Ms. Ref. No.: EGUSPHERE-2025-239

Title: A Novel Method for Sea Surface Temperature Prediction using a Featural Granularity-Based ConvLSTM Model of Data-Knowledge-Driven

Journal: GMD

Responses to RC #2:

This paper proposed a featural granularity-based and data-knowledge-driven ConvLSTM model for medium and long-term SST prediction. The paper is well written in general with clear structure, as well as extensive experiments performed in 3 different areas. Some comments for the authors' reference are listed below.

Reply: Thank you for your thoughtful review and valuable feedback. We greatly appreciate your positive assessment of the paper's overall quality, including its clear structure and the extensive experiments conducted across three different areas. Your recognition encourages us, and your constructive comments are crucial for enhancing the quality of our manuscript. We have carefully addressed all the issues you raised, and our detailed responses are presented below. Thank you again for dedicating your time and effort to this review.

It seems that the title has grammatical mistakes as the "data-knowledge-driven" is an adjective but not a noun. Maybe it can be revised to "A Novel Method for Sea Surface Temperature Prediction using a Featural Granularity-Based and Data-Knowledge-Driven ConvLSTM Model".

Reply: Thank you for your valuable guidance on the title. We fully agree with your suggestion regarding grammatical adjustment. Following your advice, we have revised the title to "A Novel Method for Sea Surface Temperature Prediction using a Featural Granularity-Based and Data-Knowledge-Driven ConvLSTM Model" to ensure grammatical accuracy and clarity.

This revised title better reflects the core content of the study while maintaining the key technical features highlighted in the original version. Thank you again for your meticulous review and helpful feedback, which have significantly improved the precision of our manuscript.

The baseline models adopted in the experiments are a little bit out of date. It's suggested that the SOTA models, i.e., transformer and GCN etc., be added for comparisons.

Reply: Thank you for your insightful suggestion regarding updating the baseline models with state-of-the-art (SOTA) methods such as Transformer and GCN-based models. We fully agree that incorporating recent SOTA models strengthens the robustness of our comparative analysis, and we have revised the manuscript accordingly.

Specifically, we have added the Graph Memory Neural Network (GMNN) proposed by Liang et al. (2023) as a new baseline model. GMNN is a representative SOTA model for SST prediction that integrates graph neural network (GCN) components for spatial feature extraction and temporal encoding, aligning with your recommendation to include GCN-based SOTA methods. We adjusted its hyperparameters (e.g., hidden layer dimensions and training iterations) while preserving its core architecture.

Comparative results with GMNN have been added to **section 3.3.4 of the revised manuscript**. The results are shown in the figure below (Figs. 1-3). Additionally, detailed information about GMNN (architecture, adjusted hyperparameters, and implementation details) has been **supplemented in the supporting materials (Text S6 and Table S1)** to enhance transparency.

