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Research Article

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Posted Date: September 24th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10892753/v1>

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Additional Declarations: No competing interests reported.

A Multi-Step Typhoon Track Prediction Method Integrating Spatiotemporal Trajectory Dynamics and Prior Structural Relations

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Abstract

Typhoons often trigger compound disasters such as torrential rain, urban flooding, and mountain torrents. Accurate prediction of their tracks is therefore critical for safeguarding life and property. However, typhoon tracks exhibit strong non-linearity, temporal variability, and uncertainty, making multi-step typhoon track prediction vulnerable to error accumulation and track deviation. To address these challenges, this paper proposes TRGF-KG (Trajectory-Relation Graph Fusion with Knowledge Graph), a multi-step typhoon track prediction method that integrates spatiotemporal trajectory dynamics with prior structural relations. The typhoon knowledge graph is formulated as a relational structural prior that organizes continuous trajectory records into structured relational representations, thereby explicitly preserving event affiliation, temporal ordering, and relational dependencies that are difficult to represent from continuous trajectory sequences alone. A dual-branch architecture is employed: a Transformer learns block-level dynamic temporal representations, while an R-GCN learns relational structural prior representations from the typhoon knowledge graph. During collaborative prediction, the two representations are aligned through time-index-based cross-modal collaborative alignment and selectively integrated through feature-wise gated residual fusion. This design preserves the temporal branch as the prediction backbone while adaptively incorporating aligned relational structural priors to mitigate long-horizon error accumulation and spatial track deviation. Experiments on the Chinese Coastal Typhoon Track Dataset show that TRGF-KG

outperforms comparison models in MAE, RMSE, R^2 , and ADE, demonstrating the effectiveness of integrating spatiotemporal trajectory dynamics and prior structural relations in improving the accuracy and long-horizon stability of multi-step typhoon track prediction.

Keywords: Multi-step typhoon track prediction, Spatiotemporal trajectory dynamics, Prior structural relations, Cross-modal collaborative alignment, Feature-wise gated residual fusion

1 Introduction

Tropical cyclones (TCs), commonly referred to as typhoons in the northwestern Pacific Ocean and the South China Sea, can cause severe casualties and economic losses through strong winds, heavy rainfall, storm surges, and associated secondary disasters. Accurate track prediction is therefore essential for disaster preparedness and emergency response. However, typhoon motion is governed by complex interactions among large-scale atmospheric circulation, air-sea interaction, topography, and storm intensity, resulting in nonlinear and time-varying trajectories. In multi-step prediction, these complexities amplify errors over increasing horizons and may lead to substantial track deviation. Therefore, robust multi-step typhoon track prediction requires the joint modeling of continuous trajectory dynamics and their underlying prior structural relations.

Recent deep learning methods have improved typhoon track prediction by learning nonlinear dependencies from historical trajectories, meteorological fields, and other observational data [1, 2]. However, recurrent and attention-based models still represent typhoon evolution mainly as continuous sequences, while explicit relations among typhoon events, time-indexed observations, and temporal connections are rarely considered. Knowledge graphs provide a means of organizing the same historical observations through explicit prior structural relations [3]. Nevertheless, directly combining graph-derived relational representations with trajectory features may introduce semantic and temporal mismatches. How to align these representations with time-indexed trajectory dynamics and adaptively exploit their complementary information remains insufficiently explored.

To address this gap, we propose TRGF-KG, a multi-step typhoon track prediction framework that integrates trajectory dynamics with knowledge-graph-derived relational representations. A Transformer-based branch captures local trajectory variations and long-range temporal dependencies, while an R-GCN-based branch encodes multi-relational structures in the typhoon knowledge graph. The graph representations are aligned with trajectory blocks using their time indices and selectively incorporated through feature-wise gated residual fusion. This design allows relational information to complement temporal dynamics while limiting noisy interactions between the two representation spaces.

The main contributions of this paper are as follows:

1. We propose TRGF-KG, a dual-branch framework that jointly models temporal trajectory dynamics and knowledge-graph-derived prior structural relations for multi-step typhoon track prediction.
2. We develop a time-index-based cross-modal collaborative alignment strategy and a feature-wise gated residual fusion mechanism to adaptively incorporate relational representations while preserving the continuity and dominant role of trajectory dynamics.
3. Comparative, ablation, and case experiments on the Chinese Coastal Typhoon Track Dataset demonstrate that TRGF-KG improves prediction accuracy and reduces track deviation over long prediction horizons.

2 Related Work

Multi-step typhoon track prediction requires models to characterize spatiotemporal trajectory dynamics while maintaining stable predictive performance over extended horizons. Early empirical statistical methods and numerical weather prediction methods provide important physical and climatological foundations, and their capabilities have been improved by data assimilation [4] and ensemble prediction [5]. However, these methods are still affected by initial condition uncertainty, parameterization errors, and high computational cost, especially when nonlinear evolution and abrupt track changes lead to error propagation in medium- and long-horizon prediction [6]. Recent deep learning methods provide a complementary data-driven approach by learning nonlinear spatiotemporal dependencies from historical trajectories, environmental fields, satellite observations, and other heterogeneous information.

2.1 Temporal Dynamic Modeling and Multi-Step Prediction

Deep learning methods have been widely used to model the nonlinear evolution of typhoon tracks. Existing studies have improved typhoon-related prediction by learning nonlinear mappings [7], mining historical trajectory dependencies [8], extracting spatiotemporal features [9], and simulating satellite cloud image evolution [10]. To better characterize spatiotemporal trajectory dynamics, recurrent neural networks and attention-based models have been introduced into typhoon track and intensity prediction. LSTM-based methods have shown the importance of recent wind speed history and central pressure for short-term temporal modeling [11], while Bayes-RNN and Bayes-LSTM have been used to support uncertainty-aware track and intensity prediction [12]. More recently, Transformer-based models have shown potential for long-range dependency modeling and interpretable multi-step prediction [13].

Although these studies demonstrate the feasibility of data-driven typhoon prediction, several limitations remain for multi-step typhoon track prediction. Recurrent models may suffer from recursive error accumulation and insufficient long-range dependency modeling, while most attention-based methods mainly rely on continuous observation sequences and rarely introduce explicit relational structural priors into the prediction process. Related spatiotemporal forecasting studies have also explored recurrent feedback, adaptive graph learning, dynamic graph modeling, temporal decomposition, and feedback-based updating to improve long-range dependency

representation and multi-step prediction stability [14–18]. However, in multi-step typhoon track prediction, how to jointly model temporal trajectory evolution and explicit prior structural relations remains insufficiently explored.

2.2 Multi-Source Heterogeneous Information Fusion and Prior Structural Relation Enhancement

Typhoon evolution is influenced by heterogeneous information, including historical tracks, satellite observations, reanalysis fields, environmental variables, and storm attributes. Recent studies have consequently moved beyond single-sequence modeling. Trj-DMFMG combines historical trajectories with satellite images, Hurricast integrates statistical features, reanalysis fields, and operational forecasts, and Deep-TCP incorporates storm intensity and environmental variables into an attention-based encoder-decoder framework [19–21]. These studies demonstrate that multi-source information can complement historical trajectories and improve typhoon prediction.

Knowledge graphs provide another means of representing heterogeneous information through explicit entities and relations. They have been applied to disaster information organization, disaster-chain analysis, meteorological knowledge extraction, and cross-source information fusion [22–27]. Related research has also investigated retrieval-augmented knowledge for short-term typhoon nowcasting [28] and physics-informed positional indexing for cross-modal representation alignment [29]. These developments indicate that structured knowledge can support meteorological prediction beyond conventional feature concatenation.

