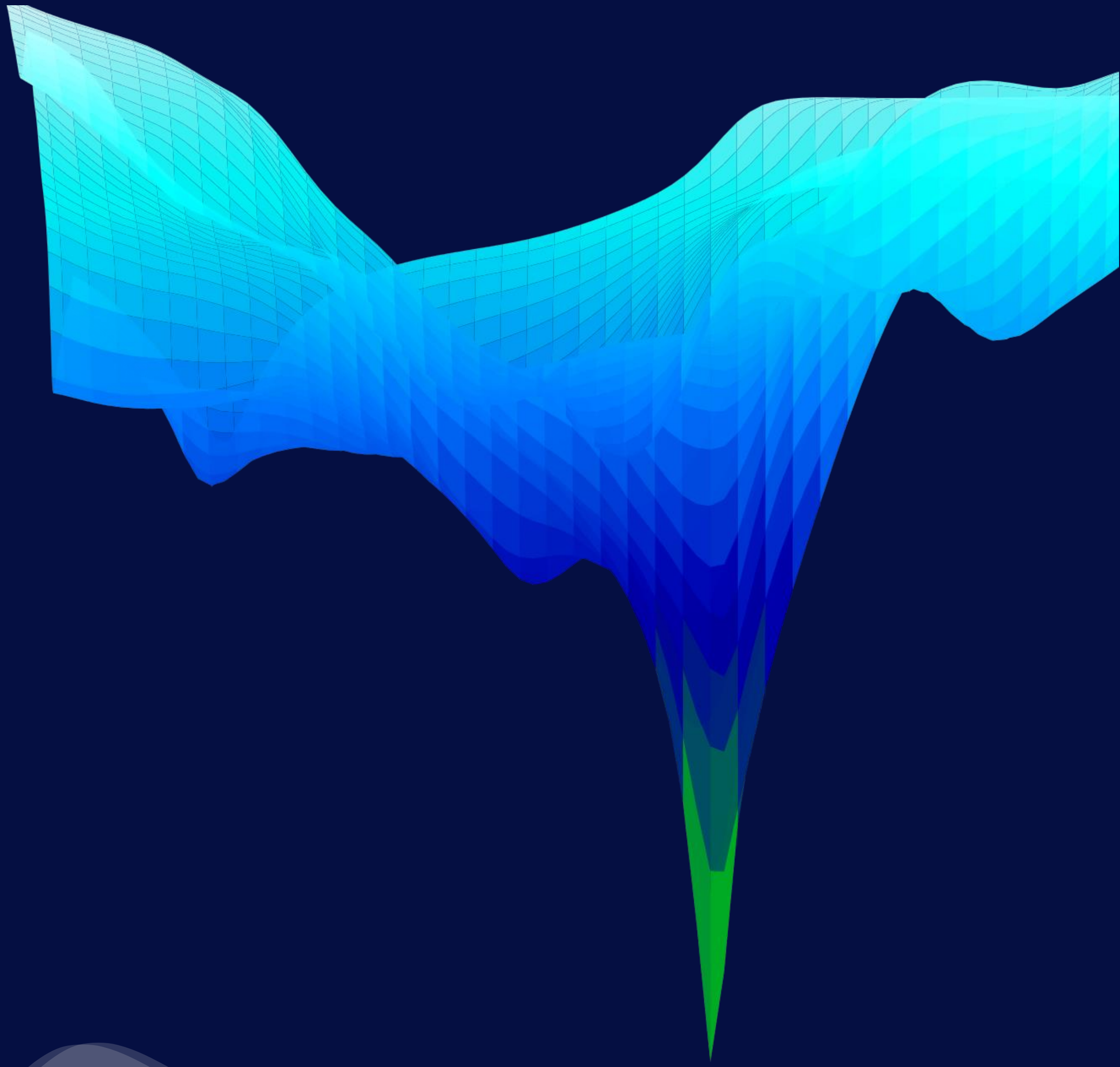
Scientific Machine Learning (SciML) for Solving PDEs

(Case Studies: two-phase flow in porous media)



University of Campinas (Nov. 2024)

A part of INTPART project, supported by NCS2030 - National Centre for Sustainable Subsurface Utilization of the Norwegian Continental Shelf.

IFE NORCE

NCS 2030 National Centre for Sustainable Subsurface Utilization of the Norwegian Continental Shelf

University of Stavanger

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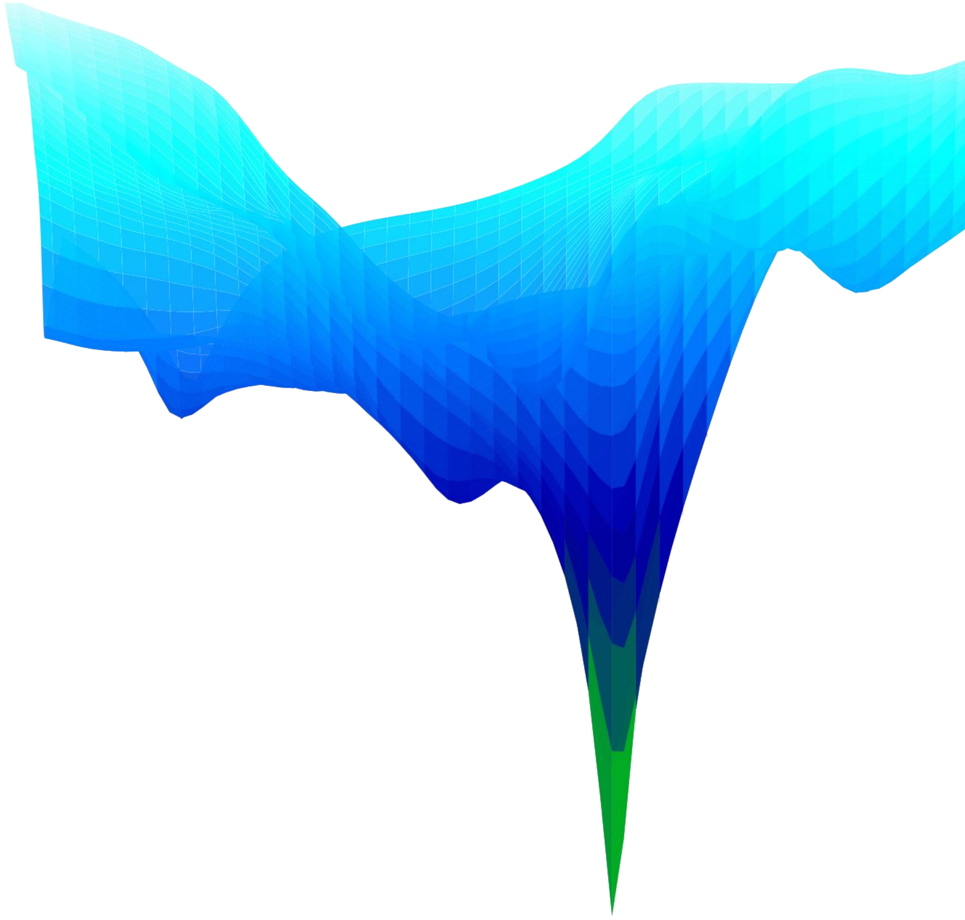
Part 4: Hands-on Experience with PINNs (2.5 hours)



Inverse Calculations on Spontaneous Imbibition Experiments

APPLICATIONS | APRIL 10 2024

Application of Physics-Informed Neural Networks for Estimation of Saturation Functions from Countercurrent Spontaneous Imbibition Tests

