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 #1:

The study proposes a novel approach for mid- and long-term sea surface temperature (SST) prediction by integrating granular computing with a data-knowledge-driven ConvLSTM model. The method is comprehensively validated through comparisons with five commonly used models, demonstrating its effectiveness. The research is interesting and holds substantial value. The manuscript is well-structured and presents thorough results. While I do not have major concerns, I offer the following minor comments to help the authors further improve their work:

Reply: Thank you for your thoughtful review and valuable feedback. We appreciate your positive acknowledgment of the potential significance of our study and your constructive comments, and we are grateful for the time and effort you've dedicated to this review. Your comments and good suggestions are very important for us to improve the quality of the manuscript. We have carefully addressed all the issues raised by you and the response is presented below.

Introduction Section: The authors should provide a more comprehensive review of recent literature. This would help highlight the research gap and better articulate the novelty of the proposed method.

Reply: Thank you for your valuable feedback. 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).”

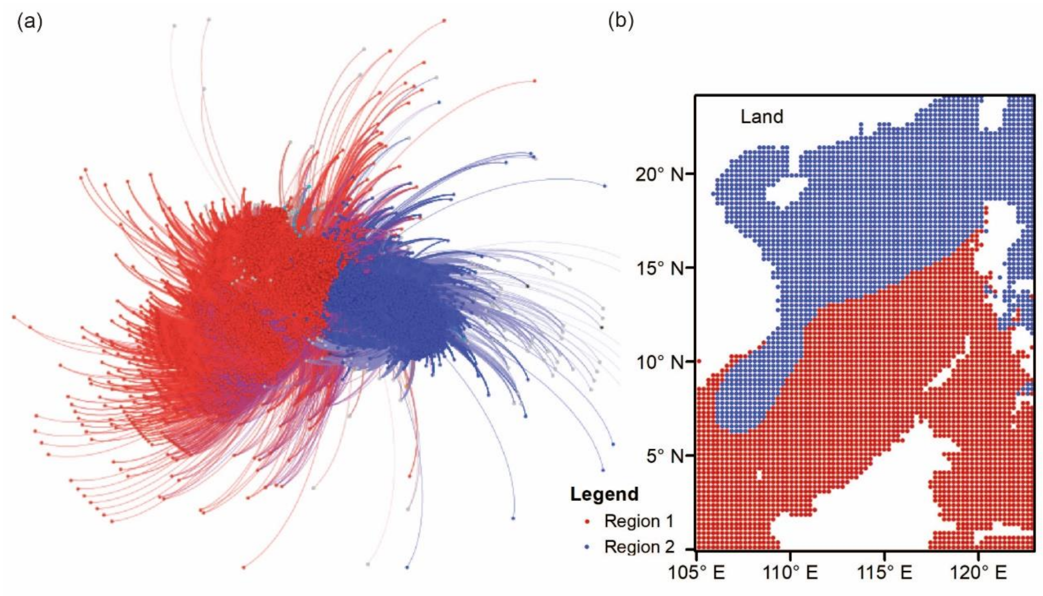
Lines 80-83 in the revised manuscript on page 3: “Graph neural networks (GNNs) effectively capture local spatial correlations through adjacent-node aggregation. However, the prevalent overemphasis on neighborhood relationships and neglect of global connections in current models inevitably undermines 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."

Line 11: It is unclear what Figure 2(a) is intended to convey. Are the two panels representing the same spatial locations? What do the pixel distributions imply? Please elaborate in the figure caption and/or the main text.

Reply: We thank the reviewer for this insightful observation. We have revised Fig. 2's caption and added explanatory text on page 5 in lines 156-161 to clarify:

Fig. 2(a) displays co-occurrence networks generated from the predictor matrix for all pixels in Study Area I (the South China Sea). In these networks, nodes represent individual pixels, and edges between nodes indicate the correlation strength between corresponding pixels. Each color denotes a distinct module, where pixels within the same module share similar meteorological and oceanic conditions (e.g., comparable temperature gradients, current patterns, or atmospheric forcing). Building on the module patterns observed in Fig. 2(a), we can explicitly determine that Study Area I can be divided into two distinct subregions, corresponding to the two primary color-coded modules in the co-occurrence networks. After identifying the specific spatial locations of each module—i.e., mapping the clustered pixels of each color to their geographical coordinates within the study area—we visualized these spatial distributions as separate subregions. This spatial mapping of the module-based partitions is presented in Fig. 2(b), where the two subregions are clearly delineated to show their respective geographical extents within the South China Sea.



