

Toward Scientific Foundation Models for Aquatic Ecosystems

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PhD Computer Science, Virginia Tech

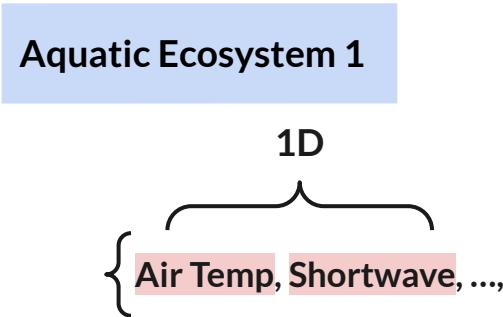
H33D: Advancing Water Science Through Artificial Intelligence:
Lessons, Strategies, and New Frontiers

AGU 2025, New Orleans, LA

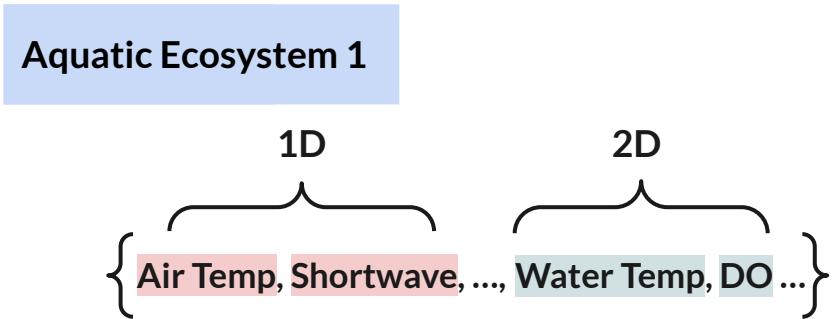
Motivation

Aquatic Ecosystem 1

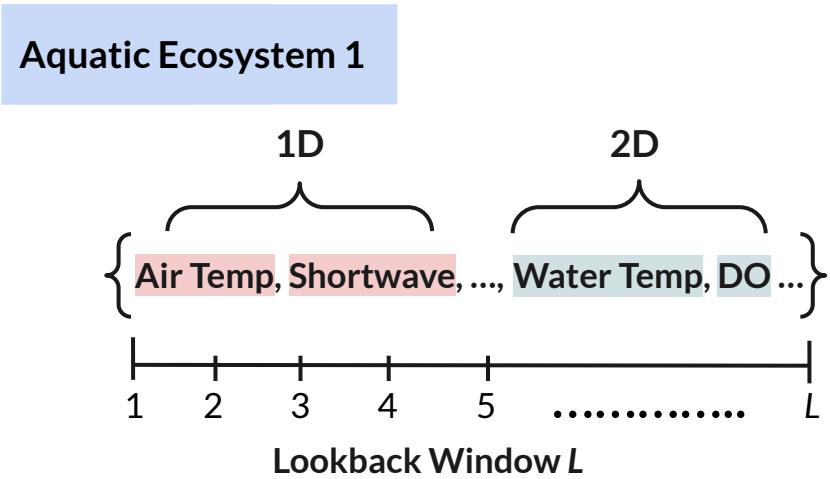
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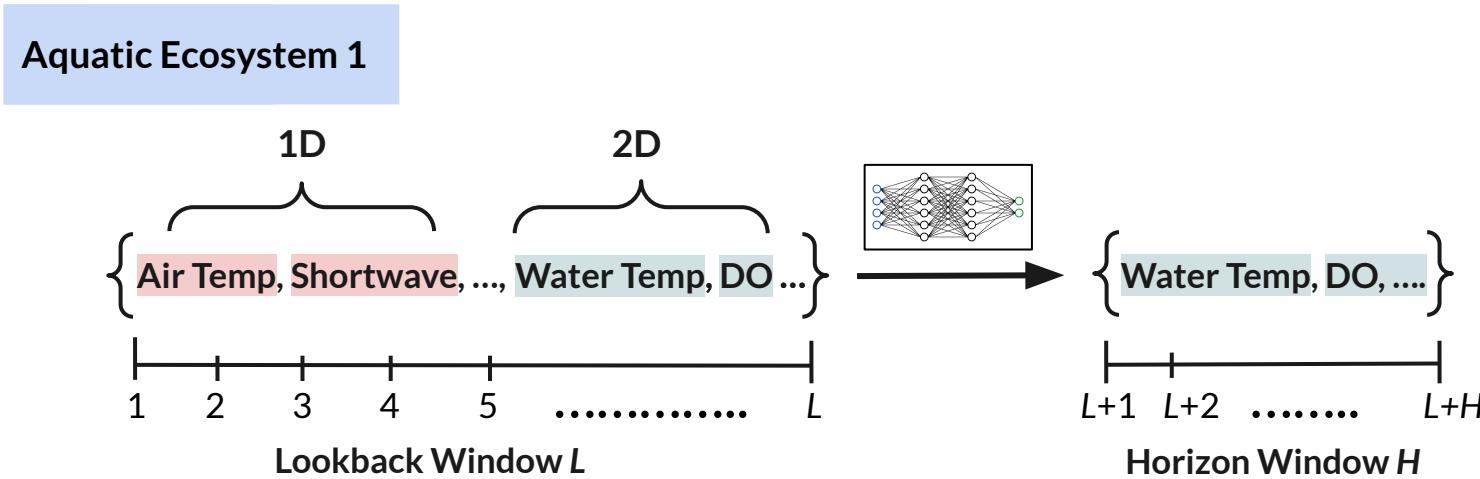
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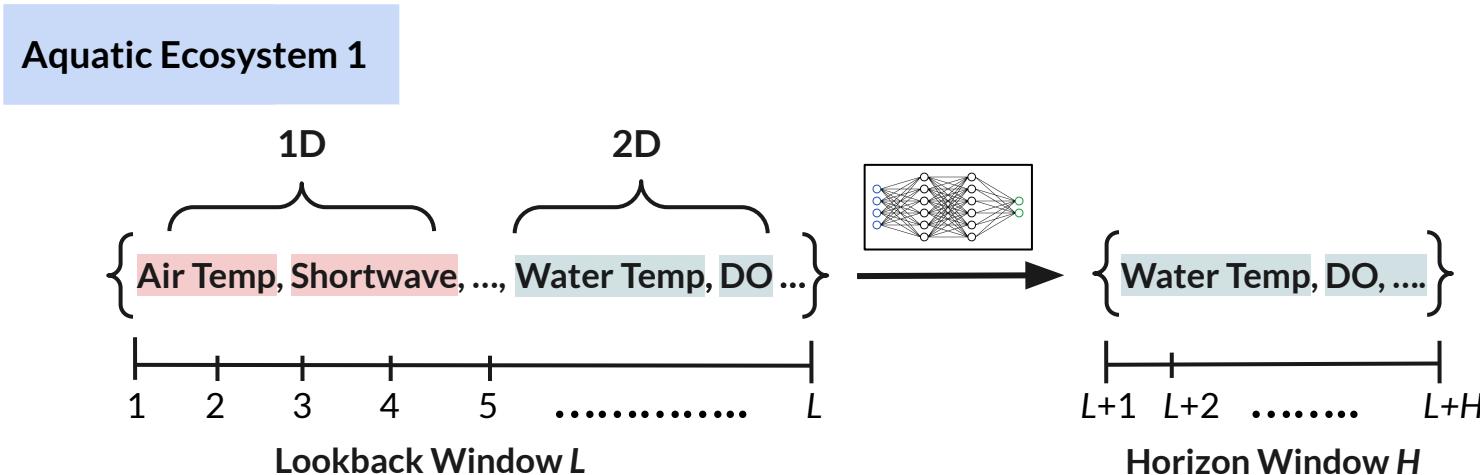
Motivation



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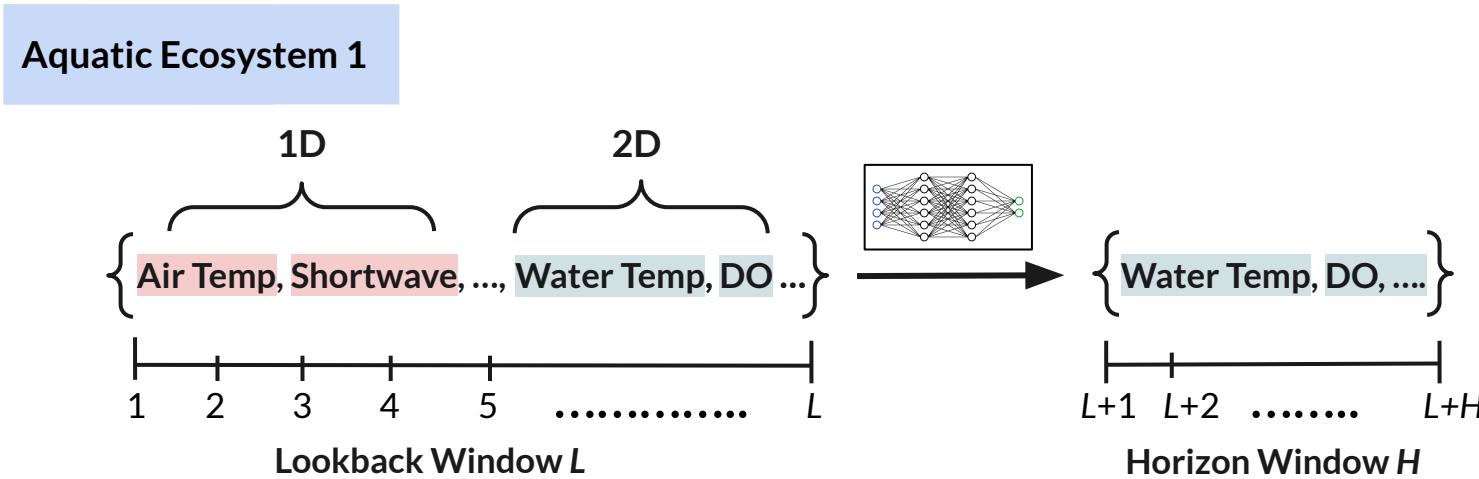