Journal Collections: Data Science & Engineering Analytics

Jassem Abbasi; Pål Østebø Andersen

SPE J. 29 (04): 1710–1729.
Paper Number: SPE-218402-PA

https://doi.org/10.2118/218402-PA Article history

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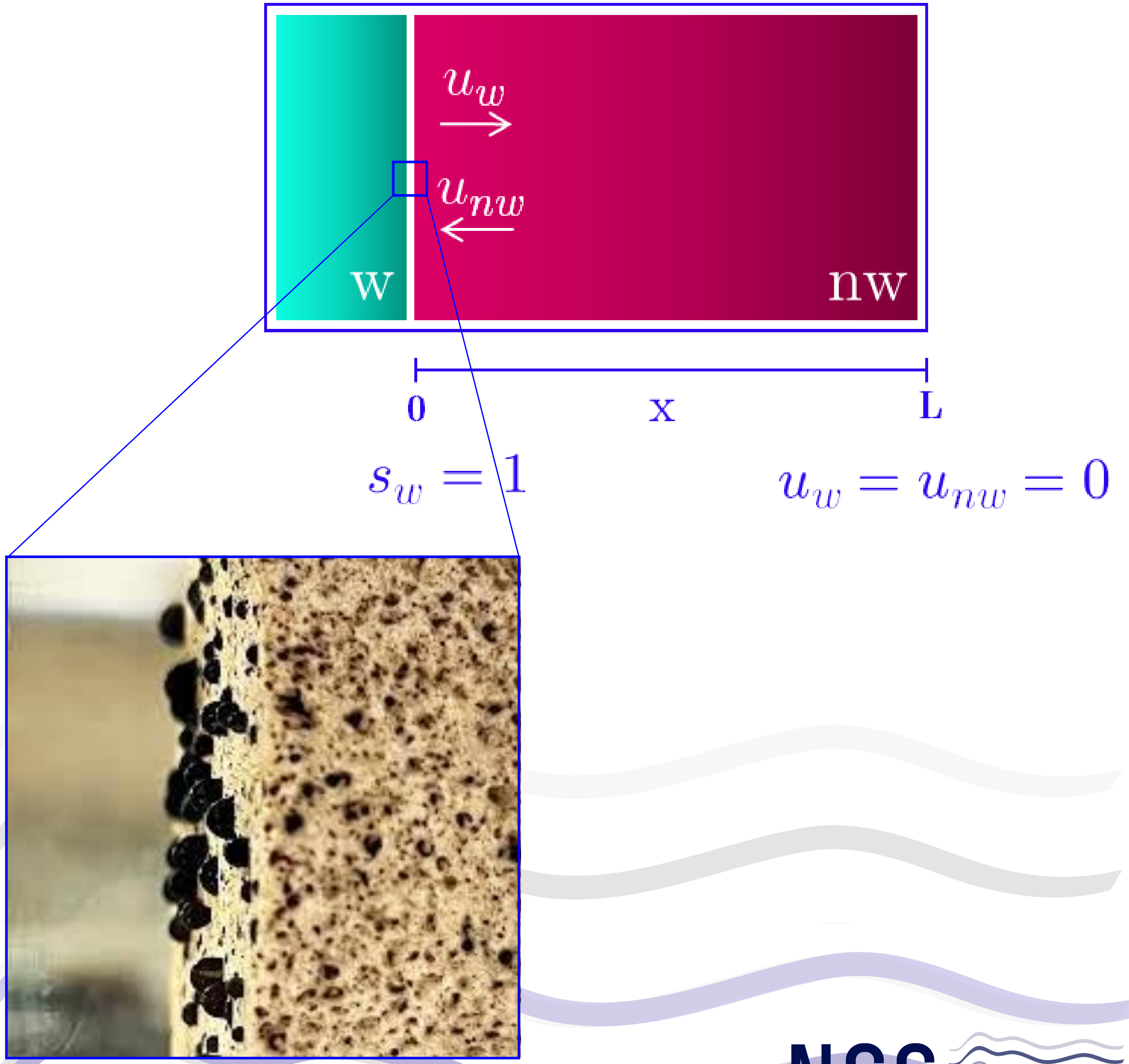
Spontaneous Imbibition

1D COUCSI

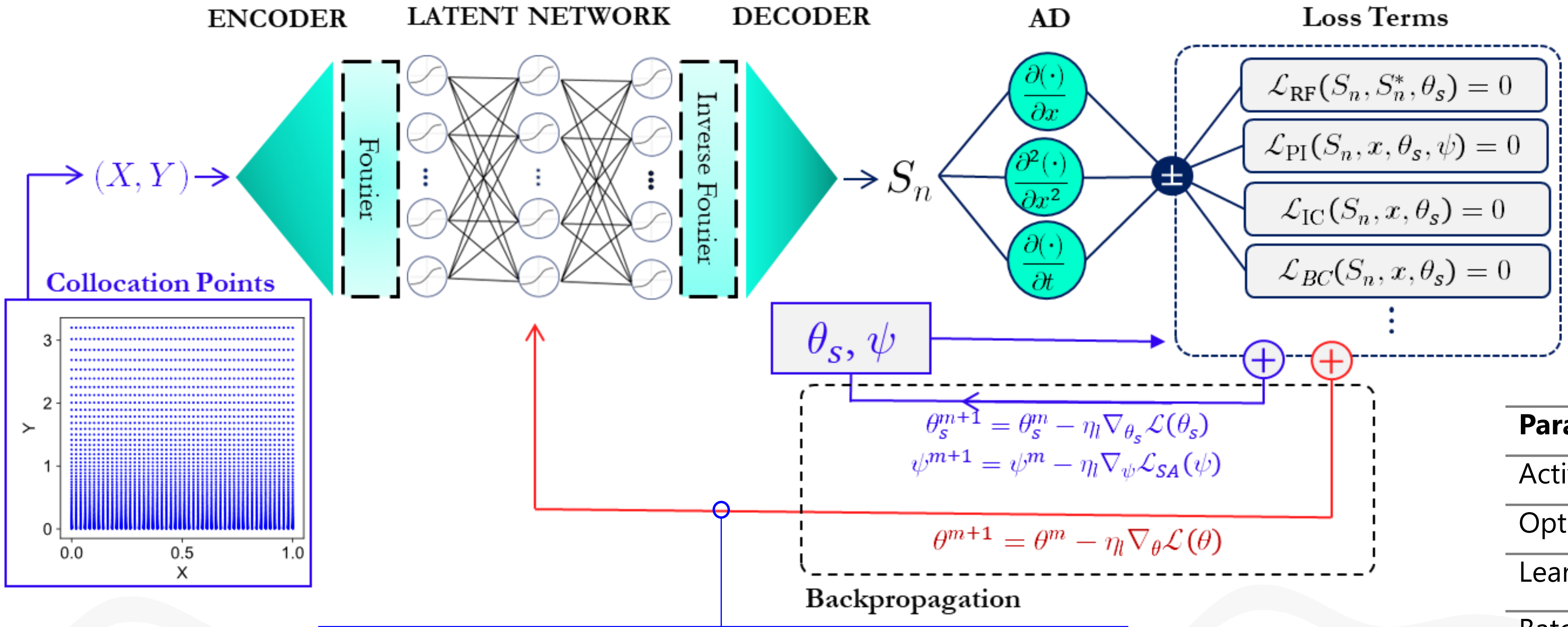
$$u_i = -\lambda_i[\partial_x p_i], \qquad \lambda_i = \frac{Kk_{ri}}{\mu_i}, \qquad (i = w, nw),$$

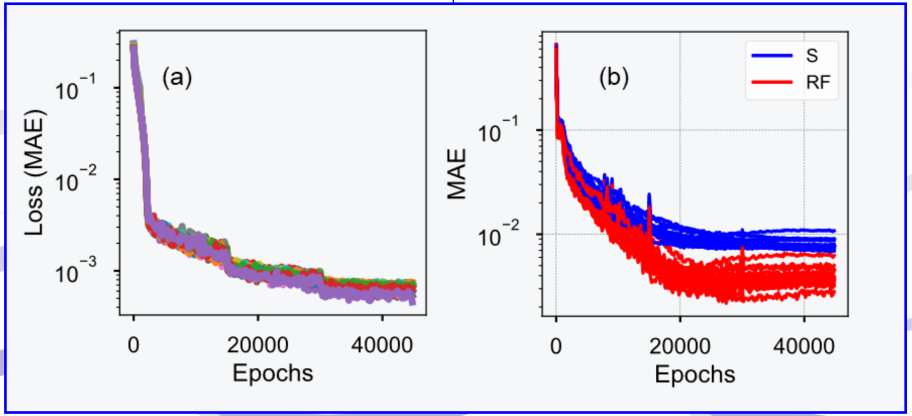
NEGLECT: Viscous and Capillary Forces

Known Parameters			
Parameters	Value	Parameters	Value
K	290 mD	μ_w	1.0 cP
ϕ	0.225	μ_{nw}	2.3 cP
s_{wr}	0.30	s_{nwr}	0.395
s_{wi}	0.395	S_{eq}	0.999
σ_{ow}	21 mN/m	L	0.1 m
Correct Values of Unknown Parameters			
Parameters	Value	Parameters	Value
k^*_{rw}	0.15	J_1	0.3
k^*_{rnw}	0.35	J_2	0.03
n_{w1}	6	n_{nw1}	2.0
n_{w2}	2.5	n_{nw2}	0.5