Revised manuscript: Fig.2 (a) Co-occurrence networks generated from the matrix of predictors for all pixels in study area I. (b) The study area I is divided into two sub-regions, corresponding to the two color-coded modules in the co-occurrence networks.

Line 87: This sentence should be revised to clearly articulate the research gap that the study addresses.

Reply: Thanks for your valuable comment. We have modified it, which can be seen in lines 98-102 in the revised manuscript.

Lines 98-102 in the revised manuscript on page 3: "Furthermore, actual SST variability is governed by complex interactions among multiple oceanic-atmospheric parameters. Prevailing data-driven SST forecasting approaches often treat SST as an isolated variable, focusing primarily on its temporal dynamics while neglecting critical cross-parameter couplings—particularly thermodynamic-dynamic interactions across spatiotemporal scales—which fundamentally limit prediction accuracy."

Line 94: Please define what constitutes "medium-term" and "long-term" predictions in this context.

Reply: Thanks a lot for pointing these out. We are sorry for our unclear expression. We have modified it, which can be seen in lines 106-107 in the revised manuscript.

Lines 106-107 in the revised manuscript on page 3: "Validation against observations and model comparisons across three heterogeneous sea areas demonstrate the method's reliability for medium-term (1 month–10 years) and long-term (>10 years) SST forecasting."

Lines 121–124: The rationale for selecting specific predictor variables should be supported with references. It would also be helpful to visualize the mechanistic relationship between these variables and SST (e.g., via mechanism plots). Additionally, are "sea-air temperature difference", "relative humidity" and "wind speed" included as predictors?

Reply: Thank you for your valuable comments regarding the predictor variables. The 13 predictor variables used in this study are as follows: total cloud cover (tcc), evaporation (e), 2m temperature (t2m), 10m u-component of wind (u10), 10m v-component of wind (v10), 2m dewpoint temperature (d2m), mean sea level pressure (msl), total precipitation (tp), sea surface temperature (SST), sea skin temperature (skt), surface net solar radiation (ssr), surface latent heat flux (slhf), and surface sensible heat flux (sshf). Notably, “sea-air temperature difference” is not included as an independent predictor, but its related components (e.g., 2m temperature and sea surface temperature) are incorporated; “relative humidity” is not directly included, though 2m dewpoint temperature (d2m) serves as a relevant indicator of moisture conditions; “wind speed” is represented by its u (u10) and v (v10) components to capture wind direction and magnitude comprehensively.

As for visualizing these mechanisms, we acknowledge the value of mechanism plots but note that the current manuscript already contains a substantial number of figures. Adding further plots might overly occupy page space and potentially disrupt the flow of information. Thus, we have supplemented relevant references in the revised manuscript to support the rationale for selecting these variables, clarifying their established links to SST variations (e.g., radiation-related variables influencing heat exchange, wind components affecting mixing processes). However, we appreciate this suggestion and note that in our ongoing work on the latest SSTA prediction article, we will adopt your recommendation to incorporate mechanism plots. The added references are as follows:

Espinosa, Z. I. and Zelinka, M. D.: The Shortwave Cloud-SST Feedback Amplifies Multi-Decadal Pacific Sea Surface Temperature Trends: Implications for Observed Cooling, Geophysical Research Letters, 51, e2024GL111039, 10.1029/2024GL111039, 2024.

Fu, S., Hu, S., Zheng, X.-T., McMonigal, K., Larson, S., and Tian, Y.: Historical changes in wind-driven ocean circulation drive pattern of Pacific warming, Nature Communications, 15, 1562, 10.1038/s41467-024-45677-2, 2024.

