JET Task Force Meeting

EUROfusion

A statistical approach for the automatic identification of the start of the chain of events leading to the disruptions at JET

E. Aymerich[1], A. Fanni[1], G. Sias[1], S. Carcangiu[1], B. Cannas[1], A. Murari[2], A. Pau[3] and JET Contributors

1 2 3 EPFL

This work has been carried out within the framework of the EUROfusion Consortium and has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 633053. The views and opinions expressed herein do not necessarily reflect those of the European Commission.

Outline

- **Introduction and Background**
  - Motivation and previous work
  - Database
- ***Warning Time Indicator (WTI)* Algorithm**
  - Benchmark analysis
  - Construction of *WTI*
  - Parameter optimization
- **Validation of *WTI* with the GTM**
  - Automatic Ti: analysis and comparison
  - Manual Ti Vs Automatic Ti: GTM performance comparison
  - Database upgrade
  - GTM automatic update for recent campaigns
- **Conclusions**

Study of disruptions

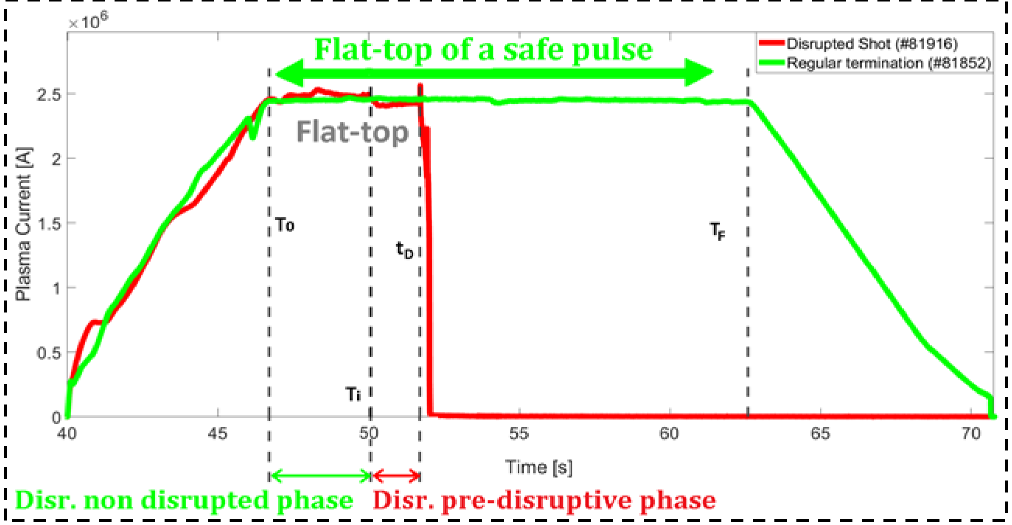
Data-based disruption predictors

- Need to be **updated**, as the operating scenario of the machine changes with time
- Need to provide an interpretable output, to be employed in a disruption avoidance scheme (detection of **specific events**)
- Supervised data-based models need a labelling of the samples to be trained

Identification of the pre-disruptive phase of the discharge

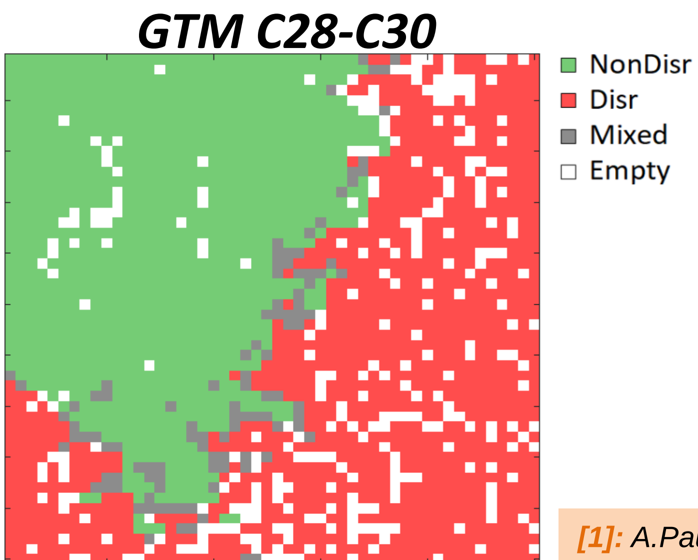
- The warning Time (Ti) is a **reference time** for *training* the predictive model
- Identification of 3 "classes"

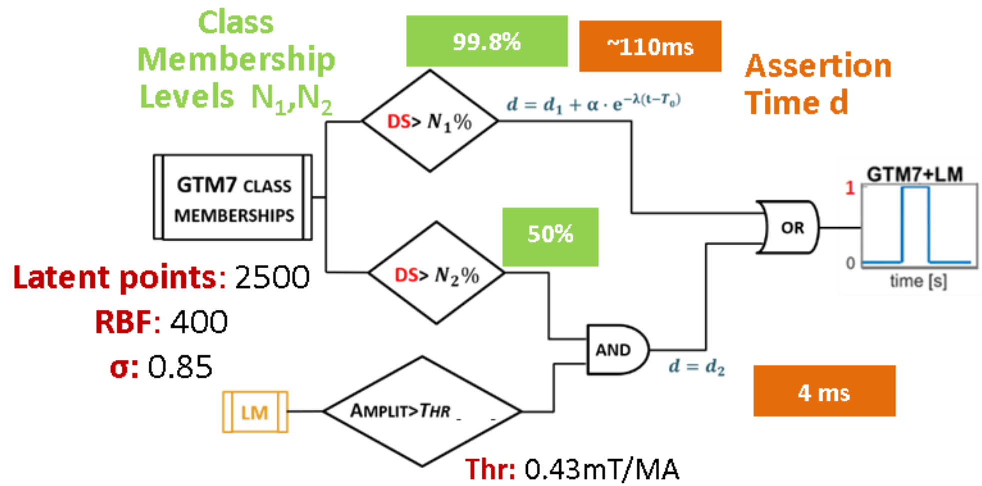
- **NonDisr. shots:** Ipla flat-top phase for safe shots [$\mathbf{T_0 - T_{end}}$];
- **Disr. non-disrupted Phase:** Ipla flat-top phase for disruptive discharges up to time identifying the start of the relevant chain of events 'destabilizing' the discharge [$\mathbf{T_0 - T_i}$];
- **Disr. pre-disruptive Phase:** from the Ti up to the disruption [$\mathbf{T_i - T_d}$].



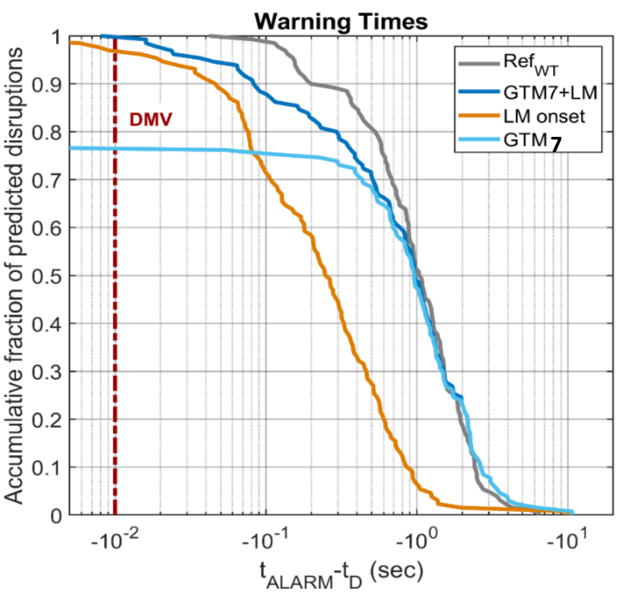
Previous results

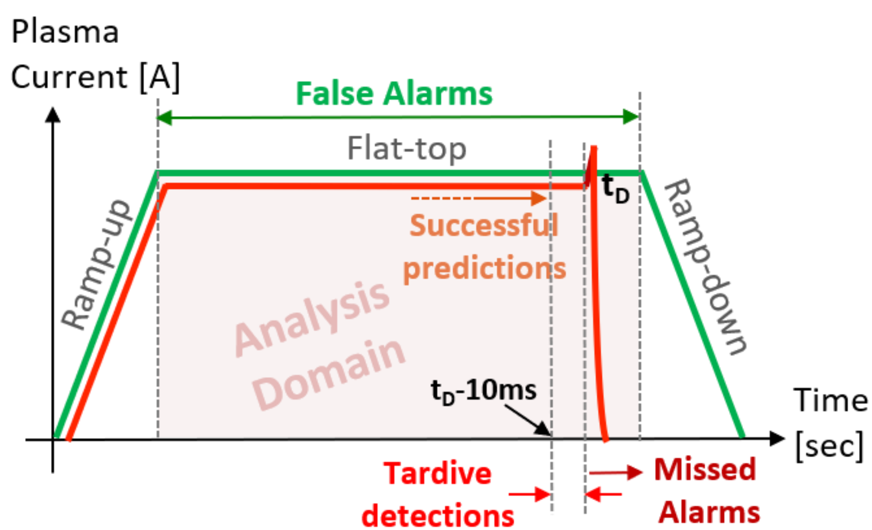
In [1], the Warning Times were obtained through a manual analysis





[1]: *A.Pau et al.,"A Machine Learning approach based on Generative topographic mapping for disruption prevention and avoidance at JET", Nucl. Fusion 2019, 106017 (22pp).*





Database

2011-2013 ILW campaigns (C28-C30)

- From previous analyses
- Mainly low power
- Manual Ti are known
- Many disruptions evolved until the loss of plasma current

2016 ILW campaign (C36)

- New dataset
- High power discharges
- Manual Ti not known
- Many disruptions killed with DMV

Same selection criteria

- HRTS, Bolometer and Li available
- X-point configuration
- No DMV (before tD)
- No VDE

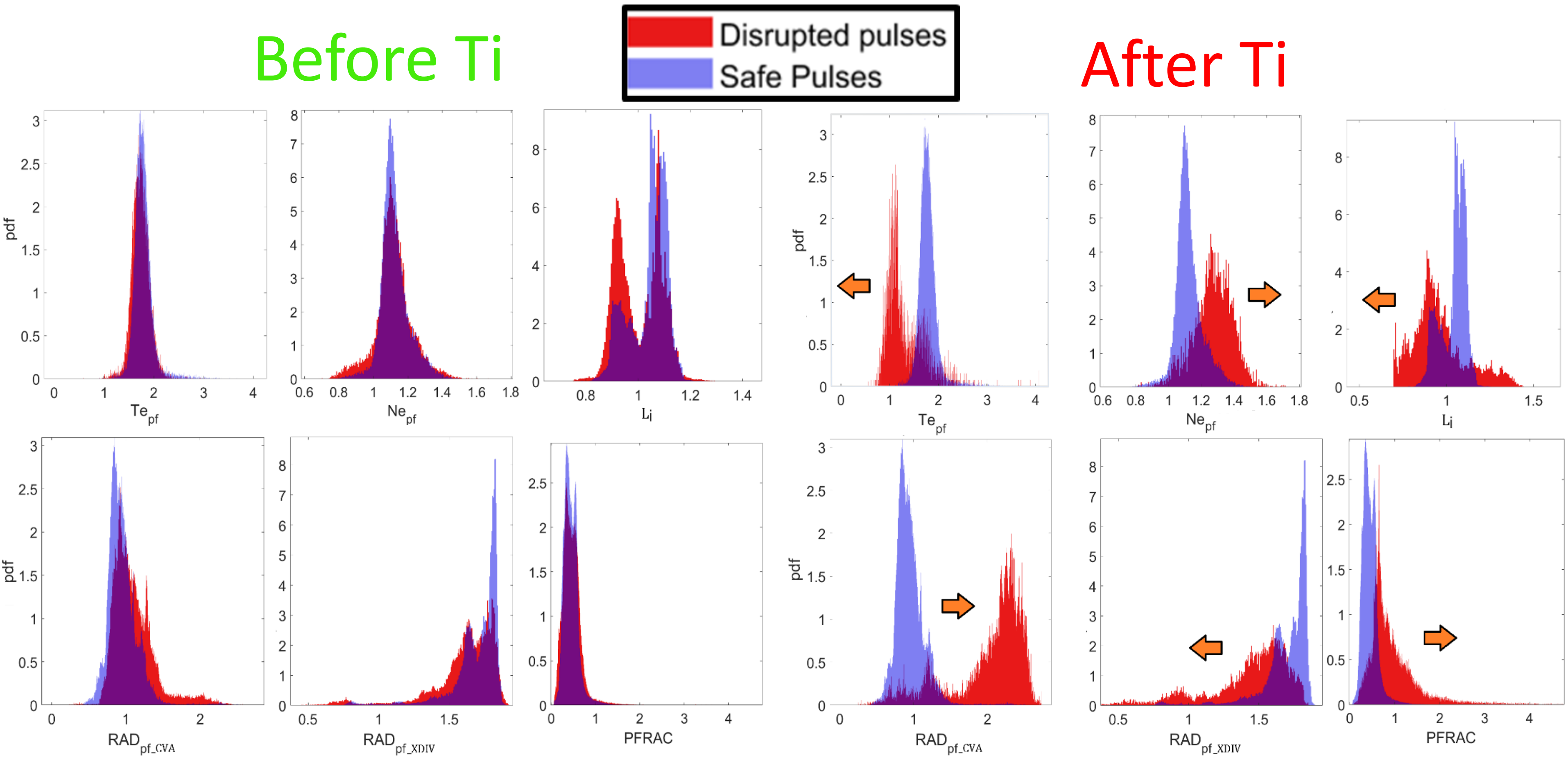
132 disrupted

115 regularly terminated

29 disrupted

41 regularly terminated

Statistical analysis on C28-C30



The plasma parameter distribution of the safe shots overlaps the distribution of the non-disrupted phase

After Ti for disrupted shots a clear shift of the plasma parameters is observed!

