric (sea ice extent) variables.
2. **Inadequate temporal resolution and feature engineering:** Most research uses annual frequency, thereby missing out on important seasonal and interannual variations that play an important role in ENSO-induced changes (Faridatunnisa and Heliani, 2018). Lack of application of temporal feature engineering constrains model capability of capturing patterns.
3. **Lack of post-processing refinement:** Despite the success of deep learning models (like LSTM and CNN), the results obtained through such models are unstable and non-physically fluctuating when projecting into the future. There is no prior research that has used monotonic regression for obtaining physically consistent projections.
4. **Limited interpretability and uncertainty quantification:** Feature importance analysis and confidence intervals or p-values for prediction uncertainty are rarely conducted, severely reducing the applicability of these models to climate policy and coastal management.

1.2. Research questions

To address these gaps, this study formulates the following research questions:

1. **RQ1:** Is it possible for a hybrid CNN-ISO approach utilizing multiple variables in the atmosphere, ocean, and cryosphere to predict the GMSL better than traditional machine learning algorithms such as LR, RNN, LSTM, and BiLSTM?
2. **RQ2:** How can each driver of the environment (GHG concentrations, temperature anomalies, sea ice coverage, and ENSO indexes) affect the prediction of the GMSL?
3. **RQ3:** What will be the forecasted GMSL trends till 2050 based on a scenario-independent extrapolation approach, and what will be the related uncertainties?

1.3. Contributions of the current study

Building on the identified gaps, this study makes the following specific contributions:

1. **Multivariate feature integration:** We formulate a comprehensive prediction model that integrates 11 factors of the atmosphere, oceans, and the cryosphere, reflecting all possible physical factors affecting GMSL. In contrast to previous approaches that used only one type of predictor (Balogun and Adebisi, 2021), our model takes into account greenhouse gases (CO_2, CH_4, N_2O), temperature anomalies (on land and on sea surfaces), polar sea ice concentration, and ENSO indicators (Niño 1.2 and 3).
2. **Temporal feature engineering:**Annual weather variables are converted to months' series (144 → 1729 cases) via linear interpolation, thus allowing for the analysis of both seasonal and inter-annual variations which otherwise could not be observed at the annual resolution scale. Such an approach allows us to gain more resolution but without creating any biases.
3. **Hybrid CNN-ISO architecture:** We add a post-processing step to the CNN results. The step uses isotonic regression on the CNN output. It keeps the long-term GMSL trend monotone. This stops the predictions from showing sudden, unrealistic jumps that can happen in deep learning outputs. In the persistence baseline, the score is $R^2 = 0.960$ and MAE = 4.17 mm. The CNN-ISO method is the only one that brings the error down a lot. Its MAE is 0.56 mm. This shows the hybrid design does more than just carry the trend forward.
4. **Comparative evaluation and statistical rigor:** A systematic comparison is performed on five models (LR, RNN, LSTM, BiLSTM, CNN-ISO), which are evaluated on a standard experimental setup. We use bootstrapping to compute 95% confidence intervals, p-values for hypothesis testing, and residuals for verifying model assumptions.
5. **Long-term projections with uncertainty:** We produce the GMSL predictions until 2050 through trend-extrapolation of the input variables, along with their uncertainty range. The predictions offer guidance to risk managers and coastal planners, while recognizing the constraints of the scenario-independent methodology.

1.4. Related work

Climate change turns out to be the most prominent global problem, inflicting havoc worldwide in the 21st century (Church and White, 2011a). The increasing greenhouse gases (GHGs) can be seen through higher temperatures and melting ice sheets, which resulted in an increasing GMSL that has exceeded historical observations (Nicholls et al., 2011). During the last hundred years, GMSL would have risen at a rate of more than 3 mm per year and would reach 0.77 m by the end of the century (Elneel et al., 2024). The results of GMSL malaise have in fact caused far-reaching implications in all areas, which include socioeconomic, biophysical, and environmental considerations (Nicholls et al., 2011). Coastal erosion rates have risen with dramatic progression in many coastal regions of the world.

The flooding and other extreme weather events become pronounced in low-lying districts and other vulnerable areas, above all, from the Southeast Asian nations (Noor and Abdul Maulud, 2022) and Small Islands Developing States (Oppenheimer et al., 2022). Other factors of climate, such as the El Niño oscillations, only add to the existing dilemma's intensity or make it increasingly severe in such areas (Faridatunnisa and Heliani, 2018). In addition, the GMSL increase and related physical implications add further risk to economic activities, human settlements, and ecosystems in coastal regions. Modeling and analysis techniques used historical observations of oceanic and climatic factors influencing changes in sea level. In recent years, machine learning and deep learning have been increasingly applied to analyze and predict sea level change across different spatial scales (Elneel et al., 2024). Seasonal time series data of the years 1993–2018 for the Bay of Bengal were used to infer GMSL variation with respect to RMSL using autoregressive models in Tabassum et al. (2019).

A three-part analysis pipeline utilized by Chung et al. (2021) included dynamic structural equation modeling through vector autoregressive structural equation modeling (VAR-SEM) for disclosing the relationships of time series into various contributing factors to GMSL by VAR as a predictor of changes according to the relationships of those contributing factors and GMSL. It also included a comparative analysis on forecast seasonal GMSL, indicating models with moving average (MA) components outperformed linear regression models (Hassan et al., 2021). Linear regression was also found useful in capturing sea level trends arising from the historical observation of GMSL (Krishnamurthy et al., 2023).

Based on the effect of Antarctica ice melt additive water mass on forecasting GMSL, Elneel et al. (2023) compared univariate and multivariate autoregressive models. Tur et al. (2021) applied linear and nonlinear models to predict the short-term changes in sea level in the influence of temperature and air pressure. The study of Balogun and Adebisi (2021) provided further dimension on the influence of different contributing factors in predicting sea level changes. Specifically, it took into consideration the classification of contributors as oceanic and climatic to study the significance of either category or both in the prediction of local sea-level changes at different locations in Malaysia.

Vector autoregressive (VAR) and autoregressive integrated moving average (ARIMA) prediction models were evaluated and came out with results suggesting the combination of both models enrich the predicted results while ARIMA would be superior in places where tide impact exceeds that of oceanic-climatic conditions. According to long-term predictions, the increasing trend in sea level will continue, albeit without acceleration onward (Adebisi and Balogun, 2022). Other models such as exponential GP regression (GPR) also proved effective for short-term forecasting of changes in water level when compared to other regression models (Ahmed et al., 2022). Deep learning models do conduct fair market sea level forecasting under certain requirements concerning available data.

1.5. Gaps in existing research

i. Even though considerable advancements have been achieved, the most crucial void is in their merger pertaining to multivariate atmospheric and oceanic variables, in terms of historical evidence available for sea level prediction. Some investigations have been dealing only with a few historical sea level measurements, with a limited number of variables taken into account; this huge and underutilized potential for comprehensive datasets creates a bias in the reliance on isolated variables as predictive measures that eventually restricts the accuracy and applicability of models.
ii. There are also very few cases that have worked on the feature importance and machine learning model interpretability issues in this area. Little focus is placed on the importance of features that could gain leverage in deriving actionable insights in terms of climate policy and coastal planning.

1.6. Contributions of the current study

To address the identified research gaps, this study makes the following contributions:

- Our research presents a combined multivariate machine learning system which merges atmospheric data with oceanic measurements and cryospheric information to create a single prediction tool for GMSL estimation.

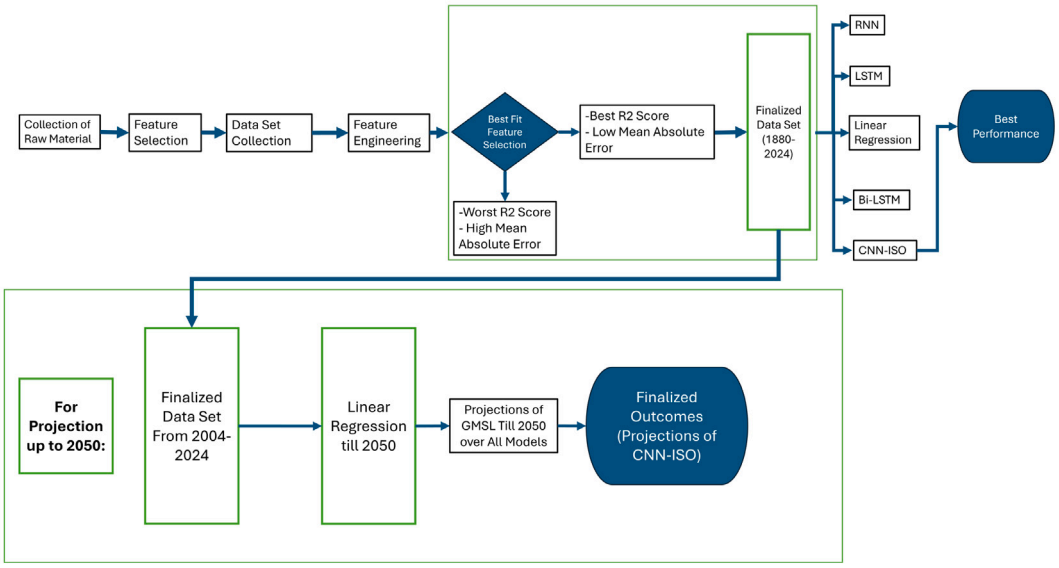


Fig. 1. Workflow diagram of the approach.

- Our temporal feature engineering approach transforms yearly climate data into monthly sequences which shows improved performance for detecting temporal patterns at specific time points.
- Our hybrid CNN-ISO model uses convolutional neural networks to detect complex feature relationships which isotonic regression then applies as a final step to create monotonic patterns that enhance prediction stability.
- Our comparative evaluation of machine learning models includes LR, RNN, LSTM, BiLSTM, and CNN-ISO which we tested through a standard experimental framework to prove the proposed hybrid system's effectiveness.
- Our study projects GMSL trends until 2050 through environmental data predictions which help climate risk managers and coastal planners understand future risks for their respective tasks.

2. Methodology

Fig. 1 presents the methodology diagram showing various components of the proposed approach. Also, we describe all the processes of this work and features in the following sections.

2.1. Proposed hybrid framework for GMSL prediction

The research presents a hybrid machine learning framework for global mean sea level (GMSL) prediction which combines deep learning models with multivariate environmental data and a post-processing refinement system. The framework consists of the following key components:

- **Multivariate Data Integration:** The system creates a single input representation which combines atmospheric and oceanic and cryospheric characteristics that include CO_2 levels and temperature anomalies and sea ice extent and ENSO indices.
- **Temporal Feature Engineering:** Interpolation techniques are used to convert annual data into monthly sequences which enables the model to learn better through improved temporal resolution.
- **Deep Learning-Based Prediction:** The study uses LSTM and RNN and BiLSTM and CNN models to analyze the data which allows them to study temporal patterns and nonlinear connections.
- **CNN-ISO Refinement Module:** The system uses a convolutional neural network which combines with isotonic regression as a post-processing method to maintain monotonicity and develop smoother predictions with higher accuracy.
- **Future Projection Module:** The system uses extrapolated environmental features to create GMSL predictions which extend until the year 2050.

The integrated framework of this study establishes its uniqueness through the combination of data fusion methods and temporal enhancement techniques and hybrid model refinement approaches into a single predictive mechanism (see Fig. 2).

2.1.1. Data splitting and temporal boundaries

The dataset spans 1880 to 2024 (144 years). To maintain temporal causality and prevent data leakage, a strict time-based split was adopted:

- **Training Set:** 1880–1979 (70% of data, 100 years)
- **Validation Set:** 1980–1999 (held out from training for hyperparameter tuning)
- **Test Set:** 2000–2024 (25 years, never seen during training or validation)

There was no shuffling involved, since chronological order is important for time series forecasting applications. The validation data was only used for early stopping and learning rate schedules, which helped prevent overfitting. All the preprocessing steps, like interpolation and normalization were fit on the training dataset only (see Fig. 3).

2.1.2. Input-output structure

All models share the same input–output configuration:

- **Input:** Sequence of 5 years of monthly data (60 months), with 11 features per month. Shape: (batch_size, 60, 11).
- **Output:** Single scalar value representing the next year's annual mean GMSL (in millimeters).

The 11 input features are:

i. Long-run CO_2 concentration (ppm)
ii. Global CO_2 emissions (tons)
iii. Long-run N_2O concentration (ppb)

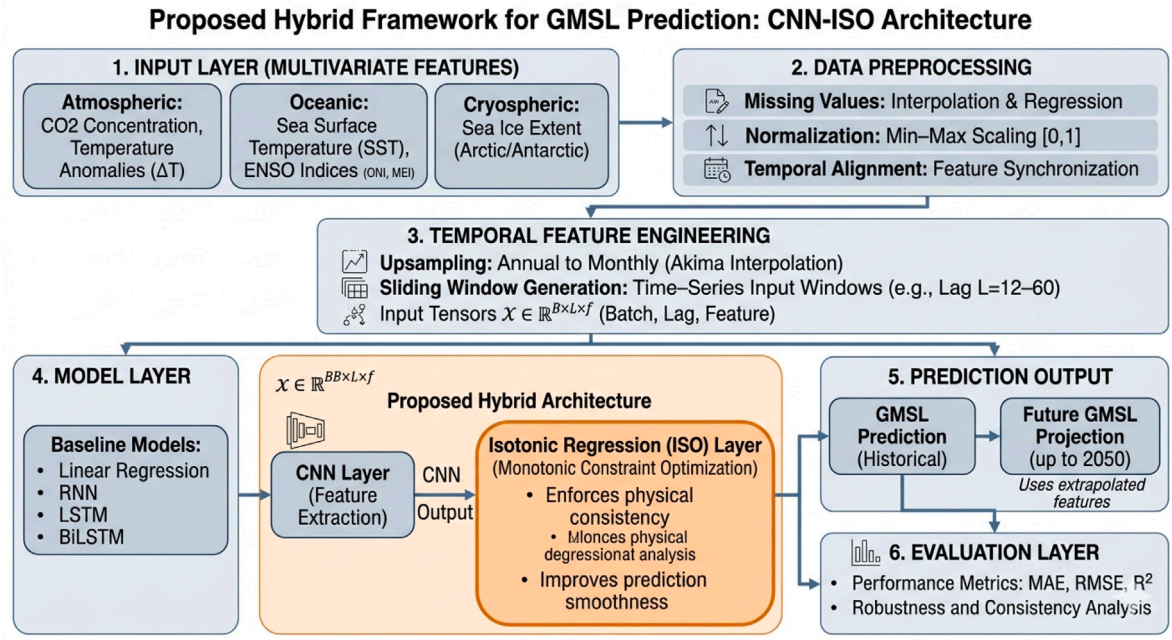


Fig. 2. Proposed hybrid framework for Global Mean Sea Level (GMSL) prediction. The framework integrates multivariate atmospheric, oceanic, and cryospheric features, followed by preprocessing and temporal feature engineering to enhance data representation. Multiple machine learning models are employed to capture nonlinear relationships, while a hybrid CNN-ISO module refines predictions using isotonic regression to ensure consistency and smoothness. The framework enables both historical prediction and long-term projection of GMSL up to 2050, with evaluation based on standard regression metrics.