Hsiao, W.-T., Hwang, Y.-T., Chen, Y.-J., and Kang, S. M.: The Role of Clouds in Shaping Tropical Pacific Response Pattern to Extratropical Thermal Forcing, Geophysical Research Letters, 49, e2022GL098023, 10.1029/2022GL098023, 2022.

Roach, L. A., Mankoff, K. D., Romanou, A., Blanchard-Wrigglesworth, E., Haine, T. W. N., and Schmidt, G. A.: Winds and Meltwater Together Lead to Southern Ocean Surface Cooling and Sea Ice Expansion, Geophysical Research Letters, 50, e2023GL105948, 10.1029/2023GL105948, 2023.

Tuchen, F. P., Perez, R. C., Foltz, G. R., McPhaden, M. J., and Lumpkin, R.: Strengthening of the Equatorial Pacific Upper-Ocean Circulation Over the Past Three Decades, Journal of Geophysical Research: Oceans, 129, e2024JC021343, 10.1029/2024JC021343, 2024.

Wills, R. C. J., Dong, Y., Proistosecu, C., Armour, K. C., and Battisti, D. S.: Systematic Climate Model Biases in the Large-Scale Patterns of Recent Sea-Surface Temperature and Sea-Level Pressure Change, Geophysical Research Letters, 49, e2022GL100011, 10.1029/2022GL100011, 2022.

Xie, S.-P., Deser, C., Vecchi, G. A., Ma, J., Teng, H., and Wittenberg, A. T.: Global Warming Pattern Formation: Sea Surface Temperature and Rainfall, Journal of Climate, 23, 966-986, 10.1175/2009JCLI3329.1, 2010.

Line 123: Please clarify whether "SST" and "sst" refer to the same variable or different ones.

Reply: Thank you for pointing out this potential ambiguity. We apologize for the inconsistency in notation. In the manuscript, “SST” and “sst” refer to the same variable: sea surface temperature. We have modified the notation to “SST” throughout the text and figure (Figs.3-4 in the revised manuscript) for consistency and clarity.

Line 135: The description of region sub-grouping using a correlation coefficient matrix lacks temporal detail. What time period is used for calculating the matrix? Do the identified subregions change over different years?

Reply: Sincere thanks for the valuable comment. The correlation coefficient matrix was calculated using the complete temporal span of our study period (1850–2021), as explicitly stated in revised Section 2.1 (Lines 149–152):

Lines 149-152 in the revised manuscript on page 5: “Therefore, by quantifying the similarity between the pixels within the study area using data from the entire study period, the study area was divided into different sub-regions, and different parameters were selected for each sub-region as predictors for SST prediction.”

Line 137: What is the spatial resolution of the individual pixels?

Reply: Thank you for your thoughtful comment. The spatial resolution of the pixels is 0.25°. We have further elaborated on the spatial resolution of the data in Section 3.1 of the revised manuscript for clarity.

Line 171: Regarding Fig. 3, it is evident that when four variables are selected, the prediction accuracy nearly reaches its maximum and stabilizes. Including eight or nine variables might lead to overfitting and increased model complexity. The authors should discuss this tradeoff more explicitly.

Reply: Thanks for your good suggestion. While four variables do yield high accuracy, our analysis of regional specificity revealed that the SST dynamics in regions 1 and 2 are driven by distinct, context-dependent interactions between meteorological and oceanic factors. For instance, region 1 exhibits stronger coupling between surface heat fluxes (sshf) and precipitation (tp), while region 2 is more sensitive to latent heat flux (slhf) and evaporation (e). These nuanced relationships, though not the top four most "globally" important variables, contribute to capturing region-specific variability that might be missed with only four predictors—especially in extreme or transitional conditions (e.g., monsoon-driven SST fluctuations in the South China Sea). Thus, we compared the outcomes derived from the co-occurrence network and the random forest analysis. The common variables identified will then be utilized as predictor variables in regional models aimed at predicting SST. We have elaborated on this tradeoff in the revised manuscript, clarifying our rationale for selecting eight variables for region 1 and nine for region 2 (Lines 175–188).

