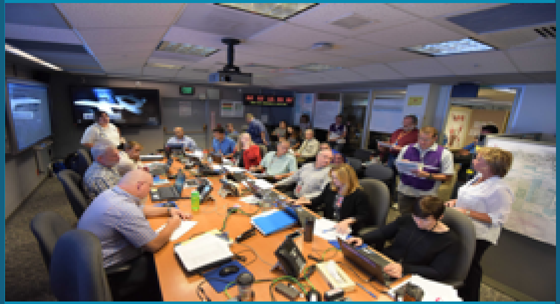
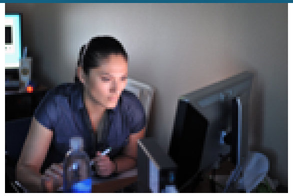
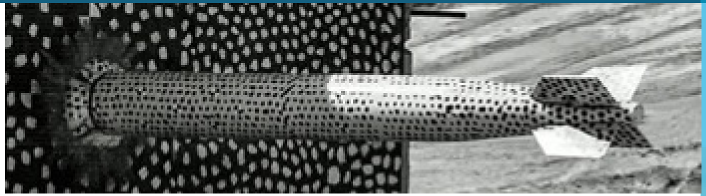
SAND2022-14272C

An autoencoder based reduced order model of low density plasma for optimal experimental design







Session CO05: ICF: Analytical and Computational Techniques

2:00 PM–5:00 PM, Monday, October 17, 2022
Room: Ballroom 111 B

Ravi G. Patel, William E. Lewis, Patrick F. Knapp

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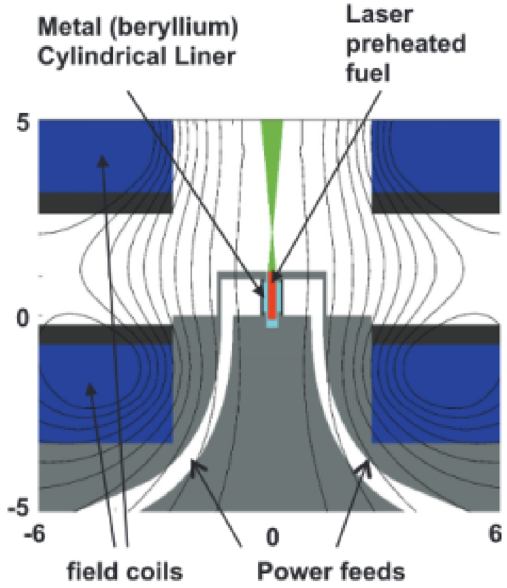
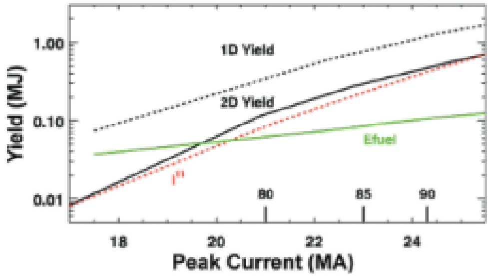
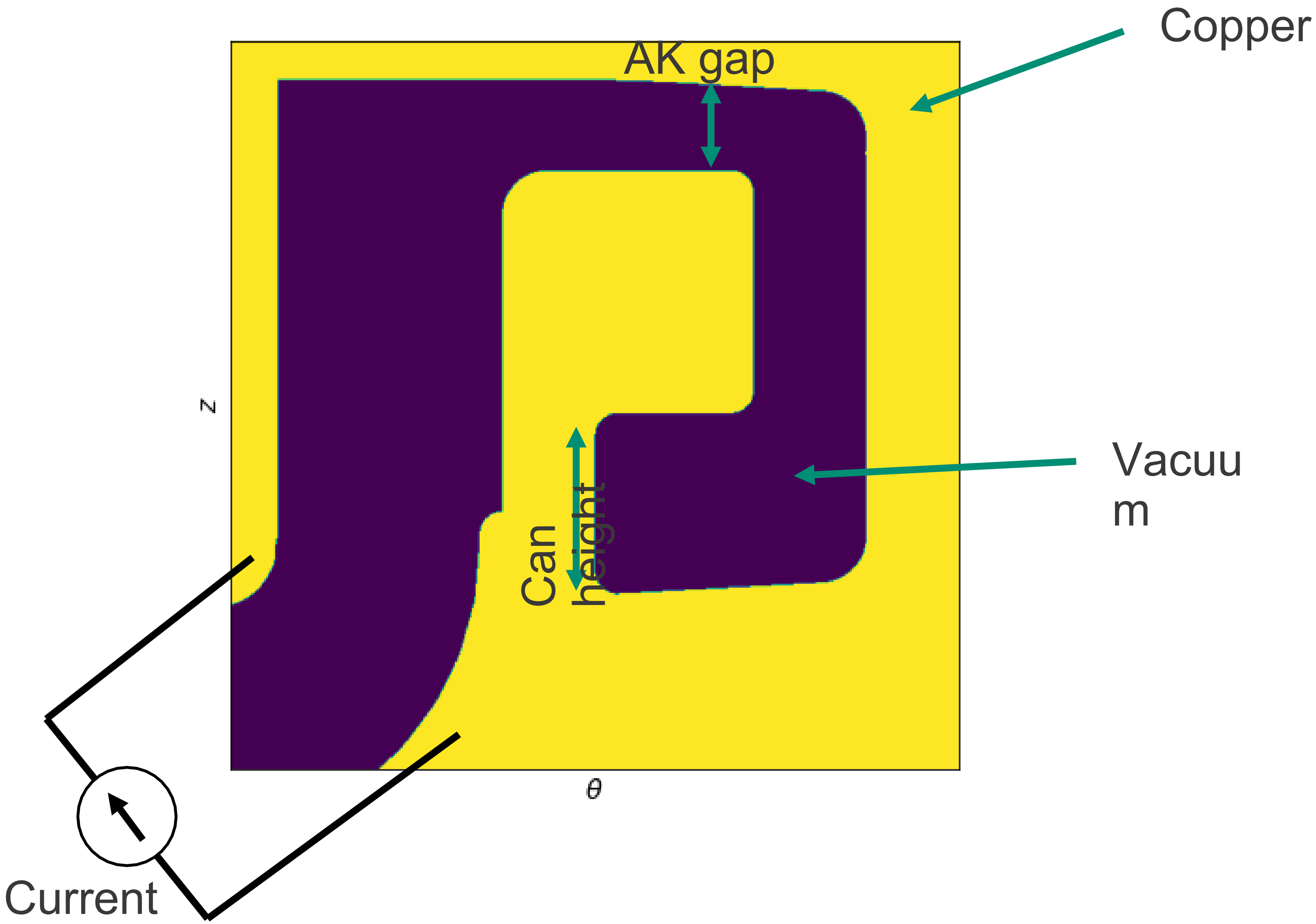
Investigating current losses at Z machine via GORGON simulations of a low density plasma system