Working principle

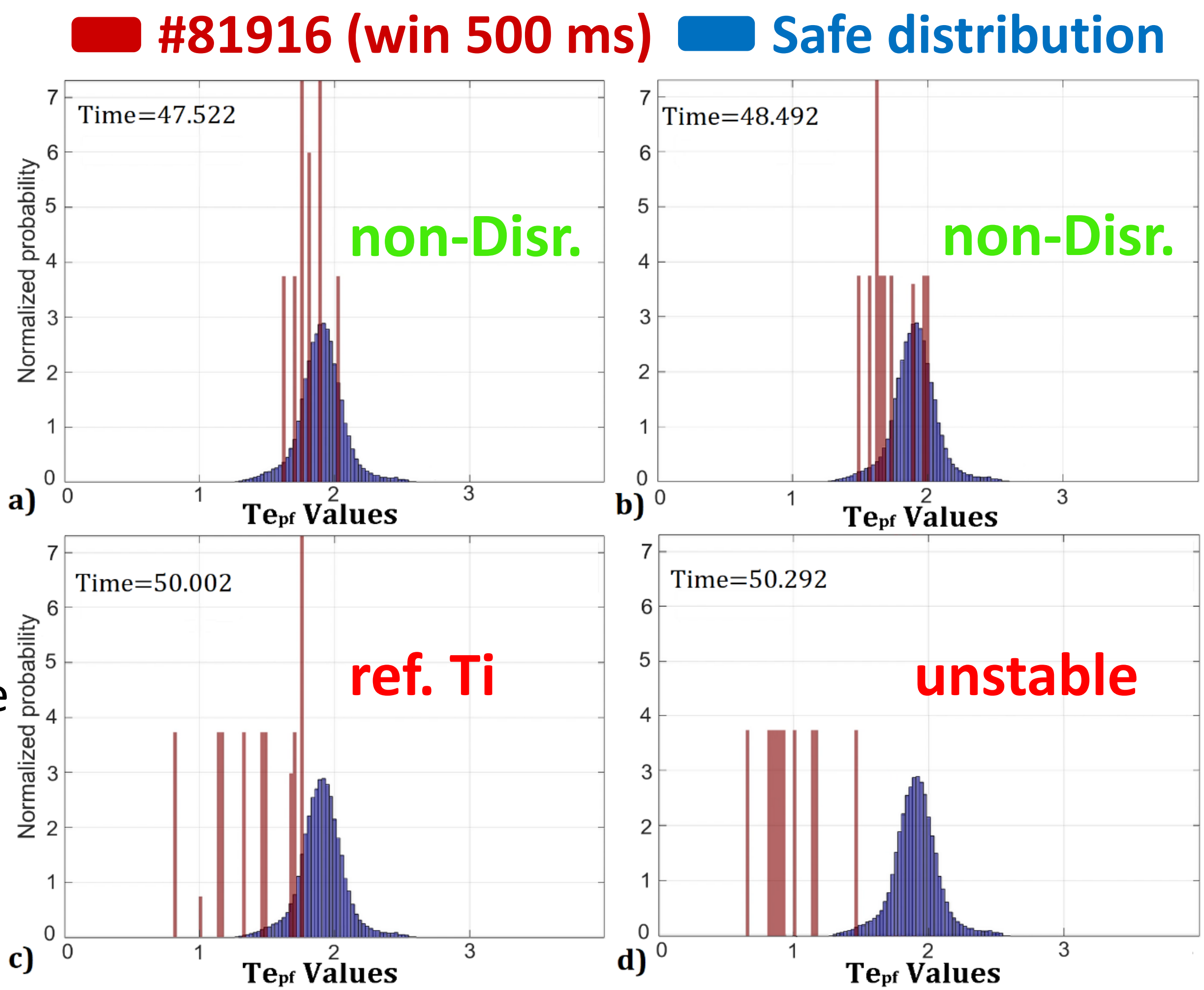
We analyze the parameter value distribution during the discharge evolution

Sliding window adapted to the flat-top length (max 500 ms)

We can observe a shift of the plasma parameter distribution as the sliding window gets closer to tD

We can estimate the deviation by using a distribution distance metric

The contribute of each parameter is weighted to detect the Ti



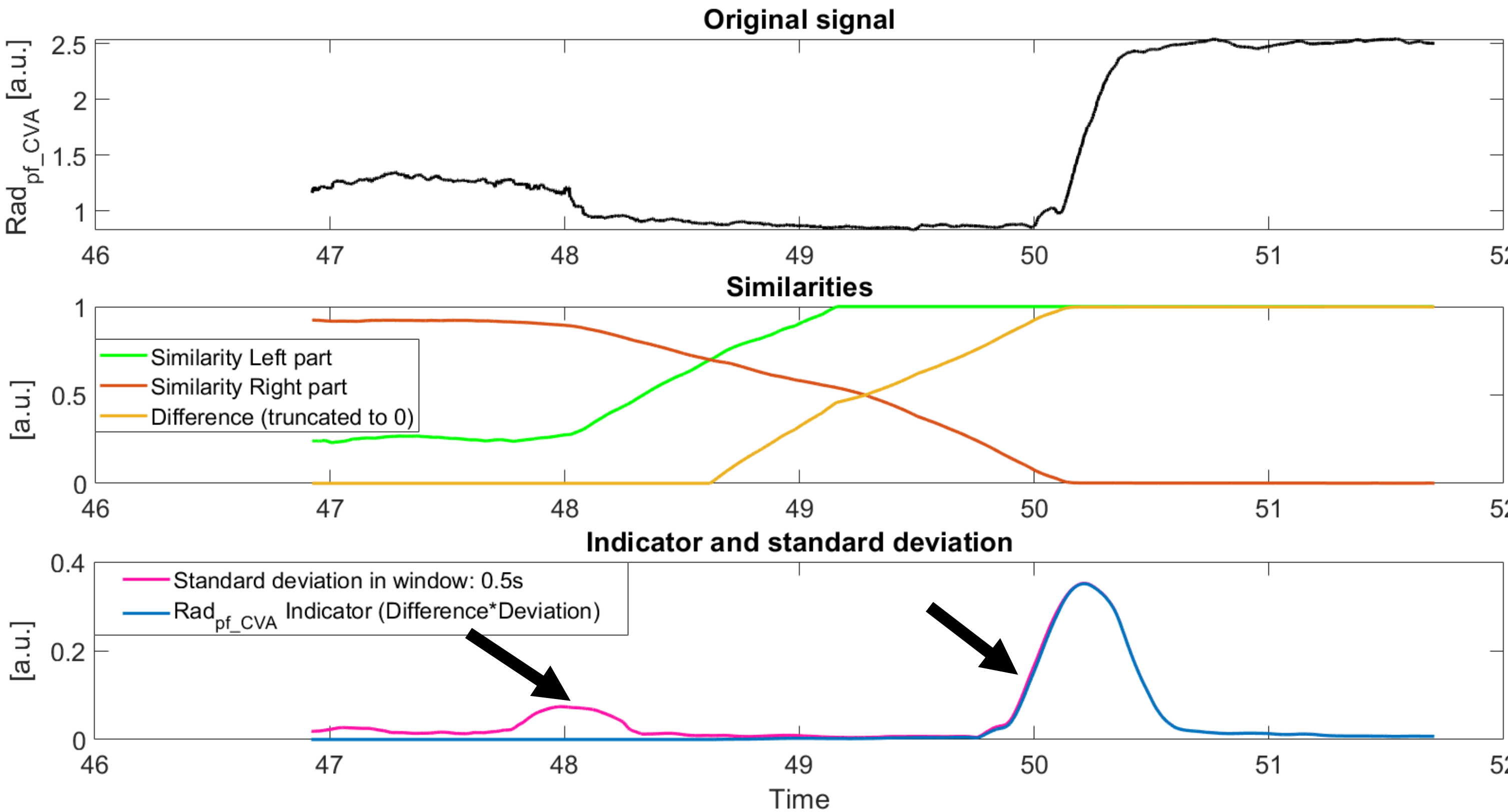
Example of construction

At each time instant ***t*** two similarity metrics are computed between the safe distribution and:

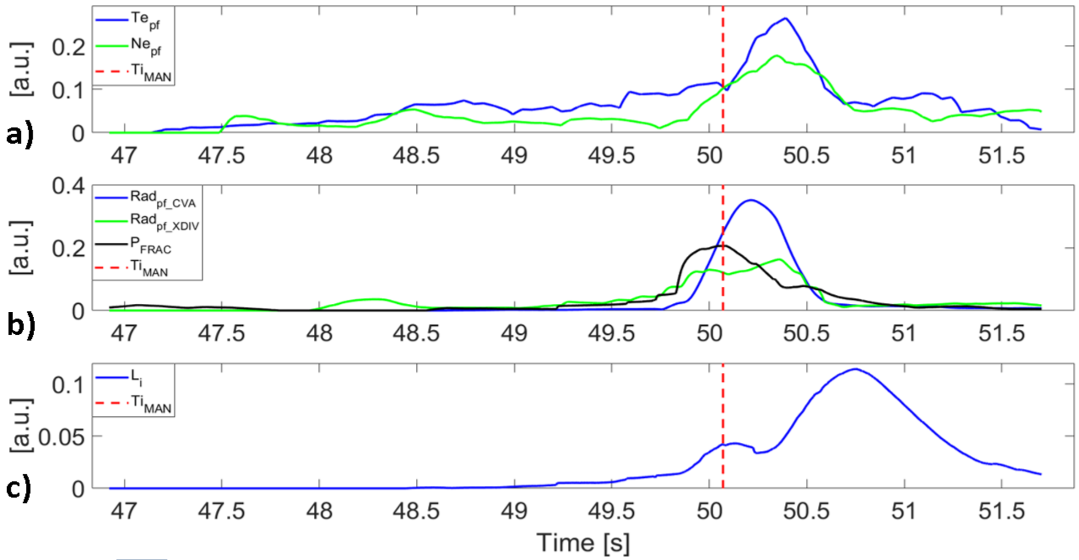
Metric: Cosine $$s_{Cos} = \frac{\sum_{i=1}^{B} P_i Q_i}{\sqrt{\sum_{i=1}^{B} P_i^2}\sqrt{\sum_{i=1}^{B} Q_i^2}}$$

1. The plasma parameter before **t** 2. the plasma parameter after **t**

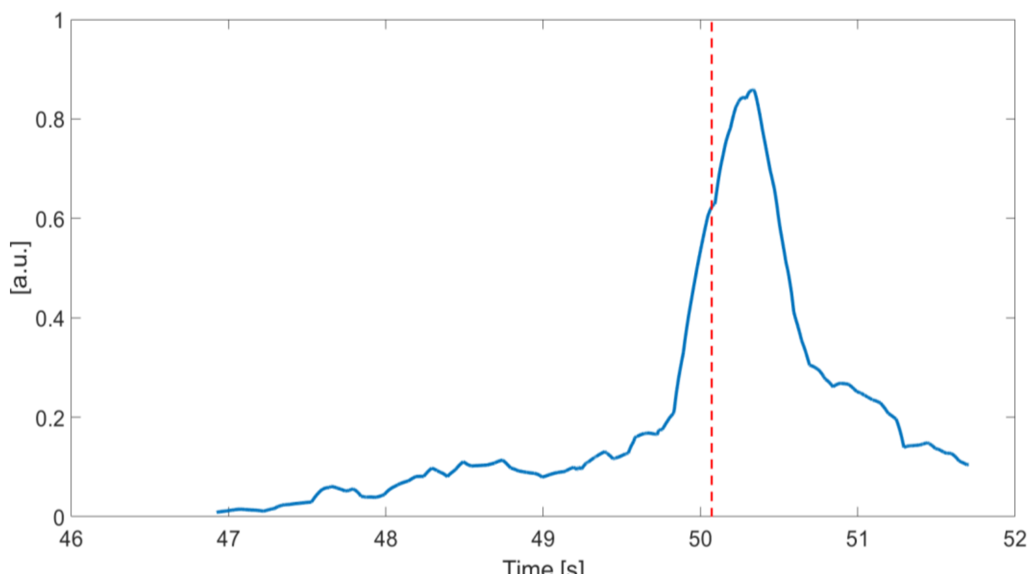
The **difference** among these 2 truncated to 0 weighs the standard deviation



