EUROfusion

Pedestal Inference Engine PIE

Local Linear Gyrokinetic Surrogate Models for Pedestal with GENE

Daniel Jordan

VTT, Helsinki, Finland

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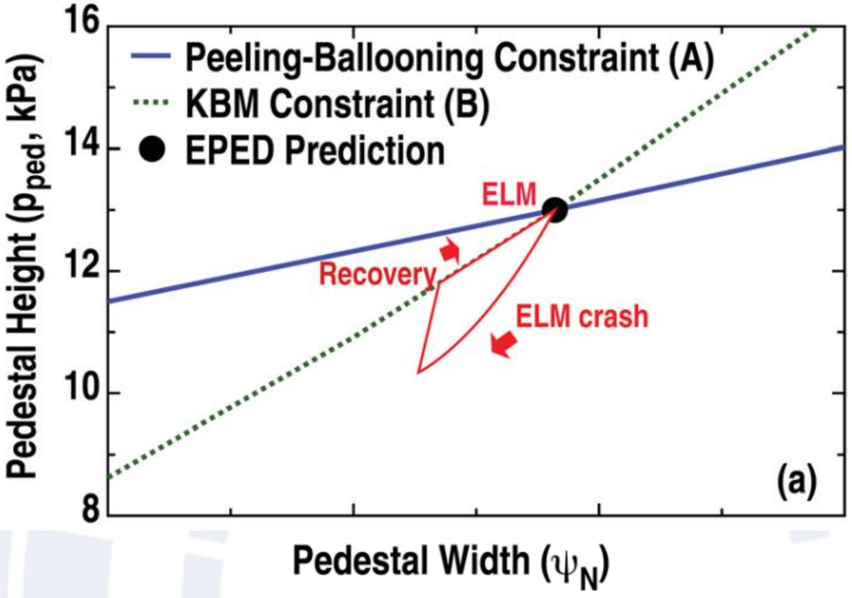
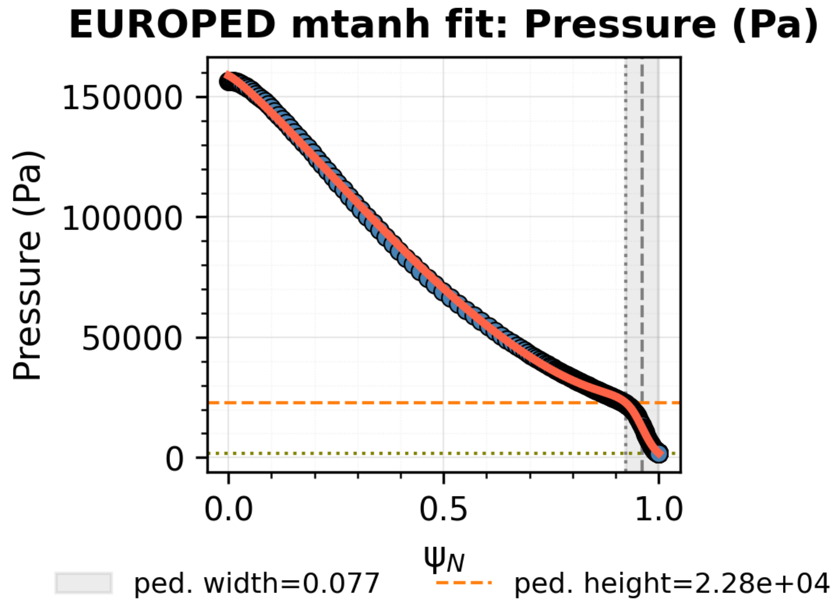
Turbulent transport constrains pedestal growth

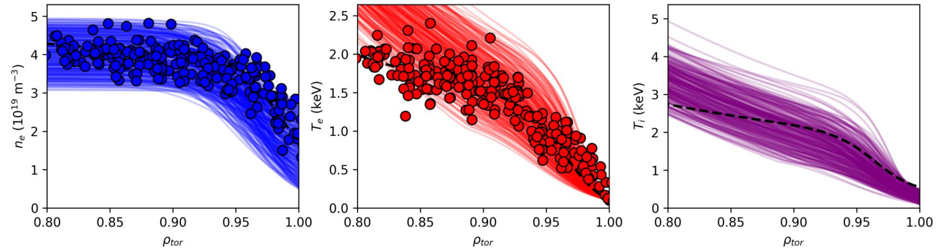
- A **transport barrier** causes rising pressure forming the pedestal
- A higher pedestal means higher core pressure and **higher fusion performance**
- Micro instability transport **constrains pedestal growth**
- Larger MHD instabilities **crash the pedestal** limiting growth
- A pedestal height predictor needs information from both

P.B. Snyder, EPED, Phys Plasmas, 2012:
10.1063/1.3699623





Motivation for GK datasets and surrogate models



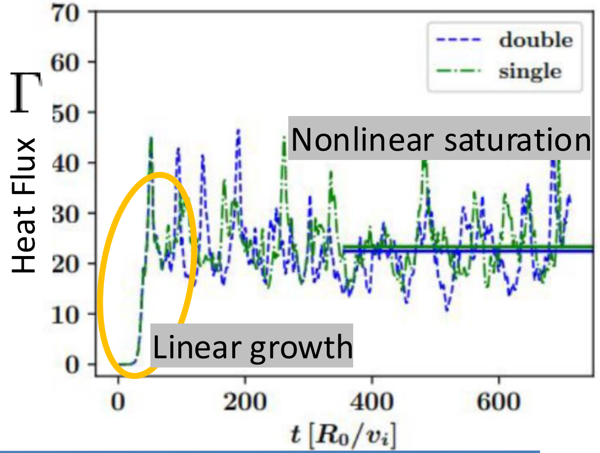
GK analysis spans uncertainty space
Beyond nominal profile analysis
Eventually Tokmak Space

Quasi linear model → transport model → pedestal prediction

$$\Gamma = \int D(k_y) \frac{\gamma(k_y)}{<k_\perp^2>(k_y)} dk_y$$

Saturation Rule:
Arbitrary function
e.g. spline, fitted to
match flux to
non-linear simulations

Mixing Length
from Linear Simulation
OR **surrogate**

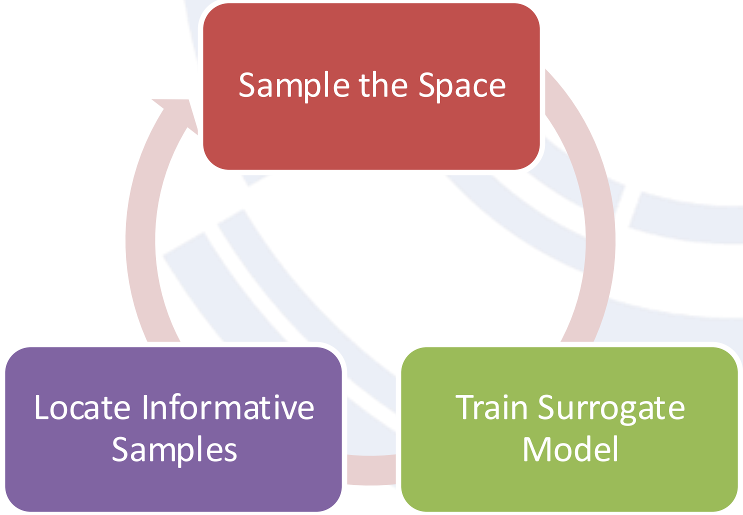


Mode Identification / Transport Channel Dominance Via diffusivity ratios:

Table 1. (A) Approximate fingerprints for modes resistant to shear suppression. (B) Approximate fingerprints for modes susceptible to shear suppression.