However, most knowledge-enhanced studies focus on semantic organization, retrieval, or decision support rather than end-to-end trajectory prediction. Existing fusion methods also commonly rely on direct concatenation, module stacking, or predictor ensembles, with limited consideration of temporal correspondence between graph-derived representations and trajectory features. Therefore, this study develops a collaborative prediction method that couples Transformer-based temporal dynamic representation learning, R-GCN-based relational structural prior representation learning, time-index-based cross-modal collaborative alignment, and feature-wise gated residual fusion to improve the stability of multi-step typhoon track prediction.

3 TRGF-KG

3.1 Overall Architecture

Typhoon trajectory sequences and knowledge-graph-derived prior structural relations provide complementary representations of the same historical observations. The former characterize continuous spatiotemporal trajectory dynamics, whereas the latter explicitly encode event affiliation, observation inclusion, and temporal evolution. Because the two representations differ in data structure, semantic granularity, and temporal correspondence, direct concatenation may introduce noisy interactions. Therefore, TRGF-KG transforms prior structural relations into time-indexed relational structural prior representations and integrates them with spatiotemporal trajectory dynamics

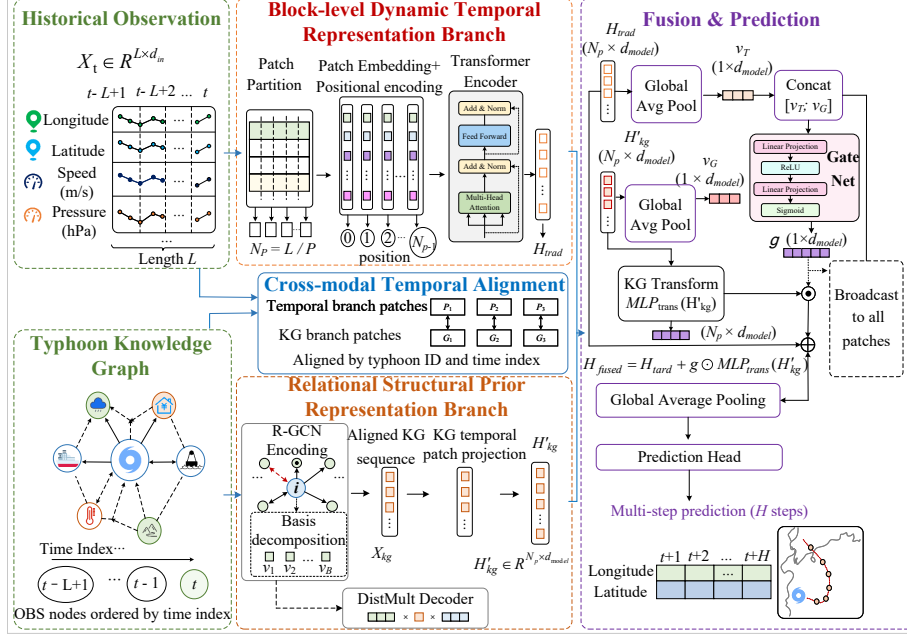


Fig. 1: Overall architecture of the proposed TRGF-KG method.

through aligned representation learning. The overall architecture of TRGF-KG is shown in Fig. 1.

TRGF-KG consists of three main components: a block-level dynamic temporal representation branch, a relational structural prior representation branch, and a fusion-prediction module. The temporal branch encodes historical observations into block-level dynamic temporal representations to capture local variations and cross-block dependencies. The structural prior branch uses the typhoon knowledge graph and R-GCN to learn relational structural prior representations from typhoon events, observation nodes, data sources, and temporal connections. These graph-derived representations are aligned with temporal representations according to typhoon identifiers and time indices, and are then selectively injected through feature-wise gated residual fusion for future multi-step track prediction.

3.2 Block-Level Dynamic Temporal Representation Branch

The typhoon prediction task requires capturing dynamic evolution patterns from continuous observation sequences. However, raw sequential observations are often affected by local fluctuations and long-horizon dependency attenuation, which may weaken multi-step prediction stability. To address this issue, we construct a block-level dynamic temporal representation branch to transform historical typhoon observations into unified temporal representations. This branch organizes continuous observations

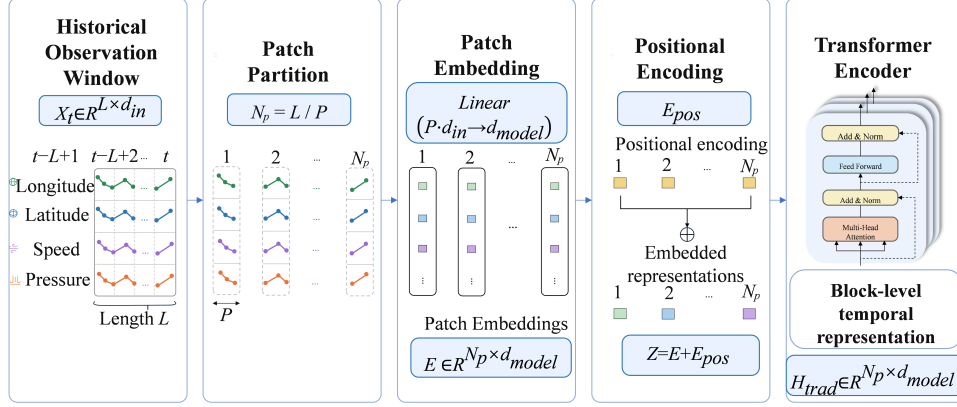


Fig. 2: Computational graph for constructing block-level dynamic temporal representations.

into temporal blocks and uses a Transformer encoder to capture both local evolutionary variations and cross-block dependencies. The computational graph for constructing block-level dynamic temporal representations is shown in Fig. 2.

Since such data are characterized by strong variable coupling, complex temporal dependencies, and uneven observation quality, directly introducing too many variables may increase modeling difficulty and interfere with the learning of typhoon evolution processes. In the block-level dynamic temporal representation branch, an input representation centered on core dynamical states is constructed. Longitude, latitude, wind speed, and pressure are finally selected as input features, and samples with missing values are removed to ensure the integrity of sequence construction:

$$F_{\text{in}} = \{\text{lng, lat, speed, pressure}\}. \quad (1)$$

To ensure that complete input-output sequences can be constructed for each typhoon sample, this paper defines a sequence length constraint. Let the total length of a single typhoon sequence be T . Only typhoon records satisfying the following condition are retained:

$$T \geq L + H + \delta. \quad (2)$$

where L denotes the historical observation window length of the model, namely the number of historical observation steps used as input; H denotes the prediction horizon, namely the number of future time steps to be predicted; and δ denotes the minimum additional order required by the second-order difference operator. This constraint ensures that each sample still has complete supervised labels after feature derivation.

We adopt a sliding-window strategy to construct supervised learning samples. Let the retrospective window length be L and the prediction horizon be H . For any time step t , the input feature tensor is composed of the features from the previous L consecutive observation time steps, denoted as $X_t \in \mathbb{R}^{L \times d_{\text{in}}}$. The target feature tensor corresponds to the physical variables to be predicted over the subsequent H

consecutive observation moments, denoted as $Y_t \in \mathbb{R}^{H \times d_{\text{out}}}$:

$$X_t = \{x_{t-L+1}, x_{t-L+2}, \dots, x_t\}, \quad X_t \in \mathbb{R}^{L \times d_{\text{in}}}, \quad (3)$$

$$Y_t = \{y_{t+1}, y_{t+2}, \dots, y_{t+H}\}, \quad Y_t \in \mathbb{R}^{H \times d_{\text{out}}}. \quad (4)$$

where the input dimension of the observational features, d_{in} , is the number of elements in the feature set, namely $d_{\text{in}} = |F_{\text{in}}|$. Similarly, d_{out} denotes the output dimension of the target features.

