Accepted at the 2026 vis4climate workshop, which is part of the IEEE VIS 2026 conference. For more information, please visit https://vis4climate.org.

GNN-VIEW: Visual Inspection and Explanation of GNN-based Weather Models

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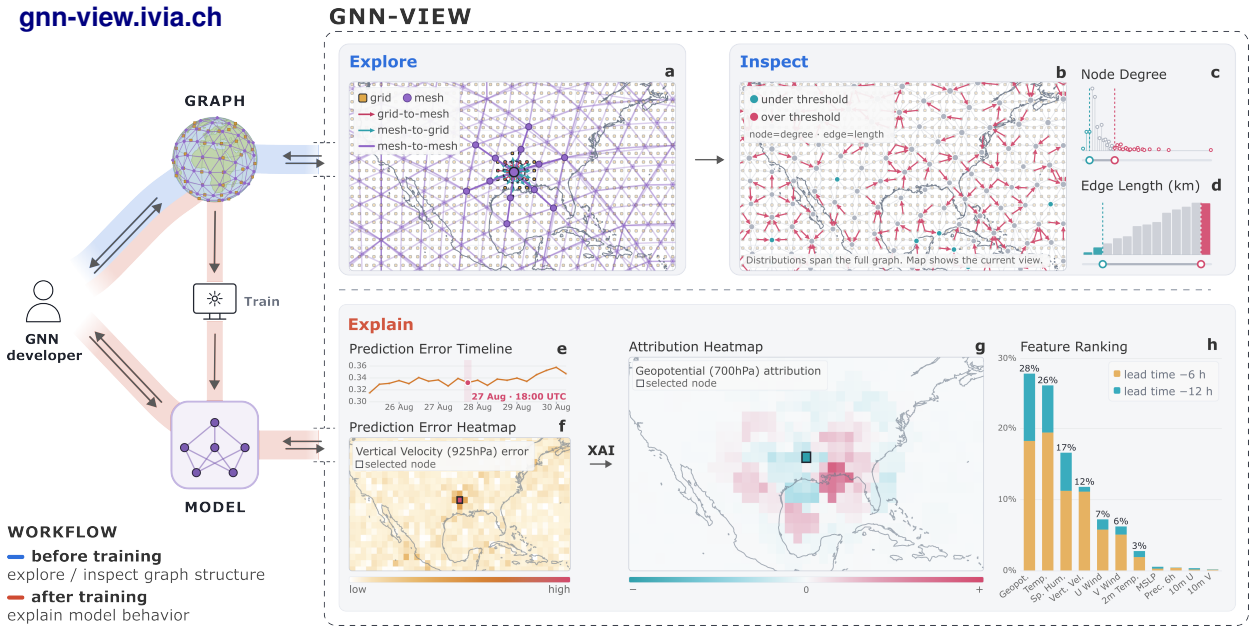


Fig. 1: GNN-VIEW lets developers explore graph structure (a–d) and explain prediction errors with attribution-based explanation (e–h).

Accurate and reliable weather forecasting plays a key role in climate change adaptation and mitigation, from early warning systems for extreme weather events to optimization of renewable power plants. ML-based models have recently emerged as a promising alternative to traditional, physics-based, weather forecasting and thanks to recent advances, they now match or exceed operational numerical weather forecasting accuracy at a fraction of the computational cost. Among these, Graph Neural Network (GNN) architectures [5, 6] are particularly prominent: they encode the spatial connectivity of the atmosphere through a graph structure, propagating information across multiple spatial scales. While increasingly adopted in both research and operational forecasting, these models remain challenging to develop, for two main reasons. **Before training**, developers algorithmically construct large-scale graphs, where structural anomalies hide in raw tensor files and can silently degrade performance. **After training**, aggregate metrics such as held-out RMSE report *where* errors occur, but not *why* the model made the inaccurate forecast. At both stages the developer's need is the same: to see what raw tensors and aggregate metrics hide.

Visual analytics has proven valuable in solving this challenge in deep learning [2] by letting practitioners explore model structure and explain predictions at scale. Adoptions for GNNs [4] and for spatio-temporal model explainability [1] have recently been proposed. Although these systems are model-agnostic and can, in theory, be used for GNN-based weather models, they are not adapted to the forecasting setting and the geographic semantics unique to this domain, where visual analytics has so far served data assimilation [3] rather than the model itself.

To fill this gap, we propose GNN-VIEW, a geographically grounded graph inspection and forecast explanation tool for GNN-based weather models. GNN-VIEW is an interactive browser-based tool that supports model developers across the entire development lifecycle through three coordinated modes: *Explore*, *Inspect*, and *Explain* (see Fig. 1).

Explore lets developers build an initial understanding of the graph structure on which their model is built. It renders the full GNN graph on a geographic map, where specific parts can be shown in isolation. Clicking on a node reveals its local connectivity (Fig. 1a).

Inspect allows developers to locate structural anomalies in the graph, turning the view into an outlier-detection workspace: full-graph node-degree and edge-length distributions are shown alongside the map, and range sliders allow highlighting graph elements of interest (Fig. 1b-d).

Explain supports post-training explainability of individual model predictions. At any timestep and location they can examine the model's predictions and errors to choose one to explain (Fig. 1e-f). Gradient-based attribution then traces the prediction back to the input features and locations most responsible for it (Fig. 1g-h).

By giving developers a direct view into graph structure and model behavior, GNN-VIEW is applicable to model development, debugging, and adaptation — possibly extending to other Earth-system domains, such as ocean, ice, and hydrology.

GNN-VIEW live demo: gnn-view.ivia.ch

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