Combining the plasma parameters



Weighing each indicator with a coefficient $\in [0, 1]$



The weights are optimized maximizing the map discriminating power

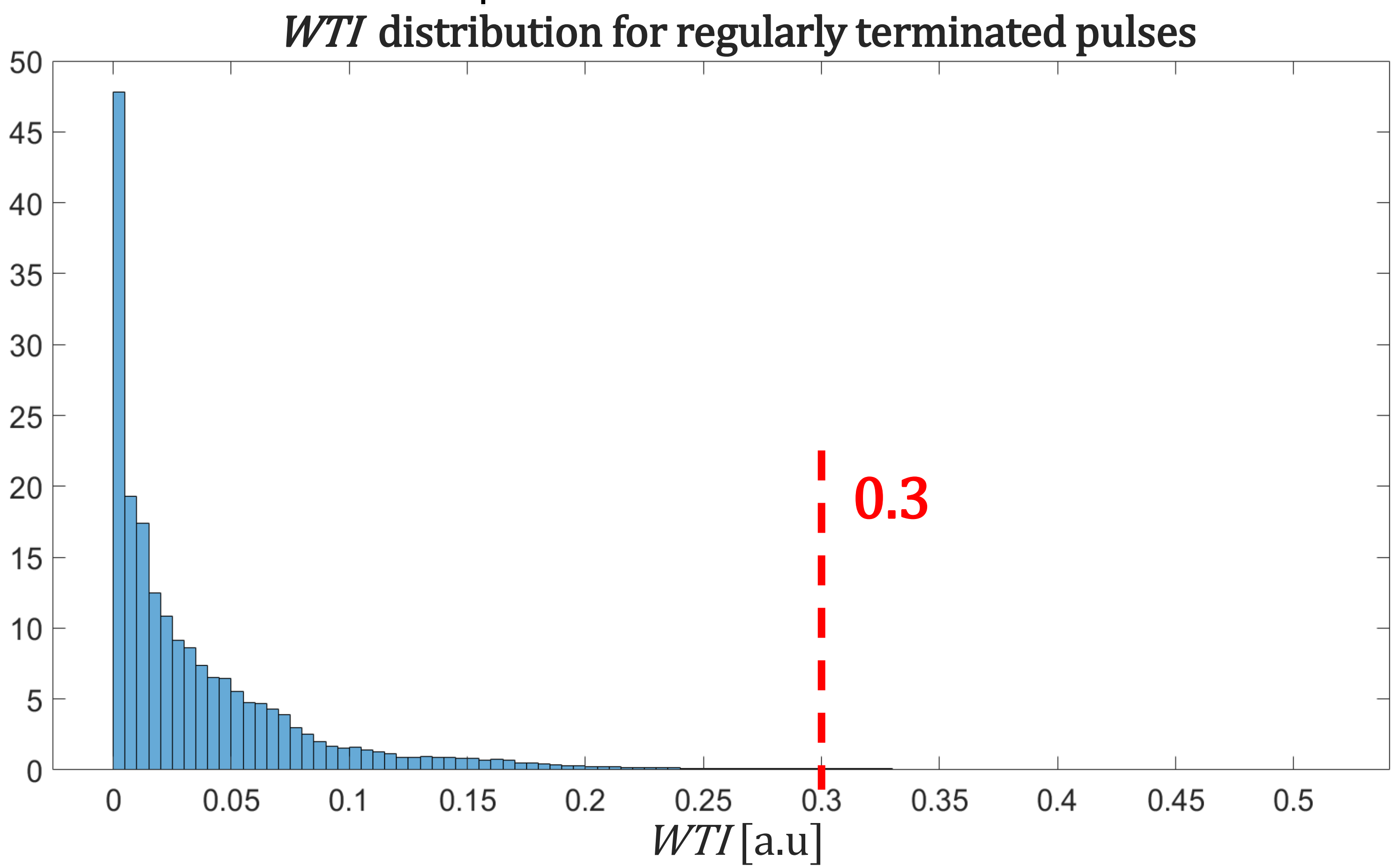
Warning Time detection

Identification of a threshold (*WTI*):

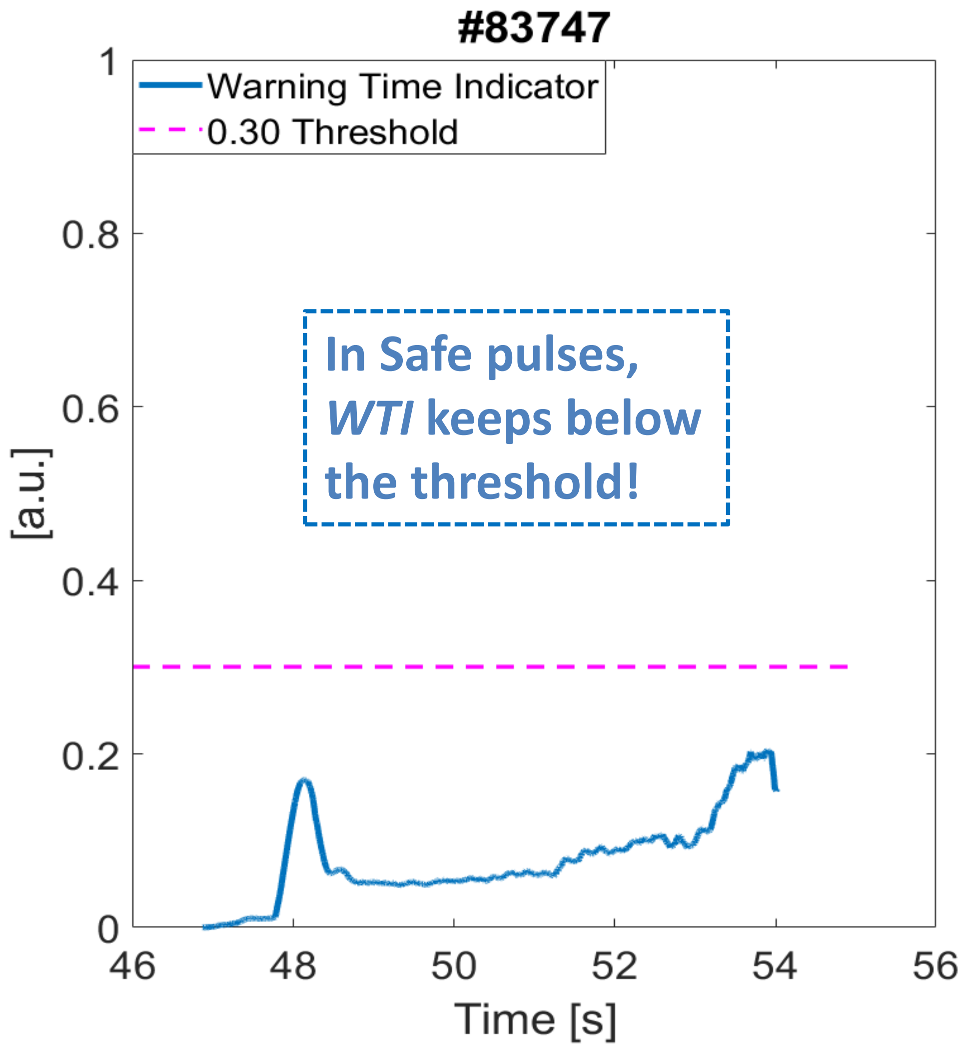
We used the 99th percentile of the *WTI* distribution in safe pulses

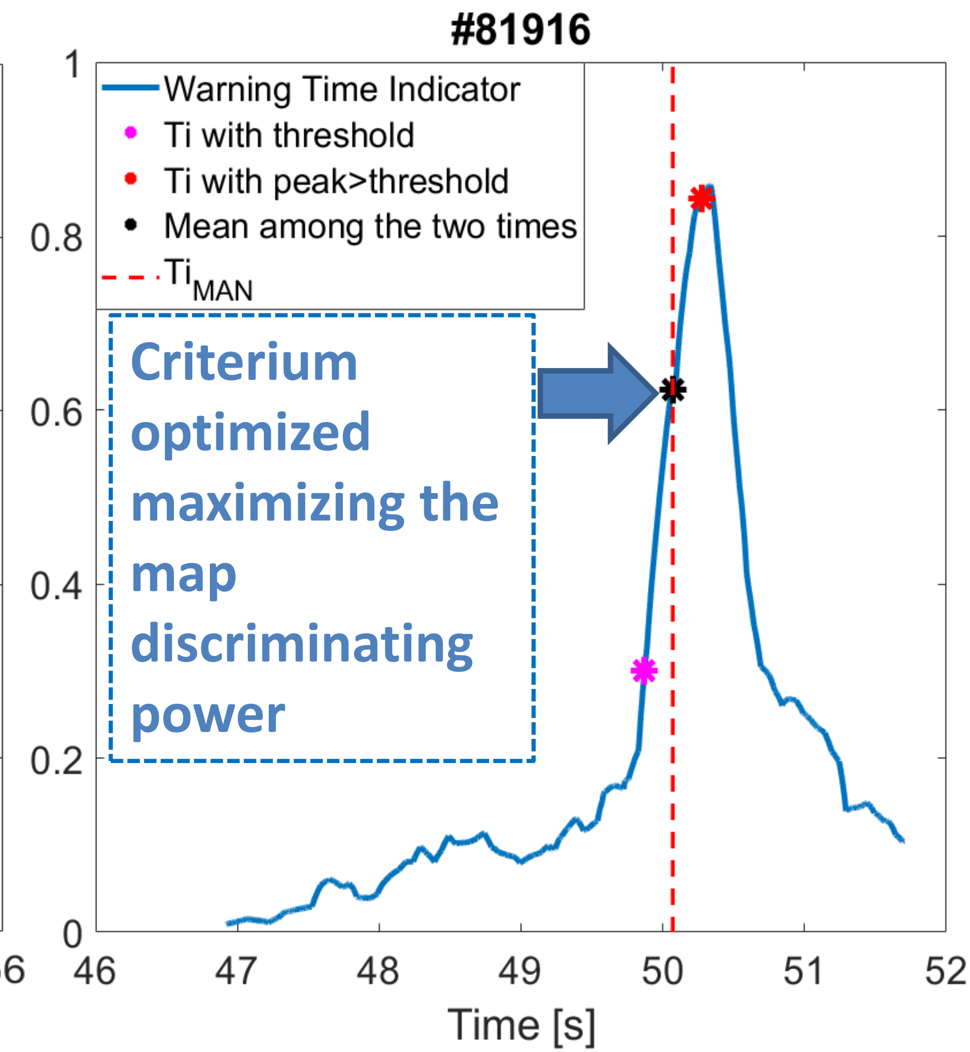
Methods for the detection: Signal higher than threshold for k consecutive samples