Model Architecture





$$\partial_T S_n = \partial_X\big(\Lambda_n(S_n)\partial_X S_n\big),$$

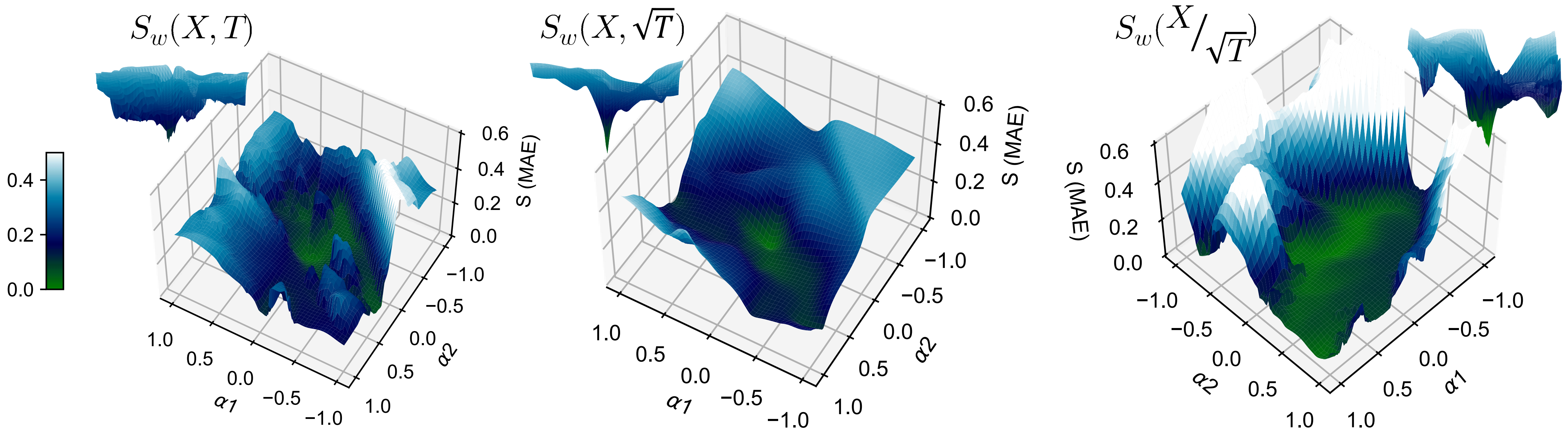
IC: $S_n(X=0,T)=1,$

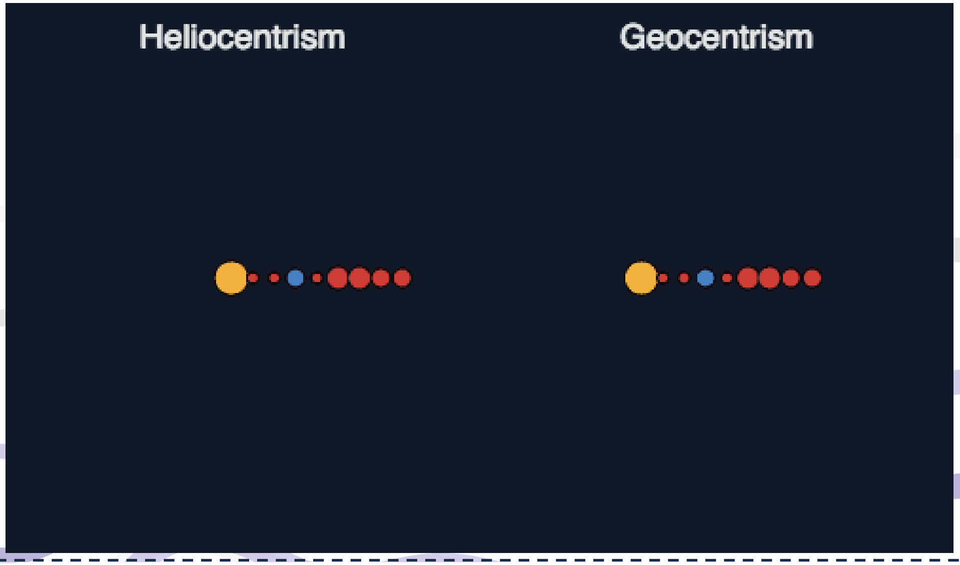
BC: $\partial_X S_n|_{X=1} = 0,$

BC: $S_n(X, T=0) = 0$

Parameter	Value
Activation function	Adaptive tanh
Optimizer	Adam
Learning rate (lr)	2e-4, 8e-5, and 1e-5
Batch size	Full batch
Length and width of the latent MLP layer	(4, 50)
Length and width of the encoder and decoder.	(2, 50)
Loss Weights	Self-adaptive loss-weight

A Comparison of Different Formulations





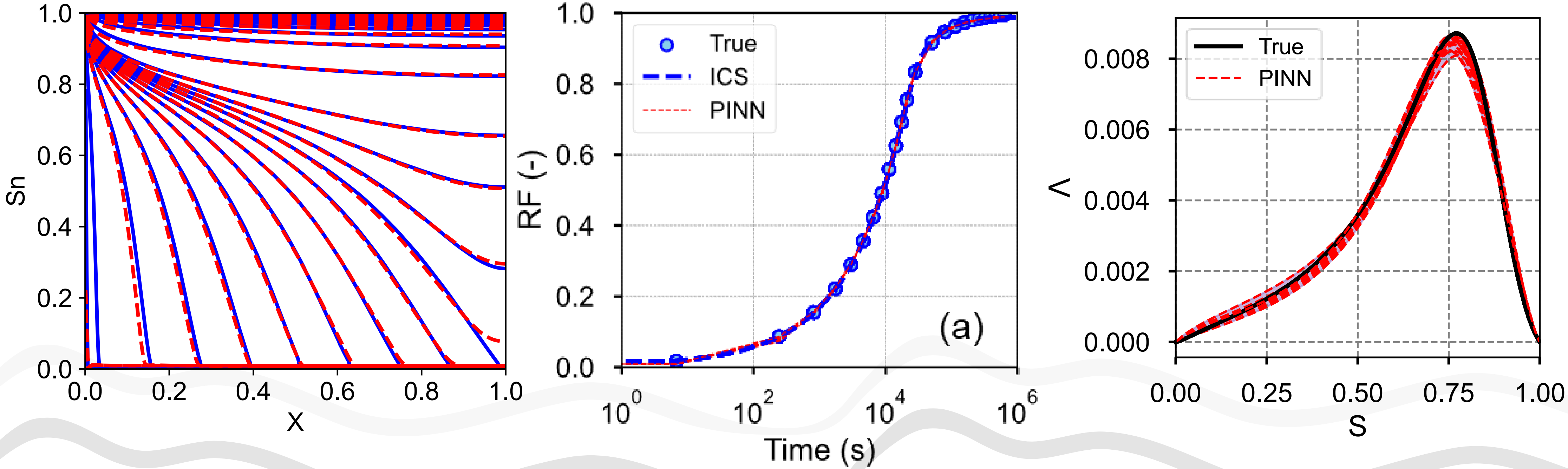
On the impact of data curation in Deep Learning

It tells us how to look at the problem!

Take advantage of Spectral Bias!

About Loss-landscapes: www.losslandscape.com/

Results of Inverse Calculations

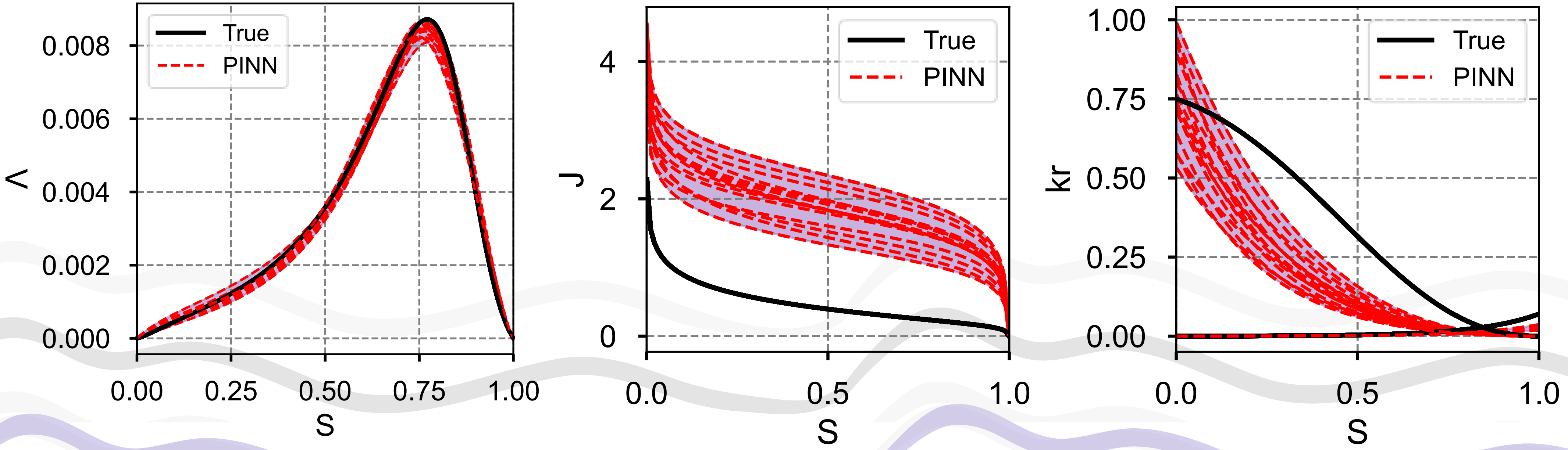


Reference Solution : IORCoreSim (2023)

Unique Solution? Infinite Solutions?

