Dear Editor and Reviewers,

Thank you for your constructive feedback. We appreciate your insightful comments and suggestions for improving our manuscript. Please find our point-by-point responses below in bold. Details of line numbers where changes were made are in red color. **Colors in some figures were updated following color-blind simulator as suggested by editorial team.**

Response to Reviewer #1 of the Manuscript: Training deep learning models with a multi-station approach and static aquifer attributes for groundwater level simulation: what's the best way to leverage regionalised information?

Chidepudi et al. used deep learning approaches to simulate and predict groundwater level dynamics. Authors compared and discussed the performance of different approaches of different combinations, such as different DL models, different inputs (i.e., dynamic factors and static factors), wavelet decomposition of precipitation, one-hot encoding etc. Using deep learning approach to simulate and predict dynamic groundwater levels is challenging. This work is important and could be a good reference for the community. The paper is generally well organized but there are still a lot of details unclear. Major revision is needed for further review.

Thank you for acknowledging the importance and potential impact of our work. We addressed all the unclear details in the revised manuscript as described below.

1. *There are no clear introductions of model structures.*

We enhanced the details in the revised version. Specifically, we included a new subsection in Section 3.1 (Theoretical modelling background), providing details of the models, including the number of layers, units, and other relevant common hyperparameter details (as shown in Table 1) for LSTM, GRU, and BiLSTM models. Though these models are widely used nowadays in all other subfields of hydrology, as highlighted in line 261, if needed, we will provide cell diagrams in a supplementary document to explain the main principle of each network type. In addition, all the final hyperparameters are provided in the supplementary document.

Table 1: Hyperparameter details (Modified and adapted from chidepudi et.,al 2023)

Hyperparameter	Value considered
Sequence length	**48**
Dropout	**0.2**
Optimizer	**ADAM**
Early stopping	**50**
Number of layers	**1**
Hidden neurons	**(10, 20, …,100) by 10**
Learning rate	**(0.001,0.01) (log values)**
Batch size	**(16, 32, …,256) by powers of 2**
Epoch	**(50, 100, …,500)**

Changes in lines 220-263 and Tables S3-S9 in the supplement.

2. *I didn't find details of the model input or the structure of the input data. I especially wanted to know this in the multi-station approach*

We clarified the input data used for each multi-station approach with standalone and wavelet models by providing a figure with the number of covariates in Section 3.2 (Experimental design) after line 276 All the models use sequences as input for point simulation. The input data is structured as a 3D tensor with dimensions (samples, sequence_length, num_features) (Provided in Tables S5), where the sequence length is set to 48 (4 years of monthly data), and the number of features includes both dynamic (time series of precipitation, temperature, surface net solar radiation…) and one-hot encoded static variables depending on the type of approach. For wavelet models, dynamic variables are also time series that are wavelet components of original inputs (time series of precipitation, temperature, surface net solar radiation…).

Figure 5 and Table S5

3. *How did you choose the training and test sets?*

In Section 3.2 (Experimental design), after line 345, we added a new paragraph detailing the selection of training and test sets for the different modelling approaches. "For the single-station approach, the data was split into training (80%) and testing sets (20%) as described in Chidepudi et al., 2023. Furthermore, the last 20% of the training data was used as a validation set to facilitate hyperparameter tuning. For the multi-station approach, the train-test split was also performed at each station, following the same procedure as the single-station approach. However, all station data was collectively combined during the training. The rationale behind the specific train-test split is to ensure that the models capture the multi-annual to decadal variability in groundwater levels (GWLs) observed in the region. To achieve this, a minimum of 34 years of data (1970-2014) was used for training, while the most recent 8.66 years of data (2015/01-2023/08) were reserved for testing. This split corresponds to approximately 80% of the data for training and 20% for testing. By following this approach, we aimed to ensure that the models were exposed to a sufficiently long period of data during training, enabling them to capture the amplitude and variability of GWL fluctuations over multi-annual to decadal timescales. The testing period was chosen to be the most recent years, allowing for an evaluation of the model's performance on the latest available data."

