

## ***Interactive comment on “Physics-inspired integrated space-time Artificial Neural Networks for regional groundwater flow modeling” by Ali Ghaseminejad and Venkatesh Uddameri***

**Ali Ghaseminejad and Venkatesh Uddameri**

venki.uddameri@ttu.edu

Received and published: 16 June 2020

The manuscript presents an integrated space-time approach for predicting one-year ahead groundwater head at multiple locations using artificial neural networks. The idea is certainly interesting and relevant for the scope of the Journal. The document is well written and the area of investigation is of extreme relevance, given the strong depletion characterizing the Southern High Plains since predevelopment. I have only minors' comments, that the authors can find below:

Response: Thank you for the overall positive comments on our paper. We appreciate your thoughtful review of the manuscript and have addressed all your specific com-

C1

ments and concerns. Specific comments:

Comment 0: Title: considering the experiment 'physically inspired' might be a little bit of a stretch. Methodologically, the study is purely a data-driven modeling exercise with the introduction of a spatial component (the coordinates and of the neighboring wells) in the input set.

Response: Thank you for your comment. While we acknowledge that ANNs are purely data-driven models (lines 15 – 20 in the original manuscript), we also contend that their development also follow the same procedures used to parameterize physically-based groundwater flow models and be guided by the governing groundwater flow equation (line 43). In the methodology section, we start with the governing groundwater flow equation as the basis for our model development and use it to discuss the parameterization of the ANN model (e.g., line 80, line 100). We recommend that such a 'physics-inspired' model development be followed as it leads to greater transparency in the development of data-driven modeling exercises to avoid being dismissed as simply 'black boxes'. As this study has more than just a methodological focus, we feel the phrase 'physics-inspired' to be relevant as it emphasizes the importance of guiding the data-driven model development not simply on statistical considerations alone but also by physical considerations governing groundwater flow.

Comment 1-1: In the introduction, some of the most recent applications of hybrid data-driven models including a spatial component are missing: Among them, Varouchakis et al., 2019: Varouchakis, E. A., Theodoridou, P. G., & Karatzas, G. P. (2019). Spatiotemporal geostatistical modeling of groundwater levels under a Bayesian framework using means of physical background. *Journal of Hydrology*, 575, 487-498

This citation can be of particular relevance since it partially addresses the 'Two-stage (ANN + interpolation) models for predicting spatiotemporal variability of groundwater levels are conceptually intuitive and pragmatic. However, this approach has limited fidelity to the groundwater system it intends to model.' issue presented by the authors.

C2

Response: Thank you for pointing us to this citation. We agree that the paper partially addresses the fidelity issues of decoupling spatial and temporal aspects of groundwater flow and have included to justify the limitations of not doing so. Line 36 of the original manuscript has been modified to include the reference as follows:

“The assumption that spatial and temporal correlations can be decoupled, is not fully consistent with conditions in the field as temporal changes in neighboring wells can locally alter flow paths and affect water level forecasts at a given well (Varouchakis et al., 2019). “

Comment 1-2: Another recent application of spatial integration in data-driven groundwater modeling in a similar case study is constituted by Amaranto et al., 2019: Amaranto, A., Munoz-ARREGL Arriola, F., Solomatine, D. P., & Corzo, G. (2019). A spatially enhanced data-driven multimodel to improve semiseasonal groundwater forecasts in the High Plains aquifer, USA. *Water Resources Research*, 55(7), 5941-5961.

Response: Thank you for pointing to this reference. We have included this reference to further justify the use of neighboring wells while building ANN models. The following additional sentence has been added following Lines 80 – 81. “A recent study also corroborates that inclusion of information from neighboring wells improved the predictive abilities of ANN models while forecasting groundwater levels (Amaranto et al., 2019). “

Comment 1-3: Furthermore, it is worth mentioning how Mohanty et al., (2014) developed a model for the forecasting of GW level at multiple sites: Mohanty, S., Jha, M. K., Raul, S. K., Panda, R. K., & Sudheer, K. P. (2015). Using artificial neural network approach for simultaneous forecasting of weekly groundwater levels at multiple sites. *Water Resources Management*, 29(15), 5521-5532.

Response: Thank you for your suggestion. We have mentioned this paper when we discuss the applications of ANNs (line 20 – 21). The modified statement reads as follows: “As such, ANNs have been widely used to model groundwater level changes

C3

at individual wells (Liu et al., 2018; Nizar Shamsuddin et al., 2017; Trichakis et al., 2011; Uddameri, 2007; Nayak et al., 2006) and simultaneously at a group of wells (Mohanty et al., 2015).

Comment 2: Overall, the methodology is well presented but could benefit from the integration of an additional section, or a flowchart, explaining how the different methodological steps are interconnected to each other.

Response: Thank for your suggestion. A workflow diagram of the research procedure has been added to the appendix (Please see attached Figure 2) and referred at line 252 of the main text and will be added to Appendix A as Figure A2 in the manuscript.

Comment 3: In the case study description, one could find interesting a comparison between the southern portion of the High Plains Aquifer (or Ogallala) and the remaining part. In this regard, it would also be worth mentioning some hydro-meteorological aspects that are afterward used in contextualizing results (low recharge rate etc.).