Motivation



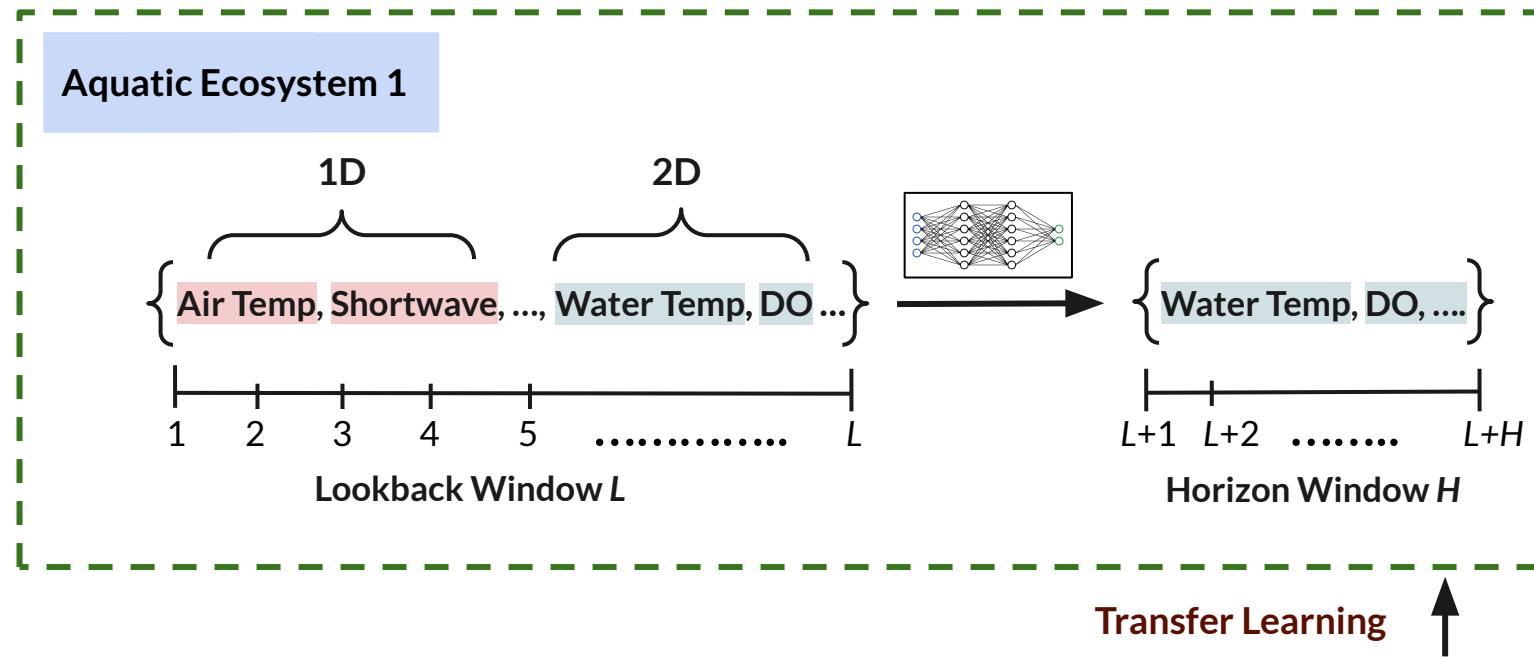
⊗ Different subset of variables available in different ecosystems

Motivation



- ⊗ Different subset of variables available in different ecosystems
- ⊗ Large amounts of missing data (e.g., *Falling Creeks Reservoir, VA, has 50% missing data, 2017-04 to 2022-10*)

Motivation

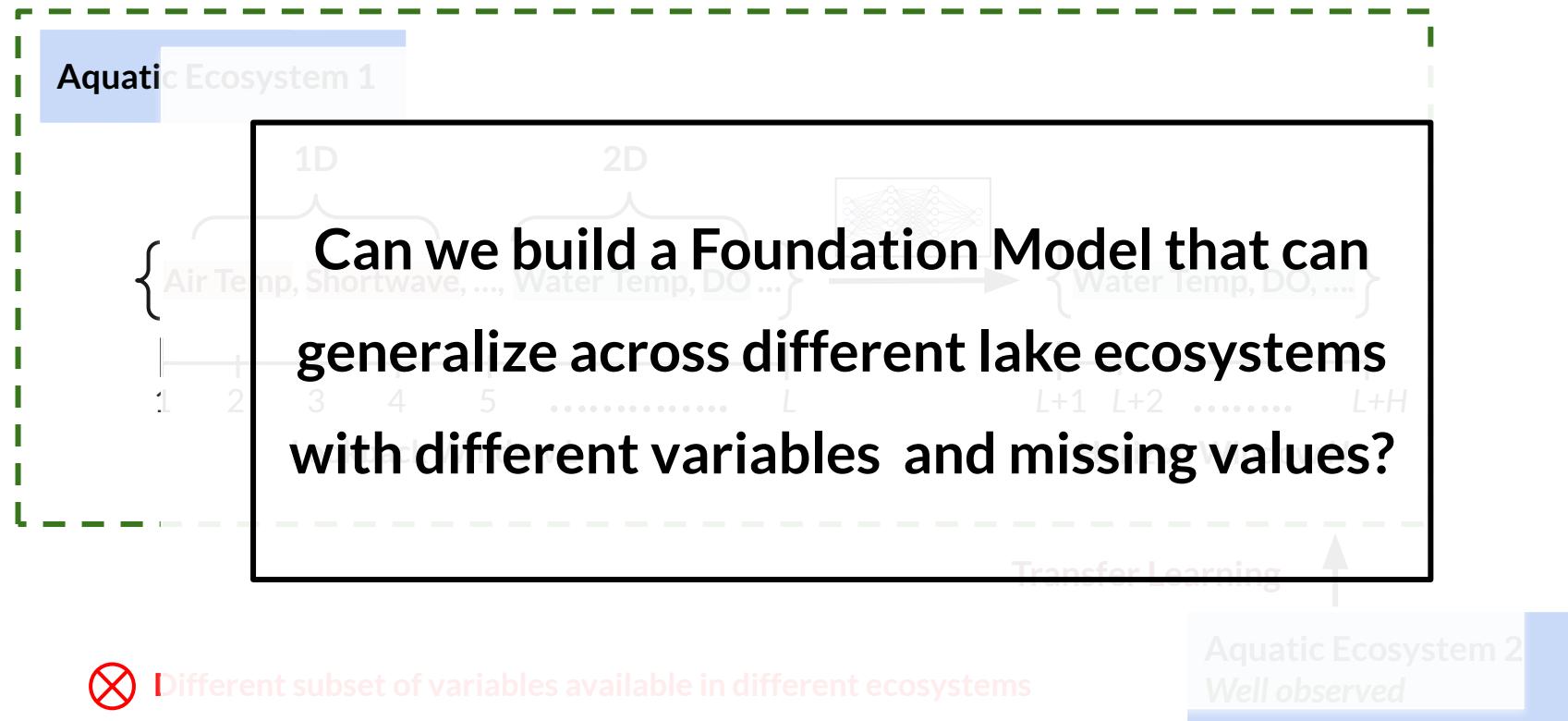


⊗ Different subset of variables available in different ecosystems

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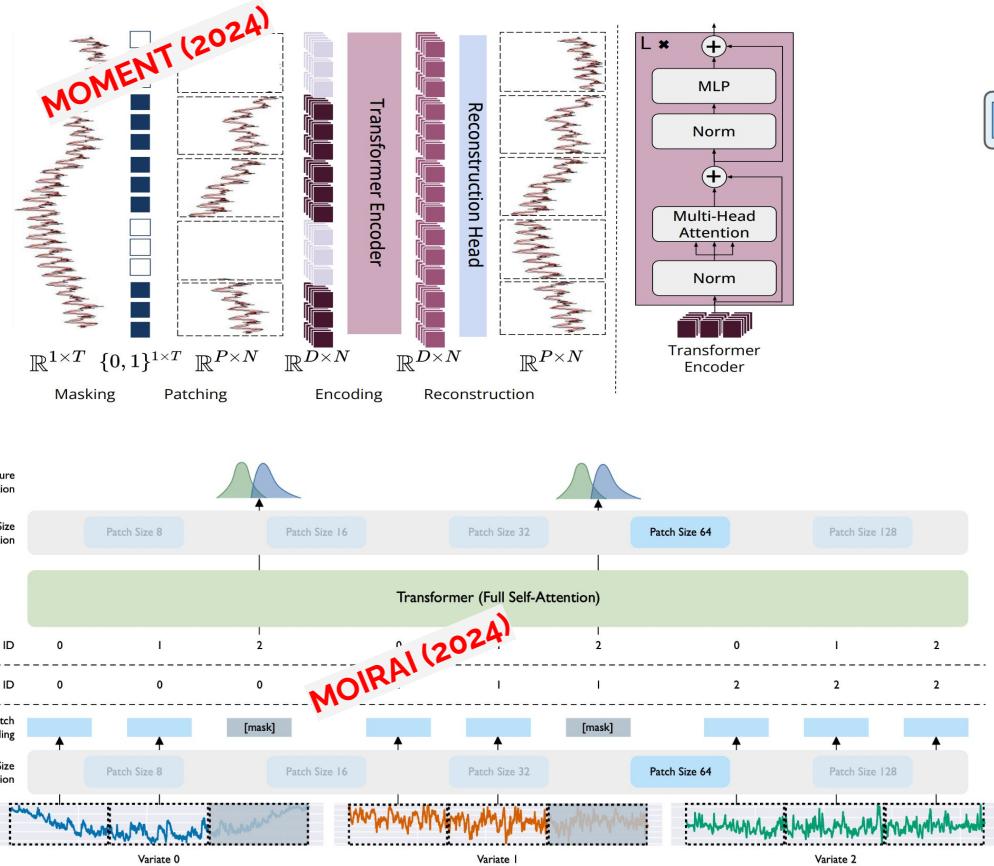
Aquatic Ecosystem 2
Well observed