MagLIF experiment configuration at Z[1]

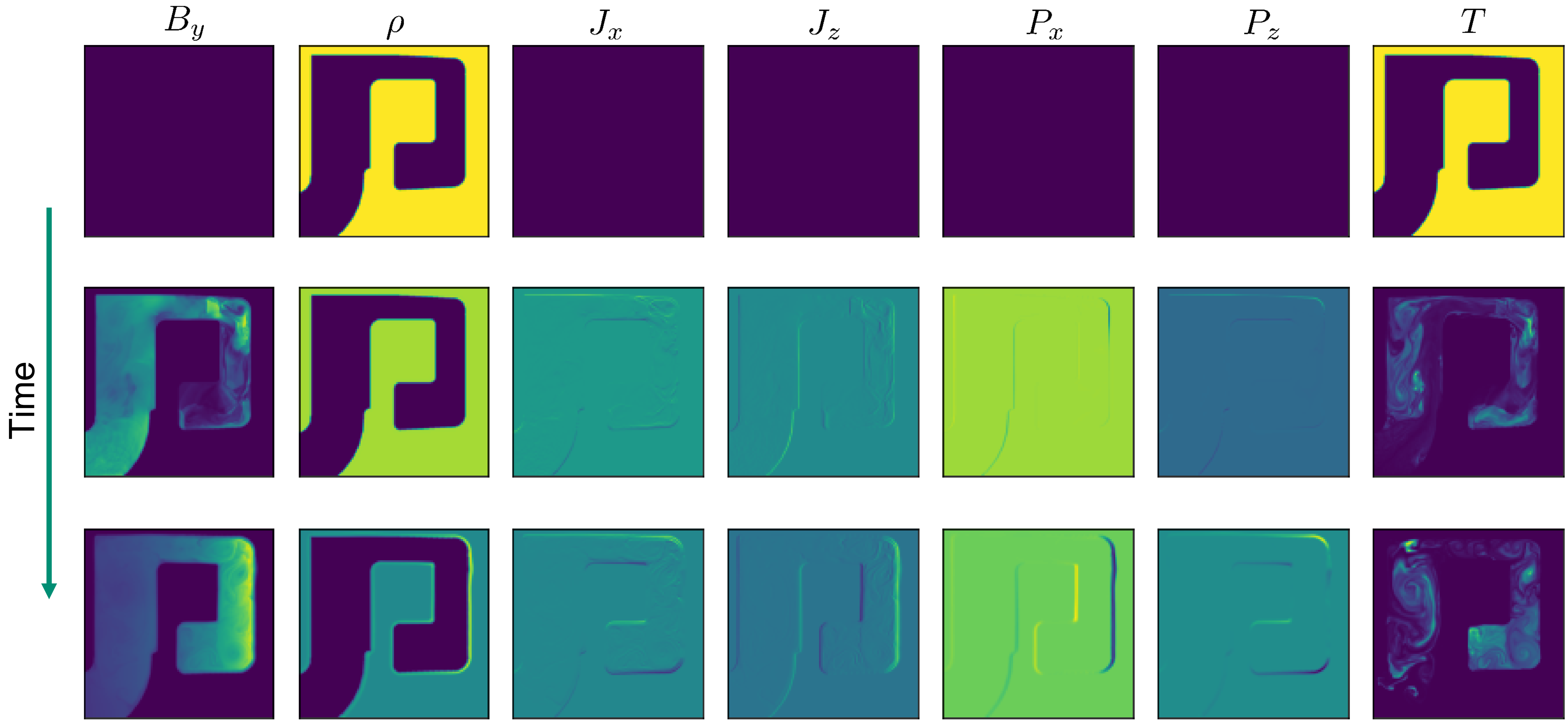


Higher peak current improves yield[1]

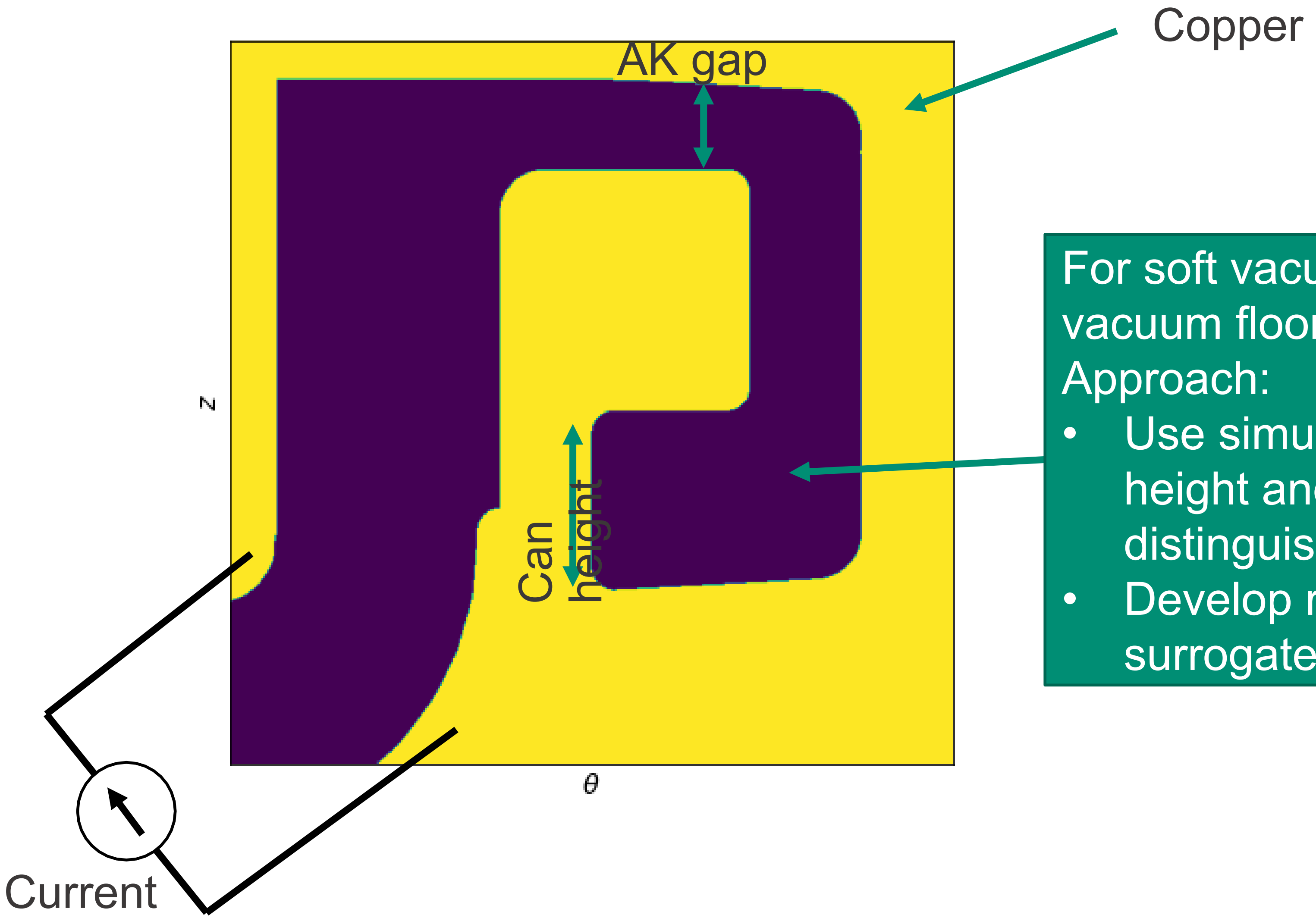


[1]Slutz et al., *Physics of Plasmas* (2016)

Investigating current losses at Z machine via GORGON simulations of a low density plasma system



Model ambiguity in vacuum and discrimination via optimal experimental design (OED)

