

Dear Editor Bo Guo:

We are grateful to receive comments and suggestions on our manuscript of 'EGUSPHERE-2025-4440' from you and the reviewer. We have carefully considered these comments and made revisions.

The modifications in the revised manuscript are highlighted in blue color.

The responses to the reviewer's comments are also appended for your convenience.

We hope the revision will be satisfactory. If you have any further questions or concerns, please let us know. Once again, we appreciate your time on this manuscript.

Yours sincerely,
Liangsheng Shi
Wuhan University

The authors have addressed most of my previous concerns, and the manuscript is recommended for publication subject to the following minor revisions.

Response:

We sincerely thank the reviewer for their time and careful evaluation of our manuscript. We have carefully considered the remaining minor comments and have made the corresponding adjustments accordingly.

Line 100 (Response 15): The revised explanation is still not sufficiently accurate. The main issues are as follows.

First, the manuscript overstates the defining characteristics of GNNs. The statement that GNNs “rely on explicit, pre-defined graph structures where topological relationships remain fixed” is too restrictive. While many GNNs do begin with an explicit graph, in many formulations the edge weights, adjacency, or effective interactions may also be learned, updated, or defined through attention mechanisms. Therefore, this is not a reliable criterion for distinguishing NLNNs from GNNs.

Second, the statement that “neighbor nodes typically share uniform transformation rules” is also not an appropriate discriminator. Although standard message-passing GNNs often employ shared functions, the actual interactions are not necessarily uniform, since they may depend on node features, edge features, attention coefficients, or edge types.

Third, the description of NLNNs as having “edges generated on-the-fly” is somewhat misleading. NLNNs are more accurately understood as computing pairwise affinities, often densely across all positions, based on the current features. This is better characterized as a dynamic, data-dependent, fully connected interaction pattern, rather than simply stating that they do not use a graph.

The authors should revise this section to present a more precise and technically accurate distinction between NLNNs and GNNs.

Response1:

Thank you very much for this insightful and technically important comment.

As the reviewer correctly pointed out, the distinction between NLNNs and GNNs should not be characterized as “static versus dynamic edges,” since many modern GNN formulations also allow learned, adaptive, or attention-based interactions, such as Graph Attention Network (Veličković et al., 2017).

We have therefore revised this description to provide a more accurate distinction. Specifically, we now emphasize that the key difference lies in the interaction mechanism and the underlying prior assumption regarding how information propagates across soil layers, rather than in whether the connections are fixed.

GNNs are fundamentally based on graph-structured message passing, where information propagation is constrained by an underlying graph topology (either predefined or learned), and each node aggregates messages from connected neighbors according to this graph structure. In contrast, NLNNs compute dense pairwise affinities across all positions (soil layers) directly from feature representations, resulting in a fully connected, data-dependent global interaction pattern. Thus, each

layer can directly interact with every other layer without being restricted by local graph neighborhoods.

The corresponding description in the manuscript has been revised accordingly (Lines92-101).

“While GNNs aggregate information through graph-structured neighborhood relationships, Non-local Neural Networks (NLNNs) directly model pairwise dependencies among all positions (X. Wang et al., 2018). This fully connected interaction pattern allows each position to directly interact with all other positions, thereby enabling the model to capture long-range global dependencies. The interaction weights are adaptively determined by the real-time soil moisture state in a fully data-driven manner. This fundamental difference reflects distinct inductive biases: GNNs rely on graph-structured message passing, whereas NLNNs explicitly model global interactions without neighborhood restrictions. For soil moisture dynamics, where relevant dependencies may exist between distant soil layers and vary over time, such global modeling capability is particularly beneficial.”

Line 215 (Response 32): The similarities and differences between NLNNs and transformers should also be explained more explicitly and clearly in the manuscript.

Response2:

Thank you for your comment. We have revised this section to clarify that both NLNNs and Transformers are based on data-dependent pairwise interaction mechanisms, where each position (soil layer) can aggregate information from all other positions through learned affinity weights.

At the same time, we now explicitly distinguish them in terms of architectural formulation. Specifically, the Transformer realizes this mechanism through the query–key–value self-attention framework, together with multi-head attention, positional encoding, and feed-forward sublayers. In contrast, the NLNN is a more general non-local dependency modeling framework that does not inherently require the full Transformer architecture.

The proposed KG-NLNN builds on the non-local interaction principle while introducing task-specific modifications tailored to soil water dynamics, rather than directly adopting a standard Transformer block.

The corresponding clarification has been added to Lines 222-229 in the revised manuscript:

“This flexibility stems from their ability to model global dependencies through data-dependent pairwise interactions. Among these formulations, the Transformer represents the most typical and widely used architectural instantiation, which models global dependencies through the query–key–value self-attention mechanism, multi-head attention, positional encoding, and feed-forward layers. From a more general perspective, the Non-local Neural Network can be viewed as a broader formulation of non-local dependency modeling, which computes interactions based on pairwise affinity functions without requiring the full Transformer architecture.”

Reference:

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., Bengio, Y., 2017. Graph attention networks. arXiv Prepr. arXiv1710.10903.