IAEA Technical Meeting on Plasma Disruptions and their Mitigation

EUROfusion

Identifying Disruption Precursors by Anomaly Detection on Bolometer Tomography

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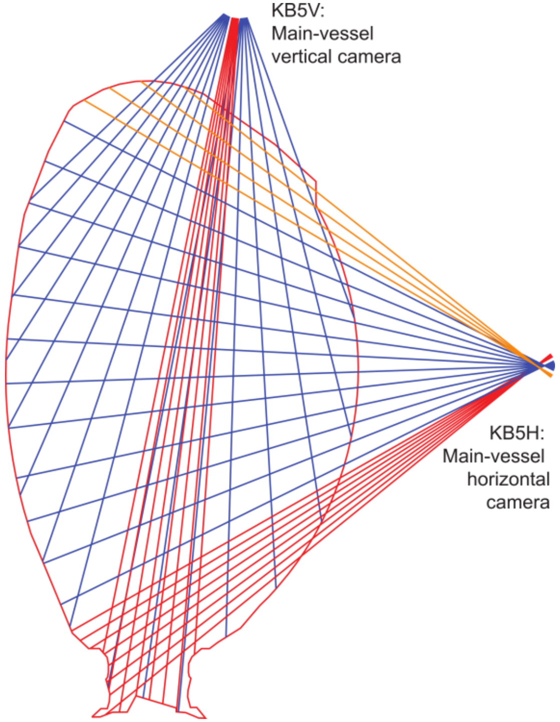
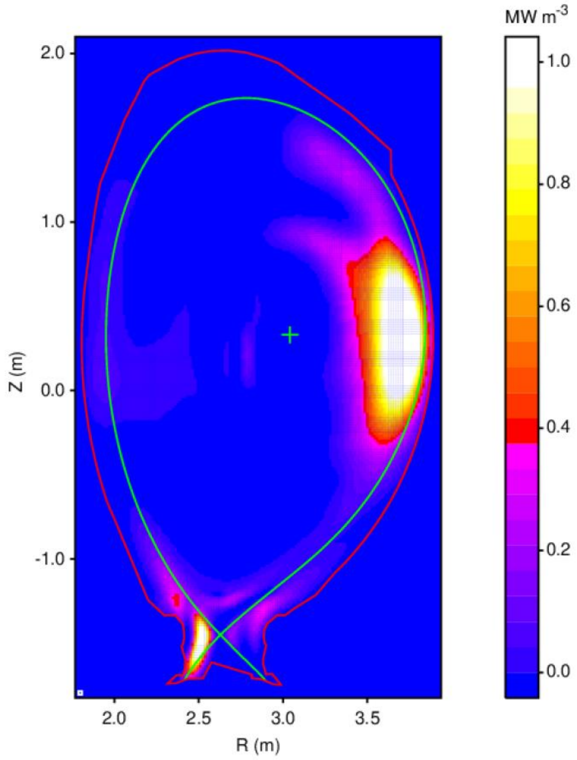
Introduction

- JET baseline scenario[1]
  - plasma current ↑ input power ↑ disruptivity ↑
  - impurity accumulation, core radiation, radiative collapse[2,3]
  - bolometer tomography[4]

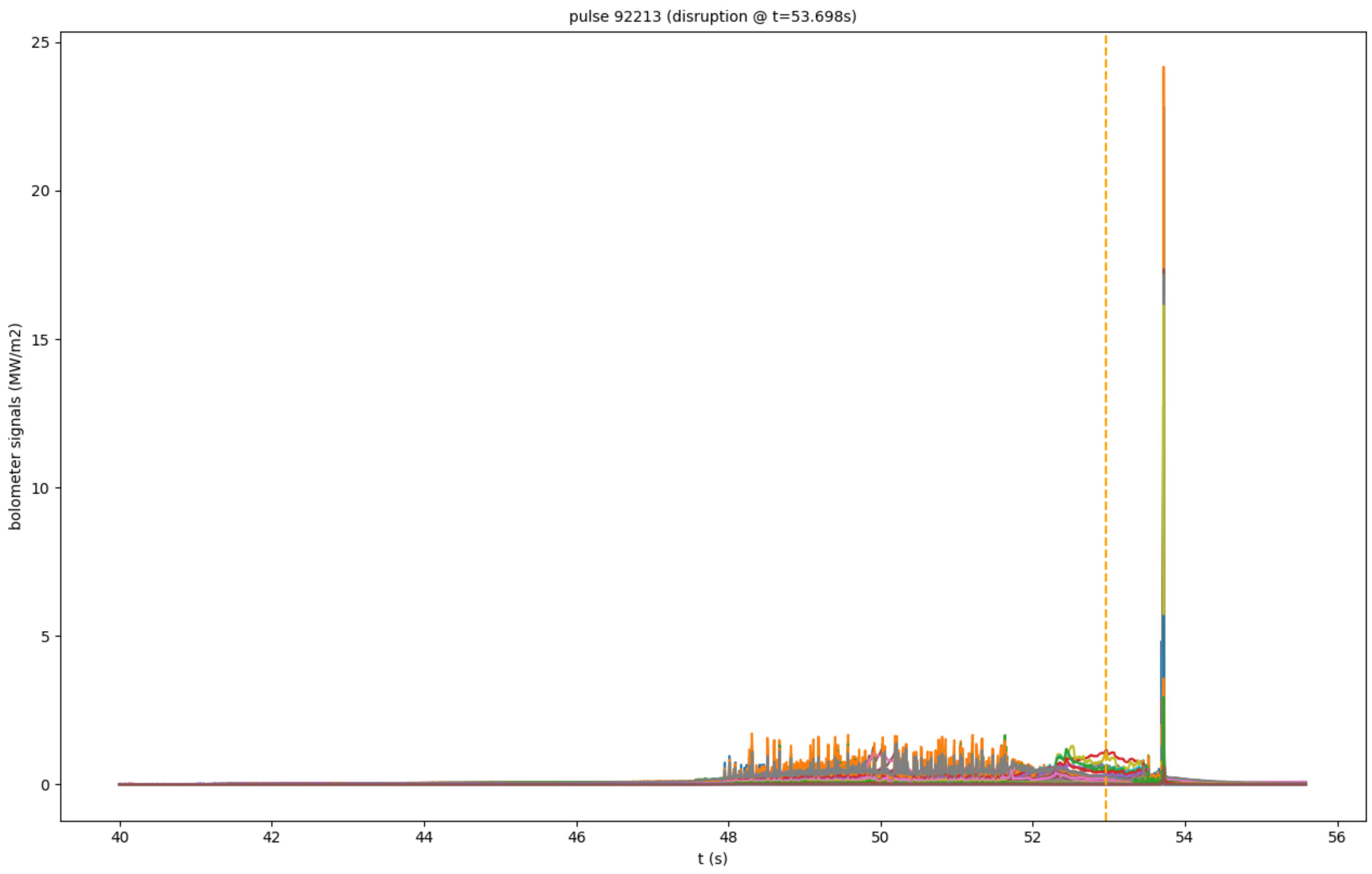


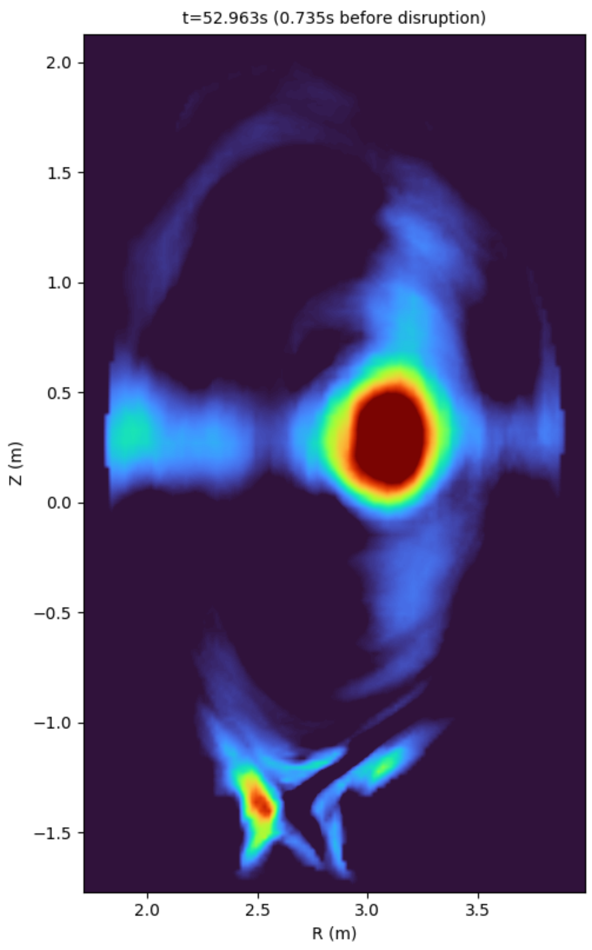


[1] L. Garzotti et al, "Scenario development for D-T operation at JET", Nucl. Fusion, vol. 59, no. 7, 2019
[2] P. C. de Vries et al, "Survey of disruption causes at JET", Nucl. Fusion, vol. 51, no. 5, 2011
[3] E. Joffrin et al, "First scenario development with the JET new ITER-like wall", Nucl. Fusion, vol. 54, no. 1, 2013
[4] A. Huber et al, "Upgraded bolometer system on JET for improved radiation measurements", Fusion Eng. Des., vol. 82, no. 5, 2007