- An ensemble with 20 members to explore the possible uncertainties in the calculations, with random initialization.

- There exists a wide range of k_r and J functions that can match the observed recovery data without coinciding with the correct curves



Abbasi and Andersen (2024) – SPE Journal

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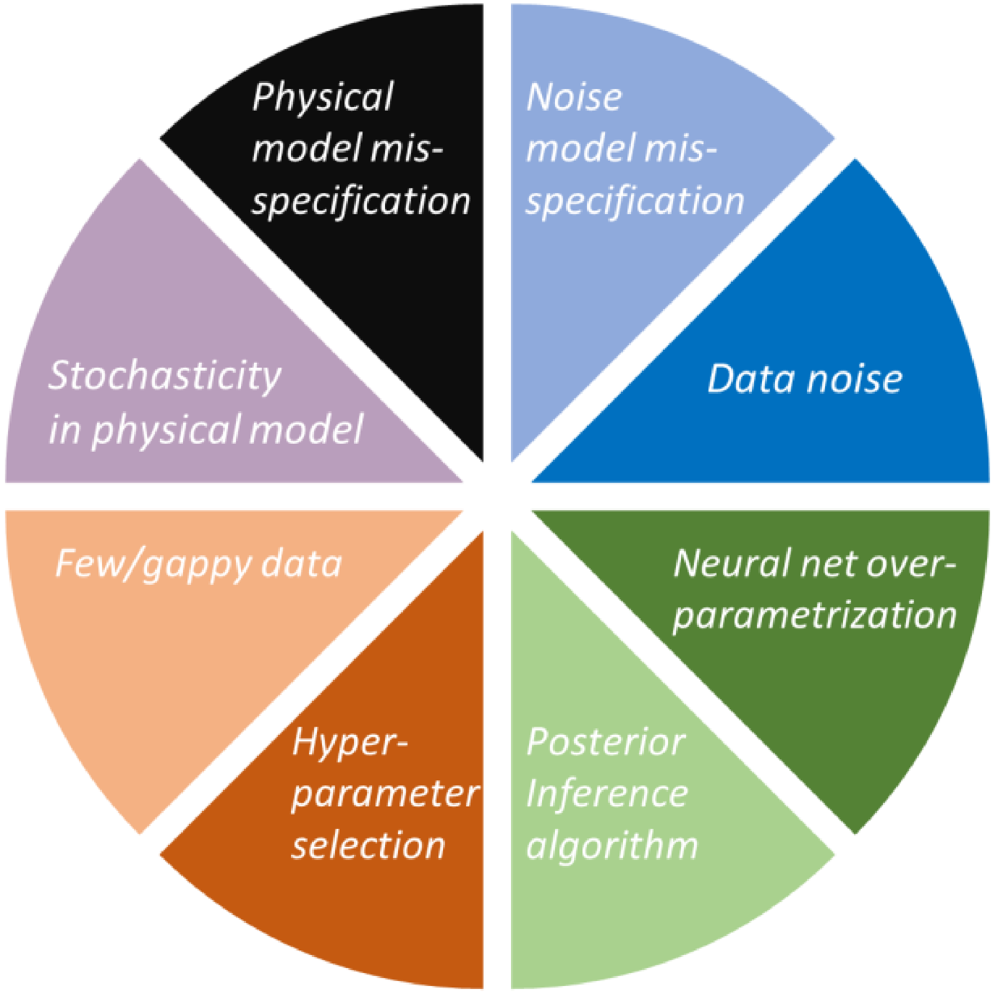
Types of Uncertainty

A qualitative breakdown of total uncertainty describing the contributions from:

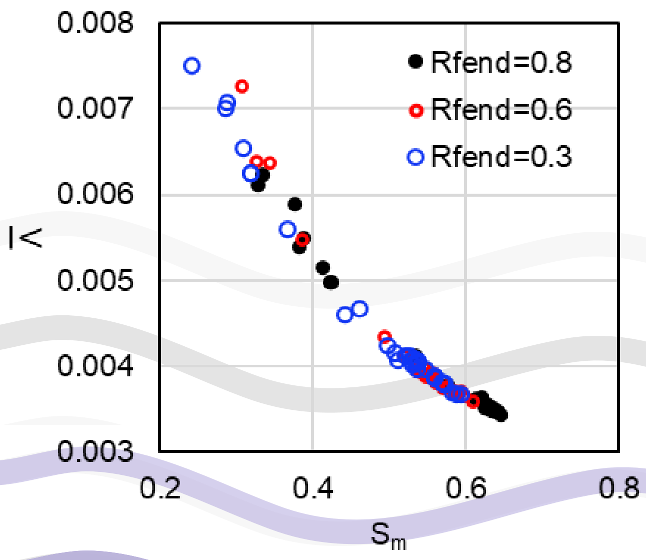
- Data (noisy, gappy);
- Physical models (misspecification, stochasticity);
- Neural networks (architecture,
- Hyperparameters, overparametrization);
- Posterior inference

