Game Theory-Optimized Attention-Based Temporal Graph Convolutional Network for Spatiotemporal Forecasting of Sea Level Rise

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***Abstract*—Predicting Sea level rise accurately is crucial in the formulation of effective adaptation plans to counteract the effects of climate change in vulnerable coastal areas, infrastructure, and people. The conventional forecasting models tend to fail in capturing the intricate spatiotemporal relationships affecting sea level variations. In order to overcome the above-mentioned challenges, this research introduces a hybrid predictive model combining a Temporal Graph Convolutional Network (T-GCN) with attention and game theory-based optimization strategy. T-GCN structure is specially tailored to capture spatial dependencies as well as temporal dynamics in sea level change, providing even deeper understanding of the changing dynamics of sea levels. The attention mechanism strengthens the model by dynamically weighing important variables, whereas the game-theoretic optimization efficiently optimizes multiple objectives, e.g., prediction accuracy and robustness. Experimental results, measured in terms of common performance indicators, show the better effectiveness of the proposed model with a correlation coefficient of 0.996512 and an overall error of 0.032154. Through the inclusion of both climatic and socio-economic variables, this methodology provides accurate, data-based insights to inform climate policy and adaptive planning. The results highlight the capabilities of state-of-the-art machine learning methods for solving actual sea level rise challenges.**

Keywords*—Temporal graph convolutional networks; attention mechanisms; game theory optimization; sea level rise prediction; climate change adaptation

I. Introduction

Melting of ice possesses a creeping threat of global significance with potential impacts and effects on any coastal area, population, structures, and ecosystems [1], [2]. Since the late 80s, the climate of the earth has been changing because of various anthropogenic factors for instance emission of greenhouse gases and deforestation and as expected the polar ice caps and the glaciers are melting [3], [4]. This phenomenon is now becoming a severe danger to millions of the lowland people, especially those in developing and overpopulated coastal zones. These several impacts of sea level rise are diverse: there are storms and their consequences such as frequent and severe floods, more powerful storm surges and also rapidly progressing coastal erosion [5]. While such changes in physical environment can result in loss of people's homes, loss of animal and plant habitats, destruction of valuable ecosystems like mangrove forests and corals that offer protection against storms [6]. In addition, sectors that depend on the coasts and sea, for instance, fishery, tourism, and shipping business experiences difficulties and higher expense charges. Most of the designed infrastructure of roads and bridges, sewage systems without which no urban development is complete, require heavier investment and modifications to withstand the prevailing and projected climate change [7].

However, when it comes to predicting sea level increase something that is so important and mandatory in the contemporary world, the traditional models fail to address the issue in a proper way. Sea level fluctuation depends on the number of factors which are interrelated and interconnected: pressure at sea level, currents at sea level, and tectonic activity [8]. These interactions produce a very complex environment that appears as being programmed and organized in which shifting one factor can influence other related factors in a rather unpredictable manner [9]. For instance, changes in pressure may affect currents and the circulation of the ocean, and movements in the earth's crust may change sea level through vertical movements of the land mass [10]. Issues concerning flexibility, capacity utilization, uncertainties and seasonality are some of the complexities that the conventional methods cannot capture easily since they depend mostly on the past data trends, which have a linear relationship. Thus, they give predictions that are rather too simplistic and can be quite off base, underestimating or even overestimating dangers that might come with the rise in sea level. Mainstream statistical and physical approaches fail to adequately capture a relationship between these factors because the typical applied parameters are not specific enough to capture the differences of coastal areas [11]. Coastal sea level management entails the physical alterations, proposed structures, and noticed events to reflect the response of the interested groups, such as the residents, business holders, ecological nature lovers, and policy makers. Both of these are crucial in comprehending the socioeconomic and cultural effects of sea level changes as well as in creating effective and fair response measures towards these changes. However, conventional models are mostly often distributed in terms of physical and environmentally related information devoid of more human factor aspects of the sea level [12].

1) Research motivation: CNN are specifically preferred for spatial pattern recognition, but in the event of a temporal sequence, their efficiency is greatly diminished with a result of creating likely errors in the forecasted values [13]. Originally, the T-GCN to analyse sea level rise are very efficient, where the data are described based on the graphs that nodes are used for spatial features while the edges focus on time features [14]. T-GCNs are less inclined towards computational efficiency, and sometimes it can cause scalability issues whenever dealing with big data sets. They also need to be fine-tuned due to the trade-off they create between the spatial and temporal dimensions, which can be difficult in some cases. In the other hand, it is useful to learn which features should be paid more attention, improve the model's temporal and spatial consideration. However, when the attention mechanism is applied separately, the overfitting occurs as it pays much more attention to the certain features while there might be other relevant features in some other context also equally important [15]. Moreover, attention mechanisms might not have the considerations of the spatial relation of the data which is important for sea level analysis. Such limitations call for the blended approach that use the strong characteristics of these methods while avoiding their related drawbacks. By connecting T-GCNs, attention mechanisms, the model developed in this article assumes to offer a more precise and complete solution for forecasting sea level rises.

2) Research significance: With the deficiency of conventional sea level rise prediction models, this paper suggests a new scheme that adopts game theory-based optimization, a self-attention mechanism, and T-GCN. T-GCNs are powerful in extracting intricate spatiotemporal information, and the self-attention mechanism allows the model to dynamically focus on the most relevant features. By adopting elements of game theory—mimicking strategic choice making and reconciling conflicting factors—the forecasting ability of the model is greatly improved. The combination of these methods leads to more robust, accurate, and actionable forecasts, providing valuable inputs to enable effective coastal adaptation planning.

3) Research contribution: The following are the contributions of this research;

a) This paper introduces a new hybrid model that integrates T-GCN, attention mechanisms, and game theory-based optimization to enhance the precision of sea level rise predictions.

b) The suggested framework efficiently describes spatial dependencies and temporal patterns from multivariate sea level datasets in a better manner than the traditional isolated deep learning techniques.

c) Attention mechanisms are used to dynamically emphasize and prioritize important spatial and temporal features, increasing interpretability of the model and concentrating attention on the most influential variables.

d) Game-theoretic approaches are employed to maximize trade-offs between two or more conflicting objectives—e.g., prediction performance and model resilience—and thus reduce overfitting and enhance generalizability overall.

The rest of the paper is organized as follows: Section II overviews related work. Section III presents the background to the study and formulation of the problem statement. Section IV outlines the method that has been proposed. In the Section V of the paper we present the experimental results and then compare them. Section VI provides the last and final conclusion of the paper and points out for the future work.