Motivation

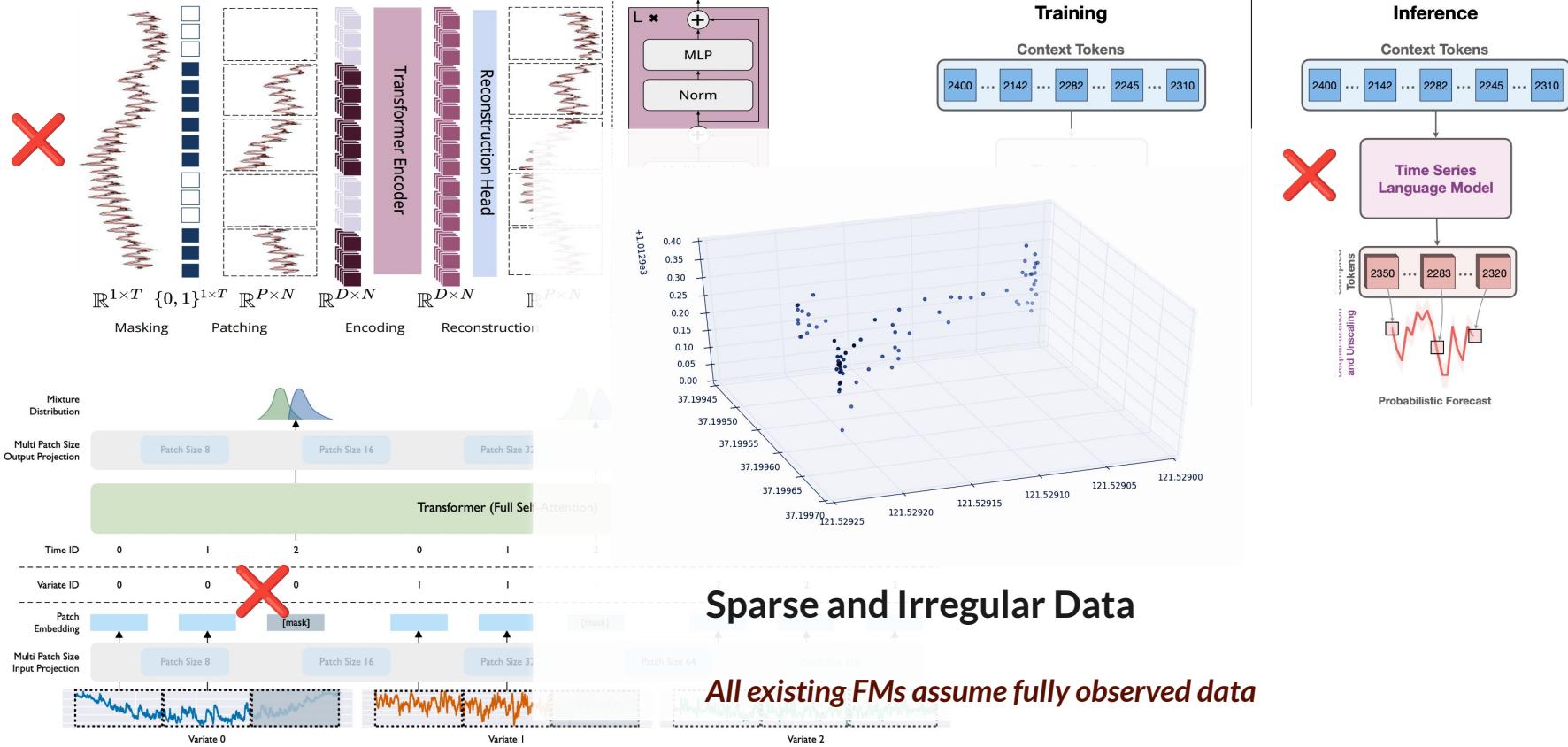


- ⊗ Different subset of variables available in different ecosystems
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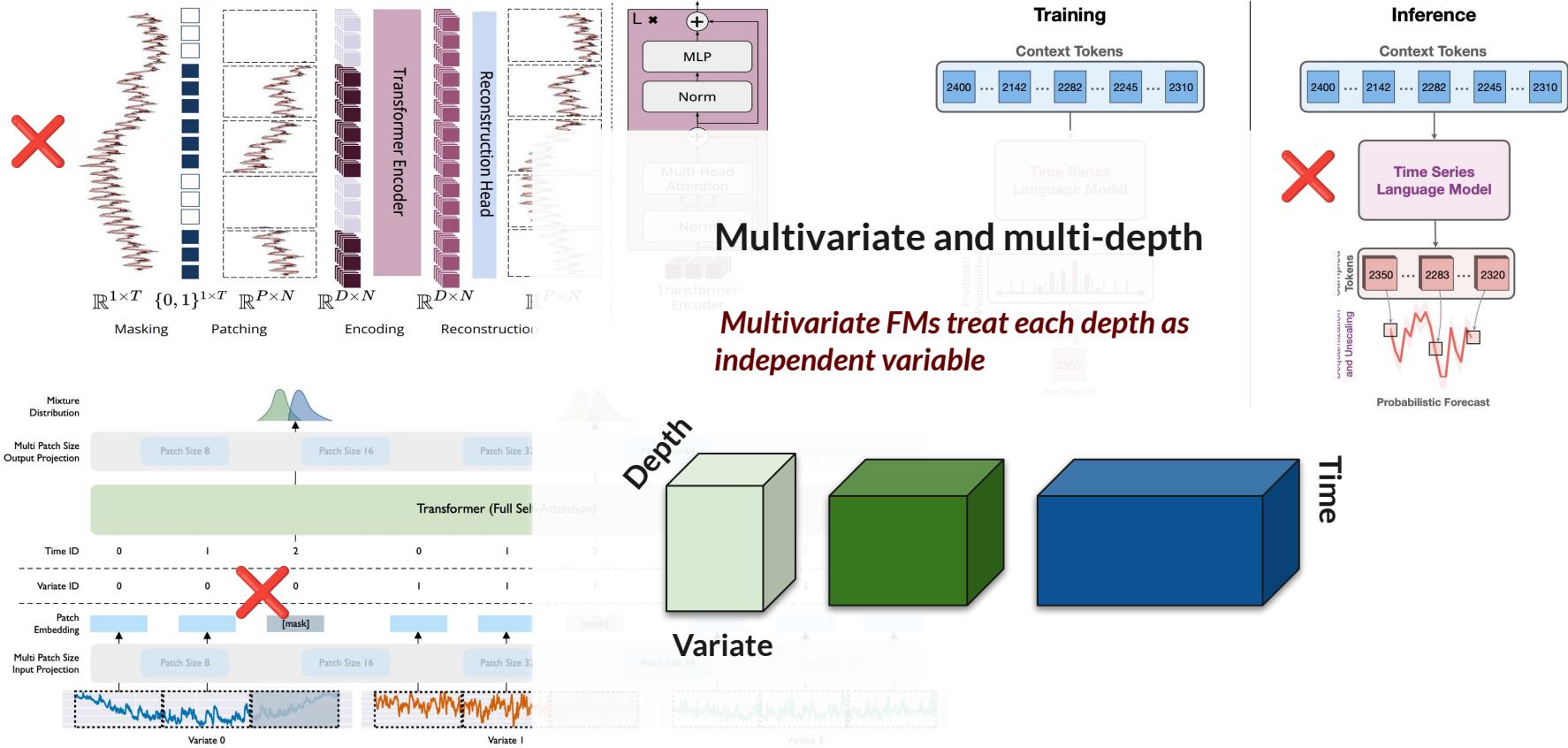
Existing Foundation Models



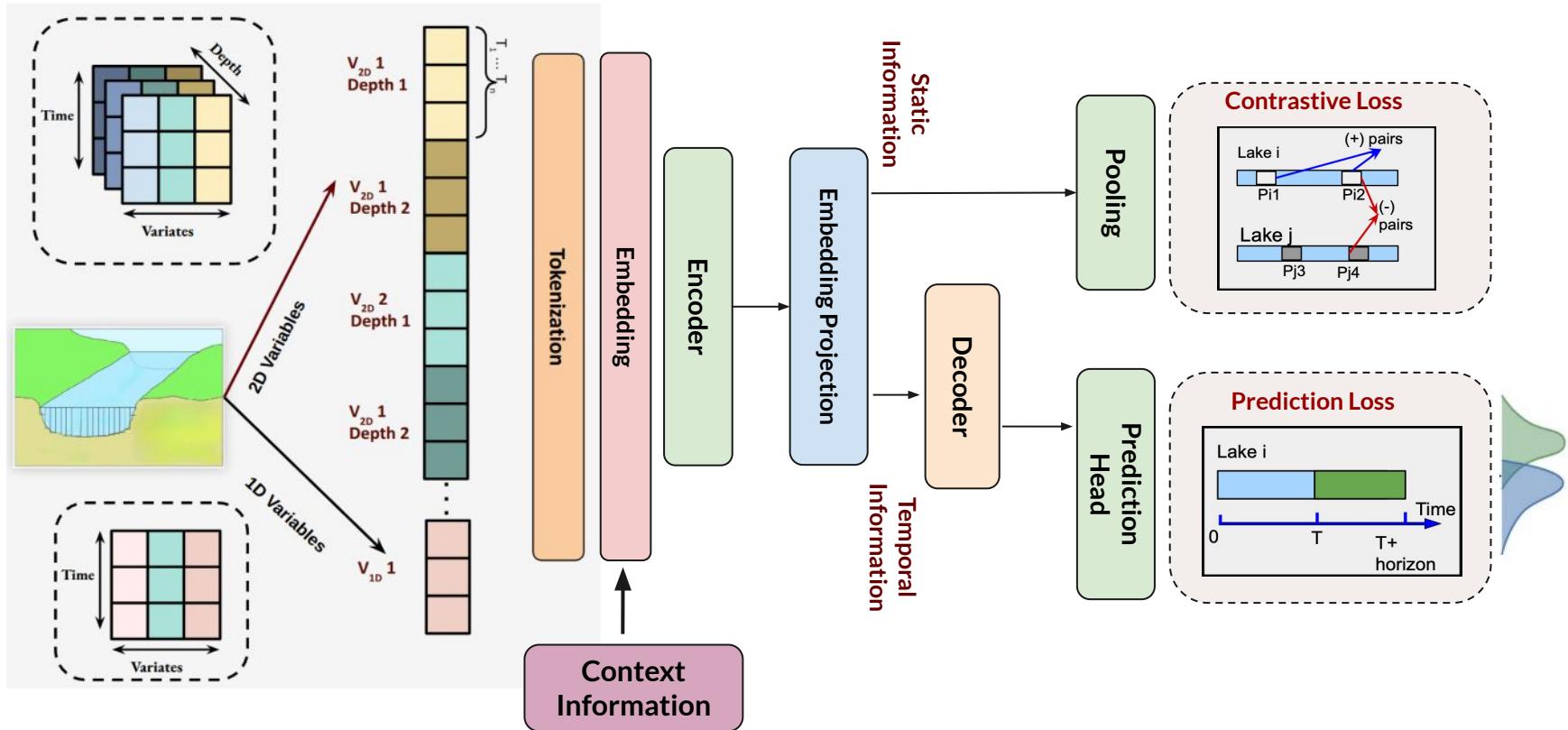
Challenges with existing Foundation Models



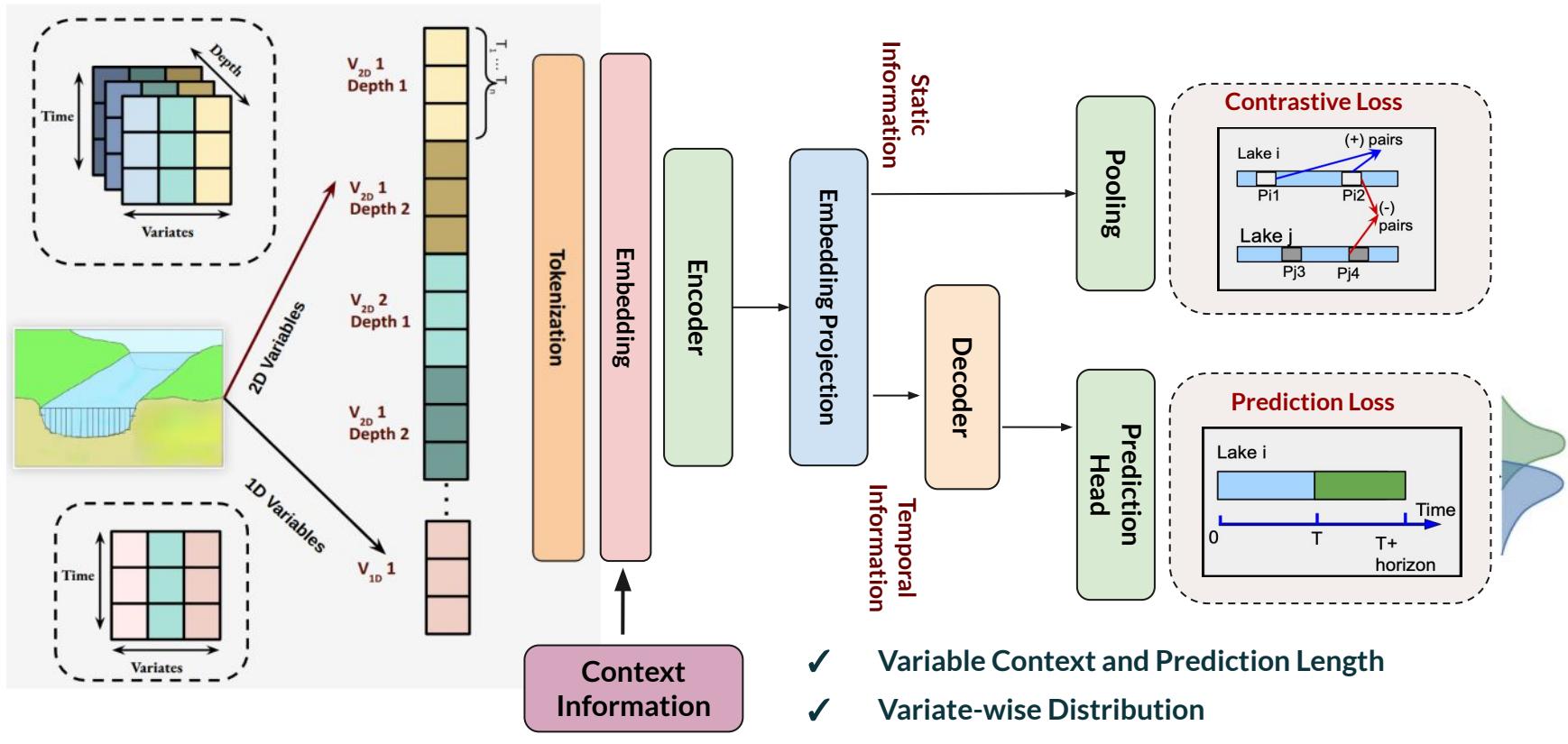
Challenges with existing Foundation Models



