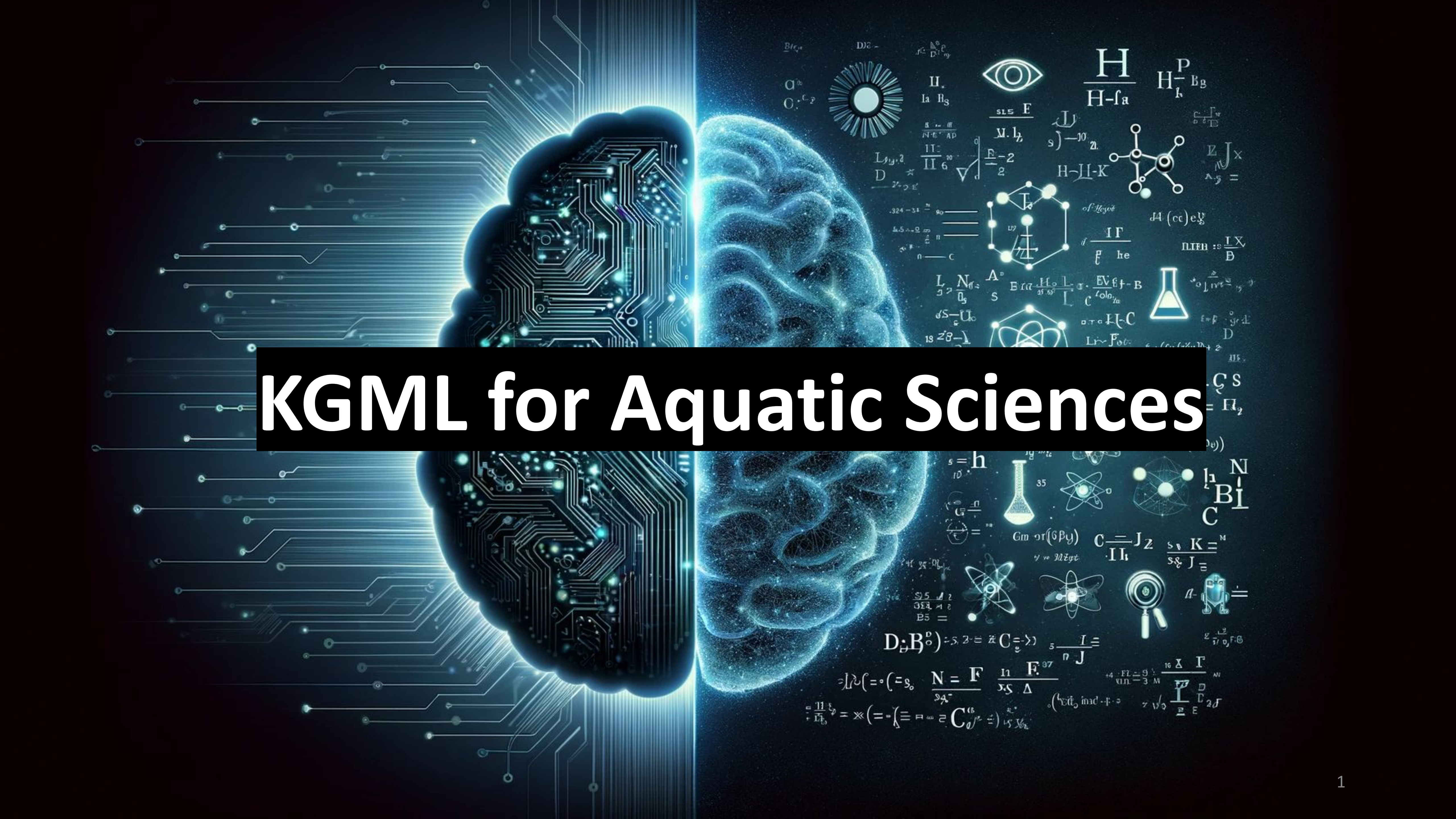


KGML for Aquatic Sciences

Organizing KGML Research: A Multi-Dimensional View

Format Used for Representing Knowledge

PDEs | Equations/Rules | Symmetries | Knowledge Graphs | Mechanistic Models

$$\frac{\partial u(x,t)}{\partial t} + \mathcal{N}\left(\lambda, u(x,t)\right) = 0$$

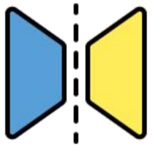
Navier Stokes Equation,
Wave Equation,
Schrodinger Equation, …

PINNs: Raissi et al. 2019

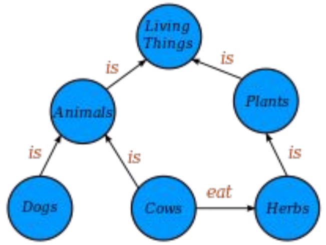
$$\frac{\partial u}{\partial x} \propto \frac{\partial^2 u}{\partial x^2}$$

$$a < \frac{\partial u}{\partial x} < b$$

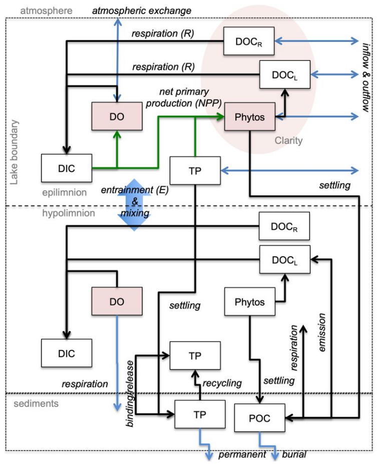
PGNN: Karpatne et al. 2017
PGRNN: Jia et al. 2019
PGA-LSTM: Daw et al. 2020



NequIP: Batzner et al. 2022
Cormorant: Anderson et al. 2019
Equivariant-Net: Wang et al. 2021



Zareian et al. 2020



MCL: Ladwig et al. 2024
dPL: Shen et al. 2023

Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Organizing KGML Research: A Multi-Dimensional View

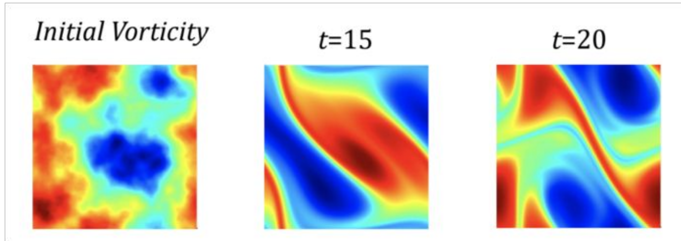
Format Used for Representing Knowledge

PDEs — Equations/Rules — Symmetries — Knowledge Graphs — Mechanistic Models

Type of Scientific Knowledge

Perfect and Complete — Imperfect and Partial

Example: Solving *known* PDEs



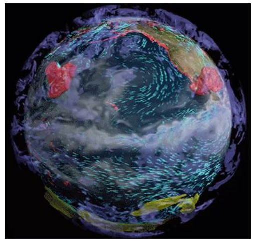
Navier Stokes Eq., Heat Eq., Wave Eq., Schrodinger Eq., …

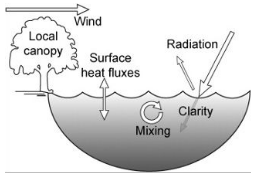
Primary Objective: Improve Computational Efficiency

PINNs: Raissi et al. 2019, **DeepONets**: Lu et al. 2021, **FNOs**: Li et al. 2021

Example: Modeling complex dynamical systems with missing/imperfect physics

Modeling Turbulence,
Multi-phase Flow,
Cloud Physics, Aerosols, …



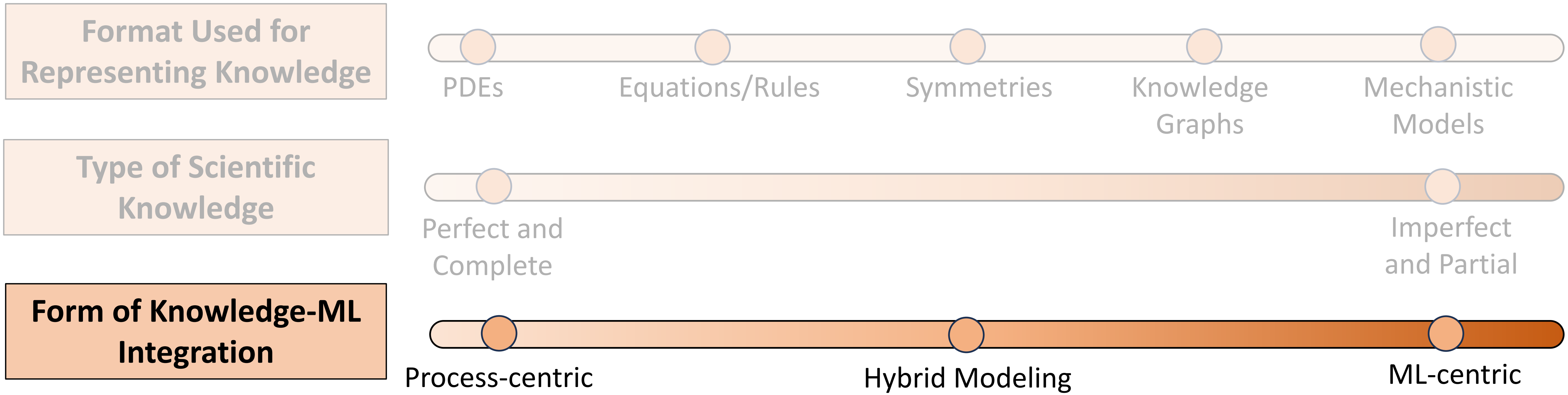


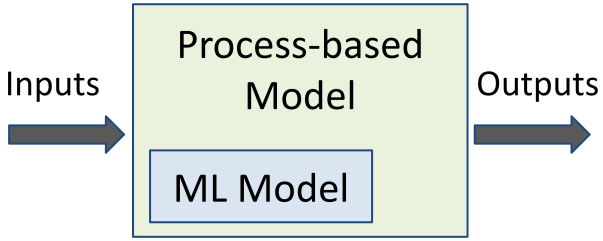
Additional Objective: Improve Modeling Accuracy

PGNN: Karpatne et al. 2017, **PGRNN:** Jia et al. 2019, **PGA-LSTM:** Daw et al. 2020

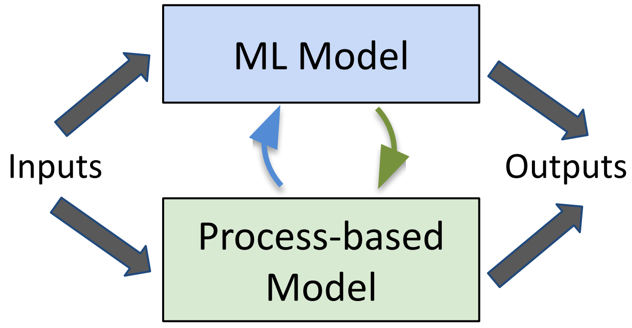
Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Organizing KGML Research: A Multi-Dimensional View

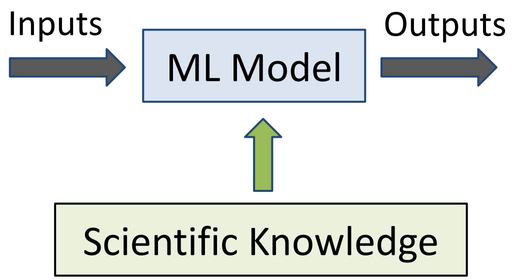




dPL: Shen et al. 2022
Subgrid Parametrization
Turbulence Closure Modeling



PGNN: Karpatne et al. 2017
MCL: Ladwig et al. 2024



PGNN: Karpatne et al. 2017
PINN: Raissi et al. 2019
Equivariant-Net: Wang et al. 2021

Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Organizing KGML Research: A Multi-Dimensional View

Format Used for Representing Knowledge

PDEs — Equations/Rules — Symmetries — Knowledge Graphs — Mechanistic Models

Type of Scientific Knowledge

Perfect and Complete — Imperfect and Partial

Form of Knowledge-ML Integration

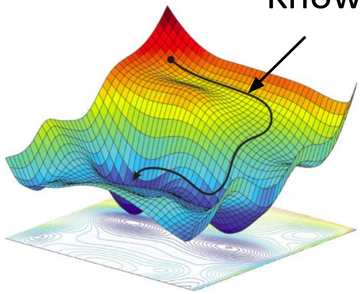
Process-centric — Hybrid Modeling — ML-centric

Method for Incorporating Scientific Knowledge in ML

Learning — Architecture — Pretraining

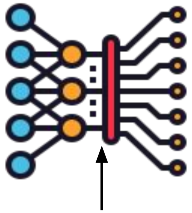
Learning

PGNN: Karpatne et al. 2017
PINN: Raissi et al. 2019



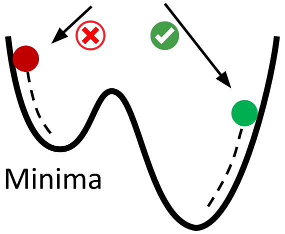
Architecture

PGA-LSTM: Daw et al. 2020
Equivariant-Net: Wang et al. 2021



Pretraining

PGRNN: Jia et al. 2019



Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Organizing KGML Research: A Multi-Dimensional View

Format Used for Representing Knowledge
- PDEs
- Equations/Rules
- Symmetries
- Knowledge Graphs
- Mechanistic Models

Type of Scientific Knowledge
- Perfect and Complete
- Imperfect and Partial

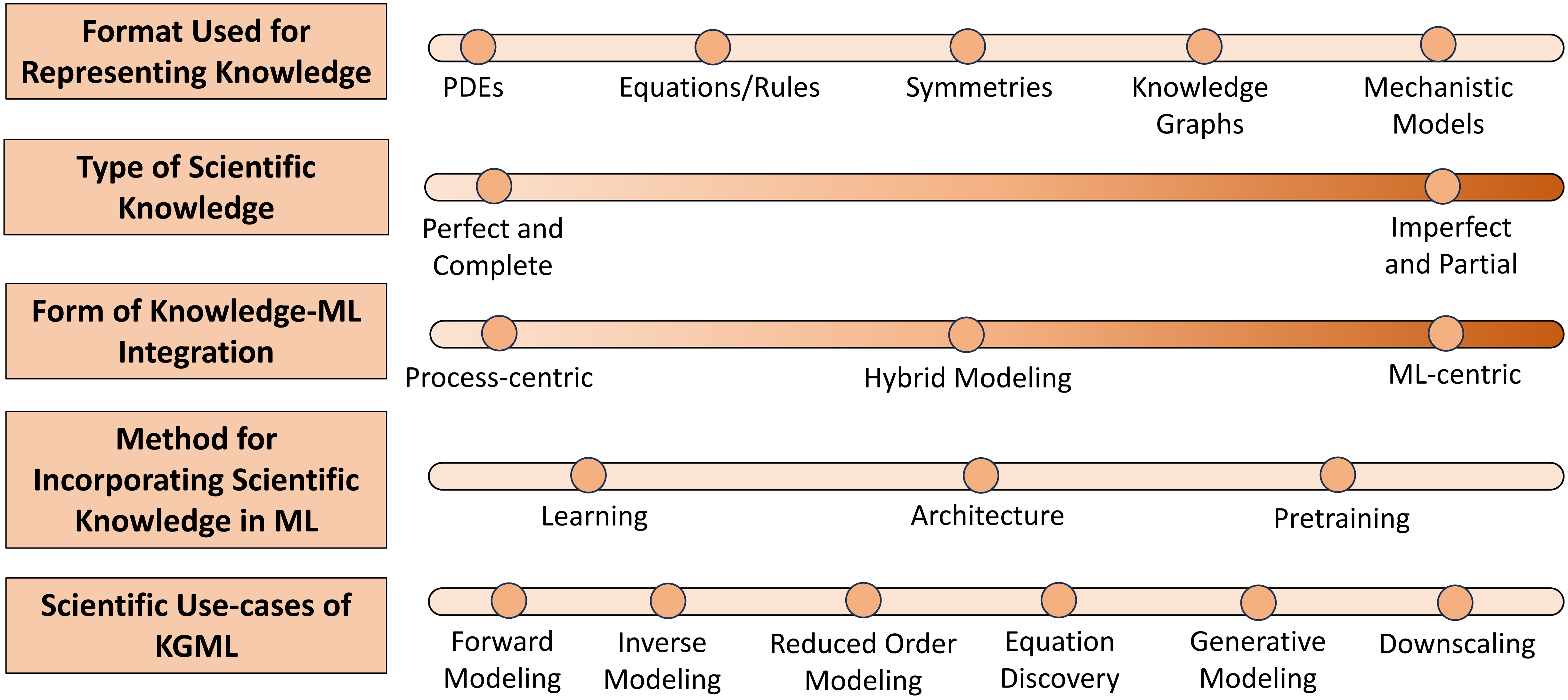
Form of Knowledge-ML Integration
- Process-centric
- Hybrid Modeling
- ML-centric

Method for Incorporating Scientific Knowledge in ML
- Learning
- Architecture
- Pretraining

Scientific Use-cases of KGML
- Forward Modeling
- Inverse Modeling
- Reduced Order Modeling
- Equation Discovery
- Generative Modeling
- Downscaling

Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Organizing KGML Research: A Multi-Dimensional View



Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

KGML Use Cases

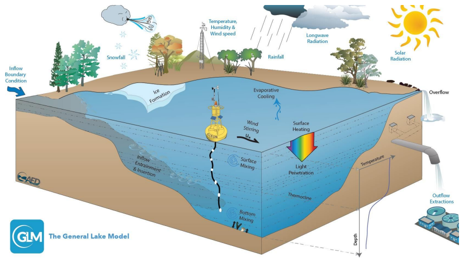
Lake Temperature Modeling

Physics-guided NNs **(PGNNs):** Daw et al. 2017

Physics-guided RNNs **(PGRNNs):** Jia et al. 2019

Goal: Predicting the temperature of the lake.