II. Related Work

According to Memarian Sorkhabi, Shadmanfar, and Al-Amidi [16] climate change was a global phenomenon and particularly the increase in sea level and frequency of floods had been recognized as one of the critical challenges for coastal cities. This study examined the temporal fluctuations of the sea-level which involves data like the SST originated from MODIS, wind speed and precipitation rates, and the change in the sea-level acquired through satellite altimetry. A weighted combination of values created a context vector that impacts the end output. T-GCNs model intricate spatial-temporal patterns, and attention boosted significance in features for accurate, area-based predictions in climate adaptation.lts and various forms of forecasting, which might not have taken into perspective all potential factors influencing the future environment. They could have been affected by the nature and resolution of the inputs used in making the prediction and there could be unknown climatic and socio-economic factors that could affected the sea level rise and floods on the resilience of cities on the coastline.

Accarino et al. [17] analyzed the effectiveness of LSTM neural network for short-term sea-level forecasting for the SANI region of the Mediterranean Sea. The work was described by multiple of models that used LSTM networks aimed at the three-day mean sea level forecast for a set of coastal regions. Concerning the evaluation of the projections, the latter were compared to observation data stemming from tide-gauge instruments and to the outputs from another model called SANIFS that had been designed at the Euro-Mediterranean Center on Climate Change. The incorporation of the LSTM-based forecasting models into the Ophidia HPDA system, would open up a vast potential of adding capabilities of carrying large scale Time Series data and functioned in realization through application of HPC and Data science capabilities. The enhancement of these reasons could have resulted in greatly improved sea level prediction models in the future.

Prediction performance analysis carried out by Altunkaynak and Kartal [18] involved applying and comparing the results of various ML models based on sea level time series data obtained under different conditions. This study used DWT to analyze three stations in the Bosphorus Strait, and using SVM, k-NN, and DT to transfer sea level signal among the stations for their regions. The models applied were compared according to their performance in as far as predicting sea levels up to 7day in advance by subjecting them to RMSE and NSE tests. The findings showed that the developed models had higher competence in transferring information from one station to the next when the station is in the proximity as opposed to when stations were periodically close. One of the studies' drawbacks partly stemmed from its limited focus, which made it difficult to apply the findings to other areas or settings.

Raj [19] employed the first China's global ocean CDRs to evaluate and forecast changes in the Yellow Sea levels that significantly varied by season. With the help of the SSA method, it was suggested to analyze the characteristic and de-noise spatiotemporal and SLAs time series data in the Yellow Sea. The research then used SSA to build an SSA based model called SSA-LSTM for forecasting trends in sea level. 04 mm for the SLA time series prediction while the RMSE was found to be 19. 68 mm for the one-year spatiotemporal SLA forecast. There were also certain limitations in this research: The data set used in this research is limited to China's first global ocean CDRs and it only examined the Yellow Sea so the application of SSA-LSTM combined model would have been slightly different when studied on other areas with different ocean and climatology processes. Furthermore, the study does not explore any interference from other external factors, including the climatic fluctuations that always occur in the world, which may in one way or the other influence the sea levels, and this therefore undermined the strength and applicability of the forecast made in other or different setting.

Zhao, Cai, and Sun [20] discussed the contemporary issue of SLR that still posed a threat to small island states such as the Kiribati and Tuvalu among others; this attested to the need to enhance the reliability of data provided in advance of policy measure. The model was benchmarked against three other AI models: Some of the boosting technique out of which are adaboost, and multilinear regression. It was mentioned at the two places measures that it presents the least error rates. Applying, for instance, the trend analysis applied to gradual change, based on the linear regression, the GNSS-VLM-corrected long-term mean sea level increase is at 2. The rate of absolute sea level rises according to the estimated for Kiribati was 1mm/year while that of Tuvalu is 3mm/year.

Raj et al. [21] explained a novel technique for estimating sea level rise in the future that was based on tide gauge stations in Darwin and Milner Bay in Australia's Northern Territory. For this study, the investigated data included mean sea level data on BOM associated with the time period between 1990 and 2022. The study modeled data using four artificial intelligence techniques: SVR, AdaBoost, MLP, and CNN-BiGRU were the best performing algorithms in descending order. The MSL interpretation revealed that the same was 6 on an upward trend showing that the increase in materialism was influencing the consumers. 1 ± 1. It was considered that one of the weaknesses of this research was the fact that there were limited numbers of tide gauge locations in the Northern territory and therefore results and predictive models might not have been applicable in other climatic regions with have different oceanographic features.

Existing studies on sea level rise (SLR) prediction incorporate a combination of hybrid and machine learning algorithms with different strengths and weaknesses. The sea surface temperature and sea level height are increasing, as per a study on Gothenburg; however, its limitation lies in its reliance on historic data, which may cause underestimation in the future. While accuracy is impaired by the lack of high-frequency data and key parameters, LSTM models have proven to be more accurate. SVM and KNN performed better than traditional models in the Bosphorus Strait, but only within a limited geographic area. The SSA-LSTM models of the Yellow Sea are very accurate, but they are not generalizable beyond the region in question. Similarly, local environmental considerations are highlighted in BiLSTM applications for small island nations. Though constrained by sparse tidal gauge data, a new model in northern Australia that applied data decomposition and AI methods gave promising results. For more accurate and scalable predictions of SLR, these papers as a group point to the need for bigger, regionally adaptive models considering a range of environmental variables.

III. Problem Statement

Accurate forecasting of sea level rise is vital for effective coastal management; however, traditional approaches often rely heavily on historical data [22], overlooking future uncertainties and critical climatic or socio-economic factors [23]. To overcome these constraints, this research proposes a new method that incorporates T-GCN, attention mechanisms, and game theory-based optimization. T-GCNs are well suited to capture the intricate spatiotemporal dependencies inherent in sea level observations, while the attention mechanism chooses important time periods and spatial coordinates. Game theory optimization further improves model performance by imitating strategic interactions among important variables, tuning predictive results. This combined framework significantly enhances prediction accuracy, providing a robust and reliable instrument for backing long-term coastal resilience and adaptation planning.

IV. Methodology for Sea Level Rise Prediction Using Hybrid Methods

The interaction of sea levels with other parameters can be effectively predicted through the proposed methodology, which combines T-GCN, attention mechanisms, and game theory optimization. The process starts with the data where data from Kaggle of sea level change is then pre-processed by cleaning, normalizing from it and then subdividing it. Temporal and spatial features are reconstructed using a T-GCN model to analyse the given data. To improve the prediction the attention mechanisms are used to increase the model's focus on the significant features. In federated learning approach, multiple clients participate and perform updates on the global model without accessing raw data. Game theory optimization extends the model by incorporating multiple objectives such as error frequencies and model overfitting. The above steps are then repeated several times till pre-specified convergence criteria are met and the final optimized model for predicting sea level rise is arrived. The proposed methodology is illustrated in Fig. 1.