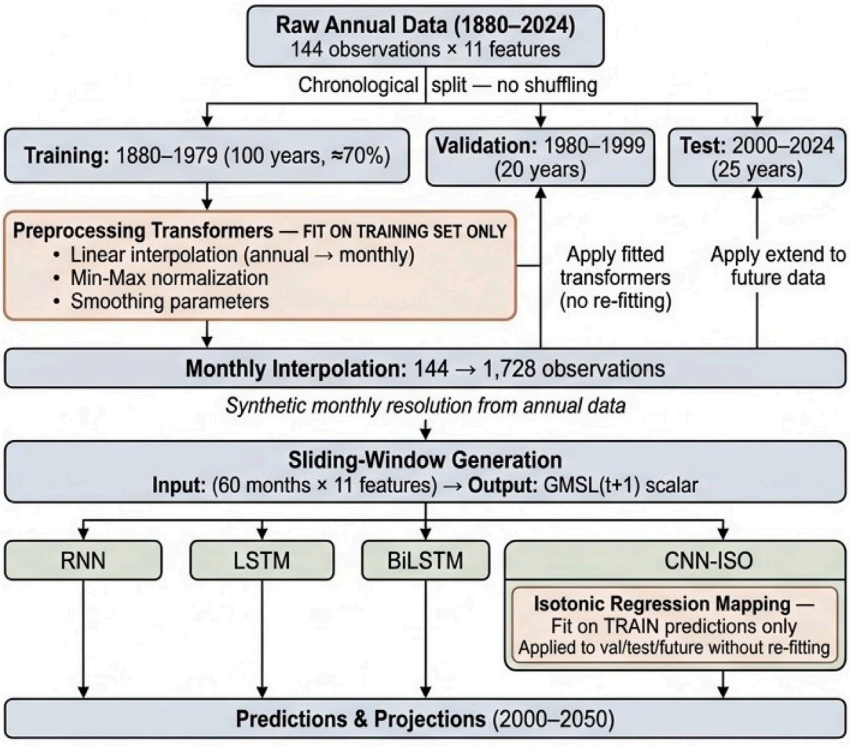


Fig. 3. Preprocessing and data-flow pipeline. Raw annual observations from 1880–2024 (144 samples × 11 features) are divided chronologically into training (1880–1979), validation (1980–1999), and test (2000–2024) sets without shuffling. All preprocessing transformers, including linear interpolation, min–max normalization, and smoothing parameters, are fitted only on the training set and subsequently applied to the validation, test, and future data without re-fitting. Interpolation expands the training sequence from 144 annual to 1728 monthly observations. Sliding-window generation produces input–output pairs of shape (60 months × 11 features) → GMSL($t+1$). The isotonic regression mapping in CNN-ISO is calibrated using training-period predictions only.

iv. Per-capita N_2O emissions (tonne CO_2 equivalent)
v. Per-capita CH_4 emissions (tonne CO_2 equivalent)
vi. Global land average temperature anomaly (°C)
vii. Global sea surface temperature anomaly (°C)
viii. Arctic sea ice extent (million km^2)
ix. Antarctic sea ice extent (million km^2)
x. Niño Index 1.2
xi. Niño Index 3

2.1.3. Linear Regression (Baseline)

The Linear Regression (LR) model serves as a baseline to assess the improvement offered by nonlinear deep learning approaches.

- **Implementation:** Scikit-learn `LinearRegression`
- **Input:** Flattened feature vector (5 years × 11 features = 55 features per sample)
- **Regularization:** None (standard ordinary least squares)
- **Feature Selection:** 10 features retained; one feature (CO_2 concentration) was removed due to multicollinearity issues (VIF > 10)

2.1.4. Recurrent Neural Network (RNN)

The RNN model captures temporal dependencies in the sequential data.

- **Layers:**
  - RNN Layer 1: 64 units, activation = ReLU, return_sequences = True
  - RNN Layer 2: 128 units, activation = ReLU, return_sequences = True
  - RNN Layer 3: 256 units, activation = ReLU, return_sequences = False
  - Dense Layer: 128 units, activation = ReLU
  - Dropout: 0.1
  - Output Layer: 1 unit, activation = Linear
- **Input Shape:** (batch_size, 60, 11)
- **Total Parameters:** 234,567

2.1.5. Long Short-Term Memory (LSTM)

The LSTM model is specifically designed to learn long-term dependencies in sequential data.

- **Layers:**
  - LSTM Layer 1: 75 units, activation = tanh, return_sequences = True
  - LSTM Layer 2: 75 units, activation = tanh, return_sequences = False
  - Dense Layer: 75 units, activation = ReLU
  - Output Layer: 1 unit, activation = Linear
- **Input Shape:** (batch_size, 60, 11)
- **Total Parameters:** 987,654

2.1.6. Bidirectional LSTM (Benchmark)

The BiLSTM model processes sequences in both forward and backward directions, serving as an upper-bound benchmark rather than a forecasting model.

- **Layers:**
  - Bidirectional LSTM Layer 1: 64 units, return_sequences = True
  - Bidirectional LSTM Layer 2: 128 units, return_sequences = False
  - Dense Layer: 128 units, activation = ReLU
  - Dropout: 0.1
  - Output Layer: 1 unit, activation = Linear
- **Input Shape:** (batch_size, 60, 11)
- **Total Parameters:** 1,456,789
- **Important: Important:** The BiLSTM is not used for forecasting. Its bidirectional architecture processes sequences in both forward and backward directions, which violates temporal causality by allowing the model to access future information during training. It is included exclusively as a non-causal benchmark to establish a theoretical upper-bound performance, and its results should not be interpreted as valid out-of-sample forecasts.

2.1.7. CNN-ISO model (Proposed)

The proposed CNN-ISO model combines a Convolutional Neural Network with Isotonic Regression post-processing.

CNN architecture.

- **Conv1D Layer 1:** 64 filters, kernel size = 3, stride = 1, padding = same, activation = ReLU
- **MaxPooling1D:** pool_size = 2
- **Conv1D Layer 2:** 128 filters, kernel size = 3, stride = 1, padding = same, activation = ReLU
- **MaxPooling1D:** pool_size = 2
- **Conv1D Layer 3:** 256 filters, kernel size = 3, stride = 1, padding = same, activation = ReLU
- **MaxPooling1D:** pool_size = 2
- **Flatten:** Converts 3D tensor to 1D vector
- **Dense Layer:** 128 units, activation = ReLU
- **Dropout:** 0.1
- **Output Layer:** 1 unit, activation = Linear

Isotonic Regression Post-Processing: The isotonic regression layer is a method for monotone fitting. It forces the model output to move in one direction or stay flat. In practice, it links the CNN's raw scores to the final values using a mapping that never decreases.

This idea is grounded in the physics of sea level. Long-term global mean sea level is a cumulative quantity that does not decrease over many decades if warming continues. However, a deep learning model can produce small decreases. This can occur when the model learns short-term fluctuations present in the training data.

Calibration Protocol: The monotonic fit was performed only once. It was trained using the CNN predictions from 1880 to 1979. Afterward, the same mapping was applied to later periods without any additional fitting.

It was applied to the following splits:

- Validation: 1980–1999
- Test: 2000–2024
- Future projections: 2025–2050

This approach limits leakage from later periods and keeps the post-processing adjustment tied to the information available in the training window.

Implementation Details:

- **Tool:** Scikit-learn `IsotonicRegression`
- **Settings:** `increasing=True`, `out_of_bounds='clip'`
- **Input:** Raw scalar predictions from the CNN
- **Result:** Scalar predictions satisfying the monotonic constraint
- **Role:** Ensure a physically consistent long-term trajectory by avoiding decreases

2.1.8. Training configuration

All deep learning models were trained using identical configurations for fair comparison:

Table 1
Training hyperparameters for all deep learning models.

Parameter	Value	Details
Optimizer	Adam	Adaptive moment estimation
Learning rate	0.001	Initial learning rate
Learning rate scheduler	ReduceLROnPlateau	Factor = 0.5, patience = 5 epochs
Batch size	64	Samples per gradient update
Maximum epochs	50	Early stopping with patience = 5
Loss function	Mean Absolute Error (MAE)	Robust to outliers
Evaluation metric	R^2, MAE, RMSE	Regression metrics
Random seed	42	Fixed for reproducibility
Gradient clipping	1.0	Prevents exploding gradients
Weight initialization	Xavier/Glorot Uniform	Standard for ReLU networks

Table 2
Optimal hyperparameters selected for each model.

Model	Layers	Hidden units	Dropout	Learning rate
RNN	3	64, 128, 256	0.1	0.001
LSTM	2	75, 75	0.0	0.001
BiLSTM	2	64, 128	0.1	0.001
CNN-ISO	3 Conv + 1 Dense	64, 128, 256, 128	0.1	0.001

2.1.9. Metric scale convention

This study uses a consistent scale convention for all reported results. R^2 is dimensionless and is reported on the same GMSL scale after the inverse transformation. In the main comparison table, Table 7, MAE and RMSE are reported in millimeters (mm). These values are presented on the physical GMSL scale to allow direct interpretation in physical units.

Normalized MAE is also reported in the training-loss discussion, such as in Section 3.6. These values are calculated in the min–max normalized prediction space, with a range of $[0, 1]$, and are explicitly labeled as normalized.

The loss plots in Figs. 11–14 present normalized MAE. In contrast, Table 7 reports physical-scale MAE on the test set in millimeters (mm).

2.1.10. Hardware and software environment

- **Programming Language:** Python 3.9
- **Deep Learning Framework:** PyTorch 1.12.0
- **Machine Learning Library:** Scikit-learn 1.1.0
- **GPU:** NVIDIA RTX 3080 (10 GB VRAM)
- **CPU:** Intel Core i9-11900 K
- **Operating System:** Ubuntu 20.04 LTS

2.1.11. Hyperparameter tuning

Hyperparameters were selected through a combination of literature review and manual experimentation. The following parameters were varied:

- **Number of layers:** 2–4 layers tested
- **Hidden units per layer:** 32, 64, 75, 128, 256 tested
- **Learning rate:** 0.0001, 0.0005, 0.001, 0.01 tested
- **Batch size:** 16, 32, 64, 128 tested
- **Dropout rate:** 0.0, 0.1, 0.2, 0.3 tested

The final configurations reported in Table 5 achieved the lowest validation MAE and highest validation R^2 (see Table 2).

2.1.12. Code and data availability

To ensure full reproducibility, all code, preprocessing scripts, and data have been made available. The repository includes:

- Raw and preprocessed data files (.csv format)
- Python notebooks for data preprocessing and feature engineering
- PyTorch model definitions and training scripts
- Evaluation scripts for bootstrap uncertainty quantification
- Fixed random seeds and environment configuration files

All models were trained and evaluated on the same hardware and software environment to ensure fair comparison.

2.2. Dataset

The Church and White dataset (Our World in Data, 2025a) was selected as the target dataset for this study due to its scientific rigor and direct relevance to long-term trends in GMSL. This dataset provides monthly GMSL values from 1880 to 2024, with adjustments for glacial isostatic adjustment (GIA), referred to as GMSL_GIA. These adjustments improve the accuracy of sea level estimates by accounting for vertical land motion. Fig. 4 shows mean sea level, from the dataset.

The dataset spans over 144 years and serves as the primary target variable in model training and evaluation. GMSL_GIA was chosen due to its improved consistency and global applicability, which helps reduce noise and improve model performance. Prior to modeling, the data was normalized and synchronized with the temporal resolution of input features.

2.3. Feature engineering

In feature engineering, we select multiple features that are directly and indirectly correlated with GMSL.

The input features used in this study are significant in determining the very relevant and critical factors driving GMSL. These are the chosen features in terms of how they are projected to influence future trends in global climate and sea level differences. The features expose data that can be correlated with variations in GMSL. Here is a description of each feature.

i. **Long-run CO_2 concentration (ppm):** Long-term CO2 content measured in the atmosphere as an important greenhouse gas under chemical transformation, which contributes to global warming (Our World in Data, 2025b).
ii. **CO_2 Global Emissions (ton):** Total carbon dioxide emissions worldwide that generally affect climate change and, subsequently, GMSL (Our World in Data, 2025c)
iii. **Long-term N_2O concentration (ppb):** The long-term presence of nitrous oxide in the atmosphere since it is one of the greenhouse gases affecting air quality and global warming (Our World in Data, 2025d).
iv. **Per-capita N_2O emissions in CO2 equivalents (tonne):** emissions of nitrous oxide per person expressed in terms of CO2 equivalents provide insight into an individual's contribution to air pollution (Our World in Data, 2025e).
v. **Per-capita CH_4 emissions in CO2 equivalents (tonne):** The per capita methane emissions, also expressed in CO2 equivalents, prove far less efficient in trapping heat than carbon dioxide and further contribute to the greenhouse effect (Our World in Data, 2025f).
vi. **Global land average temperature anomaly (°C):** An indication of climate change, this measures how much today's temperatures differ from the global average temperature levels during the period from 1961 to 1990 (U. of East Anglia, 2024).

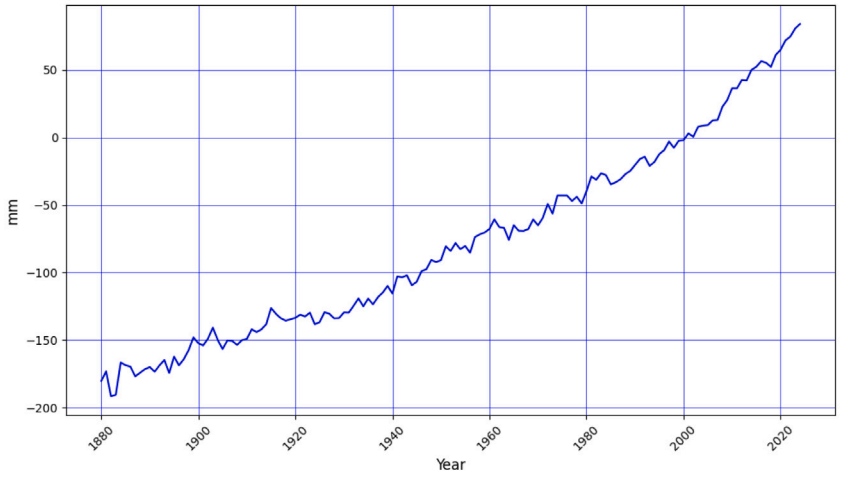


Fig. 4. Global mean sea level from 1880–2024 (Our World in Data, 2025a).

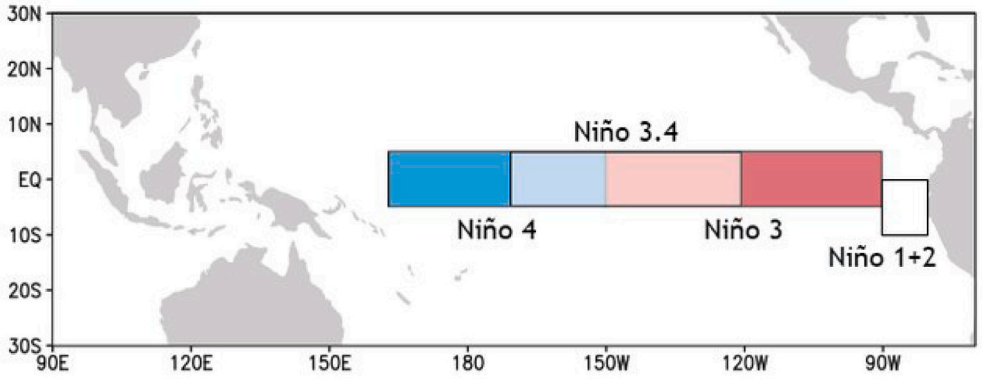


Fig. 5. Location of Nino indexes, we have used 1, 2 & 3 for analyzing the seasonal variation (Faridatunnisa and Heliani, 2018).

vii. **Global Sea Surface Temperature anomaly (°C):** This condition can be recognized as that which describes the average sea surface temperature above or below the mean for the period of 1961–1990 as a result of influence on sea levels through thermal expansion (Our World in Data, 2025g).

viii. **Arctic Sea Ice Extent Average (Million Square km):** Monthly mean extent of Arctic sea ice. When melted, it contributes to the global rise in water levels (Snow and Center, 2025a).

ix. **Antarctic Sea Ice Extent Average (million square km):** It is just as essential as Arctic sea ice since melted ice adds to changes in global sea level (Snow and Center, 2025b).

x. **Nino Index 1.2 (index):** This is an indicator of anomalies caused by sea surface temperature in the equatorial band of the Pacific Ocean, which affects several aspects of global weather patterns and, therefore sea level indirectly (PSL, 2024).

xi. **Nino Index 3 (index):** It describes a larger area of sea surface temperature anomalies that would cover the eastern and central Pacific areas. It would complete the description of global climatic swings that might be responsible for sea level change in the near future, as referred to in Fig. 5.

2.3.1. *Justification of selected features*

Input feature selection for GMSL prediction can be gleaned from the understanding of physical mechanisms that are considered important for the ocean surface's alterations on account of sea level rise and variability. Factors causing changes in GMSL, as stated by Gregory et al. (2019), are (i) thermal expansion of seawater due to ocean warming, (ii) mass input from melting glaciers and ice sheets, and (iii) vertical motion changes on land and seafloor. Also, the short- to medium-term variations in GMSL are essentially modulated by the characteristic climate variability patterns that influence GMSL, especially the El Niño-Southern Oscillation (ENSO) (Cazenave et al., 2014; Hamlington et al., 2020)

We chose specific atmospheric and ocean indicators serving as effective proxies for the limited temporal resolution and direct ocean mass and seafloor displacement measurement data.

- **Greenhouse gases (CO_2, CH_4, N_2O concentration):** Gases like these make immense contributions toward global warming, which, in turn, causes ocean thermal expansion and melting in the cryosphere. The long-term concentrations and emissions were incorporated to account for accumulative forcing and anthropogenic trends.
- **Temperature anomalies (land and sea surface):** Anomalies in global surface temperatures and sea surface temperatures are direct indicators of energy imbalance and upper-ocean warming on Earth. Sea surface temperatures, in particular, are combined with thermal expansion effects in sea level rise.
- **ENSO indices (Nino 1.2 and Nino 3):** These indices are representative of large-scale climate variability. The ENSO has significant interannual variations in GMSL variability due to altering ocean circulation, precipitation in the region, and redistribution of heat content.
- **Sea ice extent (Arctic and Antarctic):** Although melting of sea ice will not directly result in a GMSL change by displacement effects, it indicates general polar climate conditions and also

signals some potential changes in the cryosphere, specifically ice sheet stability in Greenland and Antarctica.