First peak over the threshold

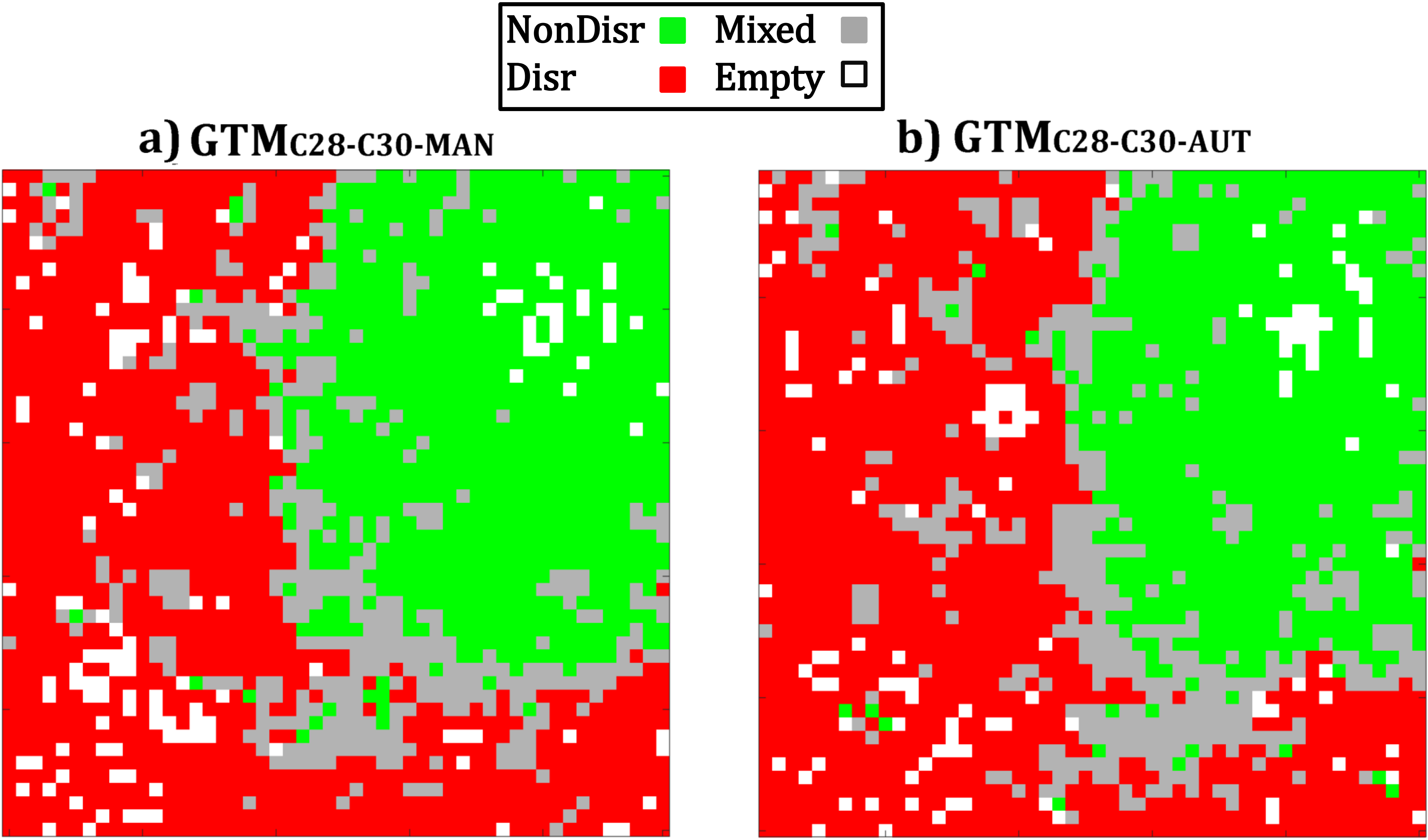


Examples


#83747
Warning Time Indicator
0.30 Threshold
In Safe pulses, *WTI* keeps below the threshold!
[a.u.]
1
0.8
0.6
0.4
0.2
0
46
48
50
52
54
56
Time [s]


#81916
Warning Time Indicator
Ti with threshold
Ti with peak>threshold
Mean among the two times
Ti_{MAN}
Criterium optimized maximizing the map discriminating power
1
0.8
0.6
0.4
0.2
0
46
47
48
49
50
51
52
Time [s]

C28-C30 Campaigns: Mapping



C28-C30 Campaigns: GTMs composition

The two maps have quite similar composition:

a) GTM C28-C30-MAN

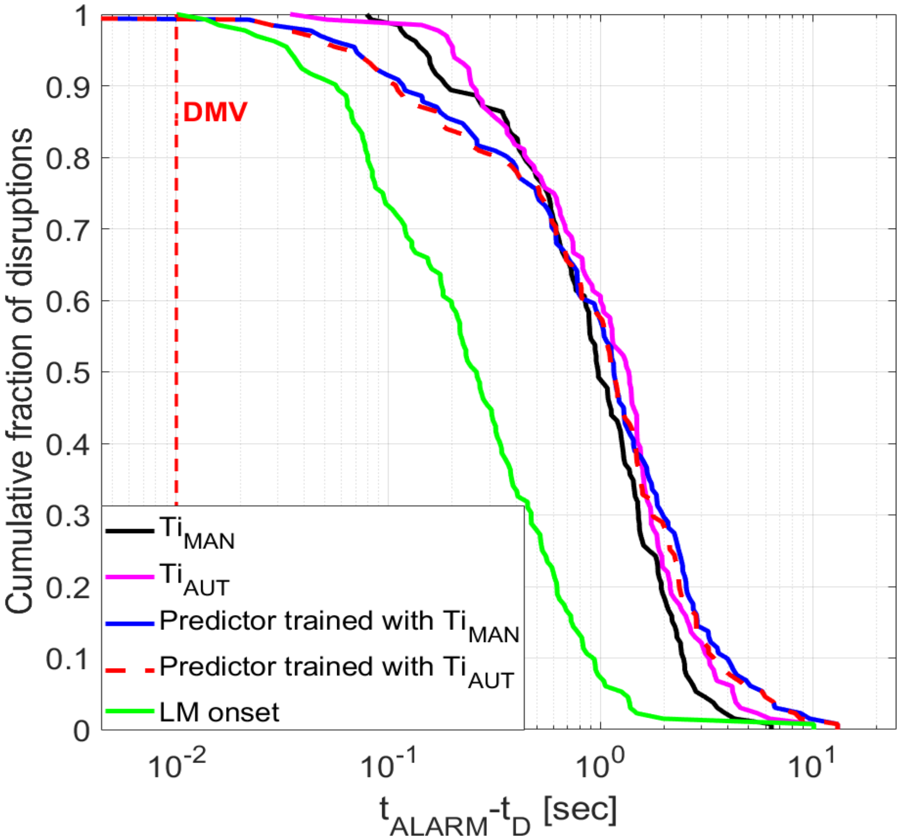
Type of cell	Number of cells	% of clusters	% of samples in the clusters	% samples of a class in a cell of the same class
Safe	861	34.44	40.74	79.17
Disrupted	1109	44.36	41.15	84.74
Mixed	392	15.68	**18.12**	-
Empty	138	5.52	-	-

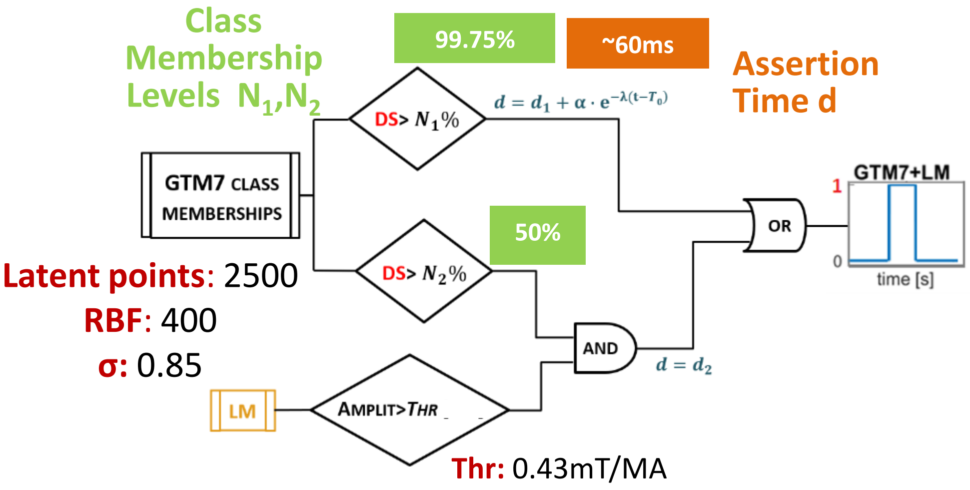
b) GTM C28-C30-AUT

Type of cell	Number of cells	% of clusters	% of samples in the clusters	% samples of a class in a cell of the same class
Safe	787	31.48	35.92	75.25
Disrupted	1176	47.04	42.60	81.51
Mixed	414	16.56	**21.48**	-
Empty	123	4.92	-	-

- The number of cells are very similar
- the percentage of samples falling in the mixed grey clusters differs by about 3% (related to **map discriminating power**)

C28-C30 Campaigns: Prediction





Database composition

Set	Train	Test	All
Disruptions	89	43	132
Safe	70	45	115

Training set prediction errors

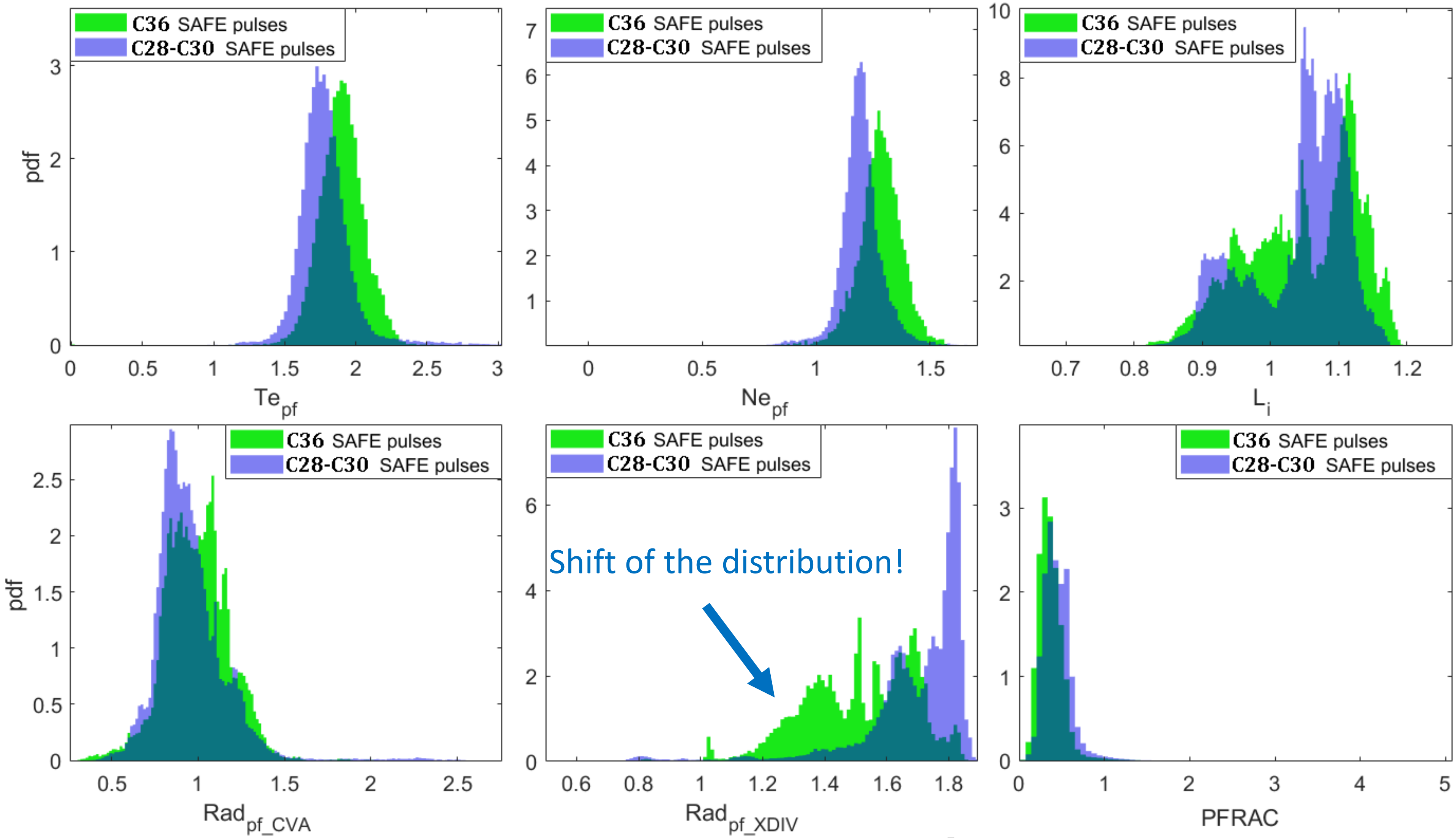
	$GTM_{C28\text{-}C30\text{-}MAN}$	$GTM_{C28\text{-}C30\text{-}AUT}$
MA	0	0
TD	1	1
FA	0	0

Test set prediction errors

	$GTM_{C28\text{-}C30\text{-}MAN}$	$GTM_{C28\text{-}C30\text{-}AUT}$
MA	1	1
TD	0	0
FA	6	3

Statistical analysis on a more recent campaign

New Dataset: 2016 Campaign (C36)