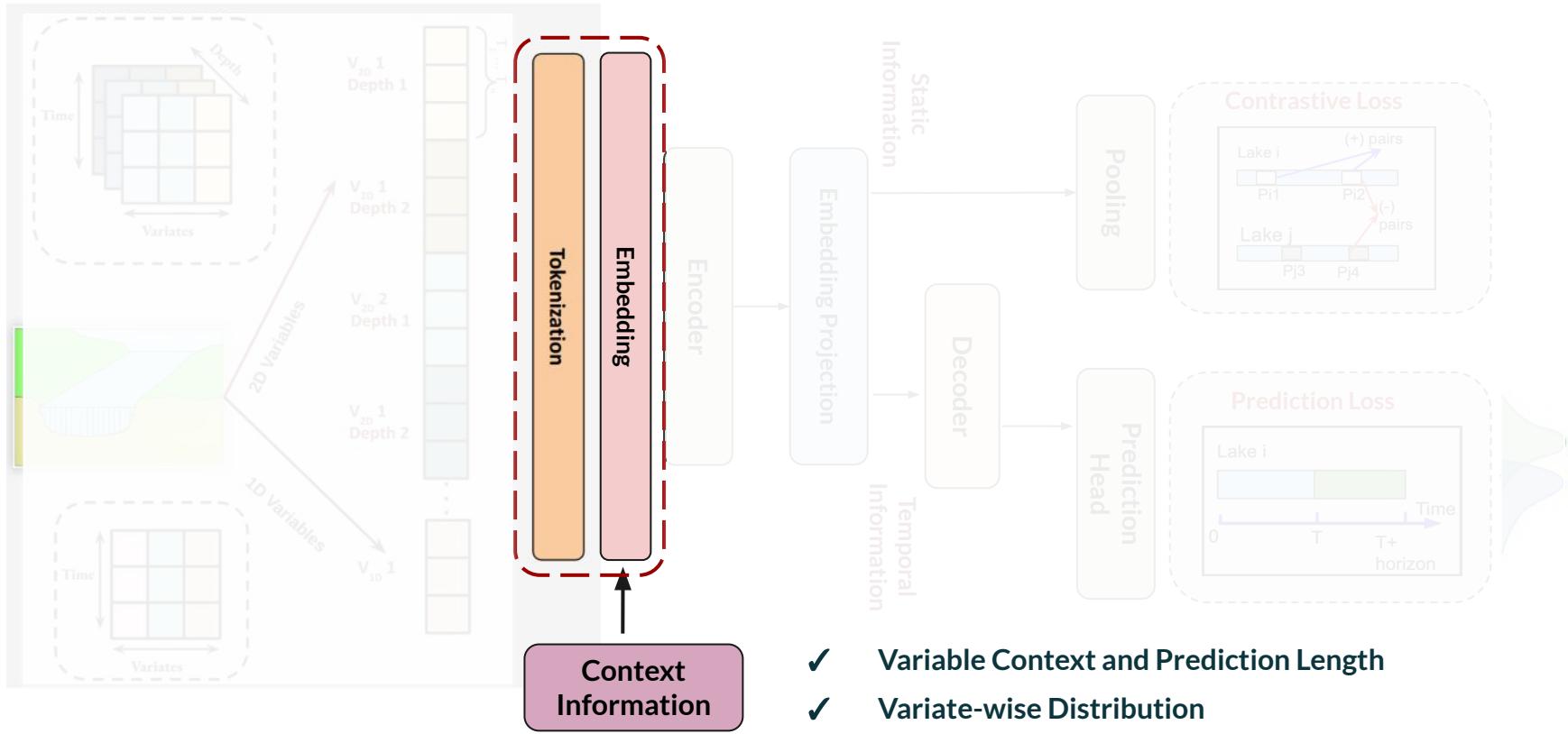
Lake Foundation Model (LakeFM) - An Overview



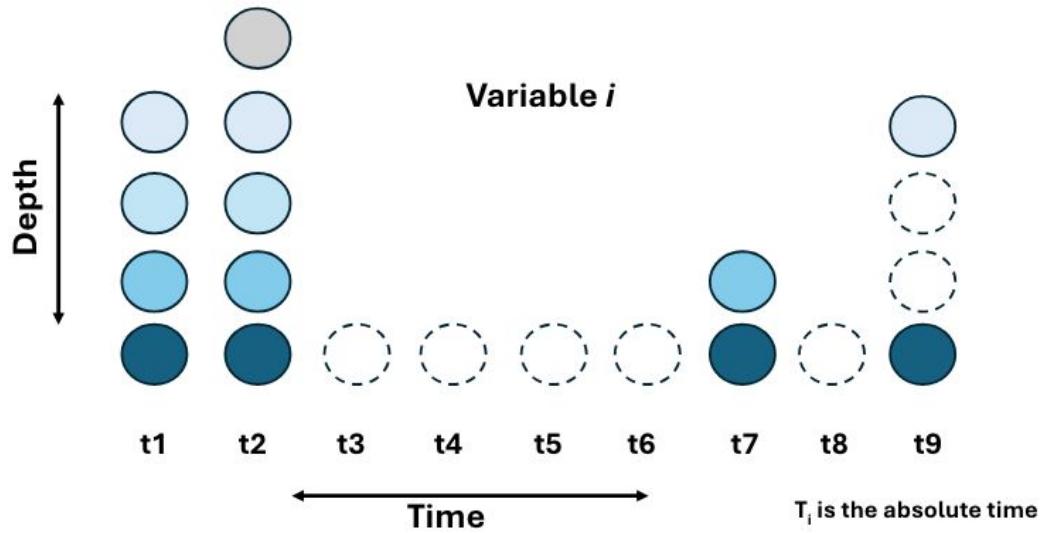
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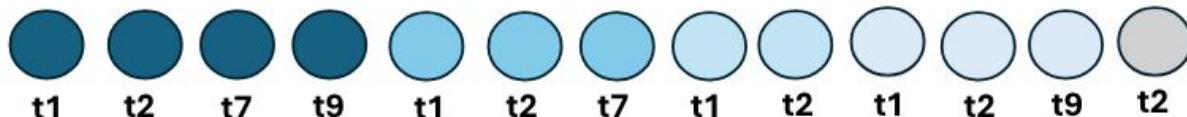
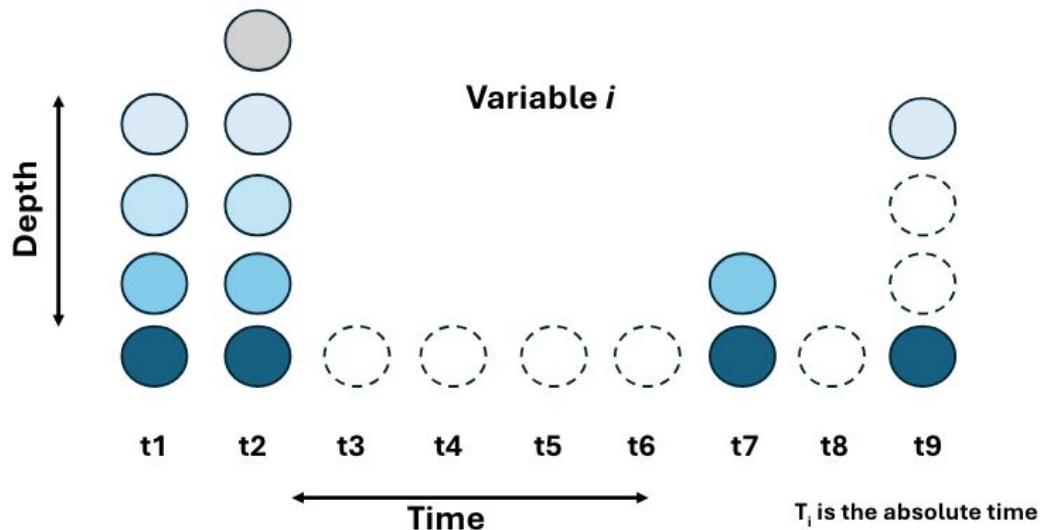
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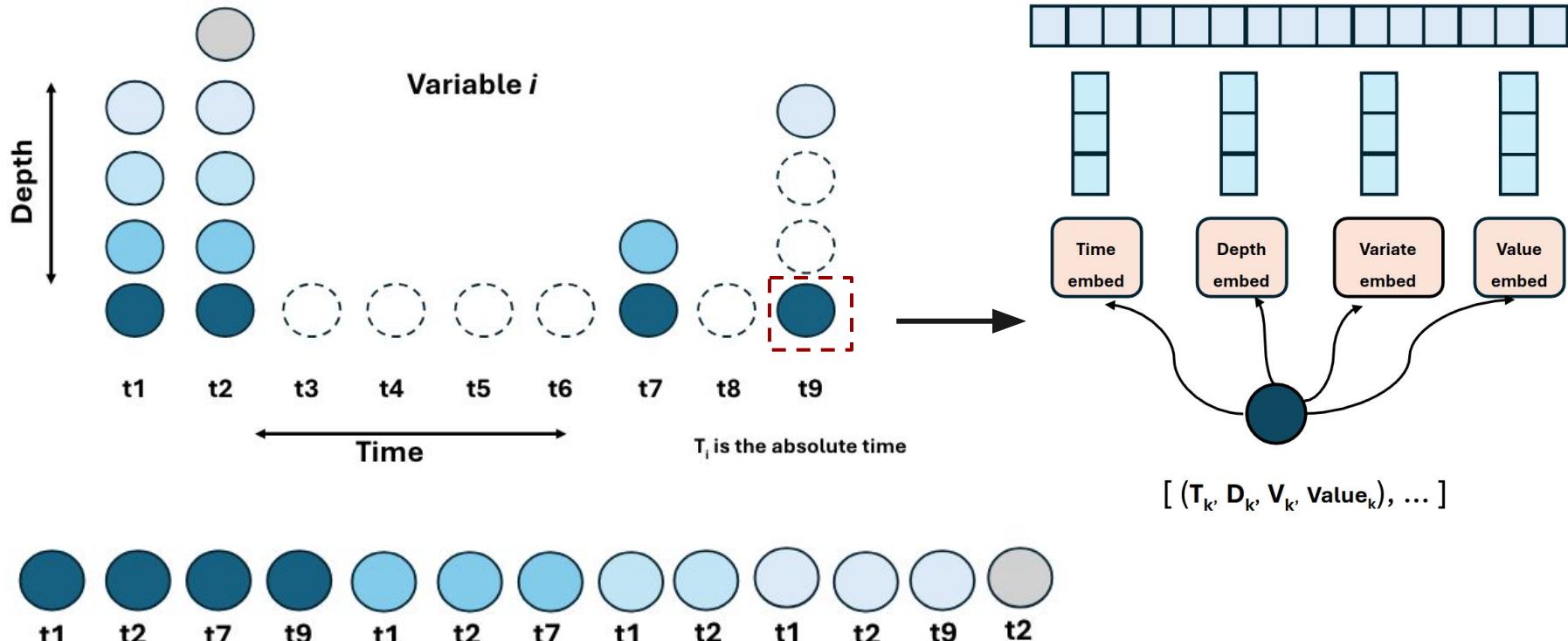
Lake Foundation Model (LakeFM) - Tokenization & Embedding