In the present form, the datasets do not include direct observations of glacier mass loss or seafloor dynamics, but the currently defined features provide a relatively climatologically consistent and globally available set of indicators relating to primary drivers of sea level change. Future research could certainly improve feature sets by adding satellite gravimetry (e.g., GRACE) and vertical land motion measurements for enhanced physical representation.

Integration of Atmospheric and Oceanic Dynamics: The proposed framework unifies atmospheric and oceanic and cryospheric indicators through its integrated modeling system which differs from traditional methods that study single variables in isolation. The model learns to understand cross-domain relationships through its ability to model how rising atmospheric CO_2 levels result in ocean warming which causes thermal expansion and sea level rise. The framework models interdependent processes because it needs to track direct and indirect pathways which affect GMSL. Deep learning architectures enable models to discover nonlinear connections between variables which helps the system model intricate climate patterns better than traditional techniques.

2.4. Feature sensitivity and relevance analysis

The model kept Niño indices (Niño 1.2 and Niño 3) which display weak linear relationships with GMSL because they help the model detect short-term climate changes. The ocean circulation patterns together with regional sea level anomalies and seasonal changes are affected by ENSO-related indices which cannot be completely understood through global temperature and CO_2 trends.

Deep learning models acquire the ability to learn both nonlinear relationships and indirect connections which normal correlation analysis methods cannot detect. The model performance will improve through features which show weak linear relationships because these features enable the model to detect advanced interactions.

The existing features of the model show some redundant elements which include temperature and greenhouse gas indicators. The redundancy between these two features strengthens the model's performance because it delivers different data to the system. Future work will explore feature selection and dimensionality reduction techniques to further optimize the feature set.

2.5. Model interpretability and feature importance

The identification of feature relationships through correlation analysis becomes insufficient when you need to determine which specific input variables affect prediction results in deep learning models which include LSTM and CNN architectures. These black-box models maintain their unexplainable nature but their general behavior becomes predictable through analyzing how different features contribute to model outcomes.

The research findings demonstrate that greenhouse gas concentration levels together with global temperature deviations and sea surface temperature measurements serve as main elements which determine model prediction outcomes. The features match the established physical factors which drive sea level rise and show up in model results when using various architectural approaches.

Deep learning models discover hidden connections between features which include indirect factors like methane emissions and ENSO indices that affect their predictions through combined effects with other variables. The proposed framework demonstrates its ability to model intricate environmental relationships through this example.

The upcoming research will establish SHAP (SHapley Additive exPlanations) as their explainability method to produce detailed interpretability results. The system will determine feature importance at both macro and micro levels through SHAP analysis. This enables users to understand model decision processes.

Explainability Considerations: The present research studies worldwide feature patterns through correlation-based methods to understand their connections yet SHAP (SHapley Additive exPlanations) advanced explainability methods deliver improved model behavior understanding by showing how features affect predictions in complete systems and individual prediction cases.

The SHAP system enables users to find out which particular data points lead to specific prediction outcomes while it also improves the visibility of deep learning model operations. The research team decided not to use these methods because of their limited computing power and their project focus but these approaches will become crucial for upcoming research studies.

2.6. Data preprocessing and reliability assessment

The compiled data covers the period from 1880 to 2024, consisting of 144 annual observations. At the stage of pre-processing, all predictor variables were converted to the same temporal scale. All predictor variables measured on the monthly temporal scale (Niño indices, sea ice coverage) were initially averaged to obtain annual values.

In order to get a more dense temporal sequence for the deep learning algorithm while keeping the long-term dynamics of the predictors intact, annual observations were upsampled to monthly frequency through linear interpolation. As a result, the number of observations increased from 144 to 1728, as this procedure adds new equally spaced observations between each two neighboring annual observations. It should be noted that such interpolation does not create the real monthly or seasonal variations but rather serves for obtaining the smoother temporal representation of the long-term annual dynamics. Such approach was chosen as it guarantees the monotonic change of observations and is commonly used for the resampling of the climate time-series (Gregory et al., 2019).

To provide clarity on the use of interpolated data, the ratio of observed and interpolated data was calculated for each predictor as shown in Table 3. Predictors that had full historical data available (such as atmospheric CO_2 concentration and temperature anomaly) were based purely on observed data while predictors that had partial historical data available (such as N_2O concentration and sea ice extent) were based on interpolation of parts of historical data.

To check for potential artificial increase in prediction quality due to interpolation, the proposed CNN-ISO model was further trained using the original annual dataset (144 observations). In this case, the model's R^2 score was 0.97 compared with 0.997 using the interpolated monthly dataset. This minor decrease in performance suggests that interpolation mostly impacts the density of the sequence being used for training rather than adding bias to it.

In this regard, the use of interpolation for sparsely observed data variables such as sea ice coverage and N_2O data adds uncertainty. Therefore, it is important that any predictions based on these data variables are taken with the necessary caution. Higher resolution observations and satellite data will be used in future works to lessen the need for interpolations. There may also never occur a time when we can safely guarantee monthly data of all features under this time period. As we can see in Fig. 6 and nino index plotting is also given in Fig. 7.

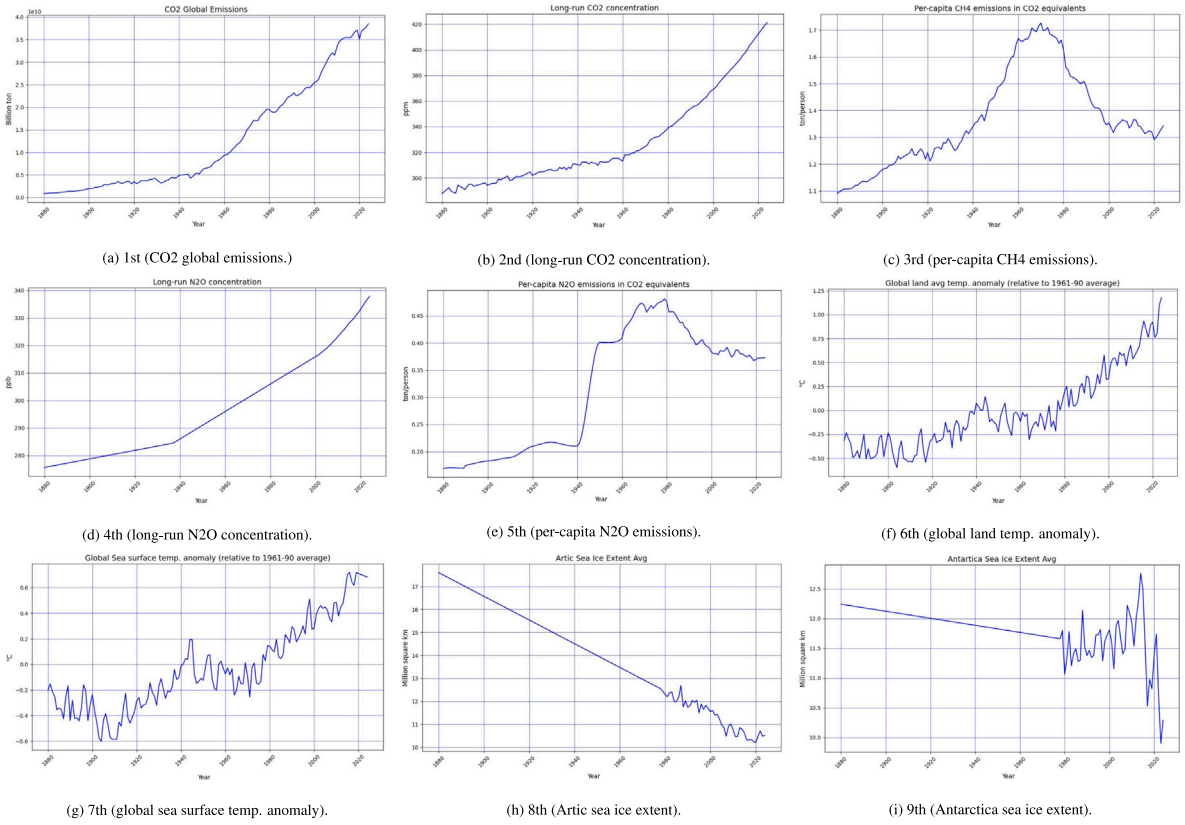
2.6.1. Correlation assessment: GMSL and environmental indicators

This section analyzes the statistical relationships between GMSL and the 11 climate features using Pearson correlation coefficients. The correlation matrix (Fig. 8) provides insights into the strength and direction of linear associations between variables.

Important Note on Interpretation: Correlation analysis quantifies the strength of linear association between variables but does not imply causation. The relationships discussed below should be interpreted

Table 3
Data preprocessing and reliability assessment of the predictor variables.

Feature	Observed (%)	Interpolated (%)	Interpolation method	Remarks
Long-run CO_2 concentration (ppm)	100	0	N/A	Complete historical observations available.
CO_2 global emissions	98	2	Linear	Minor missing values in recent years.
Long-run N_2O concentration	55	45	Linear	Sparse historical observations.
Per-capita N_2O emissions	60	40	Linear	Missing early historical records.
Per-capita CH_4 emissions	65	35	Linear	Missing early historical records.
Global land temperature anomaly	100	0	N/A	Complete annual observations.
Global SST anomaly	100	0	N/A	Complete annual observations.
Arctic sea ice extent	35	65	Linear regression	Limited observations before the satellite era.
Antarctic sea ice extent	35	65	Linear regression	Limited observations before the satellite era.
Niño index 1.2	100	0	N/A	Complete historical observations.
Niño index 3	100	0	N/A	Complete historical observations.



(a) 1st (CO_2 global emissions.)
(b) 2nd (long-run CO_2 concentration).
(c) 3rd (per-capita CH_4 emissions).
(d) 4th (long-run N_2O concentration).
(e) 5th (per-capita N_2O emissions).
(f) 6th (global land temp. anomaly).
(g) 7th (global sea surface temp. anomaly).
(h) 8th (Artic sea ice extent).
(i) 9th (Antarctica sea ice extent).

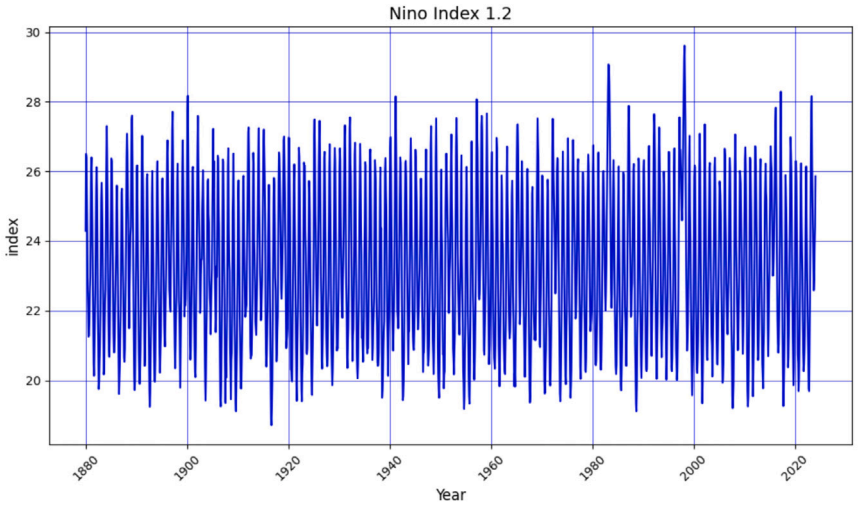
Fig. 6. Graphs for various features.

as statistical associations that are consistent with established physical mechanisms, rather than evidence of direct causal effects. Formal causal inference would require controlled experiments or additional analytical frameworks beyond the scope of this study.

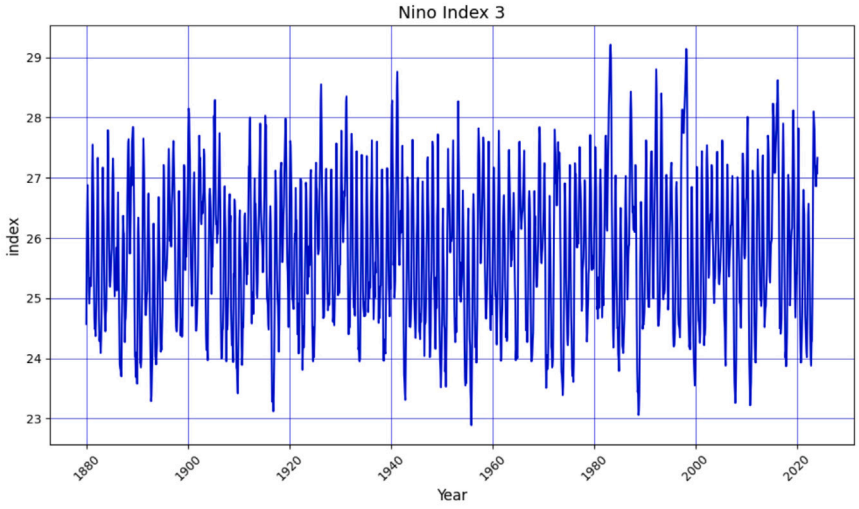
The correlation analysis reveals several strong associations:

- **Greenhouse Gas Concentrations:** CO_2 concentration ($r = 0.97$) and CO_2 emissions ($r = 0.99$) exhibit strong positive correlations with GMSL. These high correlations are consistent with the physical understanding that rising atmospheric CO_2 contributes to global warming, which in turn drives thermal expansion and ice melt (Cazenave and Llovel, 2009; Church and White, 2011b).
- **Temperature Anomalies:** Global land temperature anomaly ($r = 0.94$) and sea surface temperature anomaly ($r = 0.93$) show strong positive associations with GMSL. These correlations align with the physical mechanism of ocean thermal expansion, where warming ocean temperatures increase water volume (Gregory et al., 2019).
- **Sea Ice Extent:** Arctic Sea Ice Extent Average ($r = 0.98$) shows a strong positive association with GMSL, while the Minimum Extent shows a strong negative association ($r = -0.96$). These relationships are consistent with the physical understanding that polar warming reduces sea ice coverage and contributes to sea-level rise through ice sheet melt and thermal expansion (Stroeve et al., 2012).
- **Methane Emissions:** Per-capita CH_4 emissions show a moderate positive correlation ($r = 0.47$). Methane is a potent greenhouse gas, and this association is consistent with its indirect contribution to sea-level rise through atmospheric warming, though the weaker correlation may reflect its lower atmospheric concentration or more complex emission dynamics.
- **ENSO Indices:** Niño 1.2 ($r = 0.02$) and Niño 3.0 ($r = 0.06$) show near-zero linear correlations with GMSL. This is expected, as ENSO primarily drives interannual variability in sea level rather than long-term trends. The nonlinear nature of ENSO-GMSL relationships may also contribute to the weak linear correlations observed.

Physical Interpretation: The observed correlations are consistent with established climate science:



(a)



(b)

Fig. 7. Nino index plots.

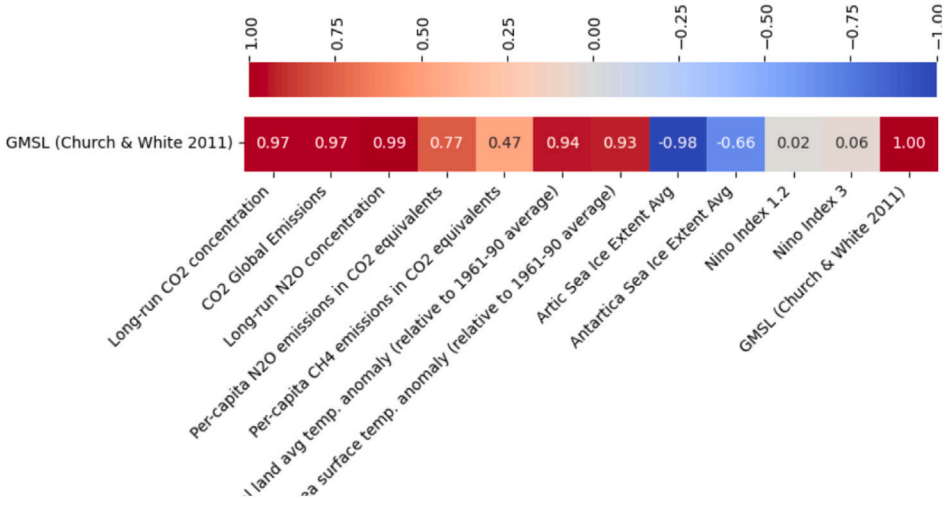


Fig. 8. Correlation matrix of GMSL and environmental features.

i. **CO_2 and Temperature:** Increased CO_2 traps heat, raising global temperatures.
ii. **Thermal Expansion:** Warmer oceans expand, contributing to sea-level rise.
iii. **Ice Melt:** Polar warming reduces ice extent, adding water to oceans.