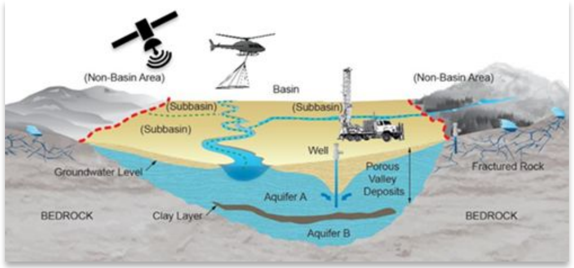
- Use *imperfect* and *partial* knowledge as loss functions
- Use *simulation data* for pre-training and *observational data* for finetuning



River-basin Characterization

Goal: Predict basin characteristics of rivers.

- Extract system characteristics from driver and response data.



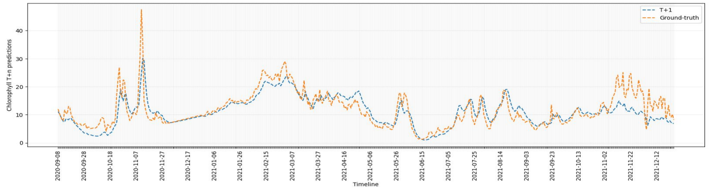
Knowledge-guided Self-supervised **(KGSSL):** Ghosh et al. 2022

Uncertainty Quantification **(UQ-KGSSL):** Sharma et al. 2022

Chlorophyll-a Prediction

Goal: Predicting the chlorophyll-a content of water bodies.

- Sparse observed data for chlorophyll
- Interested in predicting the blooms.

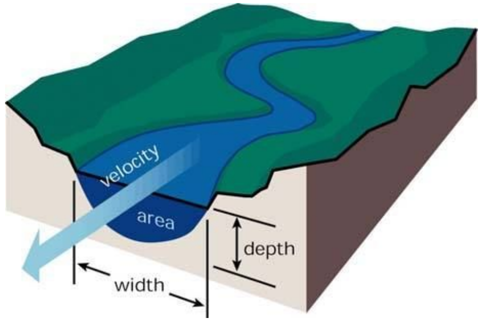


LSTM based Chl-a Prediction: Cen et al. 2022

Streamflow Forecasting

Goal: Predict the stream flow of rivers.

- Use river-network data (graph) and the knowledge of thermodynamics to improve predictions.

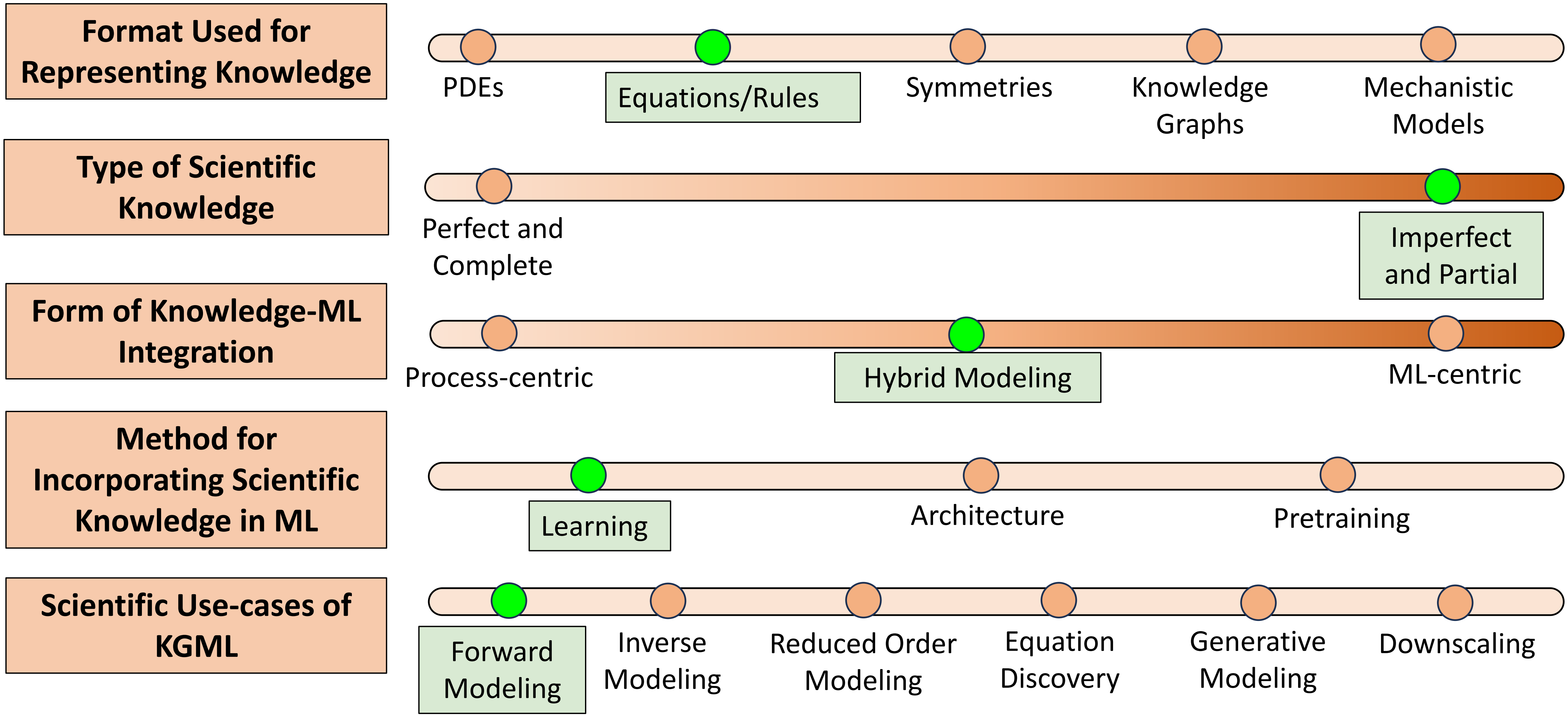


Physics-guided Recurrent Graph Model **(PGRGnN):** Jia et al. 2020

KGML for Multi-scale Process and Data Assimilation**:** Kumar et al. 2023

Use Case 1:
Lake Temperature Modeling

Organizing KGML Research: A Multi-Dimensional View

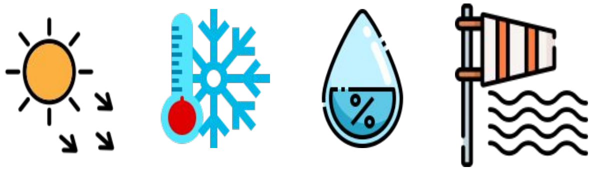


Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

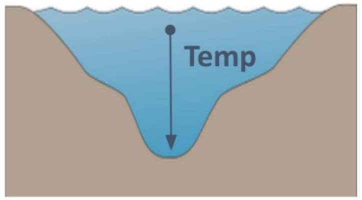
Lake Temperature Modeling

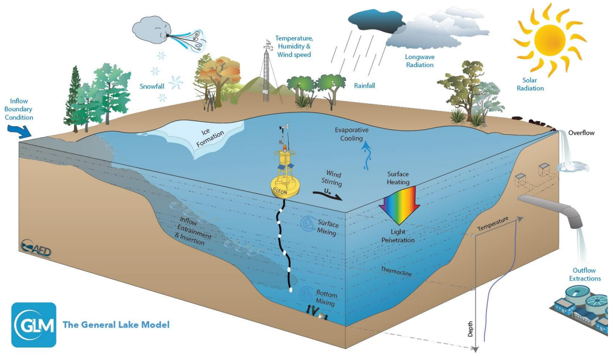
1D Model of Temperature

Meteorological Input Drivers
E.g., longwave/shortwave radiation, air temperature, humidity, wind speed, etc.



Target
Temperature of water at every depth of the lake





Motivation

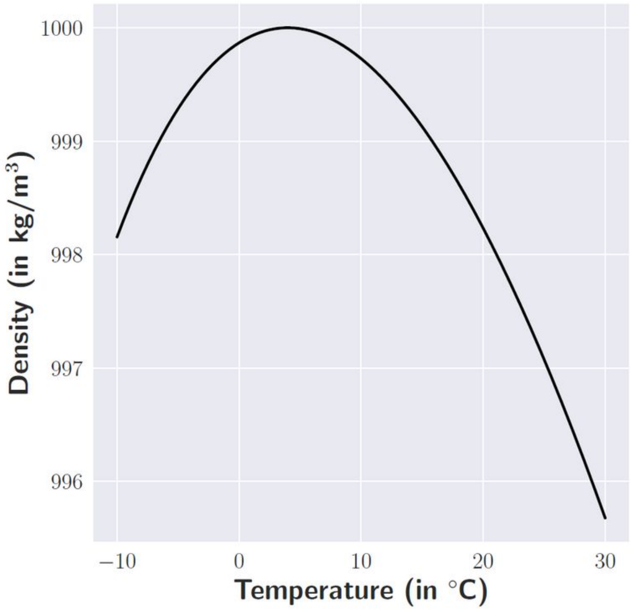
Growth and survival of fisheries

Harmful Algal Blooms

Chemical Constituents: O_2, C, N

Physical Relationships of Temperature

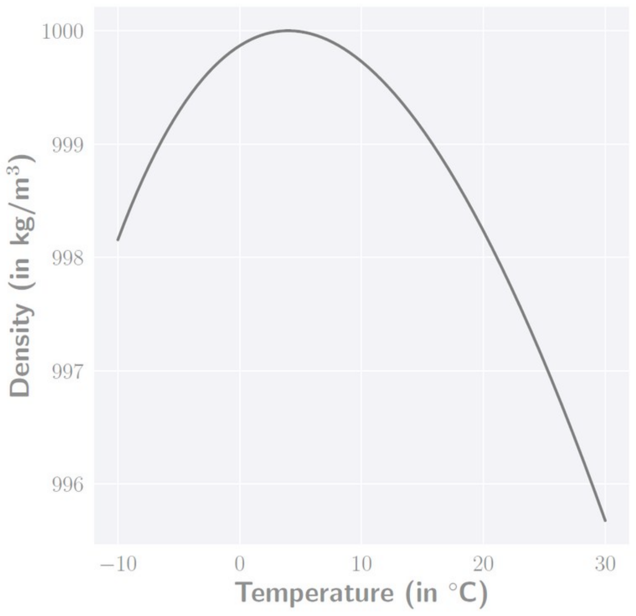
Physical Relationship 1:



Temperature directly related to density of water

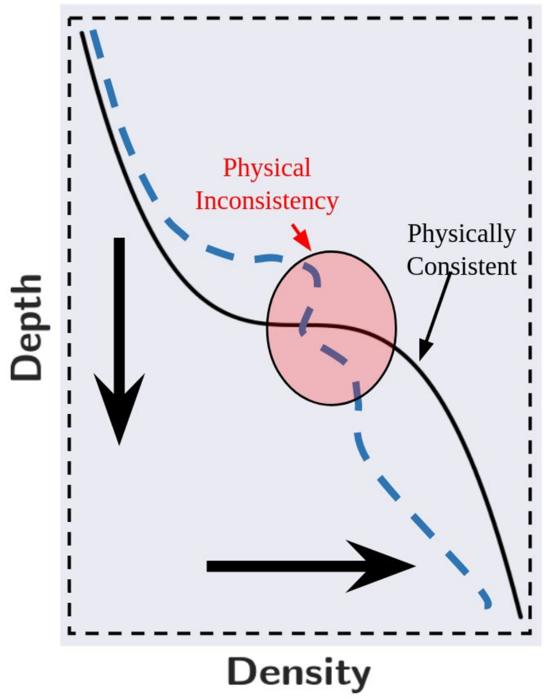
Physical Relationships of Temperature

Physical Relationship 1:



Temperature directly related to density of water

Physical Relationship 2:



Density of water monotonically increases with depth

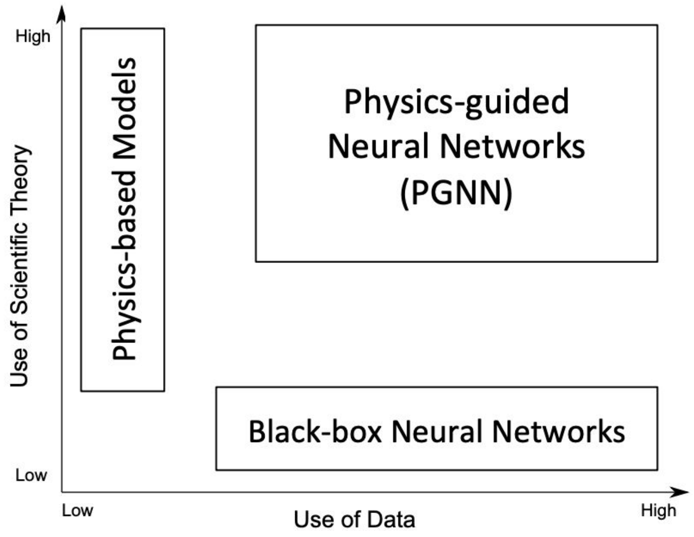
Physics-guided Neural Networks (PGNN)

The physics supervision is enforced as a soft constraint where the model is penalized when the predictions of the model violate the physics constraint.

$$\min_{\theta} \; \underbrace{\boxed{L(y, \hat{y})}}_{\text{Empirical Error}} + \underbrace{\boxed{\lambda_{PHY} \, L_{PHY}(\hat{y})}}_{\text{Physics-Loss}}$$

PROS

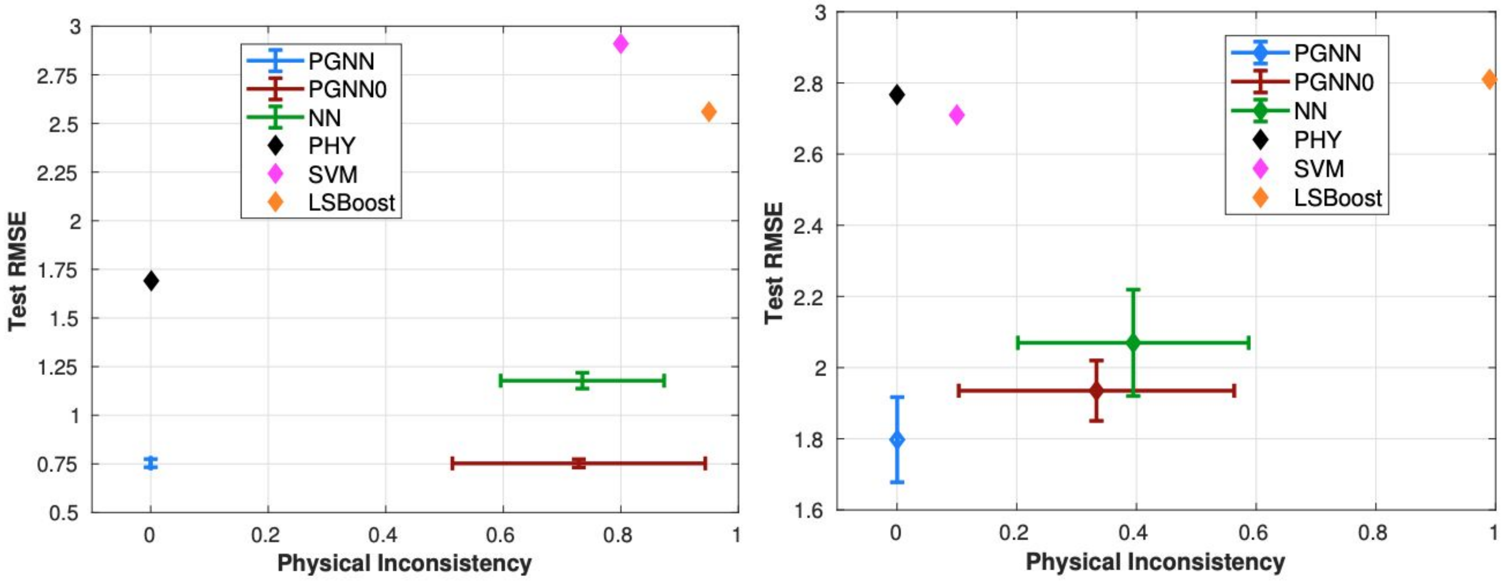
- **Easy to use:** Constraints can be easily incorporated as physics loss functions.
- **Unsupervised:** Physics loss functions can be evaluated on unlabeled data.



Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

PGNN shows improved generalization

Results on two different lakes: Lake Mille Lacs and Lake Mendota



(a) Results on Mille Lacs Lake (b) Results on Lake Mendota

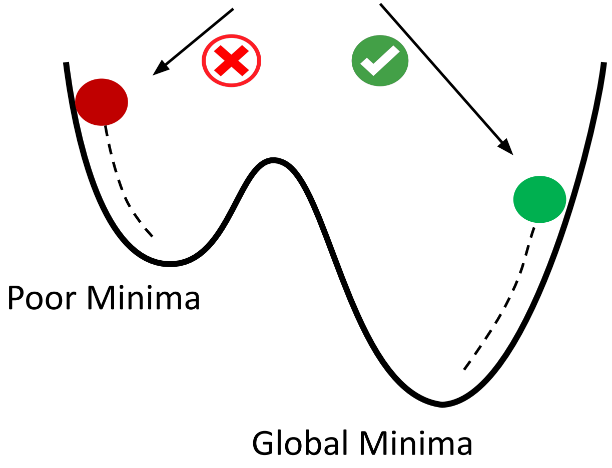
PGNN consistently outperforms the other baselines for both lakes showing better Test RMSE and Physics Consistency.

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

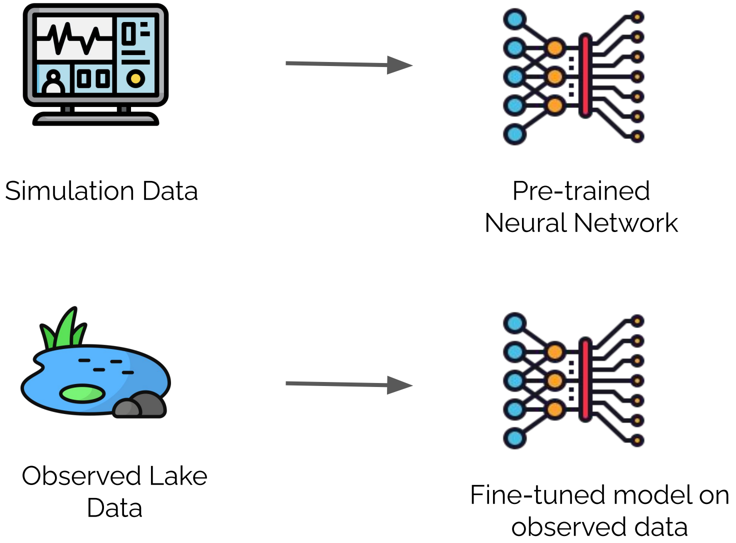
Pretraining on Simulation Lakes

Simulation Data from the different lakes can be used to pretrain the RNN model. This will serve as a “better” initialization.

Knowledge Guided Pretraining:
An Optimization Perspective



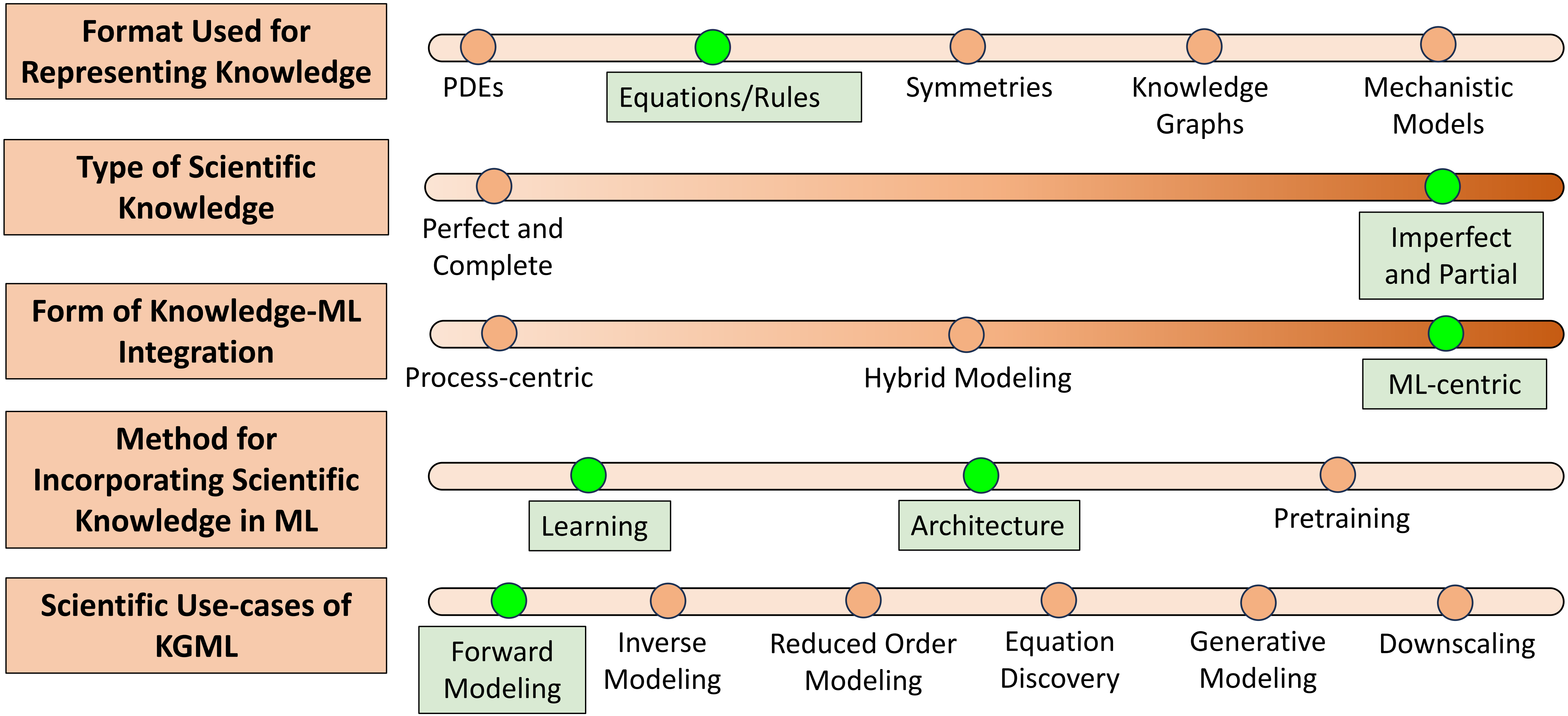
Pretraining on Simulations



Jia, Xiaowei, Jared Willard, Anuj Karpatne, Jordan Read, Jacob Zwart, Michael Steinbach, and Vipin Kumar. "Physics guided RNNs for modeling dynamical systems: A case study in simulating lake temperature profiles." In *Proceedings of the 2019 SIAM international conference on data mining*, pp. 558-566. Society for Industrial and Applied Mathematics, 2019.

Use Case 2: KGML with Uncertainty Quantification

Organizing KGML Research: A Multi-Dimensional View

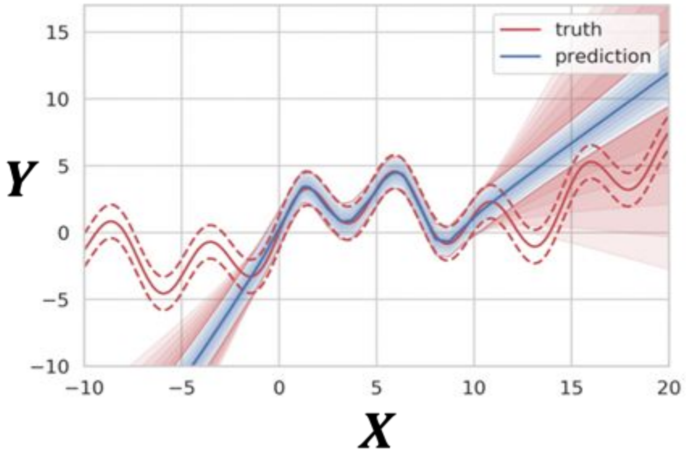


Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

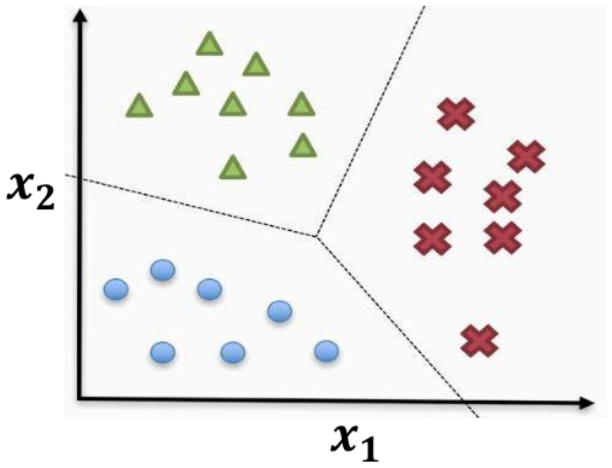
Uncertainty Quantification

Generate a distribution over the predictions rather than point estimates.

- Regression: Predict the variance along with the output mean.
- Classification: Predict the confidence along with the output labels.



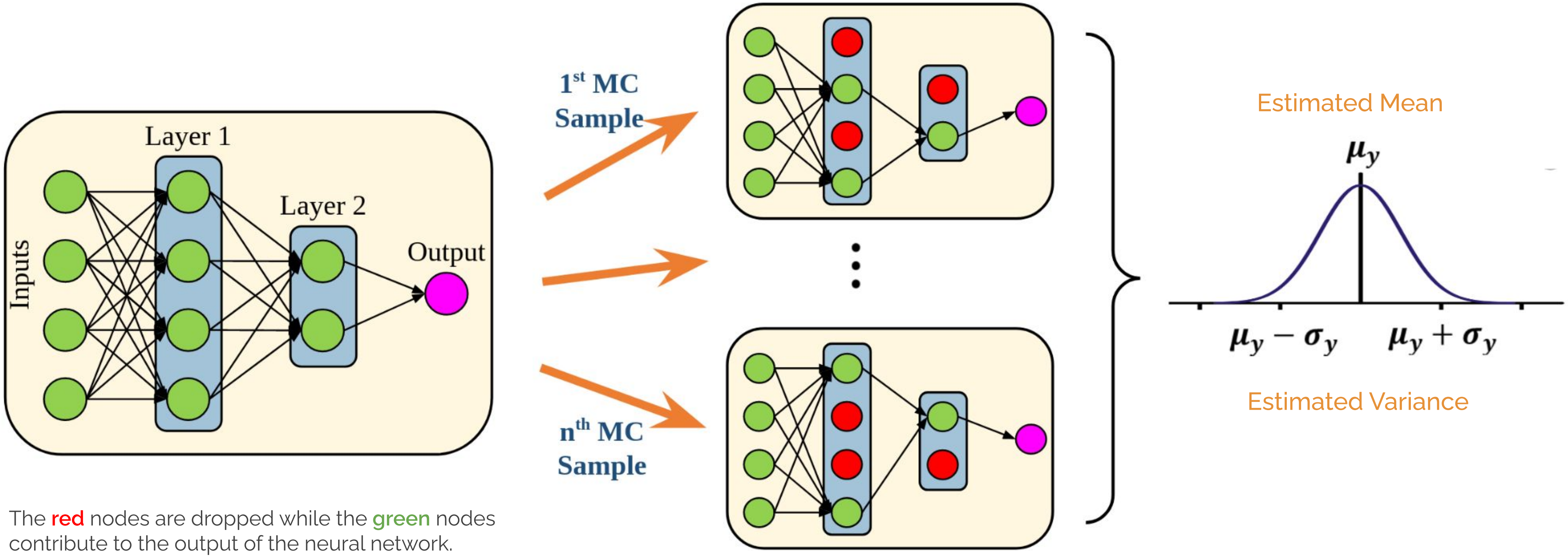
Aims to quantify the **robustness** of the ML models by assessing prediction reliability.



Daw, Arka, R. Quinn Thomas, Cayelan C. Carey, Jordan S. Read, Alison P. Appling, and Anuj Karpatne. "Physics-guided architecture (pga) of neural networks for quantifying uncertainty in lake temperature modeling." In *Proceedings of the 2020 siam international conference on data mining*, pp. 532-540. Society for Industrial and Applied Mathematics, 2020.

Uncertainty Quantification with MC Dropout

A schematic representation of using Dropouts to estimate uncertainty.

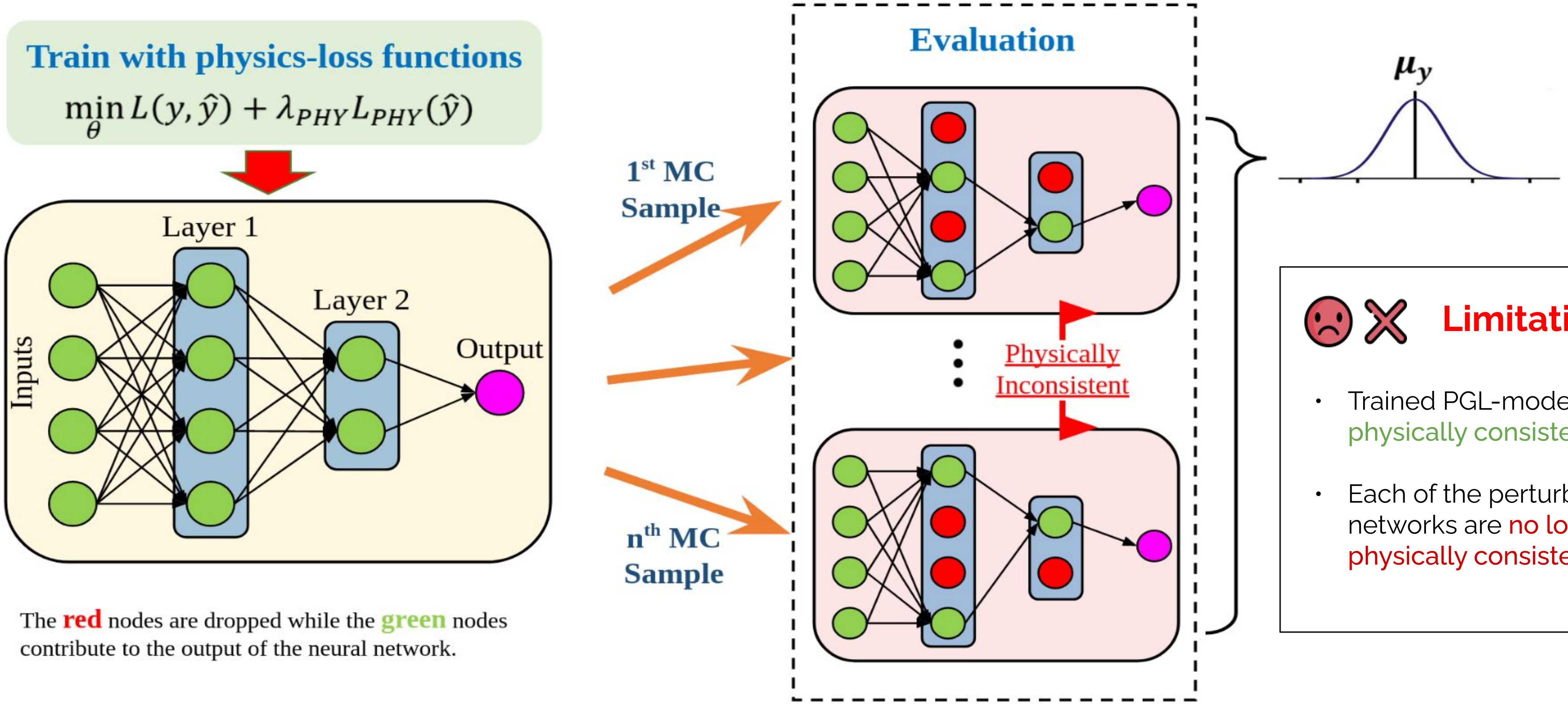


The red nodes are dropped while the green nodes contribute to the output of the neural network.

