Intro to Physics/Engineering Track

Workshop on AI for Accelerating Fusion and Plasma Science

Ryan McClarren - 28 November 2023

The physics & engineering track shows how ML is used for fusion applications.

- In this track we will see talk from magnetic and inertial confinement fusion applications that use ML to address specific problems.
- One of the themes that comes across is that ML can be a bridge between simulation, experiment, and real time control.
- ML is being used to
  - Estimate variability in potential experimental outcomes,
  - Provide fidelity in areas where reduced-order models are inadequate,
  - Model difficult phenomena in fusion plasmas,
  - Control instabilities in plasma.

Machine Learning Enabled Quantitative Prediction of the First-Ever Igniting Inertial Confinement Fusion Experiment – Bogdan Kustowski

<u>Motivations</u>

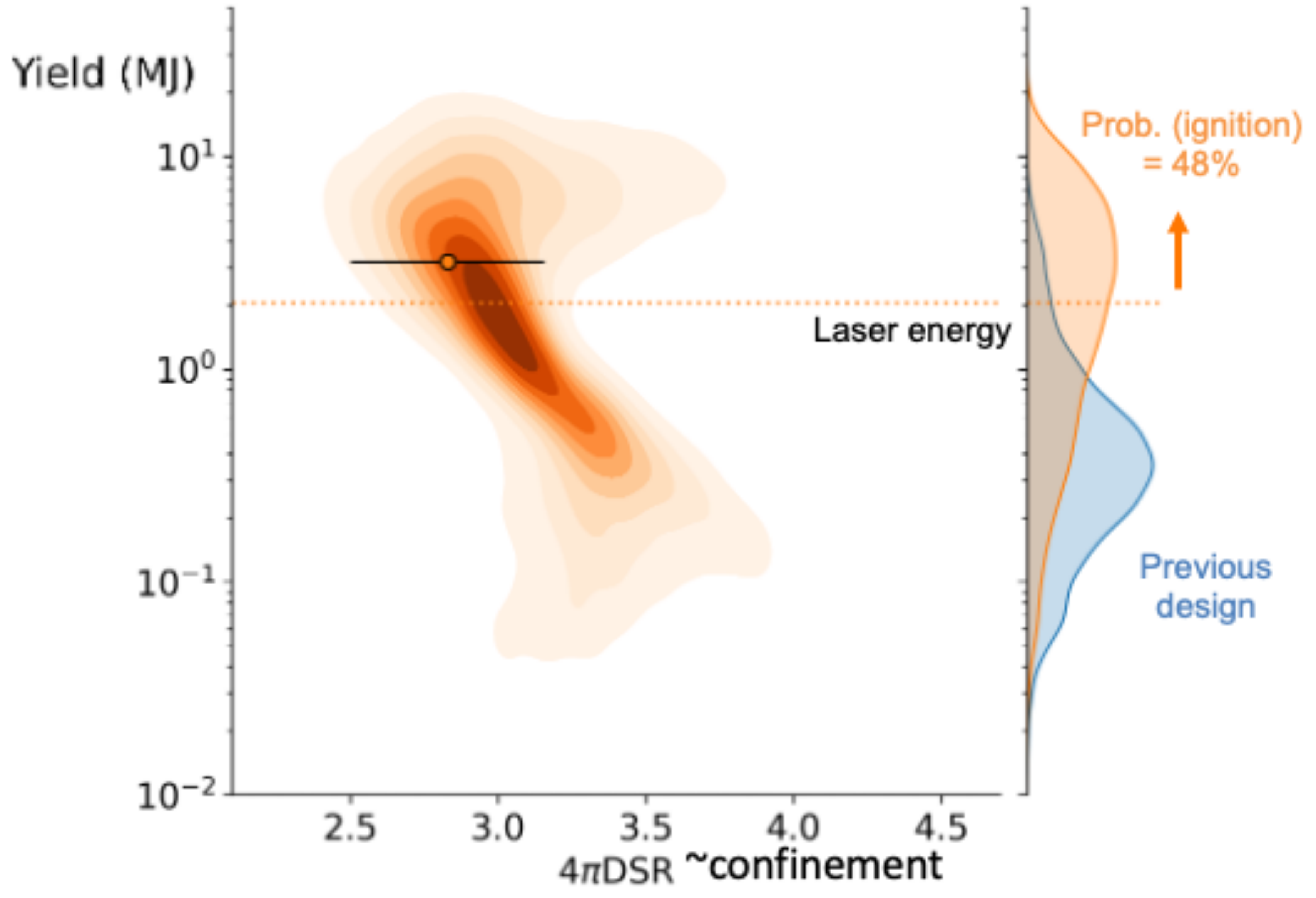
- Make physics-informed prediction with data-informed uncertainty
- Estimate the variability in new designs before they are tested experimentally