Motivation

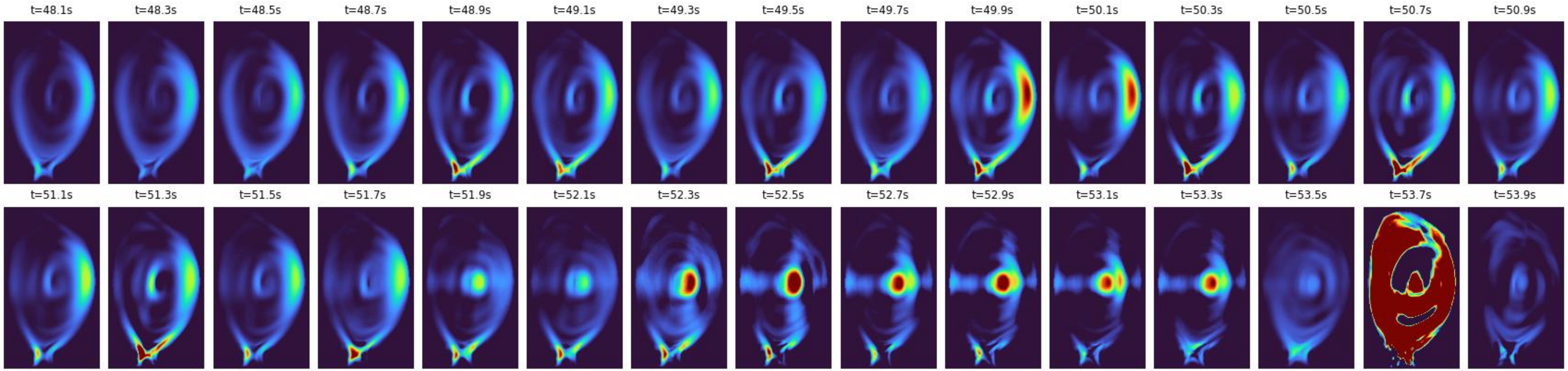
- Identify disruption precursors
  - some unusual behaviours can be observed directly in the bolometer signals
  - focus on 2D plasma profile, characterize anomalies in terms of shape and location of radiation blobs





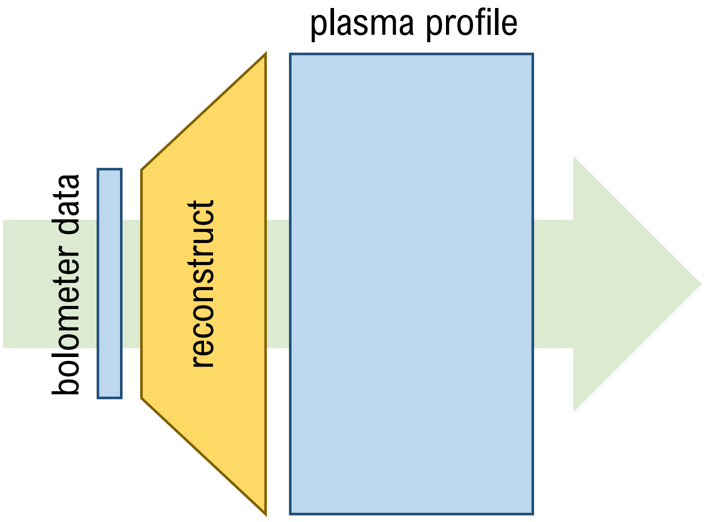
Approach

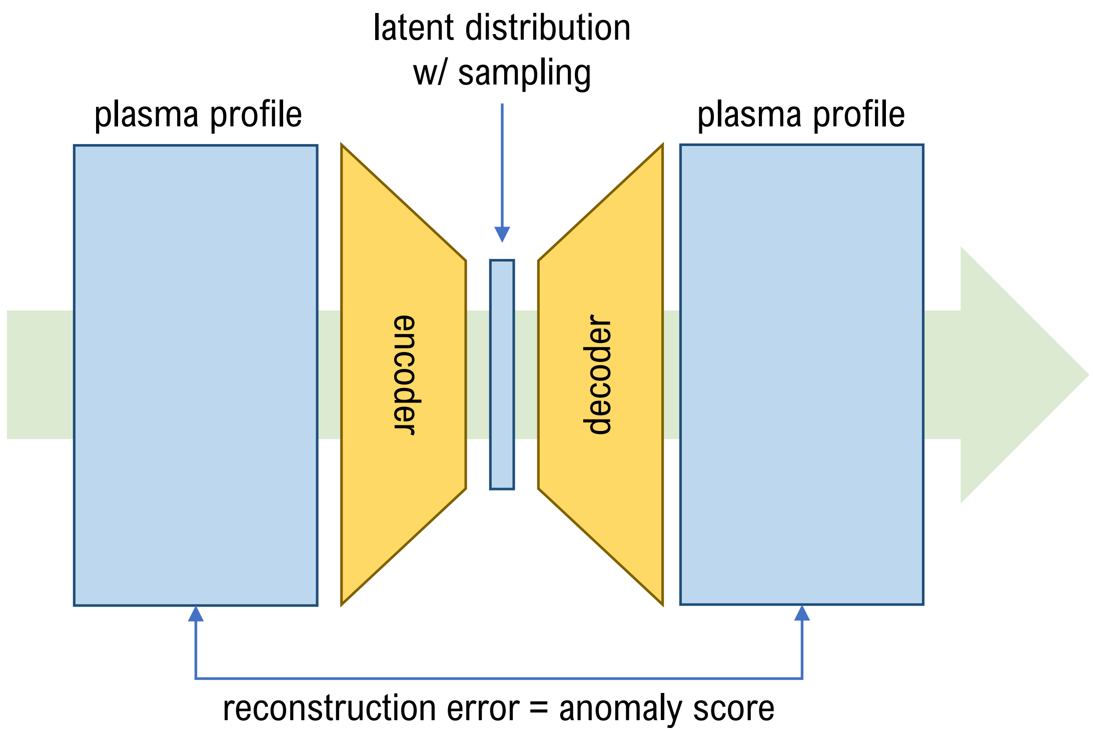
- Identify disruption precursors
  - assume non-disruptive pulses contain normal behaviour, train model to reproduce this behaviour
  - apply on disruptive pulses to detect unusual behaviour, potential anomalies before disruption
    - higher reconstruction error than the normal behaviour the model was trained on
  - large number of profiles that need to be computed from bolometer data



Approach

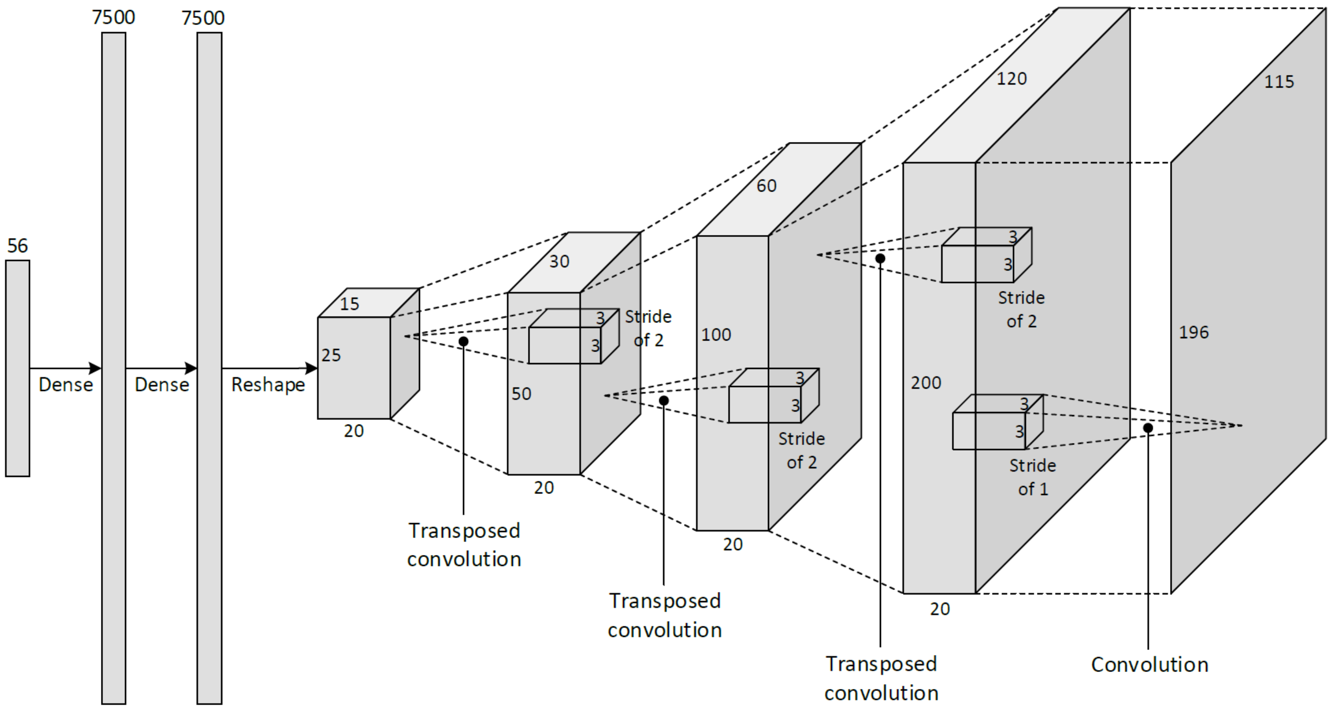
- Two components
  - a fast tomographic method
    - to generate radiation profiles from bolometer data (e.g. neural net, or even simpler)
  - an anomaly detector
    - to point out unusual profiles (e.g. variational autoencoder)

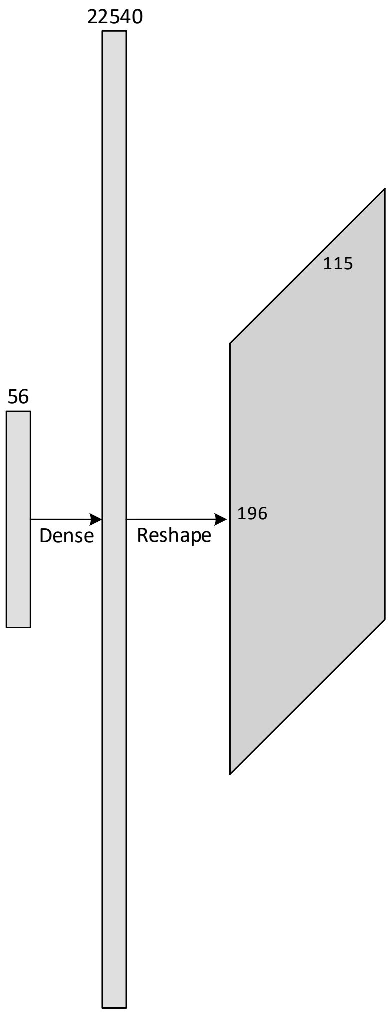




Tomographic reconstruction model

- Neural network[1] or simpler model
  - simpler model can be incorporated as pre-trained layer in anomaly detector
  - mean absolute error ~0.010 MW/m^3 for neural net, ~0.015 for simple model
  - trained on ~10k selected reconstructions; can be trained on single GPU

