Response Letter

For

Manuscript ID: **egusphere-2025-1983**

"Hybrid Lake Model (HyLake) v1.0: unifying deep learning and physical principles for simulating lake-atmosphere interactions"

Public justification (visible to the public if the article is accepted and published):
Thank you for the revisions made to the manuscript. Please address the remaining minor comments from Reviewer #2 to further improve the quality of the paper.

Response: We thank the Editor and the reviewers for their constructive feedback on our manuscript. In response to the comments received, we have carefully revised the manuscript to address the remaining minor points raised by Reviewer #4. These revisions further enhance the overall quality and clarity of the paper, ensuring it meets the publication standards of *Geoscientific Model Development*.

Below, we provide a point-by-point response to the reviewers' comments. Each reviewer comment is listed in plain text, followed by our response and a description of the corresponding revisions made in the manuscript. Key revisions include:

- Correcting grammatical inaccuracies;
- Shortening the abstract, introduction, and discussion sections for conciseness;
- Reviewing and correcting any typographical errors, including spelling and numerical inaccuracies.

Reviewer #4:

The revised version has significantly improved, but I still think it could be further improved to be more concise. The introduction and discussion are too long and would be worth to shorten these sections. Especially, the discussion is with almost 5 pages much too long for an research article.

Response: We appreciate the reviewer's positive feedback and careful review. In response to the comment regarding conciseness, we have shortened the abstract, introduction, and discussion sections as suggested. Additionally, we have verified the units and reference style throughout the manuscript.

All suggestions have been incorporated. The point-by-point responses are provided below, with the reviewer's comments in black, our responses in blue, and a description of the revisions in red (with corresponding changes marked in the manuscript).

Specific comments:

Abstract: I would suggest to shorten the abstract. The current version is quite long and giving all the numbers does not make any sense. I would suggest to only provide the most important numbers and list the others in a table and mention (discuss them in the discussion or conclusion.

Response: We thank the reviewer for this valuable suggestion. Accordingly, we have shortened the abstract by removing excessive numerical details and retaining only the most important findings. The full suite of quantitative results is now presented in the Results and Discussion sections instead. The revised abstract focuses on outlining the model development and summarizing the key findings to enhance clarity and conciseness.

Revisions:

Abstract, Lines 9-24:

"**Abstract.** Lake-atmosphere interactions play a critical role in Earth systems dynamics. However, accurately modelling these interactions remains challenging, due to their oversimplified physics in traditional process-based models or the limited interpretability of purely data-driven approaches. Hybrid models, which integrates physical principles with sparse observations, offer a promising path forward.

This study introduces the Hybrid Lake Model v1.0 (HyLake v1.0), a novel framework that combines physics-based surface energy balance equations with a Bayesian Optimized Bidirectional Long Short-Term Memory-based (BO-BLSTM-based) surrogate to approximate lake surface temperature (LST) dynamics. The model was trained using data from the Meiliangwan (MLW) site in Lake Taihu. We evaluated HyLake v1.0 against the Freshwater Lake (FLake) model and other hybrid benchmarks (Baseline and TaihuScene) across multiple sites in Lake Taihu, using both eddy covariance observations and ERA5 reanalysis data.

Results show that HyLake v1.0 outperformed all comparative models at the MLW site and demonstrated strong capability in simulating lake-atmosphere interactions. In experiments assessing generalization and transferability in ungauged lake sites, HyLake v1.0 consistently exhibited superior performance over FLake and TaihuScene across all Lake Taihu sites using both observation- and ERA5-based forcing. It also maintained excellent skill when applied to the ungauged Lake Chaohu, confirming its robustness even with unlearned forcing datasets. This study underscores the potential of hybrid modeling to advance the representation land-atmosphere interaction in Earth system models."

Introduction: Also the introduction is a bit too long and could, if possible, be shortened a bit.

Response: We thank the reviewer for this valuable suggestion. We have shortened the introduction (790 words) by reorganizing and removing repetitive sentences and maintaining the important reviews about the hybrid modeling. The revised introduction focused on the importance, advantages and disadvantages of lake models, and research objectives of this study.

