工业解析与控制实验室
Laboratory of Industrial Analytics & Control

NEURAL INFORMATION PROCESSING SYSTEMS

Uncertainty-Informed Meta Pseudo Labeling for Surrogate Modeling with Limited Labeled Data

Presenter: Xingyu Ren
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Uncertainty-Informed Meta Pseudo Labeling for Surrogate Modeling with Limited Labeled Data

Xingyu Ren∗ , Pengwei Liu∗ , Pengkai Wang∗ , Guanyu Chen, Qinxin Wu, Dong Ni†

Background: Semi-supervised Surrogates for Physics

· Problem: High-fidelity solvers are accurate but costly; scarce labels and distribution shift hinder supervised surrogates, while naïve SSL amplifies pseudo-label noise.

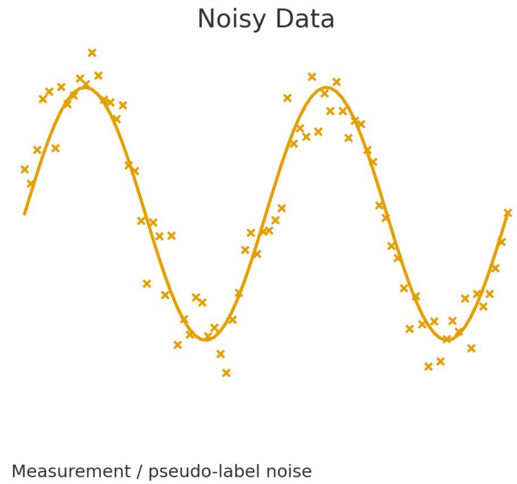
· Challenges: Noisy pseudo-labels, non-uniform meshes/time steps, and shift-robustness with calibrated uncertainty.

· Gap: Generic SSL assumes i.i.d. and ignores physics; it lacks role-aware treatment of epistemic vs aleatoric uncertainty to decide what to trust or discard.

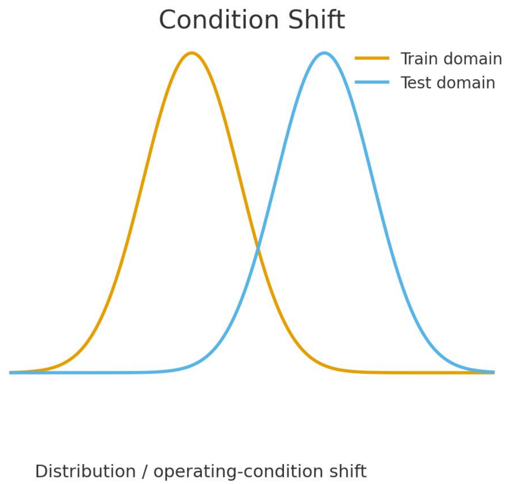
· Target: We need uncertainty-aware SSL that filters and corrects pseudo-labels and remains reliable under shift.

Scenario: (1)

(2)



(3)



