Manuscript: A hybrid Kolmogorov-Arnold networks-based model with residual compensation and physics-informed constraints for Arctic River discharge prediction

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Comments:

1. One of the primary advantages of Kolmogorov-Arnold Networks is their enhanced interpretability compared to traditional Multi-Layer Perceptrons (MLPs). KAN is usually used to improve the interpretability of the relations between inputs and output, but there is no mention of that.
The manuscript fails to leverage or discuss this fundamental strength of KAN architecture. Specifically, there is no:

• Visualization of the learned univariate functions

• Symbolic regression analysis

• Interpretation of what relationships the KAN component discovered between hydrometeorological inputs and Arctic discharge

• Physical insights into the processes governing snowmelt-driven streamflow in permafrost regions

Include a dedicated subsection on KAN interpretability analysis containing:

- Visualization of learned activation functions for key input-output relationships
- Symbolic approximations of these functions where feasible (using symbolic regression tools available in KAN libraries)
- Physical interpretation of discovered patterns in the context of Arctic hydrology
- Comparison with known physical relationships in snowmelt hydrology from the literature

2. what are the hyperparameters (epochs, batch size, learning rate) and details of the architecture of the RNN, GRU and other neural nets used for comparison.
The manuscript lacks essential details for all baseline models (RNN, GRU, LSTM):

- No specification of hyperparameters (epochs, batch size, learning rate)
- No architectural details (number of layers, hidden units, activation functions)
- No information about initialization methods
- No training procedure details (optimizer type, learning rate schedules, dropout rates)
- No stopping criteria or early stopping procedures
- No hardware specifications or training times

3. Recent papers suggest that KAN based architectures outperform classical ANN based architectures. There should have been a comparison with KAN based LSTM, GRU and other neural nets. The manuscript only compares RCPIKLA (which uses KAN) against traditional ANN-based models (RNN, GRU, LSTM), not against KAN-enhanced versions of these baseline architectures.
The comparison with no physics informed constraints and no residual has been compared. However, the current experimental design still creates an attribution problem. Observed performance improvements could stem from:

- The KAN component specifically
- The attention mechanism
- The physics-informed constraints
- The residual compensation structure
- Seasonal trigonometric encoding
- Some synergistic combination of these components

Without proper ablation comparing LSTM-attention/KAN-LSTM/KAN-GRU versus RCPIKLA, the specific contribution of KAN remains unclear.

4. The manuscript describes a physics-informed constraint that imposes an upper limit on predicted snowmelt contribution but does not explain the asymmetric treatment of constraint violations.
The asymmetric design requires clear physical justification:

- Upper bound rationale: Snowmelt contribution physically cannot exceed available snow water equivalent - this is a hard constraint based on mass conservation
- Lower bound question: Are underpredictions physically plausible? Could incomplete melting, refreezing, or sublimation make them valid? Or do they indicate model failure to capture melt processes?
- Bias implications: Does the asymmetric penalty introduce systematic bias toward underprediction?

5. Physics-informed neural networks fundamentally rely on balancing multiple loss terms through weighting parameters. The manuscript mentions α and β as weights for MSE loss and physics loss but does not report their values.
The manuscript must provide:

- Final α and β values used for all reported results
- Scenarios of hit and trials
- Search space explored

6. The manuscript lacks visualization of epoch-wise loss decomposition, which is important for assessment of convergence of all models. Without this analysis, it is impossible to assess whether the physics constraint meaningfully guides training or becomes negligible compared to the data-driven MSE loss.

Visualizing separate loss components reveals:

- Whether physics loss actually contributes to training or is overwhelmed by MSE loss
- Training stability and convergence behavior
- Potential issues: loss spikes, plateaus, phase transitions

7. Figure 6 (left): "y axis seems to be cut, the numbers are partly missing" - this affects readability and interpretation. Also, please check for spelling and grammatical errors throughout manuscript. Like a few spelling mistakes have been observed in abstract.

8. The physics-informed mechanism involves snow storage (S_t) and melt (M_t) terms that evolve over time. However, the manuscript does not specify:

- Initial values for S_0 and M_0 at the start of the simulation period
- How these initial conditions were integrated into the model?

9. It is mentioned conducting 10 independent runs but provides unclear or incomplete reporting of variability in results. Fig8 represents the rmse and nse RCPIKLA variants with all predictions, what is the average RMSE over 10 runs, how much variation is observed over independent runs?
Additionally:

- Figure 8 shows results (RMSE and NSE for RCPIKLA variants) but it's unclear whether these represent single runs, mean values, or distributions
- No explicit reporting of mean ± standard deviation for performance metrics
- No statistical significance testing comparing model variants

10. Figure 5 currently shows model predictions at 12 time intervals (representing different aggregation windows) but does not convey prediction uncertainty across the 10 independent runs. This limits the reader's ability to assess:

- Model reliability at different temporal scales
- Whether certain aggregation intervals show higher prediction variance

Summary:

The manuscript is recommended for publication if the above suggestions are addressed or answered.