Revisions:

Introduction, Paragraph 1, Lines 26-32:

"Lakes constitute a critical component of the Earth system and serve as sensitive indicators of climate-land surface interactions (O'Reilly et al., 2015; W. J. Wang et al., 2024). Lake surface temperature (LST) is a central variable in lake-atmosphere systems, governing key hydro-biogeochemical processes such as evaporation rates, ice cover duration, mixing regimes, and thermal storage) (Culpepper et al., 2024; Tong et al., 2023; Woolway et al., 2020). Globally, LST has been increasing at a rate of 0.34 °C per decade, contributing to shifts in aquatic biodiversity and alterations in ecosystem services (W. J. Wang et al., 2024; Woolway et al., 2020). These observed trends underscore the significant threats that climate change poses to global lake ecosystems (Carpenter et al., 2011; Woolway et al., 2020)."

Paragraph 2, Lines 33-49:

"Accurate prediction of LST is fundamental for assessing physical and biogeochemical changes in lakes, including phenomena like algal blooms, lake heatwaves and cold spells (O'Reilly et al., 2015; X. W. Wang et al., 2024a; X. W. Wang et al., 2024b; Woolway et al., 2024). Existing lake thermodynamics models can be categorized into process-based, statistical, and machine learning (ML) approaches. Process-based lake models, such as the Freshwater Lake model (Flake; Mironov et al., 2010), the General Lake Model (GLM; Hipsey et al., 2019), and the lake model within the Weather Research & Forecasting Model (WRF-Lake; Gu et al., 2015), are built upon simplified assumptions derived from empirical physical principles. They typically do not incorporate data-driven information and can be challenging to apply in data-scarce regions (Piccolroaz et al., 2024; Shen et al., 2023; L. J. Xu et al., 2016; Mironov et al., 2010). In contrast, statistical models, such as the Air2Water model, establish mathematical relationships between forcing variables and LST in well-mixed lakes, relying on extensive high-quality observational data but often lacking explicit mechanistic linkages (Piccolroaz et al., 2020; W. J. Wang et al., 2024; Huang et al., 2021). ML models, such as Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, often viewed as a subset of statistical models, offer greater complexity and automation by leveraging large datasets (Piccolroaz et al., 2024; Wikle and Zammit-Mangion, 2023) and have demonstrated superior performance in reconstructing LST globally (Almeida et al., 2022; Willard et al., 2022). However, their dependence on substantial training datas, high computational demands, and inherent "black-box" nature can limit model transferability and explainability (Piccolroaz et al., 2024; Korbmacher and Tordeux, 2022). These limitations highlight the potential of hybrid approaches that integrate the strengths of both process-based and data-driven models."

Paragraph 3, Lines 50-64:

"Hybrid models integrate physical principles with data-driven techniques, often featuring a multi-output structure that enhances explainability and transferability while preserving flexibility and accuracy (Piccolroaz et al., 2024; Shen et al., 2023; Kurz et al., 2022). For example, Read et al. (2019) developed a hybrid deep learning framework that embedded an energy balance-guided loss function from GLM into a Recurrent Neural Network (RNN) to reconstruct LST, outperforming process-based models when applied to unmonitored lakes (Willard et al., 2021). Despite their promise, such hybrid models can still face challenges related to computational cost, explainability, and transferability, particularly for ungauged lakes and periods (Raissi et al., 2019; Willard et al., 2023). To mitigate these issues, Feng et al. (2022) embedded neural networks into the Hydrologiska Byråns Vattenbalansavdelning (HBV) hydrological model to predict multiple physical variables, achieving performance comparable to purely data-driven models. Similarly, L. J. Zhong et al. (2024) developed a distributed framework integrating ML and traditional river routing models for streamflow prediction. By incorporating physical constraints, these hybrid models typically outperform traditional process-based models and require less training data than purely ML-based approaches, thereby providing a powerful tool for elucidating previously unrecognized physical relationships (Shen et al., 2023). Given that lake-atmosphere interactions represent a tightly coupled system where LST modulates latent heat (LE) and sensible heat (HE) fluxes (B. B. Wang et al., 2019; Woolway et al., 2015), hybrid modeling represents a promising way for advancing our understanding of these complex physical processes."