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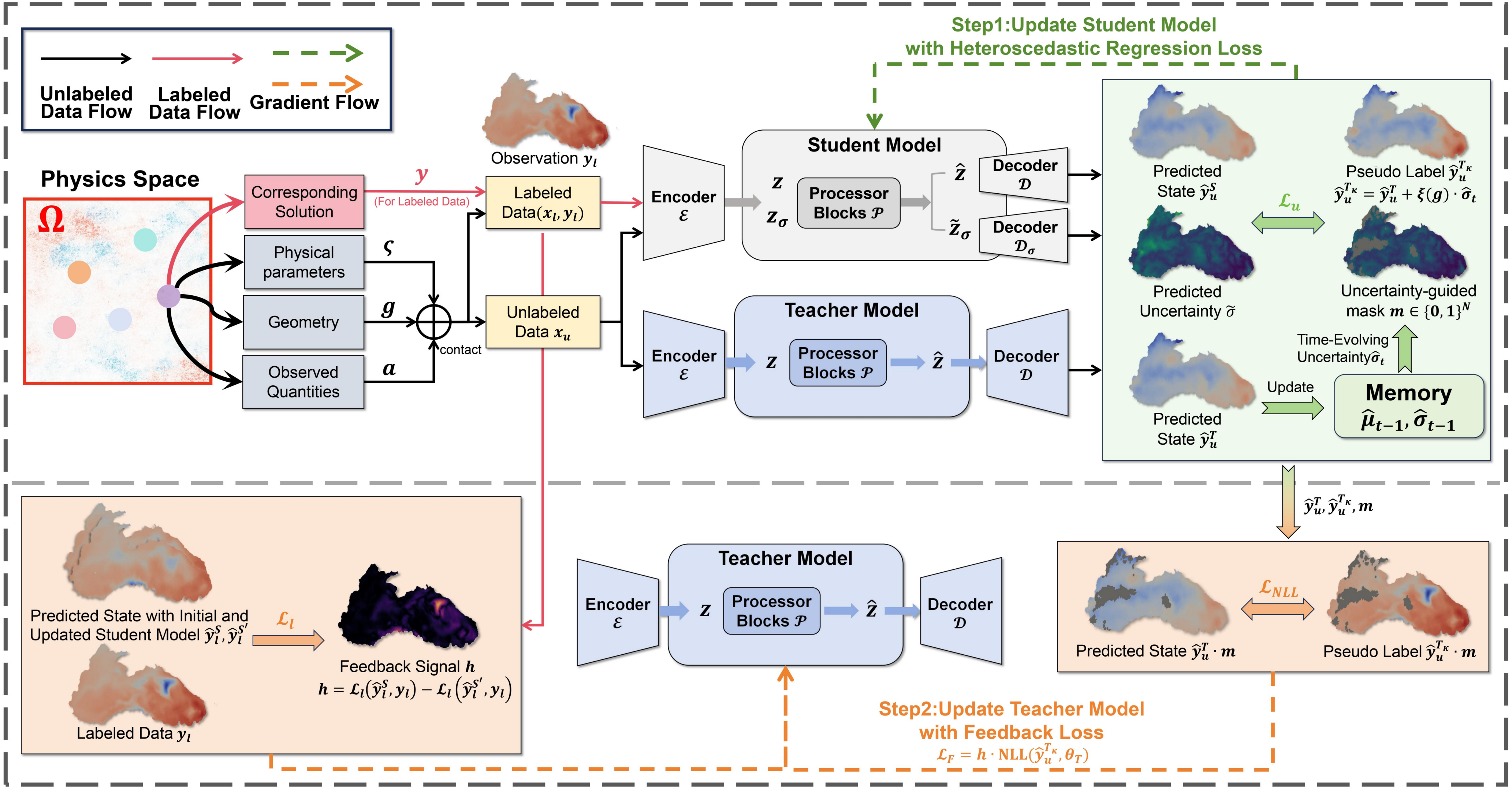
Key method: UMPL—A few shot SSL method for high dimensional PDEs



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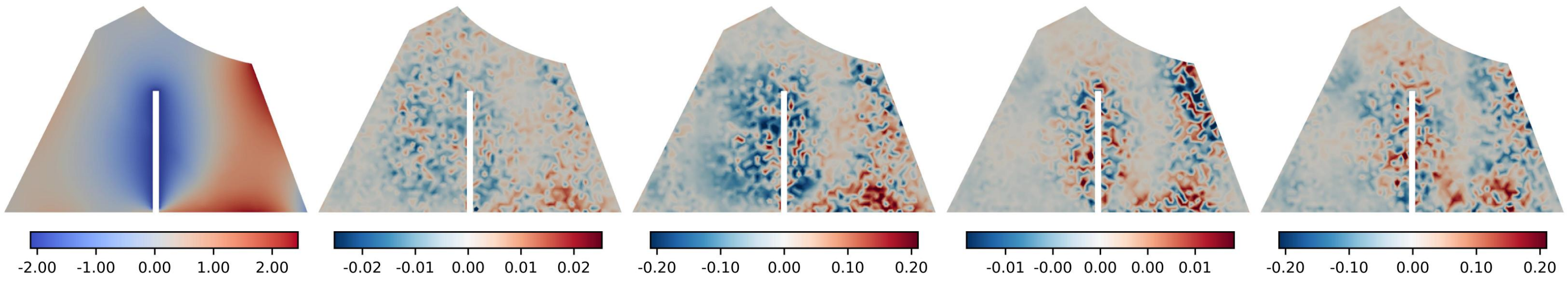
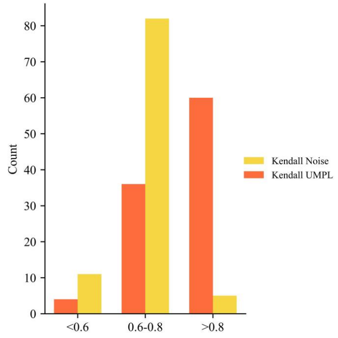
Experiments & Results