<u>Results</u>

- We predicted a high probability of achieving gain > 1 using data-informed uncertainty on the first-even ICF experiment to achieve (NAS) ignition

<u>Challenges</u>

- Only ~10 full scale experiments per year
- Large ensembles of simulations
- Building a statistical model of the variability; transferring it to a new design to make predictions



Overcoming challenges: leveraging machine learnings for efficient modeling of divertor plasmas – Ben Zhu (Lawrence Livermore National Laboratory, USA)

Motivations

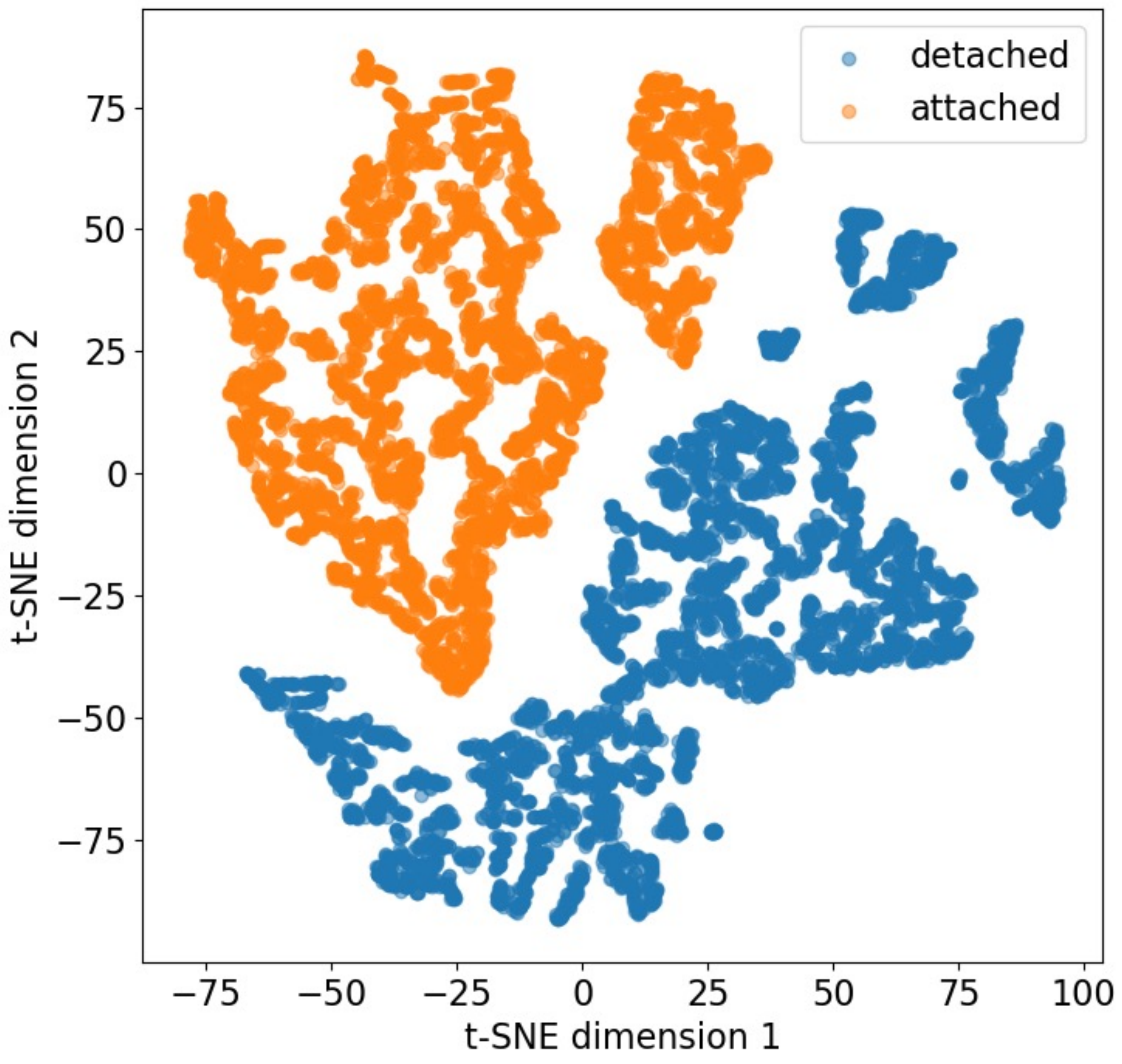
- Magnetic confinement fusion needs fast and reliable divertor plasma models to bridge the gap between fusion performance and heat exhaust. While existing models are either too slow or too crude, the emerging ML technique offers an alternative approach.