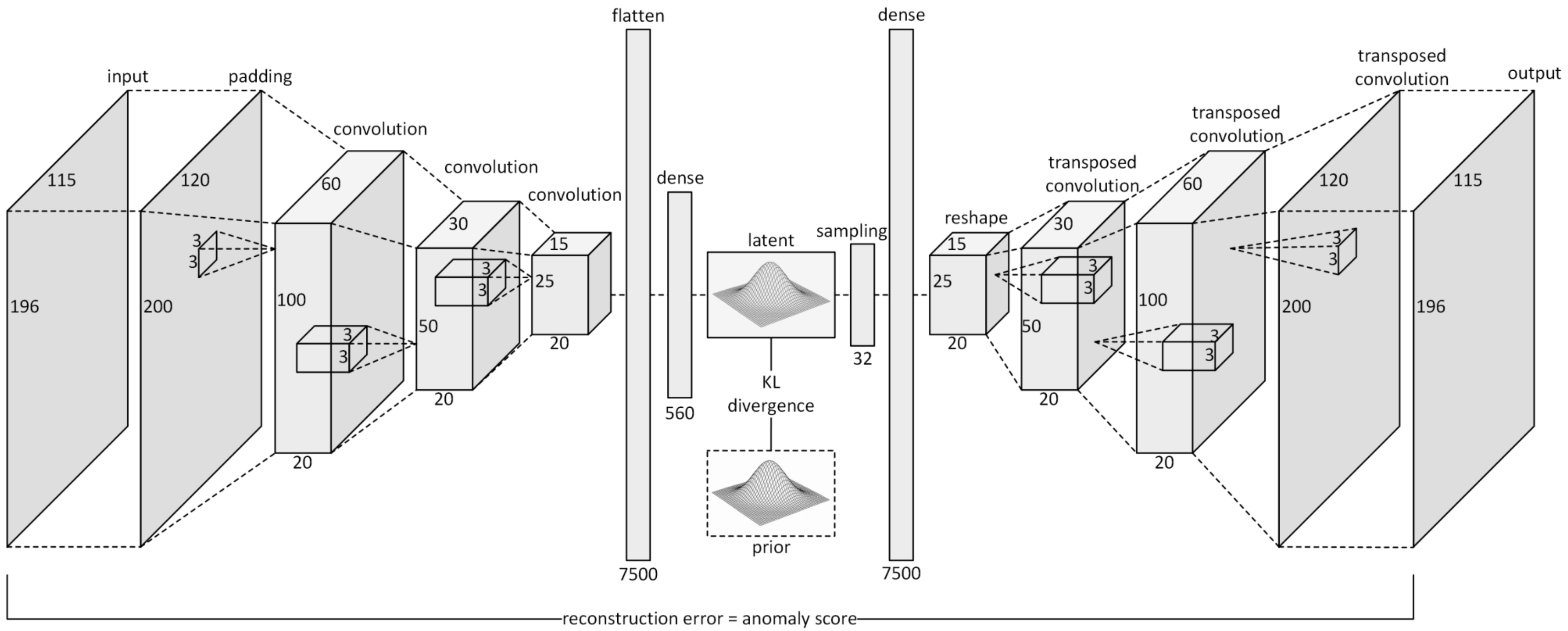




[1] D. R. Ferreira et al, "Full-Pulse Tomographic Reconstruction with Deep Neural Networks," Fusion Sci. Technol., vol. 74, no. 1-2, 2018

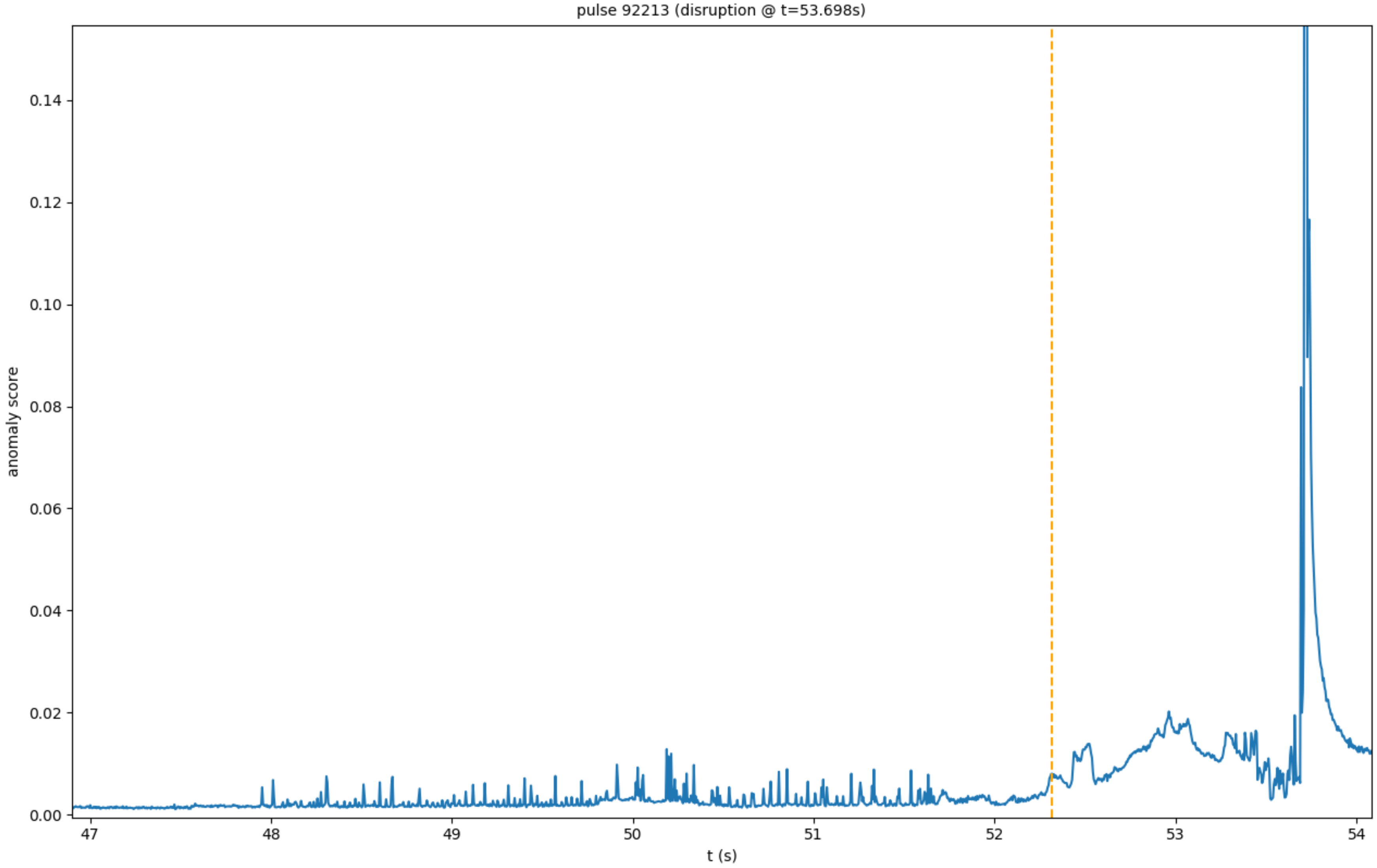
Anomaly detection model

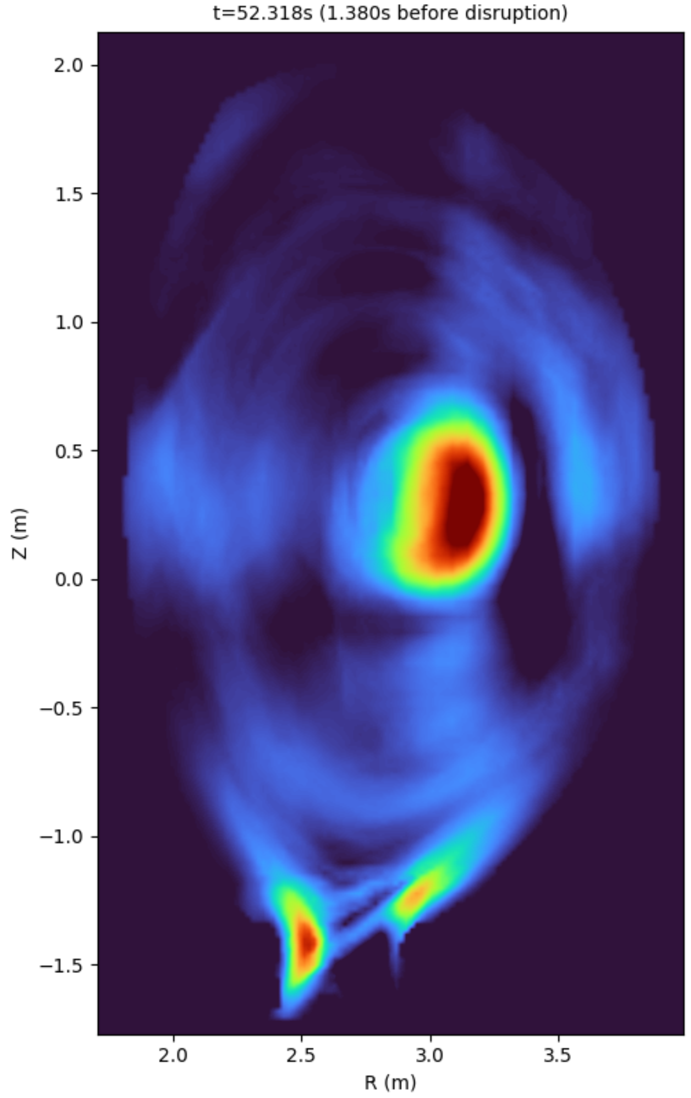
- Variational autoencoder
  - prior distribution is typically standard multivariate normal with $\boldsymbol{\mu} = \mathbf{0}$ and $\boldsymbol{\Sigma} = \boldsymbol{I}$
  - loss function = mean absolute error + Kullback–Leibler divergence
  - trained on ~1.4 million profiles from ~250 non-disruptive baseline pulses; requires multiple GPUs



