Author Response RC3 - David Nathan

Tensorweave 1.0: Interpolating geophysical tensor fields using spatial neural networks

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Dear David Nathan,

We thank you for your time and effort reviewing the submitted manuscript, and are pleased that you appreciated our results. We have incorporated your suggestions into the revised manuscript, as detailed in the following pages. Please note that to facilitate the evaluation of our revision, the line numbers of the reviewers' comments refer to the originally submitted manuscript while line numbers of our responses refer to our revised manuscript.

Kindest regards,
Akshay Kamath (on behalf of the authors)

Q1) Given that interpolated potential field data often serve as input for geophysical inversion, further discussion of the ENF approach's implications in this context would strengthen the manuscript. Specifically, the observation noted in line 293 suggests potential limitations when applying the method in ensemble-based inversion frameworks, such as the ensemble Kalman inversion. These methods rely on statistical assumptions and error covariance structures that could be influenced by interpolation artifacts or over-smoothing. A brief exploration of how ENF interpolation might influence inversion performance and uncertainty propagation would add valuable context for practitioners.

This is an excellent point raised by the reviewer. We agree with the reviewer in that the uncertainty associated with the interpolation could potentially impact inversion results between the flight lines. In general, all interpolation frameworks involve some sort of smoothing between data points: The inversion of such interpolated datasets is therefore not recommended in general. Instead, inversion results should only be compared at the points that have measurements, to avoid this interpolation bias.

However, if e.g., numerical optimations require an inversion constrained by gridded data, then we suggest that our ensemble uncertainties may serve as useful weights for each interpolated grid cell. The propagation of uncertainties through inversion is outside the scope of this contribution, but we have added the following text in Section 5.3, L413, to mention this.

“Interpolated grids alter the observation error model: smoothing and continuation introduce spatially correlated errors that, if ignored, can bias ensemble-based inversions (EnKF). Best practice is naturally to invert at the real measurement locations, however when a grid is needed we suggest that our ENF ensemble could provide a mean and a sample covariance for the pseudo-observations. It is possible (although untested) that this might be used as the observation-error covariance in the inversion.”

Minor revisions:

1. **Line 123: \hat{k} needs to be defined.** We have updated the notation for all equations, eliminating the need for \hat{k}.
2. **Line 388-389: Please update the reference Laloy et al., 2013. I was unable to find any source for it.** We have replaced the missing reference with appropriate papers for ensemble gravity and magnetotelluric inversions (L263).