Paragraph 4, Lines 65-74:

"Predicting key indicators of lake-atmosphere interactions in Lake Taihu, a large and eutrophic lake in China, remains challenging for traditional lake models due to its significant regional heterogeneity in biological characteristics (Table 1; Zhang et al., 2020; Yan et al., 2024). The lake benefits from extensive observational data collected through field investigations. To advance hybrid modeling techniques and improve the accuracy of simulating lake-atmosphere interactions, this study aims to: (1) develop a novel hybrid lake model, HyLake v1.0, by embedding an LSTM-based surrogate into a process-based lake model; (2) validate the performance of HyLake v1.0 in simulating LST, LE, and HE against observations from the Taihu Lake Eddy Flux Network; and (3) evaluate the transferability of HyLake v1.0 to ungauged sites with varying biological characteristics using ECMWF Reanalysis v5 (ERA5) forcing datasets. The results of this research are expected to enhance the representation of lake-atmosphere interactions by synergistically unifying physical principles with deep learning, particularly in data-sparse regions."

Removed reference:

Zhang, G., Yao, T., Chen, W., Zheng, G., Shum, C. K., Yang, K., et al.: Regional differences of lake evolution across China during 1960s–2015 and its natural and anthropogenic causes, *Remote Sens. Environ.*, 221, 386–404, https://doi.org/10.1016/j.rse.2018.11.038, 2019.

P5, Table 1 caption: What do you mean with "Information"? Do you mean "Characteristics" of the selected sites or are these the Experiments?

Response: Sorry for the misleading terms. This table presents the geographic coordinates (latitude and longitude), start date of observation, biological characteristics and roles in model development for selected lake sites in Lake Taihu.

Revisions:

Materials and Methodology, Section 2.1, Table 1:

"**Table 1. Overview of selected lake sites in Lake Taihu, including their geographic coordinates, observation start dates, biological characteristics, and roles in model development. The MLW site was used for model training, while the remaining sites served for validation.**

Site	MLW	DPK	BFG	XLS	PTS
Lat. (◦N)	31.4197	31.2661	31.1685	30.9972	31.2323
Lon. (◦E)	120.2139	119.9312	120.3972	120.1344	120.1086

Start date	Jun 2010	Aug 2011	Dec 2011	Nov 2012	Jun 2013
Biology	Eutrophic	Super eutrophic	Submerged macrophyte	Transitional	Mesotrophic
Purpose	Train	Validation	Validation	Validation	Validation

"

P13, L328: What is the "MLW" experiment? This should be explained at the begin of the Section.

Response: MLW experiment means the model running experiments in the Meiliangwan site, which is a typical lake site in Lake Taihu. The experiments are indeed summarized in Table 3, including MLW experiment, Taihu-obs experiment, Taihu-ERA5 experiment, and Chaohu experiment, which used distinct forcing datasets. The additional explanation were added at the section 2.3.1 and section 3.1-3.4. We added more details about these experiments in Materials and Methodology (Section 2.3.1, Lines 287-293), and Results (Section 3.1, Lines 337-339; Section 3.3, Lines 428-429; Section 3.4, Lines 474-475).

Revisions:

(Explanation of MLW experiment) Results, Section 3.1, Lines 337-339:

"…, this study conducted MLW experiment, which forced and validated by the hydrometeorological variables in MLW observations, to predict the LST, LE and HE by using Baseline and HyLake v1.0 that integrated these surrogates, ..."

(Explanation of Taihu-obs experiment) Results, Section 3.3, Lines 428-429:

"Given to the Taihu-obs experiment which was forced and validated by hydrometeorological observed variables from five lake sites in Lake Taihu, …"

(Explanation of Taihu-ERA5 experiment) Results, Section 3.4, Lines 474-475:

"This study additionally conducted Taihu-ERA5 experiment that using meteorological variables from ERA5 datasets to force several lake models demonstrate transferability of HyLake v1.0, …"

(Explanation of Chaohu experiment) Materials and Methodology, Section 2.3.1, Lines 287-293:

"Furthermore, this study implemented the HyLake v1.0 into Lake Chaohu, the 5th-largest shallow freshwater lake in China, with a deeper lake depth of 3.06 m and lake area of 760 km^2 (Fig. S6, Jiao et al., 2018), which has experienced heavy eutrophication and harmful algal blooms (Yang et al., 2020), to assess its transferability to other lakes (Chaohu experiment). A LST dataset in Lake Chaohu was obtained from MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V061 imageries (MYD11A1, https://www.earthdata.nasa.gov/data/catalog/lpcloud-mod11a1-061), which were used to validate the performance of LST derived from HyLake v1.0."

P22, L540ff: Please refer here to the respective figure or table.

Response: The referred figure has been added.