Before being fed into the model encoder, the input sequence X_t is divided into non-overlapping temporal blocks. Let the length of each block be P . The number of generated temporal blocks, N_p , is calculated as follows:

$$N_p = \frac{L}{P}. \quad (5)$$

After segmentation, the features are processed by a linear projection layer and positional encoding, and then fed into the Transformer encoder, where they are mapped into a high-dimensional hidden space. The output is a block-level representation sequence with temporal dependencies, denoted as H_{trad} :

$$H_{\text{trad}} = \text{Encoder}_{\text{obs}}(\text{Patch}(X_t)), \quad H_{\text{trad}} \in \mathbb{R}^{N_p \times d_{\text{model}}}. \quad (6)$$

where d_{model} denotes the hidden dimension of the model. This sequence serves as the block-level dynamic temporal representation and is passed to the subsequent feature-wise gated residual fusion module.

3.3 Relational Structural Prior Representation Branch

Continuous observation sequences effectively characterize spatiotemporal trajectory dynamics, but event affiliation, observation inclusion, and temporal evolution are mainly implicit in the sequential organization rather than explicitly modeled as typed relations. To provide a complementary relational representation of the same historical observations, this study constructs a typhoon knowledge graph and treats its multi-relational structure as a relational structural prior. Based on this structure, R-GCN performs relation-specific message passing to transform prior structural relations into learnable relational structural prior representations. These representations provide explicit relational contexts for subsequent time-index-based alignment and fusion with block-level dynamic temporal representations. The computational graph for constructing relational structural prior representations is shown in Fig. 3.

To enhance the information propagation capability of the graph structure, this study adds an inverse relation edge (t, r_{inv}, h) for each directed edge (h, r, t) in the graph, thereby doubling the number of relations and edges. Let the initial state of node i be $h_i^{(0)}$. To address the rapid increase in the number of parameters caused by multiple relations, this study introduces basis decomposition. In the l -th layer of R-GCN, node updates are implemented through message passing based on a linear

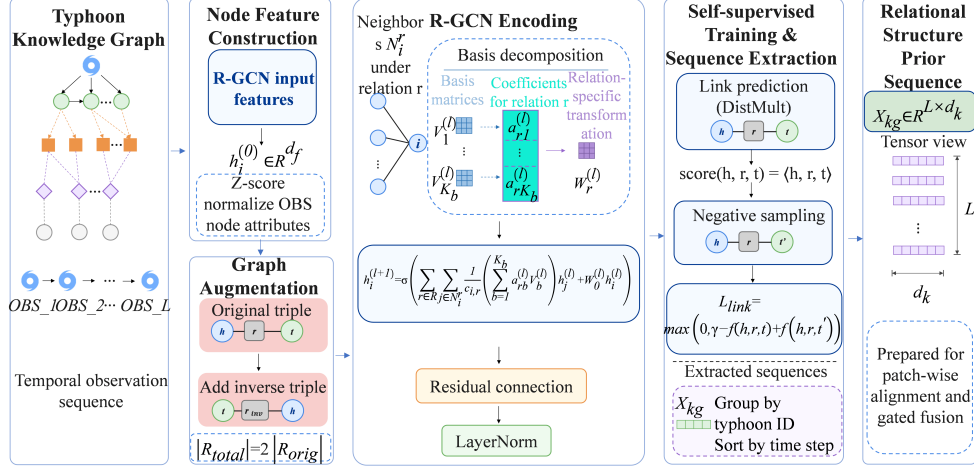


Fig. 3: Computational graph for constructing relational structural prior representations.

combination of basis matrices $V_b^{(l)}$:

$$h_i^{(l+1)} = \sigma \left(\sum_{r \in R} \sum_{j \in N_i^r} \frac{1}{c_{i,r}} \left(\sum_{b=1}^{K_b} a_{rb}^{(l)} V_b^{(l)} \right) h_j^{(l)} + W_0^{(l)} h_i^{(l)} \right). \quad (7)$$

where R denotes the relation set, N_i^r represents the neighbor set of node i under relation r , $c_{i,r}$ is the normalized in-degree of the node, K_b is the predefined number of basis matrices, and $W_0^{(l)}$ is used to preserve the self-information of the node. Residual connections and layer normalization are introduced between network layers to alleviate gradient vanishing.

To learn high-quality graph embeddings, the model adopts DistMult as the decoder to perform the link prediction task. The validity score of a triple (h, r, t) is calculated by the scoring function $f(h, r, t) = (z_h \odot R_r) \cdot z_t$, and Margin Ranking Loss with a margin γ is used for self-supervised optimization. In the downstream prediction stage, to avoid future information leakage, the model only extracts the observation-node representations within the historical observation window $[t - L + 1, t]$ that are aligned with the corresponding time indices. Any observation nodes, attribute information, or temporal edges within the prediction interval $[t + 1, t + H]$ are not used. Consequently, the relational structural prior representation sequence X_{kg} of the typhoon within the observation window is represented as:

$$X_{\text{kg}} \in \mathbb{R}^{L \times d_k}. \quad (8)$$

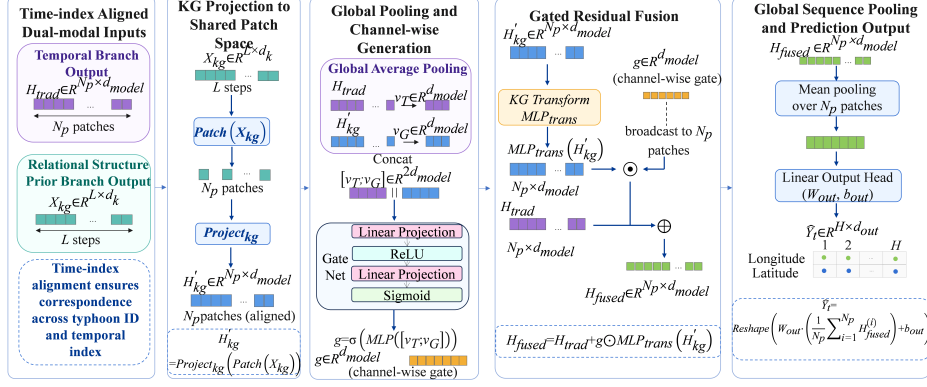


Fig. 4: Computational graph of the cross-modal feature-wise gated residual fusion module.

where d_k denotes the dimension of the graph node embedding vector. These graph-derived embeddings serve as relational structural prior representations for downstream multi-step track prediction.

3.4 Cross-Modal Feature-Wise Gated Residual Fusion

To collaboratively model block-level dynamic temporal representations and relational structural prior representations, this study adopts a feature-wise gated residual fusion mechanism. Instead of directly concatenating heterogeneous representations, this mechanism adaptively injects relational structural prior representations into the temporal representation through hidden-channel-level gating, thereby supporting feature-wise differentiated fusion. In this way, TRGF-KG can selectively exploit relational structural prior representations while preserving the continuity of trajectory dynamics, thereby improving the stability of multi-step typhoon track prediction. The computational graph of the feature-wise gated residual fusion module is shown in Fig. 4.