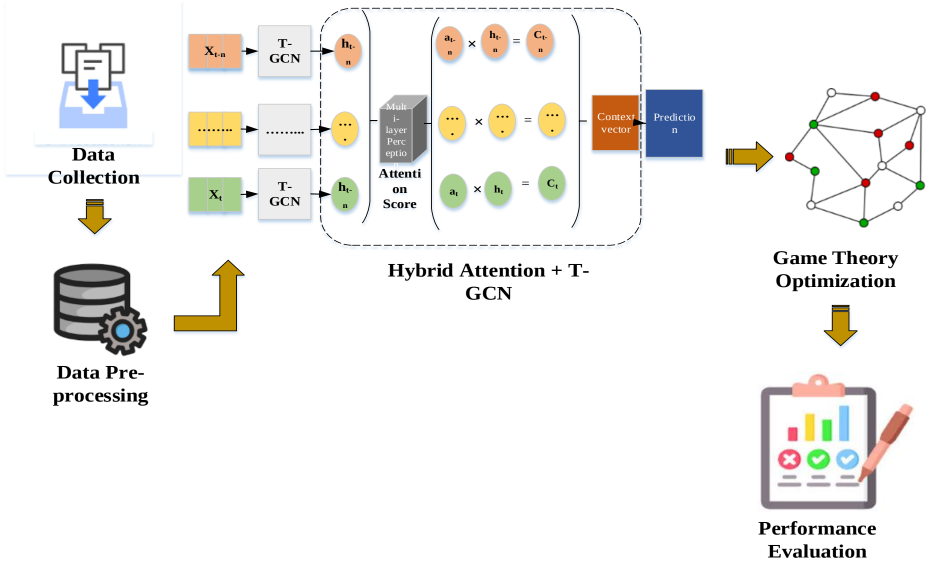

Fig. 1. Proposed methodology for sea level rise prediction.

A. Data Collection

The "Sea Level Change" Kaggle dataset [29], containing complete observations of sea level across a variety of geographic locations and historical time frames, is utilized in this study. Dates of measurement, sea level elevation, geolocation coordinates (latitude and longitude), and other climatic parameters such as temperature and precipitation are all present in the dataset. Sea level change has a huge coverage in terms of time, and thus is easier to understand long term trends and patterns in it. This research is seeking to improve the quality of predictions of sea level change with the data provided by attention and T-GCNs.

B. Data Pre-processing

The pre-processing ensure the data quality and useability in order to predict sea level rise using either mean or KNN imputation for missing values and outlier detection processes including the Z-score method to remove outliers. The next stage is normalizing the values of features using either a Min-Max Scale or Z-Score Normalization. Finally, temporal and geographical adjustments are used to synchronize data between uniform time intervals and uniform spatial resolution. These techniques are a part of the pre-processing procedure to ensure that the dataset is conducted properly for features to be extracted, and for predictive modeling.

1) Handling missing values: Handling missing values is an important step in data preprocessing to guarantee data trustworthiness. KNN addresses this problem by estimating the missing values with a weighted average of k nearest instances, based mainly on Euclidean distance. Weights are inversely proportional to distances, assuming that nearby data points have similar values. This method preserves size of data and natural data rhythms for providing quality assured data for an future analysis and model, as shown in Eq. (1) [24].

$$x_i = \frac{1}{k}\sum_{j=1}^{k} x_j \tag{1}$$

Where x_i are the values of k-nearest neighbors.

2) Data normalization: Min-Max normalization is a common transformation of calculations that make data range into a defined interval, most commonly [0,1]. This technique normalizes features so that the values lie between 0 and 1, while maintaining the relative position of the features data to each other and maximizing the importance of all features as they relate to the model characteristics. The normalization process is conducted by Eq. (2), [25]

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

where the X is the value, X_{min} is the minimum value of a feature, whereas X_{max} is the maximum value of the feature. This transformation is most helpful in scenarios where the scale of features should be made consistent to enhance models' convergence as well as the performance of algorithms in the case of machine learning. This normalization becomes more important in a situation where the features have different units of measurement because this brings all of them to the same level so that the distance calculations and the training of the model will be favoured by all of the features. This can enhance the stability of the model and also increase its general performance by mitigating effects that come with the presence of features that are big and small in magnitude.

3) Temporal and spatial alignment: Synchronization: Data points are more reliable when they are obtained in harmonized time intervals and spatial resolutions to avoid difference in results. This entails extrapolation of data, whereby the data is either interpolated or aggregated to correspond with the required frequency and location. For temporal alignment, interpolation which can be employed to approximate values in missing time points can be used. This is demonstrated by the following empirical Eq. (3), [26]

$$X_t = X_{t-1} + \frac{X_{t+1} - X_{t-1}}{2} \tag{3}$$

Where X_t represents the interpolated value at time t, X_{t-1} is the value at the previous time point, X_{t+1} and is the value at the subsequent time point.

C. T-GCN and Attention Mechanism for Feature Extraction and Classification

Sea level rise predictions need models capable of spatial dependencies between the coastal tracking stations and time series dynamics of the ocean processes. The current methods have certain limitations: (CNNs) are good in detecting spatial-based features but they lack the capability to incorporate sequential patterns, whereas (LSTMs) can capture temporal dependence patterns but not background spatial features. (GCNs) are strong at representational modeling of spatial structures but do not provide temporal modeling of evolving relationships and standalone attention mechanisms tend to over-fit due to disproportionate weighting of features. Such weaknesses make the traditional methods inadequate in capturing the highly nonlinear, and highly coupled nature of prediction of sea level rise. To overcome these shortcomings, the hybrid framework proposed has temporal GCN to learn spatiotemporal representations, attention mechanism to prioritize different features adaptively, and a game theory-based optimization strategy to balance tradeoffs between different objectives, hence enhancing robustness, accuracy, and generalizability in the coastal regions presented by different coastal environments.

The method of predicting sea level rise involves using dataset which contains sea surface temperature, wind speed, precipitation rates, and height. Then this data is pre-processed, where all the data is cleaned, normalized, and divided into train, validation and test sets. T-GCNs are then used to learn the spatial temporal structure and important features are then obtained. These features are then further brought through the use of attention mechanisms that aim to attend to important temporal and spatial details. Finally, the applicability of the hybrid model is evaluated in terms of RMSE, MAE and NSE with different level cross validation. The outcome that is expected from this approach is accuracy, completeness and flexibility of the numerical forecast of sea level increases.