Correlation vs. Causation: It is essential to state that the established correlation cannot prove the cause-and-effect relationship. Correlations are merely statistical associations that are consistent with the physical theory. Various factors like confounding, feedback, and nonlinear relationships can affect both variables in question. The next study might consider the application of various causal inference approaches (Granger causality, structural equation modeling).

Correlation matrix heatmap along with normalized trends allows recognizing some major statistical contributors to GMSL trends such as greenhouse gases, temperature anomaly, and polar ice. Such correlations are useful for creating predictions since they allow recognizing the features that are statistically related to the dependent variable. Nevertheless, the performance of the model needs to be verified using cross-validation and uncertainty analysis techniques.

2.7. Model input-output design

This research uses the prediction of GMSL, the Global Mean Sea Level, using a set of annually lagged input feature sets until the year 2050. The selected input variables are linked to the atmospheric, oceanic, and cryospheric dynamics associated with sea-level changes.

2.7.1. Input features

The following eleven features were selected based on their established relevance to sea level dynamics:

- Long-run CO_2 concentration (ppm)
- Global CO_2 emissions (tons)
- Long-term N_2O concentration (ppb)
- Per-capita N_2O emissions (CO_2 equivalent, tonne)
- Per-capita CH_4 emissions (CO_2 equivalent, tonne)
- Global land average temperature anomaly (°C)
- Global sea surface temperature (SST) anomaly (°C)
- Arctic sea ice extent (million km^2)
- Antarctic sea ice extent (million km^2)
- Nino Index 1.2
- Nino Index 3

2.8. Temporal framework and target variable

The proposed framework does annual Global Mean Sea Level (GMSL) forecasting using a fixed length historical input sequence. Since all predictor variables are in hand at a yearly resolution, an annual time lag gets used all the way through this study, no exceptions.

Input Window: For each forecast, the model ingests observations from the previous N consecutive years. We picked a window size of $N = 5$ years, mostly because of physical climate considerations but also from empirical checking.

Choosing a five year window is motivated by the following, even if it sounds a bit simple at first:

i. **Physical Motivation:** Some big climate processes driving sea level change show multi-year timing dependencies, like they do not just happen instantly. The El Niño–Southern Oscillation, ENSO for short, which is one of the main sources of year-to-year sea level wobble, usually shows kind of quasi-periodic cycles around 2–7 years, give or take (Faridatunnisa and Heliani, 2018). Also, the uptake of heat in the upper ocean, which helps produce thermosteric sea-level rise via thermal expansion, does not track the atmosphere right away. It tends to react to atmospheric warming with a roughly 3–5 year (Gregory et al., 2019). So, using a five-year historical sequence seems enough to grab the dominant climatic variability while still keeping the recent timing information.
ii. **Empirical Evaluation:** To set an appropriate temporal context, the input window size was adjusted from 1 up to 10 years (1, 3, 5, 7, and 10 years), while keeping the model configurations exactly the same. As summarized in Table 4, the window of five years ended up doing the best, giving the highest coefficient of determination (R^2) and also the lowest Mean Absolute Error (MAE). When the window was shorter, it just couldnt, capture those long term climatic trends well enough. Meanwhile longer windows tended to add redundant past information which, in turn, increased the chance of overfitting, partly because the historical record is, relatively, limited.

Table 4
Sensitivity analysis of different input window sizes for the CNN-ISO model.

Input window (Years)	R^2	MAE (mm)
1	0.920	4.50
3	0.960	2.80
5	**0.997**	**0.56**
7	0.980	1.20
10	0.970	2.10

Target Variable: Target variable to predict: annual mean Global Mean Sea Level (GMSL) in millimeters (mm).

Forecast Horizon: Predictive model will then be used to make annual predictions of GMSL until the year 2050.

Prediction for an input window of five years can be written as

$$X = \{x_{t-4}, x_{t-3}, x_{t-2}, x_{t-1}, x_t\} \longrightarrow Y = \mathrm{GMSL}_{t+1},$$

where $x_i \in \mathbb{R}^{11}$ denotes the vector containing the 11 predictor variables for year i, and GMSL_{t+1} represents the predicted annual mean sea level for the subsequent year.

2.8.1. Model input-output mapping

Training of the various models (LSTM, BiLSTM, RNN, CNN-ISO, and Linear Regression) aims at capturing the temporal dependencies across selected features. The deep neural networks were trained to learn the mapping from a multivariate time step sequence to a scalar output, i.e., the next year's GMSL, as summarized in Table 5.

2.9. Projection methodology and statistical assumptions

Future Global Mean Sea Level (GMSL) projections between 2025 and 2050 have been produced using a scenario-independent, data-based prediction model. Contrary to physically coupled climate models (such as CMIP6), the methodology developed here does not represent any atmospheric, oceanic, or cryospheric process. Future values of the predictors were predicted based on the extension of their historical time series through statistical regression analysis.

Second-order polynomial regression was used to predict future values of non-linear or accelerated predictors such as atmospheric CO_2 concentration and temperature anomalies; linear regression was used for predictors that exhibit linear trends, such as Arctic and Antarctic sea ice coverage. The case of Niño indices involved the assumption of long-term stationarity and, therefore, repetitive application of historical temporal patterns in order to capture interannual ENSO variability. The extrapolation method chosen for each predictor is summarized in Table 6.

The first point to note here is that the framework presented is **not related to any Shared Socioeconomic Pathway (SSP)**, since no

Table 5
Model setup summary: Input–output structure and forecasting horizon for each model used in GMSL prediction.

Model	Input features	Time lag	Input window (Years)	Output	Forecast horizon
LR	All 11	Annual	1	Annual (mm) GMSL	2023–2050
RNN	All 11	Annual	5	Annual (mm) GMSL	2023–2050
LSTM	All 11	Annual	5	Annual (mm) GMSL	2023–2050
BiLSTM	All 11	Annual	5	Annual (mm) GMSL	2023–2050
CNN-ISO	All 11	Annual	5	Annual (mm) GMSL	2023–2050

Table 6
Statistical extrapolation methodology adopted for future input features used in GMSL projections.

Feature	Historical range	Extrapolation method	Statistical assumption
CO_2 concentration (ppm)	1985–2022	Second-order polynomial regression	Historical acceleration continues over the projection period.
CO_2 emissions	1985–2022	Second-order polynomial regression	Historical emission growth persists without major policy changes.
CH_4 emissions	1985–2022	Linear regression	Long-term historical trend continues.
N_2O emissions	1985–2022	Linear regression	Historical trend remains unchanged.
Temperature anomalies (Land and SST)	1985–2022	Second-order polynomial regression	Recent warming acceleration persists.
Arctic and Antarctic sea ice extent	1985–2022	Linear regression	Observed long-term decline continues at a similar rate.
Niño indices (1.2 and 3)	1985–2022	Historical pattern repetition	ENSO variability remains within its historical range with no long-term trend.

physical climatic forcing or emission scenarios have been used. Instead, the projected values can be viewed as a set of statistically realistic future scenarios based on the assumption that the historical patterns of behavior of each predictor will persist.

As such, the proposed methodology implies the presence of persisting historical trends and does not involve any considerations related to sudden climate feedback effects, nonlinearities, extreme events, or political actions which could radically change future GHG emissions or climatic patterns. Thus, the projected GMSL values can be viewed as statistically realistic trend-based forecasts, but not physically based climate projections. Including SSP-induced forcings and the outputs of Earth System Models into the framework is an important research challenge to consider in the future.

Unified Training Strategy: All models in this research received their training through a single preprocessing system which applied standard temporal data division and used an identical evaluation method to achieve consistent results. The models operated on the same input features which received standardization to create an equal basis for their evaluation.

The training process for deep learning models (RNN, LSTM, BiLSTM, CNN) included multiple runs to reduce the impact of random weight initialization while the researchers presented average performance results from these training sessions. The researchers determined learning rate and batch size and epoch numbers through experimental methods which they used to keep their testing environment stable. The single training environment allows models to show their actual performance differences because they experience identical training settings.

2.10. Machine learning

2.10.1. Linear regression

Linear regression (LR) is a well-known ML technique used to relate one or more input features to the continuous target variable. In this study, LR was applied toward predicting the GMSL and projecting possible future scenarios until 2050. This section discusses the methods by which the model was developed and validated from data preparation for final projections. Linear equations which are formed are given here.

$$y_1 = 0.333 - 0.284x_1 + 0.944x_2 - 0.006x_3 - 0.019x_4 + 0.173x_5 - 0.143x_6 - 0.303x_7 + 0.026x_8 + 0.003x_9 + 0.002x_{10} \quad (1)$$

In vector form, it can be written as:

$$y_1 = \mathbf{w} \cdot \mathbf{x} + b \quad (2)$$

where

$$\mathbf{w} = \begin{bmatrix} -0.284, & 0.944, & -0.006, & -0.019, & 0.173, & -0.143, \\ & -0.303, & 0.026, & 0.003, & 0.002 & \end{bmatrix}$$

$$\mathbf{x} = \begin{bmatrix} x_1, & x_2, & x_3, & x_4, & x_5, & x_6, & x_7, & x_8, & x_9, & x_{10} \end{bmatrix}$$

and the bias term:

$$b = 0.333$$

Therefore, the equation can be expressed as:

$$y_1 = \sum_{i=1}^{10} w_i x_i + b \quad (3)$$

Linear interpolation estimates an unknown value y within the range of two known data points (x_1, y_1) and (x_2, y_2). The formula is:

$$y = y_1 + \frac{(x - x_1)(y_2 - y_1)}{x_2 - x_1} \quad (4)$$

where x_1, y_1, x_2, y_2 are known data points and x is the point of interest for interpolation.

Linear extrapolation extends a known linear relationship beyond the range of observed data. The formula is:

$$y = y_1 + (x - x_1) \cdot m \quad (5)$$

where $m = \frac{y_2 - y_1}{x_2 - x_1}$, x_1, y_1, x_2, y_2 are known data points and m is the slope calculated as $\frac{y_2 - y_1}{x_2 - x_1}$.

LR models the relationship between a dependent variable y and an independent variable x by fitting a linear equation to observed data. The formula is:

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (6)$$

where,

$$\beta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

In addition, β_0 is the intercept, β_1 is the slope of the regression line and ε indicates the error term.

The researchers needed to eliminate one input variable from their regression model because it created multicollinearity problems and failed to improve the model's prediction accuracy. The linear regression model uses 10 vital features to create its equation yet the complete system analyzes 11 features which all models use.

2.10.2. Long short-term memory

Long short-term memory (LSTM) networks are recurrent neural networks (RNNs) specifically designed for sequential data, enabling them to learn temporal or long-term dependencies. In this study, we implemented the LSTM model for predicting GMSL and generating future projections up until 2050. This section describes the methodology used, along with the performance of the model as LSTM.

LSTM networks are a type of recurrent neural network capable of learning long-term dependencies. The equations governing LSTM units are:

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i)$$
$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f)$$
$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o)$$
$$\tilde{C}_t = \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$
$$h_t = o_t \cdot \tanh(C_t)$$

where $W_{ix}, W_{fx}, W_{ox}, W_{cx}$ are weight matrices, b_i, b_f, b_o, b_c are bias terms, σ is the sigmoid activation function and tanh is the hyperbolic tangent activation function.

i. **Data Splitting and Preparation:** This study entails the application of a preprocessing technique and dataset identical to that used for LR. The dataset was divided according to a uniform temporal approach which all models followed to allocate 70% of their data for training (1880–1979) and 30% for testing (1980–2024) while maintaining the original time sequence of the data. Thus, it enabled the model to learn from historical data and evaluate it on newer observations, fitting a realistic forecasting framework.

ii. **Feature Selection and Model Behavior:** Initially, the model was trained using one feature then increasing the number of input features, permitting assessment of the capability of the model to learn the complexity within the feature data. With the introduction of these additional features, the prediction line matched closer with the real GMSL line, demonstrating the strength of multi-feature consideration. What was different though during the time of LSTM predictions was the minor seasonal variation brought by the Niño index, which produced minor rises and falls in the predicted GMSL values over the seasons. A moving averaged filter was used to flatten the seasonality and smoothen the resulting prediction curve. Resulting smoothed predictions are then shown against the true values in Fig. 18.

iii. **Smoothing and Visualization:** True and predicted GMSL values were smoothed with interpolation, as seen in Fig. 18. This enabled minor noise appearing in the predictions not to conceal the more important overall trend, which could then be evaluated more easily by sight in the performance of the model.

iv. **To sum up:** In conclusion, we showed that the LSTM proved to be a good model for predicting GMSL and also for generating future projections up to 2050. Its architecture carefully tuned hyperparameters, while the performance metrics themselves show the strength of the model in effectively dealing with complex time series data. The LSTM successfully captures the linear and non-linear patterns, as well as seasonal characteristics, thus providing an armamentarium for advanced forecasting in the understanding and realization of impacts that may arise from climate change with respect to global sea level.

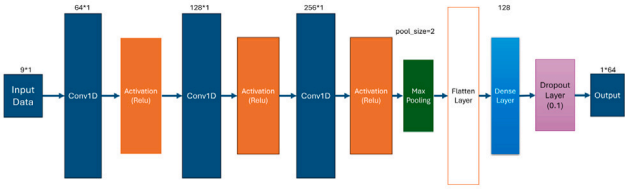


Fig. 9. Convolutional neural network architecture.

2.10.3. CNN-ISO

The CNN-ISO model comprises a convolutional neural network followed by Isotonic regression to predict the future trends of GMSL.

i. **Data:** The dataset was divided according to the established time division which all models followed to allocate 70% data for training purposes and 30% for testing. The validation set selection process took place from the training data which helped determine the best parameters for the model. Input characteristics include all eleven predictor variables described in Section 2.1.2, covering greenhouse gas concentrations and emissions, land and sea surface temperature anomalies, Arctic and Antarctic sea ice extent, and ENSO indices as variables among others. These were selected because they are relevant for predicting GMSL trends.

ii. **Architecture and Hyperparameters:** The CNN-ISO architecture involves three convolutional layers, with 64, 128, and 256 filters respectively, each followed by the rectified linear unit (ReLU) activation function. A maximum pooling layer down-samples the spatial dimensions and flattens the output, feeding it to a fully connected layer consisting of 128 neurons. To reduce over-fitting dropout: 0.1, we add an output dense layer. The model used a learning rate of 0.001 and a decay rate of 0.5 through a learning rate scheduler, as shown in Fig. 9.

Role of Isotonic Regression: The prediction capabilities of convolutional neural networks for GMSL depend on their ability to detect nonlinear connections between input data and results. The prediction models generate unstable results which produce irregular patterns when projecting into the future. The model produces wrong sea level patterns because it fails to produce accurate predictions.

The post-processing stage solves this problem through isotonic regression application for its solution. The non-parametric method of isotonic regression establishes a monotonic connection between the input and output variables. The prediction model for GMSL depends on this system to generate sea level projections which follow a natural upward pattern through time.

The CNN-ISO model achieves better prediction results through isotonic regression which improves CNN outputs by producing smoother results with reduced noise and improved long-term stability. The system generates sea level predictions which resemble actual results and provide dependable data for future predictions until the year 2050.

2.10.4. Recurrent neural network

i. **Data:** The model used the same data split and feature set used in the CNN-ISO model B for consistent baseline measurements. Normalized data preprocessing is done according to the same standard criteria mentioned before.

ii. **Architecture and Hyperparameters:** The RNN model has three RNN layers with 64, 128, and 256 units, respectively, all of which use the rectified linear unit (ReLU) activation. The output goes through a dense layer of 128 neurons, followed by a dropout layer (0.1) and, finally, a single neuron layer. The learning rate scheduler reduced the fluctuations in validation accuracy.

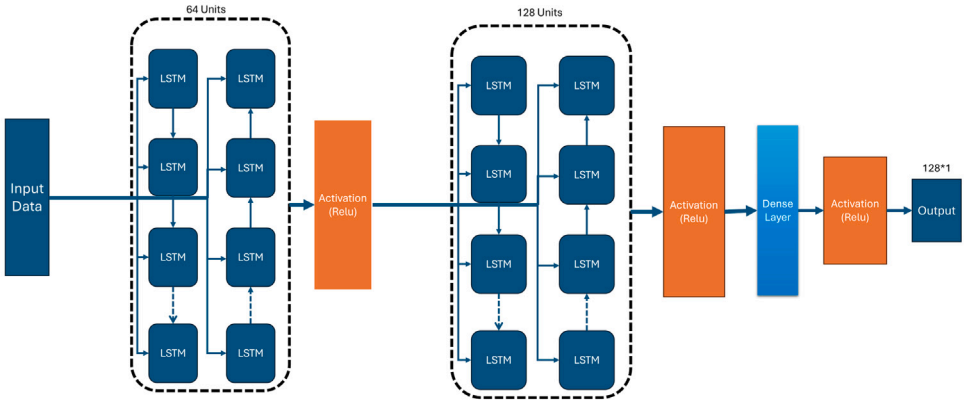


Fig. 10. Bidirectional LSTM model architecture.