Repeat this "N" times

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

Approach 1: Dropouts with Physics-based Loss



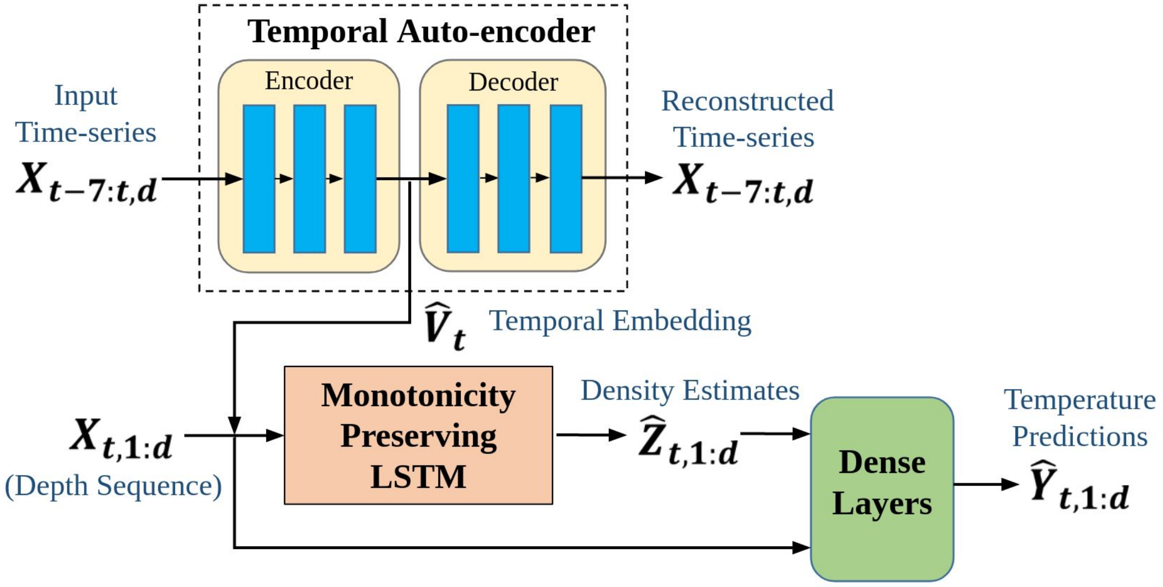
Limitations

- Trained PGL-models are physically consistent.
- Each of the perturbed dropout networks are no longer physically consistent.

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

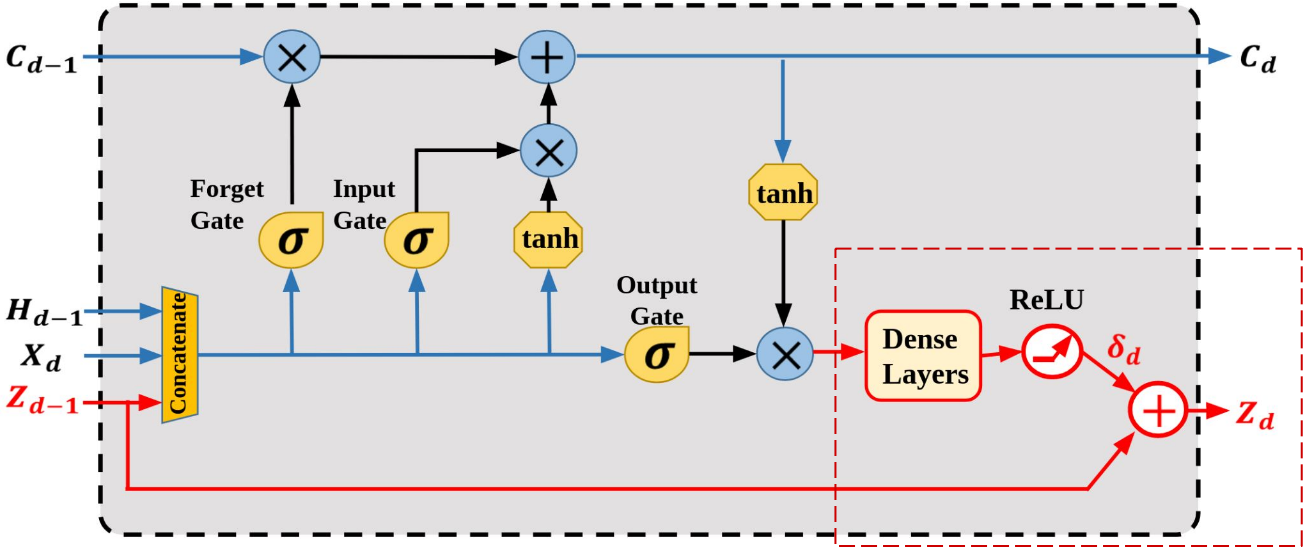
Proposed PGA-LSTM Framework

- **Temporal Autoencoder:** Encodes the input time series to obtain a temporal embedding.
- **Monotonicity Preserving LSTM:** Enforces the monotonicity constraint on the density predictions.
- **Dense Layers:** Takes the density estimates and the input drivers to predict temperature.



Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

Monotonicity Preserving LSTM



Components in red represent the novel physics-informed innovations in LSTM

Key Idea

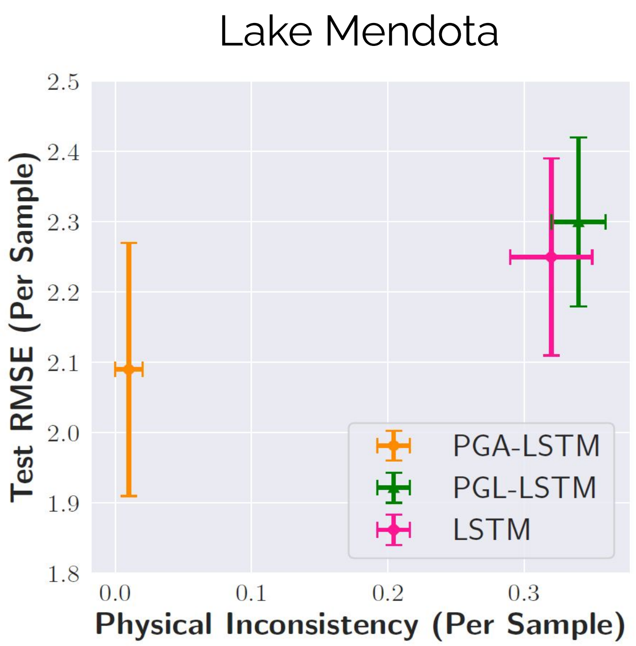
The **ReLU function** ensures that the residual outputs are non-negative, thus enforcing the monotonicity constraint.

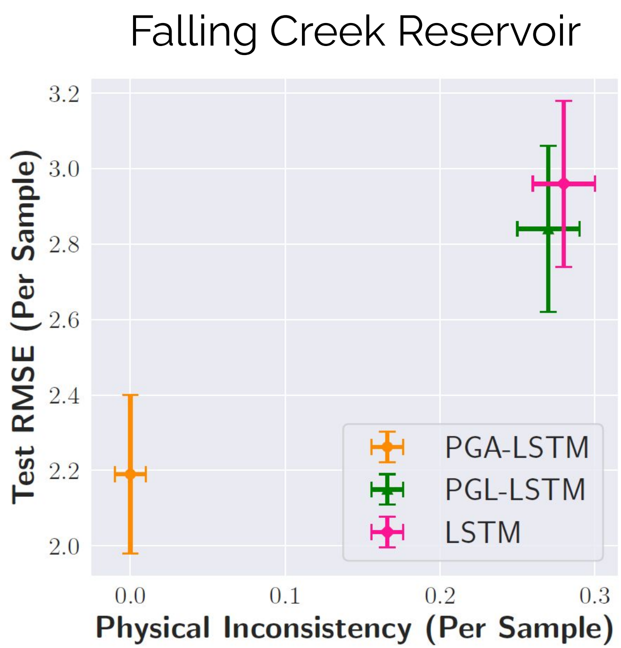
The monotonicity preserving LSTM:

1. Adds a layer of **interpretability** into the model outputs,
2. Makes it more **robust** to small perturbations in the model weights
3. Ensures physics-**generalization** on unseen test set.

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

Impact on predictive performance and physical consistency





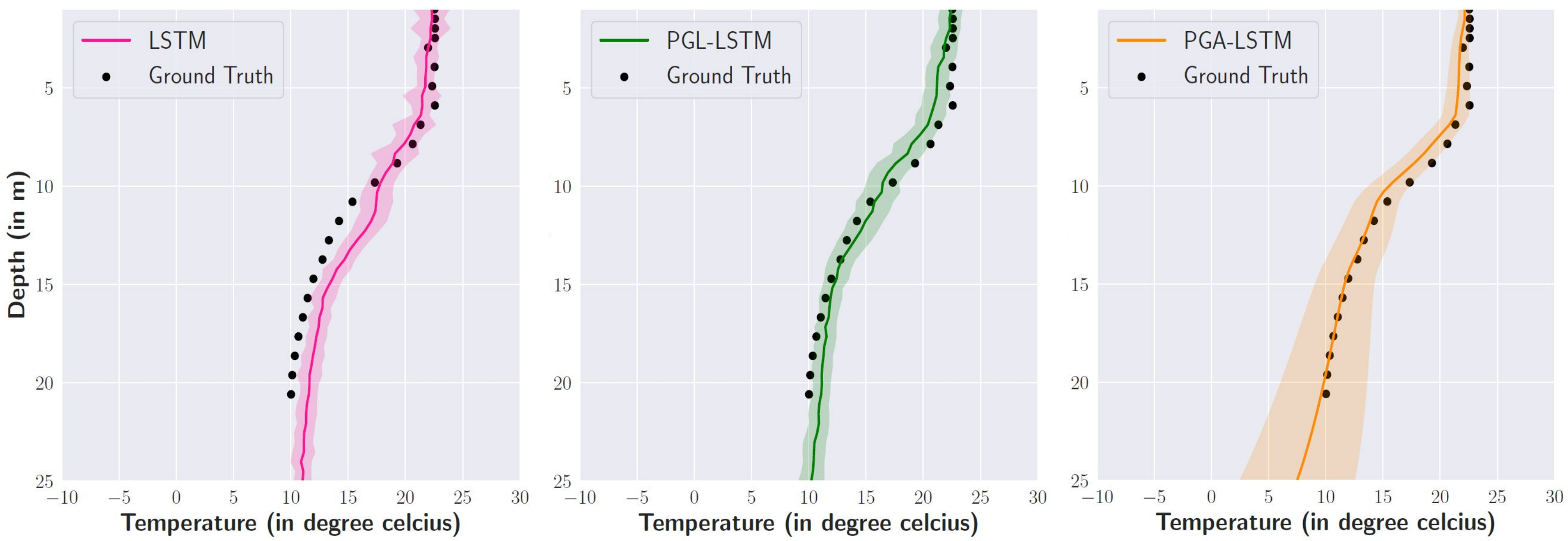
Evaluation Metrics

- Test RMSE
- Physical Inconsistency

PGA-LSTM improves the Test RMSE while always being physically consistent across both lakes.

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

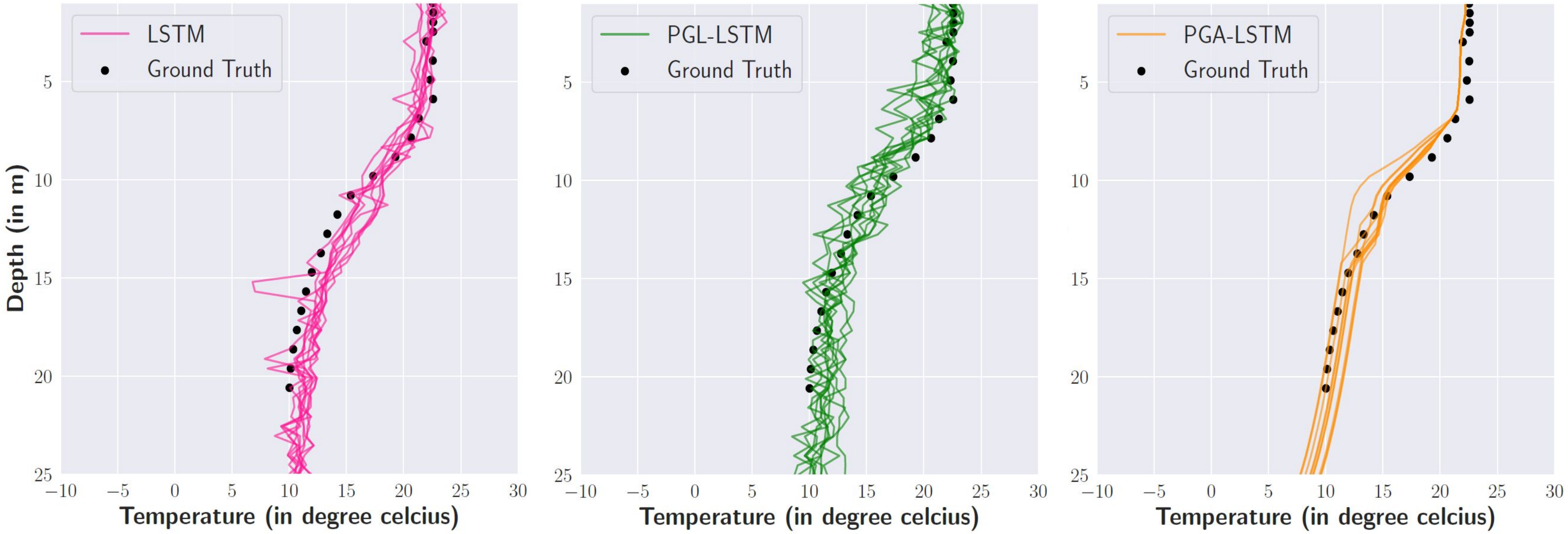
Monotonicity Preserving LSTM



The mean and the variance of the three models are computed from **100 MC-Samples**.