Results

- A pilot study confirms that divertor plasma has a low-dimensional latent space representation that could be leveraged for surrogate model development.
- The prototype ML divertor model tailored for KSTAR tokamak detachment control is close for initial deployment.

Challenges

- Divertor plasma contains rich physics and is highly nonlinear; requirements on both model accuracy and speed.



t-SNE visualization of two divertor plasma states (detached, attached) with latent space representations in pilot study.

AI for Fusion

Fast surrogate models for power and particle exhaust in fusion - Sven Wiesen

Motivations

- Accurate simulations of the scrape-off layer plasma in a tokamak employing state-of-the-art numerical models (e.g. SOLPS-ITER) require long convergence times. MHD instabilities (ELM, NTM/TM, RWM, etc) should be avoided to achieve high performance operation
- For design scoping studies or integration of models with the core-plasma, currently used reduced fidelity models lack either accuracy or capabilities.
- Other applications include control specific needs w.r.t. fast model based predictors for the level of plasma detachment in the divertor.

Results

- We created a neural network model by training on a database of reduced fidelity fluid neutral SOLPS-ITER simulations. This database includes a cross-machine size scaling, making the developed model applicable to many devices and scenarios.
- The neural network model is capable of computing the electron temperature in the whole 2D SOL and divertor domain for different physical regimes in less than a second. The deviations between the neural network model and the original simulations are less than 10 percent for the majority of cases.