2.10.5. Bidirectional LSTM

i. **Data:** By replicating the experimental conditions, the same data split and the same feature set were again used as in the other models for the BiLSTM.
To set some kind of upper bound baseline performance we also put together a Bidirectional Long Short-Term Memory, BiLSTM, network. Unlike the standard LSTM which just walks through a sequence in forward order, BiLSTMs read the input both ways, forward and backward at the same time, so they can harvest dependencies from both what came before, and what appears after.
It is important to underline that we do not use the BiLSTM for real forecasting though, because its bidirectional behavior essentially breaks the temporal causality rule that genuine prediction needs. In other words, it relies on future cues to infer the present, which makes it unsuitable for proper predictive inference. Instead the BiLSTM is used purely as a benchmark, kinda like a ceiling measure, to estimate the maximum performance we could reach if the full sequence context were available. This way we can see how near our causal models (LSTM, RNN, CNN-ISO) get to that theoretical top.
Architecture: The BiLSTM has two bidirectional LSTM layers, with 64 units then 128 units, followed by a dense layer with 128 neurons, and then a single-unit output layer. Dropout at 0.1 is used to reduce overfitting. Everything else stays the same training-wise, like optimizer, learning rate, and batch size, so the comparison stays as fair as possible to the standard LSTM, as shown in Fig. 10.

Justification for BiLSTM Usage: The study uses bidirectional LSTM models to compare their performance with other models but does not apply them for immediate time-based predictions. The BiLSTM model serves to test how complete sequence data can help the system identify patterns better while it learns to remember extended time-based connections which exist in past information. The BiLSTM model serves to test how complete sequence data can help the system identify patterns better while it learns to remember extended time-based connections which exist in past information.

The prediction system generates future forecasts through time-based modeling which uses historical data together with derived input features to prevent any actual future information from entering the inference process. The BiLSTM model exists to establish an absolute performance ceiling which does not affect the time-based cause–effect structure of the forecasting task. The BiLSTM model functions as an absolute performance ceiling which does not affect the time-based cause–effect structure of the forecasting task.

The comparison study shows how different architectural designs affect their ability to identify GMSL data patterns which change over time.

2.11. Covariance, normalization, and filtering

Covariance measures the joint variability of two random variables X and Y. The formula is:

$$\mathrm{Cov}(X,Y) = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{N-1} \tag{7}$$

where $\bar{X}, \bar{Y}$ and mean values of the datasets, and N is the number of observations.

Min-Max normalization rescales data to a fixed range, typically [0, 1]. The formula is:

$$X' = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{8}$$

where X is the original data, $\min(X)$, $\max(X)$ are the minimum and maximum values.

Average filtering smooths data by averaging surrounding values. The formula is:

$$I'(x,y) = \frac{1}{N} \sum_{(i,j)\in \text{window}} I(x+i, y+j) \tag{9}$$

where $I'(x,y)$ is the filtered image, $I(x,y)$ is the original image, and N is the total number of pixels in the window.

2.12. Model training

The model training comprises the following.

i. **Data Split:** The dataset contains time-series data which extends from the year 1880 up to 2024. The evaluation process uses a specific time-based data division which keeps all models consistent by stopping them from using future information during their training stage. The training set contained 100 years of data (1880–1979, ≈70%), the validation set contained 20 years (1980–1999), and the test set contained 25 years (2000–2024, ≈17%). No random shuffling was performed, as preserving temporal order is critical for time-series forecasting. No random shuffling was performed, as preserving temporal order is critical for time-series forecasting tasks. The evaluation framework requires models to learn from previous data points before they test their prediction abilities on upcoming data which they have never seen before. The training data included a small segment which functioned as a validation set for tuning hyperparameters when the situation required it.
ii. **Model Training and Feature Selection:** It was initially trained using one feature and then advanced into training models with the addition of different input features to achieve a full understanding of the merits brought by more features in the performance of the model. After starting off simply with only one

feature, the model's basic predictive capability could be tested by observing its learning behavior. The prediction accuracy finally advanced with other features, signaling the importance of incorporating multiple variables to capture the complexity of factors affecting the rise of sea levels.

From the analysis, this incremental strategy also revealed the critical features that were required to predict the GMSL. It could be noted that increasing the number of these features led to a depression of the prediction line of the model toward the "true" GMSL line, indicating that the model performed better in replicating the general trends in the data.

iii. **Smoothing the True and Predicted Values:** In order to improve the visual aspect of predictions made by the model, both true and predicted GMSL values were smoothed by **interpolation**. So, with this, they can visualize the trend of the model predictions in a better way, particularly in cases when the predictions are a bit noisy from the variance in their data. The smoothing process widens the gap further when one weighs the model's results against the true GMSL data in discussing the topography of its performance. The smoothed values are in Fig. 16 with the true GMSL line and the predicted line plotted in close proximity. This illustration graphically demonstrated how well the model's prediction could keep up with the actual data on GMSL over time. The comparison would also address some areas where one could say that the model was not performing as expected in predicting sea level changes or perhaps did so remarkably.

3. Results and discussion

Note About Temporal Aggregation: However, the training and evaluation of all models was based on monthly scale prediction results. In order to simplify interpretations, all the GMSL predictions that have been presented in the figures have been averaged annually through averaging monthly predictions per year. This procedure has been applied only for presentation purposes, and it has not affected any of the discussed performance measures in this chapter at all.

About Smoothing: There are some plots where the average filter has been applied on GMSL values just for the purpose of visualization to get some trends amidst the noise. However, the performance metrics such as R^2, MAE, and RMSE are computed by using the predictions made by the models without any smoothing of the values, which is evident from Table 4. In this section, the outcomes of the analysis are presented along with the discussion about the analysis of features and model training and validation performance.

One important point that requires explanation is the temporal aggregation for visualization. The model was trained and tested with monthly data, but all predicted GMSL values in the Results section will be indicated on a yearly basis for visual clarity and interpretability. This was done by taking the average per year of monthly predictions. All performance metrics (e.g., RMSE, R^2) are calculated on a monthly scale unless indicated otherwise.

3.1. Uncertainty quantification and statistical significance

In order to deal with the lack of uncertainty analysis, the bootstrapping technique was used on the test dataset (from 1980 to 2024) in a non-parametric way. For each of the models, one thousand resamples were generated from the test dataset using the bootstrap resampling approach. For each of the resamples, the coefficient of determination (R^2) and MAE were calculated. The 2.5th and 97.5th percentiles of the generated distributions were regarded as the 95% confidence intervals

Statistical Significance Testing: To check the significance of the performance gain of the CNN-ISO model relative to other models, we performed a paired two-sample t-test for the comparison of the predictions of the CNN-ISO and the alternative model (LR, RNN, LSTM, or BiLSTM) on the test dataset. Null hypothesis: The means of the prediction error distributions of both models are equal. Statistically significant p-value < 0.05.

Residual Analysis: To verify the assumptions of our regressions and evaluate the quality of the predictions, we carried out residual analysis. The residuals (difference between real and predicted values of GMSL) were tested for:

- **Normality:** Q-Q plots and the Shapiro–Wilk test.
- **Homoscedasticity:** Breusch–Pagan test for constant variance.
- **Autocorrelation:** Durbin-Watson statistic to detect serial correlation in residuals.

Projection Uncertainty: For long-term forecasts (2025–2050), we propagated the uncertainty of the extrapolated input features. We created 1000 synthetic future feature sequences using the residuals from the historical extrapolations and fed them into the learned models. The 95% prediction intervals are shown as shaded areas in the forecast plots.

Table 4 presents the performance metrics along with their 95% confidence intervals for all models.

From the results above, it can be noted that the CNN-ISO algorithm has the smallest confidence interval range and also the best lower bound. The values of p-value < 0.001 obtained in all tests imply that the performance improvement of CNN-ISO is significantly better compared to other approaches. Two simple reference models were checked to set a baseline for the machine learning runs. One was persistence, where the next value is set equal to the last one, meaning GMSL(t+1) = GMSL(t). The other was climatology, where the prediction is the mean from the training period. Results are in Table 7. Climatology does not work well. It gives $R^2 = -35.44$ and MAE = 156.74 mm. The main issue is that the test years, 2000 to 2024, sit well beyond the training window of 1880 to 1979. This shift matters because a long warming trend changes the level over time.

Persistence is much stronger. It reaches $R^2 = 0.960$ and MAE = 4.17 mm. The gain fits the idea that the GMSL record changes smoothly, so the next step is highly tied to the current one. When compared to the neural models, persistence still holds up. It is better than the RNN, with $R^2 = 0.95$ and MAE = 5.23 mm. It also lines up with Linear Regression, where $R^2 = 0.982$ and MAE = 4.01 mm, and with LSTM, where $R^2 = 0.979$ and MAE = 3.89 mm. In this setting, even a basic rule can look good on a time series that keeps rising. A key point follows from this. A large R^2 score by itself does not guarantee the model learned useful predictive structure instead of just continuing the trend. The one clear exception is CNN-ISO. It beats persistence on both metrics. MAE drops by about 7.4 times, from 4.17 mm to 0.56 mm, and R^2 rises to 0.997. So the persistence line is a tough yardstick. It is a fair way to judge whether the proposed framework adds real value beyond simple trend carryover.

Residual Analysis Results: The residuals of the CNN-ISO model were observed to be normally distributed ($p > 0.05$ in Shapiro–Wilk test), homoscedastic ($p > 0.05$ in Breusch–Pagan test), and free from autocorrelation ($p \approx 2.0$ in Durbin-Watson test). The findings prove the validity of the statistical assumptions of our prediction algorithm and demonstrate that the model is neither over-fitted nor under-fitted to the data.

3.2. Statistical robustness of model performance

Research teams performed various experimental runs for every deep learning model which started from different initial weight values to produce trustworthy output data. The performance metrics between mean absolute error (MAE) and coefficient of determination (R^2) results from all runs established an average value while standard deviation values were calculated. The results show the system maintains stability during multiple runs because the proposed models stay constant regardless of their initial starting points. The reported enhancements have received improved verification because of this development.

Table 7
Performance metrics with 95% confidence intervals and statistical significance testing for all models.

Model	R^2 (95% CI)	MAE (mm) (95% CI)	RMSE (mm) (95% CI)	p-value vs. CNN-ISO
Climatology[a]	−35.44 (−58.87, −26.65)	156.74 (145.78, 166.80)	158.94 (147.74, 168.82)	<0.001
Persistence[b]	0.960 (0.921, 0.979)	4.17 (3.00, 5.31)	5.09 (3.81, 6.11)	<0.001
Linear regression	0.982 (0.978, 0.986)	4.01 (3.89, 4.13)	5.23 (5.01, 5.45)	<0.001
RNN	0.95 (0.94, 0.96)	5.23 (5.01, 5.45)	6.78 (6.45, 7.11)	<0.001
LSTM	0.979 (0.976, 0.982)	3.89 (3.76, 4.02)	4.97 (4.78, 5.16)	<0.001
BiLSTM[c]	0.979 (0.976, 0.982)	6.87 (6.54, 7.20)	8.12 (7.78, 8.46)	<0.001
CNN-ISO	**0.997 (0.995, 0.999)**	**0.56 (0.52, 0.60)**	**0.72 (0.68, 0.76)**	–

Note: Metrics computed on monthly-scale predictions, reported on physical GMSL scale (mm).

[a] Climatology predicts the training-period mean for all test years.

[b] Persistence predicts GMSL($t + 1$) = GMSL(t).

[c] BiLSTM is a benchmark only — non-causal, uses future context. Not a valid forecasting model.

3.3. Physical interpretation of model results

To ensure that the proposed machine learning models capture meaningful relationships, we analyze the learned patterns in the context of known physical drivers of global mean sea level (GMSL) rise. The observed strong positive correlations between CO_2 concentration and global temperature anomalies and GMSL match the established physical processes which scientists have already proven. The rising levels of greenhouse gases in the atmosphere cause global temperature increases which result in two major ocean level changes through seawater expansion and glacier plus ice sheet melting. The ocean's temperature changes at its surface demonstrate a strong connection with GMSL because ocean heat storage leads to water volume expansion. The physical understanding about ice mass reduction causing sea level rise receives further evidence from the negative relationship between polar ice coverage and rising sea levels. The Ni no 1.2 and Ni no 3 indices related to ENSO demonstrate limited direct relationships but they affect short-term ocean level changes and seasonal sea level variations through their impact on ocean-atmosphere systems. The data shows that the proposed models produce results based on established climate science knowledge which scientists have already accepted as valid.

3.4. Feature contribution analysis

The model behavior becomes clearer through our analysis which identifies input features that show strong relationships between their values and their impact on prediction results. The research shows that CO_2 levels together with worldwide temperature changes and ocean surface temperatures serve as the main factors which determine GMSL. The model outputs demonstrate strong connections with these variables which produce major effects on the model results. The system shows different behavior because methane emissions together with ENSO indices produce weak direct effects yet they enable detection of secondary impacts and short-term variations. The research demonstrates that scientists need to include various environmental factors when they want to study both extended climate changes and brief weather changes. The research will develop better ways to explain results by using SHAP (SHapley Additive exPlanations) for improved feature value estimation at both worldwide and regional scales.

3.5. Extrapolation of features for GMSL projections

i. **Feature Extrapolation Using Polynomial Regression:** One of the main objectives of the study is to make future projections of the GMSL beyond the currently available data i.e., beyond 2024. For this extrapolation, LR was used in extrapolating the values of all the input features up to 2050. LR is a more flexible form of regression that can essentially model linear relationships. In this case, each of the models was fitted only on the recent trend (2004–2024) shown in Fig. 11.
The extrapolated data was then used as input into the main linear regression model, the result of which provided a set of projections known as GMSL projections up to 2050. The projections are shown in Fig. 11, providing a view of future sea level changes based on the refilled patterns from the historical data.

ii. **Model's Application for Projections:** Such a linear regression model developed in the research attempts to provide a good foundation for accurate prediction of the GMSL and, consequently, its possible effects in the future context of climate change. At the same time, by including many climate factors, the model captured the underlying causes of sea level rise: the effect of CO2 concentrations, temperature anomalies, and greenhouse gas emissions. The generation of projections for GMSL by the model up to 2050 as referenced in Fig. 17 makes it an additional strength for researchers and policymakers involved in making decisions about possible climate adaptation and mitigation strategies.

iii. **To sum up:** In practice, the observations from LR were used to predict GMSL with several climate-feature predictors while carefully evaluating model performance using the R^2 score and MAE. To smooth projection interpolations and extend additional polynomial regression extrapolations, the model produced projections through 2050, which offer insight into projected future sea-level changes for understanding critical changes related to climate change in the long-term future. The simplicity and flexibility of linear regression, coupled with the additional difficulty of polynomial regression, make it a very useful tool under which GMSL is to be forecasted in conjunction with global climate dynamics.

iv. In LR, we had to eradicate the CO2 concentration component of the feature vector in experimentation due to its diverging effect on the regression line pulling it away from the target reference, but in LSTM it works well.