To align the two modalities at the block level, the graph sequence X_{kg} is transformed into relational structural prior features H'_{kg} through temporal projection and blocking logic:

$$H'_{kg} = \text{Project}_{kg}(\text{Patch}(X_{kg})), \quad H'_{kg} \in \mathbb{R}^{N_p \times d_{\text{model}}}. \quad (9)$$

Global average pooling is then performed on the dual-modal tensors along the block-level sequence dimension, and the pooled features are concatenated and fed into

the gating network to adaptively generate hidden-channel-level fusion weights g :

$$g = \sigma \left(\text{MLP} \left(\left[\frac{1}{N_p} \sum_{i=1}^{N_p} H_{\text{trad}}^{(i)} \parallel \frac{1}{N_p} \sum_{i=1}^{N_p} (H'_{\text{kg}})^{(i)} \right] \right) \right), \quad (10)$$

$$g \in \mathbb{R}^{d_{\text{model}}}.$$

where σ denotes the sigmoid nonlinear activation function, and $\parallel$ represents the tensor concatenation operation. The weight vector g is broadcast along the sequence dimension to dynamically control the injection proportion of the nonlinearly transformed relational structural prior representation across different hidden channels. Meanwhile, H_{trad} is used as the residual backbone to preserve the original dynamical features:

$$H_{\text{fused}} = H_{\text{trad}} + g \odot \text{MLP}_{\text{trans}}(H'_{\text{kg}}). \quad (11)$$

The fused feature tensor then undergoes global sequence pooling and is projected into the output space through a linear mapping layer, yielding the final prediction tensor $\hat{Y}_t$, which covers the future H consecutive observation time steps:

$$\hat{Y}_t = \text{Reshape} \left(W_{\text{out}} \left(\frac{1}{N_p} \sum_{i=1}^{N_p} H_{\text{fused}}^{(i)} \right) + b_{\text{out}} \right), \quad (12)$$

$$\hat{Y}_t \in \mathbb{R}^{H \times d_{\text{out}}}.$$

where W_{out} and b_{out} denote the learnable parameter matrix and bias term of the output mapping layer, respectively, and d_{out} denotes the output dimension of the target features. Although the gating weights g act on the hidden-layer channels, the linear combination property of the output mapping layer enables the model to implicitly assign independent fusion proportions to specific output features. For the f -th predicted physical variable, the effective gating intensity of relational structural prior features, denoted as $\text{gate}_{\text{effective}}^{(f)}$, can be theoretically derived and quantitatively evaluated as follows:

$$\text{gate}_{\text{effective}}^{(f)} = \frac{\sum_{j=1}^{d_{\text{model}}} |W_{\text{out}}^{(f,j)}| g^{(j)}}{\sum_{j=1}^{d_{\text{model}}} |W_{\text{out}}^{(f,j)}|}. \quad (13)$$

where $W_{\text{out}}^{(f,j)}$ denotes the projection weight from the j -th hidden channel to the f -th physical variable in the output layer. The model can adaptively learn to increase the effective contribution of relational structural prior representations for variables that are more strongly affected by the external meteorological environment, while maintaining the dominant role of temporal features for high-confidence autoregressive variables.

3.5 Model Training

After completing cross-modal feature-wise gated residual fusion and outputting the prediction sequence $\hat{Y}_t$, the parameters of the dual-branch fusion prediction network are optimized in a supervised learning manner. Typhoon track prediction is a regression task for continuous multivariate time series, and the training labels have been standardized. Therefore, this paper adopts the mean squared error as the loss function in the normalized space. Let the batch size during model training be B , the prediction horizon be H , and the output dimension of the target prediction features be d_{out} . The loss function for the entire batch is calculated as follows:

$$\mathcal{L}_{\text{pred}} = \frac{1}{BHd_{\text{out}}} \sum_{b=1}^B \sum_{h=1}^H \sum_{j=1}^{d_{\text{out}}} \left(Y^{(b,h,j)} - \hat{Y}^{(b,h,j)} \right)^2. \quad (14)$$

where $Y^{(b,h,j)}$ denotes the standardized ground-truth value of the j -th predicted variable for the b -th sample at the h -th future time step, and $\hat{Y}^{(b,h,j)}$ denotes the corresponding standardized prediction output by the model after fusing the block-level dynamic temporal representation and the relational structural prior representation.

During training, the Adam optimizer, gradient clipping, ReduceLROnPlateau learning-rate scheduling, and early stopping are adopted to improve optimization stability, and the model parameters with the best validation performance are retained for final evaluation.

4 Experiment and Evaluation

4.1 Experimental Settings

4.1.1 Experimental Environment

The experiments were conducted in a computing environment equipped with one NVIDIA GeForce RTX 3080 Ti GPU with 12 GB of dedicated GPU memory. The environment supports CUDA 12.1 and is configured with Python 3.9.23, PyTorch 2.3.1, together with the required Python packages.

4.1.2 Hyperparameter Settings

The main hyperparameter settings used in the experiments are summarized in Table 1. These settings were kept consistent across comparative and ablation experiments unless otherwise specified.

4.1.3 Evaluation Metrics

After prediction, the standardized outputs are inversely transformed to the original physical scale. Model performance is evaluated using mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and average distance error (ADE). MAE and RMSE measure coordinate-component prediction errors, with

Table 1: Main hyperparameter settings of TRGF-KG.

Component	Settings
Block-level dynamic temporal representation branch	Block length $P = 4$; hidden dimension $d_{\text{model}} = 128$; attention heads = 4; Transformer encoder layers = 3; feed-forward network dimension = 256; dropout rate = 0.25.
Relational structural prior representation branch	R-GCN node embedding dimension = 64.
Training configuration	Optimizer = Adam; initial learning rate = 5×10^{-4} ; weight decay = 1×10^{-3} ; batch size = 32; maximum epochs = 100; loss function = mean squared error; gradient clipping threshold = 1.0.
Learning rate scheduling and early stopping	Scheduler = ReduceLROnPlateau; scheduler patience = 7; learning rate decay factor = 0.5; early stopping patience = 20.

RMSE being more sensitive to large deviations; R^2 reflects the fitting ability for longitude and latitude variations; and ADE measures the average great-circle distance between predicted and observed typhoon center positions. Lower MAE, RMSE, and ADE values and higher R^2 values indicate better prediction performance. The formulas are as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |x_i - \hat{x}_i|, \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2}, \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}. \quad (17)$$

where n denotes the total number of samples, x_i represents the observed value, $\hat{x}_i$ represents the model prediction, and $\bar{x}$ denotes the mean of the observed values.

The MAE, RMSE, and R^2 of longitude and latitude can only reflect the prediction errors of the two coordinate components separately, and cannot directly indicate the displacement of the typhoon center in the actual geographical space. Therefore, this paper further introduces the ADE metric. ADE is obtained by calculating the great-circle distance between the predicted and observed typhoon center positions and averaging the distance errors over all predicted points. The distance error of a single predicted point is calculated using the Haversine formula:

$$\text{DE}_i = 2R \arcsin \left(\sqrt{\sin^2 \left(\frac{\hat{\varphi}_i - \varphi_i}{2} \right) + \cos(\varphi_i) \cos(\hat{\varphi}_i) \sin^2 \left(\frac{\hat{\lambda}_i - \lambda_i}{2} \right)} \right). \quad (18)$$

$$\text{ADE} = \frac{1}{N} \sum_{i=1}^N \text{DE}_i. \quad (19)$$

where λ_i and φ_i denote the observed longitude and latitude, respectively; $\hat{\lambda}_i$ and $\hat{\varphi}_i$ denote the predicted longitude and latitude, respectively; R is the mean Earth radius, i.e., $R = 6371.0088$ km; and DE_i denotes the distance error corresponding to the i -th predicted point.