(A)			
Mode type	χ_i/χ_e	D_e/χ_e	D_Z/χ_e
MHD-like	1	2/3	2/3
MTM	~1/10	~1/10	~1/10
ETG	~1/10	~1/20	~1/20
(B)			
Mode type	χ_e/χ_i	$D_e/(\chi_i + \chi_e)$	$D_Z/(\chi_i + \chi_e)$
ITG/TEM	1/4–1	$-1/10 \pm 1/3$	~1

Data Efficient Space Exploration:



Linear GK Surrogate in Transport model matches experimental steady state for first time ever; L. Leppin UATX

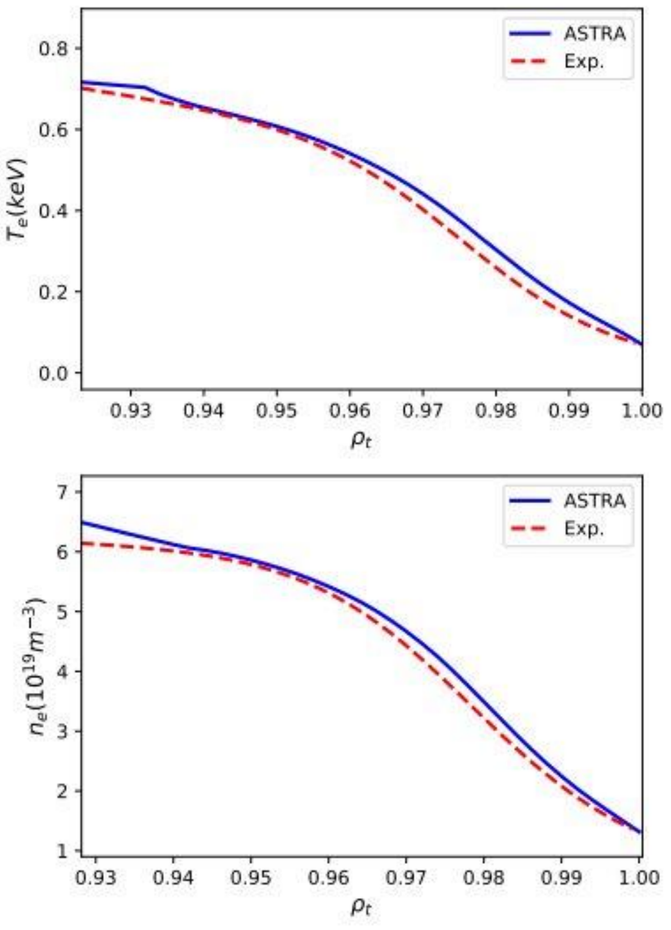
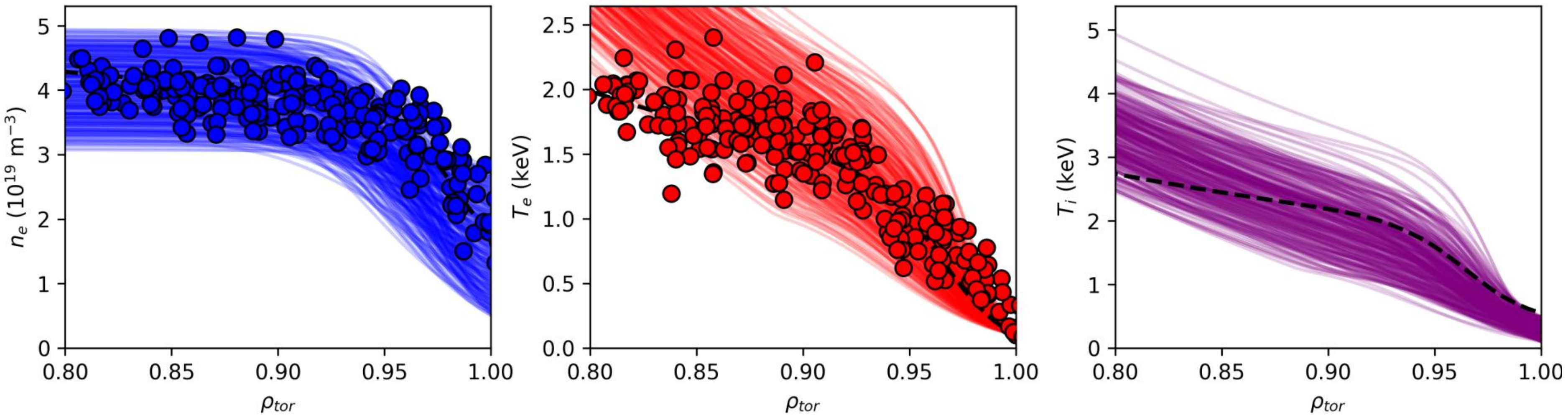


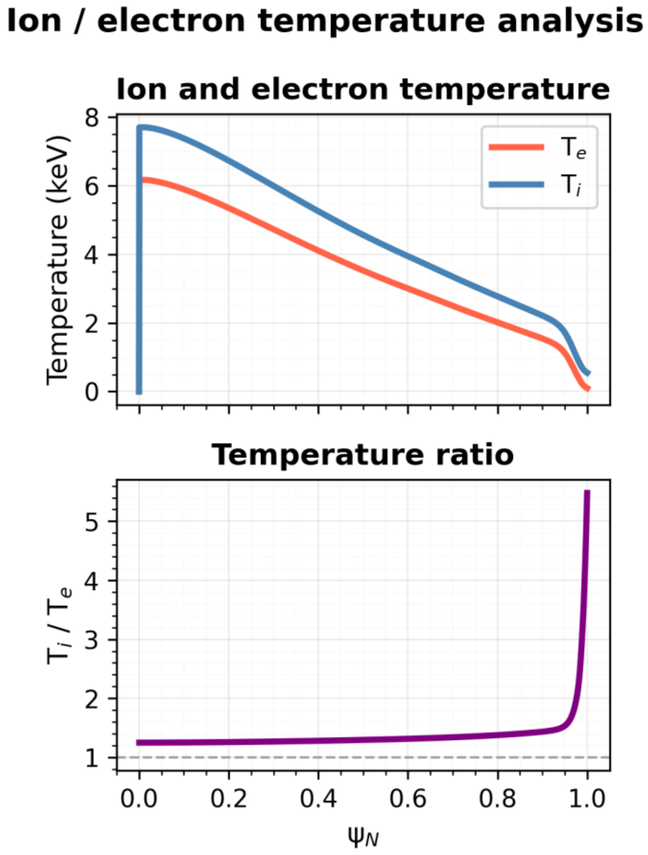
Figure 24. Experimental pre-ELM profiles (red dashed) for DIII-D shot 162940 along with the saturated ASTRA simulations (blue) based on the quasilinear mixing length model along with models for neoclassical and ETG transport.