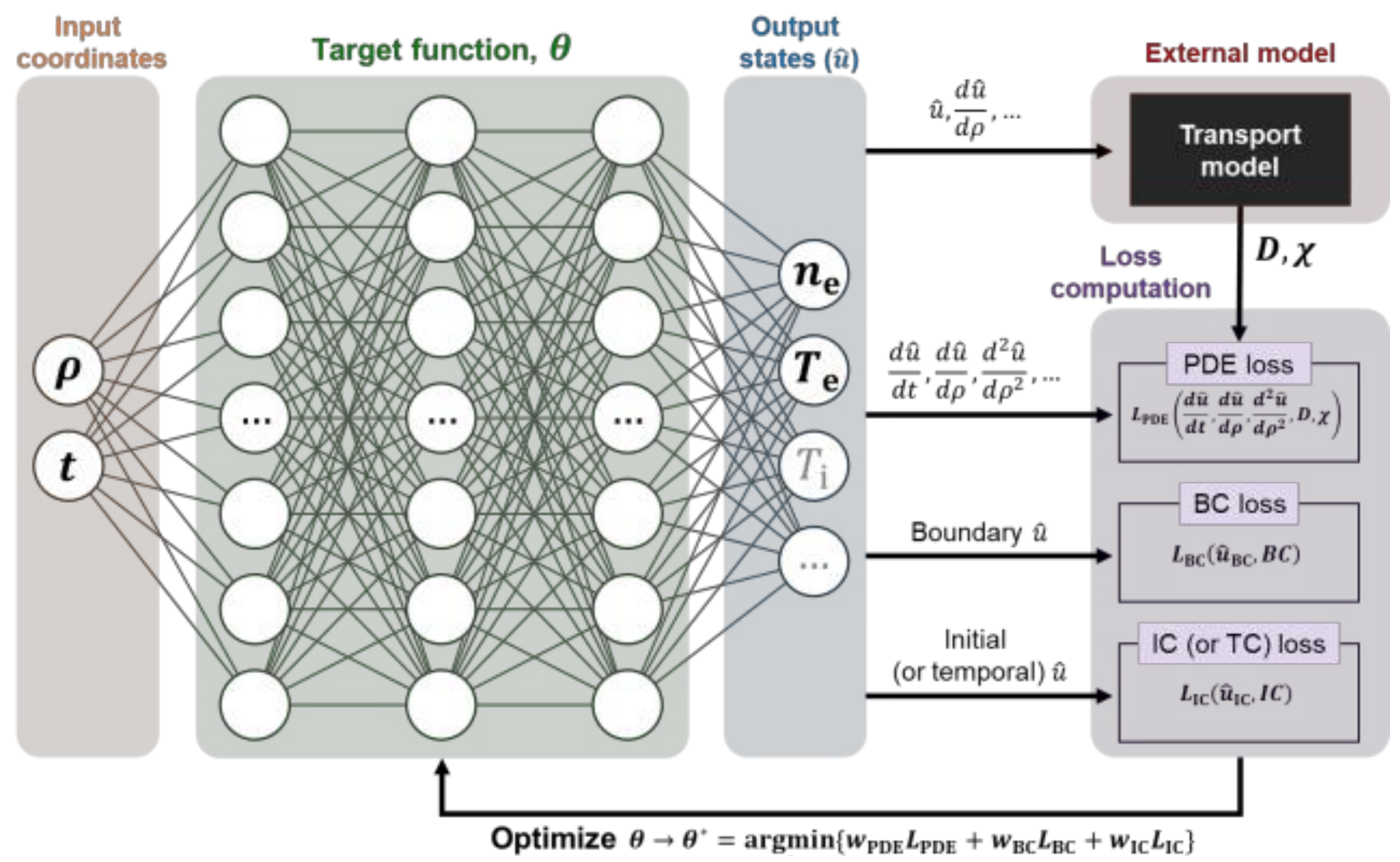
Challenges

- Two approaches are tested to reduce the deviations between the model and the ITER simulations: Scaling of the gas-puff parameters and transfer learning. While both reduce the deviations only transfer learning allows for predicting full 2D plasma profiles on the ITER geometry

Leveraging physics-informed AI computing for simulating the transport of fusion plasmas – Jaemin Seo