Lines 346-359 and Table S2

4. *I didn't find how large your research area (only a figure). The resolution of ERA5 is low and the true variations of these hydrometeorological variables may not be accurately presented by the products*
5. *What do you think about the uncertainties of data products from ERA5*

A common response for both these comments (4&5) as they seem somehow related.

Regarding the research area, we included additional details on the research area in Section 2 (Study Area) to clearly specify the geographic extent covered in our study which is approximately 80,000 km2 .

In Section 2 (Data), after line 160, we discussed the implications of spatial resolution on capturing local variations when using data products like ERA5.

While we understand your concern about the potential limitations in accurately representing localised groundwater dynamics, ERA5 is the best available global reanalysis with the data available from 1940. It is generally considered adequate for capturing regional and global hydrometeorological variations. ERA5 Reanalysis data do have uncertainty related to potential regional biases; this is an ongoing debate, as discussed in (Maria Clerc-Schwarzenbach et al., 2024). Precipitation is considered to have more bias than temperature. However, for our study area, we have been evaluating different potential alternative reanalysis products, such as the Safran reanalysis developed

specifically for France (Vidal et al., 2010). It appeared that both ERA 5 and Safran precipitation contained the same low-frequency components as detected in GWL time series as displayed in Fig.2 (this paper) and Fig.11 in Chidepudi et al 2023. ERA 5 then seems quite suitable for our purpose.

Discussing uncertainty of ERA5 is beyond the scope of this paper and can be considered research work as itself. However, we added relevant references that discussed this point.

Lines 145-185 , Figure 1

6. *Did you only conduct the wavelet decomposition on precipitation or other variables also?*

We clarified that wavelet decomposition is done only on input dynamic variables after line 200: wavelet decomposition is being performed on time series only, each input time series being eventually replaced with its 5 wavelet components (corresponding to the decomposition level selected).

Line 236-237

7. *What is the resolution of the data products of static attributes?*

In Section 2 (Data), after line 186, we provided information on the resolution and sources of the static attribute data used

Static attributes are available for different ranges of aquifer classes with different resolutions, and we took the one that was associated with the Well IDs. Static attributes, coming from BDLISA database, are point-scale information, i.e., each well received set of attributes given different possible methods (geographical imputation, rule-based, human expertise). BDLISA is based on a mix of information coming from geological maps at a scale of 25km, piezometric maps, hydrochemistry, etc.

BDLISA was originally designed at a 25km scale and later upscaled to larger scales. For our study, we kept information coming from BDLISA at its original scale (25km), which means aquifer static attributes have a resolution of 25km. This should be understood as a local to regional description of aquifers.

Lines 186-201, Table S1 and Figure 2

8. *What do you think the effects of hydraulic conductivity, elevation, slope etc. static attributes.*

The decision to include the relevant static attributes comes from a trade-off between the transposability of models and the availability of attributes, as we have to make sure that all those variables are widely available at the required resolution. Also, for some attributes like hydraulic conductivity, it might not be straightforward to get the most relevant resolution, which is needed to account for the most appropriate characteristic describing the well. For instance, 25km resolution might not be relevant when aquifers are highly heterogeneous. Exploring the role of

static attributes in more details would require much further works than what was conducted in this study.

Lines 210-216

9. Location of the well, i.e., in confined or unconfined aquifers may also be important

All the wells considered in the study are in unconfined aquifers.

Line 148

Response to Reviewer #2 of the Manuscript: Training deep learning models with a multi-station approach and static aquifer attributes for groundwater level simulation: what's the best way to leverage regionalised information?

Review comments on the manuscript: Training deep learning models with a multi-station approach and static aquifer attributes for groundwater level simulation: what's the best way to leverage regionalised information? by Chidepudi et al.

The manuscript presents several different deep learning approaches to simulate groundwater levels. Dynamic as well as static variables are used to train deep learning models to represent fluctuations on a high temporal resolution (daily data) in northern France. These different deep learning models were combined with different sets of input data (including preprocessing) and training strategies. Overall, the work is timely and covers the important topic of data-driven approaches to simulate dynamic groundwater levels. However, the manuscript has several shortcomings which are listed below. Major revision is needed.

Thank you for taking time to give detailed and constructive comments. We will address all the remaining issues listed in a revised version following our responses below.