- Simple Linear GENE surrogate coupled with a quasi-linear model in ASTRA
- Shows that Local Linear gyrokinetic surrogates can be useful in pedestal prediction
- A nice blueprint to try and replicate

Leppin Microtearing Thresholds and Second-Stable Ballooning in the DIII-D Pedestal: Reduced Modeling and Core-Edge Implications

Sampling profile experimental uncertainty space with m-tanh parameterization for JET 97781

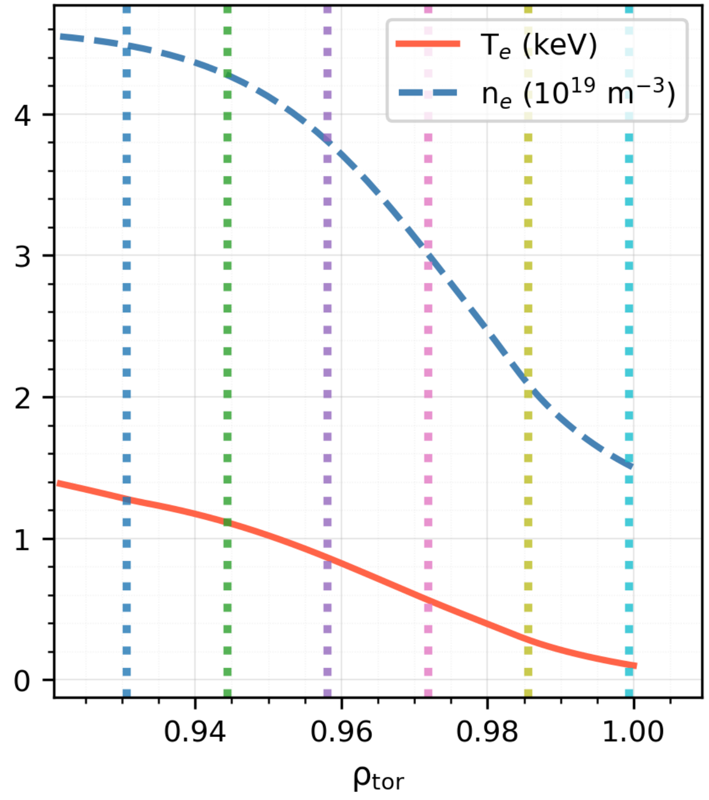


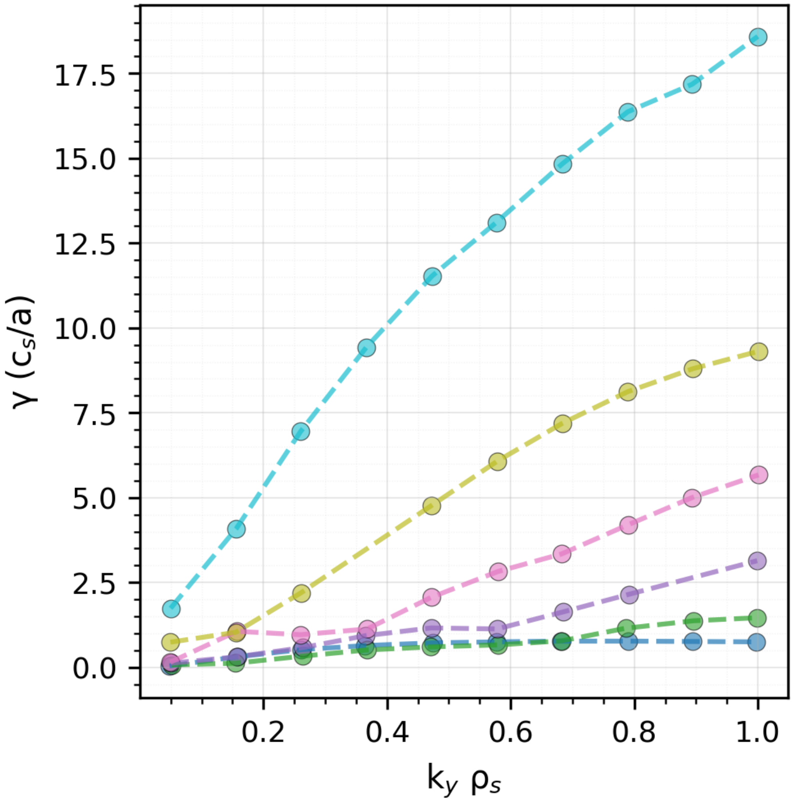


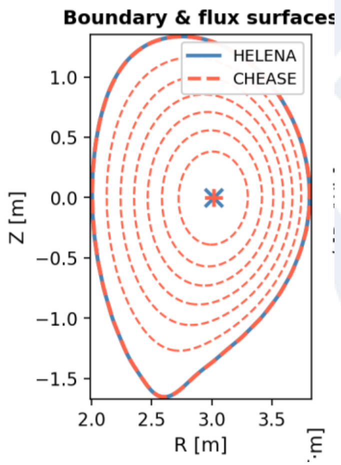
Profile Parameter	Lower Bound	Upper Bound
T_eped (keV)	1.0	1.8
n_eped (10^19 m^-3)	3.0	4.4
d_n_ped (psi_n)	0.05	0.1
d_T_ped (psi_n)	0.05	0.1
n_esep (10^19 m^-3)	0.5	2.8
Ti_ov_Te_ped	1.0	1.5
Ti_ov_Te_sep	1.0	5.0

- Bounds chosen to cover experimental uncertainty
- Sampled with space filling Sobol Sequence with shuffle

For each profile a grid of 6 radial locations and 10 ky are selected > GENE







- Radial locations are relative to the pedestal top
- GENE is passed an ITERDB, EQDSK, kymin and x0