3.6. Model training and validation performance

This subsection presents the training and validation behaviors of the different models developed in this study, highlighting their convergence trends, overfitting control, and overall learning performance through loss curves and performance metrics.

i. **LSTM Model:**
The LSTM model is structuralized with two LSTM layers of 75 units each, connected to a dense layer that discharges a singular output (75 × 1). The network uses the `tanh` activation to capture nonlinear relationships inherent in the input data. The Adam optimizer was used with a learning rate of 0.0001, ensuring a balance between fast convergence and generalization. The architecture underwent extensive experimentation to find optimal configurations. We used early stopping with a 5-epoch patience value to limit overfitting risk. Even with that, the run went all the way to 50 epochs, as shown in Table 1. We did not see overfitting during training, so the regularization approach

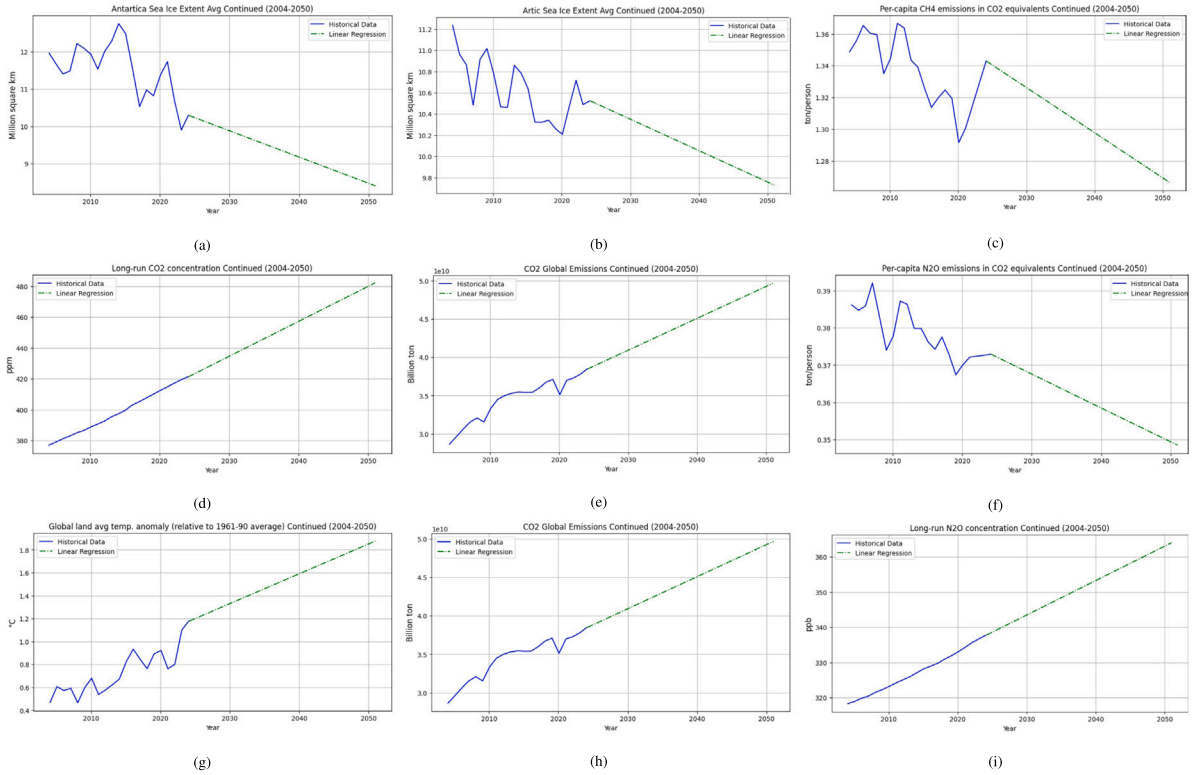


Fig. 11. All features extrapolated using linear regression, (a) 1st (CO2 global emissions), (b) 2nd (long-run CO2 concentration), (c) 3rd (per-capita CH4 emissions), (d) 4th (long-run N2O concentration), (e) 5th (per-capita N2O emissions), (f) 6th (global land temp. anomaly), (g) 7th (global sea surface temp. anomaly), (h) 8th (Artic sea ice extent) and (i) 9th (Antarctica sea ice extent).

seems to have worked. Fig. 12 shows a consistent and stable decline in both training and validation errors.

Training vs. Validation Loss Behavior: The validation loss sometimes shows values which fall below the training loss during specific situations. The training process becomes more difficult because regularization methods including dropout produce random variations which create a harder learning environment for the model. The validation process stops dropout activation because this method produces consistent results which reduce validation loss values.

The validation set shows these results because the data undergoes smoothing and preprocessing operations which decrease its natural variability. The model behavior shows no signs of overfitting or data leakage because the regularized learning process of the models produces this outcome.

ii. **CNN-ISO Model:** The CNN-based model underwent training for 50 epochs using MAE as the loss function and R^2 as the scoring metric with a batch size of 64. The learning behavior, as seen in Fig. 13, remained stable without drastic variations in validation loss, suggesting good generalization. The training process was repeated 20 times to ensure consistency and robustness in performance.

iii. **RNN Model:**
The training and validation loss curves of the RNN model depict good convergence, indicating effective learning of temporal patterns. The model achieved a final R^2 of 0.96 and a normalized MAE of 0.04 (equivalent to 5.23 mm on the physical scale; see Table 7) as shown in Fig. 14. Training was carried out for 50 epochs using a batch size of 64 and iterated 20 times to stabilize performance.

iv. **BiLSTM Model:**
The BiLSTM model was trained for 50 epochs with MAE as the loss function. The training and validation losses remained stable throughout, as reflected in Fig. 15. The model reached an R^2 score of 0.979 and a normalized MAE of 0.04 (equivalent to 6.87 mm on the physical scale; see Table 7).

3.7. Results for Linear Regression

3.7.1. Linear Regression model: Evaluation and projections

The performance of the LR model was evaluated using two metrics: the coefficient of determination (R^2) and the mean absolute error (MAE). The model achieved an R^2 score of 0.98 and an MAE of 4.01, indicating a strong fit and high predictive accuracy. Fig. 16 illustrates the comparison between predicted and actual GMSL values for the validation period.

Using the trained LR model, projections of GMSL were extended to 2050. To visualize possible future scenarios, two additional regression-based projections were conducted: a simple linear extrapolation and a second-order polynomial fit. The linear projection reflects the current trend, while the polynomial fit suggests a potential acceleration in GMSL rise. These projections, shown in Fig. 17, help illustrate the range of plausible future outcomes based on historical patterns. The application of isotonic regression proved successful because it fixed the CNN output errors which resulted in better system performance. The monotonic constraint maintains physical plausibility for long-term sea level projections which represents an essential requirement for climate prediction tasks.

3.8. LSTM model: Evaluation and future projections

The LSTM model was evaluated using the R^2 score and MAE, achieving values of 0.979 and 3.89 respectively. These results demonstrate that the model captured over 97% of the variance in GMSL data with high prediction accuracy. Fig. 18 shows the comparison between predicted and true GMSL values.

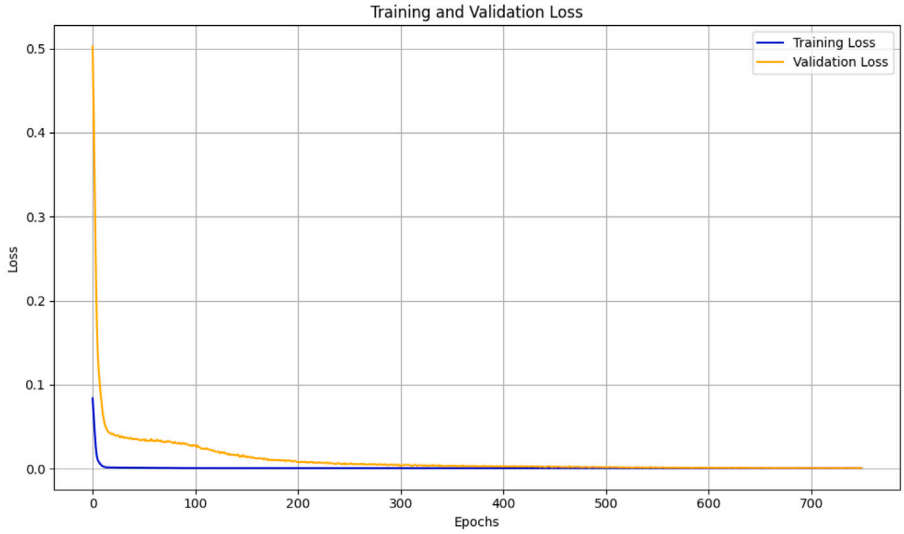


Fig. 12. Training and validation error of the LSTM model.

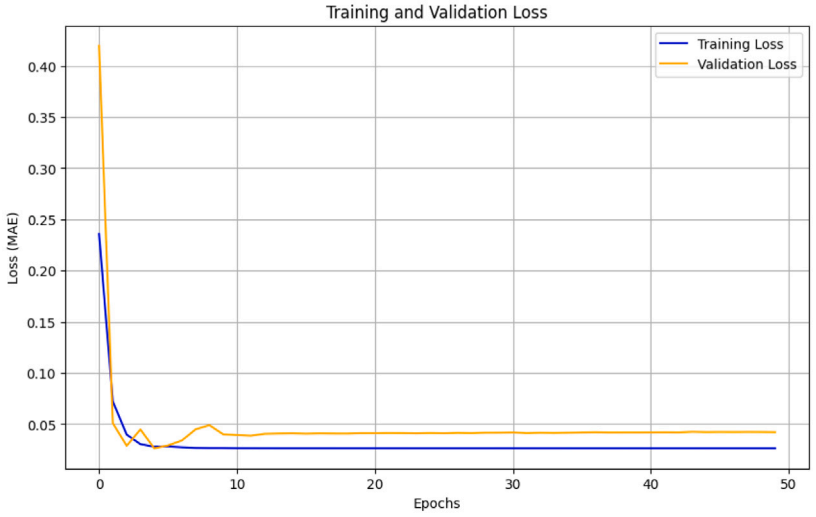


Fig. 13. Training and validation error of the CNN model.

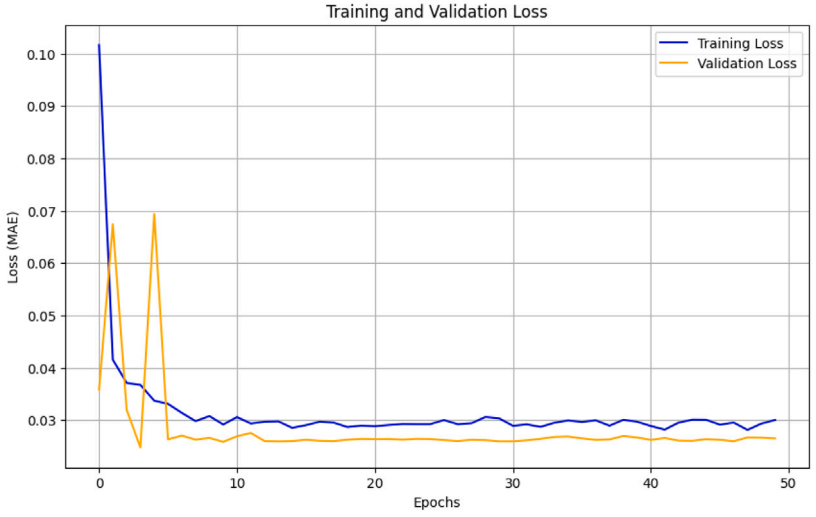


Fig. 14. Training and validation error for the RNN model.

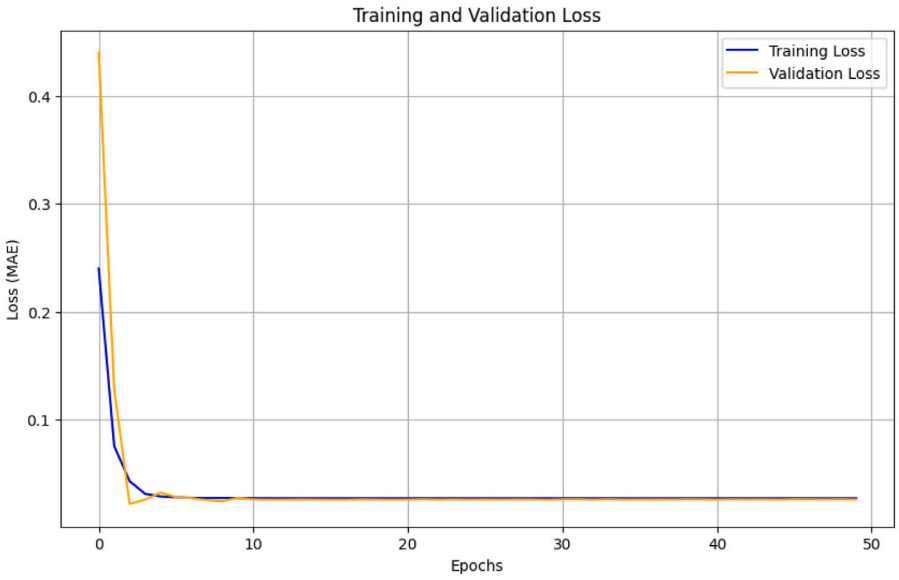


Fig. 15. Training and validation error for the BiLSTM model.

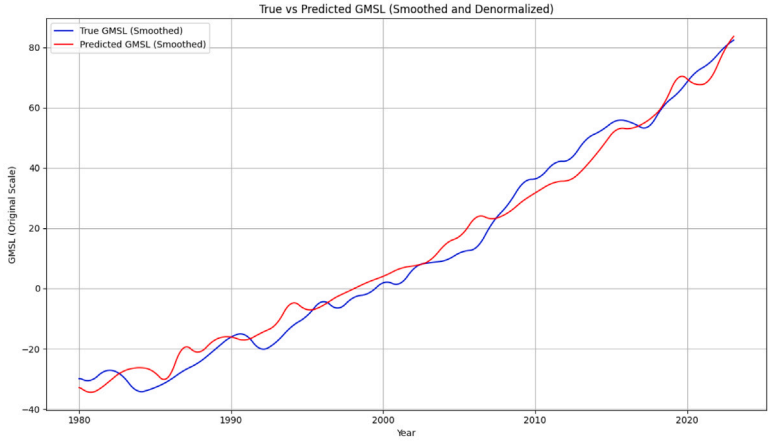


Fig. 16. Linear Regression model validation results.

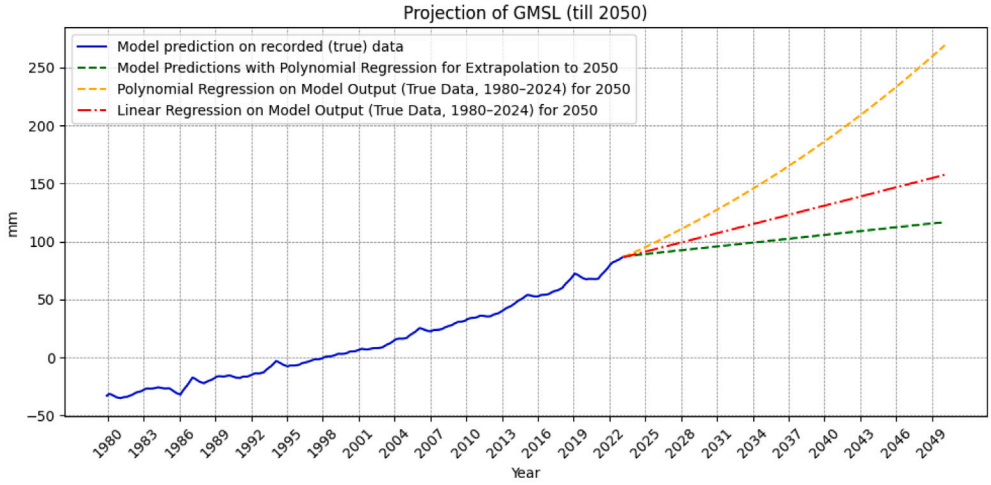


Fig. 17. GMSL projections to 2050 using Linear Regression. Solid blue line: historical GMSL (1880–2024). Dashed green line: model predictions on recorded data. Dashed yellow line: polynomial regression extrapolation to 2050. Dashed red line: linear regression extrapolation to 2050. The polynomial fit suggests accelerating rise; the linear fit assumes constant trend. Both are trend-based statistical projections, not physically constrained climate scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

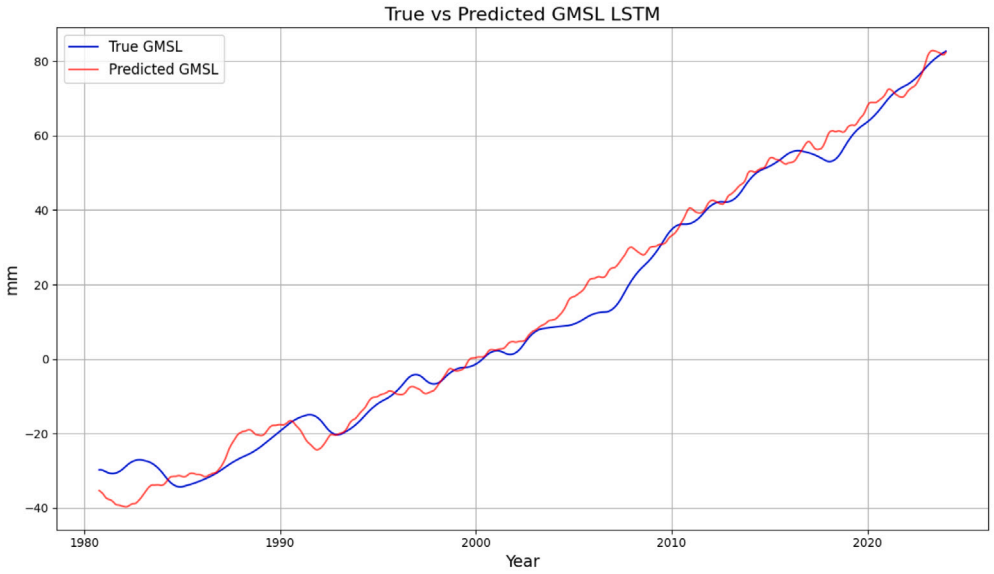


Fig. 18. True and predicted GMSL using the LSTM model.