Revisions:

Results, Section 3.4, Line 520:

"Overall, both HyLake v1.0 and TaihuScene showed reliable performance across lake sites in Lake Taihu (Fig. S5)."

Discussion: The discussion is much too long with almost 5 pages and should be shortened. This would make the paper much more concise.

Response: We shortened the discussion in each section by condensing sentences, reorganizing the sentences and removing repetitive words. Specifically, the Section 4.1 highlighted the data availability, computation efficiency, model architecture, explainability, and coupling strategies of this study and discussed the potential ways to deal with in the future. Section 4.2 discussed the potential developments of HyLake v1.0, focusing on research progress in scaling laws, surrogate architecture development, and the extension of coupled modules, all of which are crucial for lake-atmosphere interactions modeling. The revisions were given for each paragraph.

Revisions:

Discussion, Section 4.1, Paragraph 1, Lines 538-543:

"In this study, we developed HyLake v1.0 by integrating a process-based backbone (PBBM) with an observation-trained, LSTM-based surrogate for LST approximation, forming a hard-coupled and auto-regressive hybrid structure. The model was evaluated against FLake, Baseline, and TaihuScene to assess its generalization and transferability across sites in Lake Taihu and Lake Chaohu. Results demonstrate that HyLake v1.0 maintains robust predictive accuracy when forced with ERA5 data across ungauged sites in Lake Taihu and in Lake Chaohu (Table 3; Figs. S7-S9). Despite these strengths, several limitations remain, mainly concerning data availability, computation efficiency, model architecture, explainability, and coupling strategies."

Paragraph 2, Lines 544-553:

"A primary limitation lies in the increasing demand for high-quality and representative data, stemming from the expanding development and application of the deep-learning-based surrogates and parameterizations (Almeida et al., 2022; Guo et al., 2021; Read et al., 2019). Long-term, high-frequency observations of radiation, energy fluxes, and temperature are scarce and costly to maintain (Erkkilä et al., 2018; Nordbo et al., 2011). While reanalysis products such as ERA5, NLDAS-2, and GLSEA offer valuable alternatives (Kayastha et al., 2023; Monteiro et al., 2022; Notaro et al., 2022; J. L. Wang et al., 2022), they may introduce systematic forcing biases. These biases can propagate through deep-learning-based surrogates into the physical base of the model, potentially hindering a ground-truth understanding of lake-atmosphere interactions. Nevertheless, our experiments demonstrate that incorporating well-trained deep-learning surrogates, calibrated with carefully curated observations and reliable coupling strategies, into process-based backbones can yield robust and transferable performance in ungauged regions. This underscores the critical value of high-quality data for enhancing model generalization at larger scales."

Paragraph 3, Lines 554-566:

"Another limitation stems from simplified parameterizations in two critical components of the process-based backbone: the energy balance equations and 1-D vertical lake temperature transport equations (Golub et al., 2022; Mooij et al., 2010). For instance, the bulk-aerodynamic method used to solve surface flux solutions of LE and HE, based on Monin–Obukhov similarity theory (Monin and Obukhov, 1954), remains sensitive to friction velocity (u^{*}) and surface roughness length (z_{0m}). Although the estimation of these variables has evolved from constant empirical values to iterative routines (Woolway et al., 2015; Hostetler et al., 1993), substantial discrepancies still exist between simulations and observations (Fig. S6). Several recent hybrid models have employed knowledge-guided loss functions to improve prediction of lake temperature profiles (He et al., 2025; Ladwig et al., 2024; Read et al., 2019). However, the underlying 1-D transport equations, often solved using finite difference methods (e.g., Crank-Nicholson solution, implicit Euler scheme), still struggle to accurately capture diurnal variability and long-term trends (Piccolroaz et al., 2024; Sarovic et al., 2022; Subin et al., 2012). While such models may perform well on training and test datasets, their generalization and transferability require further validation, particularly given their complex coupling strategies and higher computational costs. These process simplifications introduce structural uncertainties that can only be partially compensated by the surrogate component."