Results

- Anomaly score on pulse 92213





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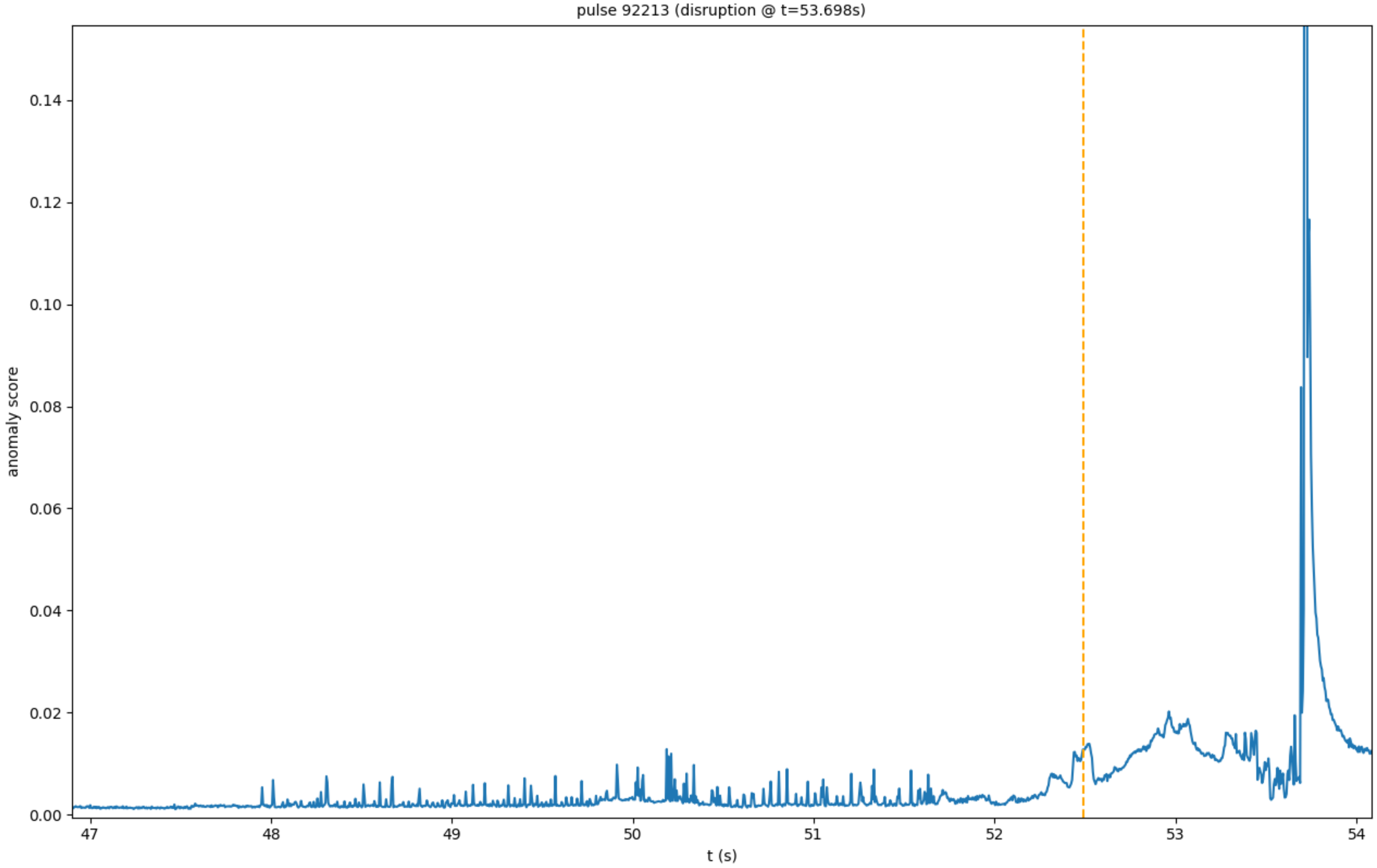

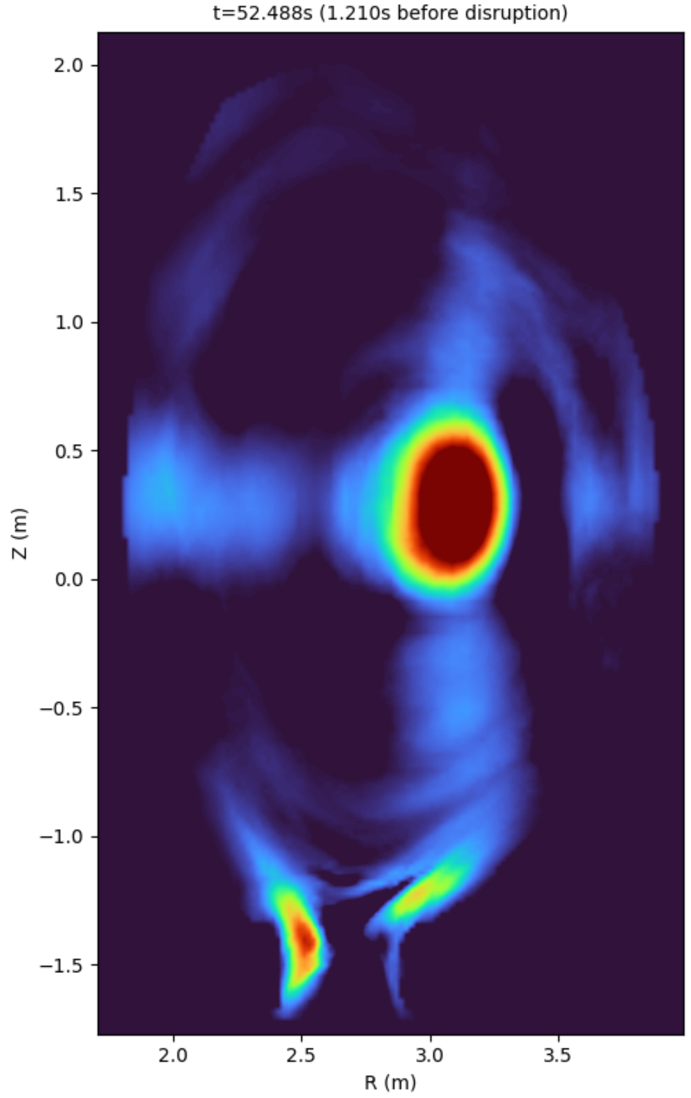

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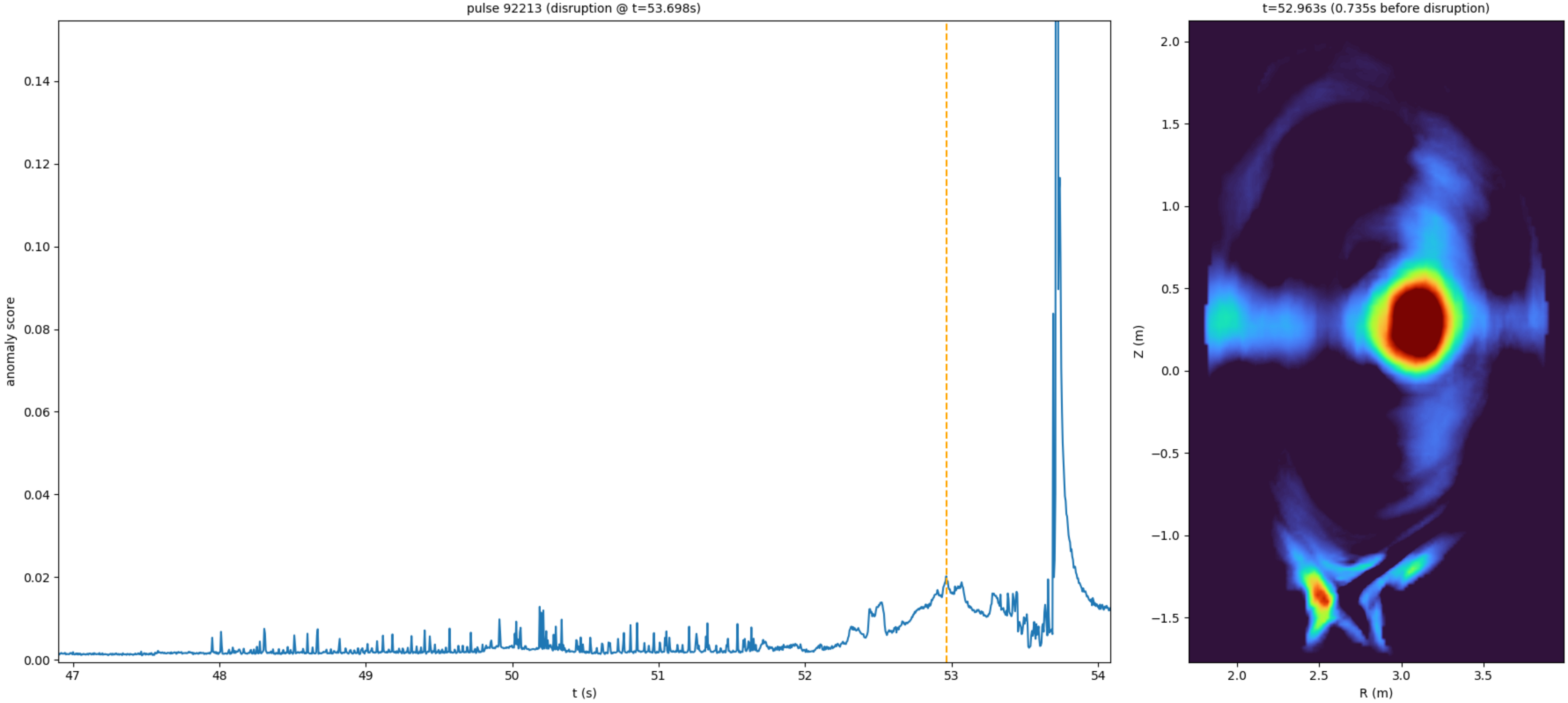