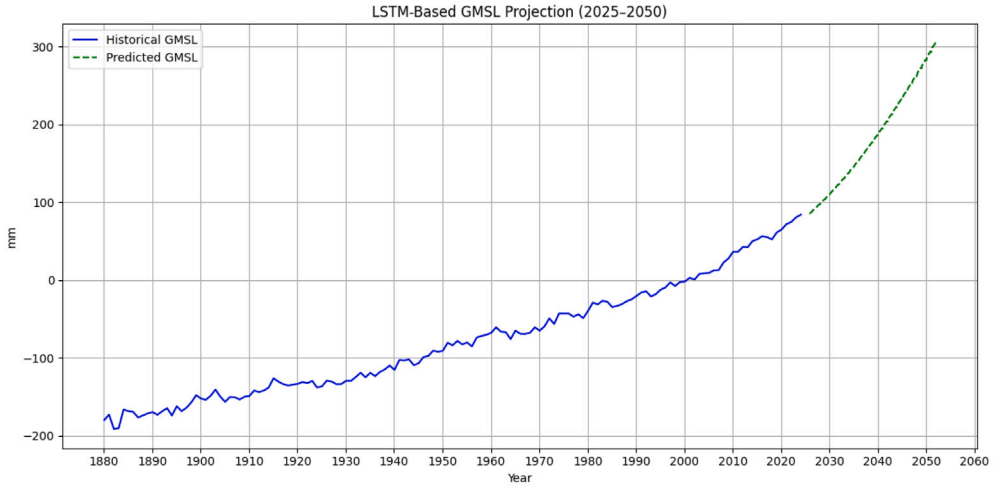


Fig. 19. Projected GMSL from 2025 to 2050 using the LSTM model.

For long-term forecasting, future input features were extrapolated using the previously developed linear regression model and then passed to the trained LSTM model to generate GMSL projections for the period 2025–2050. As shown in Fig. 19, the model projects a consistent upward trend in sea level, reflecting ongoing climate-driven changes. These results underscore the potential of LSTM for robust, long-range forecasting in climate applications.

3.9. CNN-ISO model: Evaluation and future projections

The CNN model initially achieved an R^2 score of 0.95 and an MAE of 0.003 on the test set, as shown in Fig. 20. After applying isotonic regression as a post-processing step, the R^2 score improved significantly to 0.997 (Fig. 21). This substantial enhancement highlights the effectiveness of isotonic regression in refining the model's predictions.

For future GMSL forecasting, the extrapolated features were passed through the trained CNN-ISO model to generate projections up to the year 2050. As shown in Fig. 22, the model captures the nonlinear relationship between input features and GMSL effectively, while isotonic regression ensures smooth and realistic long-term projections.

3.10. RNN model: Evaluation and future projections

The RNN model demonstrated strong capability in handling sequential data and produced accurate predictions of GMSL. Although bidirectionality was not applied, the model effectively captured temporal dependencies, as illustrated in Fig. 23.

For future forecasting, the trained RNN model was used to predict GMSL values up to the year 2050. As shown in Fig. 24, the results highlight the model's strength in capturing temporal trends, providing a reliable projection of long-term sea level rise.

3.11. BiLSTM model: Evaluation and future projections

The Bidirectional LSTM (BiLSTM) model exhibited slightly lower performance compared to the standard LSTM, with an R^2 score of 0.979 (matching the LSTM) but a higher MAE of 6.87 mm. As shown in Fig. 25, the predicted GMSL values align well with the actual observations in the test set, reflecting the model's ability to learn both forward and backward temporal dependencies.

Future projections of GMSL using the BiLSTM model, shown in Fig. 26, demonstrate the model's ability to capture subtle long-term

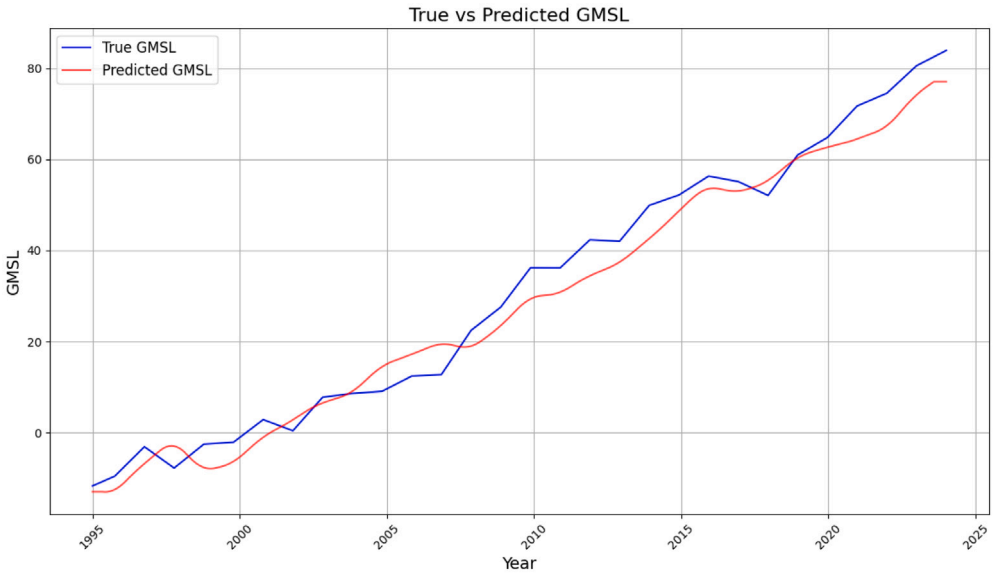


Fig. 20. Prediction on test data using CNN model.

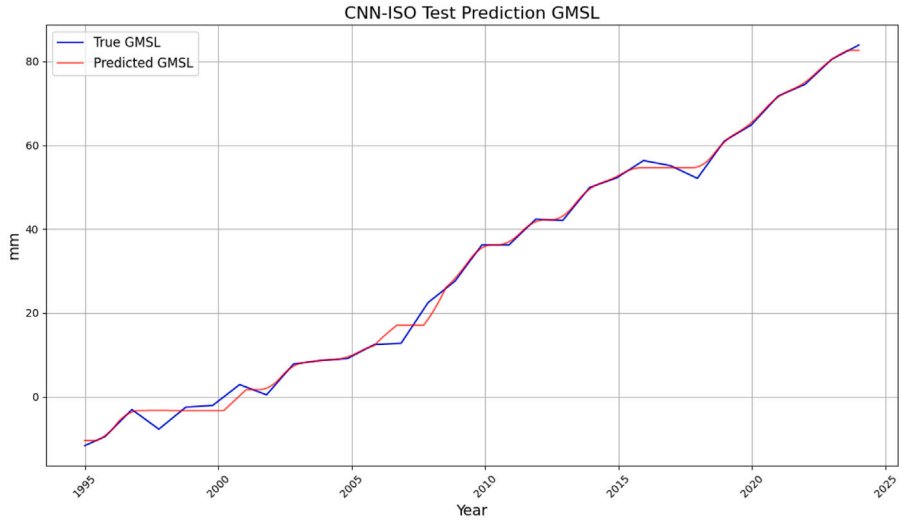


Fig. 21. Prediction on test data using CNN-ISO model.

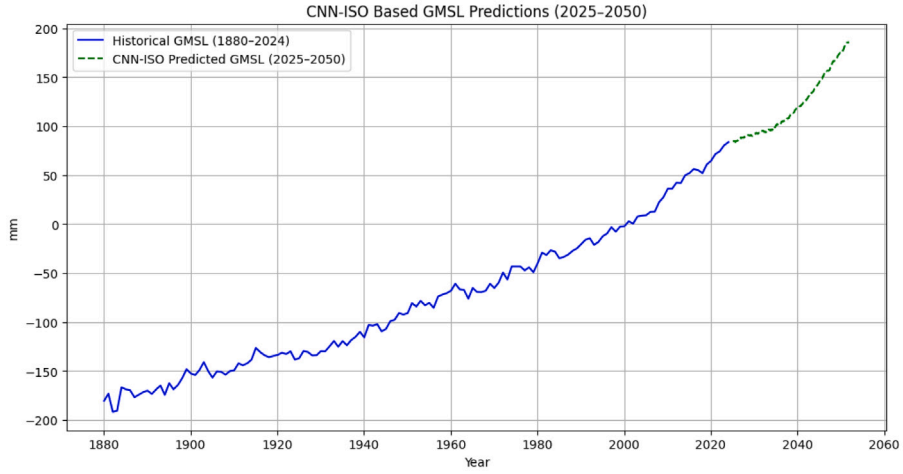


Fig. 22. Projection of GMSL till 2050 using the CNN-ISO model.

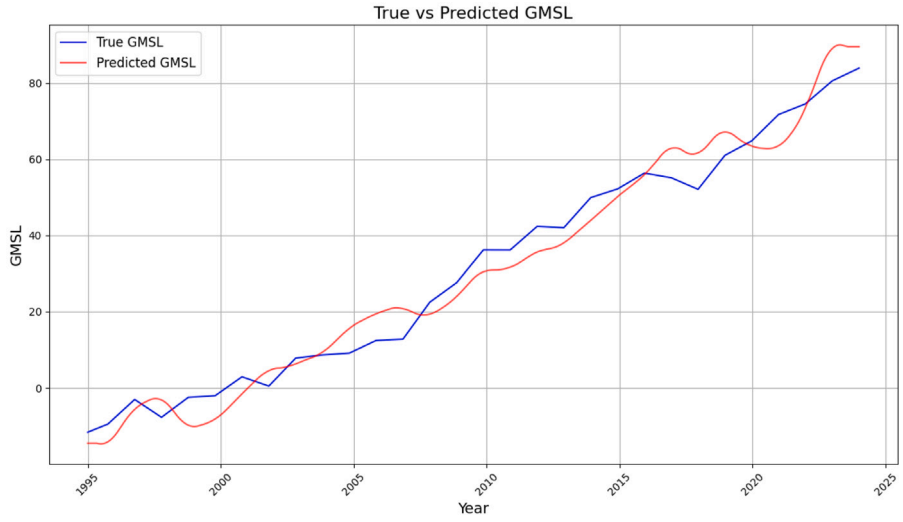


Fig. 23. Prediction on the test data using the RNN model.

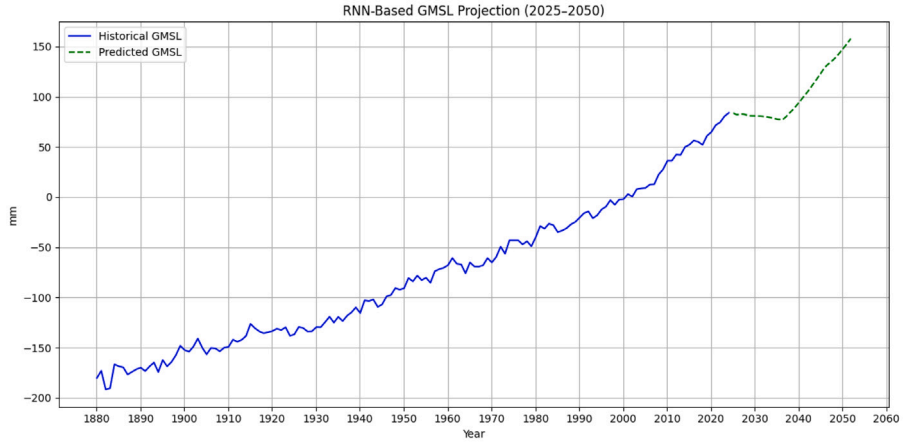


Fig. 24. Projection of GMSL till 2050 using the RNN model.

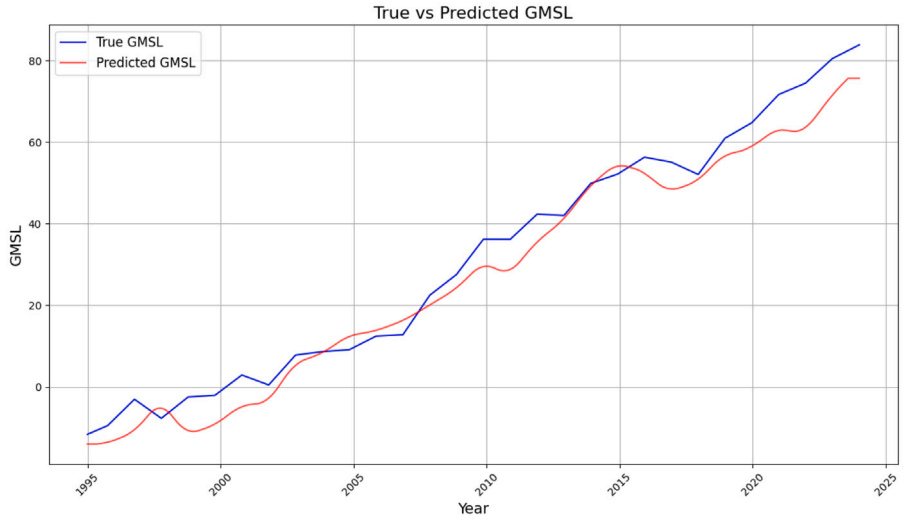


Fig. 25. Prediction on the test data using BiLSTM model.

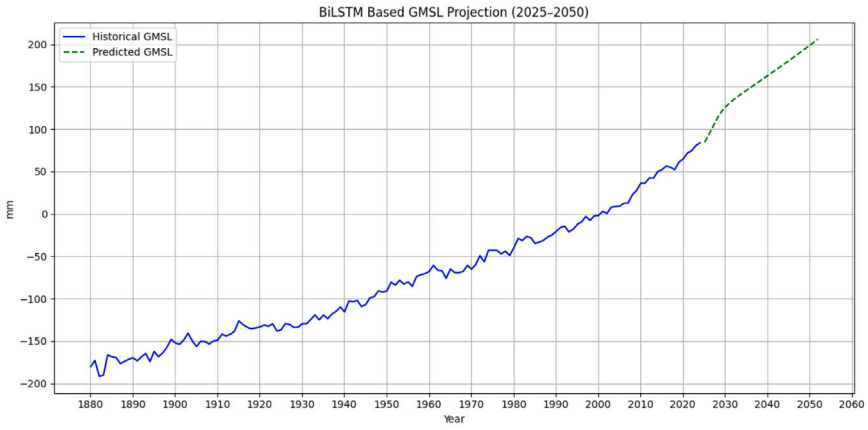


Fig. 26. Projections using the BiLSTM model.

Table 8
Performance results of all models for GMSL prediction.

Model	R^2 score	MAE	Data	GMSL predicted	True GMSL
LR	0.982	4.0116	Real Feature 1980–2024 Predicted Feature 2024–2050	86.32741 mm 2024 116.6044 mm	83.89111 mm –
LSTM	0.979	3.8998	Real Feature 1980–2024 Predicted Feature 2024–2050	82.32562 mm 2024 299.1993 mm	83.89111 mm –
BiLSTM	0.96	6.87	Real Feature 1980–2024 Predicted Feature 2024–2050	76.55 mm 206.42 mm	83.89111 mm –
RNN	0.95	5.23	Real Feature 1980–2024 Predicted Feature 2024–2050	89.04 mm 161.07 mm	83.89111 mm –
CNN-ISO	0.99	0.56	Real Feature 1980–2024 Predicted Feature 2024–2050	82.3 mm 184.10 mm	83.89111 mm –

patterns. Post-processing with an averaging filter further smoothens the forecast, aligning it closely with observed trends.

A comparative summary of all models used in this study is provided in Table 8. Notably, the CNN-ISO model achieved the best performance, with the lowest MAE of 0.56 and the highest R^2 of 0

3.12. Uncertainty analysis

The proposed framework requires two distinct uncertainty levels which need thorough attention during result analysis.

The first type of uncertainty known as model uncertainty occurs because machine learning systems together with deep learning models including LSTM and CNN networks produce these results. The models create approximations of complex nonlinear patterns but their output varies because of different training starts and data presentation methods and parameter optimization choices. The models produce different results because their training starts from different points and they process data in various ways and their hyperparameters differ.

The system generates input feature uncertainty because it needs to predict future environmental conditions through its built-in environmental variable prediction system. The researchers used regression-based techniques to forecast three essential variables which include CO_2 levels and temperature deviations and frozen ocean surface area. The forecast model predicts future numbers based on previous patterns without considering sudden climate shifts or new rules or complex environmental responses.