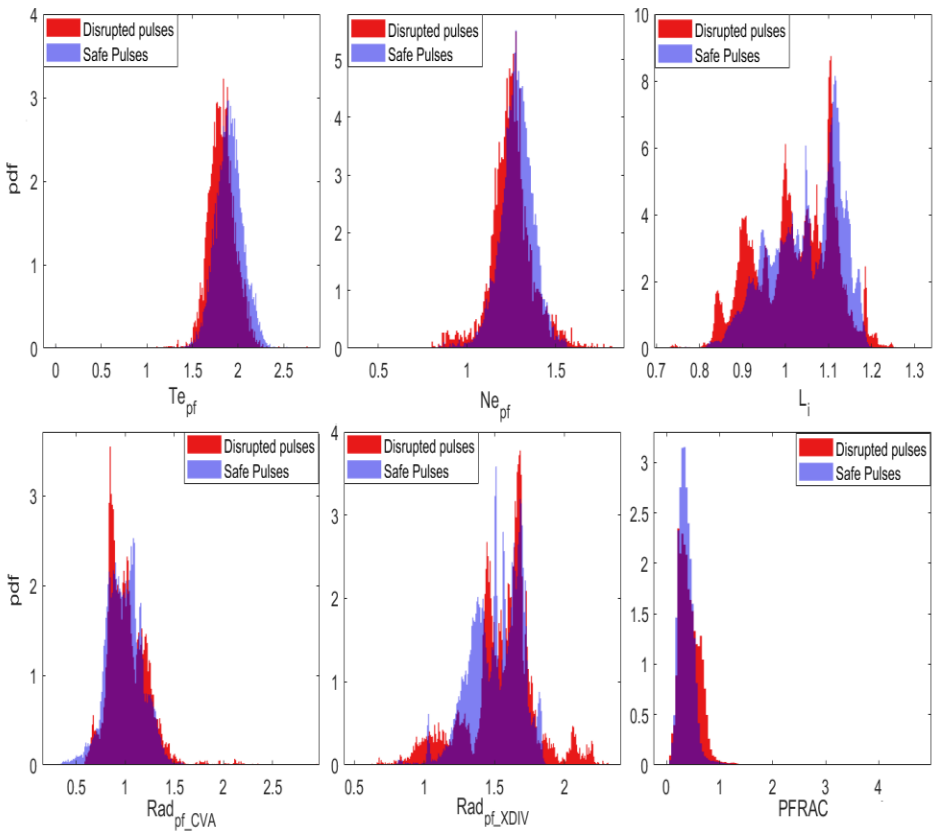


We can see that generally parameters overlap →good!

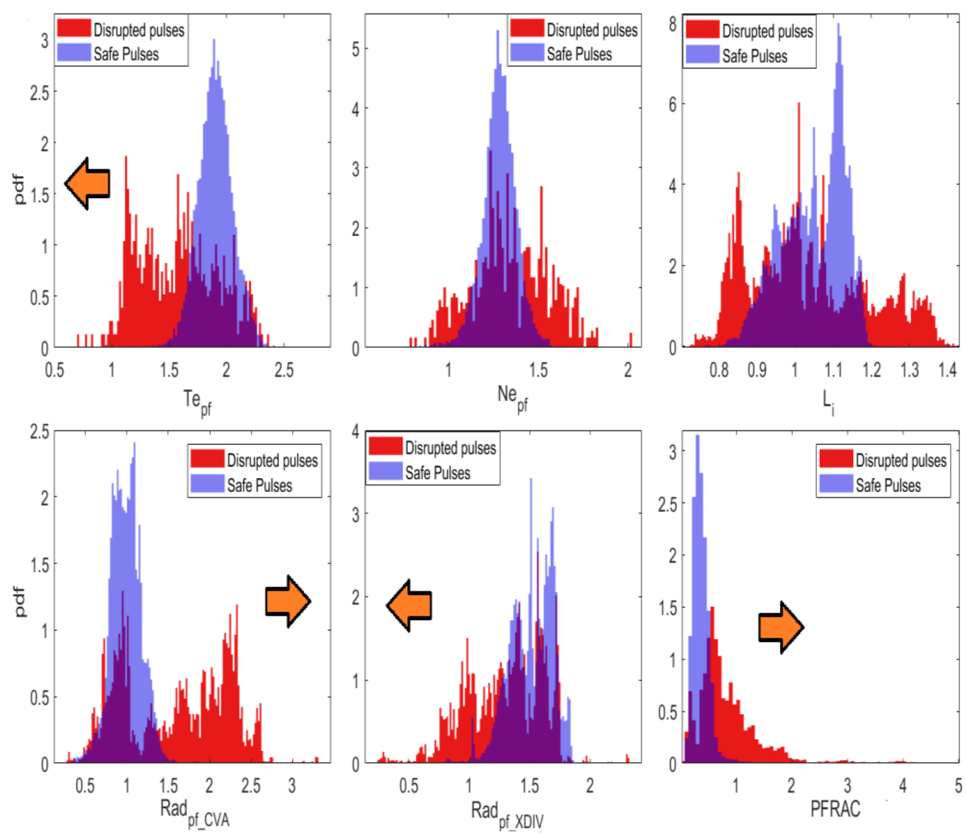
Statistical analysis on a more recent campaign

New Dataset: 2016 Campaign (C36)