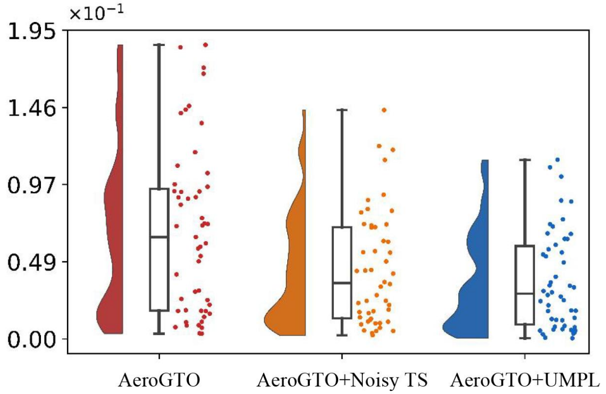
Comparison of Feedback Loss and True Pseudo-label Error during Training:



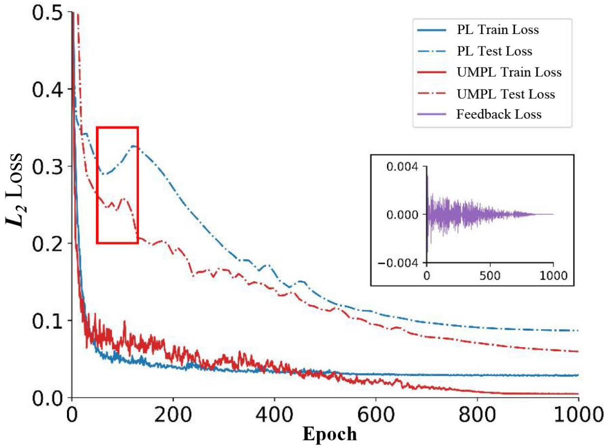


Ground Truth | Noisy TS Feedback Loss | Noisy TS Actual Error | UMPL Feedback Loss | UMPL Actual Error | Kendall-τ Correlation

The Raincloud Plot and Loss Curves:



(a) Raincloud Plots of C_d



(b) Loss Curve on Stationary Lid

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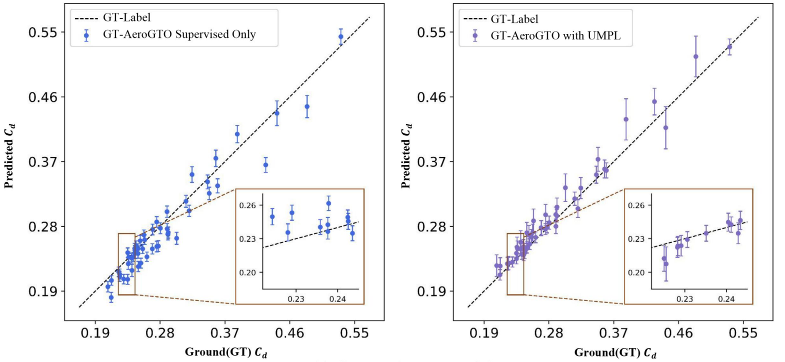
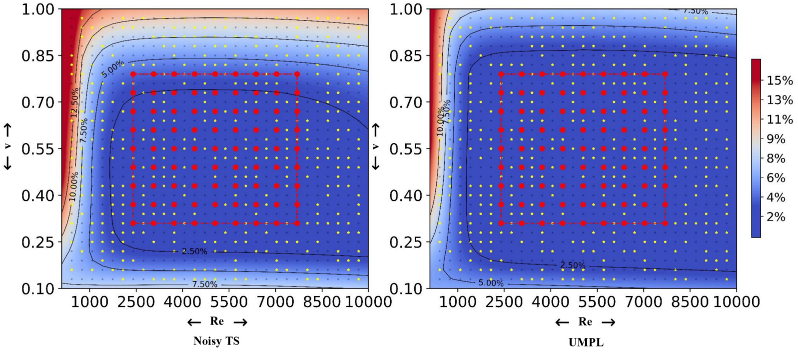
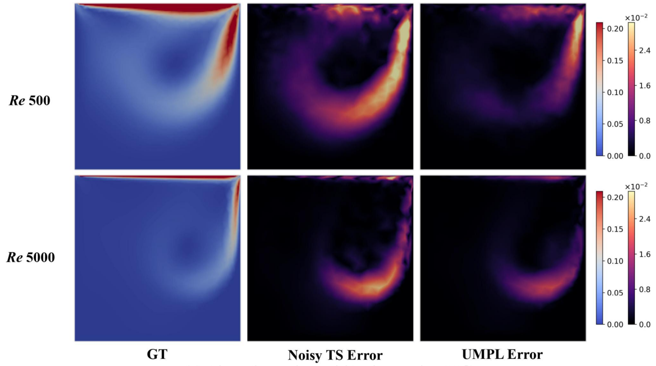
Results on Different Tasks and Models:



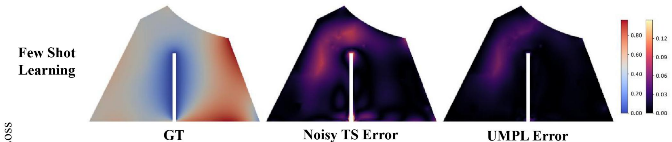
(a) Correlation Plots of C_d



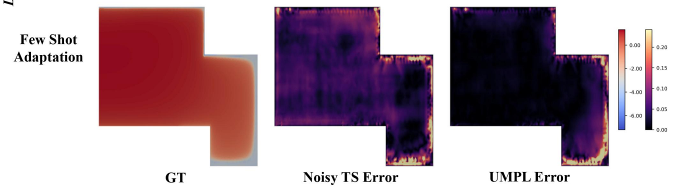
(b) Adaptation Results on Stationary Lid



(c) *Time-dependent Lid* trained with MGN



(d) *Darcy Flow* trained with DeepONet



(e) *Plasma ICP* trained with AeroGTO

Table 1: We compare the performance of our method against four baselines across four different models under a labeled data ratio of $r = 10\%$ for all tasks. **Cyan** , **Yellow** , and **Green** indicate the best, second-best, and worst L_2 loss values, respectively. \ indicates non-convergence.