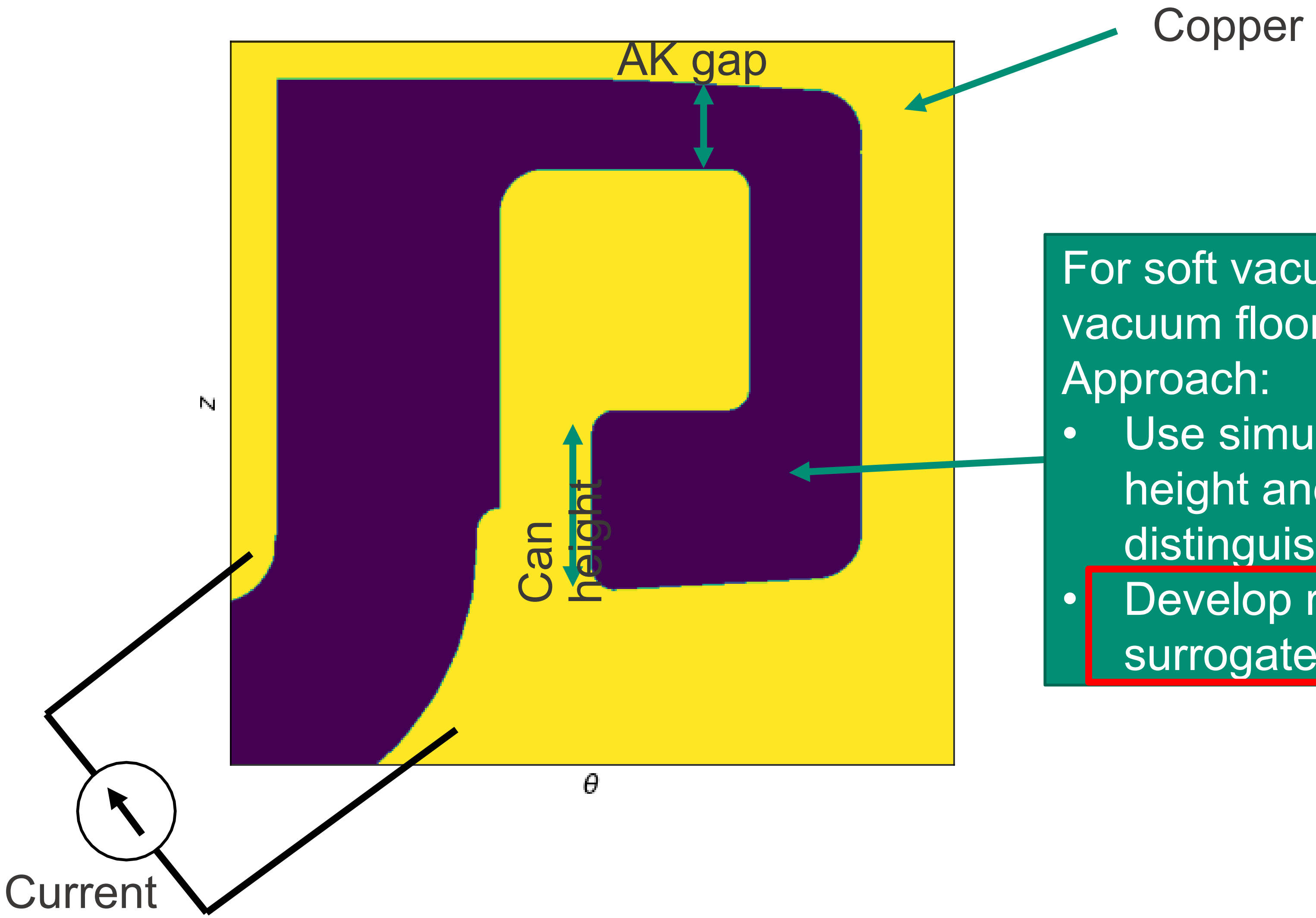


For soft vacuum model, what is the correct vacuum floor density?

Approach:

- Use simulation guided OED to select can height and AK gap that maximally distinguishes vacuum floor settings
- Develop reduced-order model (ROM) to surrogate expensive simulations

Model ambiguity in vacuum and discrimination via optimal experimental design (OED)