Lines 175-188 in the revised manuscript on pages 6-7: “Fig. 3 shows the importance ranking of the 13 predictors in regions 1 and 2 based on the random forest algorithm and the prediction errors using different numbers of predictor variables after ranking by importance. The prediction accuracy of the model increases and then decreases as the number of input predictors increases, both for region 1 and region 2. While the random forest results indicate that using just four variables as input can already yield high accuracy, our co-occurrence network analysis revealed that the SST dynamics in regions 1 and 2 are driven by distinct, context-dependent interactions between meteorological and oceanic factors. For instance, region 1 exhibits stronger coupling between sshf and tp, while region 2 is more sensitive to slhf and e. These nuanced relationships, though not the top four most “globally” important variables, contribute to capturing region-specific variability that might be missed with only four predictors—especially in extreme or transitional conditions. Thus, for region 1, the model has a high accuracy of prediction when eight variables are selected: SST, skt, t2m, sshf, msl, u10, tp and ssr. For region 2, the model has a high accuracy of prediction when nine variables are selected: SST, skt, t2m, slhf, e, u10, v10, sshf and d2m. Following this, a comparison will be made between the outcomes derived from the co-occurrence network and the random forest analysis. The common variables identified will then be utilized as predictor variables in regional models aimed at predicting SST.”

Line 190: Please explain on how the parameters θj and $\emptyset$j are determined.

Reply: Thank you for your guidance. The parameters θ_j and $\emptyset_j$ were estimated from all available temporal data (1850–2021). Now, we have modified it, which can be seen in lines 208-209 in the revised manuscript.

Line 192: The authors could explain why this type of templates was chosen. It would also be helpful to discuss how this type of specific templates contributes to approximating the information granules. Could other types of templates also be used? If so, why were they not selected?

Reply: Thank you for the valuable comment. The selection of quarter-circle sinusoids was driven by three key considerations tied to the characteristics of the target variables and the nature of the information granules:

Alignment with natural variability of oceanic/meteorological variables: Oceanic and meteorological time series (e.g., SST fluctuations) often exhibit smooth, non-abrupt trends with inherent periodicity (seasonal cycles). Quarter-circle sinusoids, by virtue of their continuous curvature and smooth transitions, naturally mirror these gradual, nonlinear dynamics—unlike rigid linear segments or discontinuous functions, which would fail to capture the subtlety of real-world variability (e.g., the slow warming/cooling phases of SST driven by solar radiation or ocean currents).

Flexibility in capturing local trend features: Information granules are defined by their monotonicity (increasing/decreasing) and concavity-convexity (upward/downward curvature), which reflect short-term (local) trend segments. A quarter-circle sinusoid, when stretched horizontally (to adjust duration) or vertically (to adjust amplitude), can flexibly approximate any combination of these local features: for example, a “concave-up increasing” granule (common in early-stage seasonal warming) or a “convex-down decreasing” granule (seen in late-stage cooling). This versatility stems from the template’s fixed curvature direction within a quarter-period, making it a modular building block for diverse local trends.

Mathematical tractability: Compared to more complex templates (e.g., exponential curves, polynomial segments), quarter-circle sinusoids have a simple parametric form, which simplifies the calculation of derived features (e.g., curvature (C), and fluctuation (F)) and reduces computational overhead during template matching. This efficiency is critical when processing large-scale spatiotemporal data. In summary, quarter-circle sinusoids were chosen for their ability to balance flexibility, mathematical simplicity, and alignment with the physical nature of the variables studied. Thank you.

Line 196: What is SKT? Is it the same as "skt" mentioned elsewhere? Consistency in terminology is needed.

Reply: Thank you for your valuable suggestion. “SKT” and “skt” refer to the same variable, i.e., sea skin temperature. We have modified the notation to “skt” throughout the text and figure for consistency and clarity.

Lines 215–216: Should the variable "i" be replaced with "t"? Please check for consistency in notation.