4.2 Dataset Description

4.2.1 Typhoon Track Dataset

This paper uses the Chinese Coastal Typhoon Track Dataset provided by the Marine Science Data Center of the Chinese Academy of Sciences (<https://msdc.qdio.ac.cn/>). The dataset contains typhoon track records in the Western Pacific Ocean from January 1945 to December 2022 at 6-h intervals. After data cleaning, typhoons from 2000 to 2022 are selected and chronologically divided into training, validation, and test sets, including 446 typhoons from 2000 to 2018, 52 typhoons from 2019 to 2020, and 47 typhoons from 2021 to 2022, respectively. This chronological split follows the temporal evolution order and avoids future information leakage. Each prediction sample uses 12 consecutive historical observation steps as input and predicts the longitude and latitude of the typhoon center over the next 24 time steps. The detailed information of the typhoon dataset is shown in Table 2.

Typhoon data are multivariate time series whose features differ in physical units and numerical ranges. If raw values are directly used for model training, variables with larger numerical magnitudes may dominate the loss function and cause imbalanced gradient updates. Therefore, all input features are processed using Z-score standardization before being fed into the model, which reduces scale-induced bias and improves training stability. The calculation formula is as follows:

$$z_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j}. \quad (20)$$

where $x_{i,j}$ denotes the original value of the j -th feature at the i -th time step, and μ_j and σ_j denote the mean and standard deviation of this feature in the training set, respectively. Z-score standardization maps variables with different physical units into a comparable scale, reducing the influence of numerical magnitude differences and facilitating stable optimization of the temporal representation branch and the feature-wise gated residual fusion module.

Table 2: Information on the typhoon dataset.

Typhoon Data	Description
Typhoon ID	Each typhoon is assigned a unique six-digit identifier, formed by the year followed by a sequential number.
Time range	2000–2022
Number of typhoons	545
Time interval	6 hours
Longitude range	[100°E, 180°E]
Latitude range	[0°N, 40°N]
Typhoon intensity	Five levels (from strongest to weakest): STY (severe typhoon), TY (typhoon), STS (severe tropical storm), TS (tropical storm), TD (tropical depression).

4.2.2 Relational Structural Representation of Typhoons

A typhoon event ontology model is constructed to provide a unified description of typhoon disaster categories, typhoon event entities, data sources, and temporal observation processes. In this ontology, typhoon events are linked to disaster categories through disaster type affiliation relations and to their observational data sources through data source relations. Each data source is further connected to time-indexed observation nodes throughout the typhoon life cycle. Adjacent observation nodes are linked by temporal order relations, forming a dynamic trajectory chain that represents the sequential evolution of typhoon movement.

4.2.3 Knowledge Graph Data

Based on the typhoon event ontology, the typhoon knowledge graph is organized as a “category–typhoon–data source–observation node” structure. Four entity types are defined: Category, Typhoon, Source, and OBS, representing disaster categories, typhoon events, data sources, and time-indexed observation nodes, respectively. Four relation types are used to describe hierarchical affiliation, data association, observation inclusion, and temporal evolution: disaster, data_source, HAS_OBSERVATION, and NEXT_OBS. These entities and relations form a graph structure that integrates hierarchical organization with sequential typhoon evolution. The main entity–relation triples are shown in Table 3.

Table 3: Main entity–relation triples in the typhoon knowledge graph.

Head Entity	Relation	Tail Entity	Meaning
Category	disaster	Typhoon	Links disaster categories to typhoon events.
Typhoon	data_source	Source	Associates each typhoon event with its data source.
Source	HAS_OBSERVATION	OBS_n	Connects data sources to time-indexed observations.
OBS_n	NEXT_OBS	OBS_{n+1}	Links adjacent observations in chronological order.

4.3 Comparative Experiments

The prediction performance of TRGF-KG is compared with several representative deep learning baselines under a unified experimental setting. For fairness, all models are trained and tested using the same data split, historical observation window, prediction horizon, input variables, and evaluation metrics. The selected baselines are organized into three groups according to their modeling focus:

1. **Temporal baselines:** LSTM and Transformer are selected to evaluate the effect of temporal sequence modeling. LSTM represents recurrent sequence modeling with gated memory units, while Transformer represents self-attention-based long-range dependency modeling [30, 31]. These two models use the same historical observation sequences as TRGF-KG but do not introduce knowledge-graph-derived relational structural priors.
2. **Knowledge graph representation baselines:** TransE-KG, TransR-KG, and GAT-KG are used to compare different graph representation mechanisms. TransE models relations as translation vectors between head and tail entities, TransR introduces relation-specific projection spaces, and GAT learns graph representations through attention-based neighborhood aggregation [32–34]. In these baselines, the graph representation module is replaced by the corresponding method, while the historical observation window, prediction horizon, input variables, and prediction targets are kept consistent with TRGF-KG.
3. **Knowledge-graph-enhanced temporal-backbone baselines:** TimesNet-KG, SegRNN-KG, and ETSformer-KG are introduced to evaluate the influence of different temporal representation backbones under the same relational structural prior setting. Specifically, only the temporal modeling backbone is replaced by TimesNet, SegRNN, or ETSformer, respectively [35–37]. The typhoon knowledge graph, R-GCN-based relational structural prior representation branch, time-index-based cross-modal collaborative alignment strategy, feature-wise gated residual fusion mechanism, and prediction targets are kept consistent with TRGF-KG.

This grouped design allows the comparison to distinguish the effects of temporal modeling, graph representation learning, and temporal backbone selection under a unified experimental setting.

The performance comparison is reported from three perspectives: coordinate-component prediction accuracy, stepwise long-horizon fitting stability, and spatial

Table 4: Performance comparison of different models in the longitude and latitude prediction task.

Methods	Longitude ($^{\circ}$ E)			Latitude ($^{\circ}$ N)		
	MAE	RMSE	R^2	MAE	RMSE	R^2
LSTM	1.2676	1.9091	0.9082	1.1898	1.7406	0.9114
Transformer	1.4255	2.0218	0.8970	1.1549	1.7255	0.9129
TransE-KG	1.4681	2.1583	0.8826	1.3751	1.8524	0.8997
TransR-KG	1.5015	2.1753	0.8808	1.4887	1.9975	0.8833
GAT-KG	1.4056	2.0327	0.8959	1.1011	1.6375	0.9216
TimesNet-KG	1.2793	1.9801	0.9012	1.1506	1.5367	0.9310
SegRNN-KG	1.5257	2.1233	0.8864	0.9692	1.3077	0.9500
ETSformer-KG	1.5118	2.1219	0.8866	1.2534	1.8750	0.8972
TRGF-KG	1.0261	1.5633	0.9384	0.9014	1.3008	0.9505

Table 5: Changes in longitude and latitude R^2 of different models under different prediction horizons.

Methods	Longitude ($^{\circ}$ E)				Latitude ($^{\circ}$ N)			
	6-step	12-step	18-step	24-step	6-step	12-step	18-step	24-step
LSTM	0.9631	0.9308	0.8795	0.8028	0.9677	0.9291	0.8744	0.7933
Transformer	0.9463	0.9155	0.8679	0.8009	0.9670	0.9279	0.8745	0.8046
TransE-KG	0.9456	0.9097	0.8539	0.7729	0.9532	0.9249	0.8607	0.7755
TransR-KG	0.9444	0.9075	0.8527	0.7699	0.9419	0.9094	0.8387	0.7454
GAT-KG	0.9521	0.9189	0.8645	0.7836	0.9663	0.9370	0.8972	0.8229
TimesNet-KG	0.9523	0.9265	0.8740	0.7984	0.9518	0.9409	0.9181	0.8705
SegRNN-KG	0.9346	0.9068	0.8621	0.7934	0.9752	0.9647	0.9374	0.8768
ETSformer-KG	0.9370	0.9045	0.8565	0.7877	0.9446	0.9164	0.8665	0.7889
TRGF-KG	0.9766	0.9561	0.9198	0.8587	0.9806	0.9621	0.9327	0.8789

distance error. First, the longitude and latitude prediction results of different models are shown in Table 4.