1) T-GCN Model: In this section, the general structure of the algorithm is described as well as specifics of the actual algorithm utilized. For the purpose of modelling both spatial and temporal dependencies the model is used. The proposed model fuses the GRU and GCN. To model complicated geographical dependence, GCN is employed to capture the dependence of radar networks' topological structure and temporal dependence GRU is used to learn the dynamic evolution of radar networks. The multi-radar network's objective in this study is to forecast the radar feature at a given time utilizing network detection data. Any of the following can be the radar characteristic in this method: beam shaping, bandwidth, amplitude, centre frequency, or sampling rate.

a) Input layer: The input layer receives multi-different time chain data collected from the network of geographically distributed C-level monitoring stations. Each data example includes several parameters, such as sea level height, sea surface temperature, atmospheric pressure, wind speed and rainfall. These comments are structured in a temporary sequence and are locally connected, which means that each station is considered a node in a graph. The edges between the nodes represent spatial relationships – either geographical proximity or statistically learnt correlation (e.g., Pearson correlation or mutual information). This graph structure allows the model to understand how the sea level in one place can change or affect the neighbouring areas. The time series aspect ensures that the temporary development of these characteristics is preserved and can be effectively modelled by downstream components such as GCN and GRU layers.

b) GCN block: The graph is responsible for learning spatial dependence between sea level monitoring stations by taking advantage of the graph structure of block data. GCN block models spatial dependence between sea level monitoring stations. It is operated by collecting information about the facility from neighbours of each node based on the adjacent matrix A. Layer is defined as a graph conversion operation on l+1:[27]

$$H^{(l+1)} = \sigma(\widetilde{D}^{-1/2}\tilde{A}\widetilde{D}^{-1/2}H^{(l)}W^{(l)}) \tag{4}$$

In Eq. (4), the adjacency matrix with added self-loops were denoted as $\tilde{A} = A + 1$. The degree of matrix of $\tilde{A}$ is denoted as $\widetilde{D}$. The input feature matrix at layer l is denoted as $H^{(l)}$ and the trainable weighted matrix is denoted as $W^{(l)}$ and finally the activation function is denoted as σ. Using an adjacency matrix, which defines the relationship between spatial nodes (stations), GCN collects information from immediate neighbours of each node. Through the resolution operation conducted on the graph, this block learns spatial representations by smoothing or mixing information in the nodes nearby, which is important to understand the regional dependence. For example, an increase in sea level at a station may indicate or affect the same pattern in nearby areas. By encoding this relevant spatial information, the GCN converts the feature vector of each node into a rich representation that captures how the local sea level behaviour is shaped by its spatial reference.

c) GRU block: The GRU block captures the temporary dependence of data by processing the sequence of spatial characteristics produced by GCN over time. GRUs are a type of RNN that are designed to handle long-term dependence in sequential data without suffering from missing gradients. They work using two gates: the update gate (z_t) determines how much previous information is retained, and the reset gate (r_t) controls how much time of the past is forgotten at each step.

Update Gate [28]

$$z_t = \sigma(W_z X_t + U_z h_{t-1} + b_z) \tag{5}$$

Reset Gate

$$r_t = \sigma(W_r X_t + U_r h_{t-1} + b_r) \tag{6}$$

These help the gate models to maintain a balance between remembering important historical trends and adapting to recent changes in data. By recurring through the stages of time, GRU learns sudden changes in temporary diversity, trends and sea level patterns. This can recall the model that simply models the model with a temporary awareness to predict future sea level values.

d) Hidden output: The final output of the GRU block is Hidden State, which enforces both spatial and temporary information learnt from data. This hidden position acts as a compact representation of a multi-compact time chain, briefly presenting the pattern seen in space (via GCN) and time (through GRU). This includes the required future features, such as the impact of neighbouring stations, historical sea level trends and the importance of different time intervals. The hidden state can be passed in later layers – such as a mediation mechanism, which refines further convenience, or directly predicts an increase in future sea levels for a prediction head (e.g., a dense layer or MLP). Its compact yet expressive nature ensures efficient modelling while maintaining all the necessary information for accurate and strong prediction.

Fig. 2 illustrates the T-GCN, which captures spatial-temporal relationships in graph-structured time series data by integrating GRU and GCN. GRUs employ hidden states h_t, regulated by reset R_t and update Z_t gates, to learn temporal patterns, whereas GCNs utilize spatial information from input nodes (X1–X4) to generate outputs (Z1–Z4). Due to its capacity to process dynamic spatial-temporal information, T-GCN is perfectly suited for sea level rise prediction with enhanced accuracy of forecasts.