GENE Parameter	Lower Bound	Upper Bound
x0_norm_ped_width	0	1
ky rho_s	0.05	1

Only a few simulations were lost

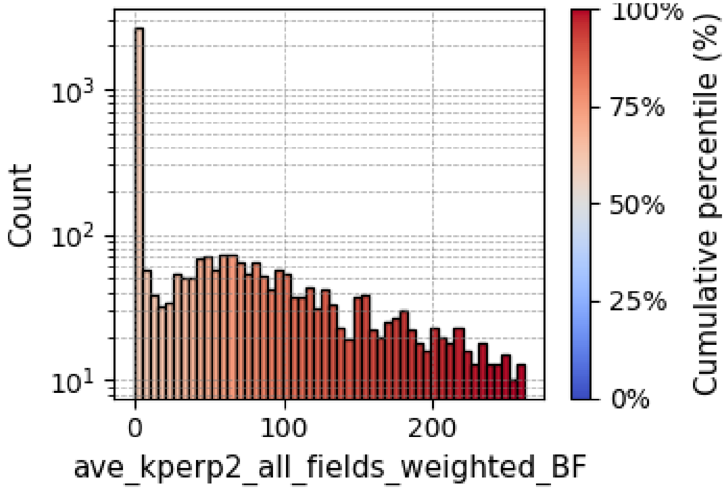
9D HELENA – GENE INPUT SPACE

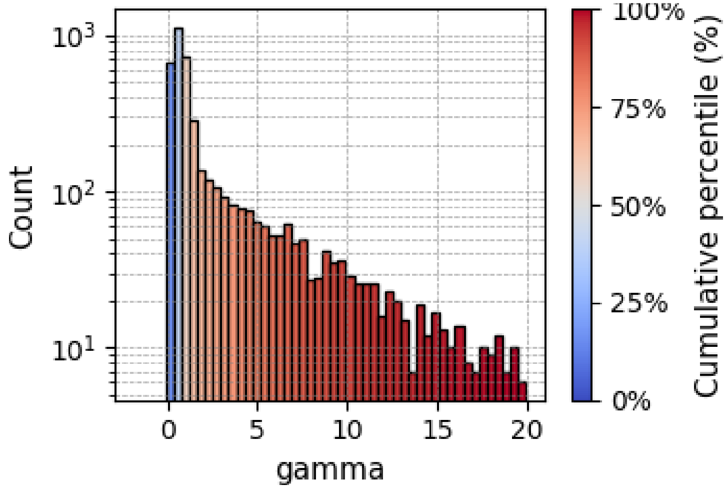
HELENA-GENE Params	Lower Bound	Upper Bound
T_eped (keV)	1.0	1.8
n_eped (10^19 m^-3)	3.0	4.4
d_n_ped (psi_n)	0.05	0.1
d_T_ped (psi_n)	0.05	0.1
n_esep (10^19 m^-3)	0.5	2.8
Ti_ov_Te_ped	1.0	1.5
Ti_ov_Te_sep	1.0	5.0
ky (Ion Scale)	0.05	1
x0_norm_ped_width	0	1

76 prof x 6 loc x 10 ky = 4560 GENE simulations

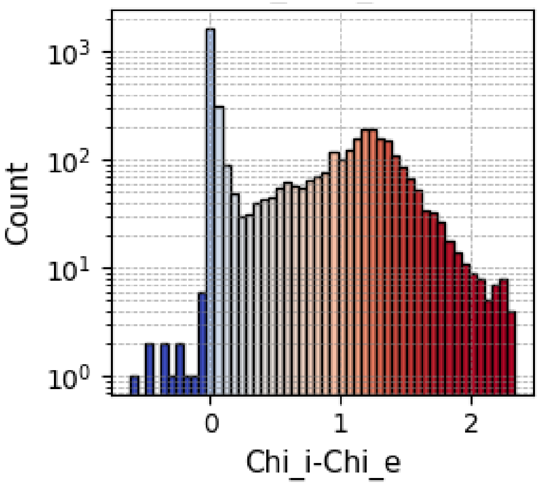
Failed: 6
Underflow: 8
Timelim 300sec: 88
Stable: 14