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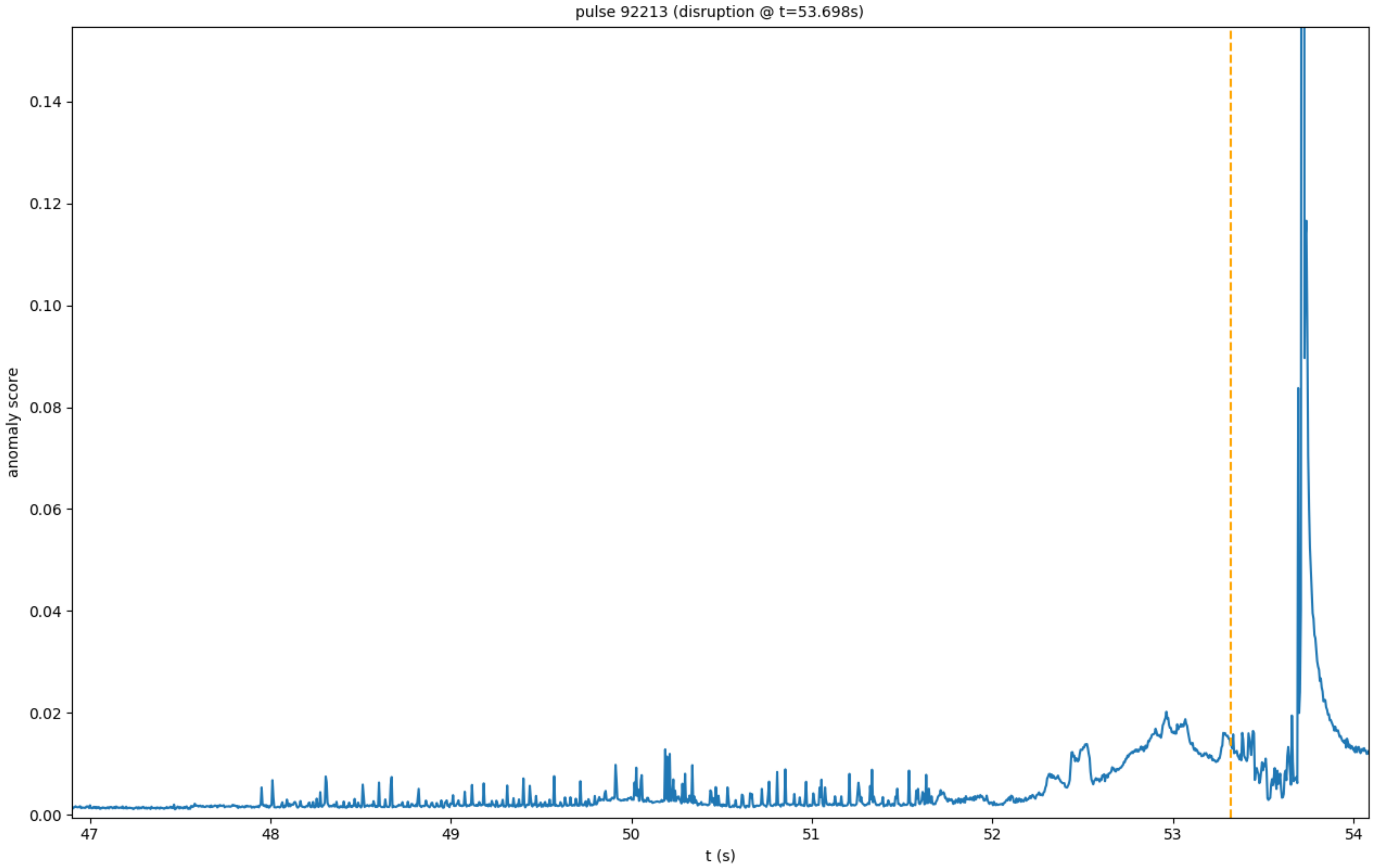

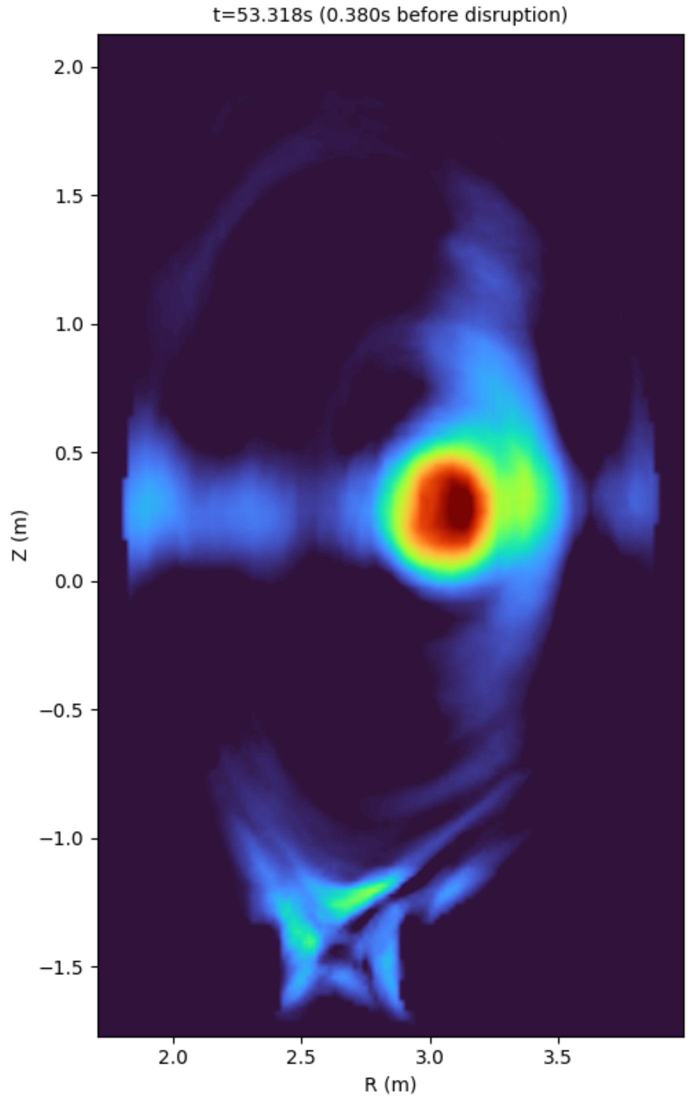

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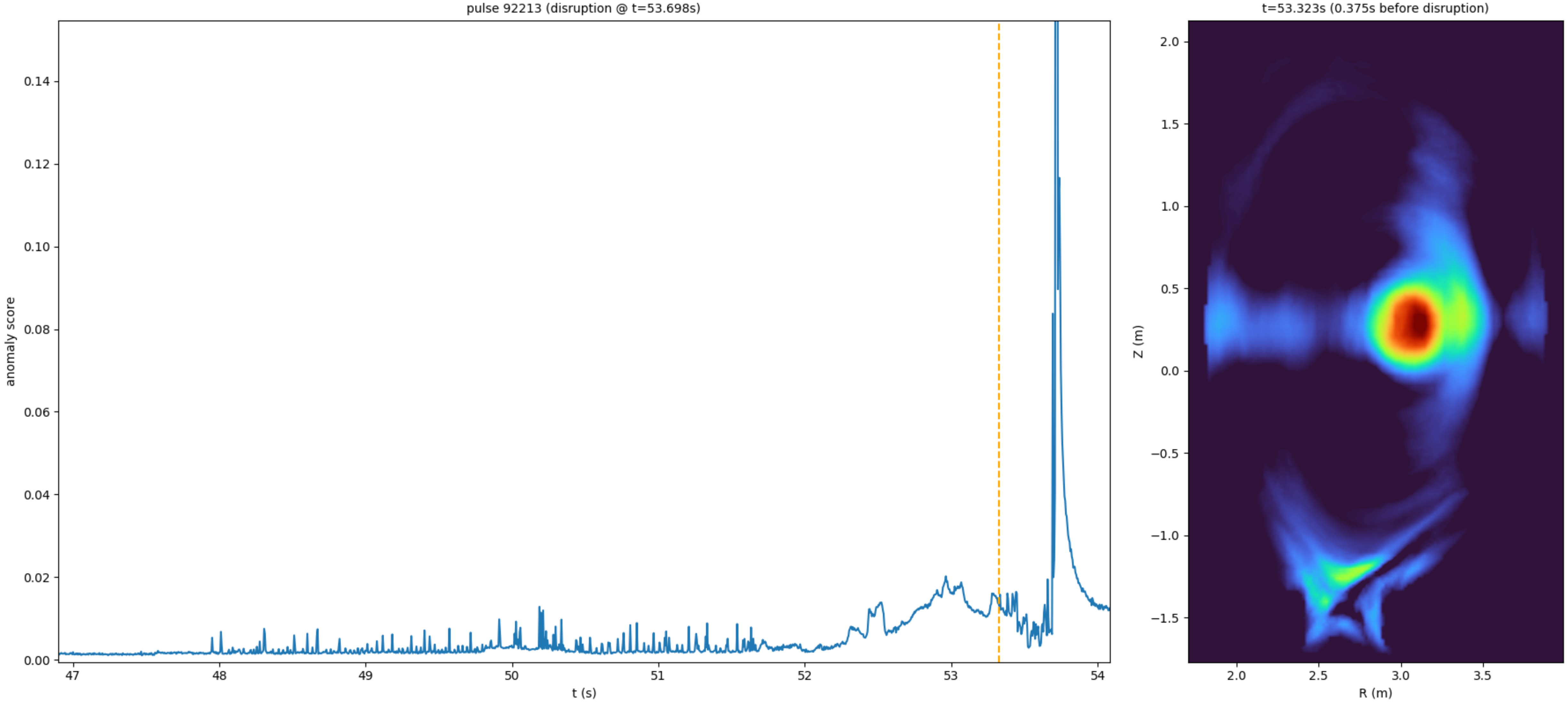