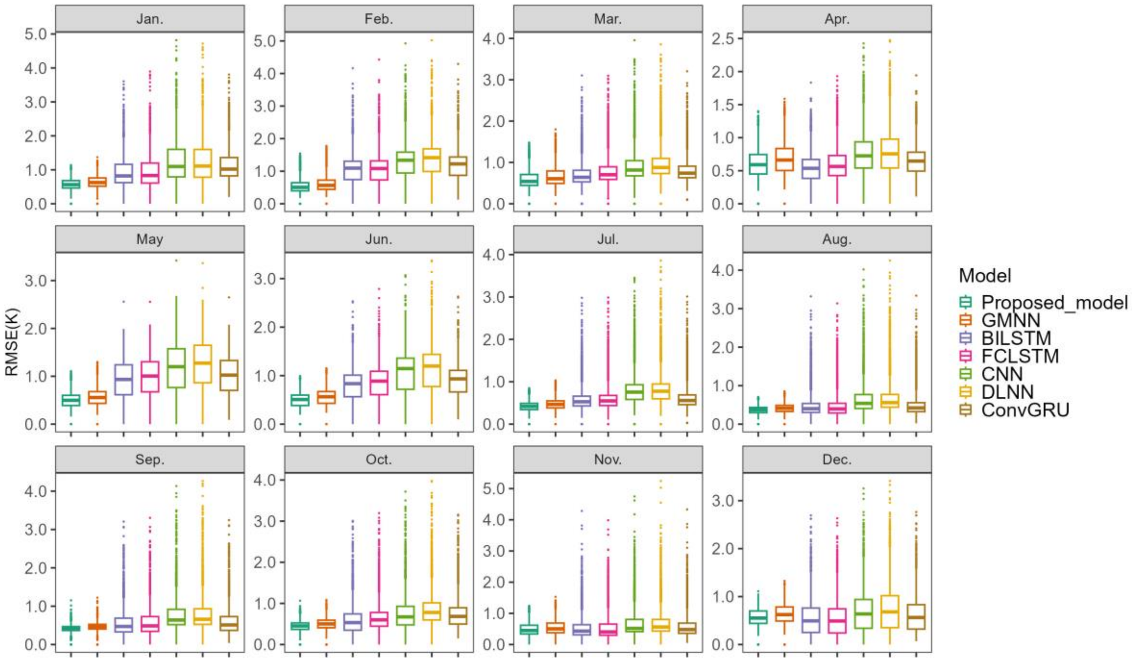

Fig.1 RMSE of SST predictions for the years 2012-2021 within study area I, obtained using the baseline models and the proposed model.

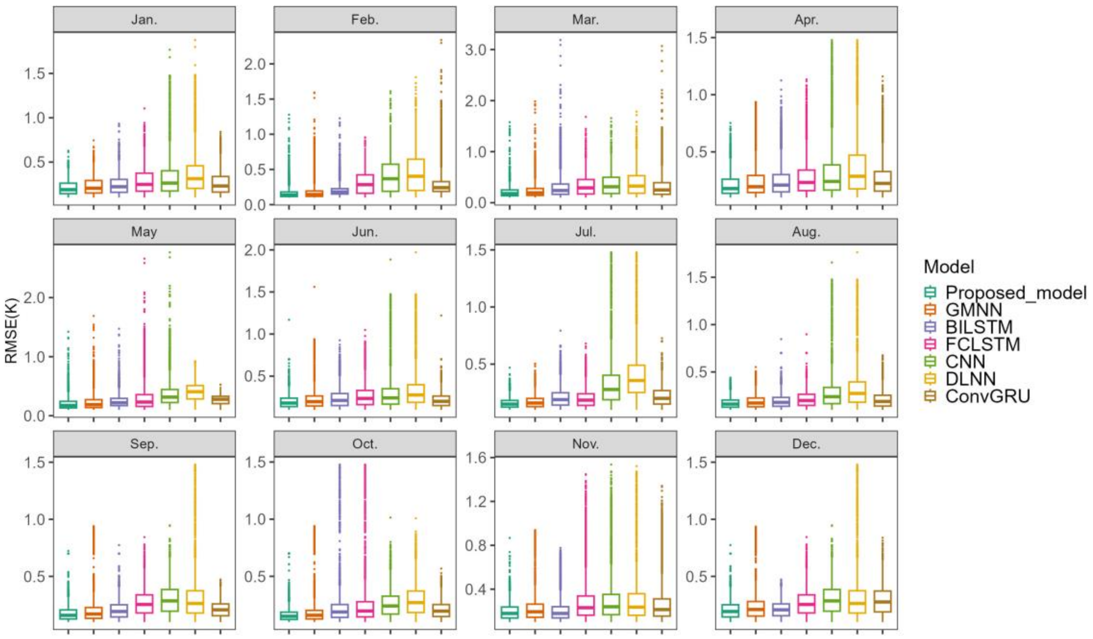

Fig.2 RMSE of SST predictions for the years 2012-2021 within study area II, obtained using the baseline models and the proposed model.