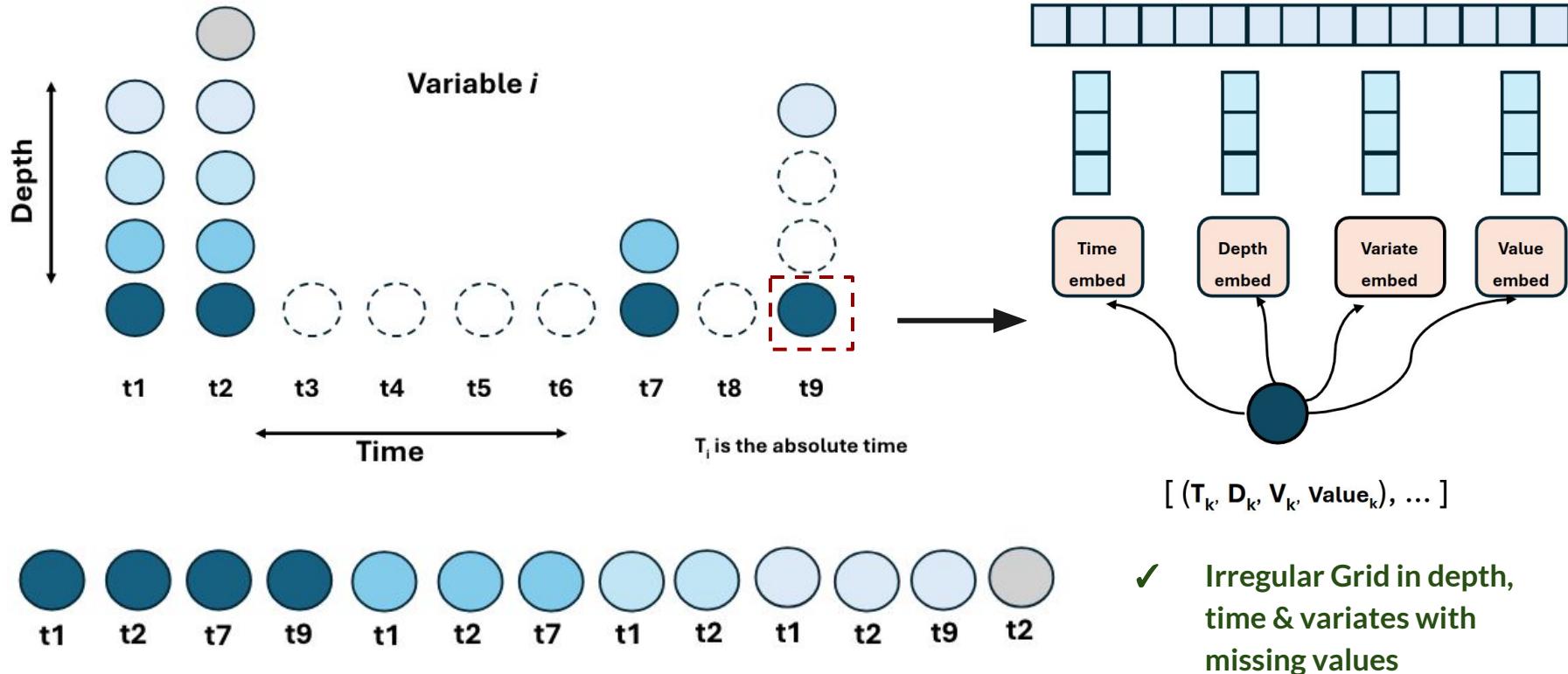
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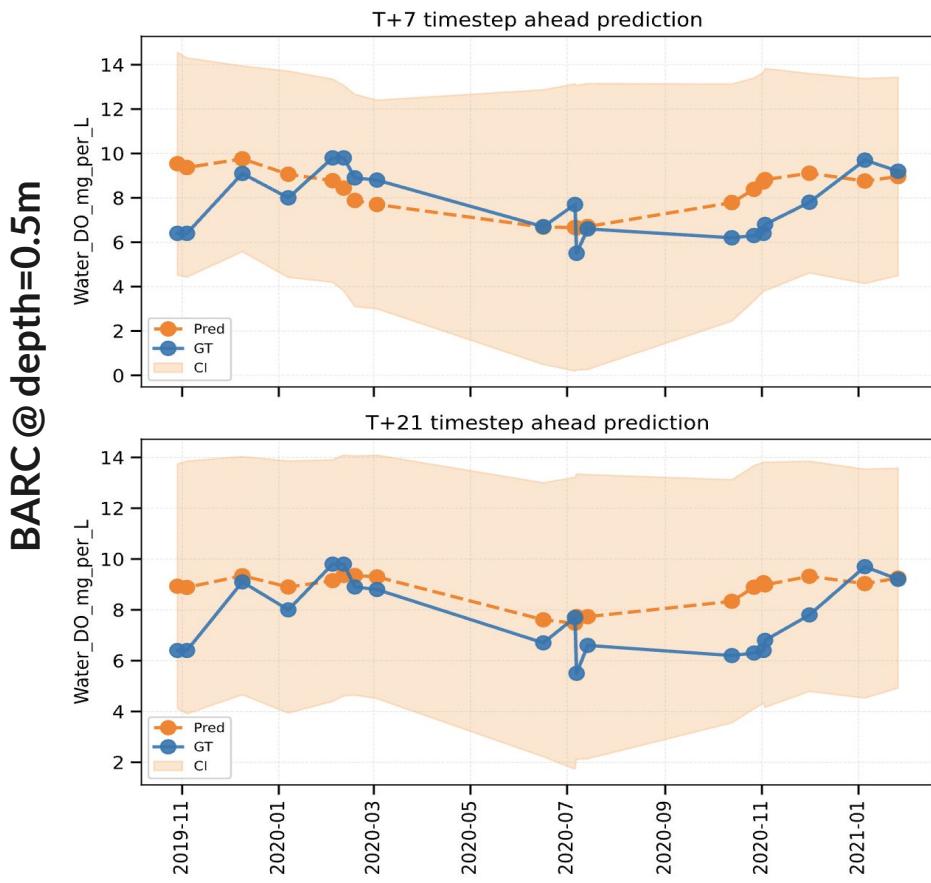
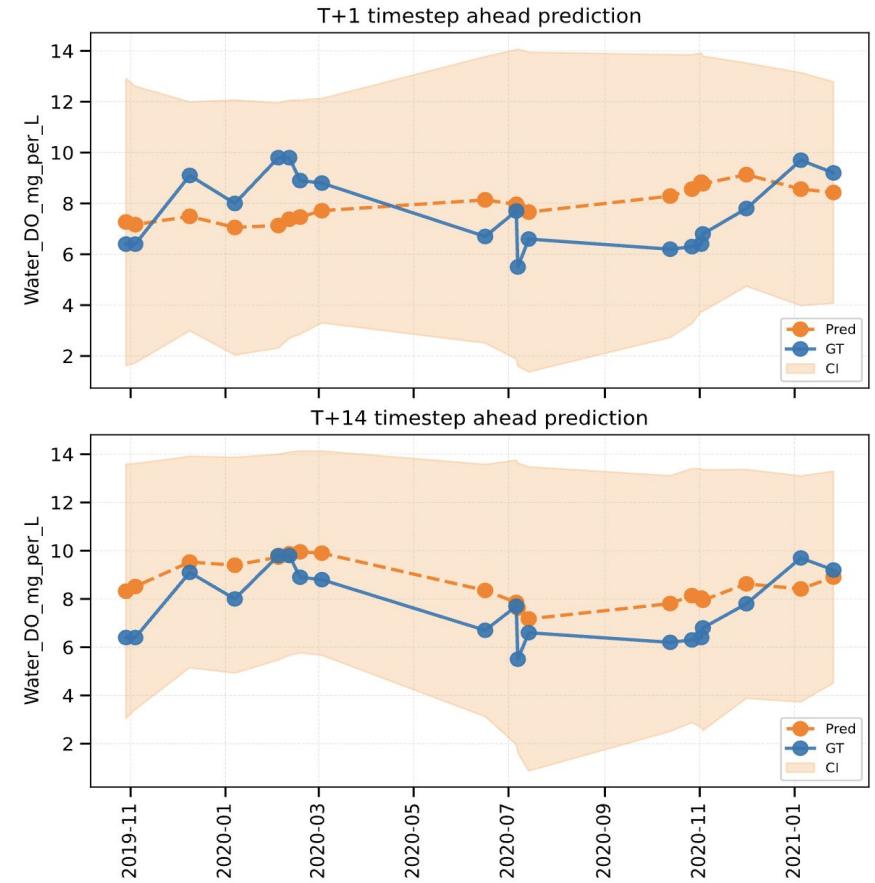


Lake Foundation Model (LakeFM) - Tokenization & Embedding

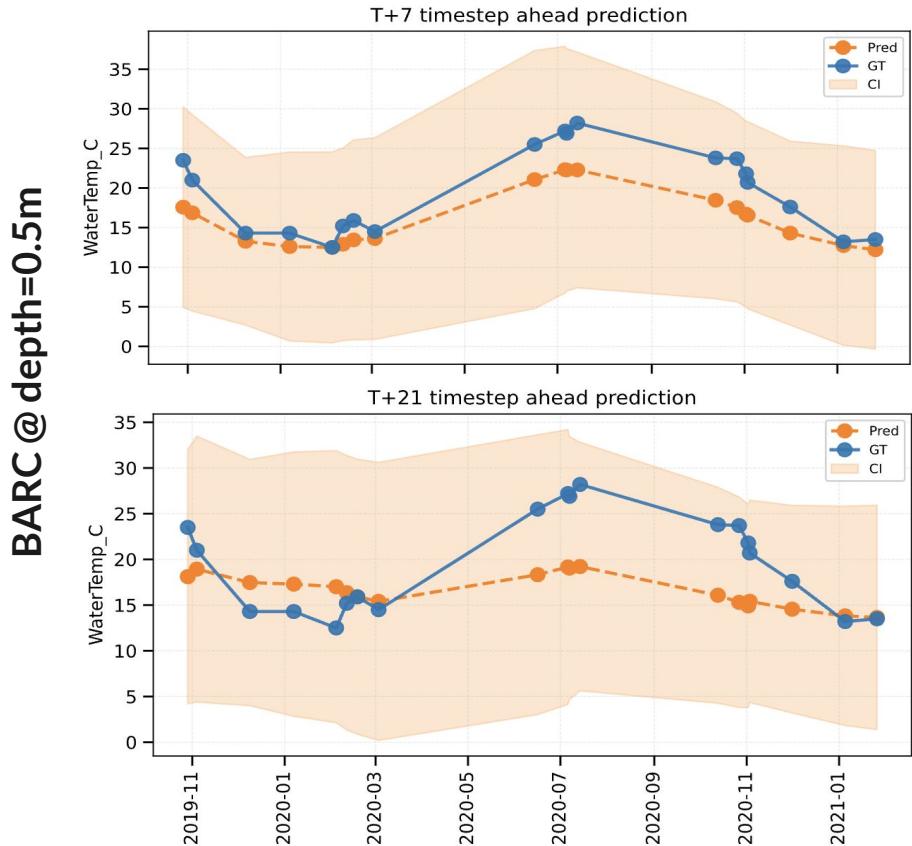
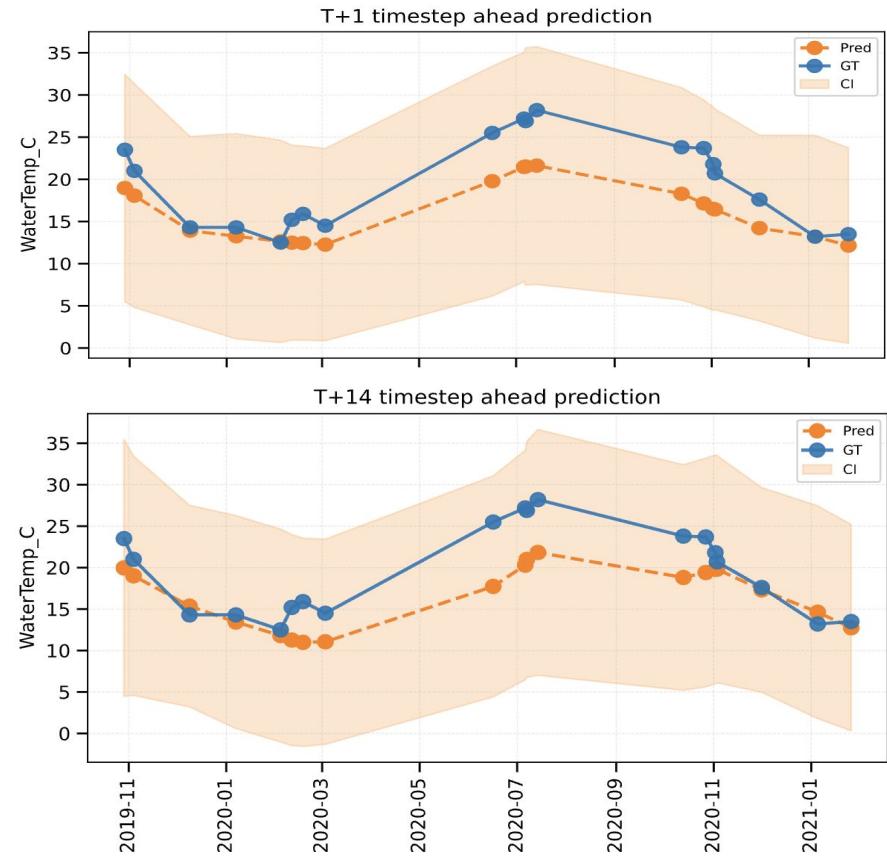