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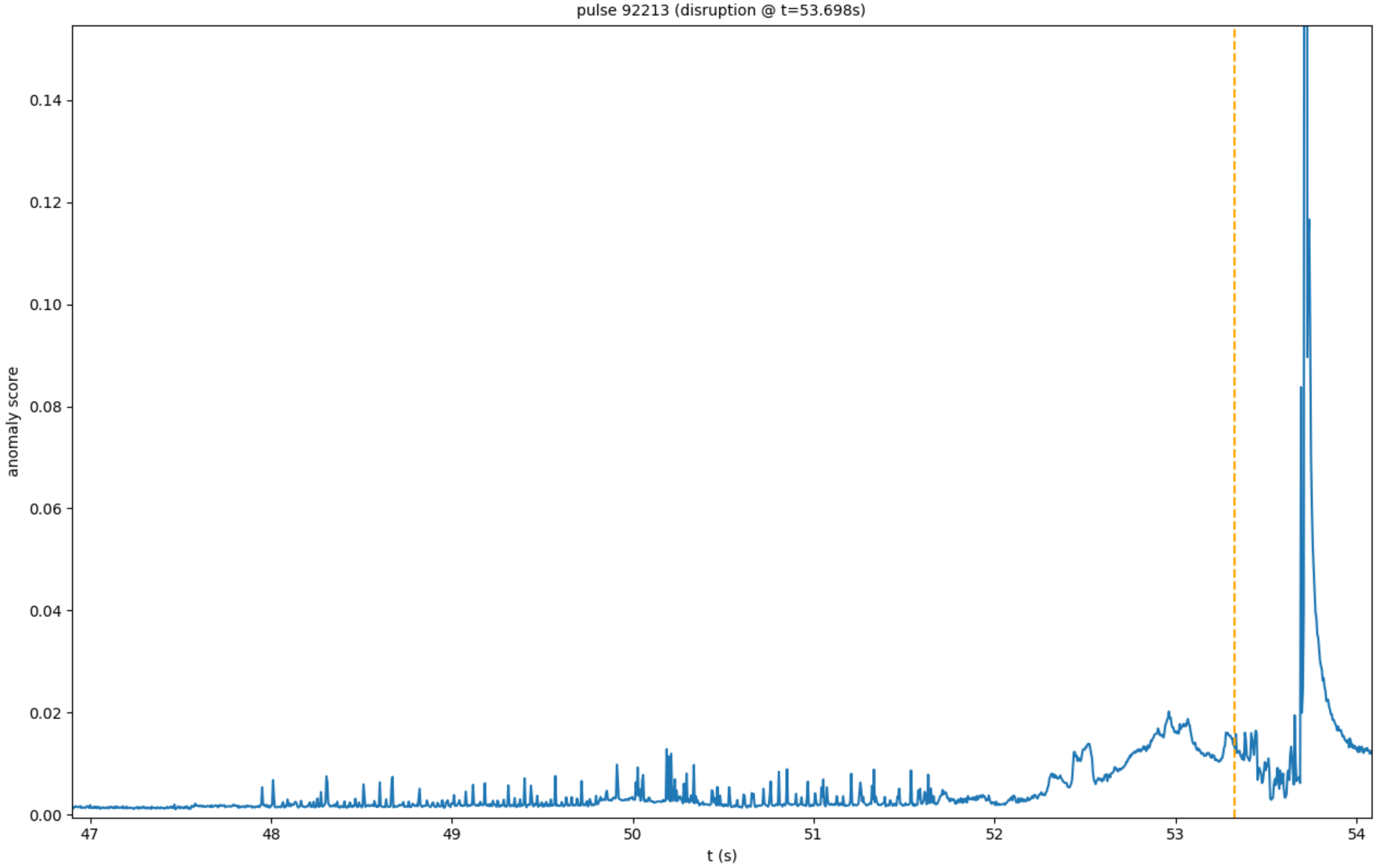

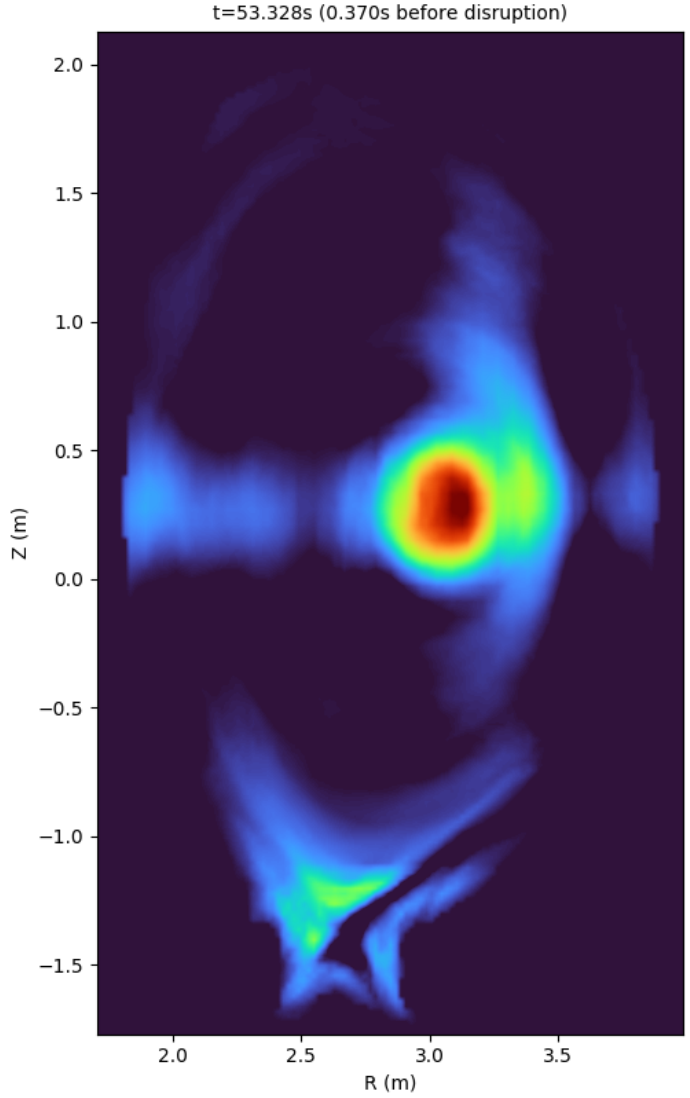

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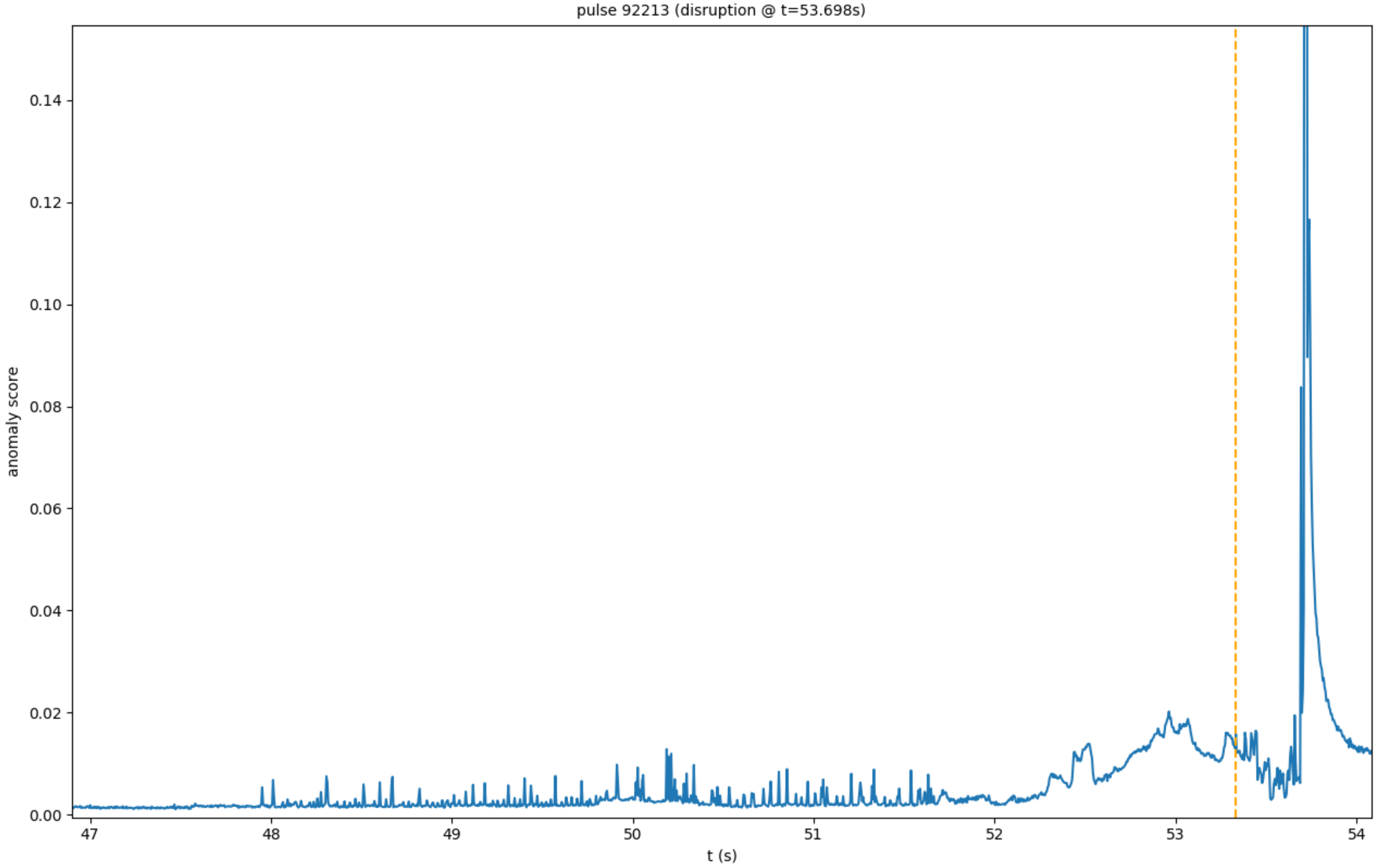