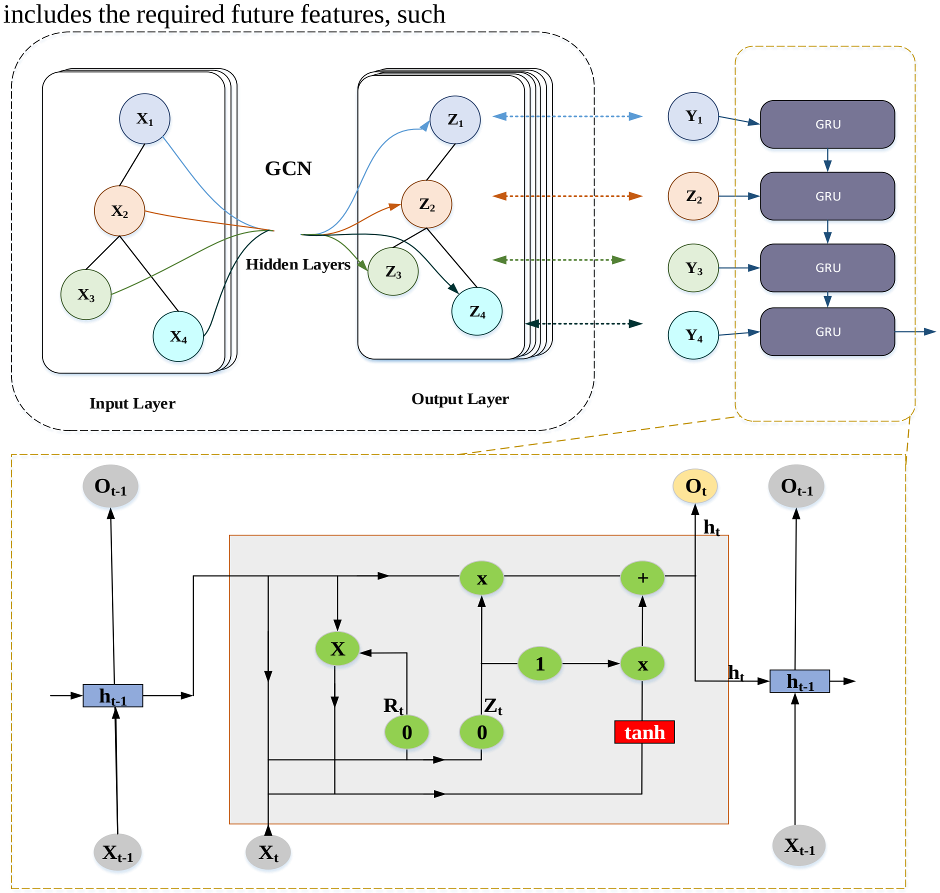

Fig. 2. Architecture of T-GCN.

2) Integration of hybrid temporal graph convolutional networks and attention mechanism: The proposed architecture enhances sea level rise prediction by integrating T-GCN with an attention mechanism. By representing geographic locations as graph nodes and employing graph convolutions to learn patterns over time, T-GCNs effectively simulate spatiotemporal dependencies. An attention mechanism that employs query, key, and value computations to assign higher weights to the most relevant spatial and temporal features is then applied to fine-tune the retrieved features. To emphasize critical information while suppressing less informative parts, attention scores are scaled by a SoftMax algorithm. As the final prediction layer runs over the improved features, the risk analysis for coastal planning is made more robust and accurate. The hybrid architecture is given in Fig. 3.

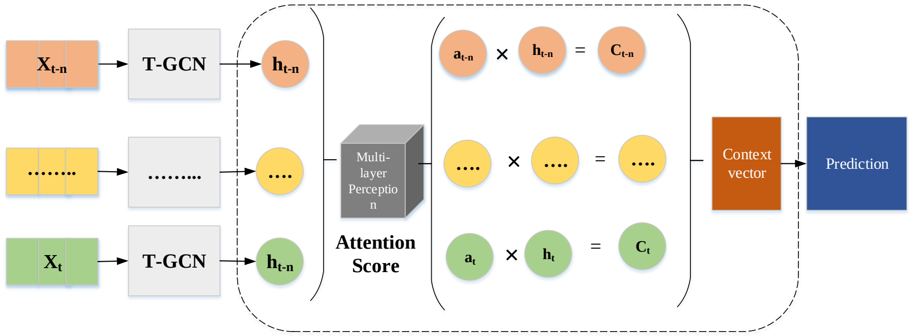

Fig. 3. Architecture of hybrid attention based T-GCN.

Fig. 3 depicts a hybrid model integrating T-GCN with attention for precise time-series prediction. Sequential input sequences from X_{t-n} *to* X_t are fed into T-GCN modules to learn spatial and temporal relationships, producing hidden representations. These are fed into a multilayer perceptron and an attention mechanism that places dynamic weights on every time step. A context vector is calculated by summing attention-weighted hidden states, focusing on pertinent temporal features. This context vector is utilized for prediction, allowing the model to provide solid and interpretable predictions for intricate spatiotemporal phenomena such as sea level rise.

Algorithm 1: Algorithm for Sea Level Rise Prediction Using T-GCN, Attention Mechanisms, and Game Theory Optimization

```
Begin
  Input: Dataset D, adjacency matrix A, time steps T, iterations K
  For each missing value in D
     Apply KNN imputation
  End
  For each feature in D
     Compute Z-score
     If |Z-score| > threshold Then
        Remove outlier
     End
  End
  Normalize features and align data temporally and spatially
  Define nodes V and construct adjacency matrix A
  For each time step t in T
     Build temporal graph Gt
     Apply GCN and GRU to extract spatiotemporal features
  End
  For each extracted feature
     Compute attention score
     If score > threshold Then
        Assign higher weight
     Else
        Assign lower weight
     End
  End
  Initialize k = 1
  While k ⩽ K
     Define objectives and update parameters
     Balance trade-offs using game theory
     Increment k
  End
  Repeat
     Extract features, apply attention, optimize
  Until stopping criteria satisfied
     Return predicted sea level values
End
     Output: Predicted sea level values
```

V. Results and Discussion

The research proves the effectiveness of the proposed T-GCN augmented with attention mechanisms and optimized using game theory approaches, leading to enhanced performance for sea level rise prediction compared to current models. The predicted values exhibit excellent correspondence to the actual measured values, which indicates the ability of the model to successfully extract prior spatial and temporal influences from the data. Moreover, the model reached a very low MAE for values, surpassing equivalent low prediction uncertainty. This serves to further demonstrate the advantage of combining temporal graph-based features with attention mechanisms to effectively incorporate complex spatiotemporal dependencies often inherent in sea level data sets.

A. Historical Trend of Global Average Sea Level Change Over Time

Fig. 4 shows the global, temporal evidence of sea level elevation, represented in millimeters (y-axis) over a time series (x-axis). The figure demonstrates a remarkable upward progression that indicates that sea levels continue to rise, at an ever-increasing rate. For the measured time frame, the sea level has risen by about 200 millimeters (about 8 inches), which points toward serious environmental issues. This increase has dire implications for coastal regions, such as saltwater intrusion into freshwater systems, higher frequency of flooding, more rapid coastal erosion, and population displacement near shorelines.

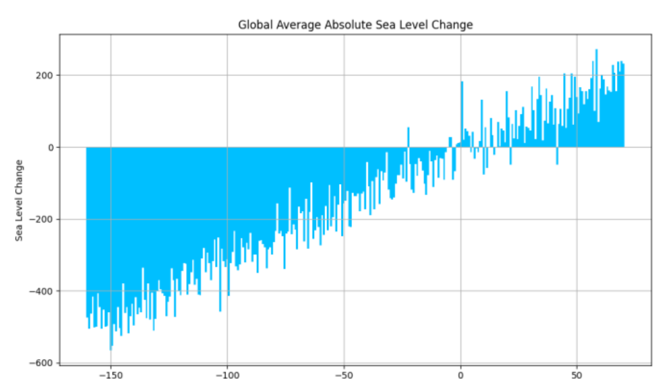

Fig. 4. Historical trend of global average sea level change over time.