As shown in Table 4, TRGF-KG achieves the best overall coordinate-component prediction performance among all comparison models. In longitude prediction, TRGF-KG obtains MAE, RMSE, and R^2 values of 1.0261° , 1.5633° , and 0.9384, respectively. In latitude prediction, it achieves MAE, RMSE, and R^2 values of 0.9014° , 1.3008° , and 0.9505, respectively. Compared with temporal-only baselines and other knowledge-graph-enhanced models, these results indicate that the proposed method can more effectively reduce coordinate-component prediction errors while improving the fitting capability for longitude and latitude variations.

To further evaluate the stability of different models under increasing prediction horizons, Table 5 reports the longitude and latitude R^2 values at 6-step, 12-step, 18-step, and 24-step horizons.

As shown in Table 5, the R^2 values of all models generally decrease as the prediction horizon extends, reflecting increasing uncertainty and error accumulation in long-horizon typhoon track prediction. However, TRGF-KG maintains the highest 24-step R^2 values, with 0.8587 for longitude and 0.8789 for latitude, indicating stronger long-horizon fitting stability in later prediction steps.

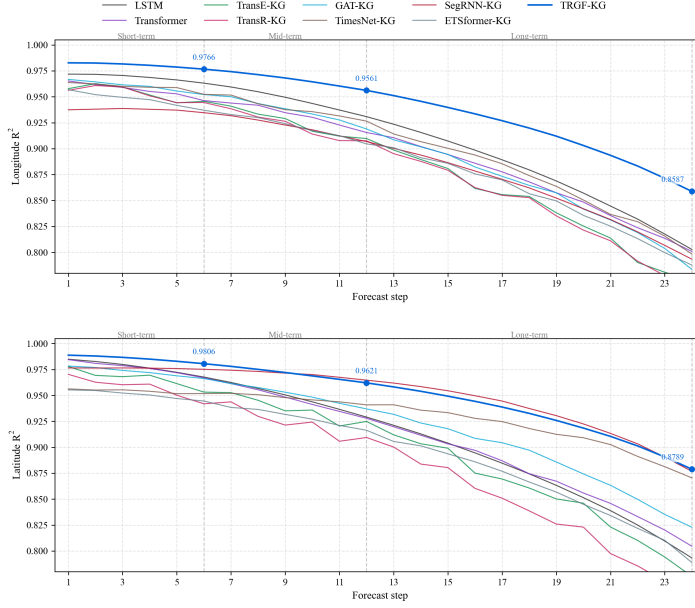


Fig. 5: Stepwise R^2 variation curves of longitude and latitude for different models.

Fig. 5 shows the variation trends of R^2 for longitude and latitude during the stepwise prediction process for different models.

Fig. 5 further illustrates the stepwise R^2 variation trends. In the short-term prediction stage, the differences among models are relatively small, suggesting that nearby historical observations provide strong constraints for near-future track extrapolation. As the prediction horizon increases, TRGF-KG shows a smoother decline than the comparison models, indicating that aligned relational structural priors help mitigate error accumulation over extended horizons.

In addition to coordinate-component errors, the actual geographical displacement of the predicted typhoon center is evaluated using ADE. The track distance error results are shown in Table 6.

As shown in Table 6, TRGF-KG obtains the lowest overall ADE of 161.8773 km and consistently achieves the smallest stepwise ADE values at 6-step, 12-step, 18-step, and 24-step horizons. In particular, its 24-step ADE is 275.6416 km, which is clearly lower than those of the comparison models. These results indicate that TRGF-KG not only improves longitude and latitude prediction accuracy, but also more effectively controls the accumulated spatial deviation of typhoon tracks.

The performance differences among the models mainly reflect how they utilize temporal dynamics and relational structural information. LSTM and Transformer depend primarily on continuous observation sequences, and therefore lack explicit structural constraints for typhoon evolution. TransE-KG and TransR-KG introduce knowledge graph embeddings, but their static entity–relation mapping is insufficient to represent temporal observation dependencies and complex multi-relational semantics. GAT-KG

Table 6: Performance comparison of different models in terms of track distance error.

Methods	ADE (km)	Stepwise ADE (km)			
		6	12	18	24
LSTM	206.3298	135.1993	191.6049	260.6868	346.0228
Transformer	215.6025	152.9353	202.1579	266.8511	348.2593
TransE-KG	238.1478	167.2980	216.1264	292.1384	377.9023
TransR-KG	251.1935	179.7302	230.2592	305.9380	392.2070
GAT-KG	210.9689	151.4955	195.8753	251.7217	340.7424
TimesNet-KG	203.9690	163.6780	186.5778	235.0895	302.9137
SegRNN-KG	208.6397	163.3846	191.3339	238.1818	315.4672
ETSformer-KG	232.6167	181.0488	216.8481	272.6284	352.0500
TRGF-KG	161.8773	107.4119	148.0570	202.0484	275.6416

improves graph-based neighborhood aggregation, but graph aggregation alone cannot fully support continuous track extrapolation. TimesNet-KG, SegRNN-KG, and ETSformer-KG enhance temporal pattern modeling through periodic variation modeling, segmented recurrence, and trend decomposition, respectively, but their interaction between temporal dynamics and relational structural prior representations remains limited. These results indicate that multi-step typhoon track prediction requires not only effective temporal representation learning, but also the aligned and adaptive integration of knowledge-graph-derived relational structural prior representations.

4.4 Ablation Experiments

We conduct ablation experiments to further investigate the contribution of each component in TRGF-KG. Three variants are constructed for testing and comparison:

1. Baseline: The relational structural prior input is removed, and only the block-level dynamic temporal representation branch is retained to predict typhoon track variables.
2. Baseline+RGCN: The R-GCN-based relational structural prior representation branch is introduced to learn relational structural prior representations from the typhoon knowledge graph. The learned relational structural prior representations are concatenated with block-level dynamic temporal representations for joint prediction.
3. Baseline+RGCN+SG: A shared gating fusion mechanism is adopted to perform unified weighted fusion of the block-level dynamic temporal representations and relational structural prior representations.

The performance results of the ablation methods are shown in Table 7.

In the ablation experiments, Baseline+RGCN improves most metrics compared with Baseline, reducing longitude MAE from 1.4255° to 1.3355° , latitude MAE from 1.1549° to 1.0877° , and ADE from 215.6025 km to 203.5570 km. This indicates that R-GCN-based relational structural prior representations can supplement block-level temporal modeling with graph-structured information involved in typhoon evolution. Baseline+RGCN+SG further improves longitude prediction, but its latitude MAE

Table 7: Performance comparison of different components of TRGF-KG.

Methods	Longitude (°E)			Latitude (°N)			Distance Error (km)
	MAE	RMSE	R^2	MAE	RMSE	R^2	ADE
Baseline	1.4255	2.0218	0.8970	1.1549	1.7255	0.9129	215.6025
Baseline+RGCN	1.3355	1.9784	0.9014	1.0877	1.6207	0.9232	203.5570
Baseline+RGCN+SG	1.2769	1.8599	0.9128	1.1620	1.6775	0.9177	204.1109
Baseline+RGCN+PG	1.0261	1.5633	0.9384	0.9014	1.3008	0.9505	161.8773

increases to 1.1620° and its ADE is slightly higher than that of Baseline+RGCN, suggesting that a shared gating weight cannot fully adapt to the differentiated requirements of different prediction dimensions. In contrast, Baseline+RGCN+PG, namely the complete TRGF-KG method, achieves the best results across all metrics and reduces ADE to 161.8773 km, validating the effectiveness of feature-wise gated residual fusion.