Model	Method	Darcy Flow	Ahmed	NSM2d	Plasma ICP	Stationary Lid w/o OOD	Stationary Lid w/ OOD	Black Sea In-T	Black Sea Out-T
DeepONet[3]	Supervision Only	7.98e-2	\	3.07e-1	\	6.07e-2	1.69e-1	1.45e-1	2.41e-1
	Pseudo Label[1]	8.37e-2	\	2.82e-1	\	5.65e-2	1.73e-1	1.51e-1	2.35e-1
	Mean Teacher[5]	8.36e-2	\	2.77e-1	\	5.57e-2	1.77e-1	1.46e-1	2.22e-1
	Noisy TS[6]	7.83e-2	\	2.57e-1	\	5.38e-2	1.42e-1	1.24e-1	1.67e-1
	UMPL(ours)	6.94e-2	\	2.23e-1	\	4.57e-2	1.08e-1	9.61e-2	1.43e-1
	PROMOTION	**11.36%**	\	**13.22%**	\	**15.05%**	**23.94%**	**22.50%**	**14.37%**
MGN[4]	Supervision Only	8.06e-2	9.11e-2	5.62e-1	\	3.82e-2	1.02e-1	9.84e-2	1.13e-1
	Pseudo Label[1]	7.33e-2	8.76e-2	4.95e-1	\	2.22e-2	1.13e-1	9.97e-2	1.08e-1
	Mean Teacher[5]	7.33e-2	8.32e-2	4.41e-1	\	1.97e-2	1.07e-1	9.83e-2	1.07e-1
	Noisy TS[6]	6.49e-2	6.92e-2	3.85e-1	\	2.20e-2	9.48e-2	8.51e-2	9.67e-2
	UMPL(ours)	5.74e-2	6.34e-2	3.51e-1	\	1.64e-2	7.91e-2	8.19e-2	8.99e-2
	PROMOTION	**11.55%**	**8.38%**	**8.83%**	\	**16.75%**	**16.56%**	**3.76%**	**7.03%**
Transolver[7]	Supervision Only	6.14e-2	7.69e-2	2.71e-1	1.90e-1	3.69e-2	9.55e-2	9.34e-2	1.12e-1
	Pseudo Label[1]	5.24e-2	7.30e-2	2.35e-1	1.85e-1	1.79e-2	1.08e-1	9.16e-2	9.79e-2
	Mean Teacher[5]	5.34e-2	7.21e-2	2.21e-1	1.72e-1	2.19e-2	1.31e-1	9.26e-2	9.68e-2
	Noisy TS[6]	4.66e-2	5.89e-2	1.79e-1	1.56e-1	1.64e-2	9.53e-2	8.81e-2	9.17e-2
	UMPL(ours)	4.37e-2	5.17e-2	1.51e-1	1.41e-1	1.24e-2	7.32e-2	7.74e-2	8.53e-2
	PROMOTION	**6.22%**	**12.22%**	**15.64%**	**9.61%**	**24.39%**	**23.18%**	**12.14%**	**6.97%**
AeroGTO[2]	Supervision Only	3.82e-2	6.88e-2	1.72e-1	9.30e-2	3.51e-2	9.44e-2	8.95e-2	1.10e-1
	Pseudo Label[1]	3.17e-2	5.85e-2	1.51e-1	7.20e-2	8.75e-3	1.17e-1	8.24e-2	1.03e-1
	Mean Teacher[5]	3.03e-2	5.86e-2	1.45e-1	6.97e-2	2.17e-2	1.24e-1	9.07e-2	1.02e-1
	Noisy TS[6]	2.85e-2	4.71e-2	1.39e-1	6.24e-2	1.09e-2	7.98e-2	7.42e-2	9.38e-2
	UMPL(ours)	2.56e-2	3.63e-2	1.21e-1	5.25e-2	6.91e-3	6.33e-2	6.66e-2	8.12e-2
	PROMOTION	**10.17%**	**22.92%**	**12.94%**	**15.86%**	**21.02%**	**20.67%**	**10.78%**	**13.43%**

References

[1] Pseudo label [Lee et al., ICML 2013]

[2] AeroGTO [Pengwei Liu et al., AAAI 2025]

[3] DeepONet [Lu Lu et al., Nature machine intelligence]

[4] MGN [Tobias Pfaff et al., ICLR 2020]

[5] Mean Teacher [Antti Tarvainen et al., NIPS 2017]

[6] Noisy TS [Antti Tarvainen et al., AAAI 2024]

[7] Transolver [Haixu Wu et al., ICML 2024]