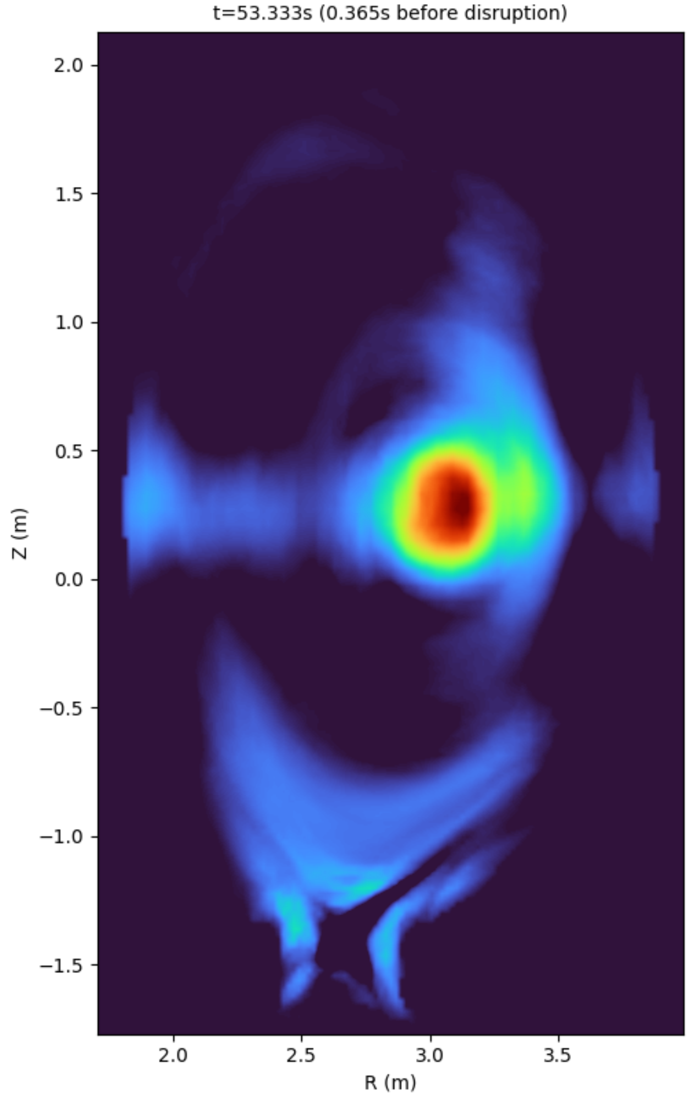

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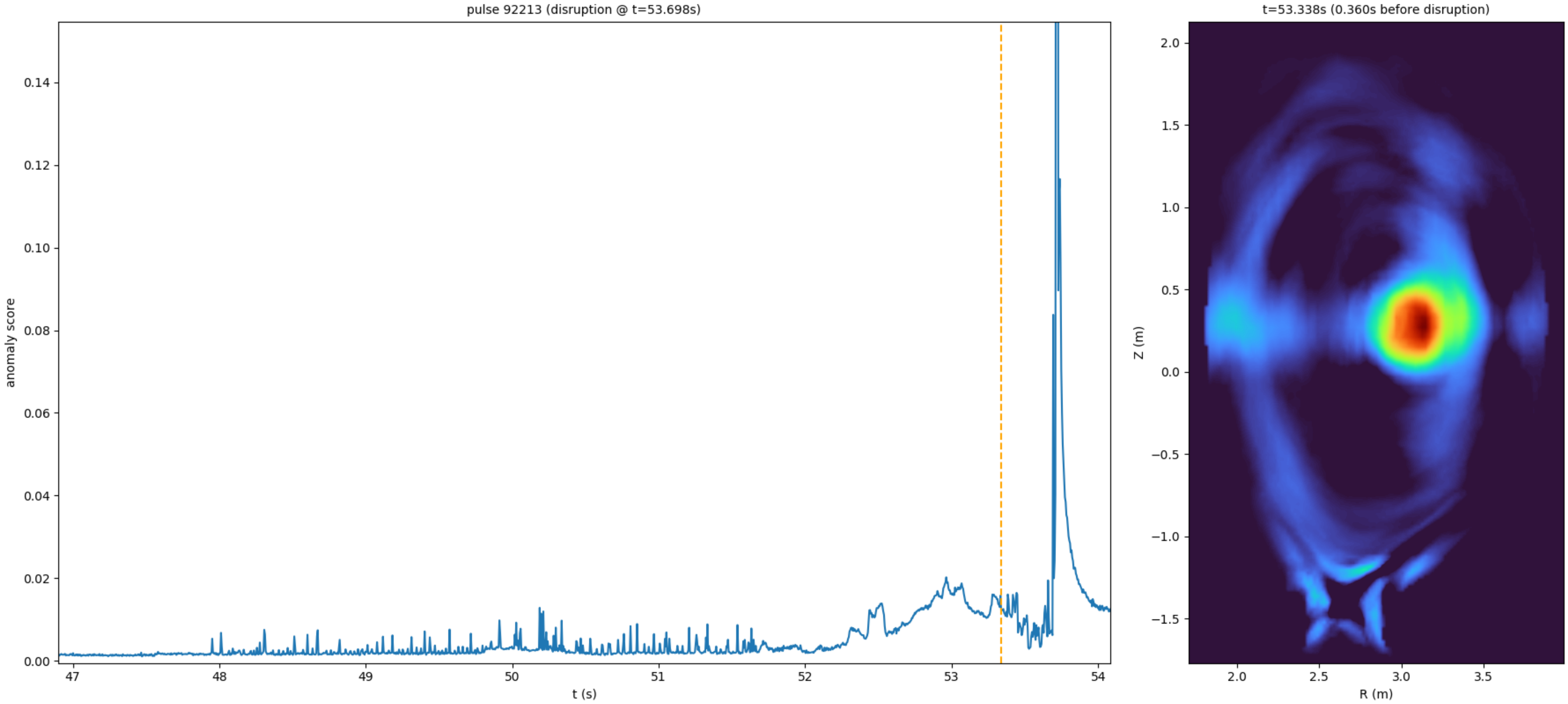

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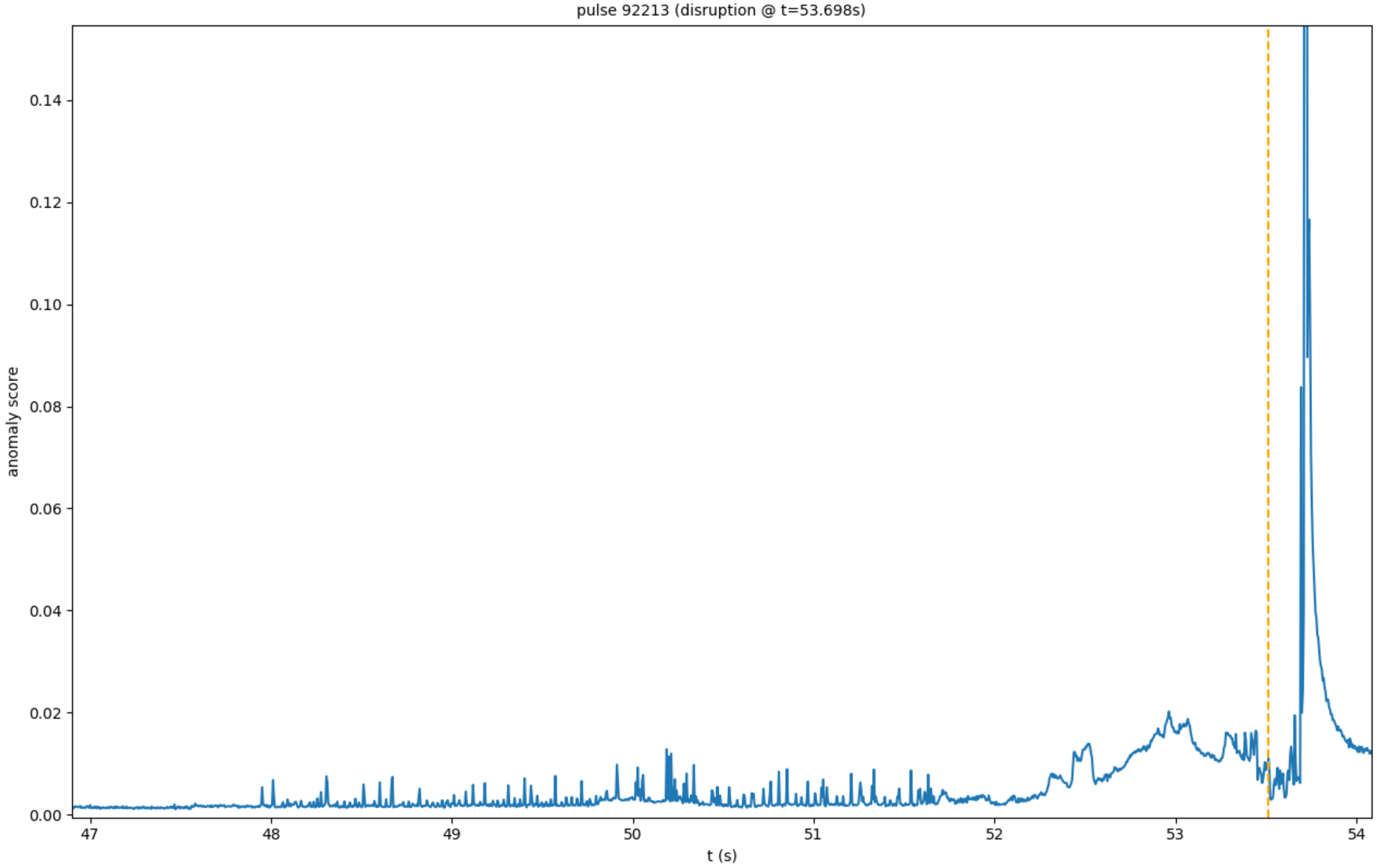