Reply: Thank you for your guidance. We have carefully checked the relevant sections and confirm that “i” in these lines should indeed be replaced with “t” to align with the consistent notation used throughout the manuscript for temporal indices. We apologize for the oversight. In the revised manuscript, we have corrected “i” to “t” in Lines 234–235 and conducted a full review of the entire text to ensure uniform use of notation for temporal variables, thereby enhancing clarity and consistency.

Line 217: Are m_t and m_{t-1} correctly written? Please verify and ensure consistent use of subscripts throughout the section.

Reply: Thank you for the valuable comment. We have revised the relevant notation to ensure accuracy and consistency. The modifications can be found in Lines 236–237 of the revised manuscript, where we have clarified the subscript conventions for m_t and m_{t-1} to align with the overall notation framework of the section.

Lines 346–350: Consider summarizing the three types of inputs into a table for clearer comparison and explanation.

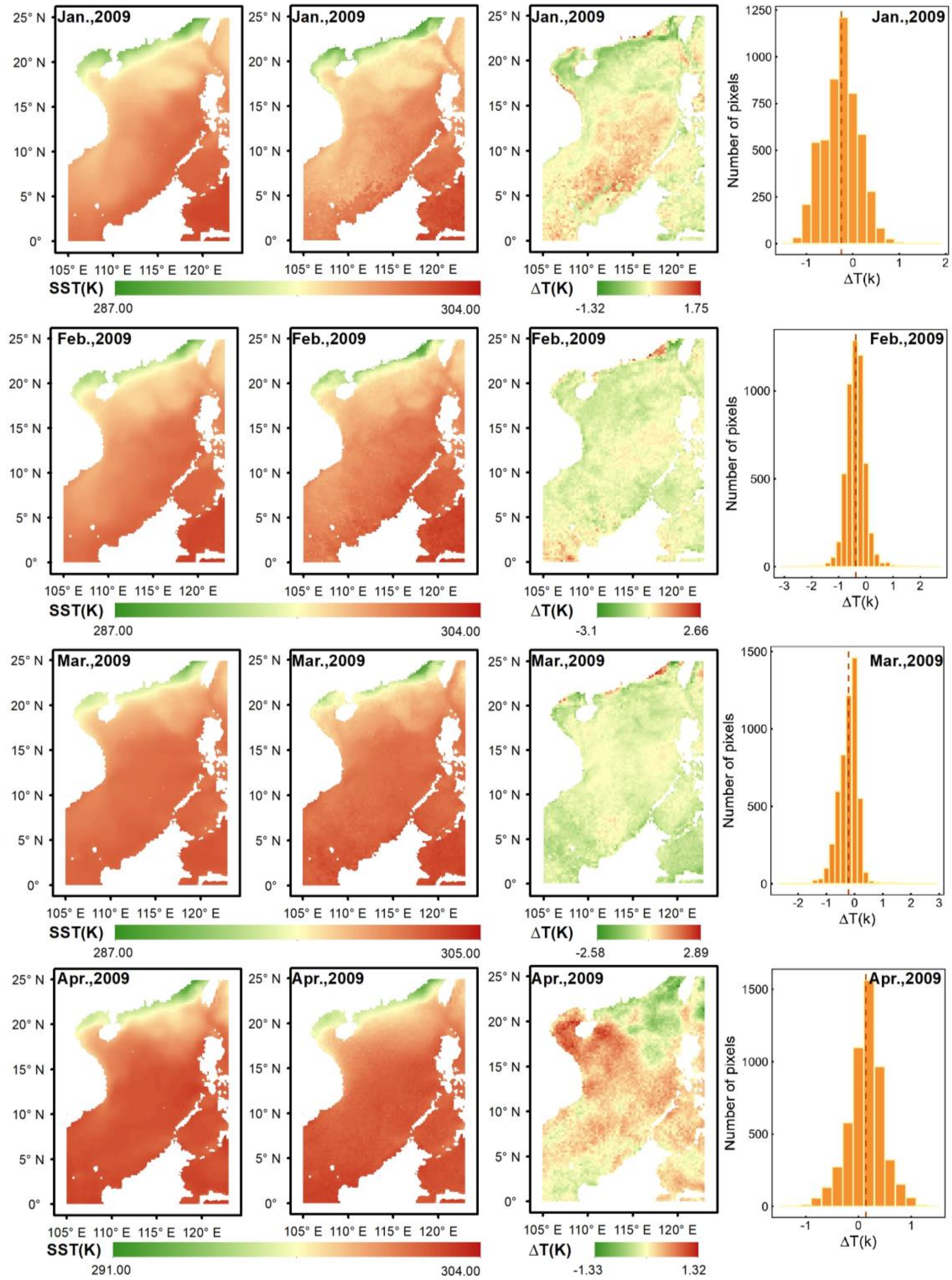
Reply: Thank you for your constructive suggestion to summarize the three types of inputs in a table for clearer comparison. We fully agree that tabular presentation can enhance readability and have carefully considered this approach. Following your advice, we attempted to construct a table to organize the input types. However, due to the complexity of our experimental design, the table structure became overly large and cumbersome: our study includes 3 main study areas, which are further divided into 7 sub-regions, and each sub-region involves 3 sets of comparative experiments. This resulted in a table with 22 rows (covering all sub-regions and experiments) and 4 columns (including the three input types and relevant annotations). Additionally, the input indicators for each column, which consist of multiple variables and feature descriptors, would require excessive width to present clearly. Such a large table would occupy an inordinate amount of page space and potentially disrupt the flow of the manuscript, making it less reader-friendly. Therefore, we retained the original textual description. We appreciate your understanding.