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

Monotonicity Preserving LSTM



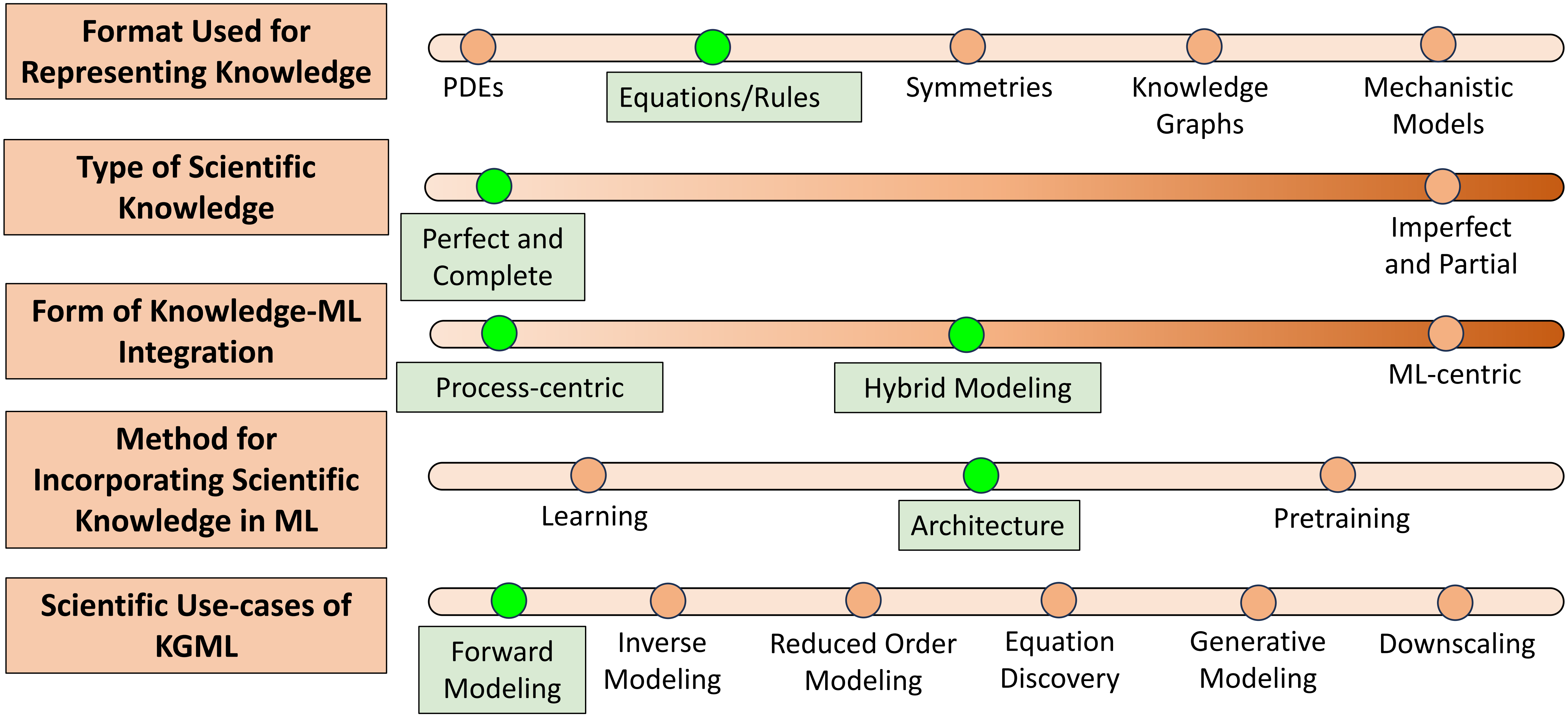
The PGA-LSTM samples are always physically consistent while PGL-LSTM and LSTM samples are very much physically inconsistent.

Predictions are **more robust to minor perturbations** in model weights!

Daw, Arka, Anuj Karpatne, William D. Watkins, Jordan S. Read, and Vipin Kumar. "Physics-guided neural networks (pgnn): An application in lake temperature modeling." In *Knowledge Guided Machine Learning*, pp. 353-372. Chapman and Hall/CRC, 2022.

Use Case 3:
Hybrid Modeling

Organizing KGML Research: A Multi-Dimensional View

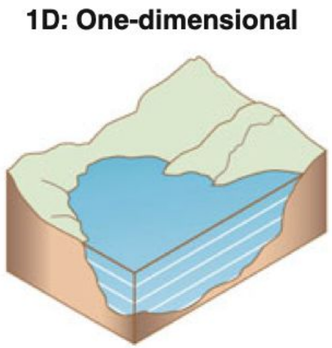


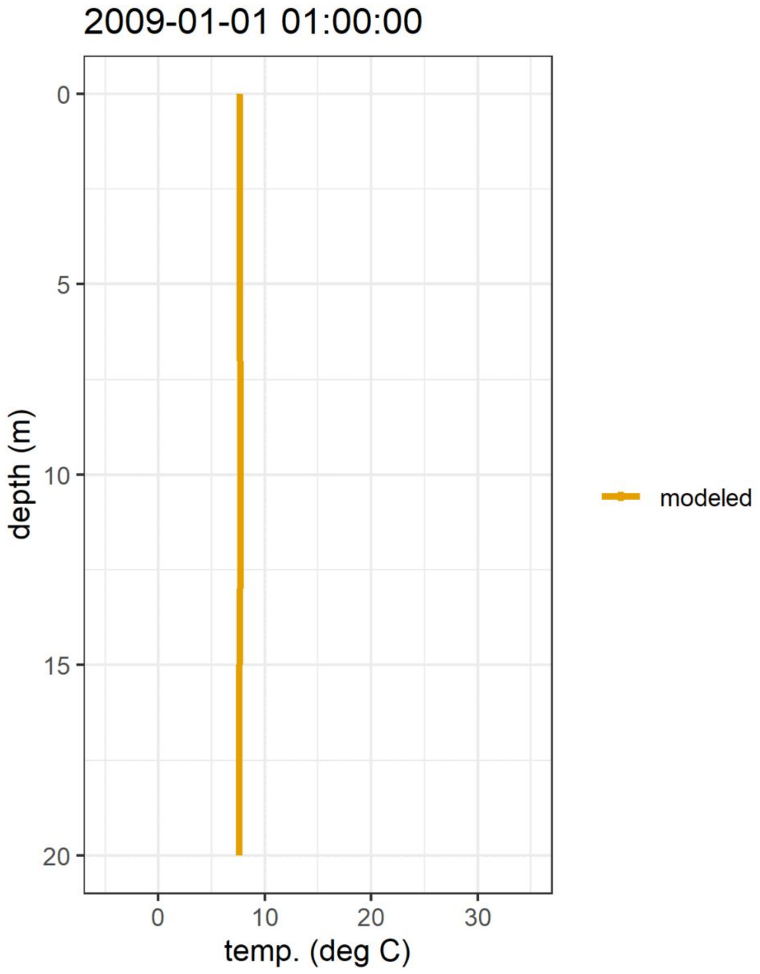
Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

Slides courtesy of Robert Ladwig

Process-based Modeling

- plethora of model approaches:
  - **energy-balance** models: mixing depth by external energy
  - **turbulence-based** models: advanced turbulence-closure





Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

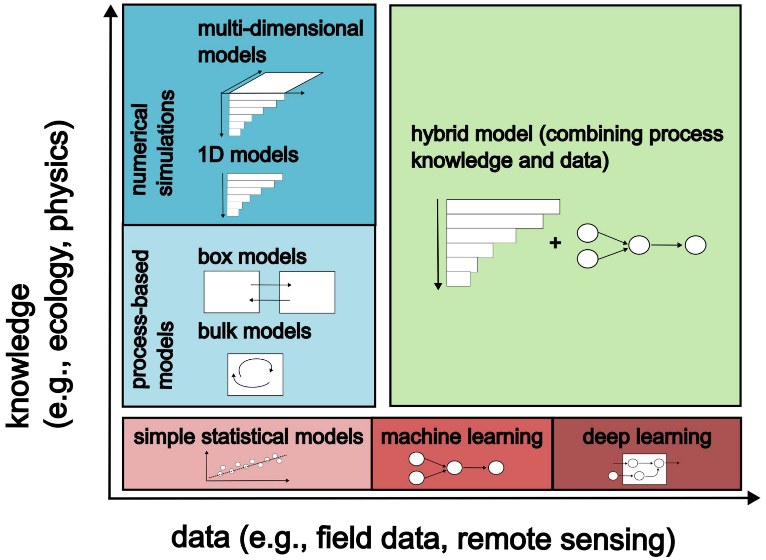
Slides courtesy of Robert Ladwig

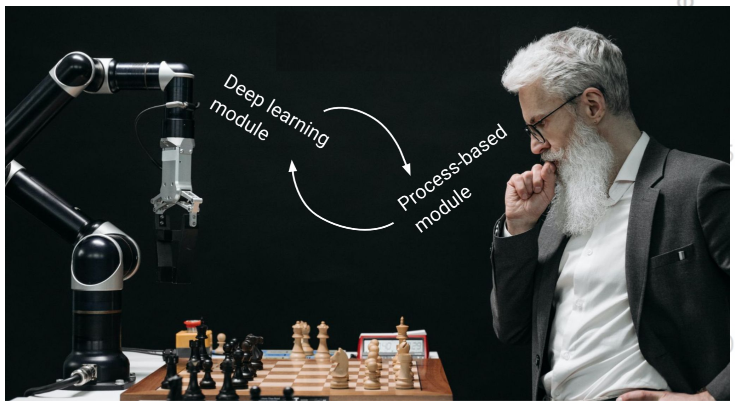
Process-based Modeling

- plethora of model approaches:
  - **energy-balance** models: mixing depth by external energy
  - **turbulence-based** models: advanced turbulence-closure

1D: One-dimensional

Can we combine these process models with data?





Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

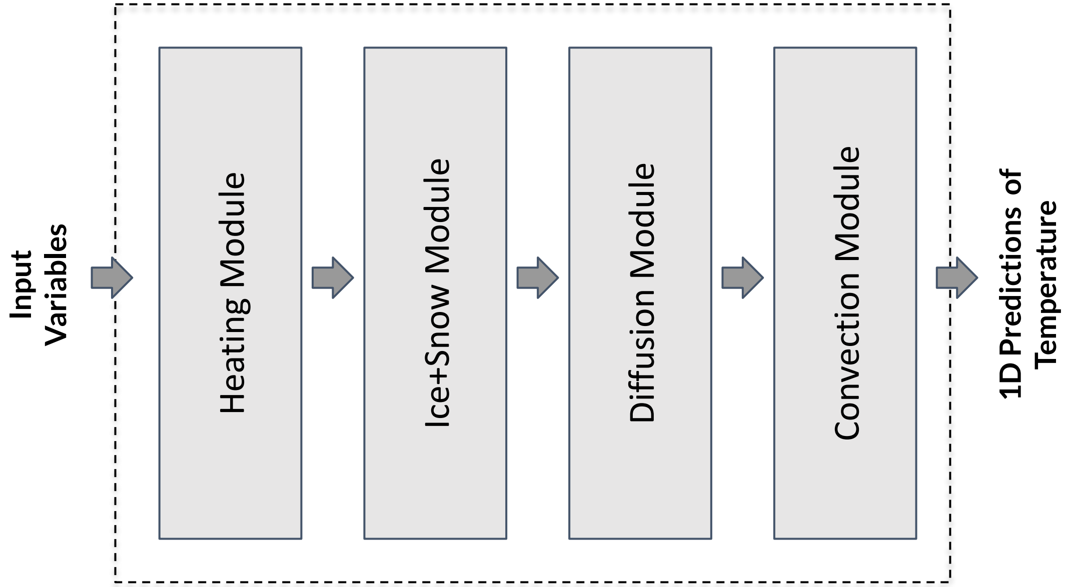
Modularized 1D Model

Modularized Process Models:

a) heating (atmosphere and geothermal)
b) ice, snow and snow-ice formation
c) vertical diffusion
d) convective overturn

CONS

- **Imperfect Module:** All of the physics modules are not perfect, i.e., some of the physical phenomena are more complex.



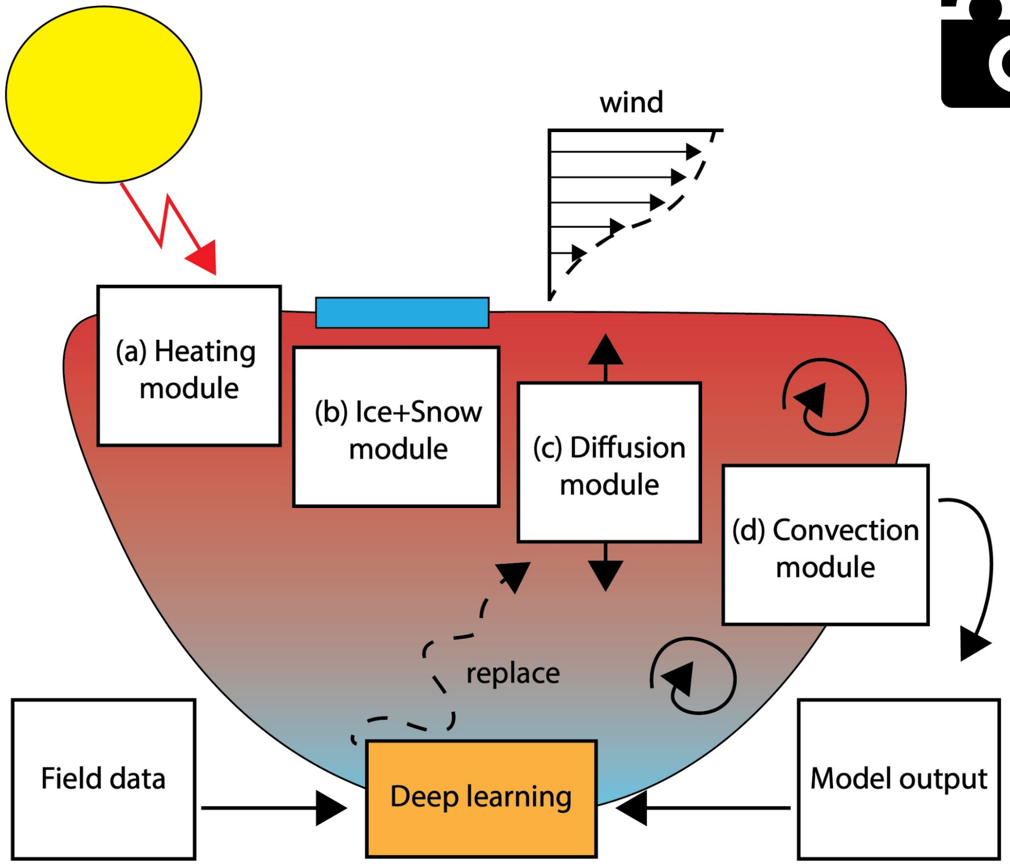
Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

Modular Compositional Learning (MCL)

Imperfect Modules: Diffusion Module

Idea: Replace the imperfect modules with deep learning based models.



PROS

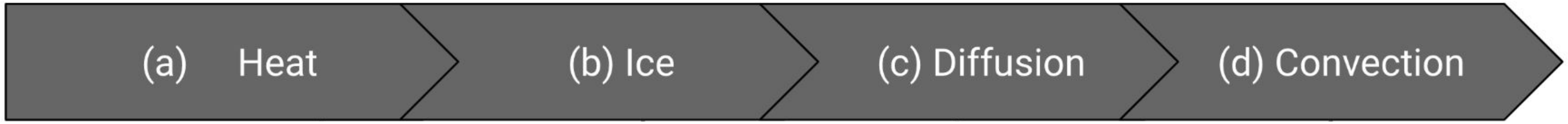
- Richer Physics knowledge: We retain the interpretability and knowledge of the modular process based modules.
- Hybrid modeling: Deep learning modules learns to dynamics of the necessary "missing" module (in this case diffusion module) to learn a more accurate model.

Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

Modular Compositional Learning (MCL)

Process-based framework



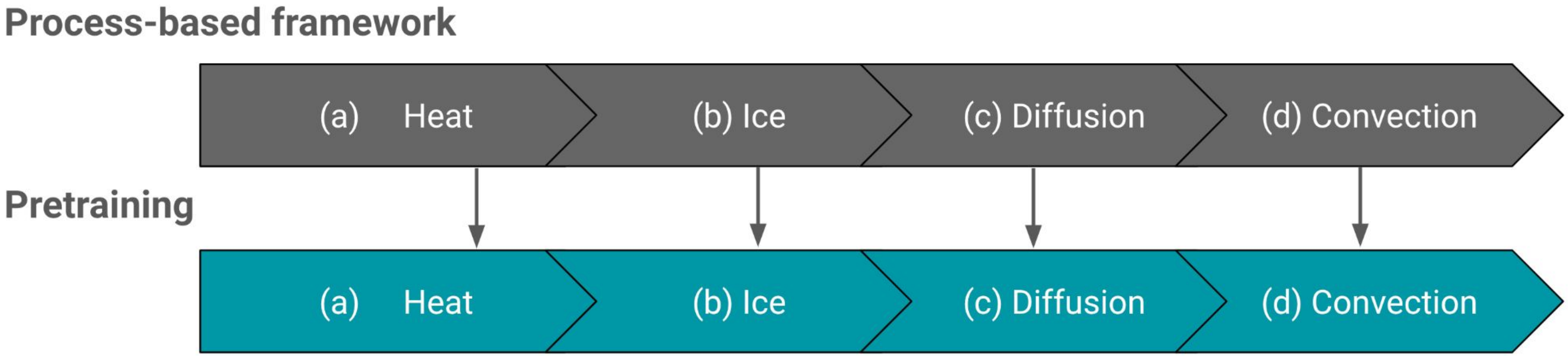
Process-based, pretrained deep learning, finetuned deep learning

Robert Ladwig

Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

Modular Compositional Learning (MCL)



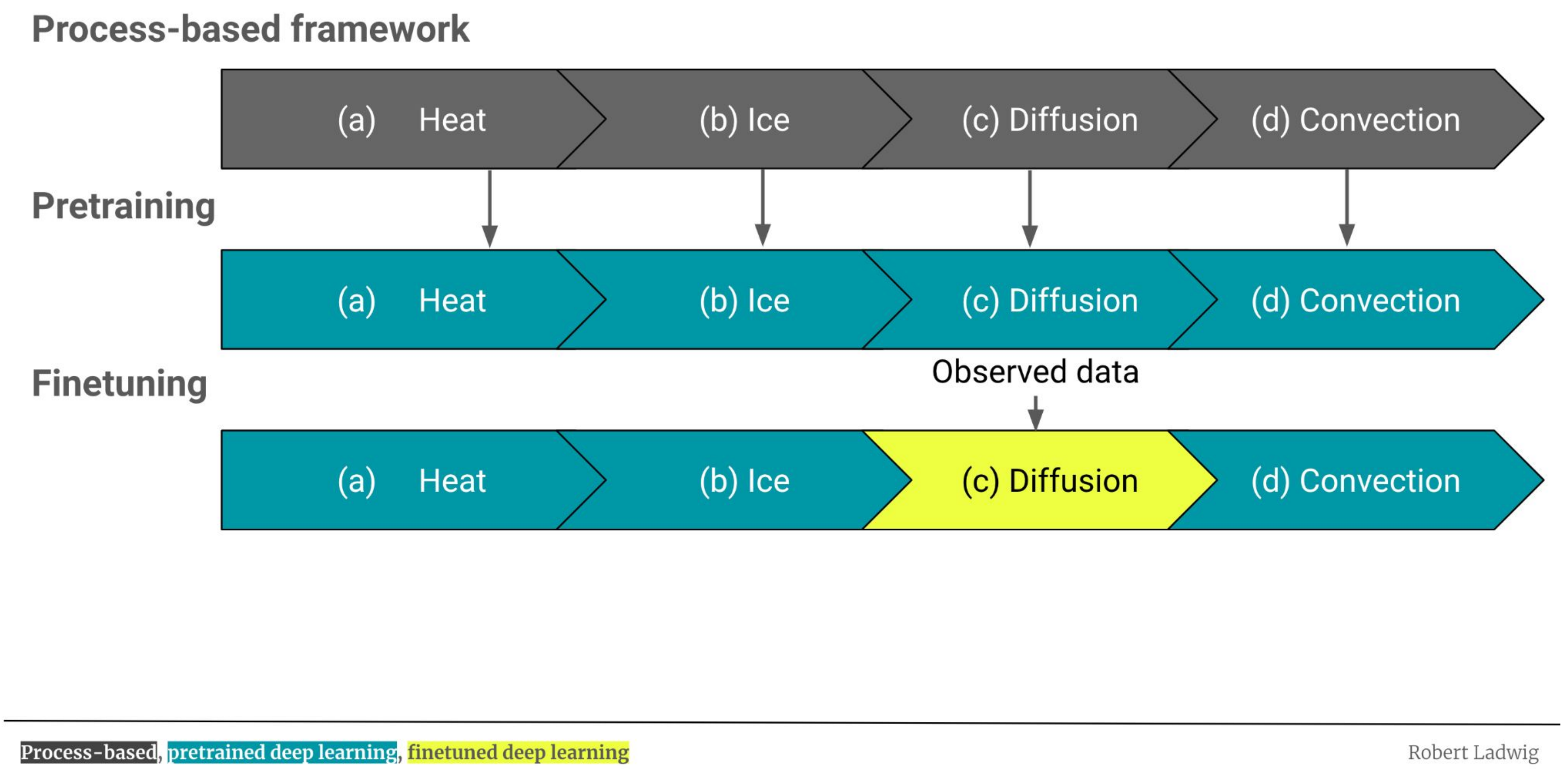
Process-based, pretrained deep learning, finetuned deep learning

Robert Ladwig

Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

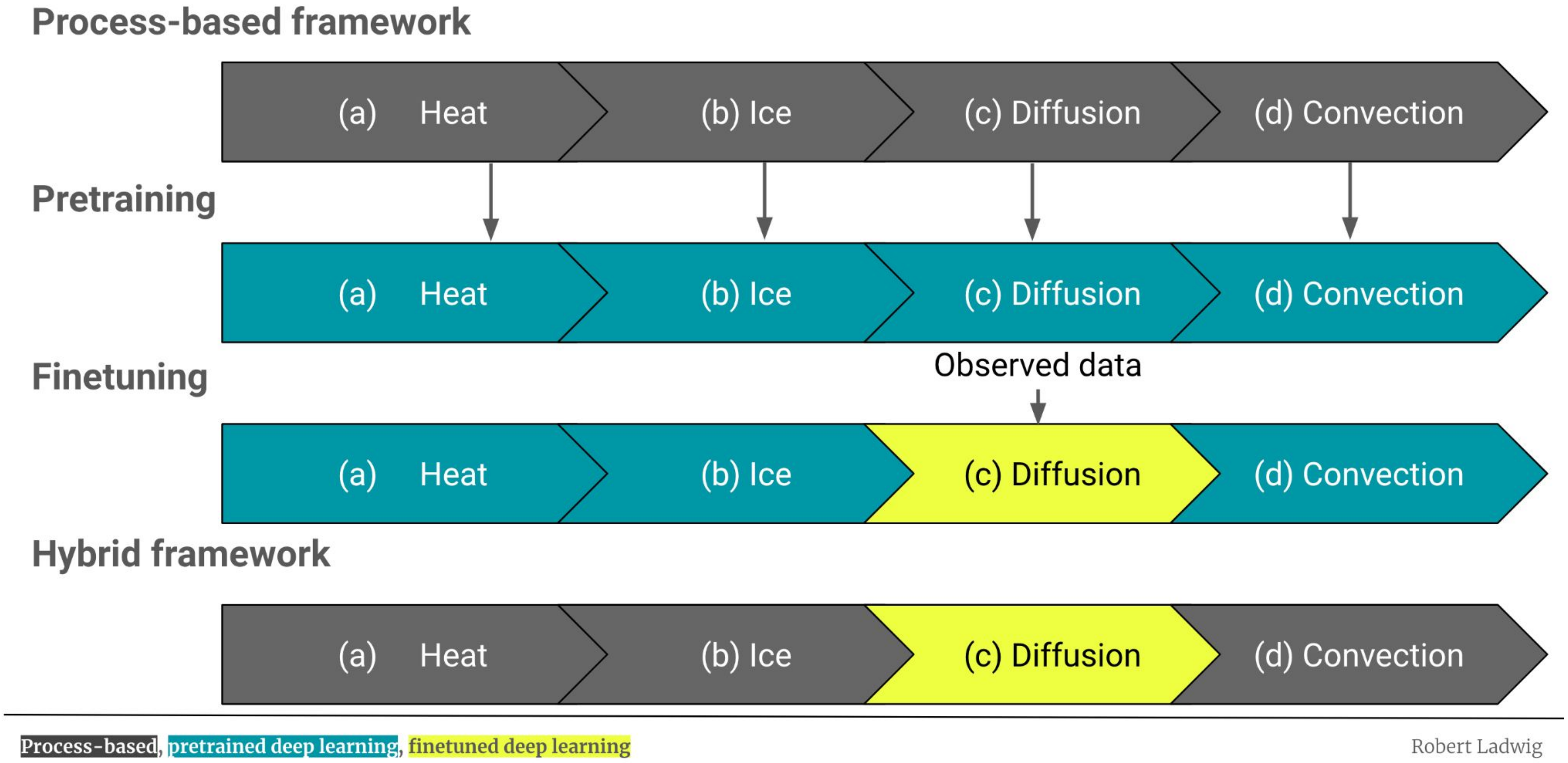
Modular Compositional Learning (MCL)



Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

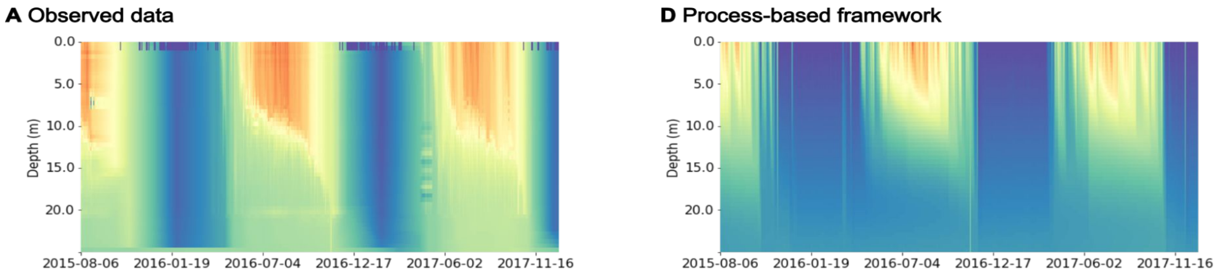
Modular Compositional Learning (MCL)



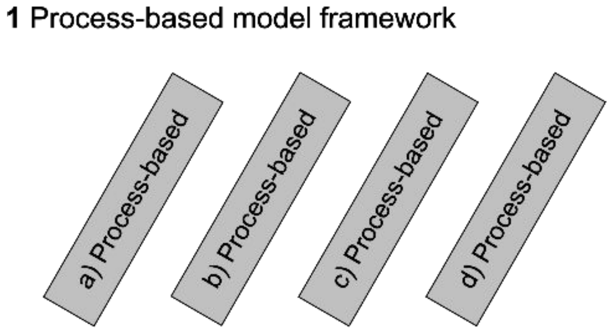
Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

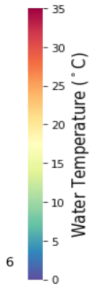
Empirical Evaluation (Test Period 2015-17)

Comparing Observed Data and Processed-based model



Test RMSE: 4.46





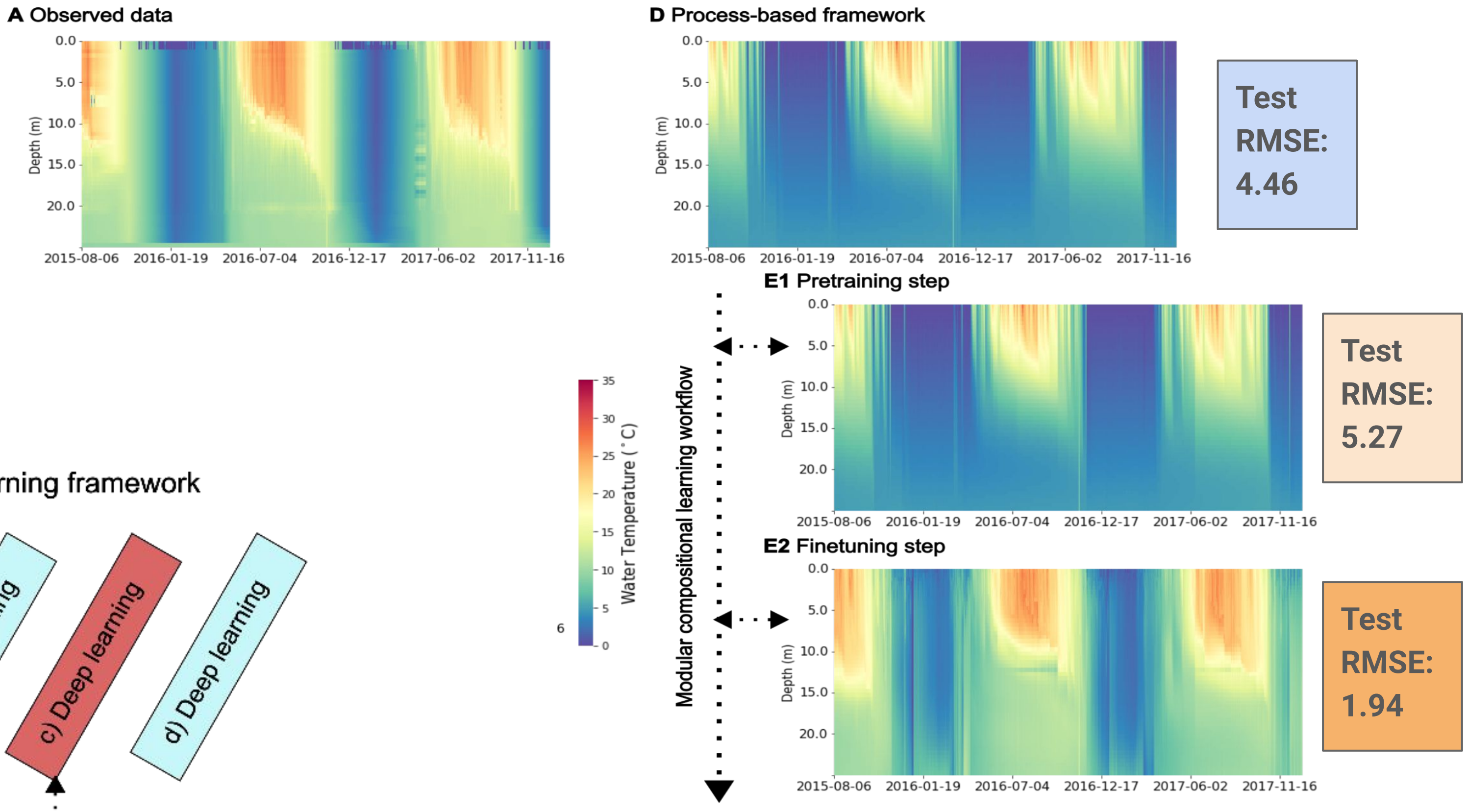
Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

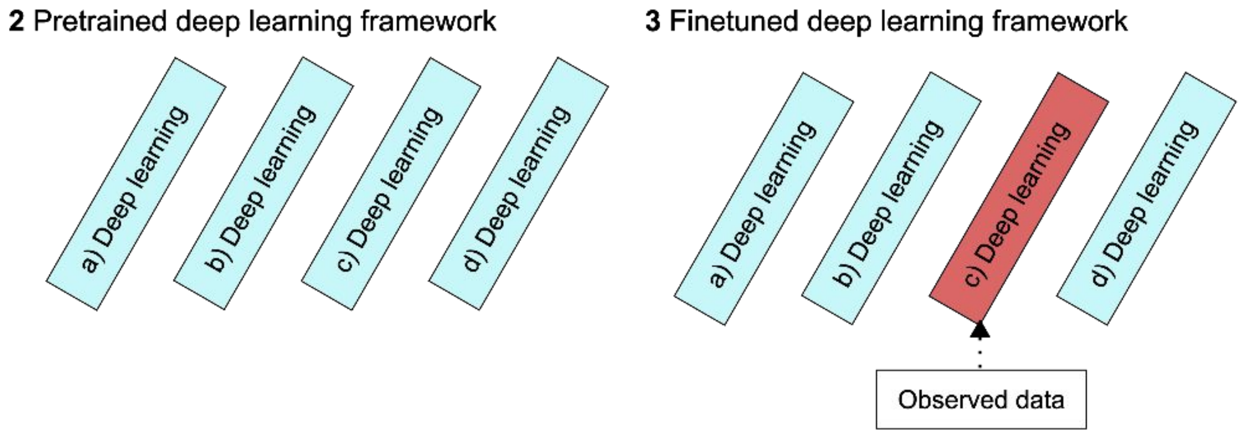
Slides courtesy of Robert Ladwig

Empirical Evaluation (Test Period 2015-17)

Comparing the models:

1. After pretraining each of the deep learning models on simulation data.
2. Finetuning the entire deep learning pipeline on observed data.

