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**Title:** Explaining the high skill of Reservoir Computing method in El Niño prediction

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# Answer to the comment by Paul Pukite

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**Comment:**

Because of the importance of the thermocline in ENSO behavior, the impact of long-period tides in a reduced effective gravity environment has to be included in any predictive analysis. This is particularly appropriate for machine learning, where known tidal data can be straightforwardly included as with any other input. It's obvious from the paper that the concentration focuses on natural responses (see the reproduced Fig.A2(a ) below) which clearly shows the damping characteristic of the perhaps stochastically-selected (via noise) eigenvalue solution to a differential equation.

" This distinction hinges on whether ENSO variability occurs as a sustained oscillation or limit cycle (supercritical) or is a damped oscillation excited by stochastic forcing (subcritical)."

Yet, it's more than likely that ENSO is the result of a forced response to tidal forces, with the annual nonlinear interaction creating an erratic cycling about the approximate 4 year mean period estimated from an index such as NINO3. For the main long-period tidal factors of Mf and Mm, the annually sidebanded periods are calculated at 3.8 and 3.9 years. The complete nonlinear solution of the shallow-water Laplace's tidal equations used to model oceanic fluid dynamics is described in [5]. A similar training/validation/test procedure is used for finding an optimal predictive fit as that used in machine learning. The main point in this type of modeling is that predictive analysis can conceivably be made years in advance. The continually forcing of the mixed lunar and annual cycles will create the requisite temporal boundary/guiding conditions to maintain coherence over a long range, much like conventional tides do for sea-level height (SLH) analysis.

**Author's reply:**

Including tidal information as an input variable during the training phase of a Machine Learning (ML) framework could be interesting to investigate. However, previous studies [1], [2], [4] have already demonstrated outstanding ENSO forecasting performance using a combination of sea surface temperature anomalies (SST) and upper ocean heat content anomalies (OHC), or even only using SST anomalies [3]. These findings suggest that SST and OHC anomalies provide enough information for skillful ENSO predictions. Furthermore, our study relies on data generated by the Zebiak and Cane model (ZC), which has been used as a testbed. Since the ZC model does not account for long-period tidal effects, incorporating tidal information during the training of our ML framework would be impossible.

**Changes in manuscript:**

No changes required in the modified manuscript.

# References


[1] Yoo-Geun Ham, Jeong-Hwan Kim, and Jing-Jia Luo. Deep learning for multi-year ENSO forecasts. *Nature Publishing Group*, pages 1–17, September 2019.

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[3] Chibuike Chiedozie Ibebuchi and Michael B Richman. Deep learning with autoencoders and LSTM for ENSO forecasting. *Climate Dynamics*, 62(6):5683–5697, June 2024.

[4] Jahnavi Jonnalagadda and Mahdi Hashemi. Long lead enso forecast using an adaptive graph convolutional recurrent neural network. *Engineering Proceedings*, 39(1), 2023.

[5] P. Pukite, D. Coyne, and D. Challou. *Mathematical Geoenergy: Discovery, Depletion, and Renewal.* Geophysical Monograph Series. Wiley, 2019.