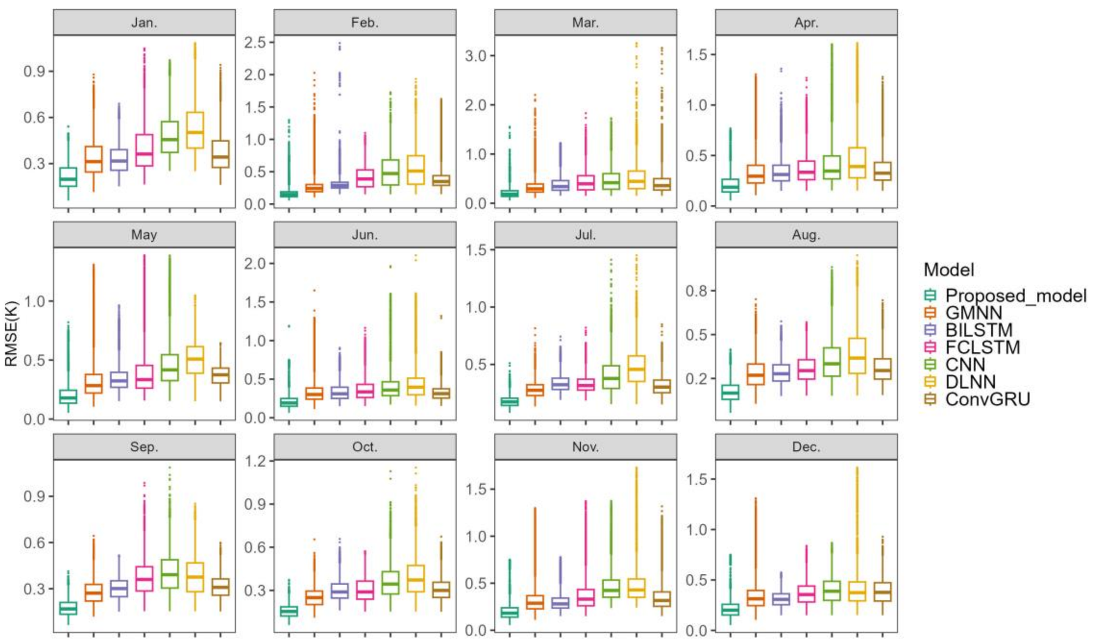

Fig.3 RMSE of SST predictions for the years 2012-2021 within study area III, obtained using the baseline models and the proposed model.

More literatures concerning the SST predictions in the period of 2022 – 2025 should be reviewed in the introduction section.

Reply: Thanks for your good suggestion. We fully agree with your suggestion and have revised the introduction section accordingly. Specifically, we have supplemented the review of data-driven SST prediction methods, incorporating relevant references to enhance the comprehensiveness of the literature review. You can find these revisions in the revised manuscript on pages 2-3 at lines 62-65, 80-83, and 91-94.

Lines 62-65 in the revised manuscript on page 2: “Some data-driven models have been used, such as Markov models (Xue and Leetmaa, 2000), support vector regression(Imani et al., 2017), empirical canonical correlation analysis (Collins et al., 2004; Tang et al., 2000), linear regression (Kug et al., 2004), empirical orthogonal functions (Neetu et al., 2011), and artificial neural networks (ANNs)(Azhary and Minaoui, 2025; Liu et al., 2024; Philippus et al., 2024).”

Lines 80-83 in the revised manuscript on page 3: “Graph neural networks (GNNs) effectively capture local spatial correlations through adjacent-node aggregation. However, the prevalent overemphasis on neighborhood relationships and neglect of global connections in current models inevitably undermines SST prediction accuracy, particularly given the ocean’s interconnected nature where geographically distant sites exhibit correlated patterns (Dai et al., 2025; Liang et al., 2023).”

Lines 91-94 in the revised manuscript on page 3: “Azhary and Minaoui (2025) proposed an encoder-decoder dual attention ConvLSTM model that leverages convolutional operations for spatial dependencies, LSTM for temporal sequences, and dual attention (contextual + spatial) to prioritize critical spatiotemporal features. The model achieves significant improvements in prediction accuracy and computational efficiency for Moroccan coastal SST forecasting compared to single-attention baselines.”