B. Rolling Mean and Rolling Deviation of Sea Level Change Over Time

Fig. 5 presents a time series plot of the rolling mean and deviation, illustrating the overall trend and fluctuations in sea level change. The rolling mean shows an initial sea level decline from -200, gradually rising, crossing the x-axis at time 0, and reaching 200—indicating a clear upward trend over the period. Thus, while the mean shows a steady upward trend over the period, the rolling deviation remains relatively stable, indicating consistent variability around the trend. Sea level rise occurs as a continuous process, but the fluctuations around its rate remain relatively stable over time, indicating no consistent pattern of acceleration or deceleration in the short term.

C. Training and Testing Accuracy

Fig. 6 shows the accuracy curves for only the training and the testing phase of the improved Temporal Graph. Convolutional Network known as T-GCN over 100 epochs. Here the solid blue line stands for the training accuracy and the orange dotted line stands for the testing accuracy. At first, both increase significantly; training one rises above 100 % while testing one increases to nearly 90 % by about the 10th iteration. This means that the model gains a relatively fast adjustment to the patterns and relationships of the data. After this point, both the accuracies decrease a little and then become almost stagnant with the training accuracy being slightly higher than testing accuracy. Both accuracies for train and validate data are quite impressive and gradually rises until the 100th epoch, and are very close to the 100% and show model's capability of generalizing well though unseen data after number of epochs.

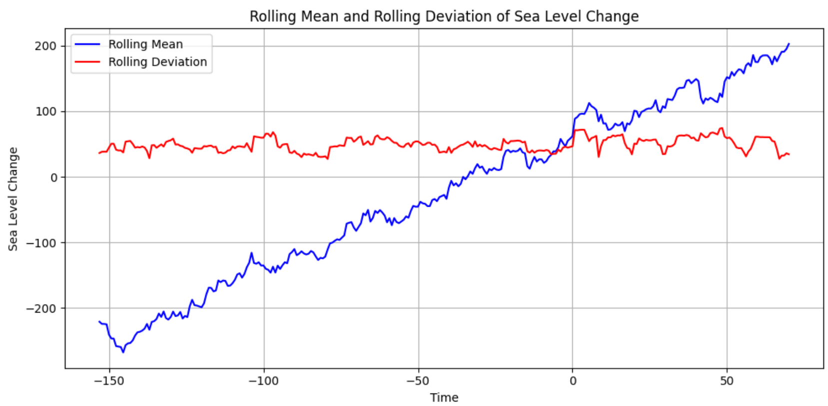

Fig. 5. Rolling mean and rolling deviation of sea level change over time.

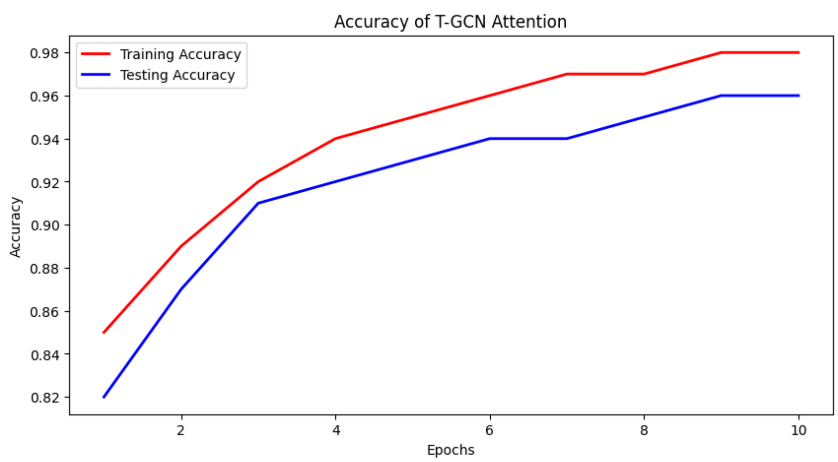

Fig. 6. Training and testing accuracy.

D. Training and Testing Loss

Fig. 7 shows the training and testing loss curves of T-GCN model with attention mechanisms on 60 epochs. The blue curve represents the training loss whereas, the orange line indicates the testing loss. First, both losses are high; the training loss is more than two for all the epochs except epoch 15. 5 and the testing loss is slightly less than 2. 5, which means great discrepancies in the predictions during the initial phases of the model training process. However, as the training process goes further both losses rapidly decrease, the training loss reaches even the negative values below 0. 5 in the 10 th epoch and the testing loss which also trended downward in the same way. As for epoch 30, both the training and testing losses reduce continuously and smoothly which almost reached the testing value equal to zero after 60 epochs. The training and testing loss curves of T-GCN model with attention mechanisms on 60 epochs.

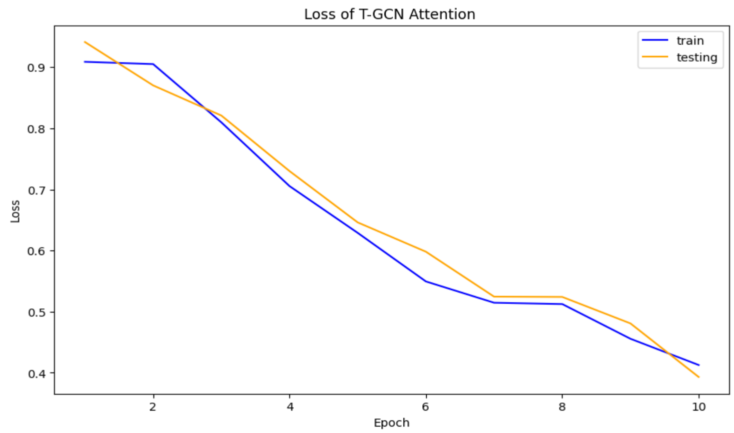

Fig. 7. Training and testing loss.

E. Performance Evaluation

Correlation coefficient, Willmott's Index of Agreement, Nash-Sutcliffe Coefficient, Legates and McCabe's Index, and Nash-Sutcliffe Coefficient are among the performance assessment metrics used to assess the models' dependability in terms of predicted accuracy. In order to determine the extent of the model's inaccuracy and to compare the outcomes, other error statistics such as Root Mean Squared inaccuracy, Mean Absolute Error, Relative Root Mean Squared Error, and Mean Absolute Percentage Error are also utilized.