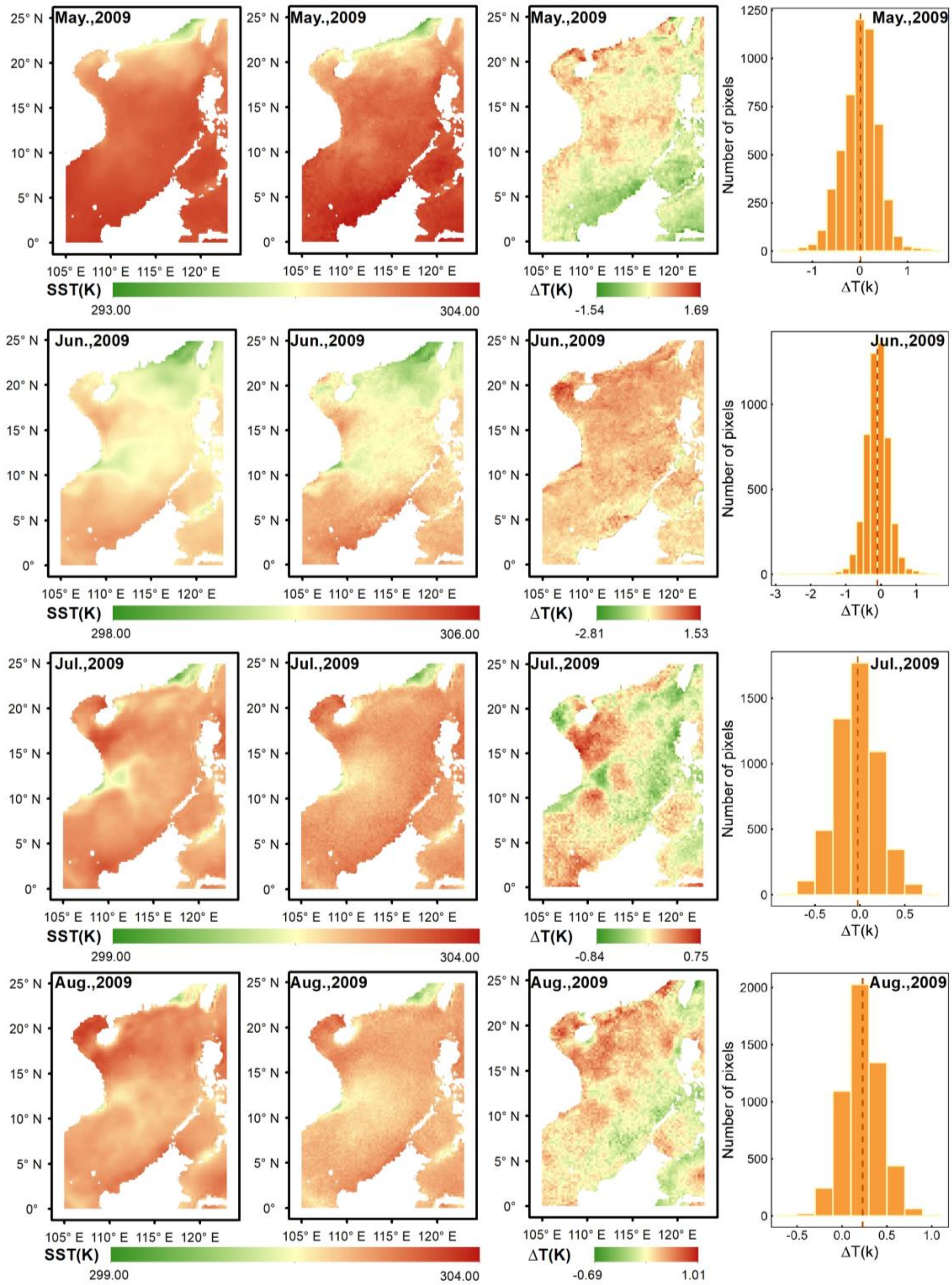
Lines 375–377: These lines could be deleted, as the same information is already presented in the figure caption.