Newly Incorporated References (2023-2025):

Azhary, F. Z. E. and Minaoui, K.: EDDA-ConvLSTM: Encoder-Decoder Dual Attention ConvLSTM for Moroccan Coastal Sea Surface Temperature Prediction, IEEE Geoscience and Remote Sensing Letters, 22, 1-5, 10.1109/LGRS.2025.3551623, 2025.

Bilgili, M., Pinar, E., and Durhasan, T.: Global monthly sea surface temperature forecasting using the SARIMA, LSTM, and GRU models, Earth Science Informatics, 18, 10, 10.1007/s12145-024-01585-z, 2024.

Chen, F., Li, X., and Wang, Y.: A knowledge-augmented deep fusion method for estimating near-surface air temperature, Remote Sensing of Environment, 326, 114819, 10.1016/j.rse.2025.114819, 2025a.

Chen, H., Chen, Y., and Zhang, Z.: SVRNN: A Spatiotemporal Prediction Model for Sea Surface Temperature Prediction in the Taiwan Strait, IEEE Geoscience and Remote Sensing Letters, 22, 1-5, 10.1109/LGRS.2025.3554296, 2025b.

Dai, W., He, X., Geng, X., Zhang, S., and Gao, Z.: Sea Surface Temperature Prediction Based on Spatio-Temporal Graph Contrastive Learning Network, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 18, 14228-14239, 10.1109/JSTARS.2025.3571494, 2025.

Kim, Y. J., Kim, H.-c., Han, D., Stroeve, J., and Im, J.: Long-term prediction of Arctic sea ice concentrations using deep learning: Effects of surface temperature, radiation, and wind conditions, Remote Sensing of Environment, 318, 114568, 10.1016/j.rse.2024.114568, 2025.

Liang, S., Zhao, A., Qin, M., Hu, L., Wu, S., Du, Z., and Liu, R.: A Graph Memory Neural Network for Sea Surface Temperature Prediction, Remote Sensing, 15,3539, 10.3390/rs15143539, 2023.

Liu, Y., Zhang, L., Hao, W., Zhang, L., and Huang, L.: Predicting temporal and spatial 4-D ocean temperature using satellite data based on a novel deep learning model, Ocean Modelling, 188, 102333, 10.1016/j.ocemod.2024.102333, 2024.

Philippus, D., Sytsma, A., Rust, A., and Hogue, T. S.: A machine learning model for estimating the temperature of small rivers using satellite-based spatial data, Remote Sensing of Environment, 311, 114271, 10.1016/j.rse.2024.114271, 2024.

Song, N., Nie, J., Wen, Q., Yuan, Y., Liu, X., Ma, J., and Wei, Z.: GL-ST: A Data-Driven Prediction Model for Sea Surface Temperature in the Coastal Waters of China Based on Interactive Fusion of Global and Local Spatiotemporal Information, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 18, 2959-2974, 10.1109/JSTARS.2024.3515638, 2025.

Vytla, V., Baduru, B., Kolukula, S. S., Ragav, N. N., and Kumar, J. P.: Forecasting of sea surface temperature using machine learning and its applications, Journal of Earth System Science, 134, 25, 10.1007/s12040-024-02483-0, 2025.

Yang, Y., Lam, K.-M., Dong, J., and Ju, Y.: Multi-Factor Deep Learning Model for Sea Surface Temperature Forecasting, 10.3390/rs17050752, 2025.

The structures and parameters of the baseline models could be given.

Reply: Thank you for your guidance. In response to your request, we have created comprehensive Supplementary Materials that details the complete architecture, hyperparameters, and implementation specifics of all baseline models. Thank you.

Additional remark:

Lines 519-520 in the revised manuscript (Manuscript with author details): "The authors are grateful to three reviewers and the editor for their constructive comments and suggestions on this paper." has been added to Acknowledgments.

Special thanks are extended to you for your valuable comments.

We have tried our best to improve the manuscript and made substantial changes to the manuscript to correct certain shortcomings.

We greatly appreciate your help and hope that the corrections will meet with approval.

Once again, we would like to extend our sincere gratitude and appreciation for the valuable comments and suggestions.