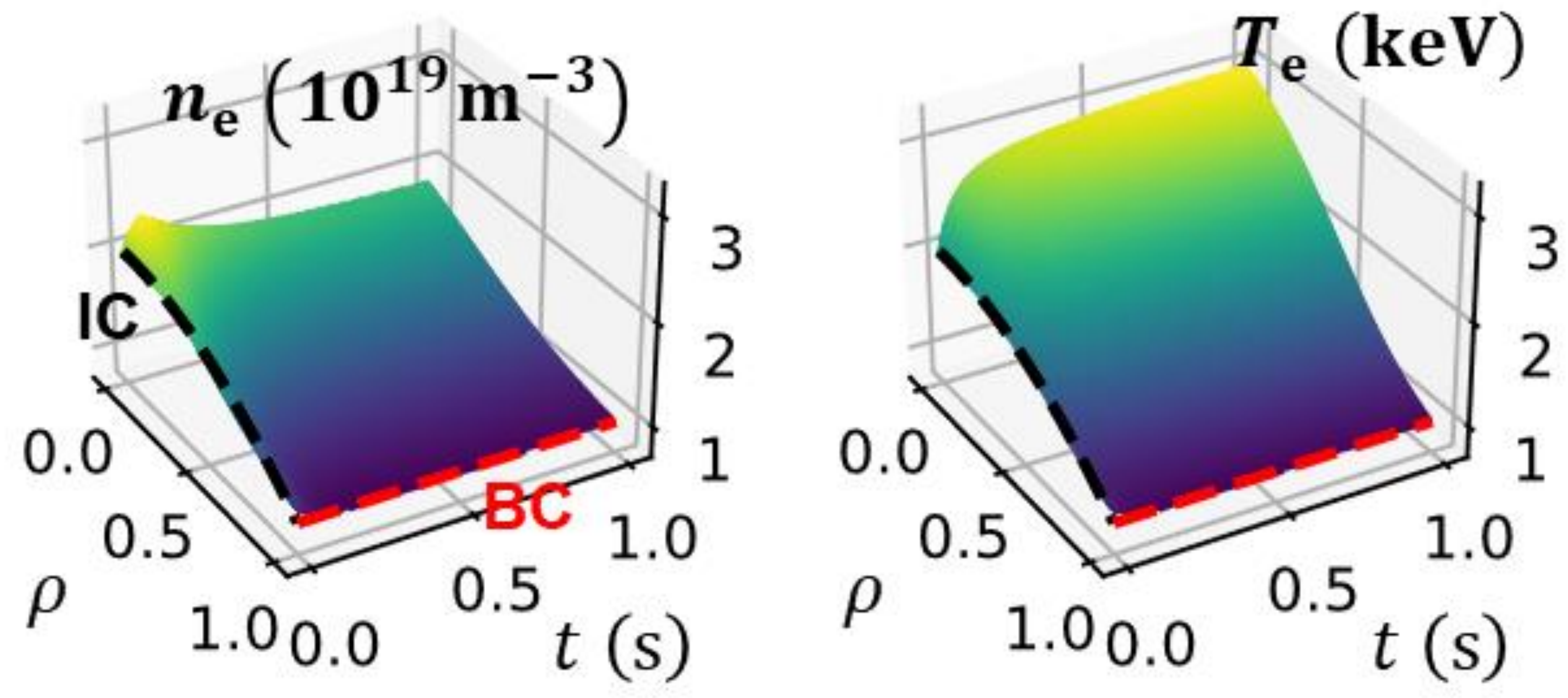
Motivations

- Conventional tokamak transport simulation schemes using FDM has low synergy with parallel computing, mesh-induced numerical instability, and low versality.
- Let's try physics-informed neural network (PINN) for transport simulation.



Results

- Transport simulation with PINN shows potentials of computationa efficiency, numerical stability, and scientific versality.



Challenges

- It still needs future works of dealing with randomness and testing more complicated profiles like H-mode plasmas.

Avoiding plasma instabilities with artificial intelligence – Egemen Kolemen

<u>Motivations</u>

- For stable and efficient fusion energy production using a tokamak reactor, maintaining high-pressure hydrogenic plasma without plasma disruption is essential.
- it is necessary to actively control the tokamak based on the observed plasma state, to maneuver high-pressure plasma while avoiding tearing instability, the leading cause of disruptions. This presents an obstacle avoidance problem for which artificial intelligence (AI) based on reinforcement learning has recently shown remarkable performance.

<u>Results</u>

- We developed a multimodal dynamic model that estimates the likelihood of future tearing instability based on signals from multiple diagnostics and actuators.
- This dynamic model not only predicts the possible onset of tearing instability during tokamak operation but can also be used as a training environment for AI that controls actuators to avoid instabilities.

<u>Challenges</u>

- The tearing instability is difficult to forecast and highly prone to terminating plasma operations.
- We demonstrate AI control based on reinforcement learning to lower the possibility of disruptive tearing instabilities in DIII-D.