Paragraph 4, Lines 567-580:

"A third issue involves computational efficiency and model architecture. The BO-BLSTM-based surrogate in HyLake v1.0 improves stability and performance in autoregressive forecasting but incurs computational costs compared to traditional process-based models (Table 3). We observed that the computational efficiency of HyLake v1.0 is sensitive to the number of parameters. For example, in the MLW experiment, HyLake v1.0 required ~9 times longer to run than FLake, with a cost of 151.46 seconds. As modeling objectives shift toward long-term predictions, the inherent limitations of LSTMs in capturing long-range dependencies will become more pronounced, motivating the integration of more advanced deep-learning surrogates, such as those in the Transformer-based family (K. F. Bi et al., 2023; L. Chen et al., 2023). Future improvements should explore state-of-the-art architectures, including Transformers, Graph Neural Networks, Temporal Convolutional Networks, TimesNet, and Kolmogorov-Arnold Networks, which have shown exceptional capability in time series forecasting (Z. Liu et al., 2024; Wen et al., 2022; Wu et al., 2022; Bai et al., 2018), and are increasingly applied in hydrological modeling (Koya & Roy, 2024; Z. C. Wang et al., 2024; Sun et al., 2021).

However, developing powerful surrogates such as the Fuxi and Pangunot only demands large-scale observational datasets but also substantial computational resources (K. Bi et al., 2023; Lei Chen et al., 2023). This underscores a critical trade-off among model complexity, predictive accuracy, and computational efficiency, highlighting the need for more compact and efficient surrogate designs."

Paragraph 5, Lines 581-591:

"Although the hard-coupled structure of the HyLake v1.0 enhances interpretability compared to purely data-driven approaches, the LSTM-based surrogate still function partially as a "black box", limiting physical transparency (de la Fuente et al., 2024; Chakraborty et al., 2021). Developing deep-learning surrogates that inherently incorporate physical knowledge is an active research area (Piccolroaz et al., 2024; Willard et al., 2023; Read et al., 2019). For example, Read et al. (2019) proposed a process-guided deep-learning model that incorporated a GLM-based energy budget loss function and evaluated it across 68 lakes. Ladwig et al. (2024) developed a modular framework integrating four deep-learning models with an eddy diffusion scheme to improve temperature predictions in Lake Mendota. However, such approaches often rely on simplified parameterizations, exhibit opaque inter-module relationships, and entail high computational costs, factors that currently constrain model generalization and transferability. Future versions of HyLake should prioritize the development of physically informed surrogates and more transparent coupling strategies to enhance explainability, numerical stability, and physical consistency."

Discussion, Section 4.2, Paragraph 1, Lines 593-595:

"HyLake v1.0 demonstrates strong generalization capability across different lake sites, establishing a promising foundation for further extensions. Subsequent improvements should focus on three key areas: investigating data scaling laws, advancing surrogate architectures, and extending the range of coupled physical modules."

Paragraph 2, Lines 596-608:

"Expanding the training dataset to include lakes with diverse morphometric and climatic characteristic will enhance model robustness. However, simply adding more data does not guarantee improved performance; rather, physically informative and highly representative samples from distinct lake regimes are more beneficial. This aligns with observations from other large deep-learning models, where training on heterogeneous datasets without strategic sampling can hinder performance gains (Wang et al., 2025). In this study, we hypothesized that training LSTM surrogates individually for each site would better represent localized lake–atmosphere interactions, a premise largely supported by our results. While surrogates trained on data from sites with limited observations (DPK, PTS, XLS) performed comparably in estimating ΔLST (except for XLW; Table S1), the surrogate trained at BFG, despite its relatively complete dataset, underperformed the proposed BO-BLSTM surrogate in capturing diurnal LST patterns (Fig. S10). As HyLake is scaled to more lakes or larger regions, the computational architecture must efficiently handle large training datasets, which may otherwise constrain site-specific performance. Furthermore, scaling laws for deep-learning models indicate that performance diminish with increasing model size beyond a certain point (Hestness et al., 2017). Adopting more advanced deep-learning surrogates will thus be essential to improving HyLake's representation of lake-atmosphere interactions in ungauged settings."

Paragraph 3, Lines 609-615:

"Although the BO-BLSTM surrogate improves model robustness, its complex architecture increases training costs (Peng et al., 2025; Ferianc et al., 2021). Simplified Bayesian architecture may offer comparable uncertainty quantification capabilities at a lower computational expense (Klotz et al., 2022). Notably, HyLake v1.0 holds potential for future uncertainty assessment, such as predictive variance and the probability of extreme lake events, by further developing its surrogate component (Kar et al., 2024; Gawlikowski et al., 2023). To overcome current limitations related to high computational demand and performance ceilings, future work should explore novel surrogate architectures that are both efficient and scalable, trained on larger and more diverse datasets."