Before Ti



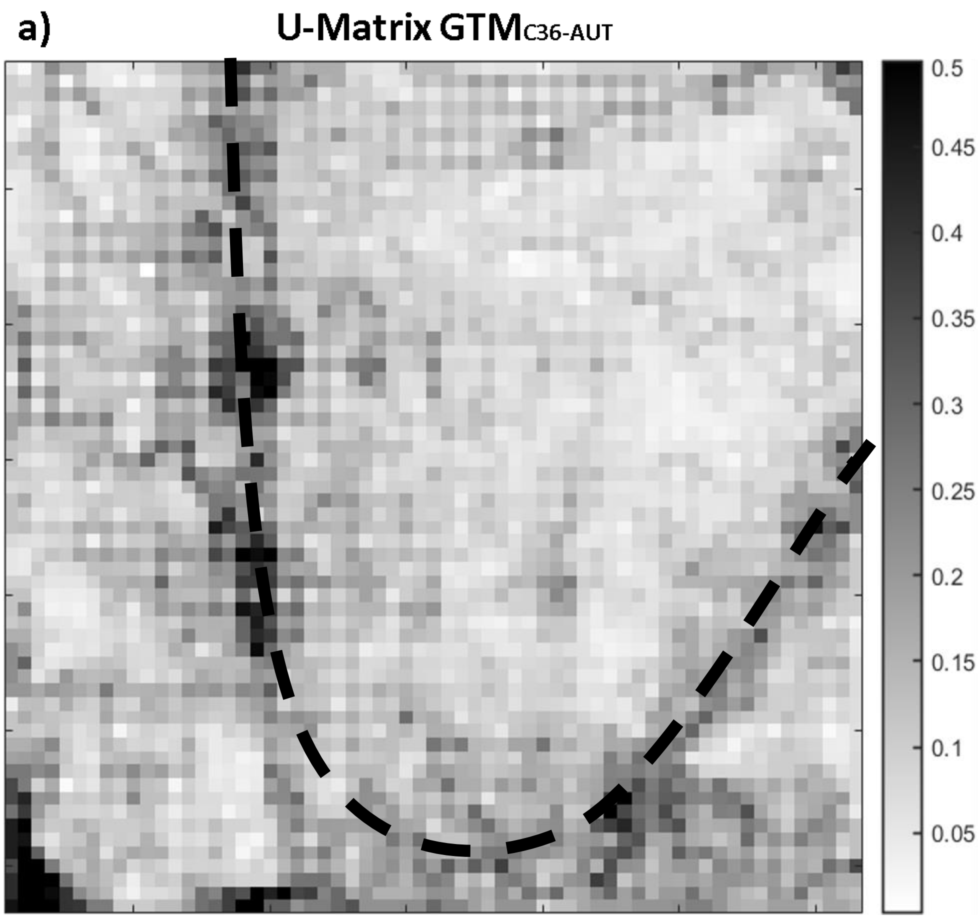
After Ti



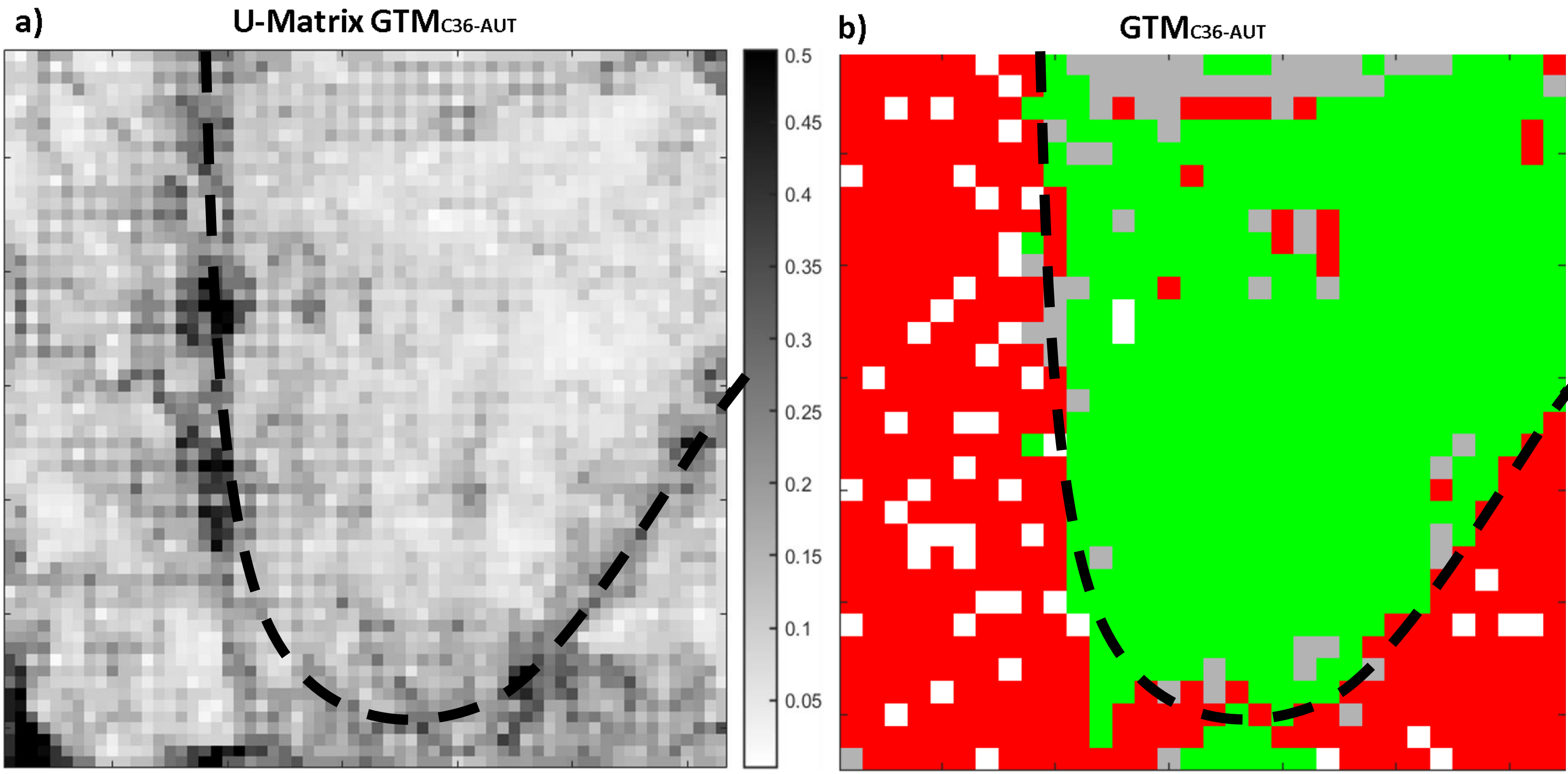
Consistency with the C28-C30 results

Similar shift of plasma parameters

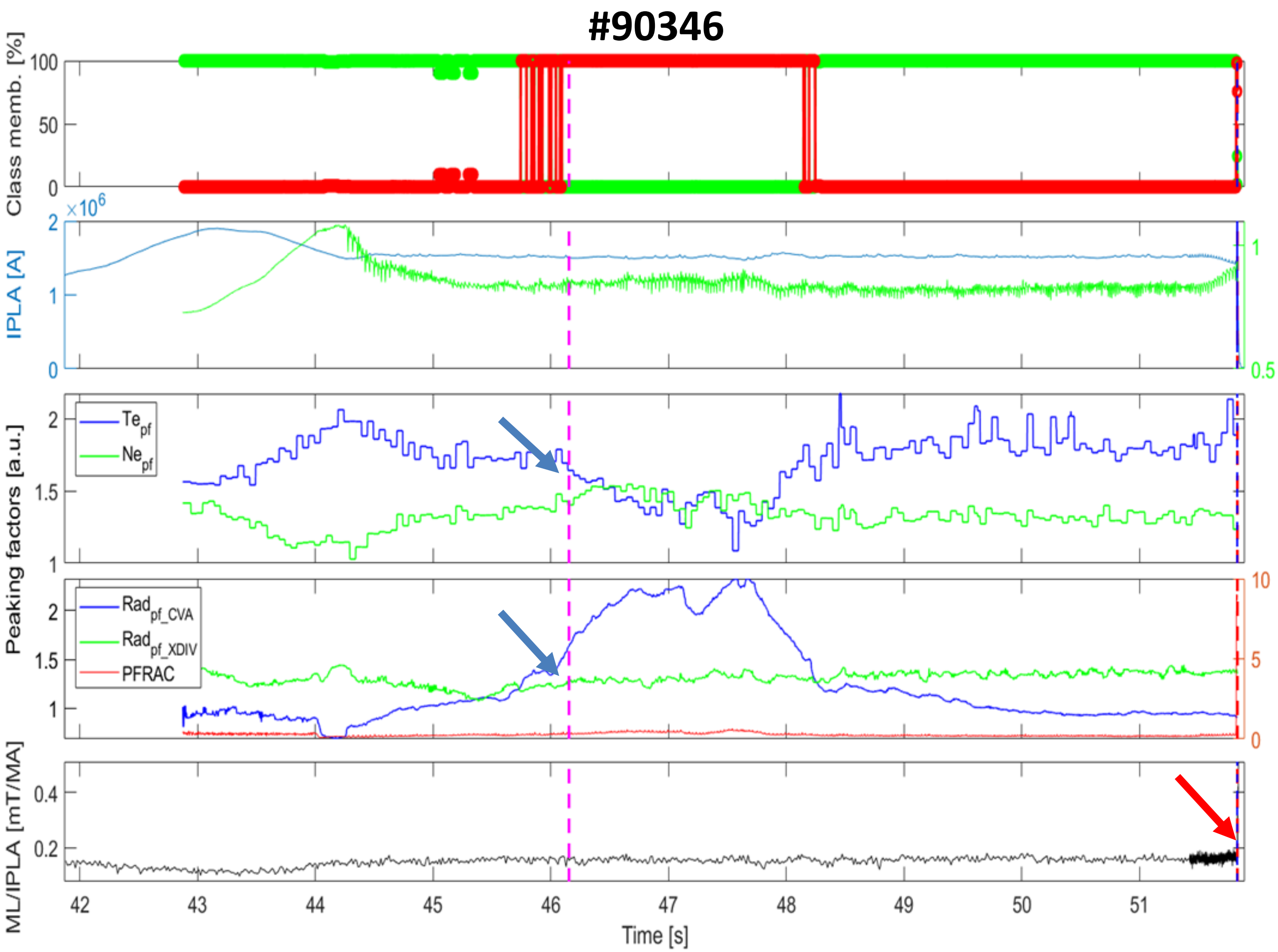
Unsupervised learning

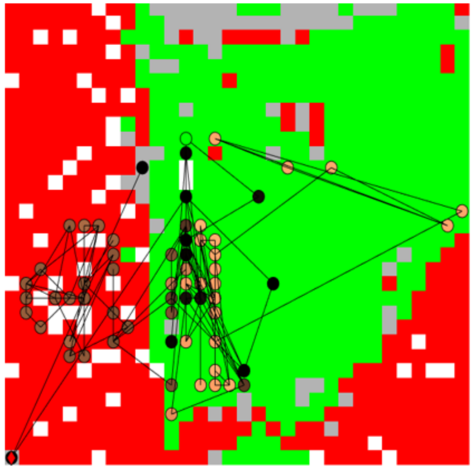


Unsupervised learning



Projection of a disrupted discharge





Impurity Accumulation pattern:

- **Decrease of Te_{pf}**
- **Increase of Ne_{pf}**
- **Increase of $Rad_{pf\text{-}CVA}$**

ML signal rises at the very end

Comment in a shotlist given by Peter Lomas
No sawteeth. But Zeff rises, possibly due to mid-z impurities. End of pulse stable, but mode lock and disruption at the very end

Conclusions & Perspectives

General concepts:

- the integration of ML models with physics-based models (for plasma control and in a disruption avoidance framework) requires intepretability!
- the automatic Warning Times automate the predictive model update while not compromising the interpretability of the model itself

The *WTI* algorithm

- exploits intrinsic data properties (distance between the safe and disrupted distribution of each parameter) to detect the pre-disruptive phase of a disruption
- can help automating the analyses and the predictive model update in an interpretable machine learning framework
- has led to very good results in disruption prediction in the C28-C30 dataset
- has been validated with C36 shots, with an unsupervised algorithm (GTM), providing similar topological properties and well-defined map borders

BACKUP SLIDES

Features

Plasma parameter	Definition
Te_{pf}: *electron temperature peaking factor*	$Te_{pf} = \frac{mean(Te_{Core})}{mean(Te_{all})}$
Ne_{pf} : *electron density peaking factor*	$Ne_{pf} = \frac{mean(Ne_{Core})}{mean(Ne_{all})}$
$Rad_{pf\text{-}CVA}$: *core peaking factor*	$Rad_{pf-CVA} = \frac{mean\ (Rad_{Core})}{mean\ (Rad_{All} - Rad_{XDIV})}$
$Rad_{pf\text{-}X\text{-}DIV}$: *divertor radiation peaking factor*	$Rad_{pf-XDIV} = \frac{mean\ (Rad_{XDIV})}{mean\ (Rad_{All} - Rad_{Core})}$
PFRAC: *fraction of P_{rad} with respect to the P_{tot}*	$PFRAC = \frac{P_{rad}}{P_{tot}}$
li: *internal inductance*	*Signal from JET database*

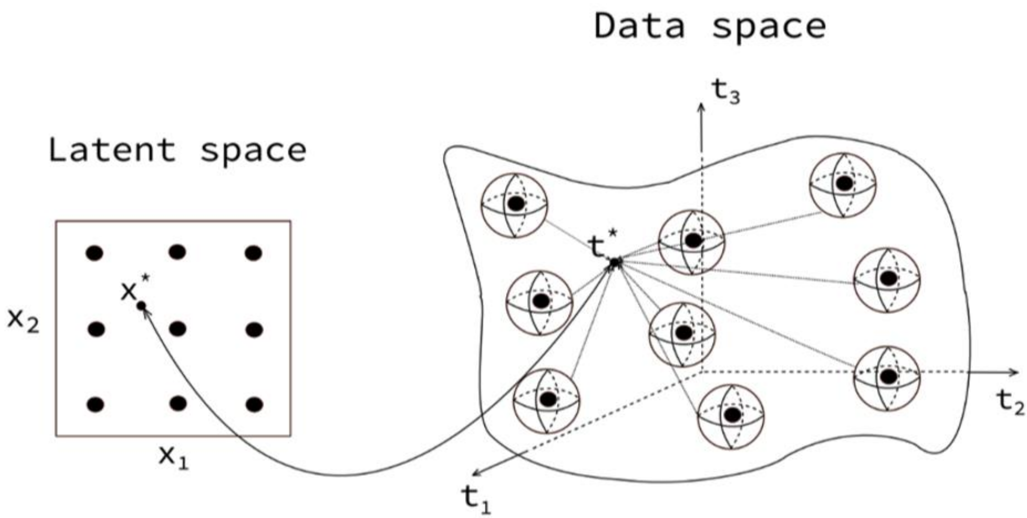
Generative Topographic Mapping

It is an unsupervised machine learning algorithm, hence it exploits only data properties [2]

- It maps a data space $t \in \Re^D$ **in a latent space** $x \in \Re^L$
- The mapping function is a linear combination of functions Φ: $y(x, W) = W \cdot \Phi(x)$
- The algorithm models data uncertainty as gaussian noise
- An **Expectation-Maximization** (EM) procedure is used to update the model
- The algorithm **preserves** the topographic ordering properties of the data space

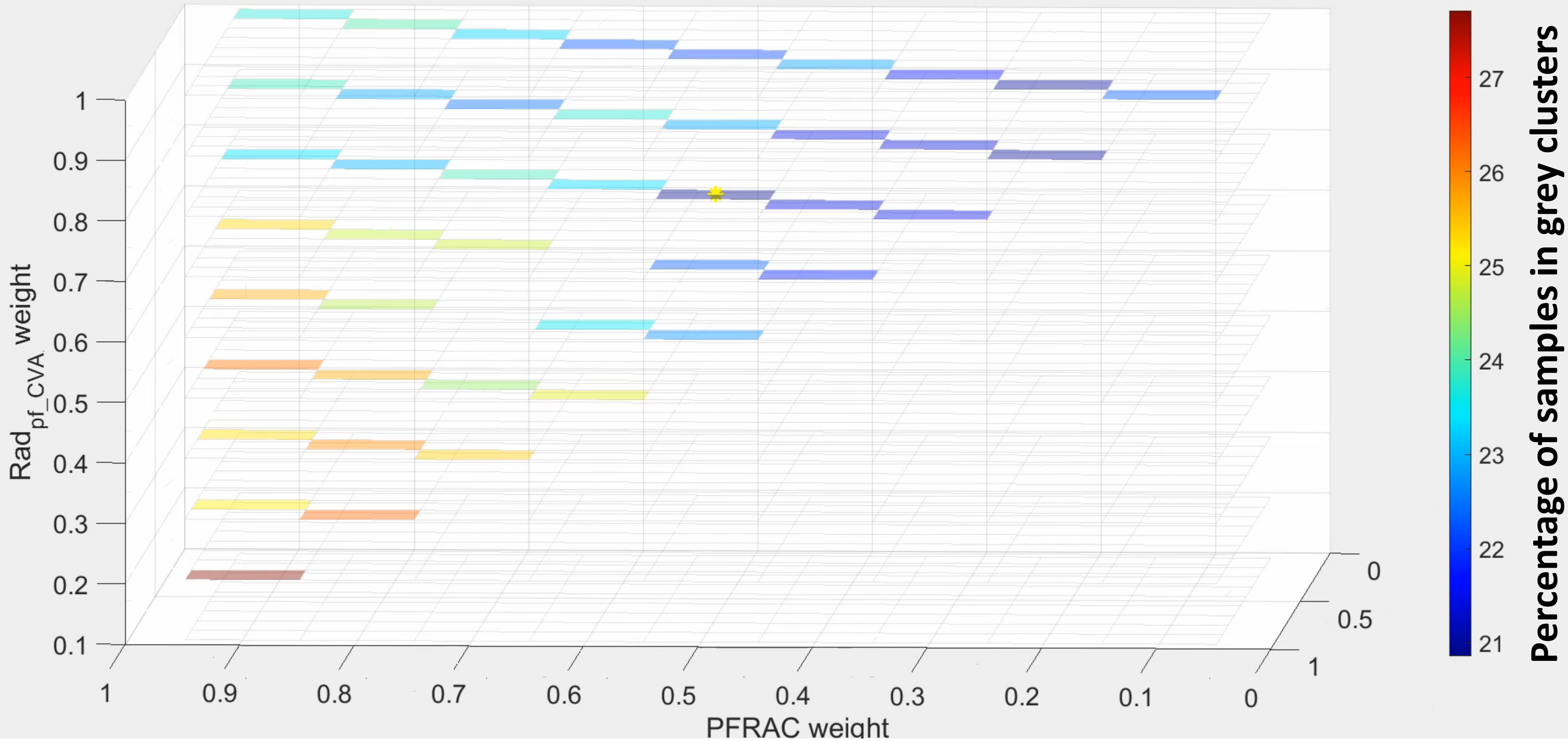
*[2]: Bishop C., Svensén M., Williams C. (1998) "**GTM: The generative topographic mapping**", Neural Computation 10215–34.0*