AI-driven tokamak control in HL-2A/3 – Shuo Wang

<u>Motivations</u>

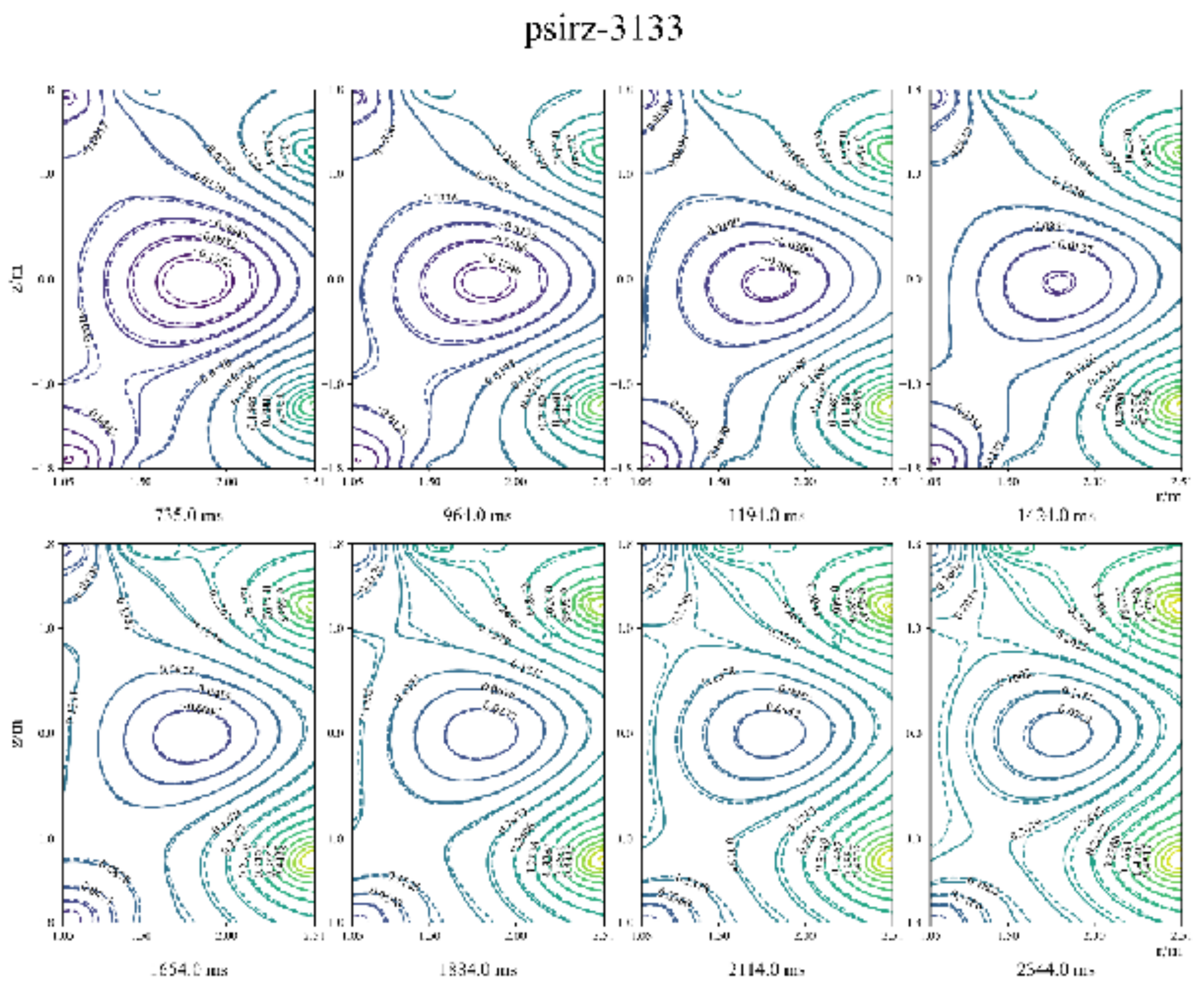
- Disruption with high plasma current is dangerous for HL-3
- MHD instabilities (ELM, NTM/TM, RWM, etc) should be avoid to achieve high performance operation
- A more accurate and real-time equilibrium reconstruction model should be trained for configuration and profile control for HL-3.

<u>Results</u>

- 1.5D CNN+LSTM algorithm is used to predict disruptions in HL-2A/3 in the closed loop