Main Comments

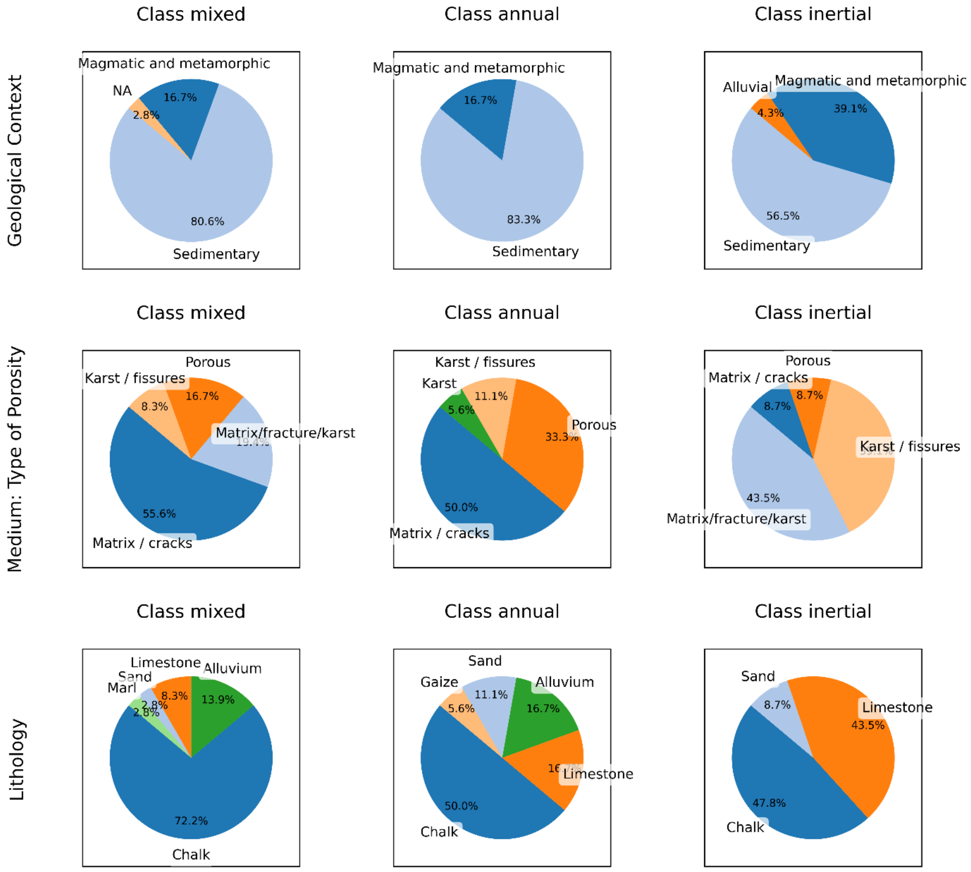
What is the best way to leverage regionalised information? - The authors raise this question in the manuscript title but in my opinion, they do not answer the question in a sufficient way. This has mainly two reasons:

- *The manuscript seems to be a combination of a technical note and a case study which leads to the result that a lot of essential information are missing. Reviewer 1 already pointed out several of the technical issues. In addition, a description of the data set is entirely missing. The only information available for the reader is the rough distance between the observation wells and the density in the region. Important information to understand the results and therefore the feasibility of the applied methodology is not supplied by the authors. For example: What is the distribution of static attributes in the different cluster groups? Looking at the attributes presented in Table 1, large differences between lithologies are to be expected (e.g karst vs. clay). Could it be that the annual group consist mainly of observation wells located in karstic/fractured areas and what would this tell us about the outcome of the study? Are these static attributes even presented/discussed in Chapter 4 (I assume that you can see them in Fig. 9 but they are not even named somewhere?*

Technical issues also pointed out by Reviewer #1 mainly concerned the presentation of the hyperparameters eventually selected or optimized, and the architectures of the recurrent-based models. We explained how these comments can be addressed in our response to Reviewer #1. Regarding dataset presentation issue: in the version

of the paper submitted, we presented the databases used, including the number duration, and sampling rate of the groundwater level time series, as well as a table of static attributes. Missing information or not provided at the right place, as pointed out by Reviewer #2 (e.g., the number of stations in each class, which was initially presented in the discussion section) moved to the appropriate data section. For instance, we added an in-depth comparison of attributes available for different types of groundwater levels, along with improved details of the datasets. The three static attributes for different types of groundwater are shown in the pie plots below. However, it is important to keep in mind that such information is always very local and only valid for a given well. A full description of all these attributes included in the form of a table in the supplement.