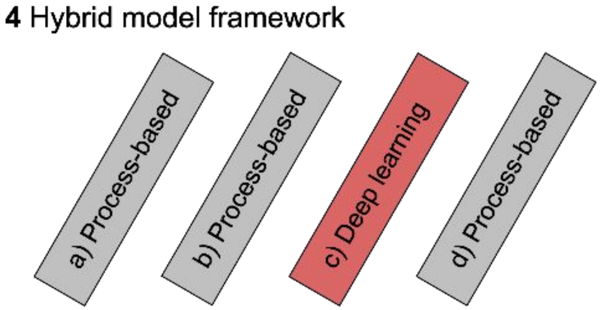


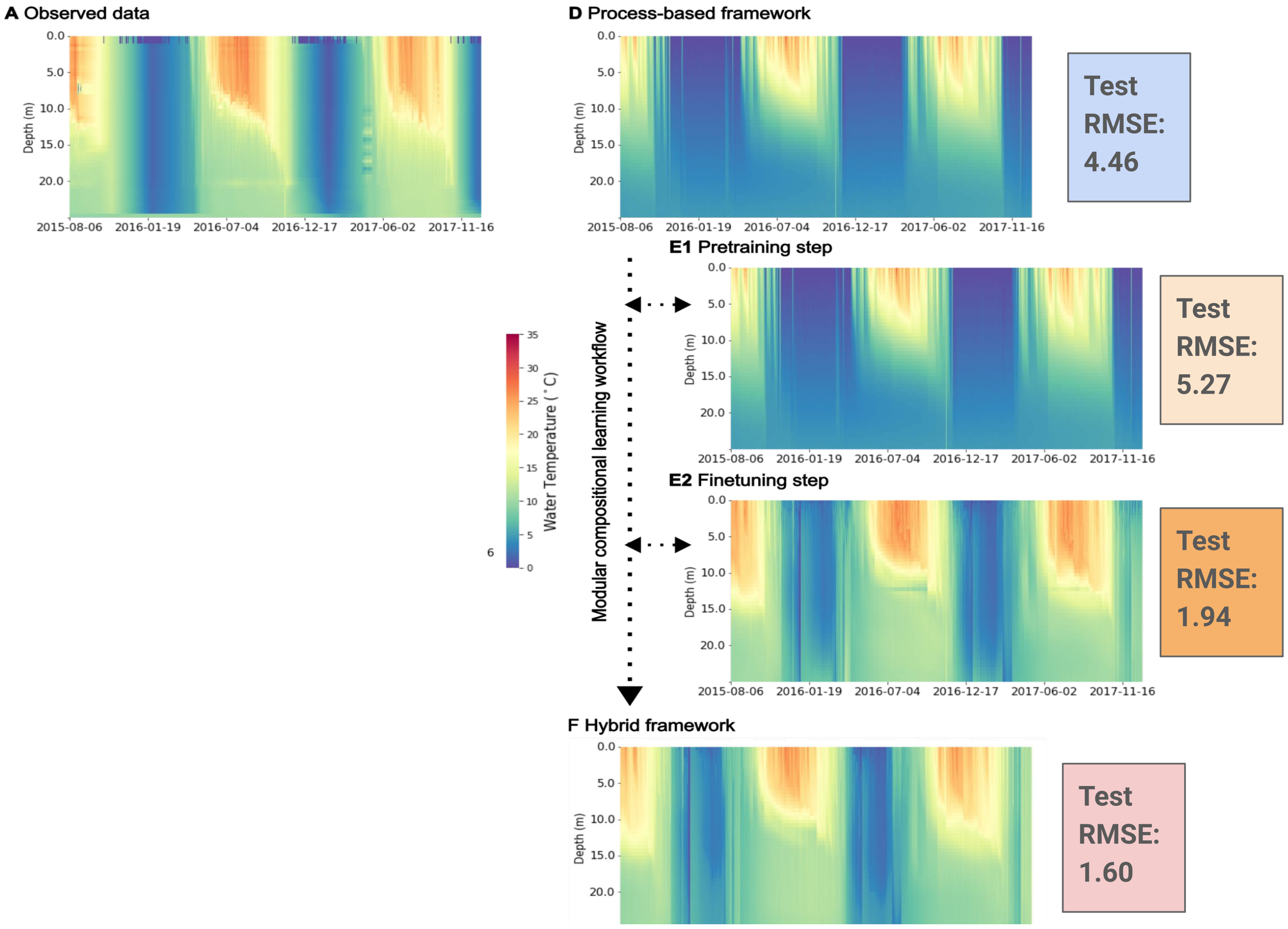


Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Empirical Evaluation (Test Period 2015-17)

Plugging the deep-learning module into the process-based module pipeline.

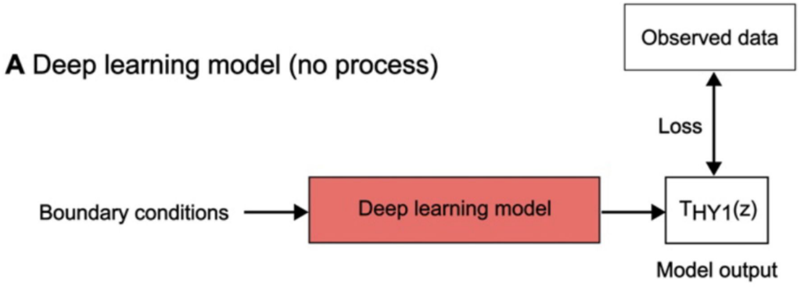




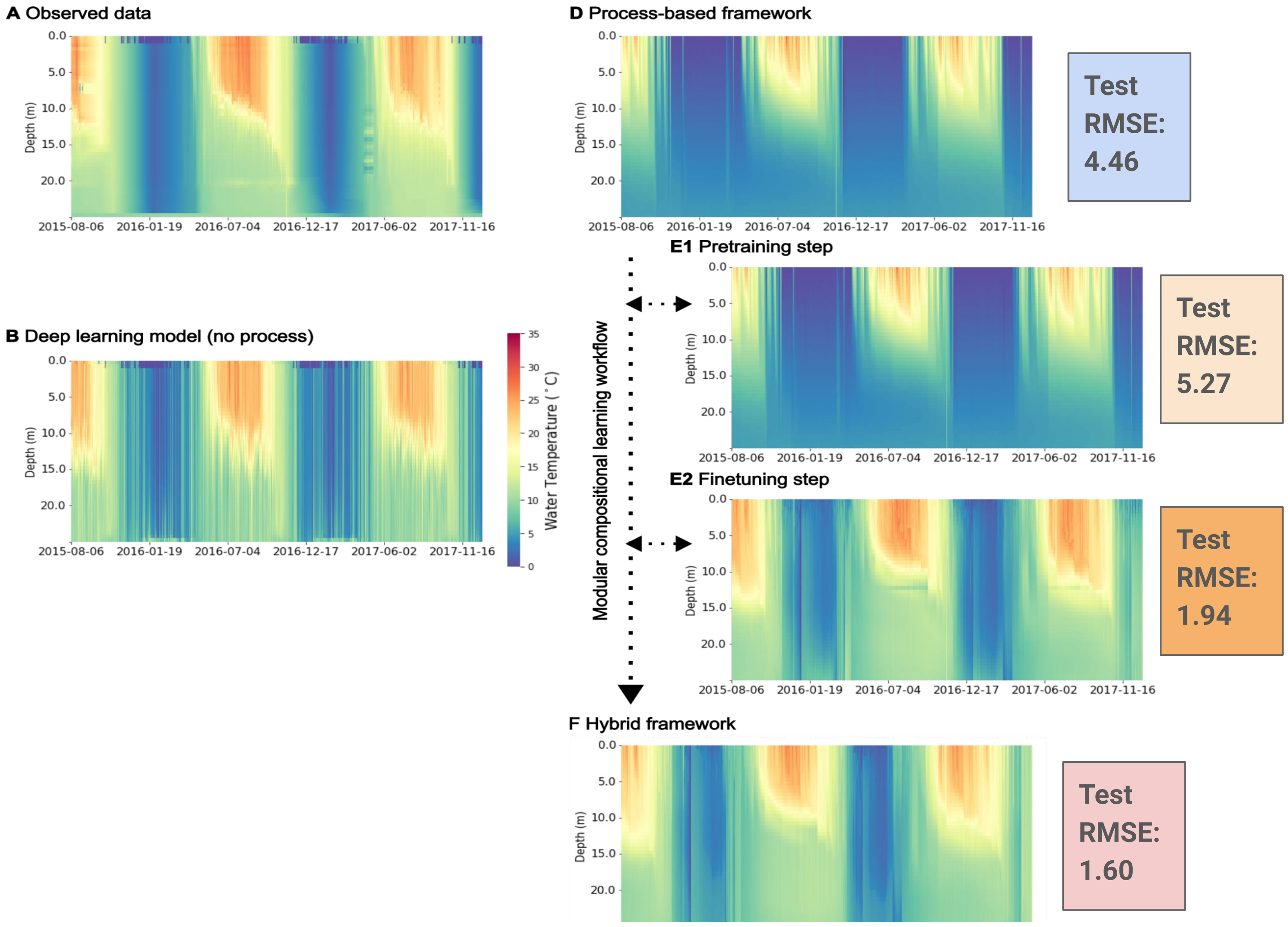
Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Slides courtesy of Robert Ladwig

Empirical Evaluation (Test Period 2015-17)

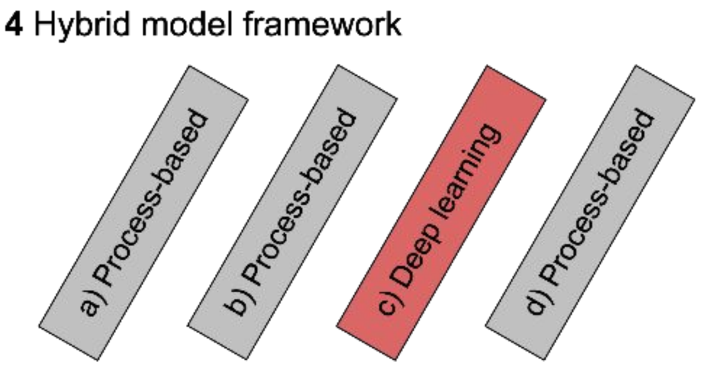


Test
RMSE:
2.10



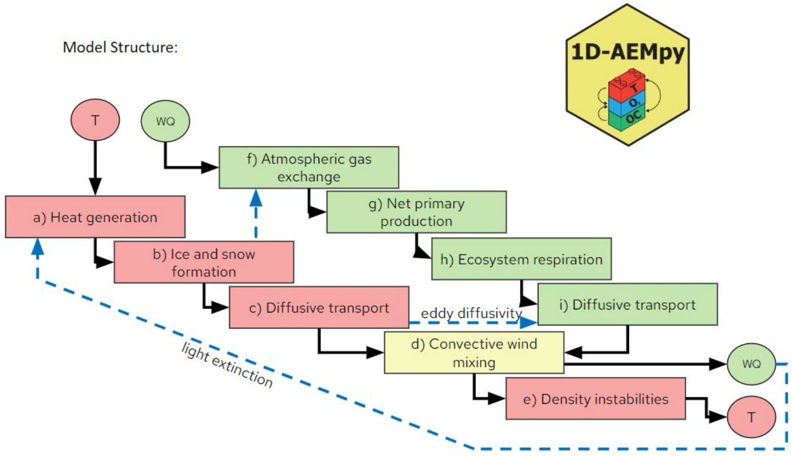
Ladwig, Robert, Arka Daw, Ellen A. Albright, Cal Buelo, Anuj Karpatne, Michael Frederick Meyer, Abhilash Neog, Paul C. Hanson, and Hilary A. Dugan. "Modular Compositional Learning Improves 1D Hydrodynamic Lake Model Performance by Merging Process-Based Modeling With Deep Learning." Journal of Advances in Modeling Earth Systems 16, no. 1 (2024)

Current Work in MCL



1D Lake Physics with MCL

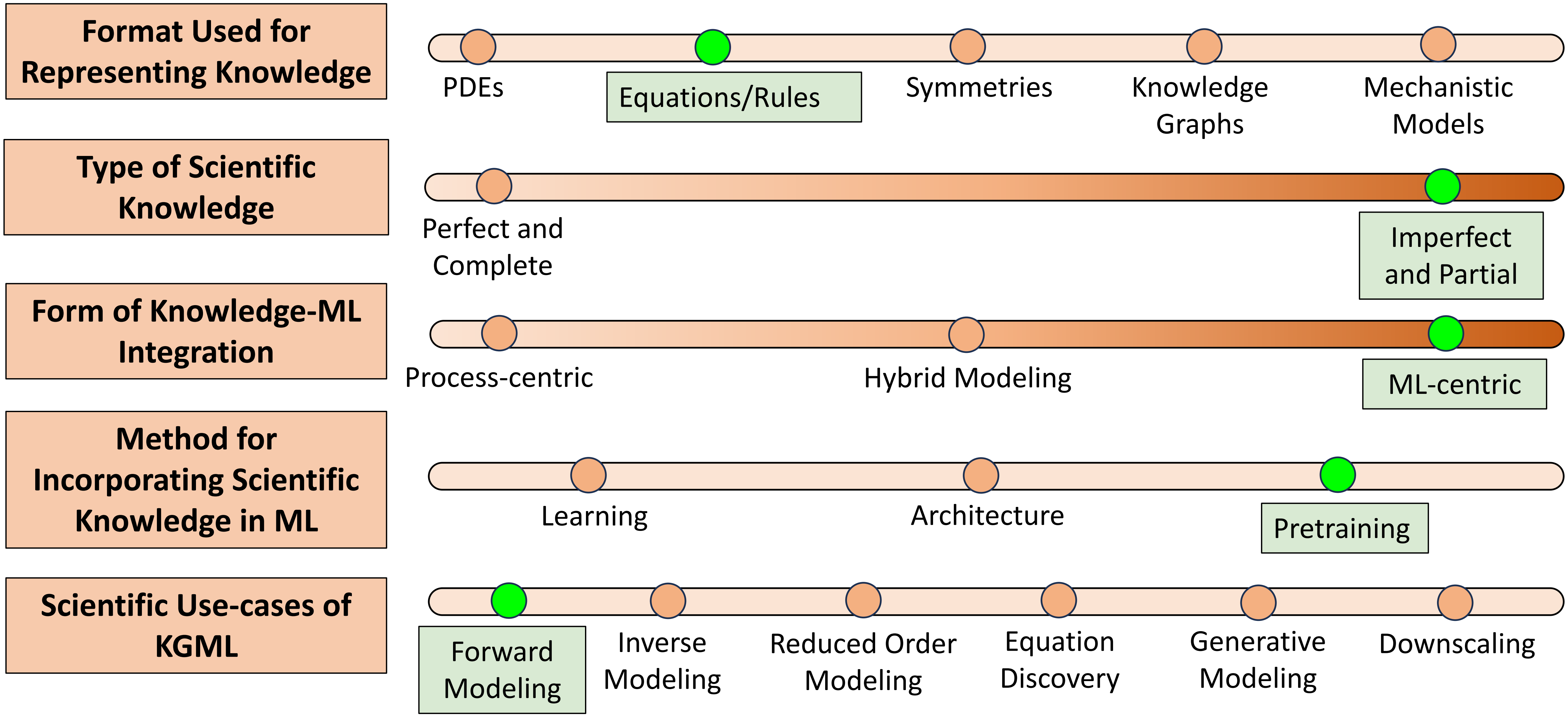
1D Water Quality with MCL



1D Lake Physics with MCL: memory for multiple lakes

Use Case 5:
Lake Chlorophyll-a Prediction

Organizing KGML Research: A Multi-Dimensional View



Karpatne, Jia, and Kumar. "Knowledge-guided Machine Learning: Current Trends and Future Prospects." *arXiv:2403.15989* (2024).