- Several models has been trained to identify the MHD instabilities
- A plasma reconstruction model based on NN is ready to be tested in the iso-flux control in HL-3

<u>Challenges</u>

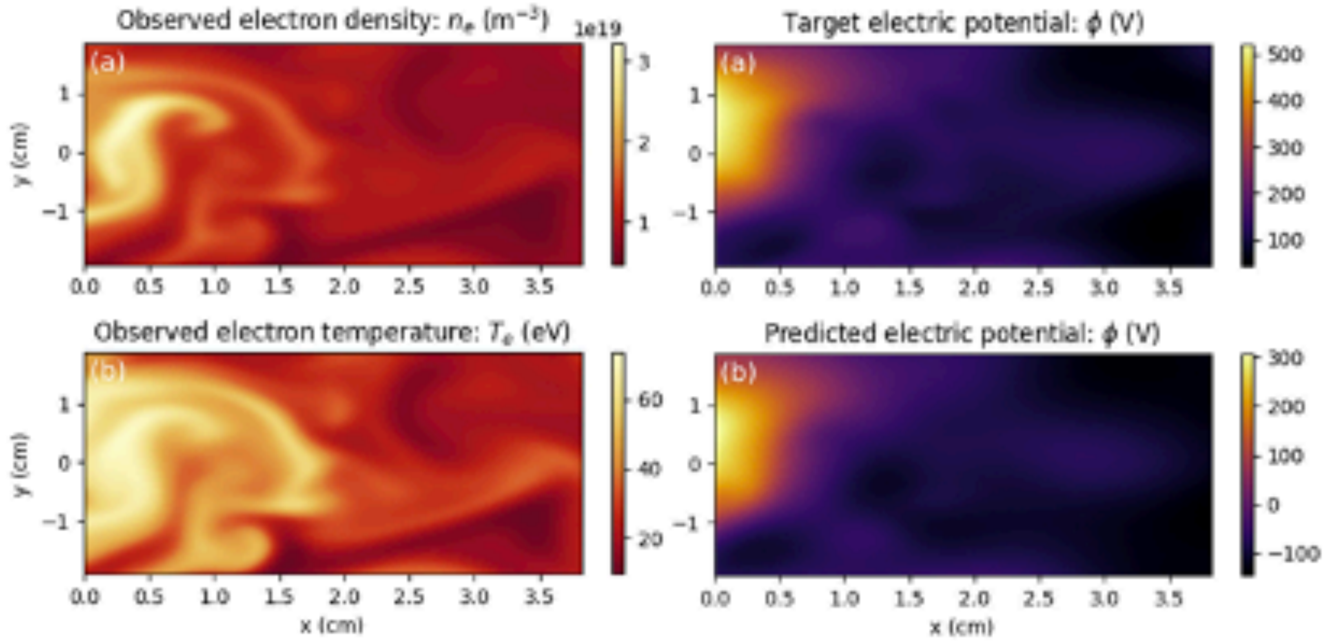
- The total shots and scenarios for now cannot cover all the missions HL-3 aims to. So the OOD of the models challenges a lot for the new experiments in HL-3, especially for the shots with more heating power input in the future.