There is a ready Matlab tool for its use **[3]**

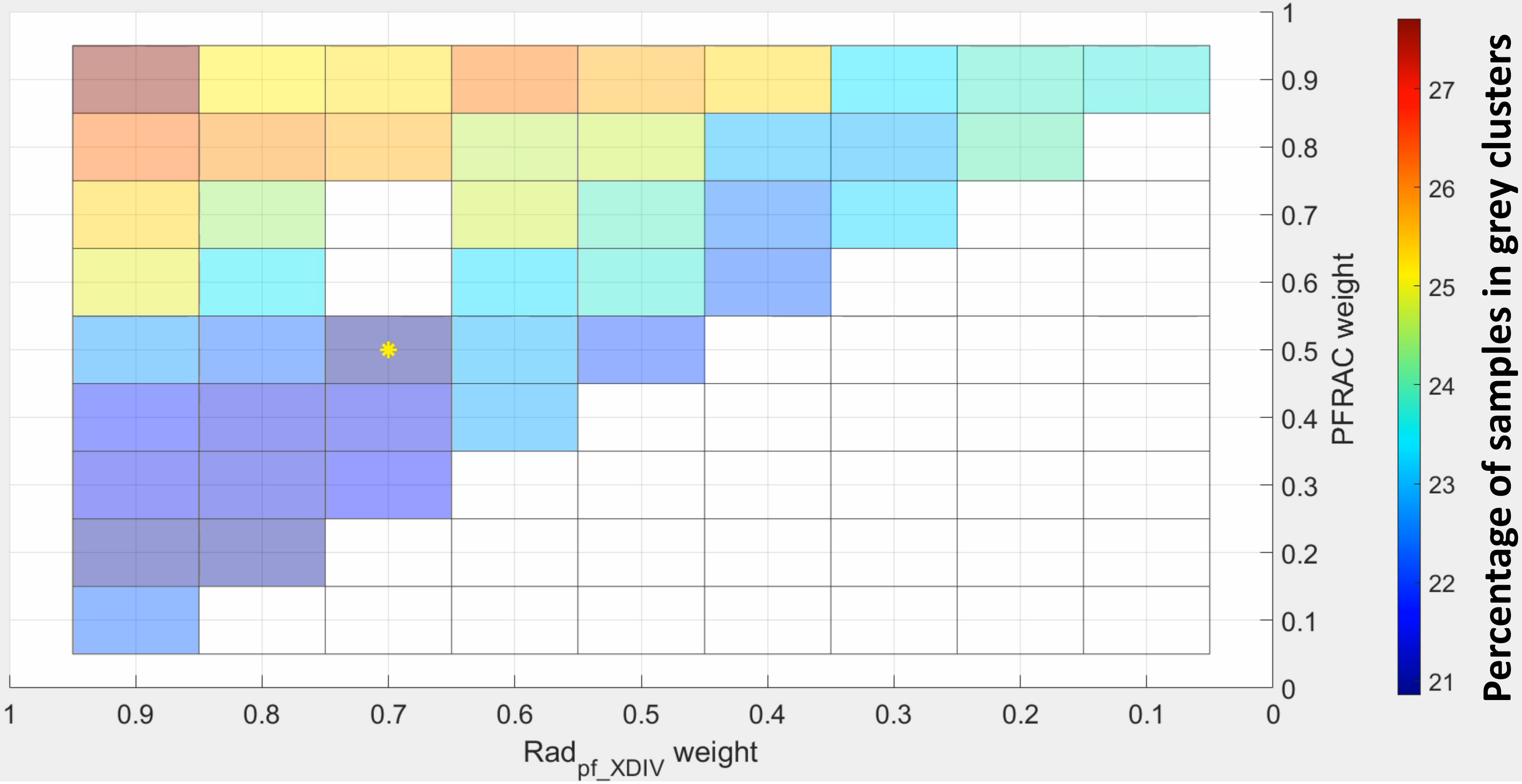


*[3]: A. Pau, **"Techniques for prediction of disruptions on TOKAMAKS"** [Ph.D Thesis], http://paduaresearch.cab.unipd.it/6664/, 2014*