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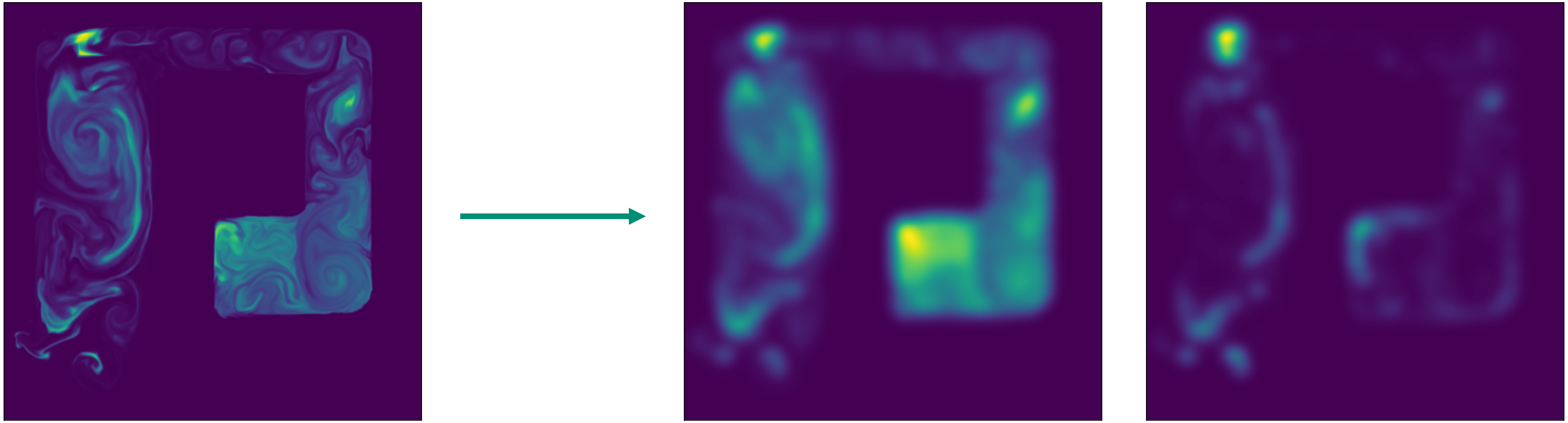
Reduced–order model – Featurization

Large Eddy Simulation (LES)-like spatial decomposition

- Decompose fields as $z = \bar{z} + z'$

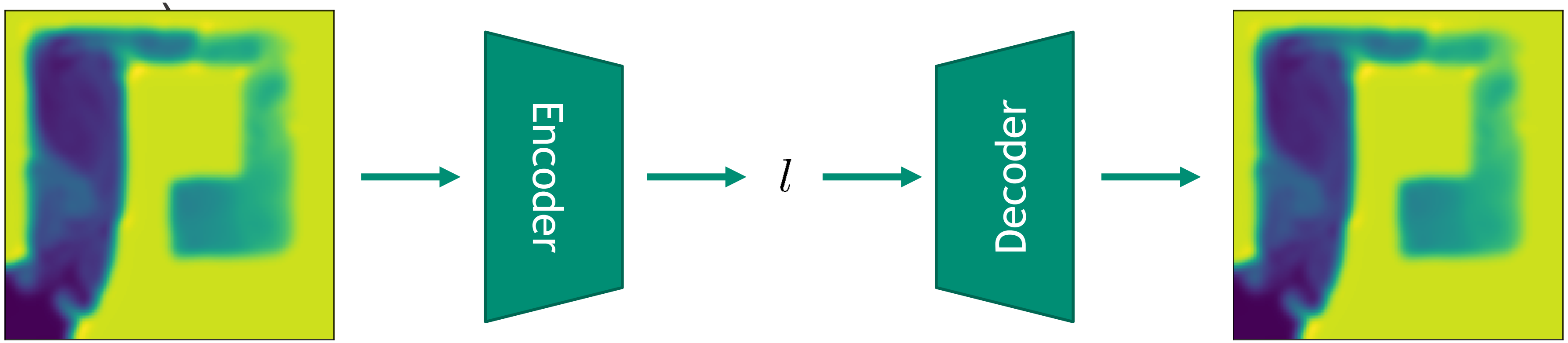
  where $\bar{z}$ is Gaussian filtered z
- New features $u \in \left\{ \bar{z}, \overline{z'^2} \text{ for } z \in \{B_y, \rho, Jx, Jy, T\} \right\}$