Paragraph 4, Lines 616-628:

"The modular Python-based framework of HyLake v1.0 offers greater flexibility than traditional process-based models for coupling additional modules, such as those for lake temperature profiles, greenhouse gas exchange, oxygen dynamics, and lake-watershed interactions (Saloranta and Andersen, 2007; Stepanenko et al., 2016). Emphasizing energy-mass balance closure and parameter sharing across modules will improve physical consistency and reduce uncertainty propagation. Precedents for such integrated modeling exist: Lake 2.0 (Stepanenko et al., 2016) coupled methane and carbon dioxide modules to study gas dynamics in Kuivajärvi Lake, while MyLake (Saloranta and Andersen, 2007) has been extended to include modules for DOC degradation, DO dynamics, microbial respiration, gas exchange, sediment-water interactions, dynamic light attenuation, nitrogen uptake, and even floating solar panels (Exley et al., 2022; Salk et al., 2022; Kiuru et al., 2019; Pilla and Couture, 2021; Markelov et al., 2019; Couture et al., 2015; Holmberg et al., 2014). Many of these hydro-biogeochemical processes are currently described by simplified PDEs or empirical models, introducing structural uncertainties (L. Li et al., 2021). The flexible design of HyLake v1.0 enables the integration of deep-learning surrogates to approximate complex processes such as temperature dynamics, gas flux, and oxygen variability, potentially outperforming both purely process-based and purely data-driven models."

Paragraph 5, Lines 629-631:

"In summary, HyLake v1.0 provides a flexible and extensible framework for advancing hybrid lake modeling. Future development should prioritize enhancing physical consistency, improving uncertainty quantification, and increasing computational efficiency to better represent complex lake–atmosphere processes across diverse settings."

Technical corrections:

General: Use the ACP style

- for referencing (no "&" between authors and references in the text with surname and year (and not with any letters of first names).

Response: Corrected. Here are two examples:

Revisions:

Introduction, Line 45:

"Wikle and Zammit-Mangion, 2023"

Line 48:

"Korbmacher and Tordeux, 2022"

- write units according to the ACP style (e.g. W/m -> Wm-1).

Response: We have corrected the unit of heat fluxes from "W/m^2" to "W m^{-2}" throughout the manuscript. Other units have been double-checked as well.

- Figure should be abbreviated "Fig." in the text unless it appears a the begin of the sentence.

Response: We have changed "Figure x" to "Fig. x" throughout the manuscript.

P1, L21: Abbreviation MLW not introduced.

Response: The full name of abbreviation MLW (Meiliangwan) was mentioned when it first appeared in the Abstract (Lines 15-16).

Revisions:

Abstract, Lines 15-16:

"The model was trained using data from the Meiliangwan (MLW) site in Lake Taihu."

P1, L27: It -> This

Response: Corrected.

P5, L133: add "where" -> that where obtained.

Response: Added.

P6, Figure 2 caption: timestep -> time step

Response: Corrected.

P7, L185: a …..transport equations…..-> mixture of singular and plural. I guess it should read "equation".

Response: Corrected.

P11, L291: Repetition in the sentence "description" and "describe". Please rephrase the sentence.

Response: Corrected.

Revisions:

Materials and Methodology, section 2.3.1, Line 271:

"The descriptions of these models are listed as follows:…"

P11, L292: "and" missing? ….and was constructed………..?

Response: Added a word "and".

P12, L297: ….is suitable……? "and" missing? Should it read "and is suitable"?

Response: Corrected.

P12, L306: was -> were

Response: Corrected.

P12, L306: Two times "datasets".

Response: Removed the repetition.

Revisions:

Materials and Methodology, section 2.3.1, Line 286:

"FLake and TaihuScene were additionally intercompared using the ERA5 datasets in Taihu-ERA5 experiment."

P14, L371: delete "the" and write "Sect." instead of "section".

Response: Corrected.

P22, L520: which located -> which is located

Response: Corrected.

P22, L523: train -> training

Response: Corrected.

P28, L706: "the and" not correct. Please check the sentence and correct.

Response: Sorry. Removed the word "and".

Revisions:

Conclusion, Lines 639-641:

"Additionally, this study used different forcing datasets, including observations from 5 lake sites in Lake Taihu and the ERA5 datasets, to evaluate the transferability of HyLake v1.0 in ungauged regions and unlearned datasets."