Figure 2 and Tables S1 , Lines 145-215



- *The presentation and discussion of the results lacks the already mentioned discussion of the regional context but also a discussion of the results in a broader context. For example, the authors write L398:"However, wavelet pre-processing shifts the importance towards dynamic components, reducing the contributions of static features or OHE. When clustering is combined with wavelet preprocessing, low-frequency precipitation components emerge as key contributors, improving model performance.*

  Does this mean that the importance of all dynamic components is higher by default, and we do not need to consider geological/hydrodynamic/topographic features? Does this apply to all kind of unconfined aquifer systems (shallow, deep, karstic…)? Here it would be interesting to combine/compare your results with/to other available publications considering static attributes on a regional scale (e.g. Heudorfer et al., 2024 or Haaf et al., 2023).

  In the present paper, we aimed only to assess whether, in our context of relatively parsimonious availability of basin properties, considering such attributes within the framework of DL modeling would significantly improve the simulations. For the sake of the generalization capabilities of DL models, we also probably need to find a reasonable trade-off between the use of all possible/relevant static features and their availability over large areas.

  We cannot expect static characteristics to be more important than precipitation, temperature, or other variable time series of the water cycle in explaining groundwater level (GWL) time series variations. As mentioned above, the aim here is to assess to what extent available static attributes, in combination with indispensable forcing hydrological variables, may help refine and improve GWL simulations for stations in various (hydro)geological contexts. This (hydro)geological information is largely accounted for in the weights of the neural network model, but the question remains whether additional static information can be helpful. Our results suggest that in some cases, particularly for the most inertial groundwater level types that mainly record low-frequency, climate-like information, improvements can be gained by adding static features.

  We agree that a more thorough comparison with papers that have used static attributes on a regional scale was needed and now added to the discussion section.

  Since the purpose of the paper presented here is not to determine the forcing factors of groundwater level variations, comparison with such state-of-the-art studies will help to put our results into perspective, inasmuch as a comprehensive evaluation of such links would require specific approaches. Such approaches have already been undertaken and presented in numerous previous works that we will use to feed the discussion about this important topic as in (Lee et al., 2019; Heudorfer et al., 2019; Liesch and Wunsch, 2019; Haaf et al., 2020; Giese et al., 2020). In our own previous works (albeit for the Normandy region only), the linkages between groundwater level variability and potential forcing factors such as the thickness and lithology of surficial

formations, aquifer thickness, vadose zone thickness, upstream/downstream location along the flow path, distance to the river, presence of karst, etc., were investigated using dedicated approaches (Slimani et al., 2009; El Janyani et al., 2012, 2014).

Lines 516-543, 576-595

The quality in writing (language, clarity etc.) differs a lot throughout the manuscript. This makes it difficult to follow the central theme and therefore requires revision. Sometimes sentences reoccur, e.g. L73: DL models have proved effective on a local scale, and are also on a larger scale by collectively training a significant number of piezometers (Chidepudi et al., 2023b; Heudorfer et al., 2024) vs. L80: The DL models have proved effective at local scale and are also proving more effective on a larger scale. At the same time the introduction of terms and abbreviation is totally off, some examples: GWLs is first introduces in the Introduction and then again in line 185, 308, 378 and 436; SHAP is first introduced in line 231 and then again in 461; an introduction (even though they are quiet common) for AI/DL/KGE and NSE is entirely missing. Altogether it feels like sections/paragraphs of different origin were put together.

We improved the text with appropriate introduction of terms wherever needed. Also the entire text checked for homogenization of the writing quality.

All over the text

Secondary Comments

*L85: sensitivity to human activities - I do not really understand why this is an **additional challenge compared to runoff data**. Does it mean runoff data are not sensitive to human activities (e.g. river straightening, dam construction etc.)?*

We agree that “additional challenge” was certainly not the most appropriate term. Here we meant to say that groundwater level data are affected by different types of challenges with respect to human activities. This can be confusing and then modified in the text.