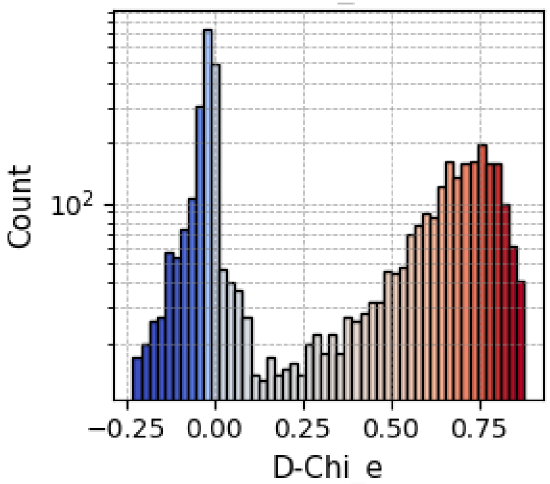
Mixing Length Output Distributions

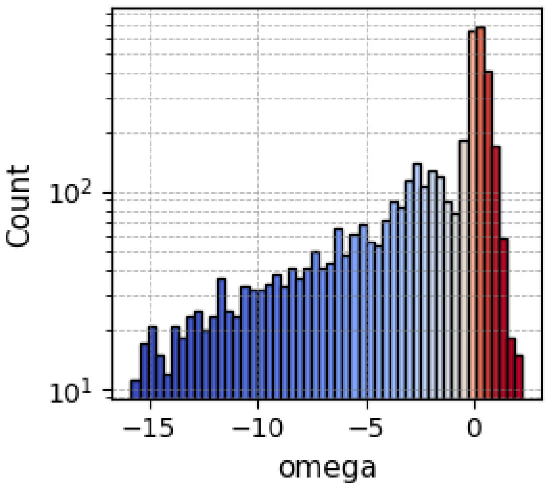


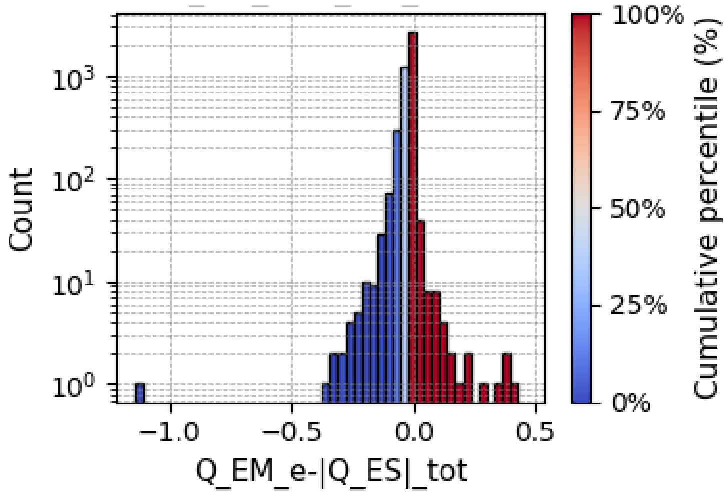


Mode ID Output Distributions









Mode identification is key for a quasilinear flux model

$$\Gamma = \int D(k_y) \frac{\gamma(k_y)}{<k_\perp^2>(k_y)} dk_y$$

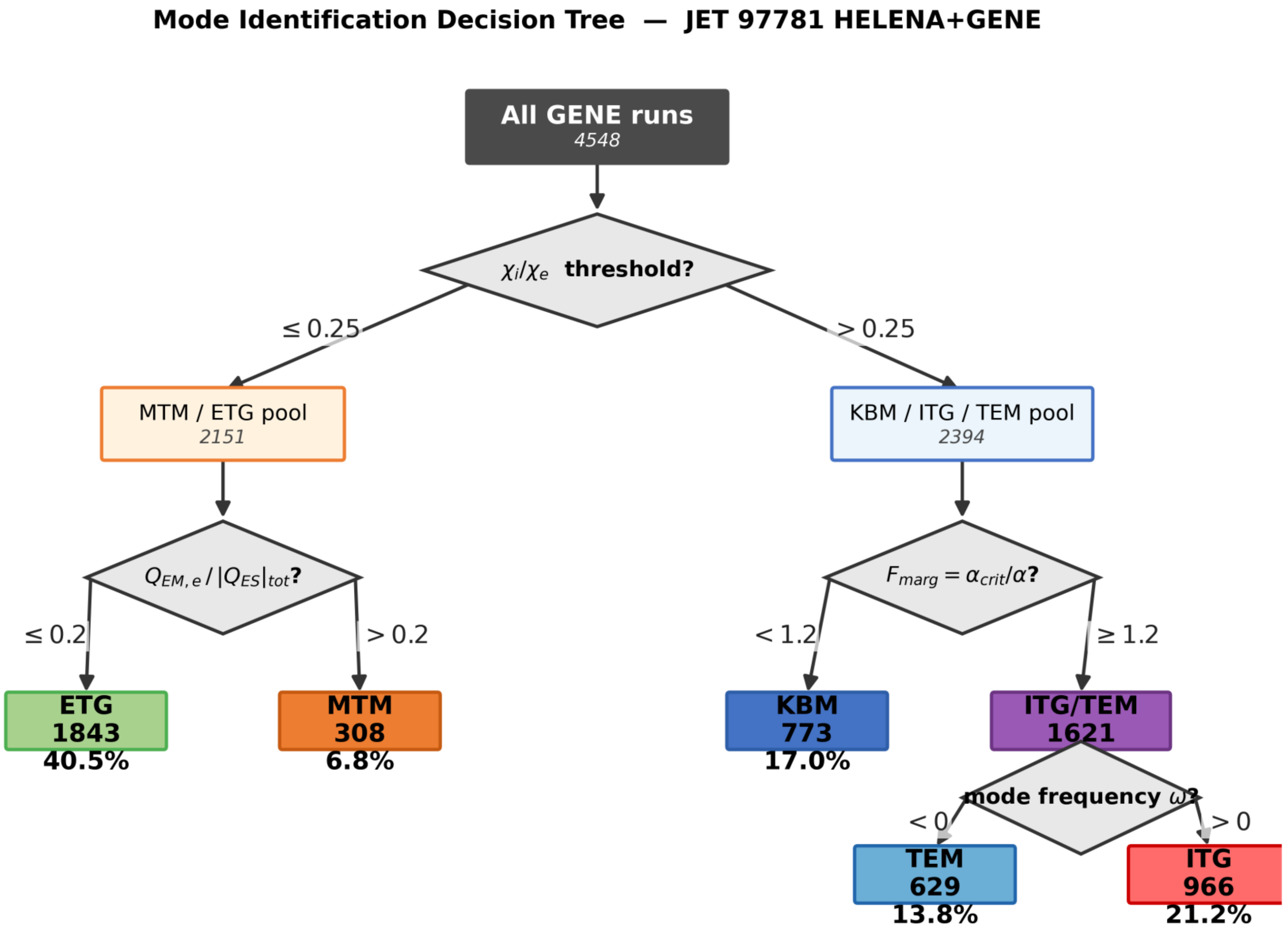
Saturation Rule:
Arbitrary function
e.g. spline, fitted to
match flux to
non-linear simulations

Mixing Length
from Linear Simulation
OR **surrogate**

D_{ETG} D_{MTM} D_{KBM} D_{ITG} D_{TEM}

- Each instability flavour has unique saturation mechanisms
- A different saturation rule should to be fitted for each instability
- This makes mode identification a key part of the quasilinear workflow

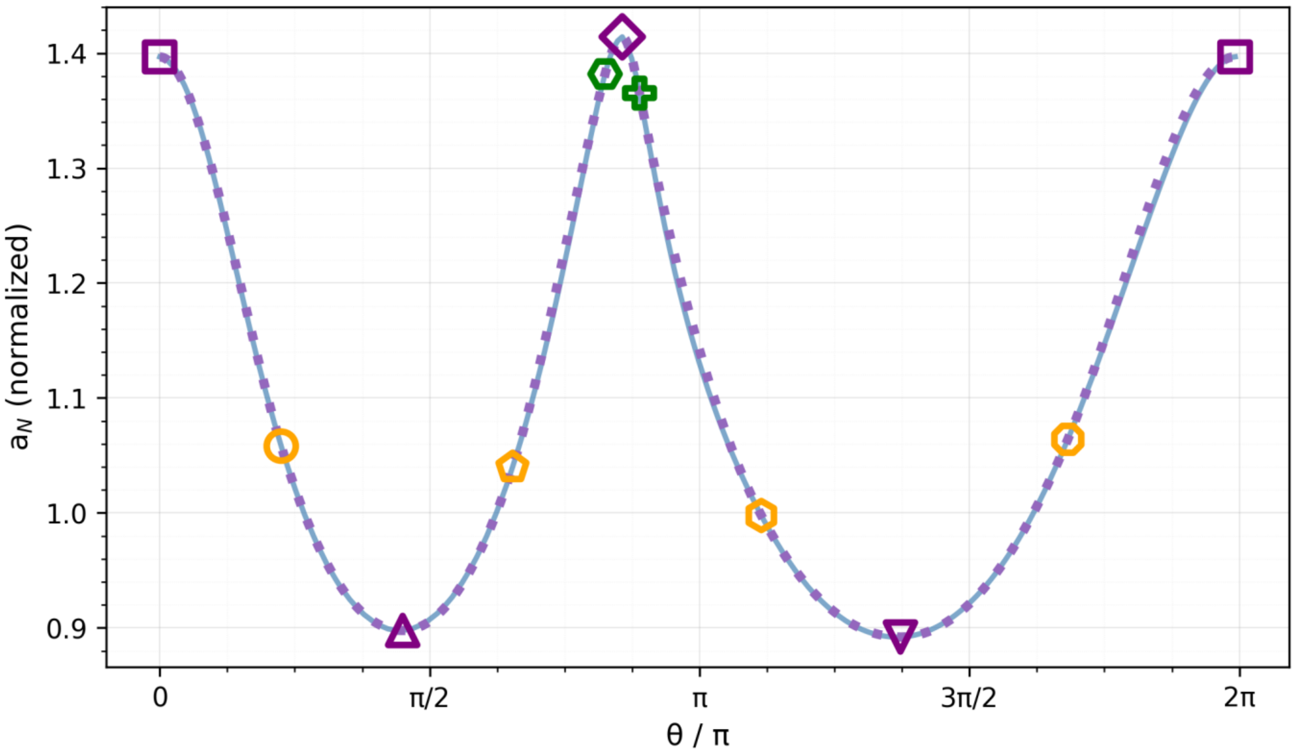
Mode identification by setting thresholds for physics metrics