✓ Irregular Grid in depth, time & variates with missing values

Lake Foundation Model (LakeFM) - Findings (I) - Increasing Horizon Length

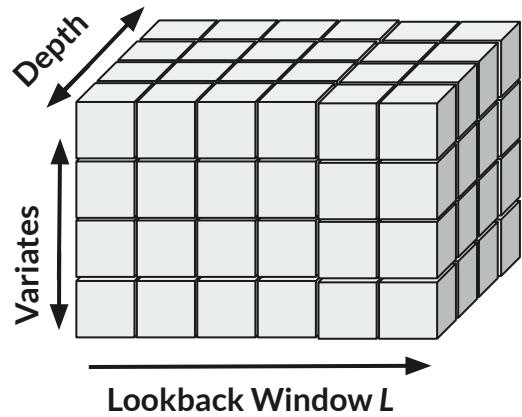


Lake Foundation Model (LakeFM) - Findings (I) - Increasing Horizon Length

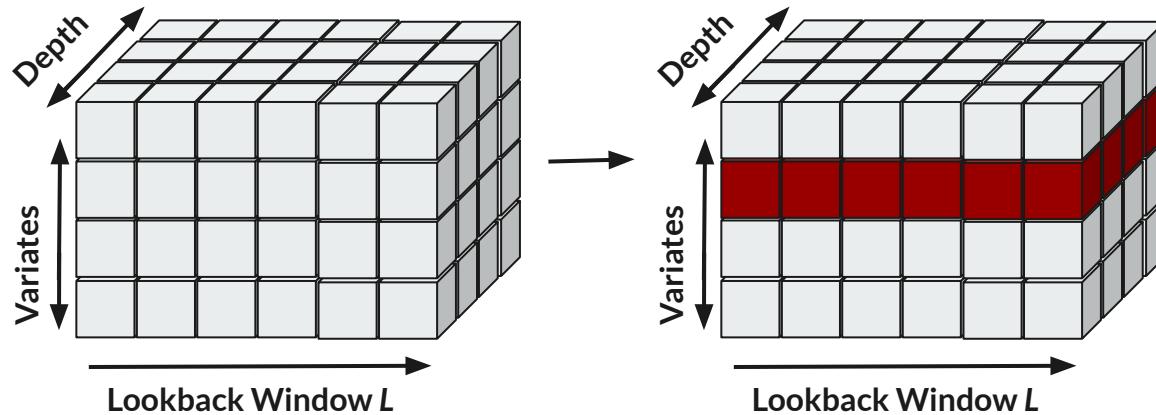


Key Observation : Overall, LakeFM maintains stable performance across increasing horizon lengths

Lake Foundation Model (LakeFM) - Findings (II) - Incomplete Data (Variables)

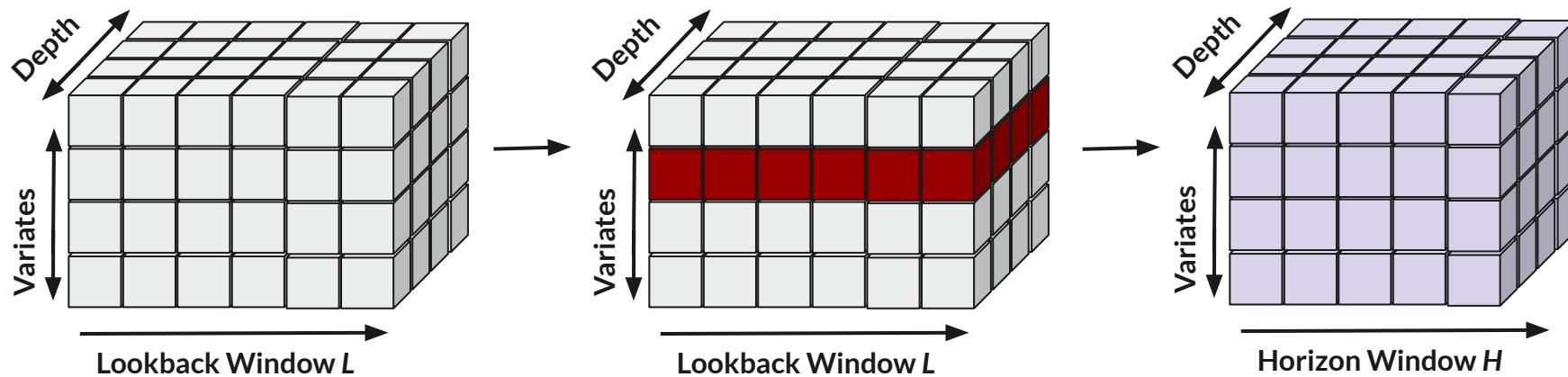


Lake Foundation Model (LakeFM) - Findings (II) - Incomplete Data (Variables)



$\left\{ \text{Air Temp, Shortwave, ..., Water Temp, DO ...} \right\}$

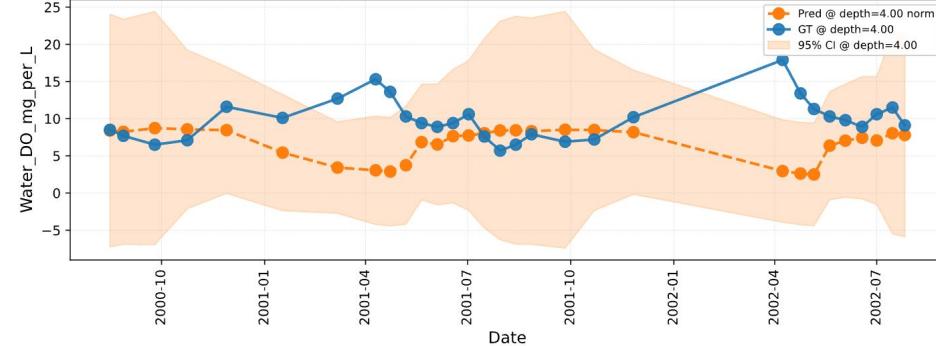
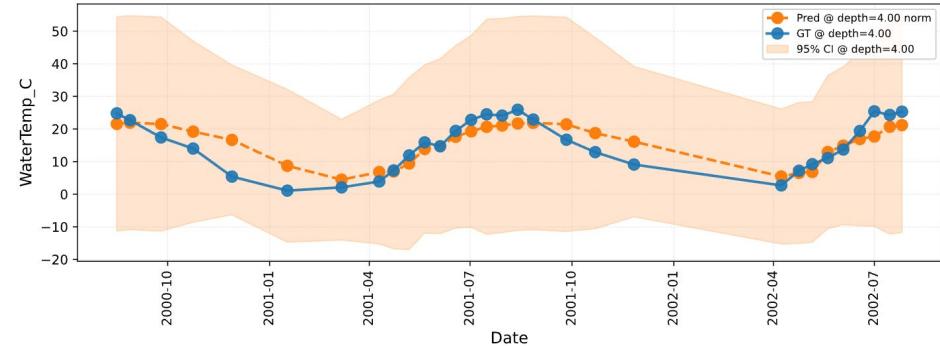
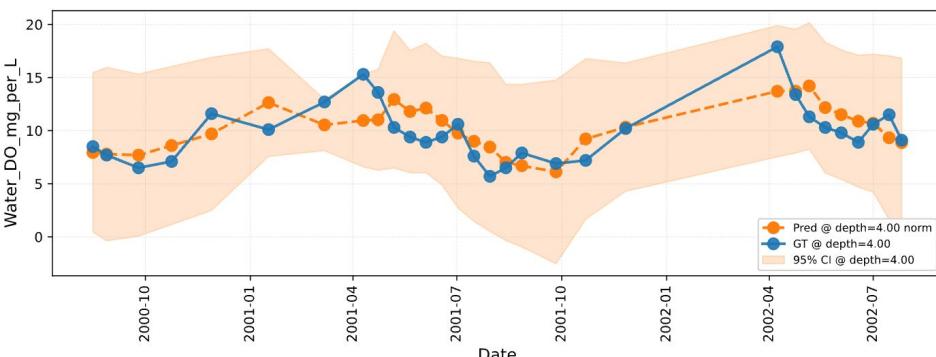
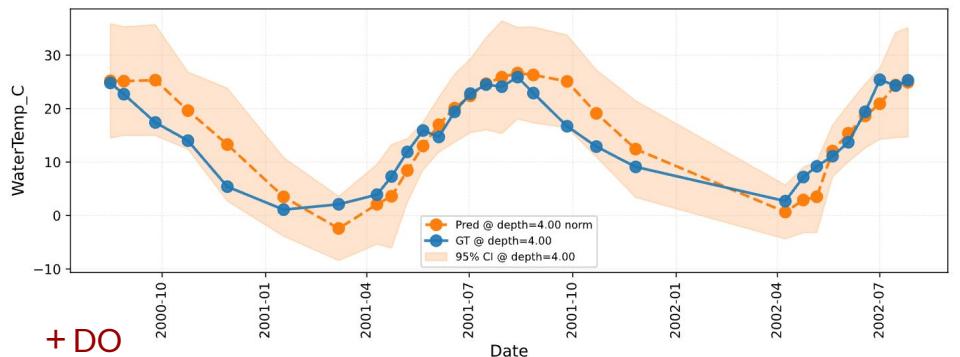
Lake Foundation Model (LakeFM) - Findings (II) - Incomplete Data (Variables)



$\left\{ \text{Air Temp, Shortwave, ..., Water Temp, DO ...} \right\} \rightarrow \left\{ \text{Air Temp, Shortwave, ..., Water Temp, DO ...} \right\}$