Lines 74-79

L121: their application to GWL simulation is still questionable. – Do you really mean questionable?

We agree "questionable" is clearly not the right term. revision: "their application to GWL simulation is still not fully explored or validated across diverse hydrogeological settings."

Line 108

L141: We refer to (Beven and Young, 2013), for differences in the use of the terms simulation and forecasting. - I do not see the connection between the sentence and the rest of the paragraph. Maybe a few more words are needed?

We updated it as : "We would like to highlight at this point that the present study is not dedicated to 'forecasting' as it is the case in most applications of DL to groundwater modeling. The reader can be referred to Beven and Young (2013) for distinctions between 'simulation' and 'forecasting'. In brief, according to their framework, 'simulation' means reproducing system behavior without using observed outputs, while 'forecasting' involves reproducing system behavior ahead of time based on past observations. This study focuses on simulation to understand GWL dynamics, rather than forecasting future levels. This distinction is important for framing our approach and interpreting our results."

Lines 131-136

L164: Although they seem somehow redundant, they are expected to provide complimentary information about the hydrogeological nature of the hydrosystems – This could and should be tested at one point (which does not mean that you have to add it here).

We agree that it would certainly be interesting to conduct some statistical analysis (multivariate, for instance) to assess the potential redundancy of the information provided by the different static features, but 1- we agree with reviewer #2 that this should probably be undertaken in the framework of one dedicated study (cf. our response to some previous comments), 2) from the DL point of view, redundancy should not be an issue, DL models are basically designed to handle (and learn from) as much information as possible without taking into account any possible redundancy within the data (the model will adjust its parameters according to the most useful information detected). For instance, one part of the useful information can be common to 2 features, and at the same time one other part can be specific to each. It will not be detrimental to the performance of the model. As hydrologists, we only ensured that the input data are hydro-geologically relevant (albeit strictly speaking, from the DL standpoint, the models can even get rid of irrelevant data itself during the learning process).

L167/ L173/180/323: Baulon et al., 2022a/b?

Corrected to a/b in all instances.

L187: Bidirectional LSTM - I would be good to provide a reference especially since you write in L192: BiLSTM […] are particularly good at identifying various patterns in data sequences, making them ideal for simulating GWLs that change over time. or is this already a result of your study?

This was not the outcome of this study but a general advantage of the model and references will be provided.

Lines 222-229

L304: Further explanation needed. The figure does not provide any details, especially no comparison, as written by the authors.

We agree these 2 sentences are confusing. It is also true that the difference between the various models is never extremely noticeable, because all the models performed well eventually. A thorough examination of the results of figure 3 (comparison of the 3 model types in single-station mode) and of figure 5 with figures A1 and A2 led us to the conclusion that GRU performed slightly better. Another reason why GRU was preferred is also related to its computational efficiency. Since the difference in performances is not very noticeable, we suggest the following modification:

"All models tested in the case of this study, performed more or less equivalently and eventually led to very satisfactory results. This can be attested by performance comparison shown in figure 3 (comparison of the 3 model types in single-station mode) and by comparing figure 5 with figures A1 and A2 (multi-station mode). We finally decided to favor the GRU architecture owing to its recognised computational efficiency over more traditional LSTM-based architectures (Cho et al., 2014; Cai et al., 2021; Chidepudi et al., 2023, 2024)".

Lines 369-374

L355: This is an information you expect earlier in the manuscript.

Agreed, we moved this information to the data section for better context.

Line 155

L372: Why do you formulate "new research questions" here, is this necessary?

We agree, formulating new research questions again at this stage can be misleading. We then removed them as it doesn't change the discussion.

L425: No_ohe_no_stat approach?

We updated it to use consistent and clear naming conventions for all approaches throughout the paper.

Line 512, Figures 12 & 13

References: Nourani, V., Alami, M. T., & Vousoughi, F. D. (2015). - I do not find a citation of this paper.