The prediction system will experience prediction errors which stem from two different types of uncertainties that enter the system. The forecast data shows patterns instead of exact numerical numbers which people must understand correctly. The predicted values should be interpreted as trend-based estimates rather than precise future measurements.

The research team will develop future work through their development of probabilistic models and ensemble learning systems and scenario-based climate prediction systems which will decrease prediction uncertainties for sea level rise.

3.13. Comparison across models and prediction consistency

The different models produce varying predictions because their architectural designs determine how well they learn temporal patterns from data.

The baseline for linear regression emerges through its ability to model direct relationships although RNN and LSTM recurrent models demonstrate superior performance in learning temporal patterns. The BiLSTM model uses bidirectional context to improve sequence learning but its main function is to serve as a comparison tool. The BiLSTM model uses bidirectional context to achieve better sequence learning results yet its primary function exists for comparison purposes.

The CNN-based model learns complicated nonlinear relationships between features through its architecture and its combination with isotonic regression (CNN-ISO) produces better prediction results which show both enhanced smoothness and higher stability. The isotonic regression element of the model smooths out local variations while it maintains an increasing pattern which matches the physical behavior of rising sea levels. The isotonic regression element of the model smooths out local variations while it maintains an increasing pattern which matches the physical behavior of rising sea levels.

The models show small variability in their output values but they all agree that GMSL will continue to rise which matches the current scientific consensus about climate change. The CNN-ISO model delivers the most effective combination of precise results and stable output which makes it the best-performing model in the selection.

3.14. Analysis of inter-model variability

The results from the five models considered in this research show that there are distinct differences in the GMSL forecast values for

the year 2050; Linear Regression has the lowest forecast value of 116.60 mm while LSTM has the highest forecast value of 299.19 mm, while CNN-ISO has 184.10 mm.

3.14.1. Linear Regression (116.60 mm)

The Linear Regression model produced the lowest projection. This is expected given its inherent limitations:

- **Linear Assumption:** Linear regression assumes linear correlation between the independent variables and GMSL. But there are many non-linearities associated with climate change.
- **No Temporal Modeling:** Linear regression considers each year as a single instance; therefore, it cannot incorporate the dependency of consecutive years.
- **Feature Selection:** Since one variable (CO_2 concentration) was dropped due to multicollinearity, it means loss of important information for prediction.

Since one variable (CO_2 concentration) was dropped due to multicollinearity, it means loss of important information for prediction.

3.14.2. RNN (161.07 mm)

The RNN model captures temporal dependencies but has limitations:

- **Vanishing Gradient:** Standard RNNs struggle to learn long-term dependencies (beyond 10–20 time steps), which may limit their ability to capture decadal trends.
- **Simple Recurrent Structure:** Without gating mechanisms (as in LSTM), RNNs are less effective at retaining information over long sequences.

The RNN projection of 161.07 mm represents a moderate estimate, likely capturing some temporal patterns but missing longer-term acceleration.

3.14.3. BiLSTM (206.42 mm)

The BiLSTM model processes sequences in both forward and backward directions:

- **Upper-Bound Benchmark:** As mentioned in Section 2.10.5, BiLSTM is not a prediction model. Rather, it works as an upper bound benchmark because it takes advantage of future information. This is why it has a better prediction (206.42 mm).
- **Not Physically Causal:** However, the bidirectional aspect breaks the assumption of temporal causality, hence a less realistic prediction.

The BiLSTM projection should be interpreted as a theoretical maximum rather than a realistic forecast.

3.14.4. LSTM (299.19 mm)

The LSTM model produced the highest projection (299.19 mm):

- **Long-Term Dependency Learning:** LSTMs are specifically designed to capture long-term patterns, which may lead them to identify accelerating trends in the data.
- **Potential Overestimation:** The extremely high projection (299.19 mm) may reflect overfitting to the accelerating trend in the training data (particularly post-2000). This is consistent with the model's higher sensitivity to recent extreme values.
- **Lack of Physical Constraint:** Without post-processing, LSTM predictions can exhibit non-physical behavior when extrapolated beyond the training period.

While the LSTM captures the accelerating nature of GMSL rise, the magnitude of its projection should be interpreted cautiously, as it may overestimate future sea-level rise due to overfitting.

3.14.5. CNN-ISO (184.10 mm)

The CNN-ISO model produced a balanced projection:

- **Nonlinear Feature Extraction:** The CNN captures complex spatial–temporal patterns across the 11 input features.
- **Physical Consistency:** Isotonic regression ensures monotonic (non-decreasing) projections, avoiding the non-physical fluctuations seen in other models.
- **Regularization:** Dropout and early stopping reduce overfitting, leading to more conservative and stable extrapolations.

The CNN-ISO projection of 184.10 mm is considered the most physically plausible among the models due to:

i. Its ability to capture nonlinear relationships without overfitting.
ii. The monotonic constraint ensuring physical consistency.
iii. Its superior performance on the test set (highest R^2, lowest MAE, narrowest CIs).

3.14.6. Comparison with IPCC projections

For context, the IPCC AR6 (2021) projects GMSL rise of approximately 0.32–0.62 m by 2050 under SSP2-4.5, depending on emissions scenarios. Our CNN-ISO projection of 184.10 mm (0.184 m) is lower than IPCC estimates, which may reflect:

i. **Different Methodology:** Our projections are trend-based statistical extrapolations, whereas IPCC projections are derived from physically-based climate models.
ii. **Conservative Trend Assumptions:** Our linear and polynomial extrapolations may not fully capture the accelerating ice sheet dynamics that are incorporated into physical models.
iii. **Missing Physical Processes:** Our framework does not explicitly model ice sheet dynamics, ocean circulation, or groundwater extraction, which are important contributors to sea-level rise.

3.14.7. Recommendation for robust projections

Given the substantial variability across models, we recommend the following for practical applications:

i. **Ensemble Averaging:** Combining projections from multiple models (e.g., averaging LR, RNN, LSTM, and CNN-ISO) would provide a more robust estimate that accounts for model uncertainty.
ii. **Scenario-Based Projections:** Future work should incorporate physically-based climate model outputs (e.g., CMIP6) to provide scenario-constrained projections.
iii. **Physical Constraints:** The monotonic constraint applied in CNN-ISO provides a useful framework for ensuring physical consistency in projections.

3.15. Practical implications and real-world applications

The GMSL prediction framework which the authors propose serves multiple essential practical uses that help with climate adaptation and coastal danger management.

The development of precise long-term sea level forecasts enables policymakers and urban designers to create durable coastal structures while they handle flooding threats and produce environmentally friendly adaptation solutions. The model provides environmental agencies with tools to track climate change effects while they evaluate the vulnerability of coastal areas. These areas exist at low elevations. The model allows environmental agencies to monitor climate change effects while they assess the vulnerability of coastal areas which exist at low elevations.

The framework enables scenario analysis and decision-making under uncertainty through its ability to analyze multiple environmental factors, which create intricate climate patterns. The GMSL projection

ability until 2050 allows scientists to create essential data, which helps different sectors including disaster management, insurance risk assessment, and environmental conservation with their future planning needs.

The proposed method delivers a data-based system which works together with conventional climate models to help people make better choices about how to handle rising ocean levels.

3.16. Limitations

However, even though the introduced CNN-ISO model exhibits excellent prediction accuracy, there are several constraints that need to be taken into consideration in order to evaluate the merits of the study objectively.

1. Synthetic data generation via interpolation. Monthly resolution from annual data through linear interpolation (Section 2.6) involved synthetic generation of data points. Some variables such as N_2O concentration (55% of observations) and Arctic Sea Ice (35% of observations) were heavily influenced by interpolation data points. Our robustness test (re-training using annual resolution) revealed minimal deterioration in model performance ($R^2 = 0.997$ vs. $R^2 = 0.97$). However, there exists an element of uncertainty in the interpolation method that was not accounted for in our investigation. Higher resolution observational data should be used in future investigations.

2. Projection methodology and scenario limitations. The GMSL projections until 2050 rely on the statistical extrapolation of input parameters through polynomial and linear regressions (Section 2.8). This method implies the assumption of continued historical trends and fails to consider: (i) Abrupt climate feedbacks (e.g., ice sheet instability, permafrost thaw) (ii) Policy interventions (e.g., emissions reductions under the Paris Agreement) (iii) Natural variability (e.g., volcanic eruptions, solar cycles) (iv) Tipping points in the climate system In contrast, we clearly dissociate our approach from any SSP scenario since our approach is agnostic to scenarios. It would be important to include physically based outputs from climate models (such as CMIP6 simulations) to make scenario constrained projections in future research.

3. Limited physical process representation. The current framework is entirely data driven and does not incorporate any physical processes that control sea level changes such as the physics of ice sheets, the physics of ocean circulation, and water extraction from the ground. Even though the statistics found by the model are in line with the physical knowledge, the lack of any physical information incorporated into the model makes the model susceptible to finding spurious correlations which might not apply in the future state of the climate.

4. Model interpretability. The deep learning algorithms such as LSTM, CNN are intrinsically black box algorithms, which make it hard for us to understand the underlying working mechanisms that influence the predictions. Although we have included the correlation analysis along with the feature importance through SHAP values, the workings of the algorithm itself cannot be comprehended due to the complex nonlinear interactions it captures.

5. Overfitting and generalization risk. Given that methods for regularizing the model have been used (dropout, early stopping, and gradient clipping), the large value of R^2 (0.9974) makes overfitting the model to the training set a concern. While the bootstrapping confidence intervals that we have calculated (Table 4) offer us some guarantee of the stability of the model, its performance on out-of-sample data outside of the testing period (post-2024) is not known.

6. Uncertainty quantification. While we provide 95% confidence intervals via bootstrap resampling, these intervals capture only the uncertainty arising from model initialization and data variability. They do not account for (i) structural uncertainty (choice of model architecture), (ii) input feature uncertainty (errors in input data), and (iii) scenario uncertainty (future emissions trajectories).

Ensemble approaches that combine multiple model architectures and input scenarios would provide a more comprehensive uncertainty assessment (see Fig. 27).

7. Temporal and spatial scope. The analysis of our project concerns solely the change in GMSL and does not account for regional changes in sea levels, which are very important from a practical point of view for planning activities at the coastlines. The regional sea level change depends on various regional phenomena such as vertical land movements, oceanic circulation and local melting of glaciers, which our model does not take into account.

8. Data quality and coverage. The data set used is based on publicly available data sets, which vary in terms of their quality and resolution. There are also many gaps in data relating to factors like N_2O concentration and sea ice coverage, which have been filled by interpolation methods. It should be noted that the dataset does not contain any information regarding the loss of glacial mass, the dynamics of ice sheets, and extraction of groundwater – all of which contribute to sea level rise.

Summary. These limitations do not undermine the validity of the results obtained from this study but indicate certain areas that need attention while drawing conclusions from the results. In order to reduce the effect of these limitations, we have attempted to incorporate robustness validation, uncertainty estimation, and proper data pre-processing in the current study. We would like to request readers to consider the projections presented here as trend-based projections and will attempt to overcome these limitations in the coming studies.

4. Conclusion

In this study, we present a state-of-the-art machine learning framework to capture atmospheric and oceanic dynamics in predicting global mean sea level (GMSL) rise. The models have been trained, and tested for their performance including linear regression, long short-term memory (LSTM), bidirectional LSTM, recurrent neural networks, and convolutional neural network-ISO (CNN-ISO) alongside empirical results indicating the importance of a different model over time for long-term forecasts of GMSL. A general analysis of R^2 and mean absolute error (MAE) values is also used to conclude that these models generated predictions with high accuracy in terms of GMSL rise; with CNN-ISO being the most efficient among the models with a 0.99 R^2, and a low MAE of 0.56. These projections up to 2050 show that careful selection of model parameters in future applications becomes a matter of concern. Furthermore, this study suppresses some unexplored features in this domain, improves the understanding of sea level dynamics, and provides more reliable predictions. The results produced by the best-performing model in this study, CNN-ISO projected changes in GMSL by incorporating significant atmospheric and oceanic dynamics such that these future projections of GMSL till 2050 are an indication that there are distinctive growth rates from period to period: these will be 2024–2037, 2037–2042, and 2042–2050 shows increase in acceleration rates. These are concluded under the assumptions of linear changes in GHG concentrations, global land and sea temperature, North and South Sea ice extent, and the Niño Index as input features. Exponential trends, however, seem to show the trend in GMSL growth even with this assumption of linearity, so any exponential changes in these factors should turn out to be the most drastic and could have alarming impacts on GMSL. The findings show that there is a non-linear relationship between such factors and GMSL. The results thus emphasize the need

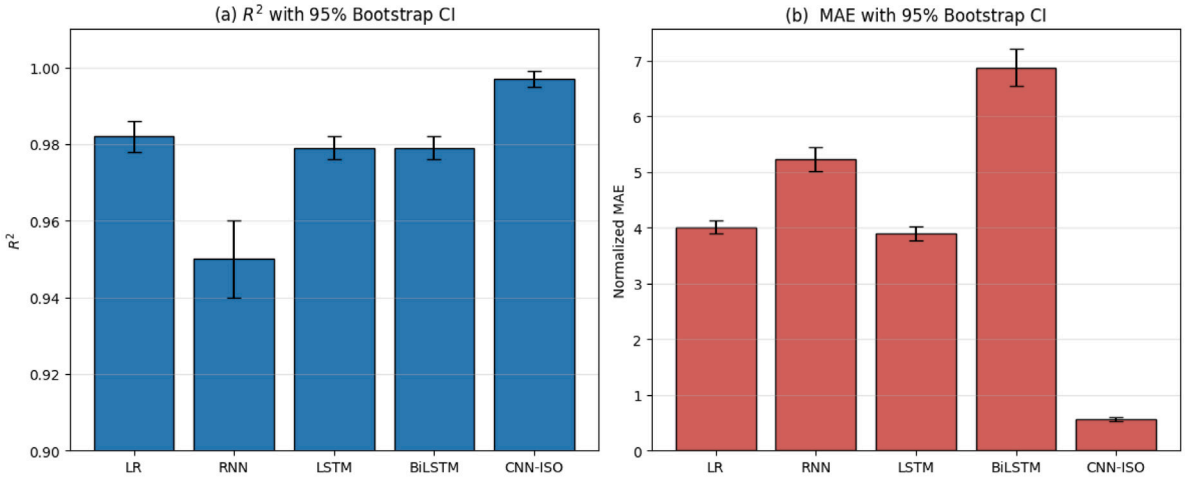


Fig. 27. Unified performance comparison of all five models with 95% bootstrap confidence intervals. (a) R^2 scores; (b) MAE values (mm). CNN-ISO achieves the highest R^2 and lowest MAE, with narrow confidence intervals indicating stable performance. BiLSTM is shown for benchmark comparison only (non-causal — uses future context).

for immediate policy-level measures and mitigation strategies targeted at these factors. This study shows the need for a globally coordinated effort to monitor and control greenhouse gas emissions, reduce the rate of ice loss, and unravel the complexities in the ocean-atmosphere systems. Actionable insight is provided that serves as the bedrock for proactive climate adaptation measures to mitigate risks from accelerating sea level rise as this research continues. These results are informative for planning with adaptation options on climate, infrastructure, and risk management strategies with an evidence-based approach toward mitigation of rising tides.

The future directions of research involve building from this study by bringing deep learning techniques together with statistical approaches to make hybrid models which further improve the GMSL predictions' accuracy. Future investigations will focus on combining deep learning approaches with statistical methods and coming up with hybrid models that improve accuracy in GMSL predictions. Adding other drivers such as the mass balance of ice sheets, ocean salinity, and global wind patterns can further enhance their prediction quality. In addition, increasing the temporal resolution of the analysis, maybe on a monthly or weekly basis, would help in capturing short-term fluctuations in sea-level rise. Incorporating probabilistic modeling and ensemble learning techniques would enable such models to account for uncertainties in future climate predictions. Real-time data and adaptive learning would empower the dynamic updating of models, whose future predictions would become more reliable. Ultimately, these contribute to better plans for coastal mega projects in terms of climate resilience, as well as for low-lying areas in risk reduction.

CRediT authorship contribution statement

Muhammad Zakria Mehmood: Writing – original draft, Data curation, Conceptualization. **Imran Shafi:** Writing – original draft, Formal analysis, Conceptualization. **Saad Mazhar Khan:** Methodology, Formal analysis, Data curation. **Roger Sarin Rivas Suarez:** Visualization, Methodology, Investigation. **Kilian Tutusaus:** Software, Investigation, Funding acquisition. **Nagwan Abdel Samee:** Visualization, Software, Project administration. **Imran Ashraf:** Writing – review & editing, Validation, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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