Lake Foundation Model (LakeFM) - Findings (II) - Incomplete Data (Variables)

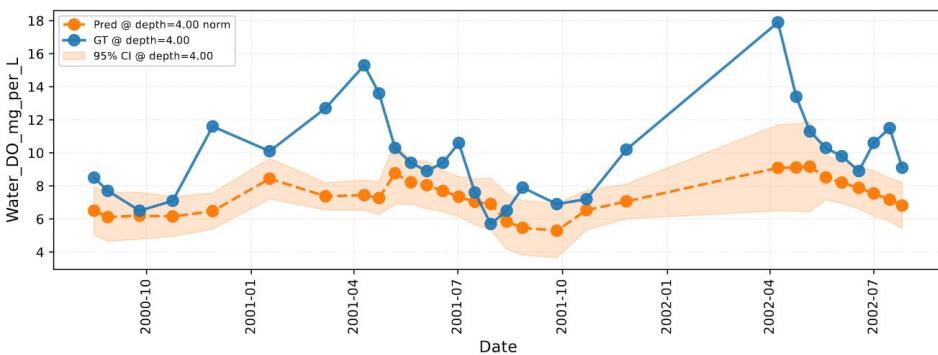
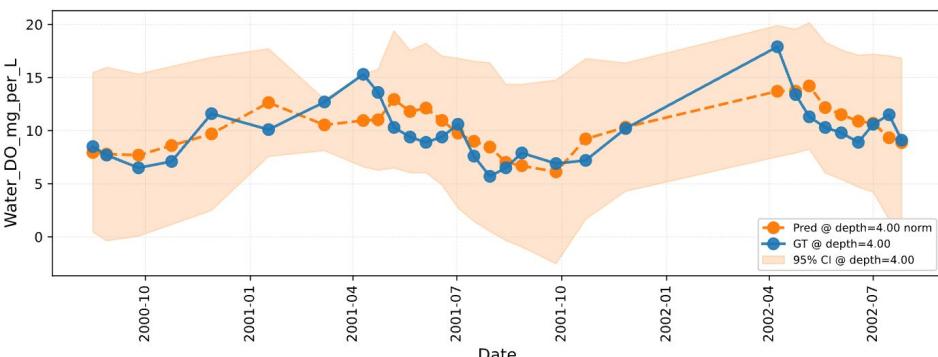
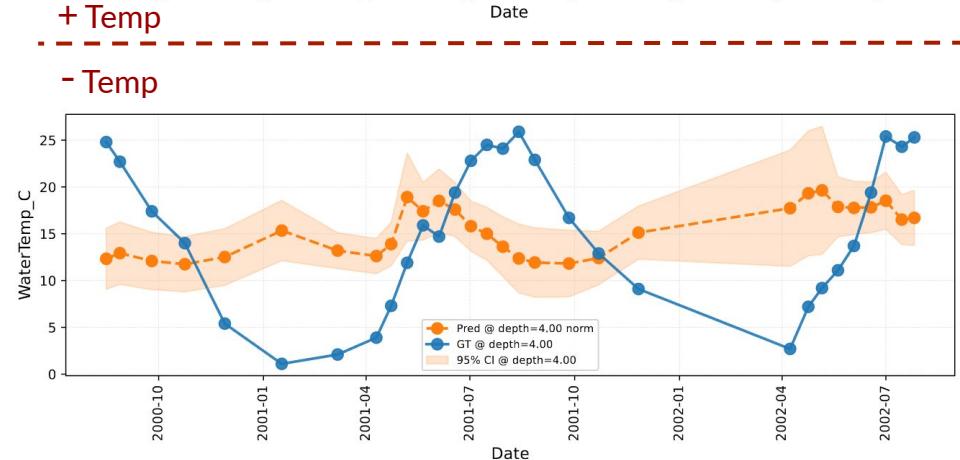
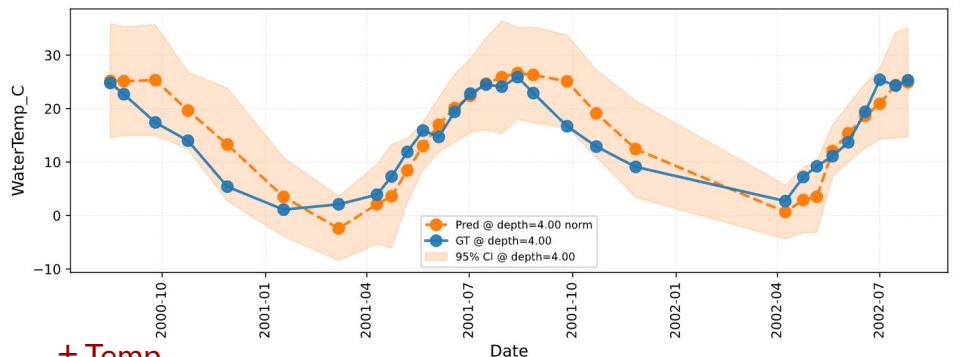
ME : 30 timesteps ahead forecast, at Depth 4.00m (shaded = 95% CI)



Key Observation : Removing DO from inputs increases uncertainty in predictions of water temperature

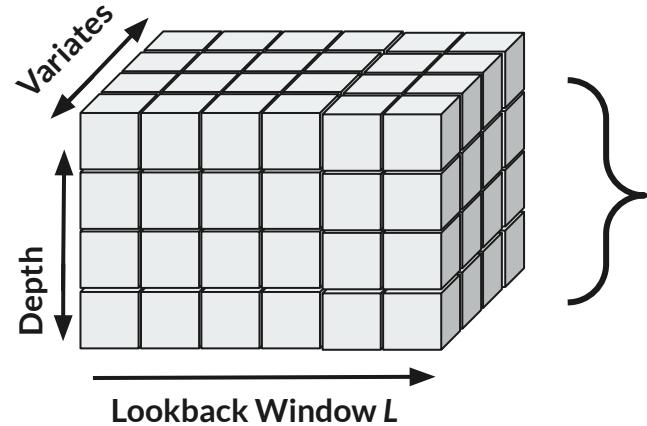
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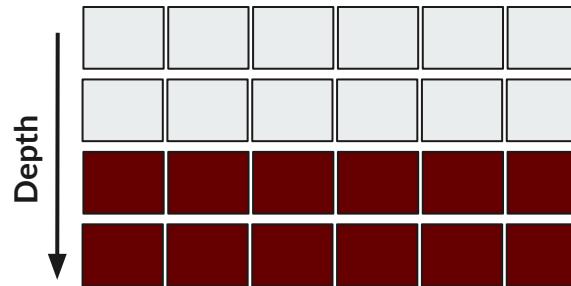


Key Observation : Water temperature is a critical variable. Removing it degrades all predictions.

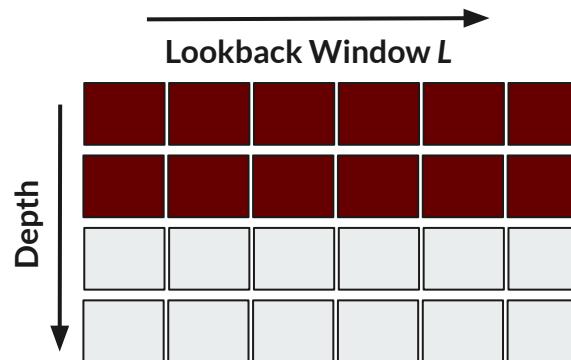
Lake Foundation Model (LakeFM) - Findings (III) - Incomplete Data (Depth)



(1)



(2)

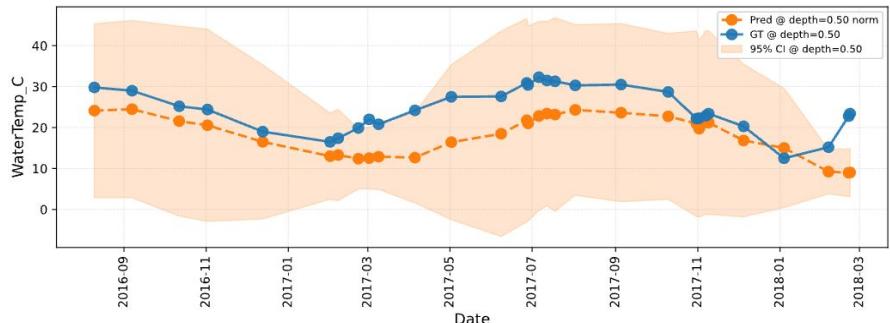


No data in the
deeper layers of
the lake

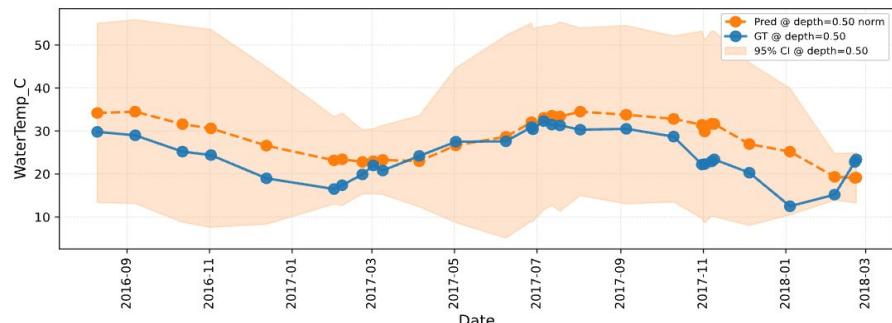
No data in the
shallow layers of
the lake

Lake Foundation Model (LakeFM) - Findings (III) - Incomplete Data (Depth)

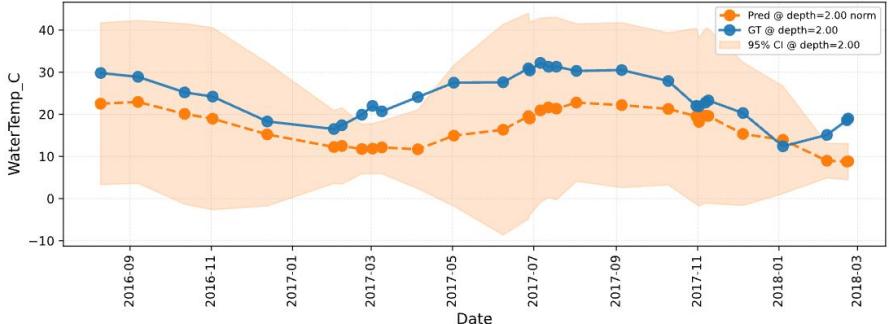
Water Temp Predictions @ 0.5 m using full-depth history



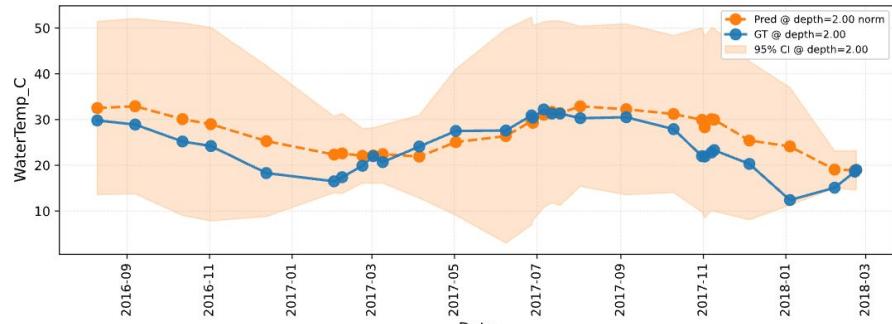
Water Temp Predictions @ 0.5 m using only deeper-depth history