Response: Thank you for your comment. We have added some additional information on hydroclimatic variables as well the presence of climatic gradients at line 175 to provide context to the future discussion. We discuss limited recharge on line 200 of the manuscript. The revised paragraphs are as follows:

“Annual precipitation exhibits high temporal variability and decreases moving westward. The average maximum daily temperature varies between 21.6 C to 24.4 C with cooler temperatures noticed in the northern portions of the study area. However, summer temperatures over 37 oC can be experienced over the entire study area. Seasonal precipitation is often insufficient to meet crop water demands which are exacerbated by high temperatures during critical growth phases. Groundwater from the underlying Ogallala Aquifer is heavily used for irrigation.”

Comment 4: Point comments:

“Line 11 'Incorporation of spatial variability was more critical than capturing ground-

C4

water level persistence'. Not very clear

Response: We thank the reviewer for this comment. We have modified this sentence to be clearer. The state after modification is as below: "Incorporation of spatial variability was more critical than capturing temporal persistence."

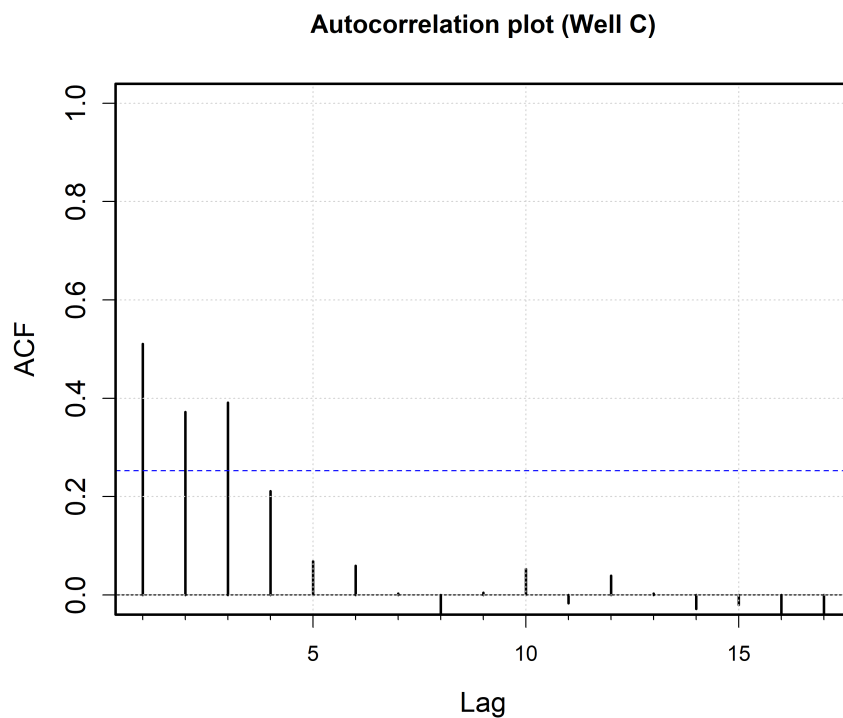
Line 226: were deemed sufficient based on autocorrelation analysis. Would be nice to see some values

Response: Thank for your suggestion. We have added a statement that presents the numeric values of lag-4 and higher and also present a representative example in the appendix (Figure A1 in appendix A, see below). "Higher order lags were noted to have very low ( $< 0.2 \pm 0.25$ ) autocorrelation (see Fig. A1 to be added to appendix A of the manuscript) for a representative example."

---

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., <https://doi.org/10.5194/hess-2020-117>, 2020.

C5



**Fig. 1.** Figure A1: Illustrative Autocorrelation Function Plot Indicating the Insignificance of Higher-Order Lags

C6

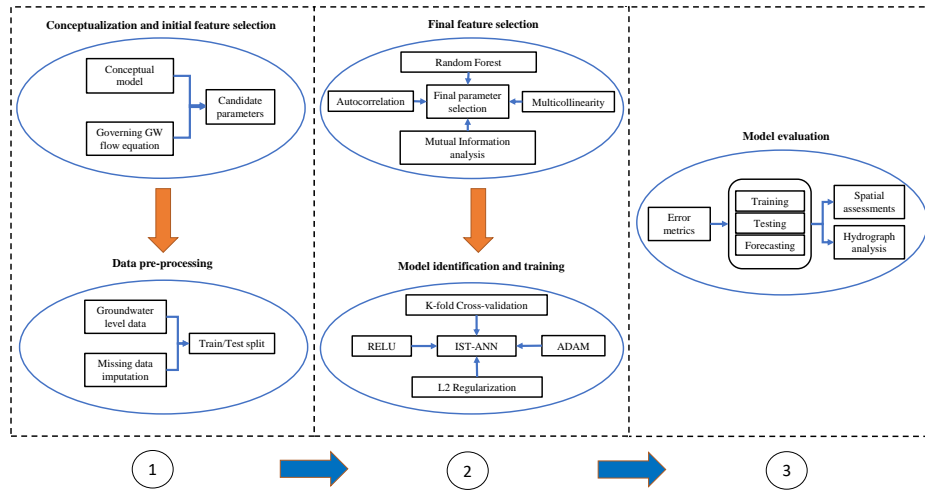


Fig. 2. Figure A2: Workflow of the IST-ANN Modeling Procedure