These results further show that the performance gain does not simply result from adding graph-based representations. The improvement of Baseline+RGCN over the temporal-only Baseline indicates that relational structural prior representations provide complementary structural information for trajectory prediction. However, direct concatenation and shared gating cannot fully exploit this information. TRGF-KG achieves the best performance because the relational structural prior representations are aligned with trajectory blocks by time index and selectively incorporated through feature-wise gated residual fusion. Therefore, the contribution of the knowledge graph lies in providing explicit, alignable, and adaptively controllable prior structural relations rather than simply increasing model complexity.

Fig. 6 describes the error distribution characteristics of different models during prediction through multi-step longitude and latitude error boxplots.

Fig. 6 further compares the multi-step longitude and latitude error distributions of different ablation settings. The Baseline boxes are generally located at higher error levels, indicating that using only block-level temporal representations leads to larger deviations during multi-step extrapolation. After R-GCN is introduced, the box positions shift downward, suggesting that relational structural priors help reduce the overall error level. However, Baseline+RGCN+SG still shows relatively large box heights and whisker ranges, indicating that shared gating cannot sufficiently adapt to the differentiated fusion requirements of different prediction dimensions. In contrast, TRGF-KG has lower box positions, lower median lines, and narrower box and whisker ranges, demonstrating that feature-wise gated residual fusion reduces both the overall error level and error fluctuation, thereby improving the stability of multi-step track prediction.

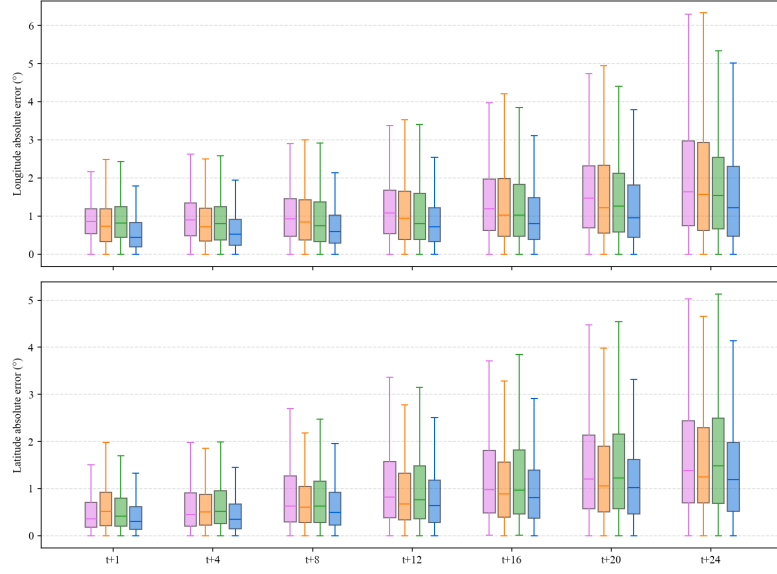


Fig. 6: Multi-step longitude and latitude error boxplots in the ablation experiments.

4.5 Experimental Cases and Visualization

To further evaluate the prediction capability of the proposed method under different real-world track patterns, two representative cases are selected: Typhoon “Chanthu”, which exhibits pronounced turning behavior and large track variations, and Typhoon “Muifa”, which shows a relatively smooth track and stable movement trend. These two cases are used to examine model performance in complex turning and regular movement scenarios, respectively.

4.5.1 Visualization of Experimental Results

Figs. 7 and 8 show the prediction results of the two representative cases, Typhoon “Chanthu” and Typhoon “Muifa”, from the perspectives of track fitting and map-based spatial comparison, respectively.

For Typhoon “Chanthu”, which exhibits pronounced turning behavior, Trans-former captures the general movement direction but shows a noticeable spatial bias in the middle and later prediction stages, indicating that temporal modeling alone is prone to trend drift in complex turning scenarios. TransE-KG presents larger local fluctuations, suggesting that translation-based graph embedding is insufficient to represent the temporal and multi-relational structure involved in typhoon evolution. TimesNet-KG and SegRNN-KG improve temporal pattern modeling to some extent, but still show deviations near the turning segment. By contrast, TRGF-KG follows the curved evolution of the observed track more stably and better reconstructs the movement process near Taiwan and the East China Sea.

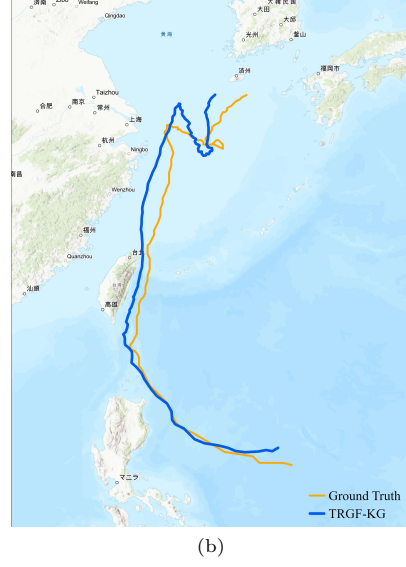
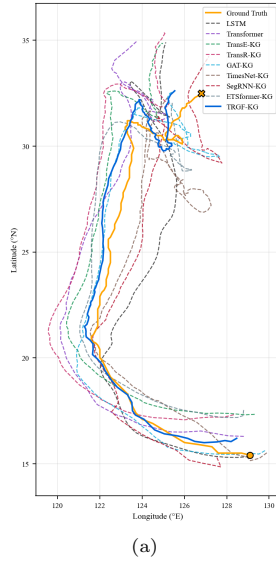


Fig. 7: Typhoon “Chanhu”, the 14th typhoon in 2021: (a) comparison of predicted tracks by representative models; (b) map-based comparison between the observed track and the TRGF-KG predicted track.

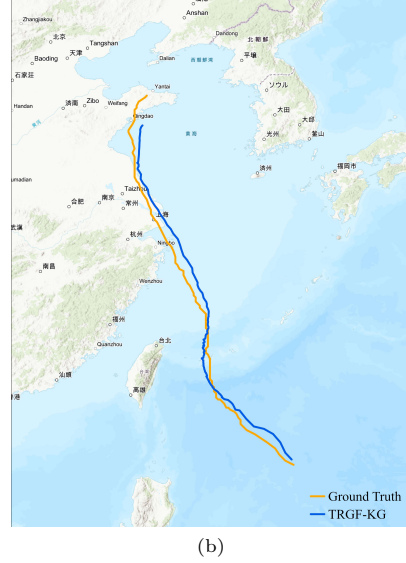
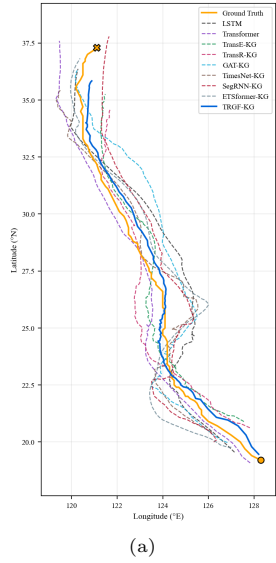


Fig. 8: Typhoon “Muifa”, the 12th typhoon in 2022: (a) comparison of predicted tracks by representative models; (b) map-based comparison between the observed track and the TRGF-KG predicted track.