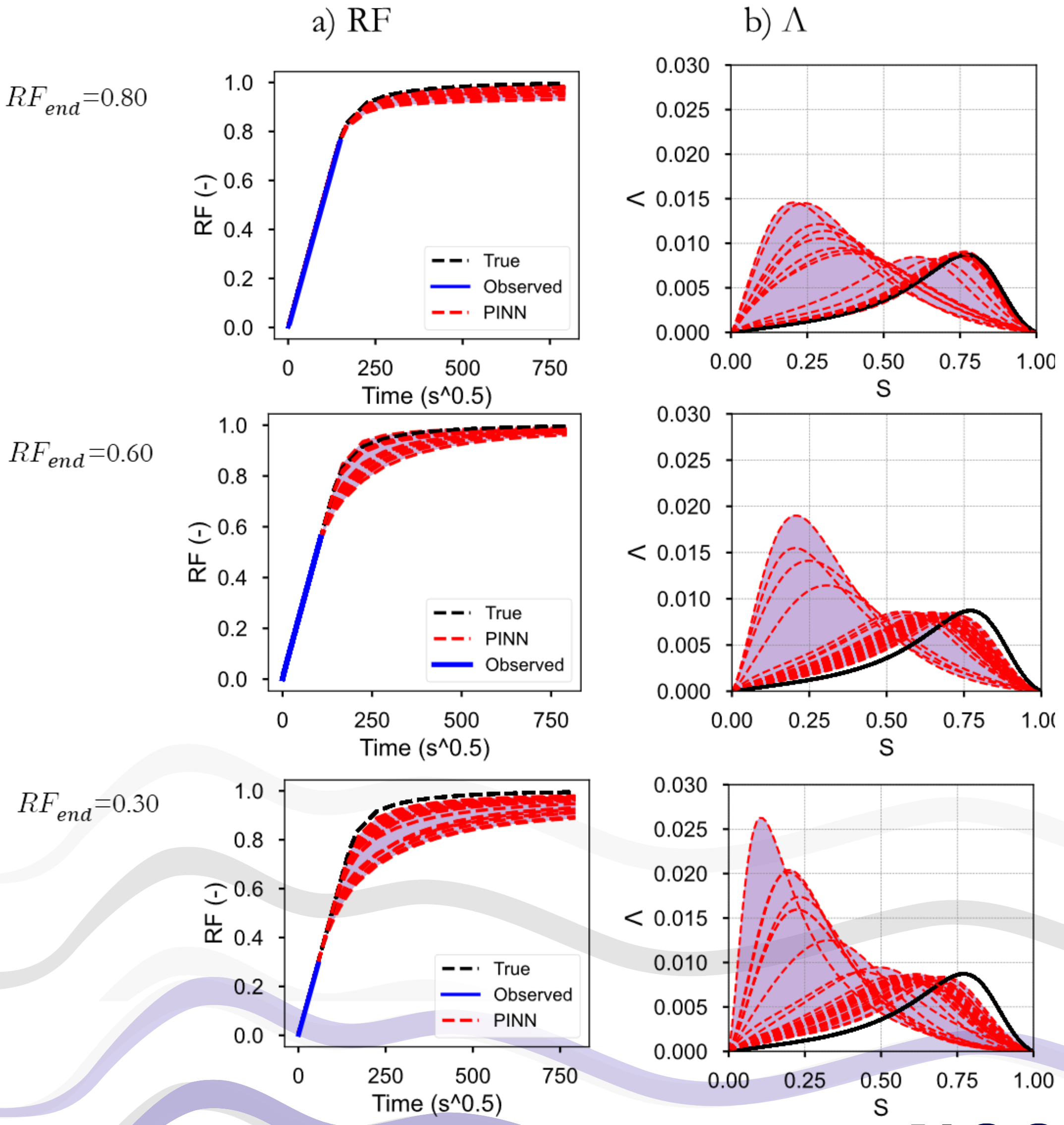


Apostolos F Psaros et al., 2022, Uncertainty Quantification in Scientific Machine Learning: Methods, Metrics, and Comparisons

Incomplete Data (infinite-acting range)

- With more observational data (higher RF_{end}), the errors in the estimated curves reduced.
- If the observed recovery data are proportional with square root of time, there can be a large variation in CDCs explaining the observations.





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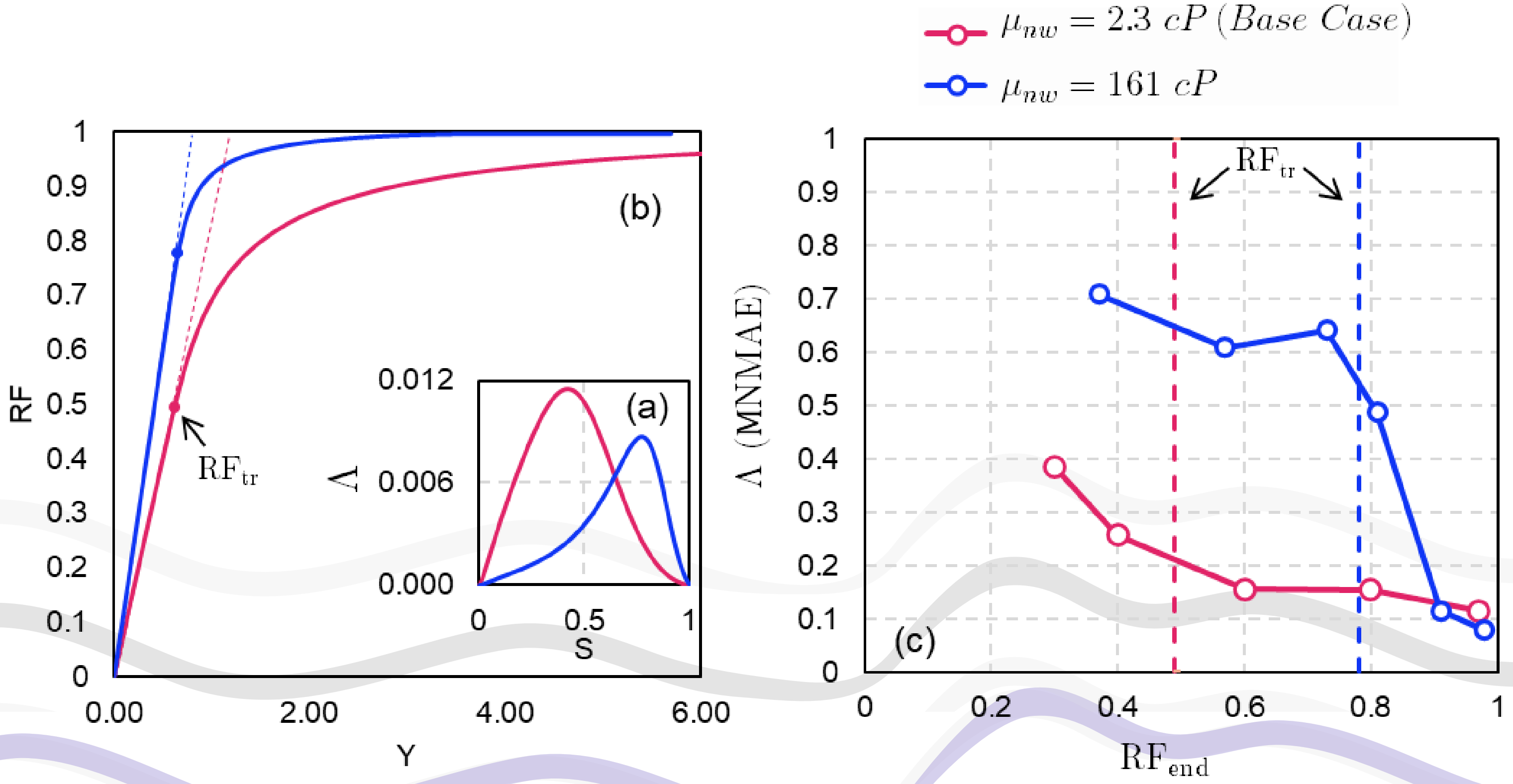
Incomplete Data (finite-acting range)

- We recommend to measure recovery at least until the data are visibly deviating from the initial square root of time profile.



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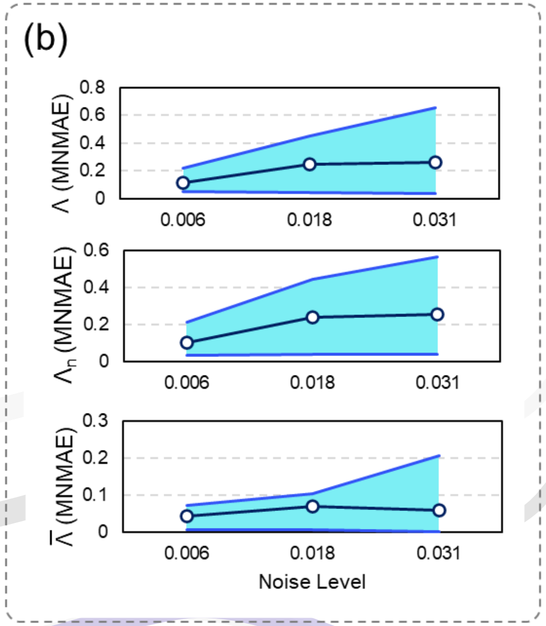
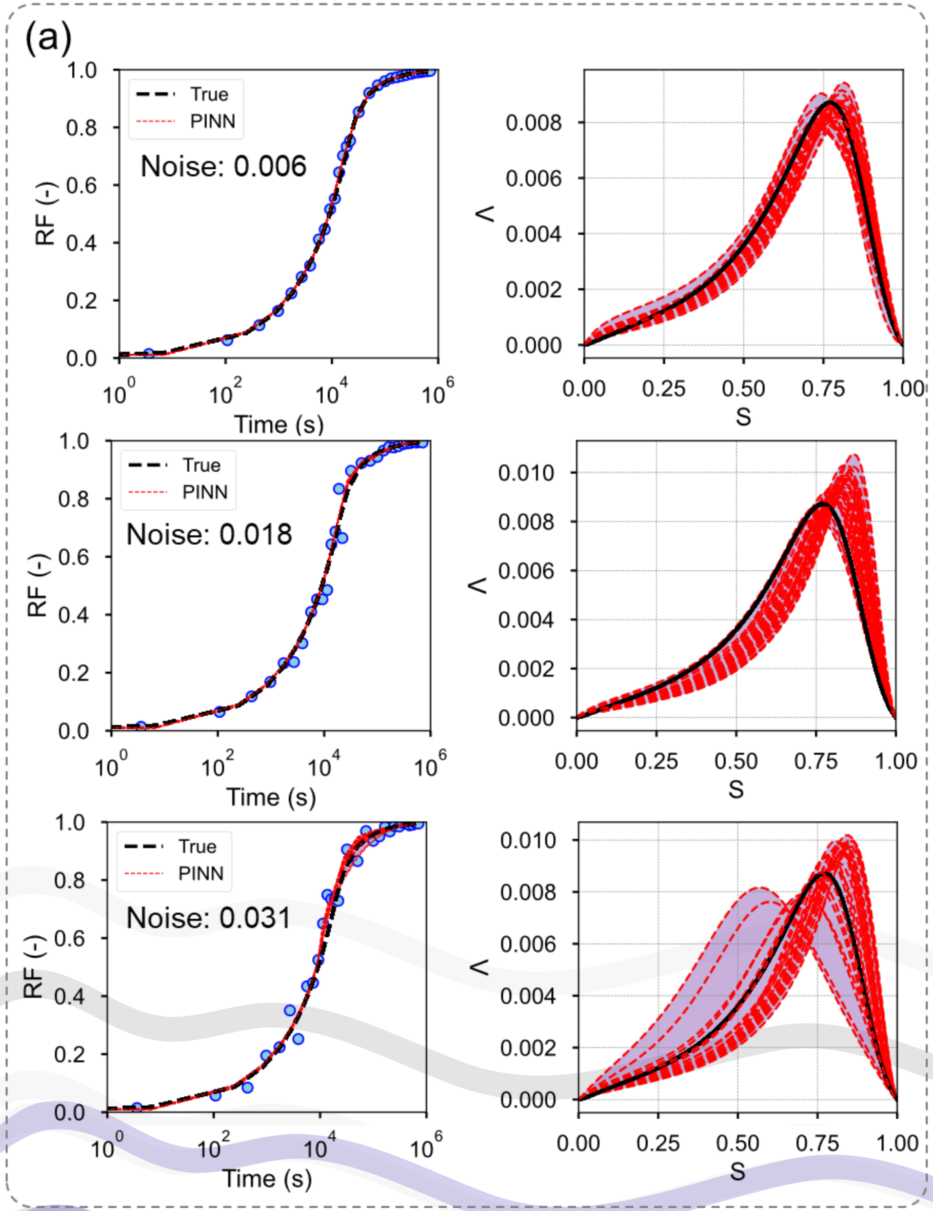
Impact of Noisy Data