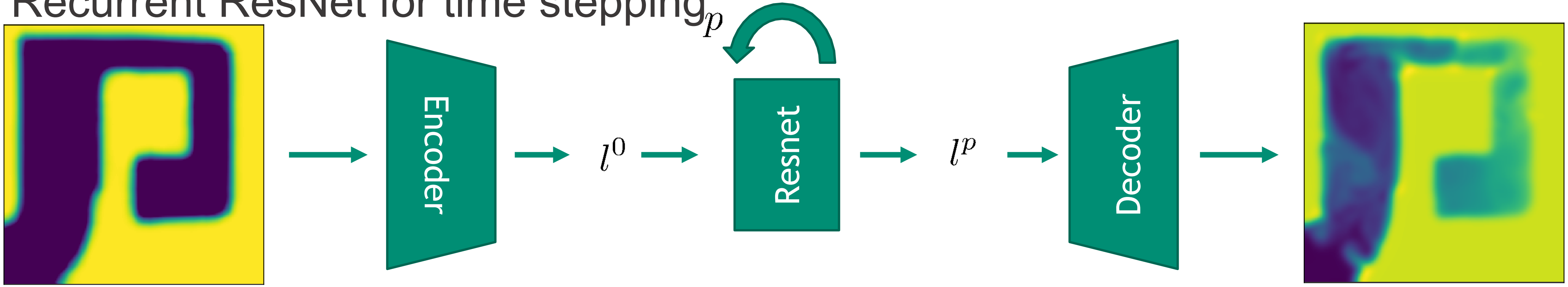
Reduced–order model – Architecture

Two neural networks,

- Convolutional neural network autoencoder for compressing state (latent



- Recurrent ResNet for time stepping



Reduced–order model – Training

$$\begin{tikzcd}
u^n \arrow[r, "\mathcal{E}"] \arrow[d] & l^n \arrow[r, "\mathcal{D}"] \arrow[d, "\mathcal{T}_l"] & \hat{u}^n \\
u^{n+1} \arrow[r] \arrow[d] & l^{n+1} \arrow[r] \arrow[d] & \hat{u}^{n+1} \\
\vdots \arrow[d] & \vdots \arrow[d] & \\
u^{n+p} \arrow[r] & l^{n+p} \arrow[r] & \hat{u}^{n+p}
\end{tikzcd}$$

u^n : Features

l^n : Latent space representation

$\mathcal{E}$: Encoder

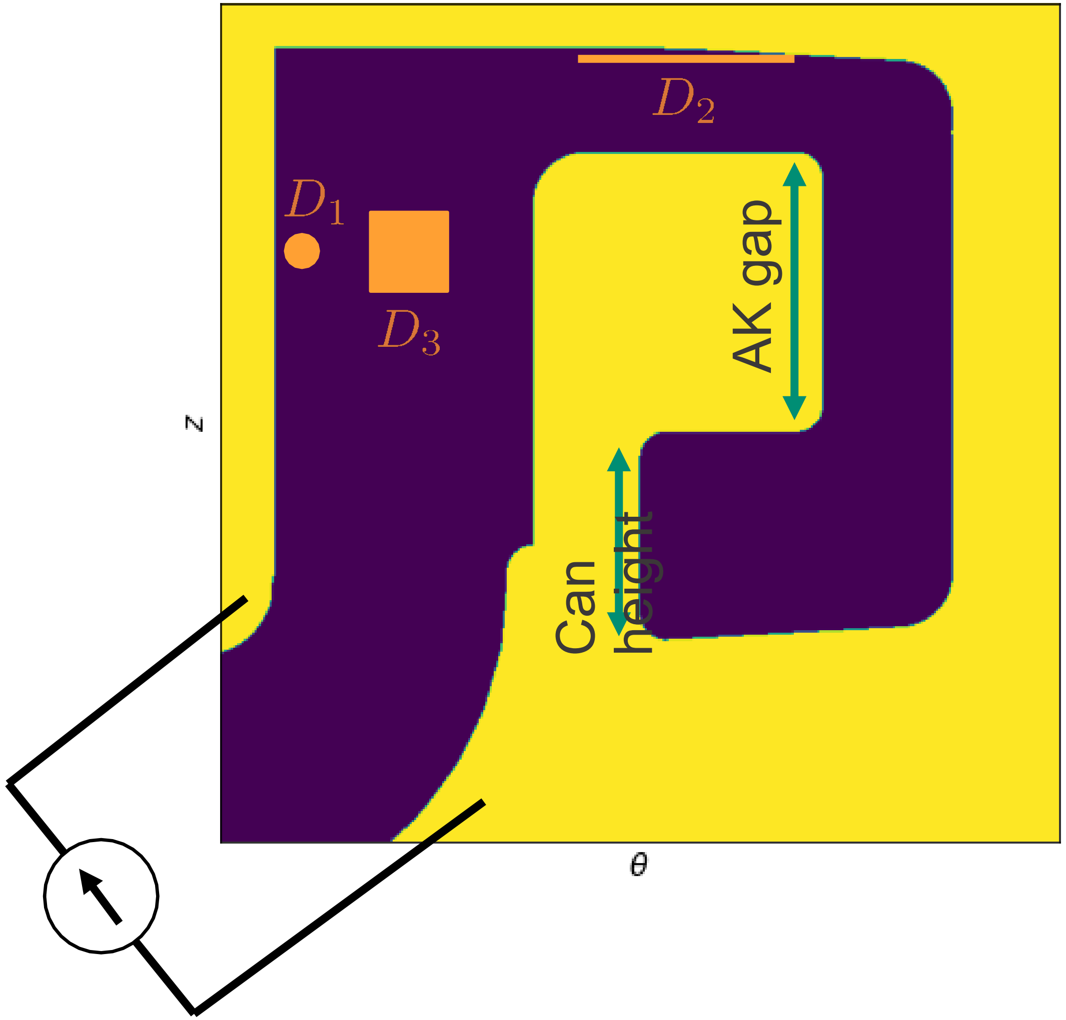
$\mathcal{D}$: Decoder

$\mathcal{T}_l$: Latent space timestepper

Optimize with training data,

$$\min_{\mathcal{E},\mathcal{D},\mathcal{T}_l} \sum_{p=0}^{p_{\max}} w_p \left|\left| u^{n+p} - \mathcal{D}\mathcal{T}_l^p \mathcal{E} u^n \right|\right|_2^2$$

