Multiresolution Hash Encoding with a Transformer Architecture, for Groundwater Depth Prediction Across the Continental US

Department of Mathematics, University of Alabama

Colin Hanley, Qingyuan Dai, Tianfang Xu, and Jia Zhao

1. Motivation

Groundwater makes up **99 % of the freshwater resources** on the planet [4] and is being rapidly depleted, largely as a result of the effects of climate change [5]. The development of new modeling methods is critical in shaping how this resource is managed going into the future.

This project proposes a deep-learning framework for predicting groundwater depth (GWD) across the continental United States. The goal is a model capable of providing **accurate GWD projections with minimal computational requirement while utilizing only surface-level features**, making it practical to apply at national scale.

Research Questions:

1. Can the proposed model outperform traditional numerical methods using a minimal number of surface-level features?
2. Is the model able to predict future GWD trends across regions, potentially identifying areas at risk of depletion?

2. Data & Study Area

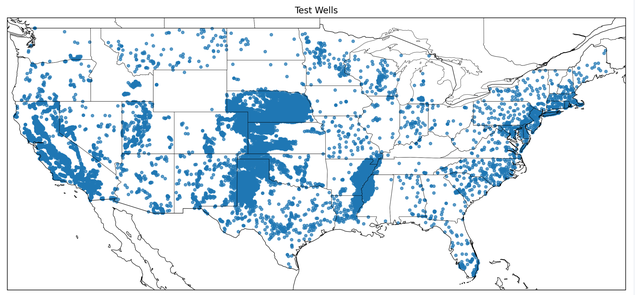


Figure: Spatial distribution of 43,000+ USGS NWIS monitoring wells across CONUS used in this study. Wells are split temporally: 2012–2019 for training, 2020–2021 for validation, and 2022 for testing.

Observ.	43,000+ USGS NWIS wells, annual avg. GWD (ft)	
Terrain	DEM, slope, aspect	
Soil	Clay, sand, silt (%); depth to bedrock	
Geology	Rock type, drainage class, hydrologic group	
Land cover	Developed, forest, pasture/crop, wetland (%)	
Climate	Monthly P, T, PET (36-month sequences) Aggregated windows & water-balance indices	
Train	2012–2019	(183,926 well-years)
Val	2020–2021	(37,864 well-years)
Test	2022	(17,402 well-years)

The **temporal split** prevents data leakage: the model must generalize forward in time rather than interpolate within the training window.

3. Model Architecture

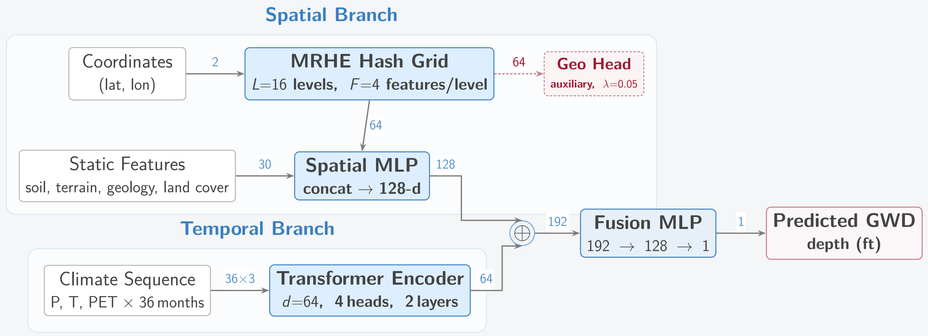


Figure: MRHE-Transformer architecture. Coordinates are encoded via multiresolution hash grids [1] and concatenated with static features through a spatial MLP. A Transformer encoder [2] processes 36-month climate sequences. Both branches are fused to predict groundwater depth.

Table: Training configuration for the MRHE-Transformer model.

Parameter	Value
Optimizer	AdamW
Learning rate	10^{-3}
Weight decay	10^{-5}
Loss function	MSE + geo-head (λ=0.05)
Gradient clipping	$\|\nabla\| \leq 1.0$
Batch size	2,048
LR schedule	ReduceLROnPlateau
Early stopping	patience 35 epochs
Total parameters	33,722,276

4. Results — 2022 Test Set

Table: Test set performance on 17,402 well-year observations from 2022. The MRHE-Transformer reduces RMSE by 37 % relative to XGBoost.

Model	RMSE (ft)	MAE (ft)	R^2
MRHE-Transformer	**19.05**	**7.73**	**0.968**
XGBoost baseline	29.99	18.72	0.921
Naïve mean	106.93	80.06	≈0

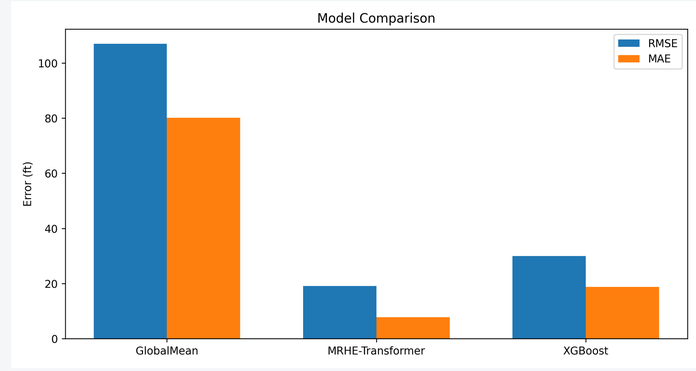


Figure: RMSE comparison across models on the 2022 test set. The MRHE-Transformer achieves the lowest error, outperforming XGBoost by 37 %.

5. Diagnostics

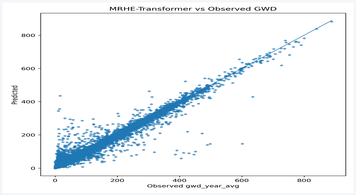


Figure: Predicted vs. observed groundwater depth on the 2022 test set. Points cluster tightly along the 1:1 line, indicating strong agreement ($R^2 = 0.968$).

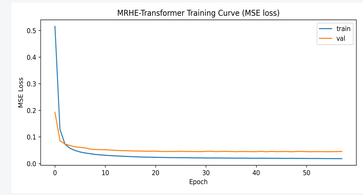


Figure: Training and validation loss curves over epochs. Both curves converge smoothly, with early stopping triggered at epoch 65.

6. Conclusions & Future Work

Key Findings:

- MRHE-Transformer achieves $R^2 = 0.968$, RMSE = 19.05 ft on 2022 test data
- **37 % RMSE improvement** over XGBoost baseline
- Multi-task geo head and temporal split improve generalization and training stability

Future Work:

- Evaluate on **wells with no prior training history**
- Incorporate groundwater use and recharge data when available
- Extend training data back to 2001 with PRISM/NLDAS-2 reanalysis

Acknowledgements

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