- An increased uncertainty in the inverse calculation from increasing the measurement noises.

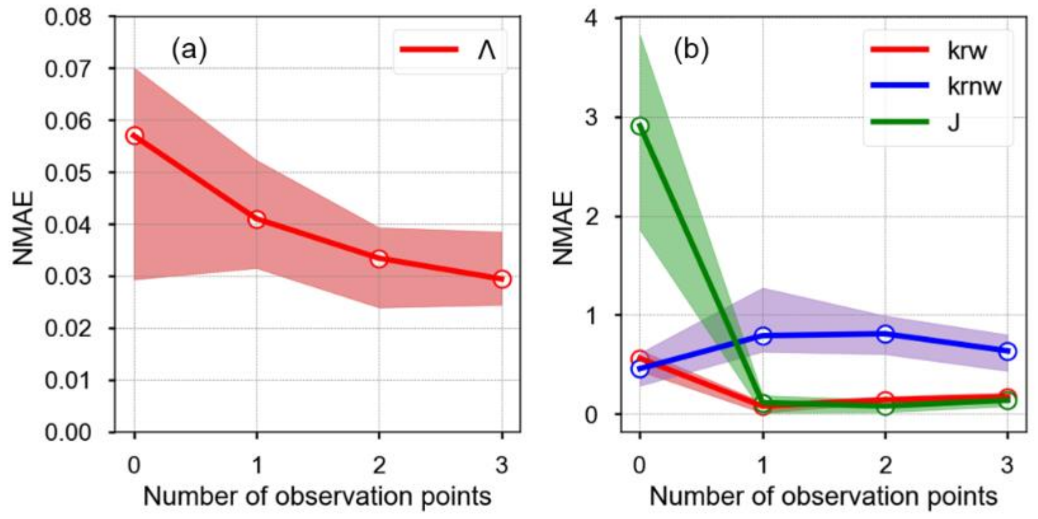


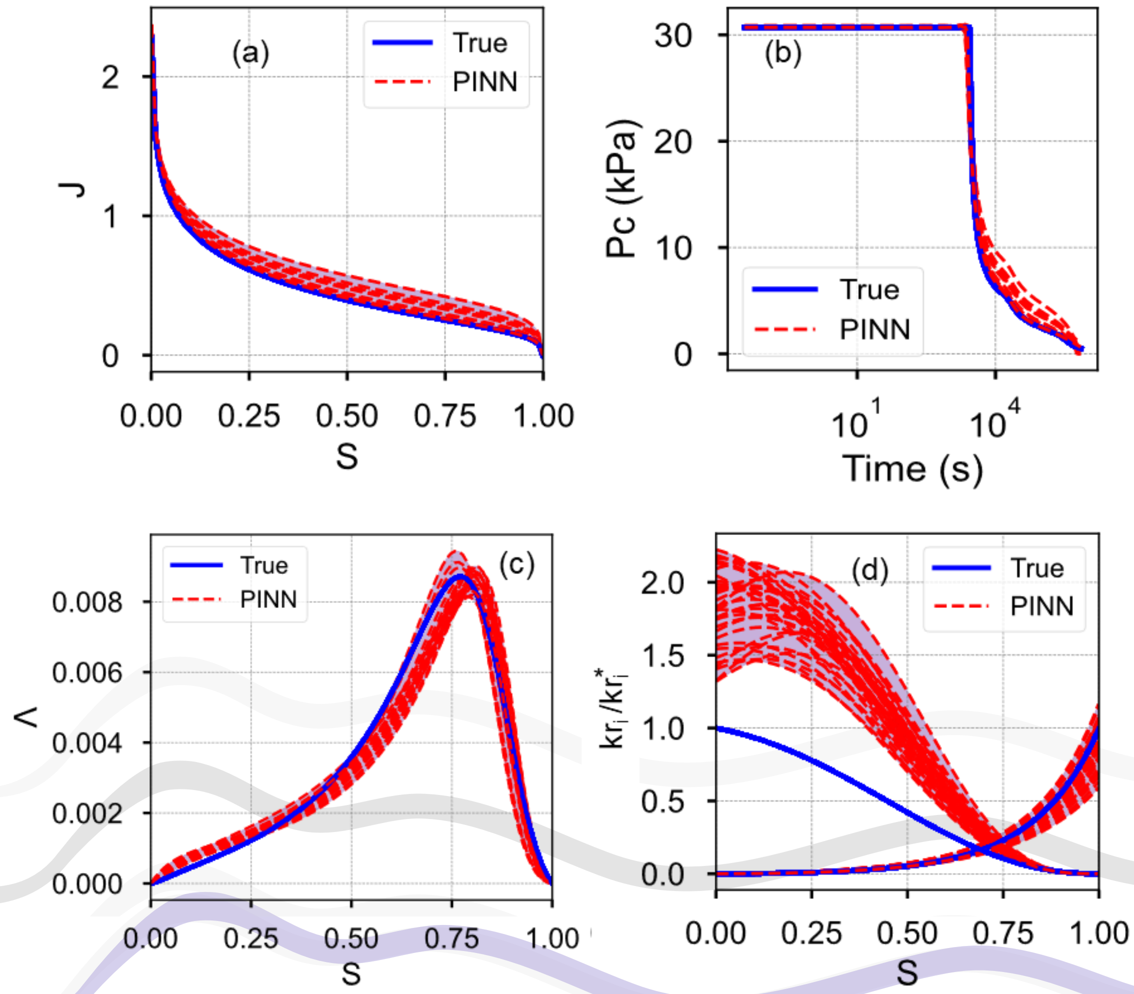


Multi-Fidelity Data (in-situ pressure)

- Utilizing the in-situ measurements helps in reducing the uncertainties in the predictions!