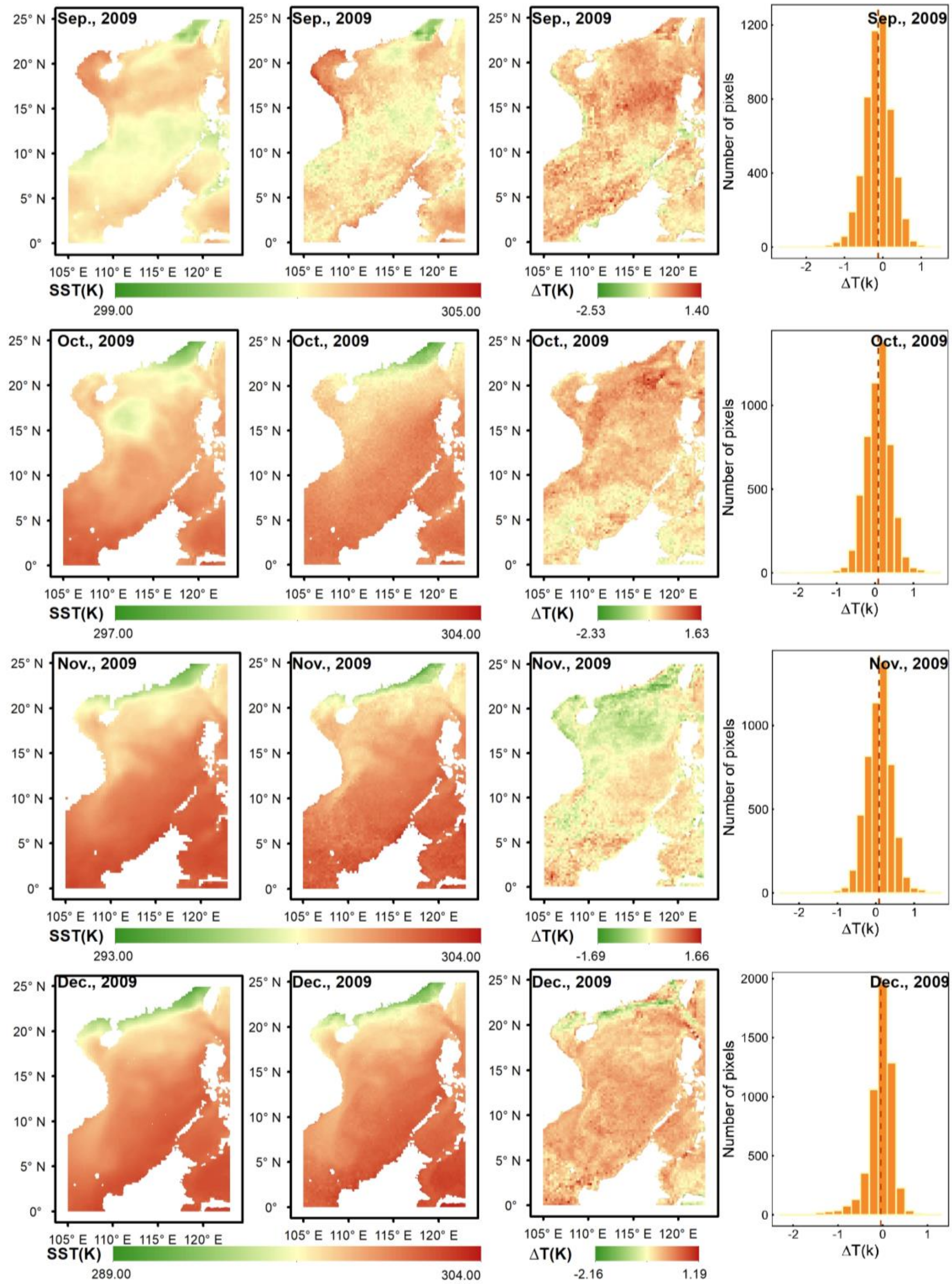
Reply: Done as suggested, thanks.