1) Correlation Coefficient (r): Coefficient of determination reflects the reliability of the regression equation and the correlation coefficient r quantifies the linearity of the observed and simulated data. It varies between -1 and + 1 where a value closer to - 1 represents a perfect negative correlation and a value closer to + 1 perfect positive correlation, no linear relationship is given by Eq. (7) as follows, [29].

$$r = \frac{\sum_{i=1}^{n} DO_i - MDODS_i - MDS}{\sum_{i=1}^{n} DO_i - MDO^2 \sum_{i=1}^{n} DS_i - MDS^2} \tag{7}$$

2) Willmott's index of agreement: Willmott's Index of Agreement (d) is a widely used measure of prediction accuracy against a group of consensus observed data. The expected range of values is from 0 to 1, with 0 indicating no agreement at all, and 1 indicating perfect agreement between predicted and observed values. The index differs from basic correlation measures in that it emphasizes errors by their magnitude, providing a more sensitive measure of prediction accuracy.

$$d = 1 - \frac{\sum_{i=1}^{n} DO_i - DS_i^2}{\sum_{i=1}^{n} DS_i - MDO + DO_i - MDS^2} \tag{8}$$

3) Nash-sutcliffe coefficient: Consequently, to check the potential accuracy of fitted models, the Nash-Sutcliffe Coefficient NS is used. It also shows that an NS value of 1 reflects perfect model performance while an NSNSNS of 0 reflects the model performance in terms of observed means. This is given by Eq. (9),

$$NS = 1 - \frac{\sum_{i=1}^{n} DO_i - DS_i^2}{\sum_{i=1}^{n} DO_i - MDO^2}, -\infty \leq NS \leq 1 \tag{9}$$

4) Legates and McCabe's index: LM is the other measure that is used to evaluate the performance of given models. It highlights the gross dissimilarities of observed and simulated data, which is downplayed for outlying values. LM is a value between 0 and 1 with the higher value representing better results of the model. This is provided by Eq. (10)

$$LM = 1 - \frac{\sum_{i=1}^{n} |DS_i - DO_i|}{\sum_{i=1}^{n} |DO_i - \overline{DO}|} \tag{10}$$

5) Root mean square error: RMSE is a measure of the ordinary used in the assessment of the differences between the estimations and the observations. It imposes more penalty for larger errors than for small ones, owing to the fact that, the residuals are squared before averaging. This corresponds to the value expressed by the Eq. (11),

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} DS_i - DO_i^2} \tag{11}$$

6) Mean Absolute Error: MAE is computed from the average of the absolute differences between the predicted and the actual values, without a regard to the sign of the differences. Basically, it is easy to understand and easy to interpret. This is as given by the Eq. (12).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} DS_i - DO_i^2 \tag{12}$$

7) Relative Root Mean Square Error: RRMSE gives an RMSE percentile value which is the RMSE of a normalized set of values, expressed as a percentage. It scales the RMSE to the range of the observed data thus being suitable when comparing models on different ranges of data. This is given by Eq. (13).

$$RRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} DS_i - DO_i^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} DO_i}} \times 100 \tag{13}$$

8) Mean Absolute Percentage Error: MAPE expresses the average prediction error as a percentage of the observed values. It's useful for understanding the relative size of errors. This is given by Eq. (14),

$$MAPE = \frac{1}{n}\sum_{n}^{i=1}\frac{DS_i - DO_i}{DO_i} \times 100 \quad (14)$$

Where DO_i_i is the observed data, DS_i is the simulated data, MDO is the mean of observed data, and MDS is the mean of simulated data.

Table I and Fig. 8 offer a summary of the performance of the T-GCN + Attention model. The model is good at prediction and has close correspondence between predicted and observed values as indicated by the Nash-Sutcliffe Efficiency of 0.9925, Willmott's Index of Agreement of 0.9958, and Correlation Coefficient of 0.9965. The MAE and RMSE, which reflect small prediction errors, are low at 0.0322 and 0.0412, respectively, yet the Legates and McCabe Index is comparatively high at 0.9321.Though the model is still very reliable across evaluation metrics, relatively high Mean Absolute Percentage Error (1.95%) and Relative RMSE (2.38%) values reflect high unpredictability.

TABLE I. PERFORMANCE AND ERROR METRICS

Metric	T-GCN + Attention
Nash-Sutcliffe Coefficient	0.992452
Willmott’s Index of Agreement	0.995804
Correlation Coefficient	0.996512
Legates and McCabe Index	0.932145
RMSE	0.041203
MAE	0.032154
RRMSE	2.381204
MAPE	1.953214

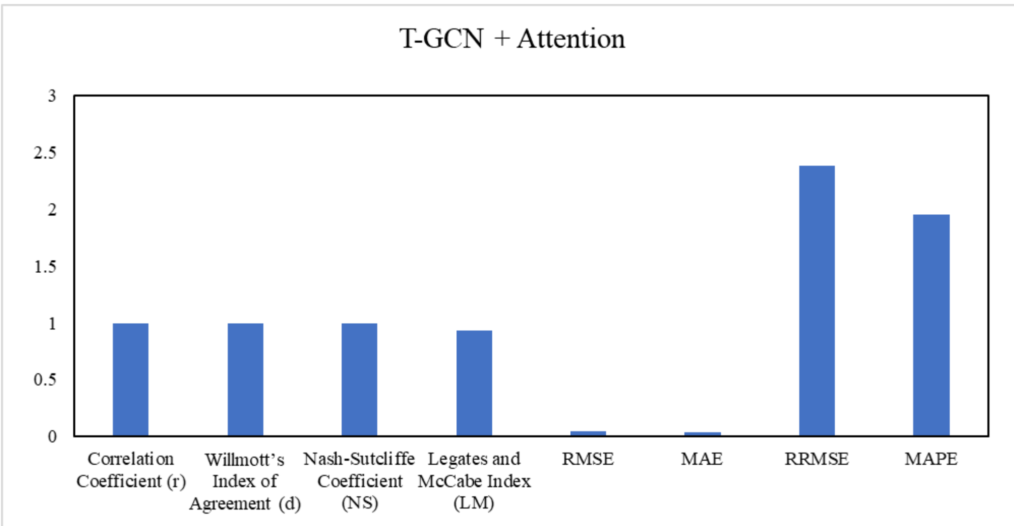

Fig. 8. Performance and error metrics comparison.