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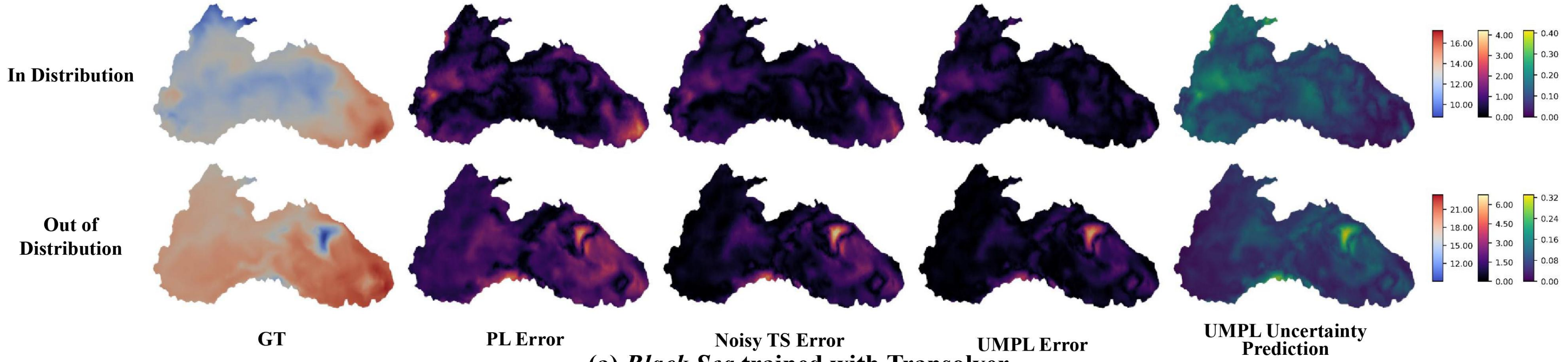
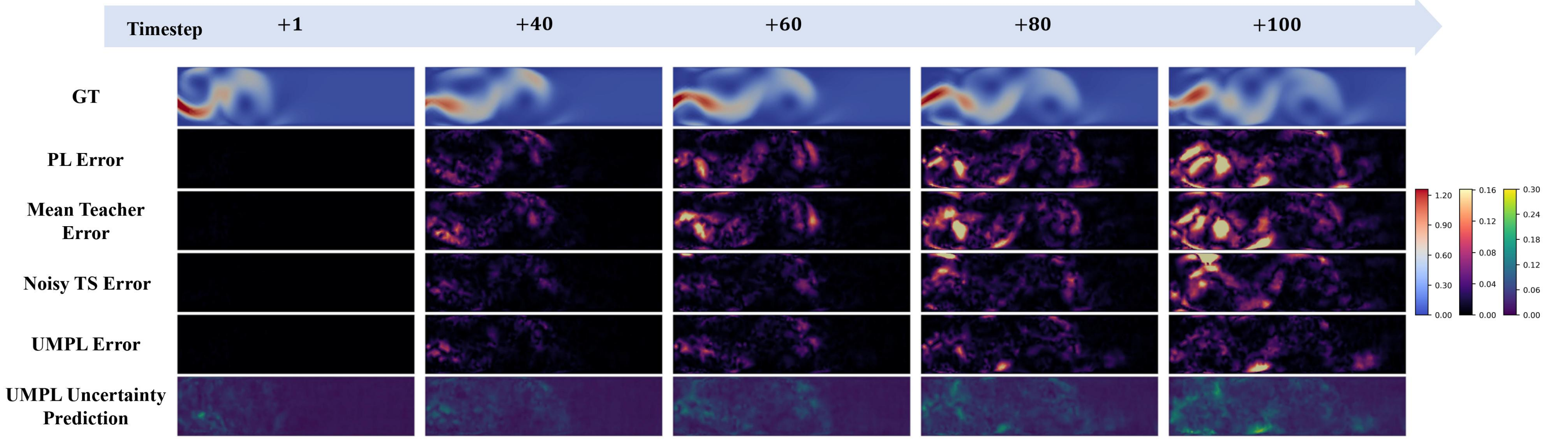
Experiments & Results

Visualization Results across Multiple Methods and Models:



(a) *Black Sea* trained with Transolver



(b) *NSM2d* trained with PhysGTO

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Thank you!

Code& Model: **https://github.com/small-dumpling/UMPL**
Email: **12332063@zju.edu.cn**