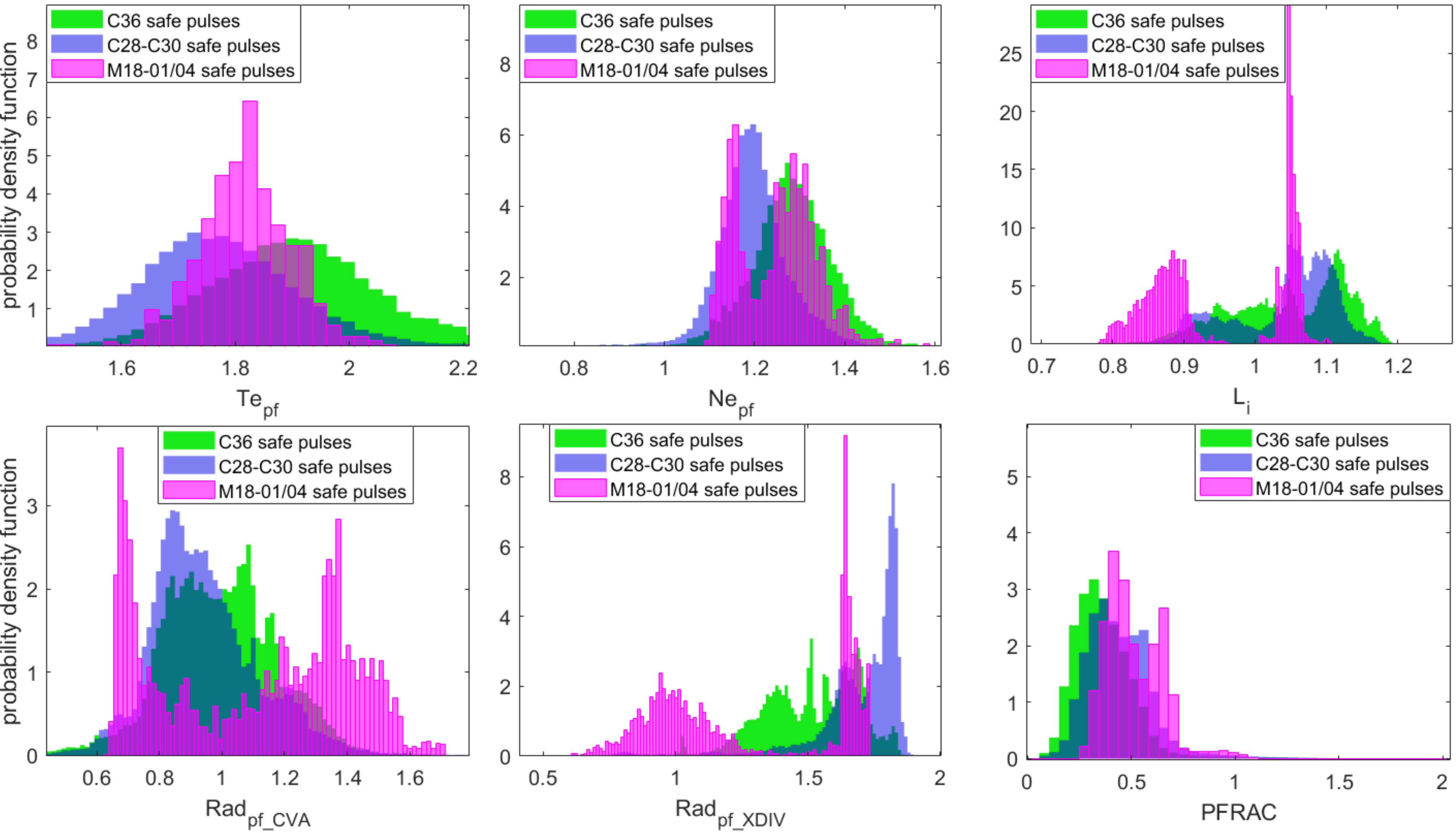
Radiation parameters weights



Radiation parameters weights

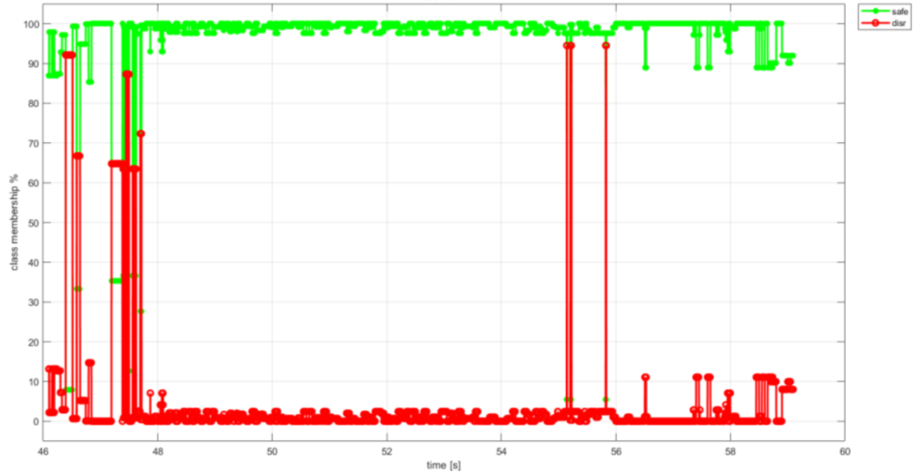


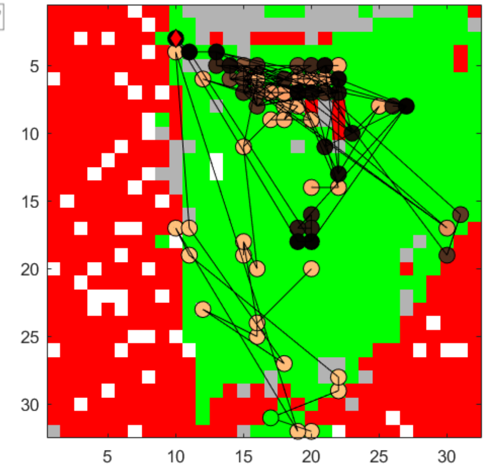
Some recent discharges

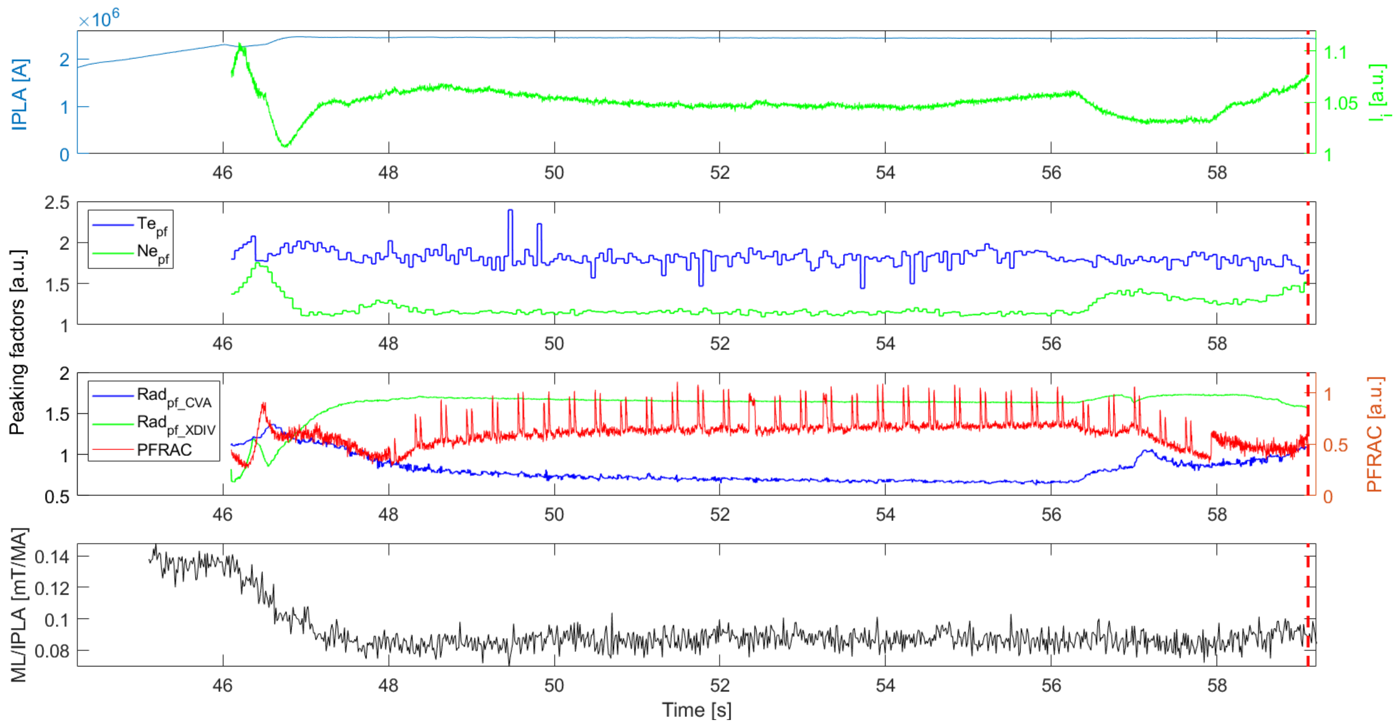


A recent safe discharge

#94757

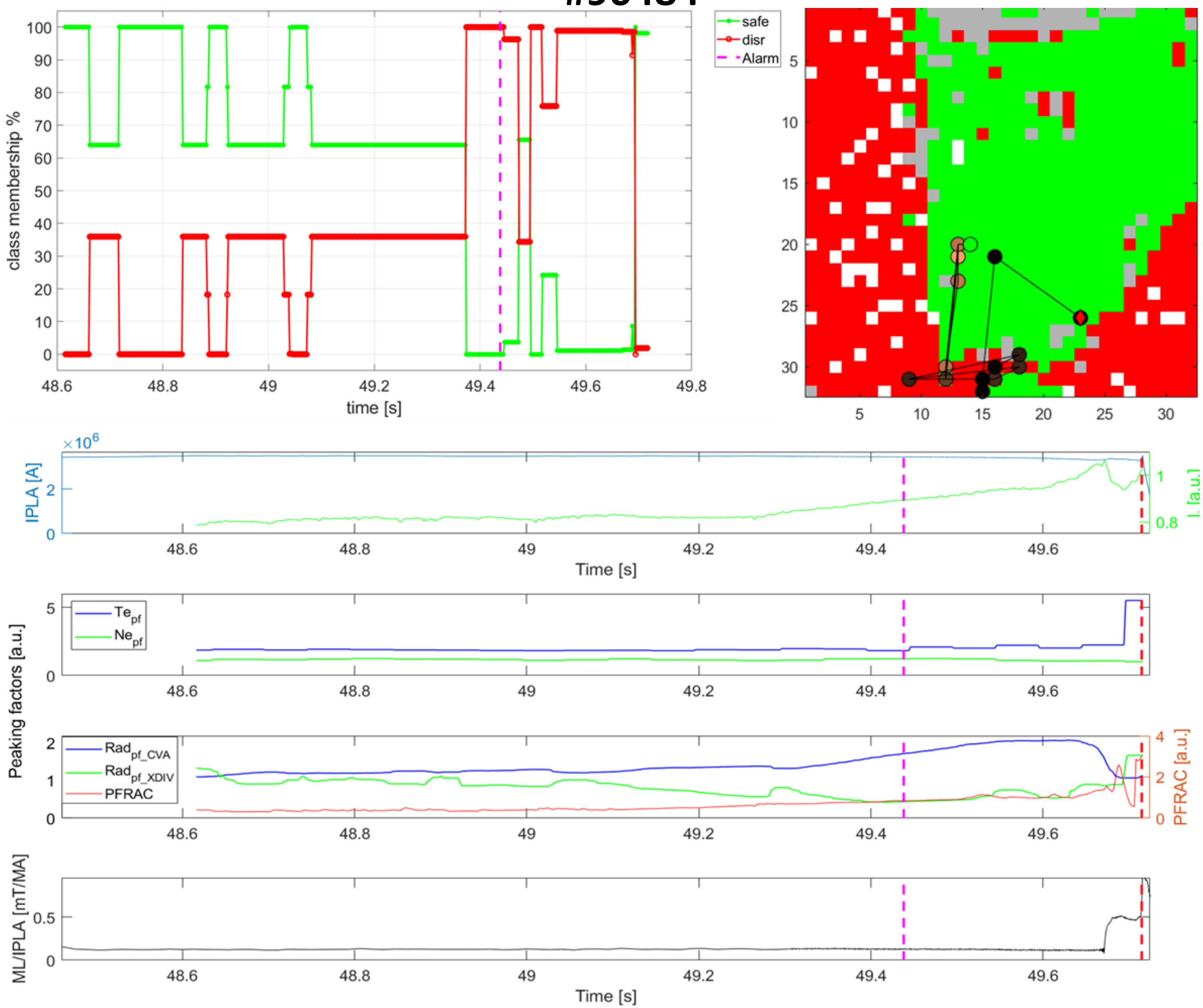






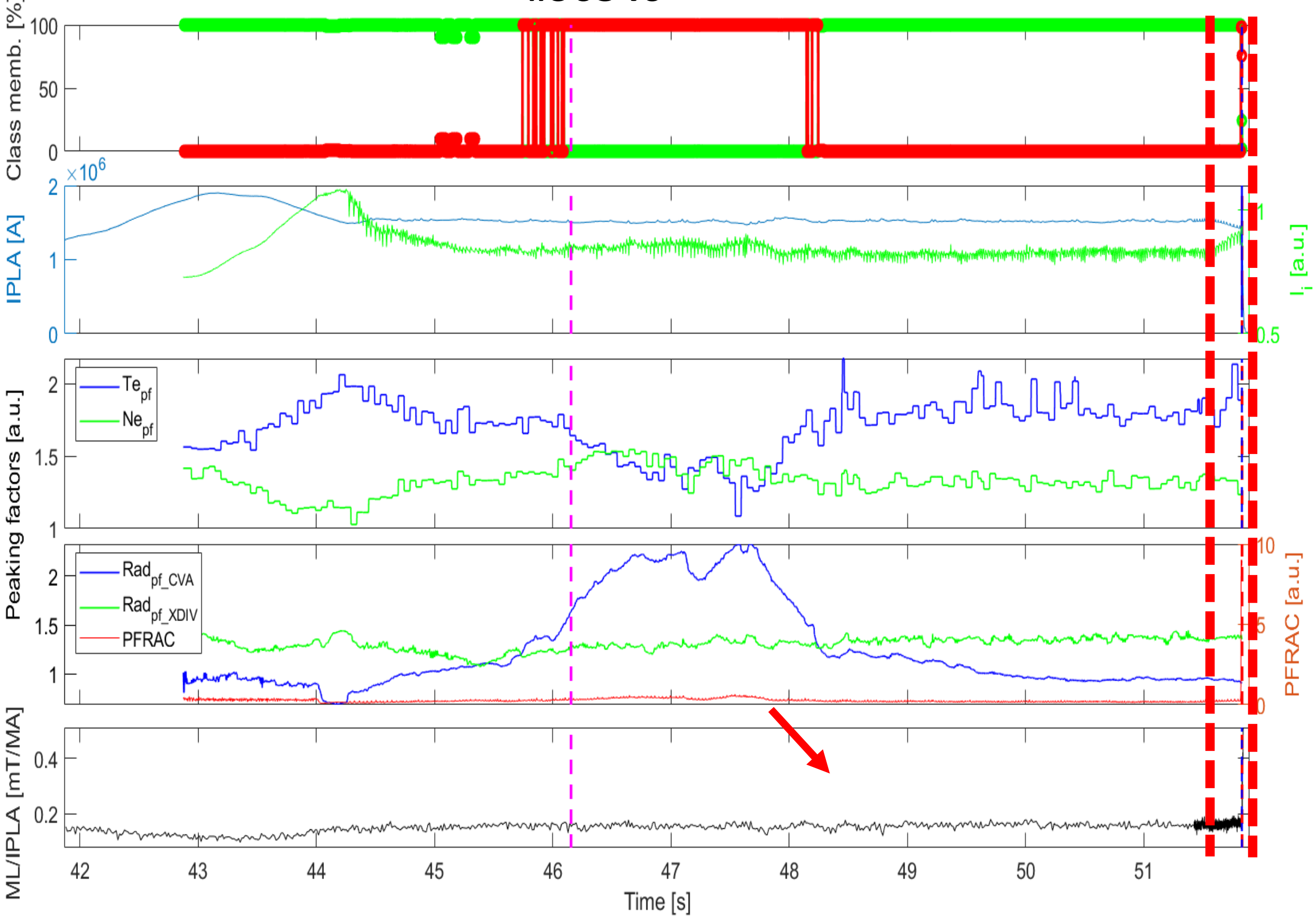
A recent disrupted discharge

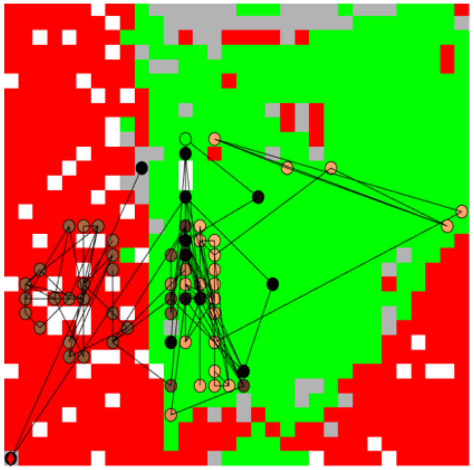
#96484



Projection of a disrupted discharge

#90346

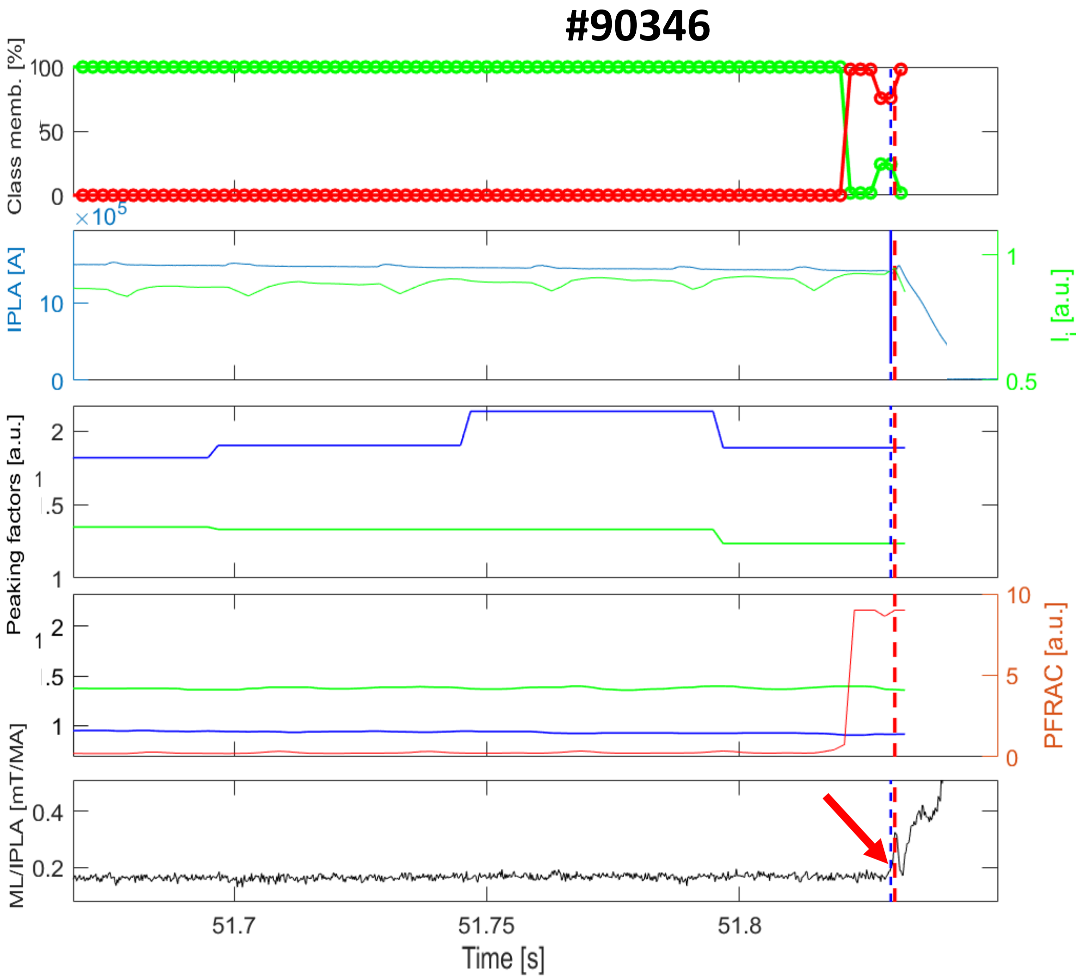


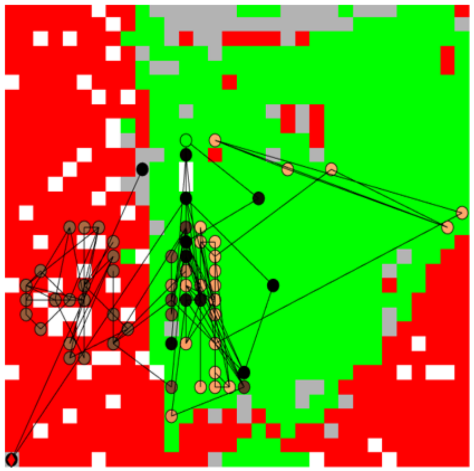


ML signal rises at the very end

Comment in a shotlist given by Peter Lomas
No sawteeth. But Zeff rises, possibly due to mid-z impurities. End of pulse stable, but mode lock and disruption at the very end

Projection of a disrupted discharge





ML signal rises at the very end

Comment in a shotlist given by Peter Lomas
No sawteeth. But Zeff rises, possibly due to mid-z impurities. End of pulse stable, but mode lock and disruption at the very end