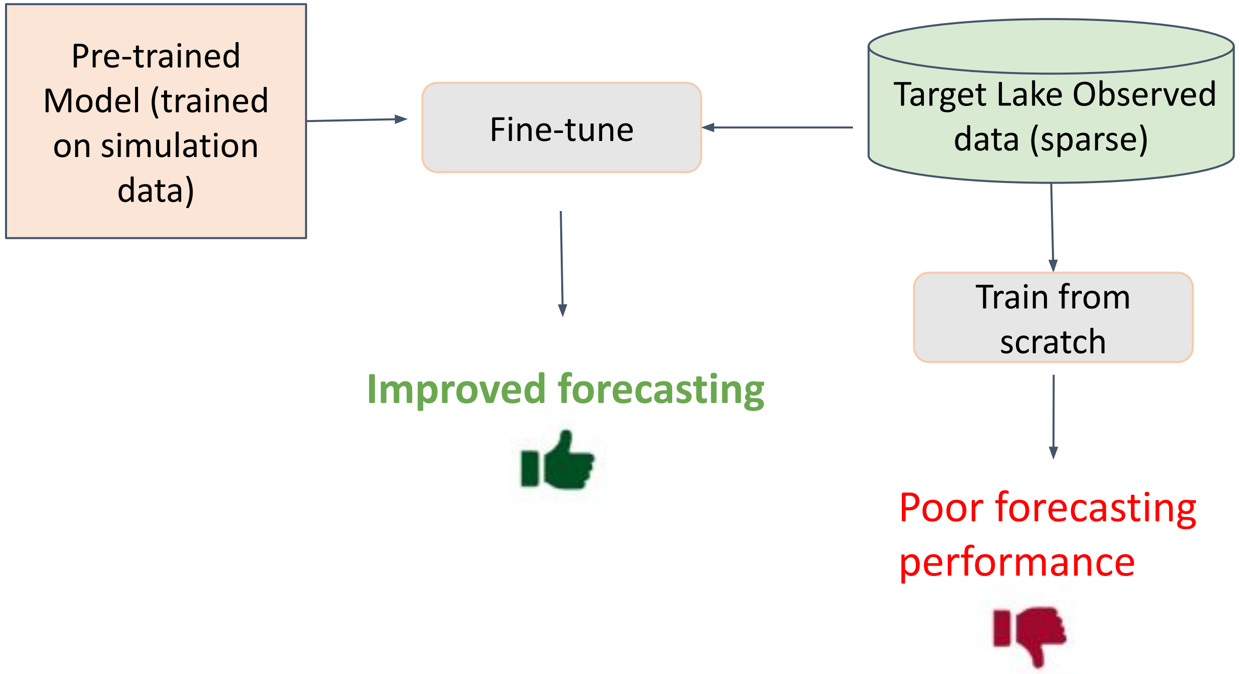
Transfer Learning for Chlorophyll-a Prediction

Problem Context:

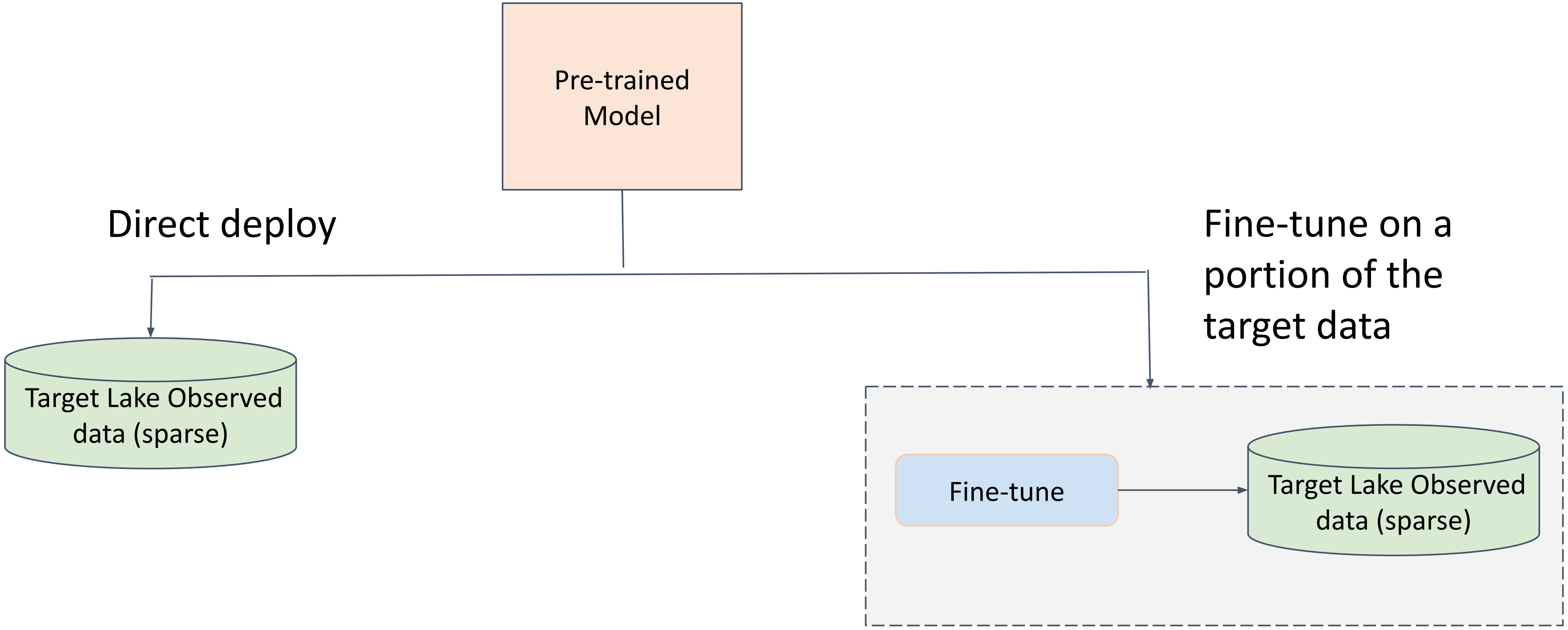
- Observations of chlorophyll-a vary across lakes, some being well-observed, others less-observed.
- Deep learning models are data-hungry, show poor forecasting performance on target lakes with sparse data.

Research Question: ***How can we improve forecasting performance of chlorophyll-a on lakes with few observations?***

Approach: Instead of “training from scratch” *transfer Learning* enables us to transfer knowledge learned from data-rich source lakes (in the form of pre-trained models) to target lakes.



Types of Transfer Learning methods



Zero-shot

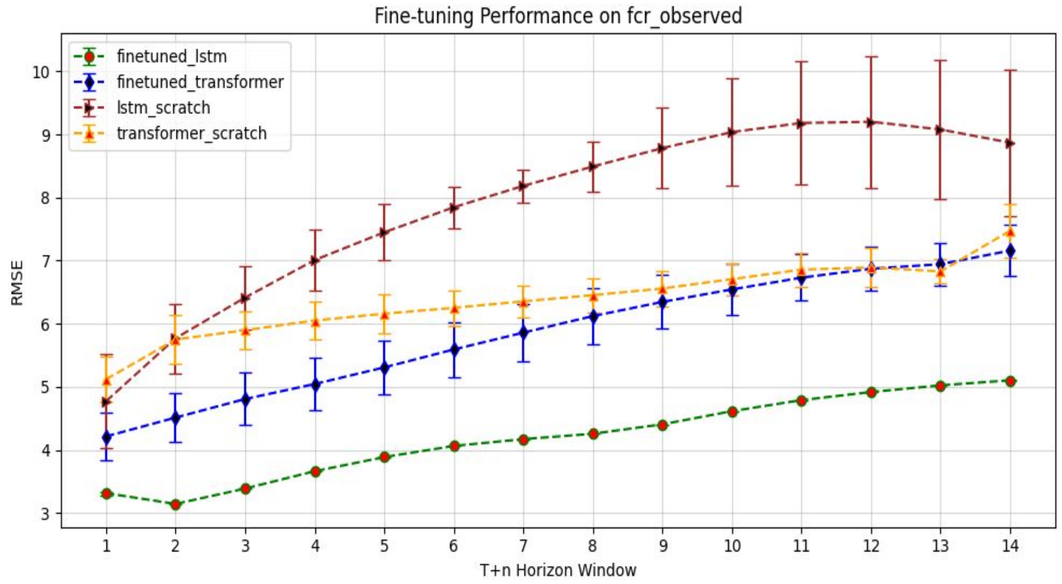
Fine-tuning

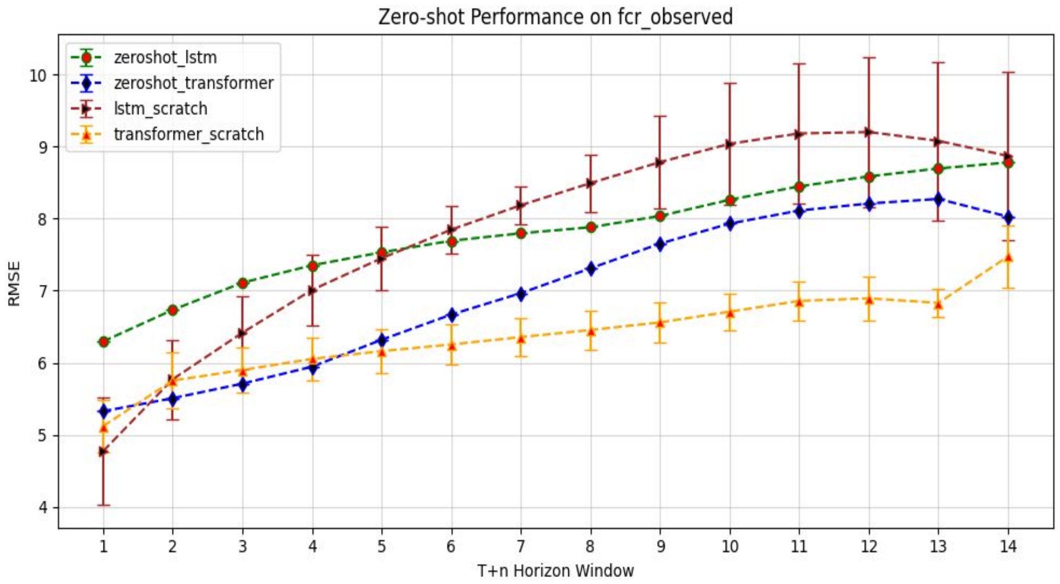
Transfer Learning for Chlorophyll-a Prediction

Problem Setup
Pre-training: Model pre-trained on simulation data of lakes Mendota, Sunapee, FCR.
Models: LSTM [1], Transformer [2]

Data split in target lake = 70:30
Model trained/fine-tuned on the 70% and tested on the 30% data.

>Following results are on the test set (i.e. 30% of data)





1. Hochreiter, S., & Schmidhuber, J"urgen. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.
2. Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).

Transfer Learning for Chlorophyll-a Prediction

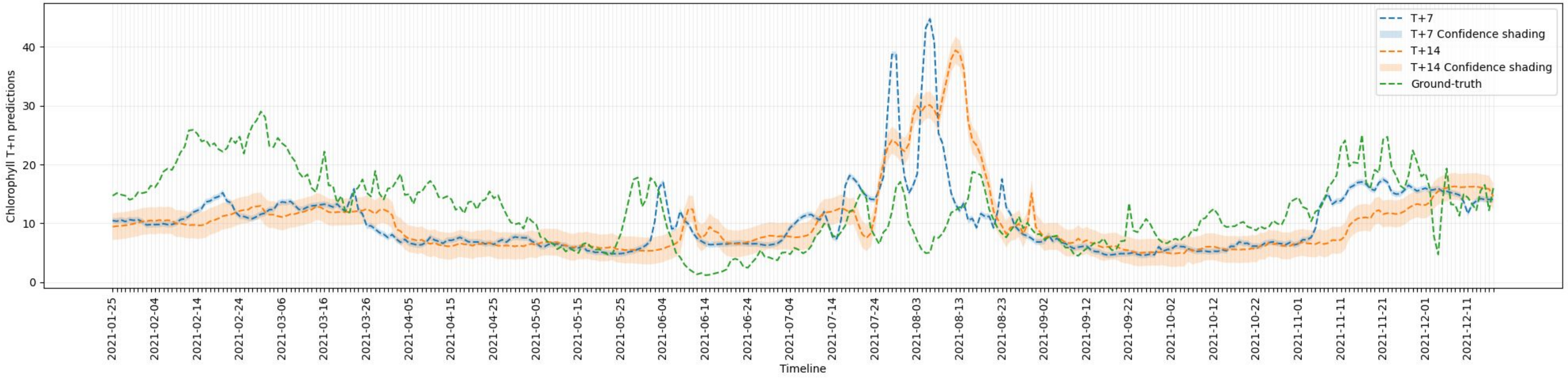
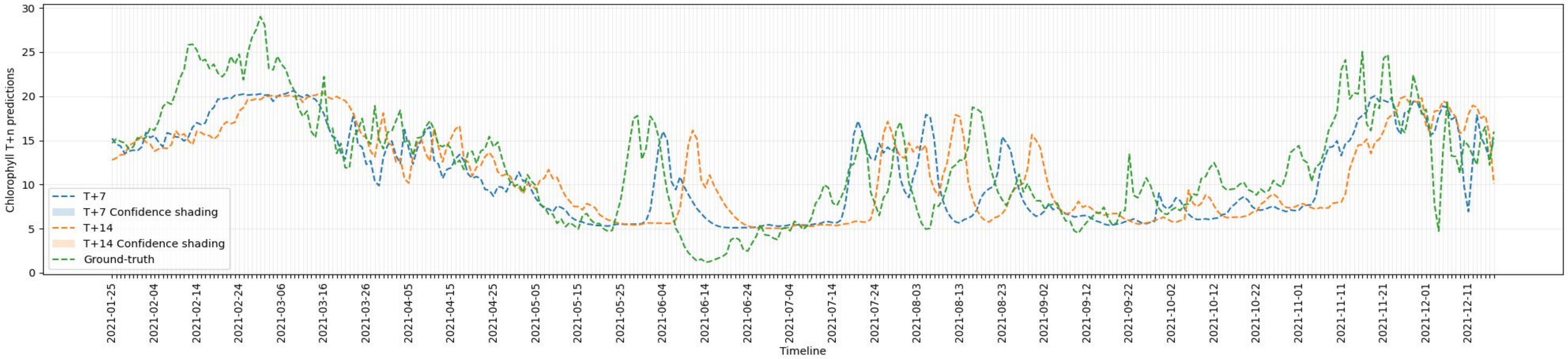


Fig. 1 Predictions on FCR observed Test portion - Model trained from scratch

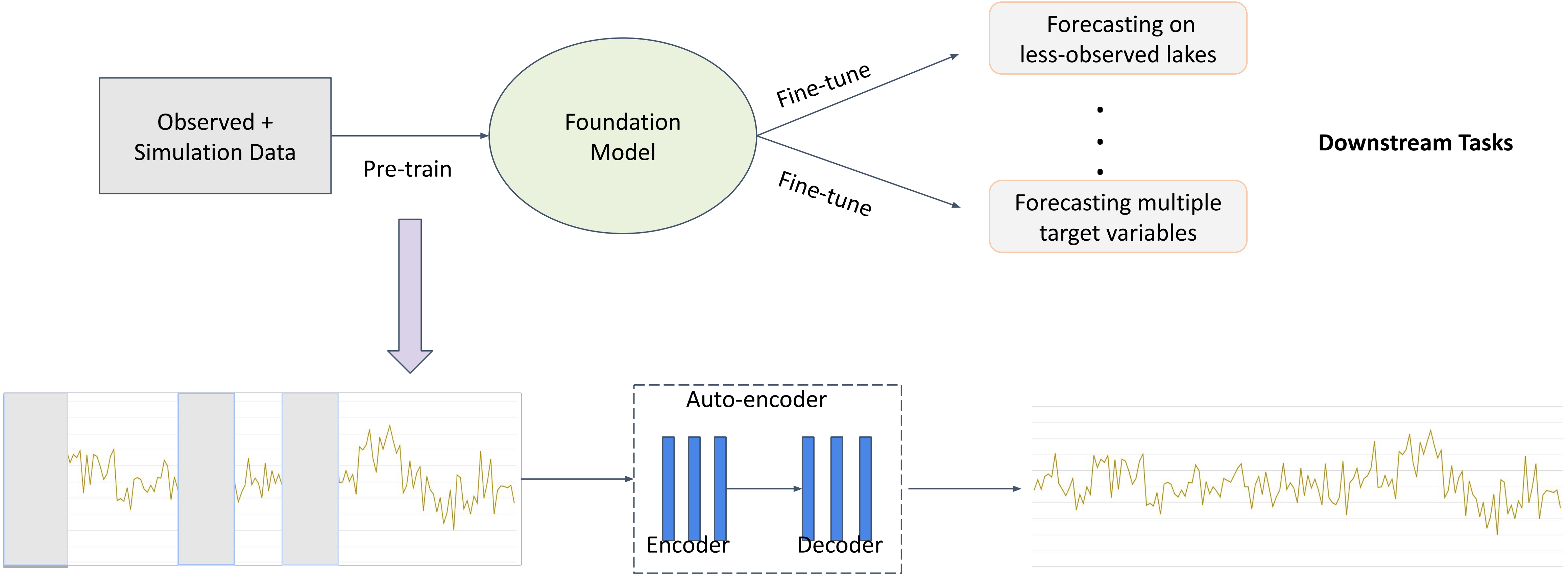
- Fine-tuned model aligns with the ground-truth scale of chlorophyll data
- Fine-tuned model shows relatively more confident predictions



LSTM model

Fig. 2 Predictions on FCR observed Test portion - Model fine-tuned on FCR observed

Towards a Foundation Model



Learning Time-series representation