Corrected the citation in line 101

References:

- *Heudorfer, B., Liesch, T., & Broda, S. (2024). On the challenges of global entity-aware deep learning models for groundwater level prediction. Hydrol. Earth Syst. Sci, 28, 525–543. https://doi.org/10.5194/hess-28-525-2024*
- *Haaf, E., Giese, M., Reimann, T., & Barthel, R. (2023). Data-driven estimation of groundwater level time-series at unmonitored sites using comparative regional analysis. Water Resources Research, 59, e2022WR033470. https://doi.org/10.1029/2022WR033470*
- **Slimani, S., Massei, N., Mesquita, J. et al. Combined climatic and geological forcings on the spatio-temporal variability of piezometric levels in the chalk aquifer of Upper Normandy (France) at pluridecennal scale. Hydrogeol J 17, 1823–1832 (2009). https://doi.org/10.1007/s10040-009-0488-1**
- **El Janyani, S., Dupont, JP., Massei, N. et al. Hydrological role of karst in the Chalk aquifer of Upper Normandy, France. Hydrogeol J 22, 663–677 (2014). https://doi.org/10.1007/s10040-013-1083-z**
- **Sanae El Janyani, Nicolas Massei, Jean-Paul Dupont, Matthieu Fournier, Nathalie Dörfliger. Hydrological responses of the chalk aquifer to the regional climatic signal, Journal of Hydrology,Volumes 464–465,2012, Pages 485-493,ISSN 0022-1694, https://doi.org/10.1016/j.jhydrol.2012.07.040**
- **Giese, M., Haaf, E., Heudorfer, B., & Barthel, R. (2020). Comparative hydrogeology – reference analysis of groundwater dynamics from neighbouring observation wells. Hydrological Sciences Journal, 65(10), 1685–1706. https://doi.org/10.1080/02626667.2020.1762888**
- **Haaf, E., Giese, M., Heudorfer, B., Stahl, K., & Barthel, R. (2020). Physiographic and climatic controls on regional groundwater dynamics. Water Resources Research, 56, e2019WR026545. https://doi.org/10.1029/2019WR026545**
- **Heudorfer, B., Haaf, E., Stahl, K., & Barthel, R. (2019). Index-based characterization and quantification of groundwater dynamics. Water Resources Research, 55, 5575–5592. https://doi.org/10.1029/2018WR024418**
- **Lee, S., Lee, KK. & Yoon, H. Using artificial neural network models for groundwater level forecasting and assessment of the relative impacts of influencing factors. Hydrogeol J 27, 567–579 (2019). https://doi.org/10.1007/s10040-018-1866-3**
- **Tanja Liesch, Andreas Wunsch, Aquifer responses to long-term climatic periodicities,Journal of Hydrology,Volume 572,2019,Pages 226-242,ISSN 0022-1694,https://doi.org/10.1016/j.jhydrol.2019.02.060**
- **Hejiang Cai, Haiyun Shi, Suning Liu, Vladan Babovic, Impacts of regional characteristics on improving the accuracy of groundwater level prediction using machine learning: The case of central eastern continental United States,Journal of Hydrology: Regional Studies, Volume 37,2021,100930,ISSN 2214-5818, https://doi.org/10.1016/j.ejrh.2021.100930**

- Cho, K., Van Merriënboer, B., Bahdanau, D., & Bengio, Y. (2014). On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1259
- Maria Clerc-Schwarzenbach, F., Selleri, G., Neri, M., Toth, E., van Meerveld, I., & Seibert, J. (2024). HESS Opinions: A few camels or a whole caravan? https://doi.org/10.5194/egusphere-2024-864
- Vidal, J.P., Martin, E., Franchistéguy, L., Baillon, M., Soubeyroux, J.M., 2010. A 50-year high- resolution atmospheric reanalysis over France with the Safran system. Int. J. Climatol. 30 (11), 1627–1644. https://doi.org/10.1002/joc.2003
- Chidepudi, S. K. R., Massei, N., Jardani, A., Henriot, A., Allier, D., & Baulon, L. (2023). A wavelet-assisted deep learning approach for simulating groundwater levels affected by low-frequency variability. Science of the Total Environment, 865, 161035. https://doi.org/10.1016/j.scitotenv.2022.161035