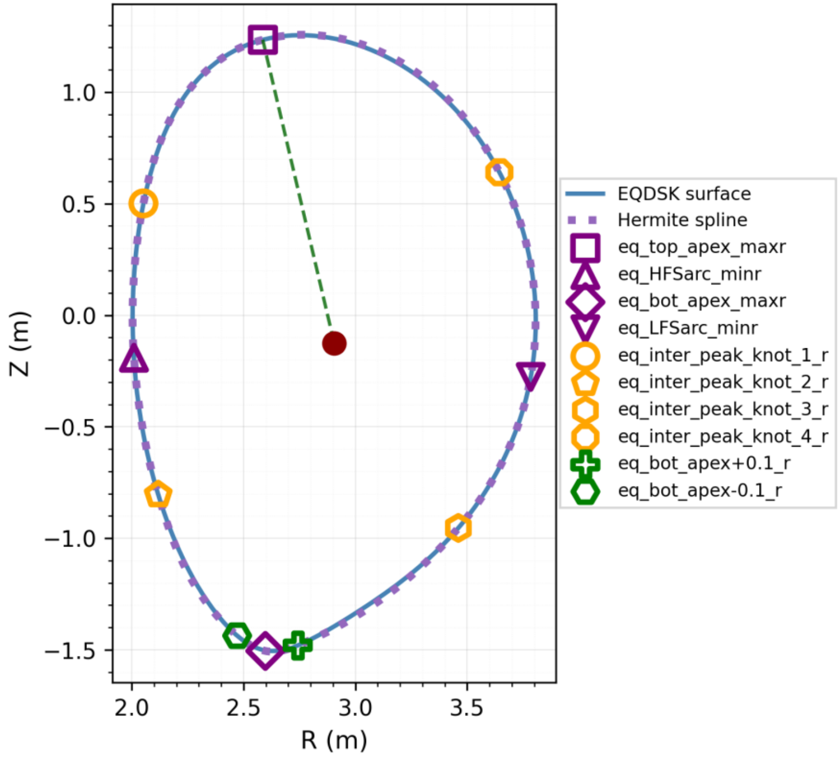


Inputs for the GENE ML surrogate:

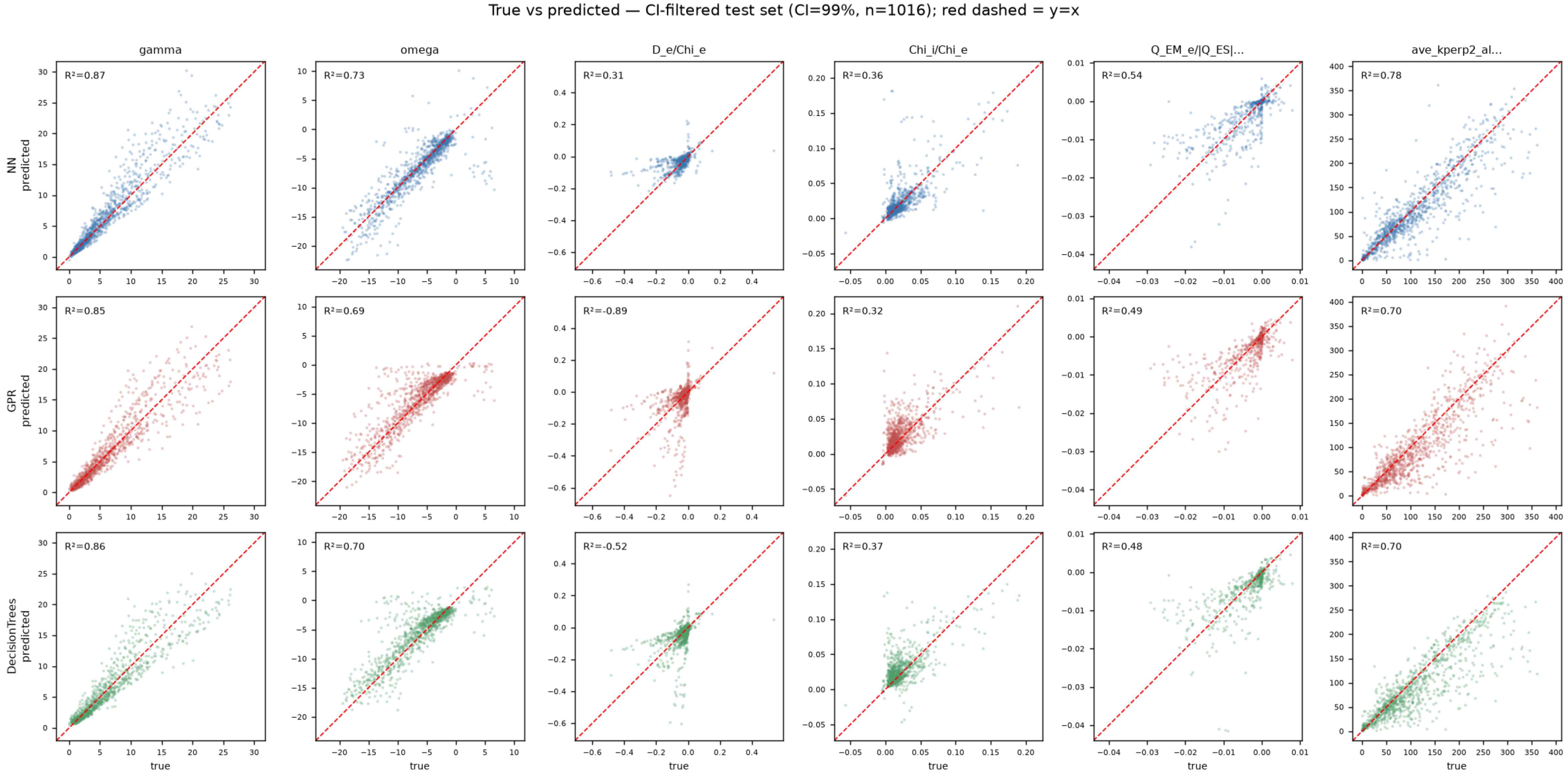
- Miller geometry does not capture X point
- 60 Fourier components is too high dimensional
- Knot values and gradients for local EQ
- SciPy Hermite Spline fit shows good agreement