Validation of ROM – interpolating simulation parameters



1. Generate training data varying can height, AK gap, and vacuum floor density
2. Train ROM with training data
3. Compare evolution of fields and diagnostics from ROM to GORGON simulation for new simulation parameters

Diagnostics

$D_1 : B_y$ at point

$D_2 : B_y$ along line

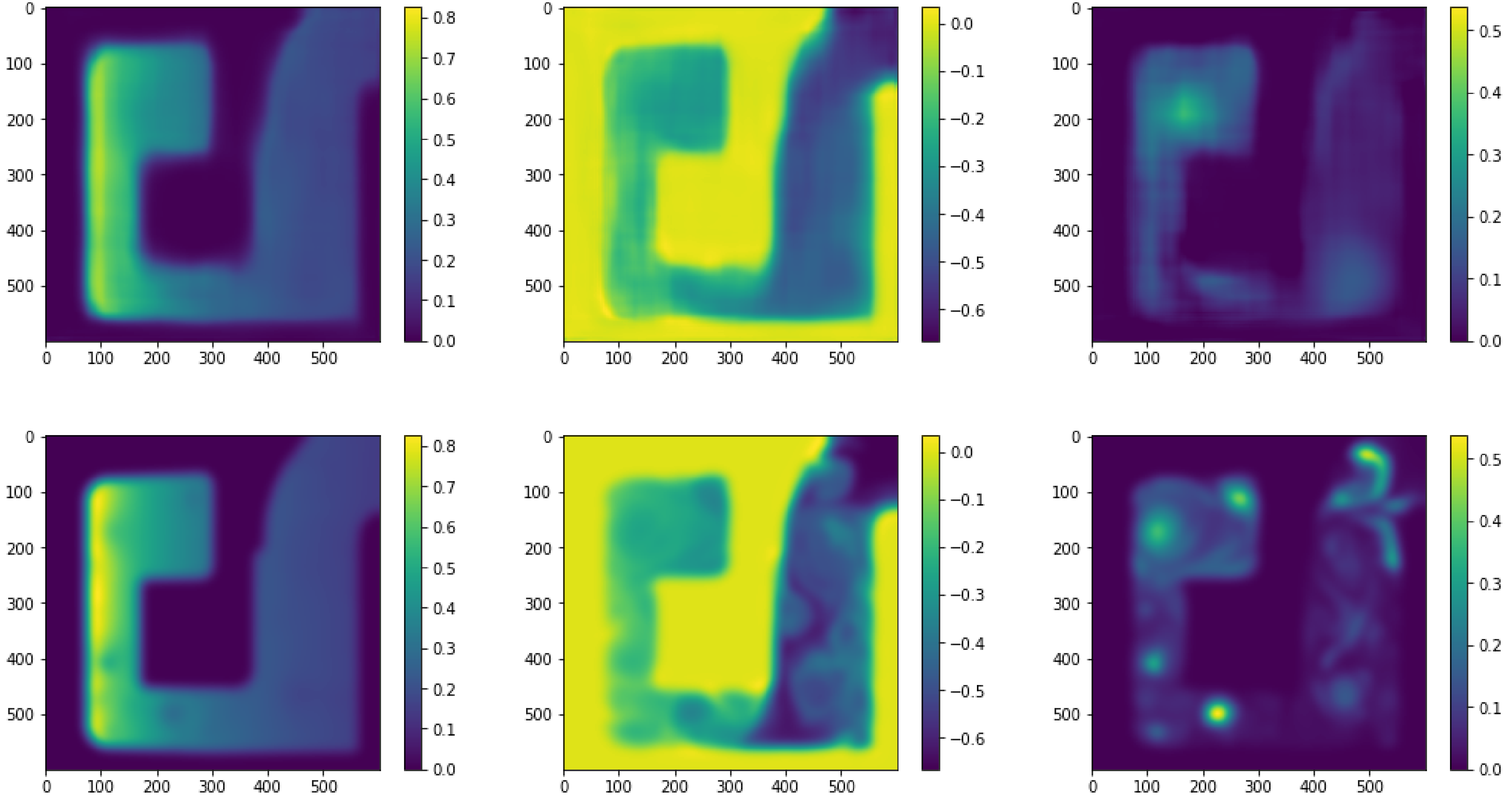
$D_3 : \rho$ averaged in patch

Validation of ROM – interpolating simulation parameters – Fields

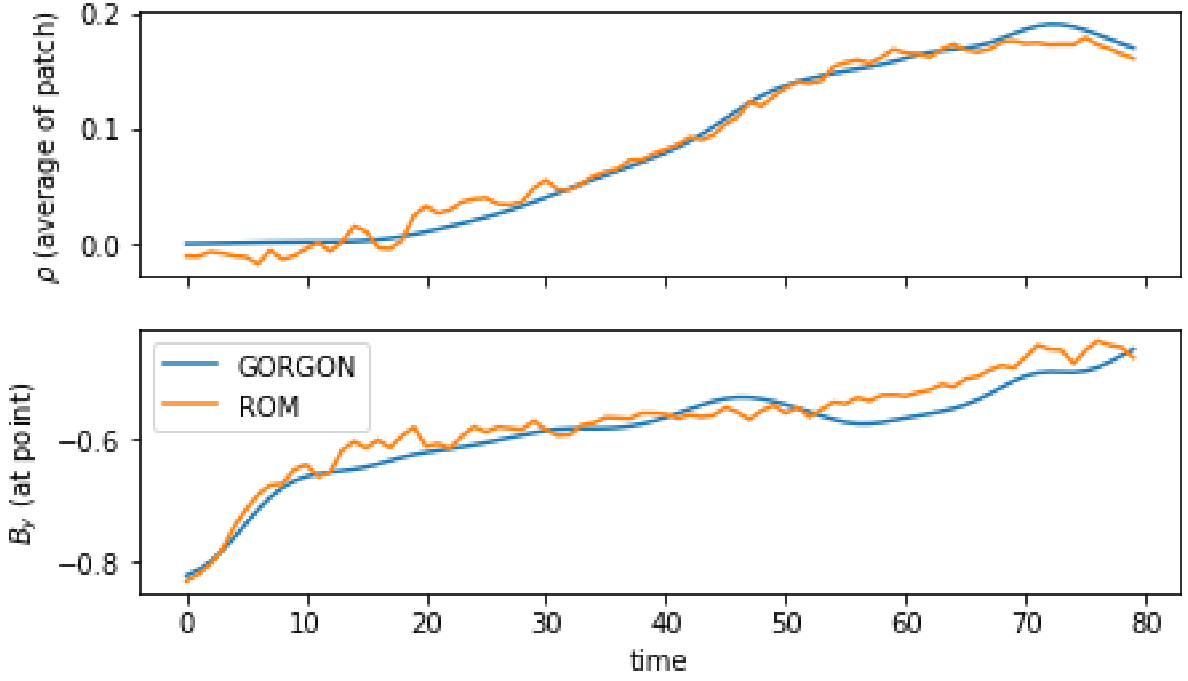
Magnetic field | Density | Temperature