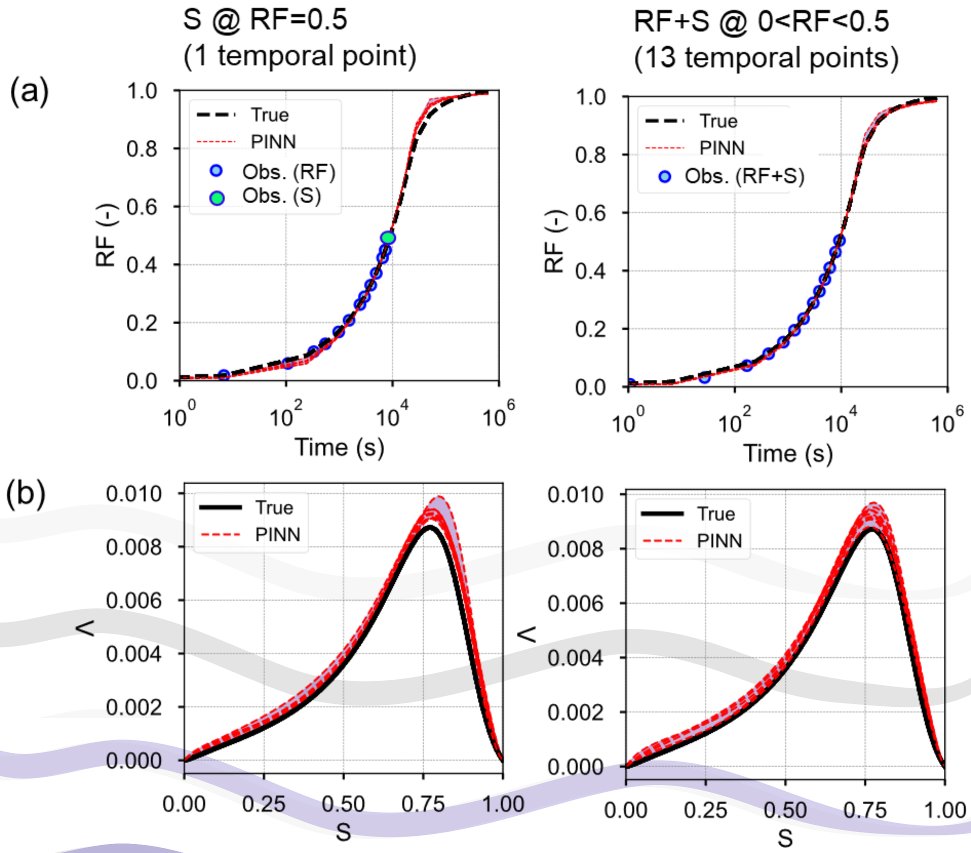
Full recovery curve with local capillary pressure data



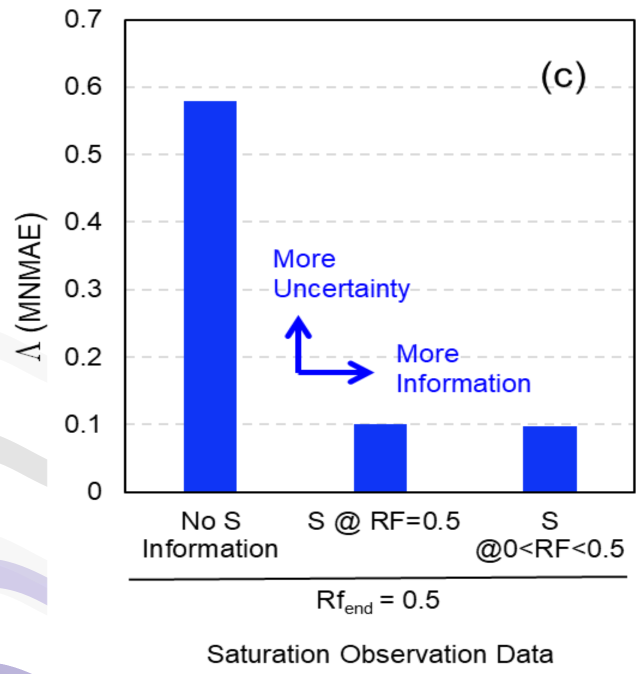


Incomplete + In-situ Data

> combined utilization of RF and in-situ saturation data provide enough information within short time to accurately estimate the CDC curve (allows to significantly reduce laboratory test duration)



> from ~10^6 to ~10^4 seconds



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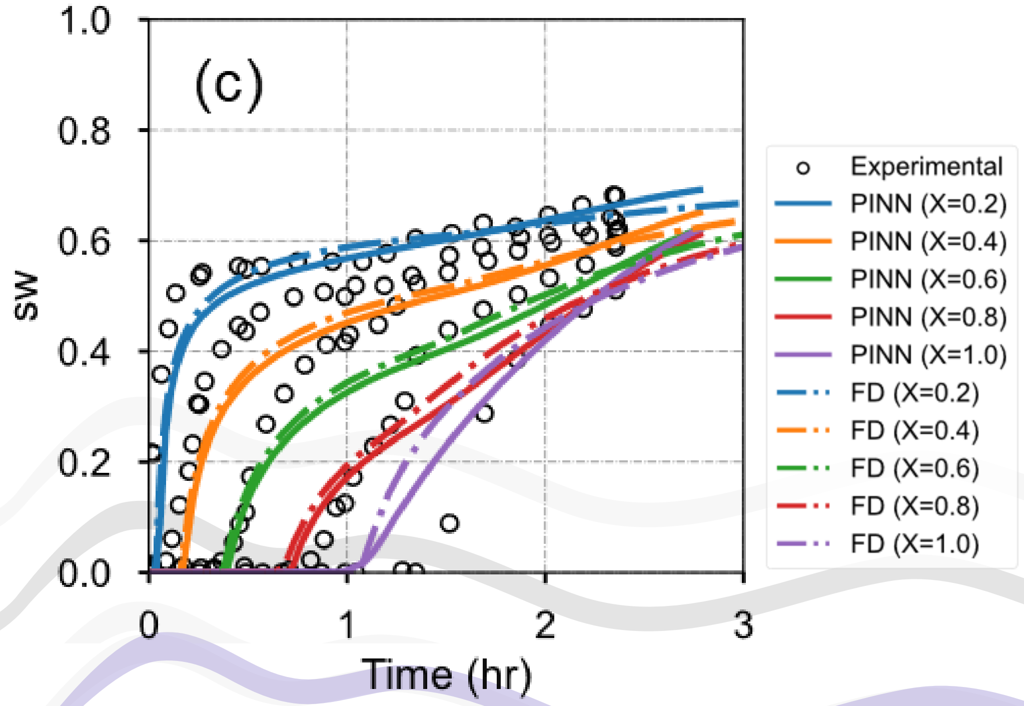
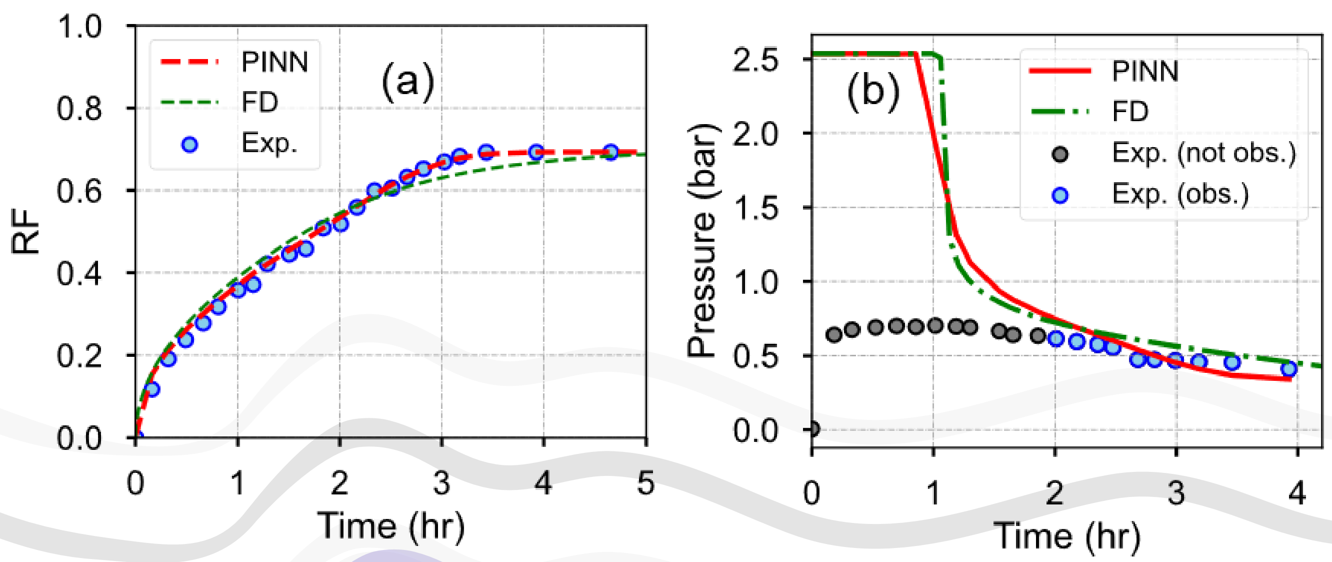
Real Experimental Data

1. The produced volume of non-wetting phase (oil) versus time,
2. Pressure versus time at $X = 1.0$,
3. The local saturation versus time, at positions $X = \{0.2, 0.4, 0.6, 0.8, 1.0\}$.