For Typhoon “Muifa”, whose track is relatively smooth, the differences among models are smaller; however, Transformer still shows directional bias and TransE-KG exhibits local fluctuations, whereas TRGF-KG better preserves the initial position, movement direction, and subsequent extension trend. These visualization results indicate that TRGF-KG has stronger track fitting capability in both complex turning and relatively stable movement scenarios.

4.5.2 Analysis of Experimental Results

Figs. 9 and 10 further quantitatively analyze the prediction performance of different models from two perspectives: the average longitude–latitude component errors and the stepwise track distance errors.

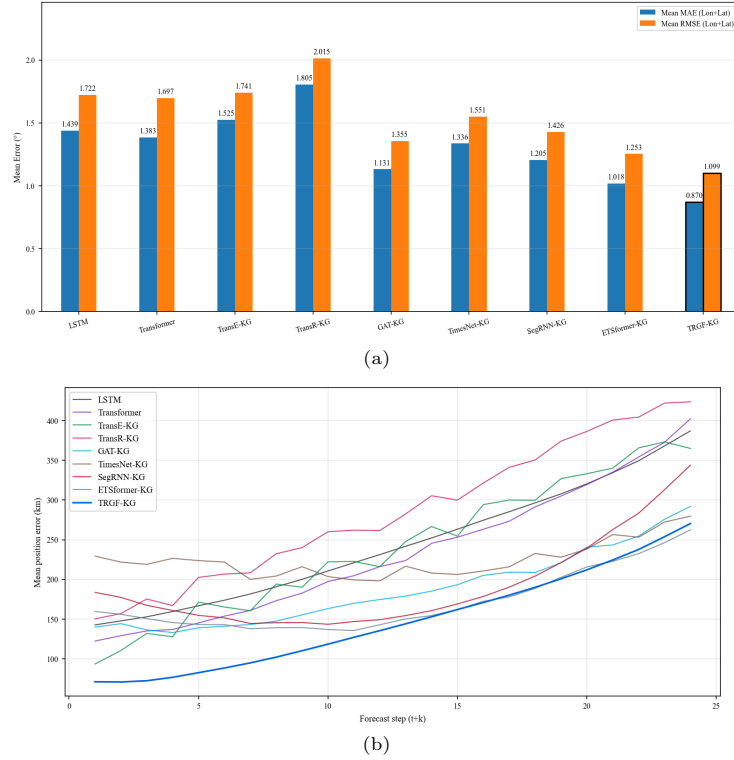


Fig. 9: Typhoon “Chanthu”, the 14th typhoon in 2021: (a) comparison of average MAE and RMSE of longitude and latitude for representative models; (b) comparison curves of stepwise track distance errors.

For “Chanthu”, which exhibits pronounced turning behavior, the error differences among models are more evident, indicating that complex tracks impose higher requirements on long-horizon trend modeling and turning variation capture. As shown in Fig. 9(a), TRGF-KG achieves the lowest average MAE and RMSE, with values of

0.870° and 1.099°, respectively. Fig. 9(b) further shows that its stepwise track distance error increases gradually from approximately 70 km in the early stage to about 270 km at the 24-step horizon, whereas the late-stage errors of Transformer and TransE-KG exceed 400 km and 360 km, respectively. These results indicate that TRGF-KG can better suppress error accumulation and track deviation in complex turning scenarios.

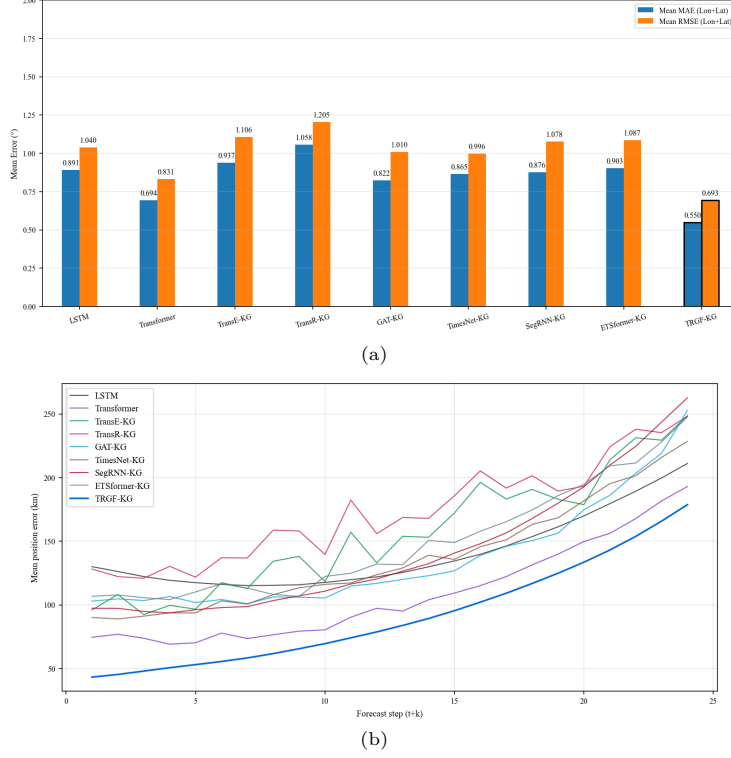


Fig. 10: Typhoon “Muifa”, the 12th typhoon in 2022: (a) comparison of average MAE and RMSE of longitude and latitude for representative models; (b) comparison curves of stepwise track distance errors.

For “Muifa”, which has a relatively stable movement trend, all models show lower overall errors and smaller inter-model differences, but TRGF-KG still maintains the best performance. As shown in Fig. 10(a), TRGF-KG obtains the lowest average MAE and RMSE, with values of 0.550° and 0.693°, respectively. Fig. 10(b) further shows that its stepwise track distance error remains at a relatively low level throughout the prediction process and reaches approximately 178 km at the 24-step horizon. These results indicate that the advantage of TRGF-KG is not limited to complex turning samples; instead, the joint use of block-level temporal representations, relational structural priors, and feature-wise gated residual fusion also improves prediction stability in regular track scenarios.

5 Conclusions

This study proposed TRGF-KG for multi-step typhoon track prediction. The method jointly models spatiotemporal trajectory dynamics and prior structural relations through two complementary branches: a Transformer learns block-level dynamic temporal representations from continuous trajectory sequences, while an R-GCN learns relational structural prior representations from the typhoon knowledge graph. Through time-index-based cross-modal collaborative alignment and feature-wise gated residual fusion, the relational structural prior representations are selectively incorporated into the temporal prediction backbone. Experimental results demonstrate that TRGF-KG consistently outperforms the comparison models. The ablation and case studies further show that the aligned and adaptive integration of prior structural relations mitigates error accumulation and improves track fitting for both turning and relatively smooth trajectories. These findings indicate that explicit relational structural representations provide an effective complement to continuous temporal modeling in multi-step typhoon track prediction. As the current knowledge graph is primarily derived from historical observations, future work will incorporate richer meteorological and physical information and evaluate the model across different ocean basins.

Declarations

Ethics, Consent to Participate, and Consent to Publish

Not applicable.

Clinical Trial Number

Not applicable.

Competing Interests

The authors declare no conflicts of interest relevant to this study.

Funding

This work is supported by the Natural Science Foundation of Jilin Province under grants 20240302083GX.

Data availability

The original typhoon track data used in this study were obtained from *A dataset of typhoon tracks in offshore China* [38], provided by the Marine Science Data Center, Chinese Academy of Sciences, with the DOI <https://doi.org/10.12157/IOCAS.20210804.001>. The processed data and materials supporting the analyses and results of this study are available from the corresponding author upon reasonable request.

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