Water Temp Predictions @ 2.0 m using full-depth history

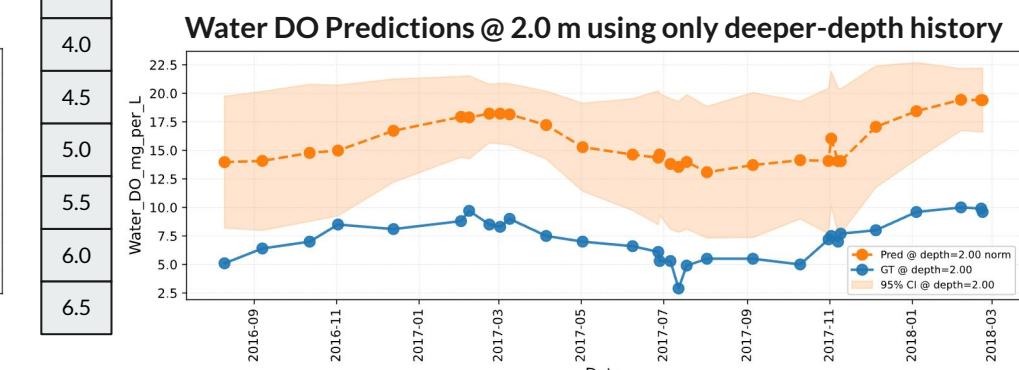
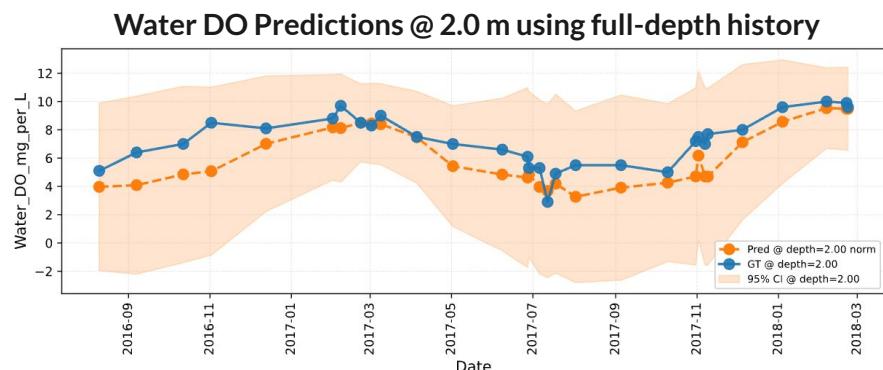
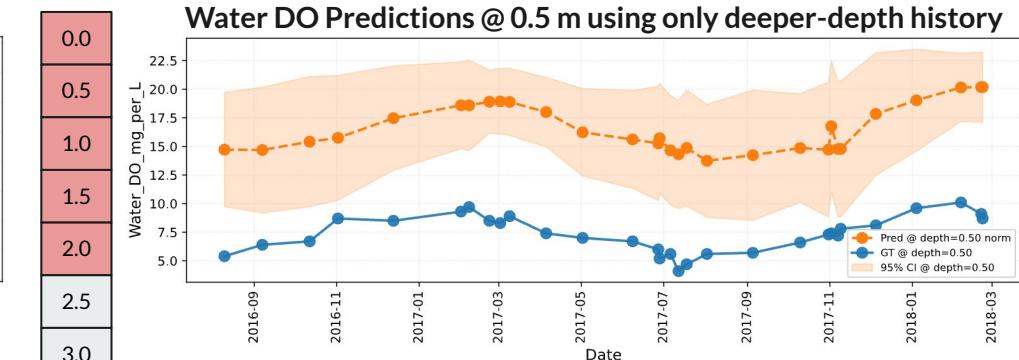
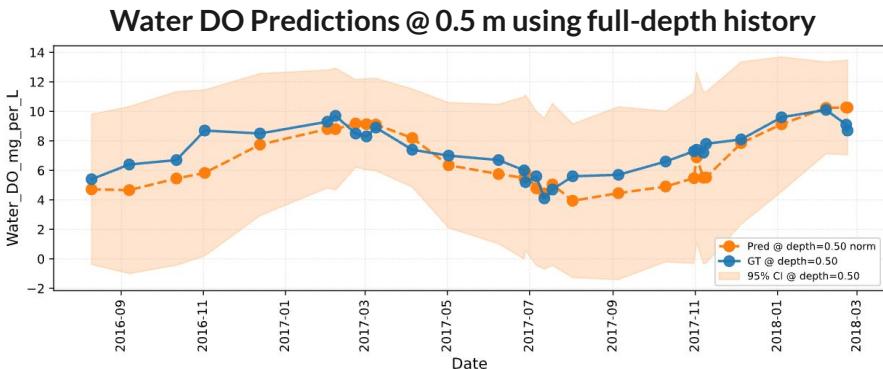


Water Temp Predictions @ 2.0 m using only deeper-depth history



Key Observation : Water temperature predictions remain stable even without shallow-layer variables

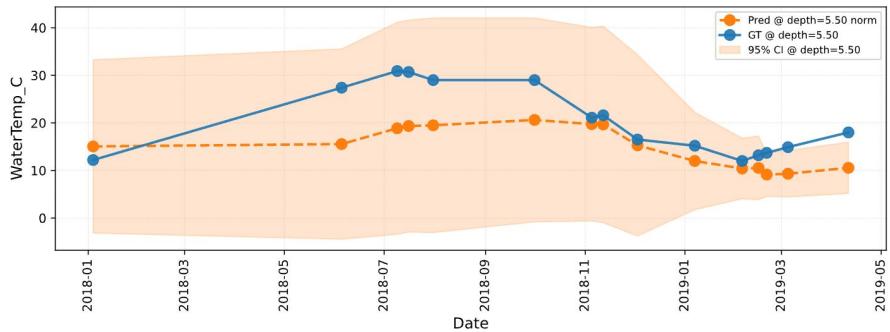
Lake Foundation Model (LakeFM) - Findings (III) - Incomplete Data (Depth)



Key Observation : In contrast, DO predictions cannot rely on deeper-layer variables, indicating stronger vertical variability along the water column

Lake Foundation Model (LakeFM) - Findings (III) - Incomplete Data (Depth)

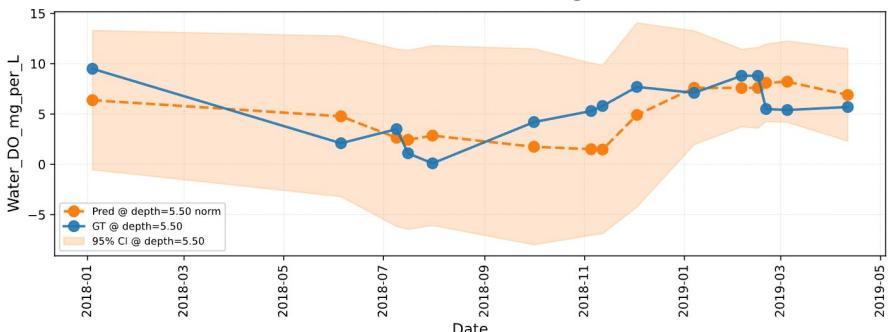
Water Temp Predictions @ 5.5 m using full-depth history



Water Temp Predictions @ 5.5 m using only shallow-depth history



Water DO Predictions @ 5.5 m using full-depth history



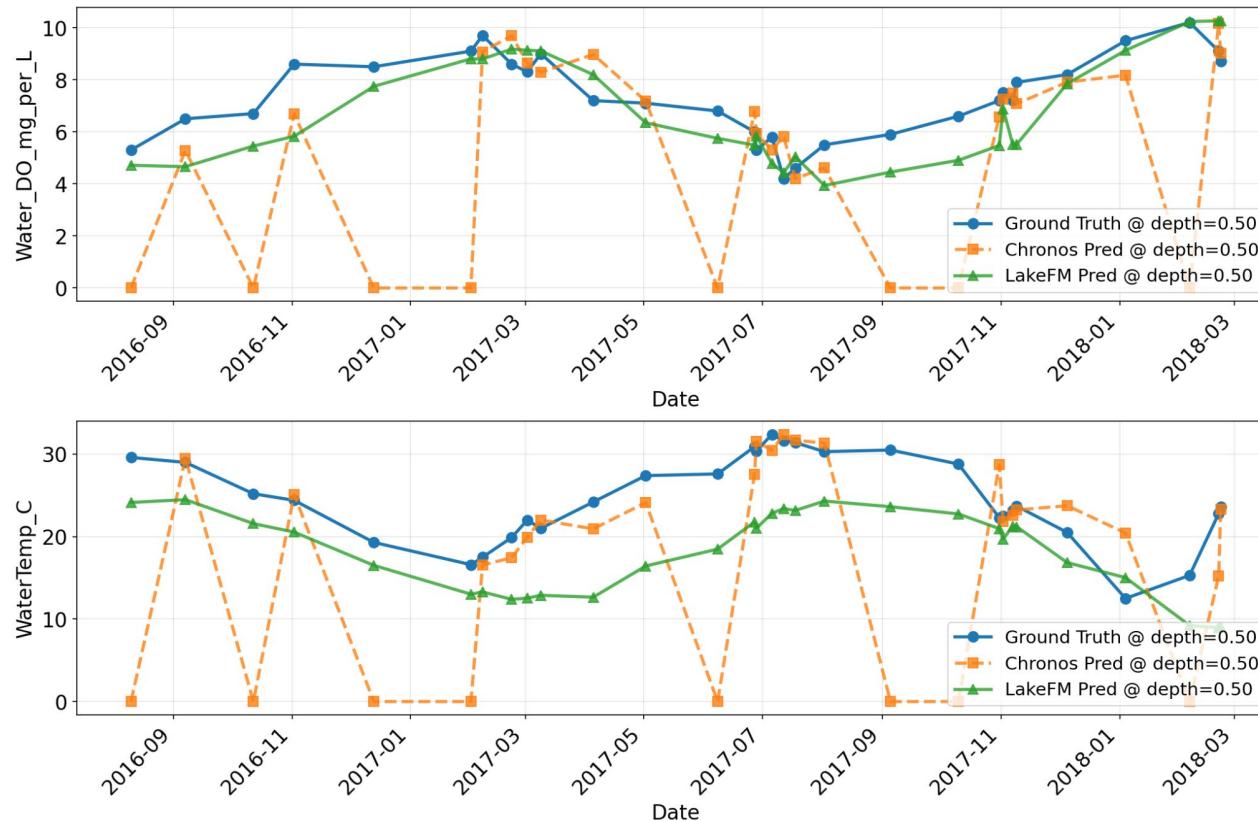
Water DO Predictions @ 5.5 m using only shallow-depth history



Key Observation : In general, water temperature remains stable and is predictable using either shallow or deeper layers, while DO dynamics are tightly coupled to the local depth.

Lake Foundation Model (LakeFM) - Findings (IV) - Performance Comparison

Comparing LakeFM predictions (on a horizon window of 30 timesteps) with Chronos Foundation Model on Lake BARC at Depth 0.5m



Key Observation :

Chronos struggles with missing data, leading to context-dependent instability, whereas LakeFM remains stable under the same conditions

Lake Foundation Model (LakeFM) - Ongoing Work

Lake representation analysis

- ❖ Visualization of learned lake embeddings
- ❖ Analyzing seasonal clustering patterns in lake representations
- ❖ Analyzing temporal trajectories of lake representations over time
- ❖ *Geographic structure emerging in embedding space*

Variable representation analysis

- ❖ Visualization of learned variable embeddings
- ❖ Analyzing variable similarities inferred from embedding clusters
- ❖ Empirical verification of embedding-based variable similarities

Thank you