PINNs vs. IORCoreSim



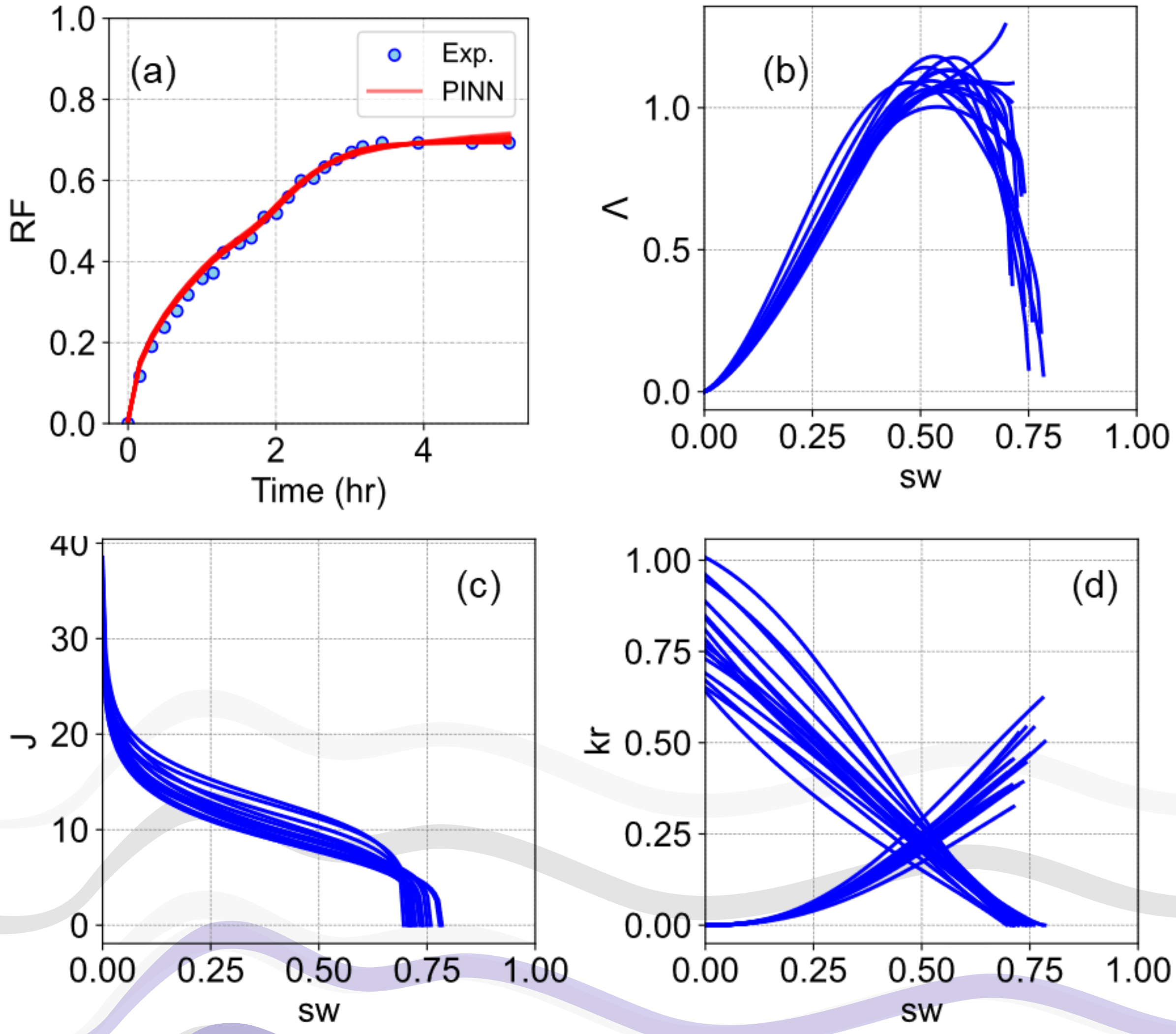
Source of Data: Ruth et al. (2016)

Real Experimental Data

> Access to a full recovery profile and detailed in situ saturation profiles can yield accurate predictions of the CDC

> Noise/uncertainty in the data can be reflected in uncertainty in the estimated CDC function.

Observation Data	MNAAD in Λ	
	Experimental Case	Synthetic Case
RF	0.062	0.042
RF + S + P_c	0.087	0.028



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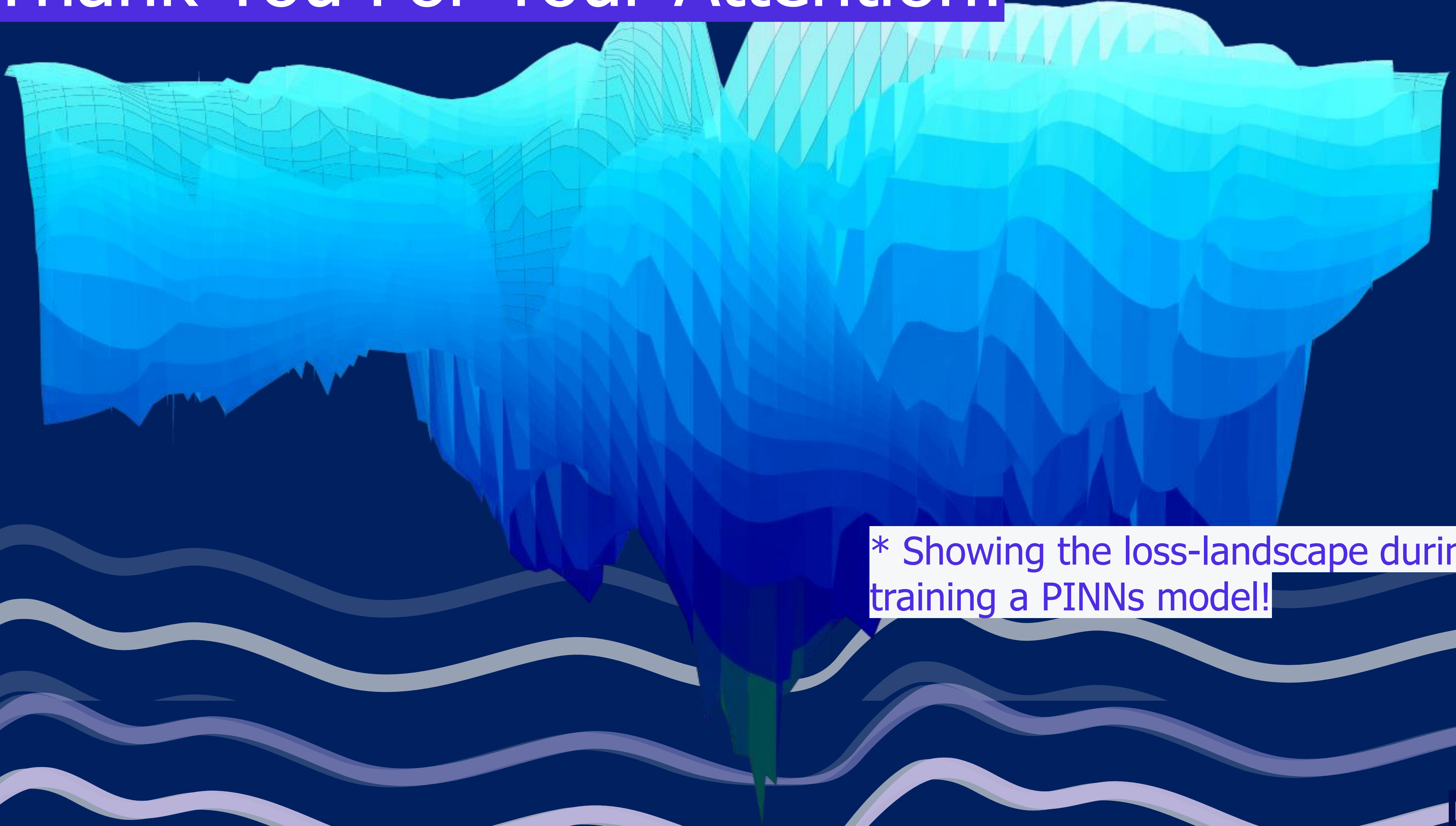
Thank You For Your Attention!



* Showing the loss-landscape during training a PINNs model!