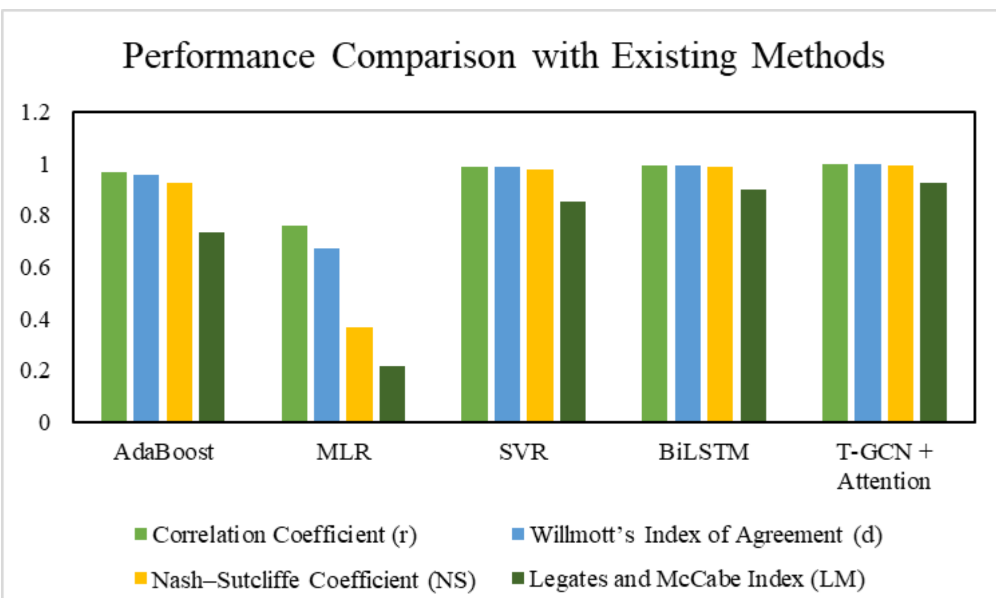

Fig. 9. Performance comparison with existing methods.

Fig. 9 and Table II illustrate a comparative study of five models—AdaBoost, MLR, SVR, BiLSTM, and T-GCN with Attention—based on four performance metrics: Correlation Coefficient (r), Willmott's Index of Agreement (d), Nash–Sutcliffe Efficiency (NS), and the Legates and McCabe Index (LM). The Correlation Coefficient (r) varies between 0.759946 for MLR and 0.996502 for the T-GCN + Attention model, which shows that the latter has the highest linear correlation between predicted and observed values. The Nash–Sutcliffe Efficiency (NS), which is one of the most important indicators of predictive performance, varies from 0.368981 for MLR to 0.993021 for T-GCN + Attention, which indicates greater forecast capacity for the proposed hybrid model. Also, the Legates and McCabe Index (LM), the measure of reliability of model predictions, varies from 0.217703 for MLR to 0.925741 for T-GCN + Attention. Overall, the results clearly show that the proposed T-GCN + Attention model outperforms the other methods on all evaluation metrics, and it confirms there are overall strong, accurate, and effective in predicting sea level rise.

TABLE II. PERFORMANCE COMPARISON WITH EXISTING METHODS

Model	Correlation Coefficient	Willmott's Index of Agreement	Nash–Sutcliffe Coefficient	Legates and McCabe Index
CNN-BiGRU [30]	0.988909	0.987155	0.974866	0.952321
BiLSTM [31]	0.974207	0.964079	0.988219	0.939868
SVMD-BiLSTM [32]	0.954311	0.987647	0.983809	0.913546
CEEMDAN-CNN[33]	0.968946	0.982739	0.988981	0.927703
Proposed T-GCN + Attention	0.996502	0.996312	0.993021	0.985741

a) Paired t-test on MAE between Proposed Model and BiLSTM

TABLE III. PAIRED TWO-TAILED T-TEST

Fold	T-GCN + Attention (Proposed)	BiLSTM
1	0.031	0.043
2	0.032	0.046
3	0.033	0.042
4	0.030	0.045
5	0.031	0.044

Table III paired two-tailed T-test was held in five cross-validation folds to statistically evaluate the performance difference in the meaning of the T-GCN + meditation model and the Bi-LSTM baseline in the proposed T-GCN + MAE. The results detected a low MAE for the proposed model in all folds, and the calculated T-statistic was much higher than the significant value, indicating sufficient difference in performance. With a particularly low p-value ($p < 0.01$), the improvement obtained by the proposed hybrid model is statistically important. This confirms that the T-GCN + attention model not only provides a better future accuracy, but continuously does so, offering a strong and reliable solution to increase sea level compared to traditional deep learning approaches.

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Paired t-test result:
t-statistic: 13.4164
p-value: 0.000195
Result is statistically significant (p < 0.05).
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Fig. 10. T-test outcome.

To validate the performance of the T-GCN + attention model proposed on baseline methods, a coupled two-wheel T-test on MAE values obtained from 5-fold cross-fold was organised as mentioned in Fig. 10. Results ($T = 13.4$, $P < 0.01$) indicate a statistically significant decrease in predicted error compared to BILSTM; it confirms that the proposed model provides a consistent and average improvement.

F. *Discussion*

Precise forecast of sea level rise is essential for climate mitigation and adaptation planning. A new hybrid model that combines T-GCN, attention mechanisms, and game theory optimization is introduced in this research to overcome the limitations of classical models to address highly complex spatiotemporal patterns. The T-GCN models temporal dependencies and spatial correlations, and the attention mechanism emphasizes prominent features such as glacier melt and ocean thermal expansion. Game theory reinforces model strength by encoding feature interactions as a multi-objective strategy, enhancing generalizability and mitigating overfitting. Results of evaluation indicate high predictive efficacy and minimal error rates. The framework is a solid instrument for scientists and policymakers that facilitates data-driven, fine-grained planning for coastal resilience to climate change.

VI. CONCLUSION AND FUTURE WORK

The study introduced a novel Hybrid Forecasting Framework that integrates T-GCN, attention mechanisms and game theory-based adaptations to increase the accuracy of sea level rise prediction. Mixing GCN's spatial modelling abilities with the GRU's temporary learning strength, the proposed T-GCN structure effectively captures the complex spatiotemporal dependence contained in sea level figures. The meditation mechanism further enhances performance by emphasising important characteristics in both dimensions, while the game theory refines the model by reducing optimisation over fitting and ensuring balanced performance in different environmental conditions. As displayed through a high correlation coefficient and low error rates, the model displays strong future-stating capacity, making it a valuable.

Further, the model can be increased by incorporating additional data sources such as demographic profiles, population density, regional melted water rates and extreme weather indicators. These enrichers will not only improve future accuracy but will also enable field-specific risk assessment. Real-time data acquisition and integrating adaptive local calibration will make the system more dynamic and responsible for on-ground changes. Ultimately, deployment of this model within the decision-support structure can assist policy makers and planners in crafting data-operated responses for climate-inspired sea level changes, promoting permanent and flexible coastal growth.

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