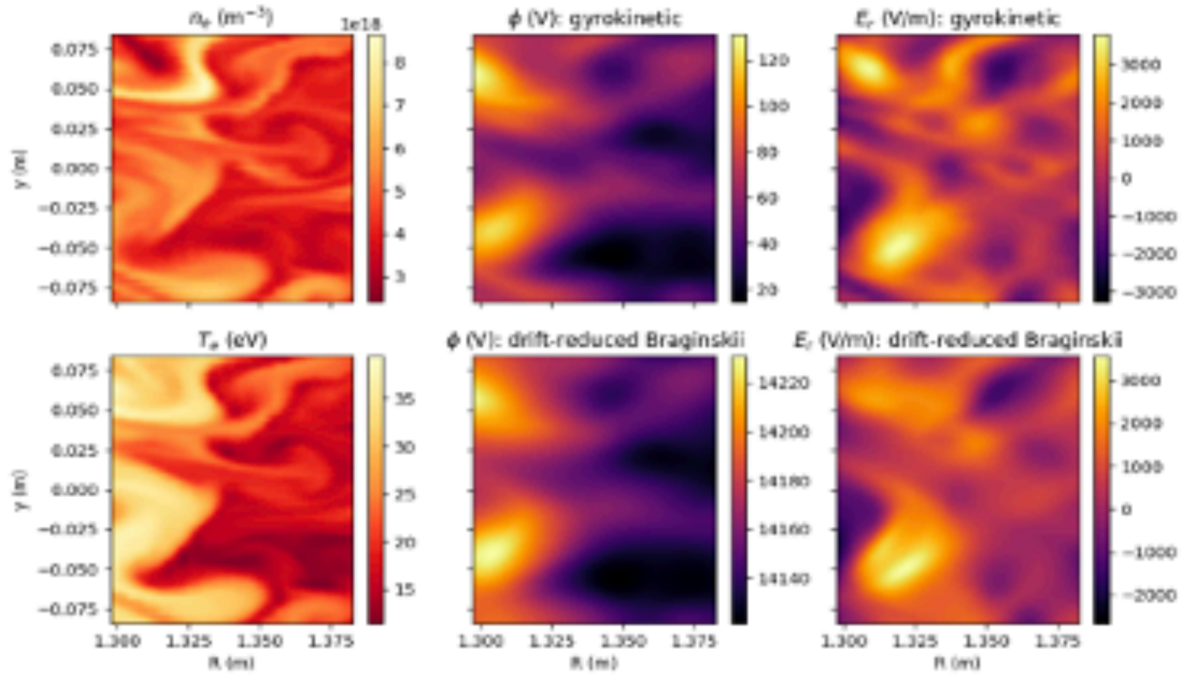


Talk summary: physics + ML = better way to study edge turbulence

PART I: SYNTHETIC PLASMA

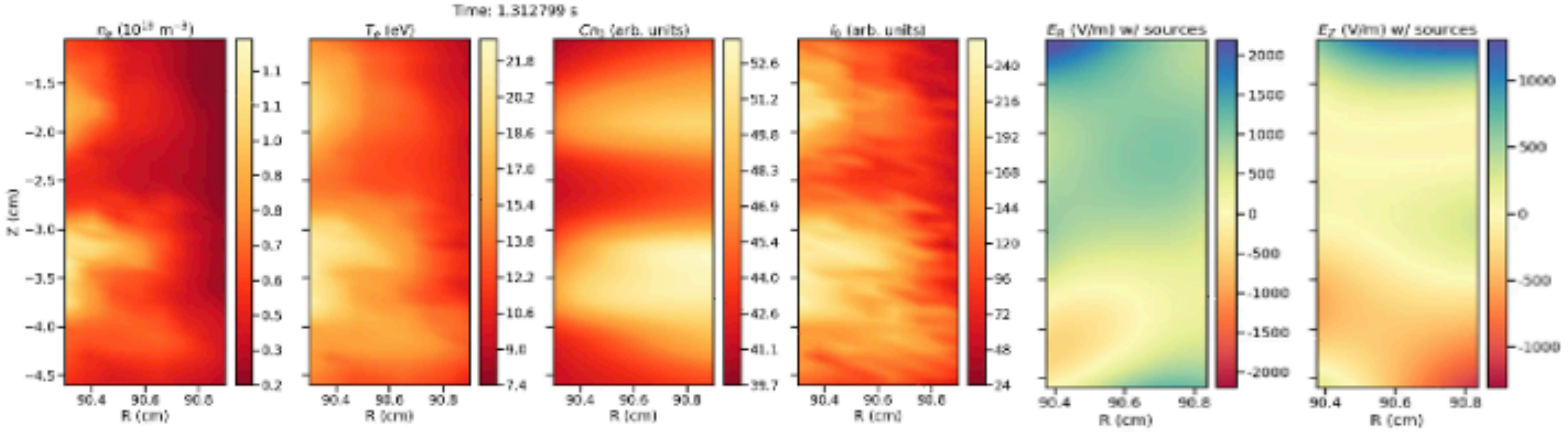
We can predict the turbulent electric field for a widely applied reduced turbulence model given 2D n_e and T_e observations

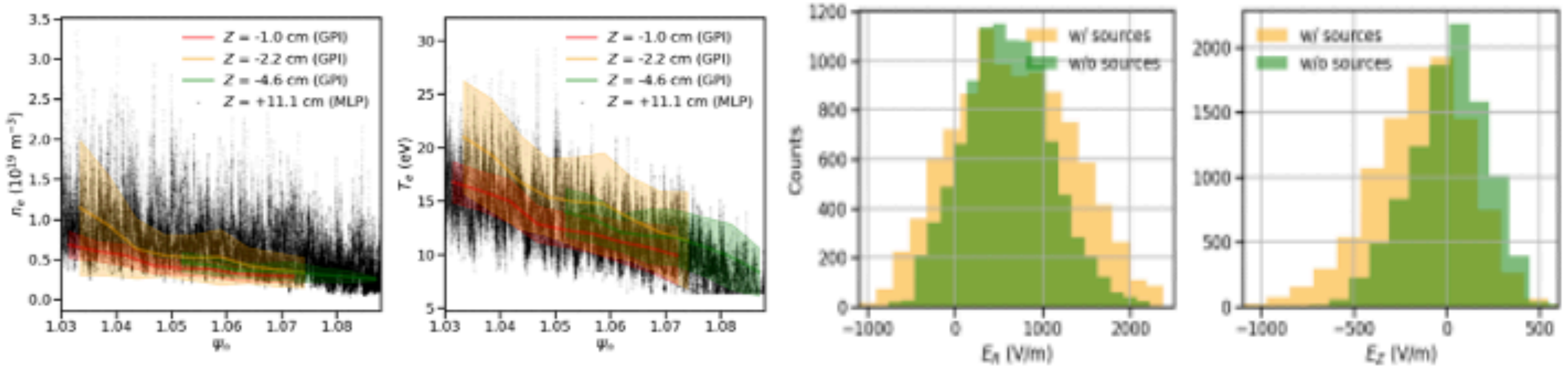




PART II: EXPERIMENTAL PLASMA

We can get 2D n_e and T_e in an experimental plasma for quantitative testing of a reduced turbulence model's electric field predictions





Enjoy the session

- Remember we have a discussion session at the end of the day to see how the running themes in these talks
  - can be applied to other areas,
  - formulate grand challenges, and
  - unify the work of our attendees.