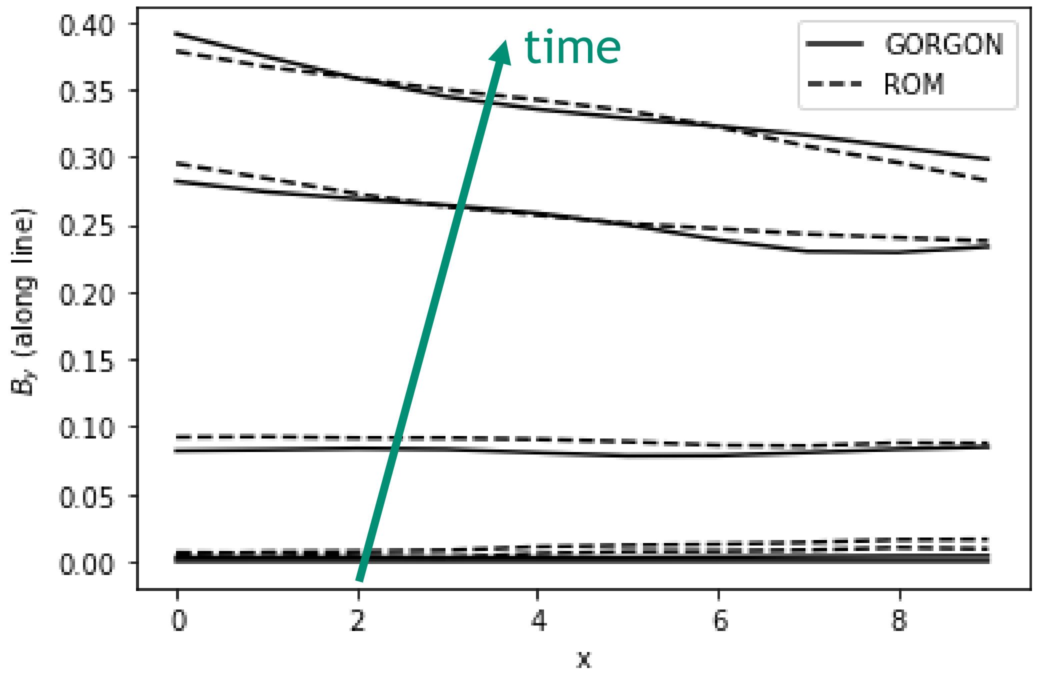
ROM

GORGON



Validation of ROM – interpolating simulation parameters – Diagnostics





Conclusion

Developing framework optimal experimental design to study vacuum floor setting in low density plasma system

Demonstrated reduced order model for low density plasma system

- Convolutional Autoencoder for compressing state
- Recurrent neural network for time stepping
- Recovers synthetic diagnostics

Future work

- Integrate in an OED framework to select geometric parameters for simulations
- Apply framework towards other experiments