Figure 11: The color scales used for temperature in different panels are inconsistent, even within the same time period for predicted and observed values. This limits direct visual comparison across columns 1 and 2. A consistent colormap should be used.

Reply: Done as suggested, thanks. To aid your review, the revised figures are also provided below.


Jan.,2009
Feb.,2009
Mar.,2009
Apr.,2009
25° N
20° N
15° N
10° N
5° N
0°
105° E 110° E 115° E 120° E
SST(K)
287.00
304.00
305.00
291.00
ΔT(K)
-1.32
1.75
-3.1
2.66
-2.58
2.89
-1.33
1.32
Number of pixels
ΔT(k)


May.,2009
Jun.,2009
Jul.,2009
Aug.,2009
25° N
20° N
15° N
10° N
5° N
0°
105° E 110° E 115° E 120° E
SST(K)
ΔT(K)
293.00
304.00
-1.54
1.69
298.00
306.00
-2.81
1.53
299.00
304.00
-0.84
0.75
299.00
304.00
-0.69
1.01
Number of pixels
ΔT(k)



Revised manuscript: Fig.11 The predicted SSTs (first column), observed SSTs (second column), and spatial distribution (third column) and statistics (fourth column) of prediction errors for study area I in 2009

Line 416: What is the rationale for comparing results between 2020 and 2021 specifically? Clarifying this would help contextualize the results.

Reply: Thank you for the valuable comment. This is a valuable point, and we appreciate the opportunity to clarify. In our 10-year prediction period (2012–2021), 2021 showed the lowest prediction accuracy, while 2020 ranked second-lowest in accuracy. Due to space constraints, we were unable to present all 120 months of prediction results. By showcasing these two years with relatively lower accuracy, we aim to demonstrate that even in less optimal scenarios, the model maintains reliable performance, thereby supporting the robustness of predictions for other years with higher accuracy. The modifications can be found in Lines 429–433 of the revised manuscript.

Line 477: The expression "-0.7–0.7K" is confusing.

Reply: Thanks a lot for pointing these out. We have revised this part to clarify the range of differences, which can be seen in Line 501 of the revised manuscript

Line 486: I guess the word ‘aperiodic’ should be deleted, right?

Reply: Thank you for your guidance. We agree with your observation and have deleted the word “aperiodic” from the revised manuscript.

Additional remark:

Lines 519-520 in the revised manuscript: “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.