General Inputs	Local EQ Shape	Output Columns
kymin	eq_bot_apex_maxr	gamma
beta	eq_bot_apex_rad	omega
coll	eq_bot_apex+0.1_grad	D_e/Chi_e
q0	eq_inter_peak_knot_3_grad	Chi_i/Chi_e
shat	eq_inter_peak_knot_2_r	Q_EM_e/|Q_ES|_tot
rhostar	eq_HFSarc_minr_rad	ave_kperp2_all_fields_weighted_BF
dpdx_pm	eq_bot_apex-0.1_r	
omn_e	eq_inter_peak_knot_1_grad	
omt_e	eq_LFSarc_minr_rad	
Tref	eq_bot_apex-0.1_grad	
nref	eq_inter_peak_knot_2_grad	
	eq_inter_peak_knot_3_r	
	eq_top_apex_maxr	
	eq_inter_peak_knot_4_grad	
	eq_bot_apex+0.1_r	
	eq_LFSarc_minr	
	eq_inter_peak_knot_4_r	
	eq_HFSarc_minr	
	eq_inter_peak_knot_1_r	

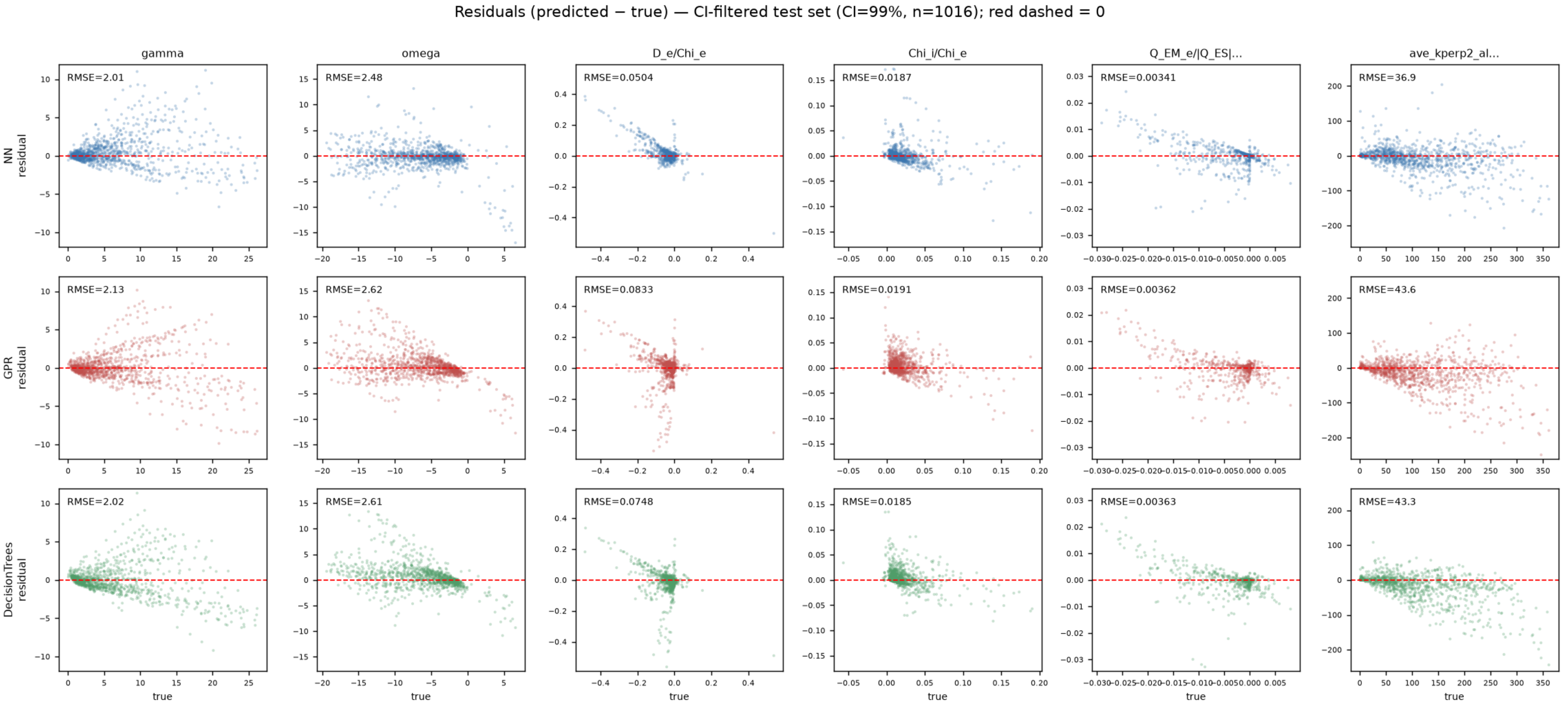




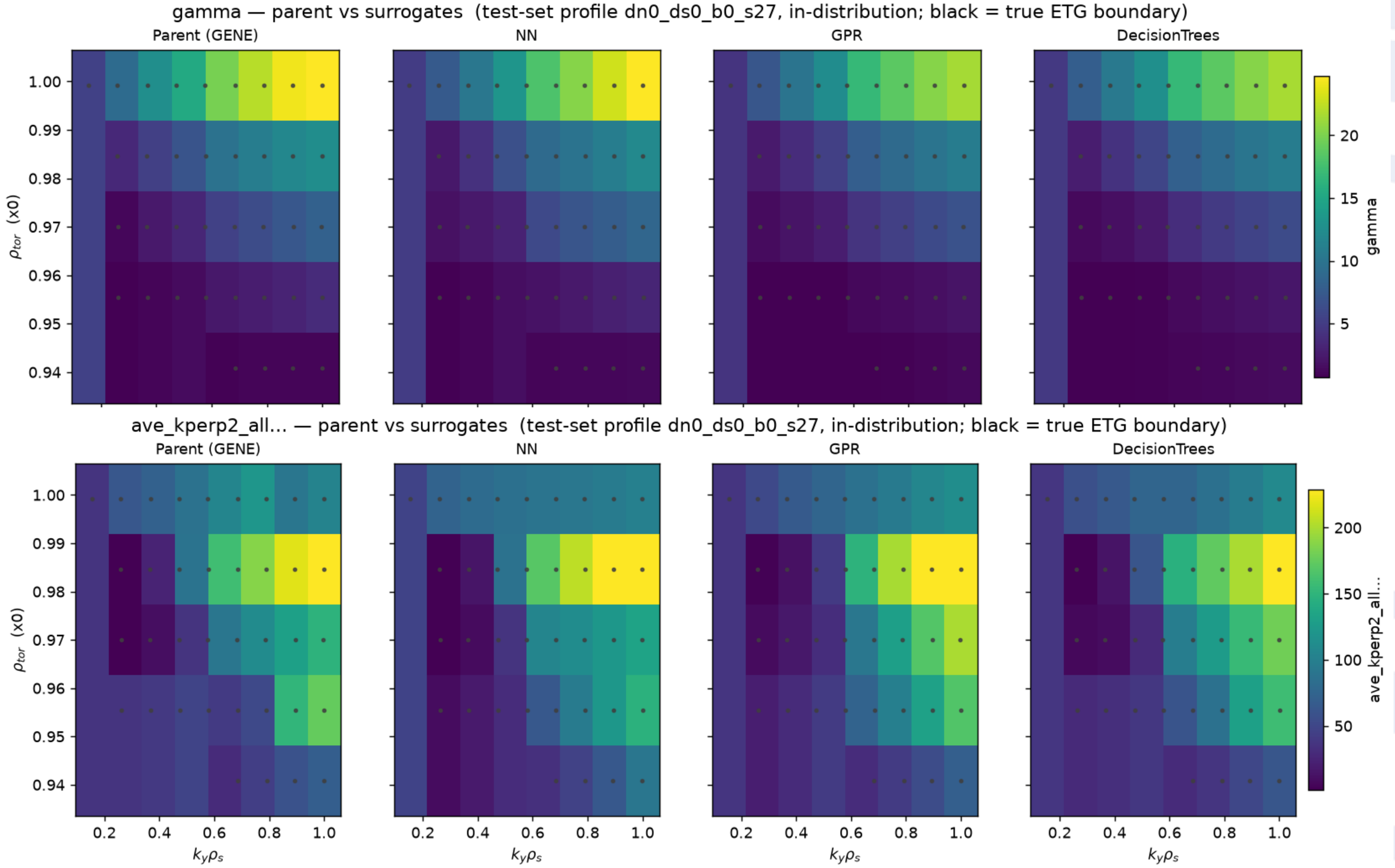
ML methods, GPR-Matern, NextTrees-350tr, NN-2x70-relu



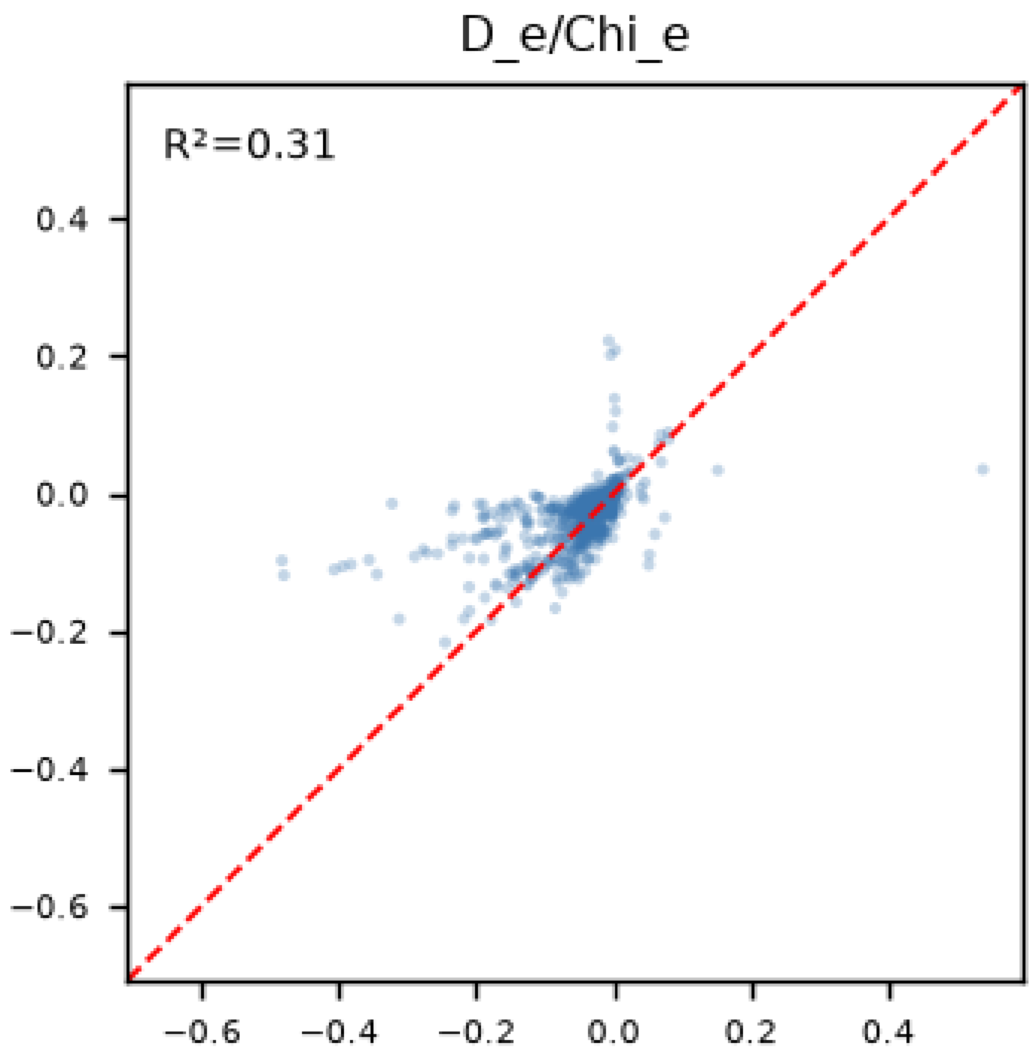
ML methods, GPR-Matern, NextTrees-350tr, NN-2x70-relu



Random test profile x0, ky grid for gamma and k_perp (Matches Well)



Should we make a regression model or classification model for mode identification???



- The diffusivity ratios, needed for mode identification are more difficult to surrogate
- I suspect that training a classification surrogate would have more success at identification