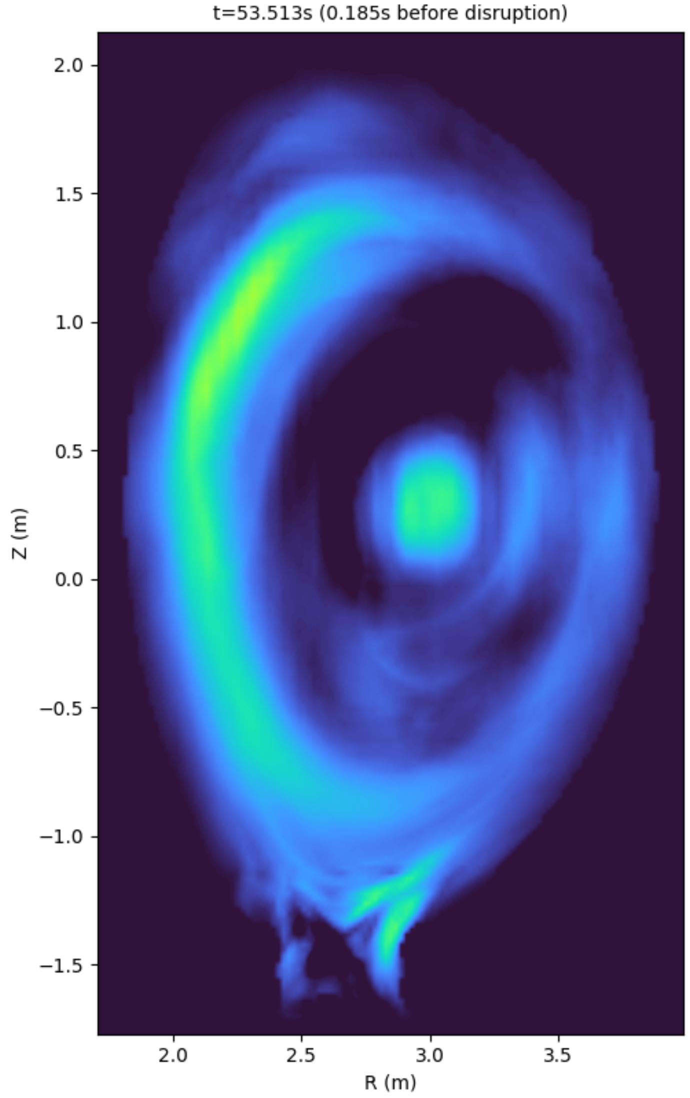

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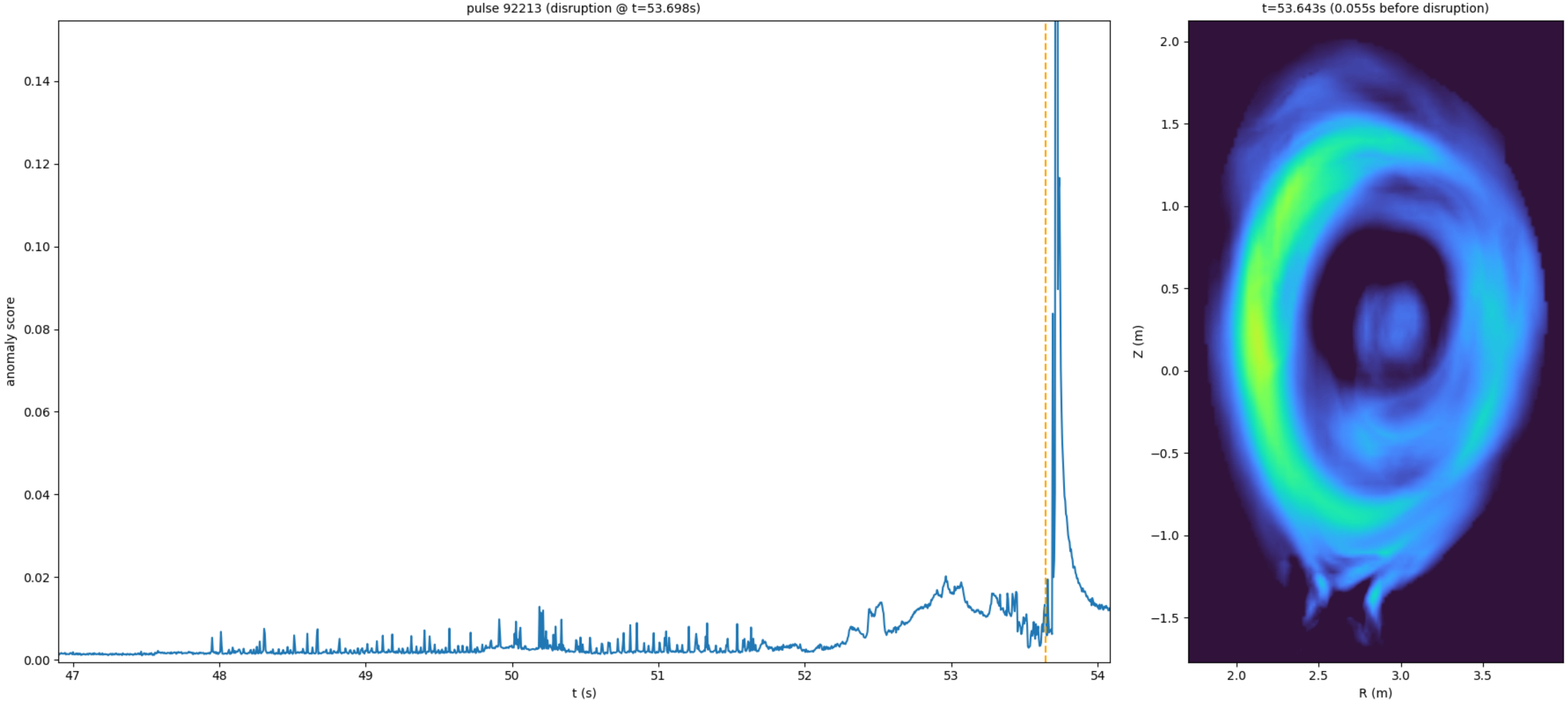

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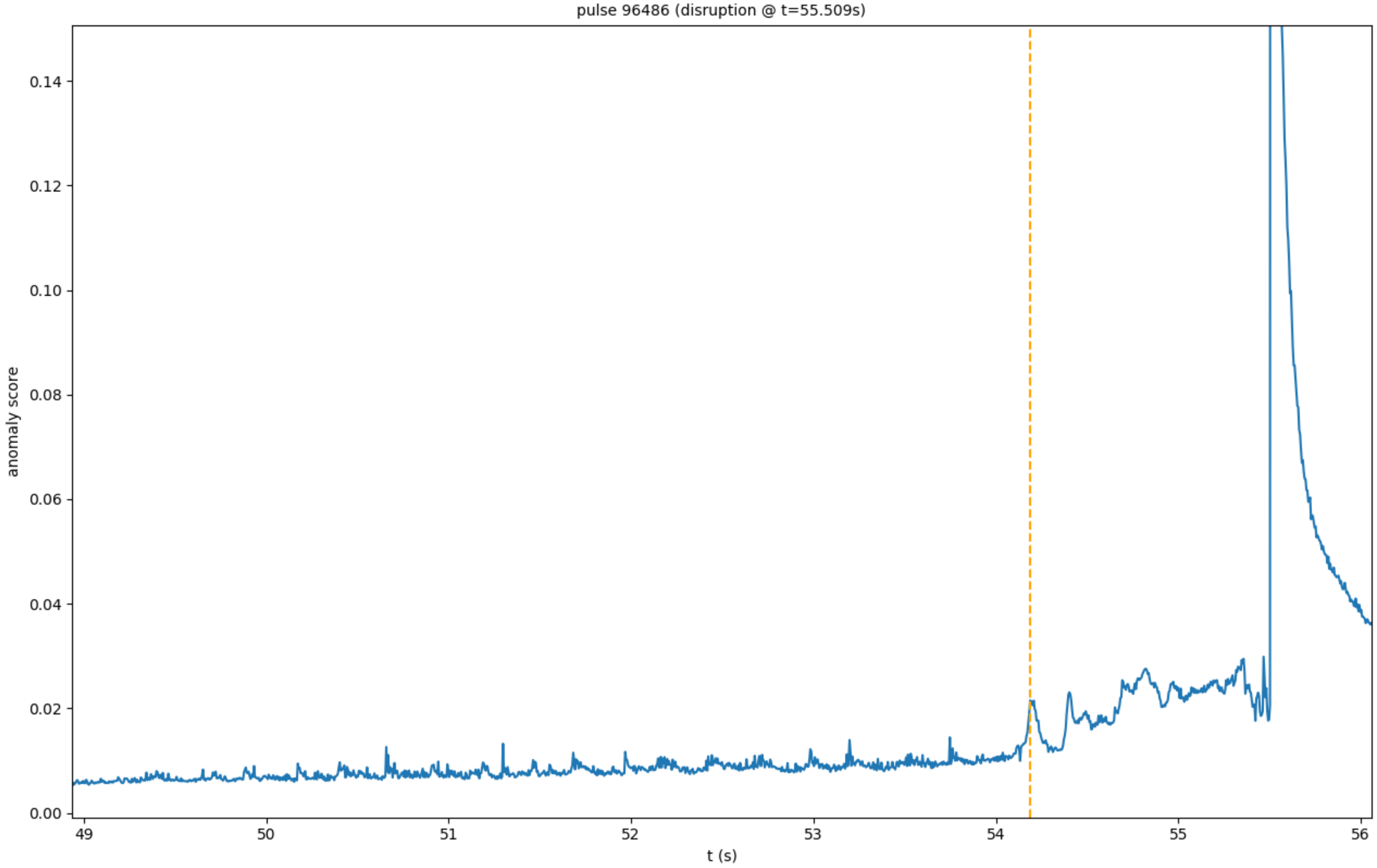

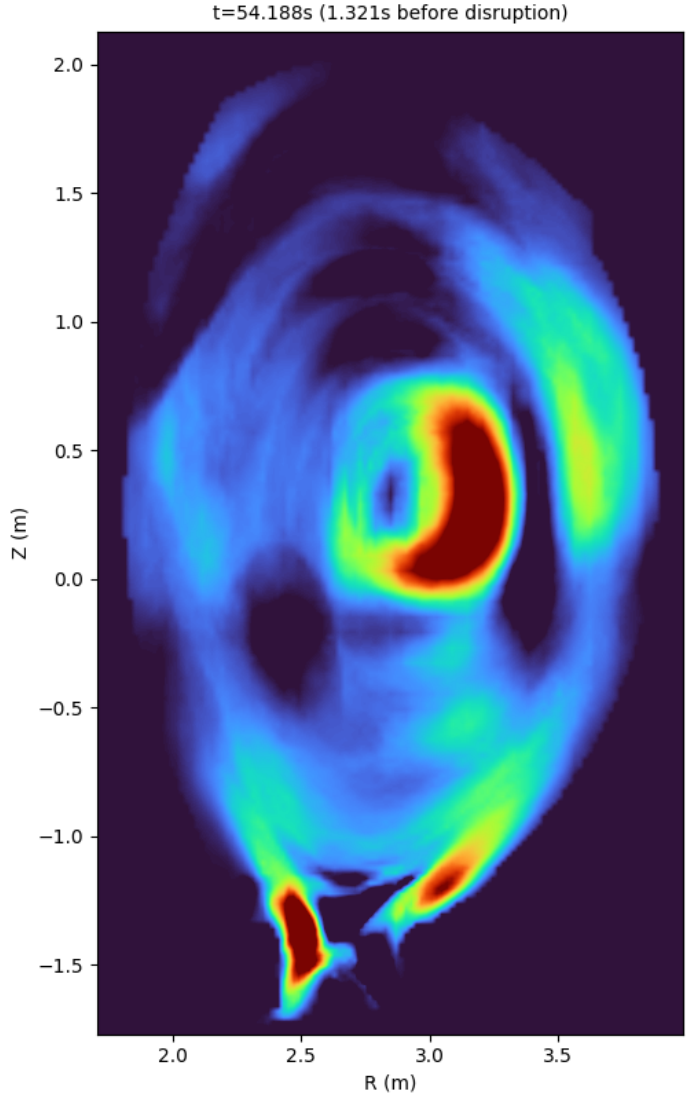

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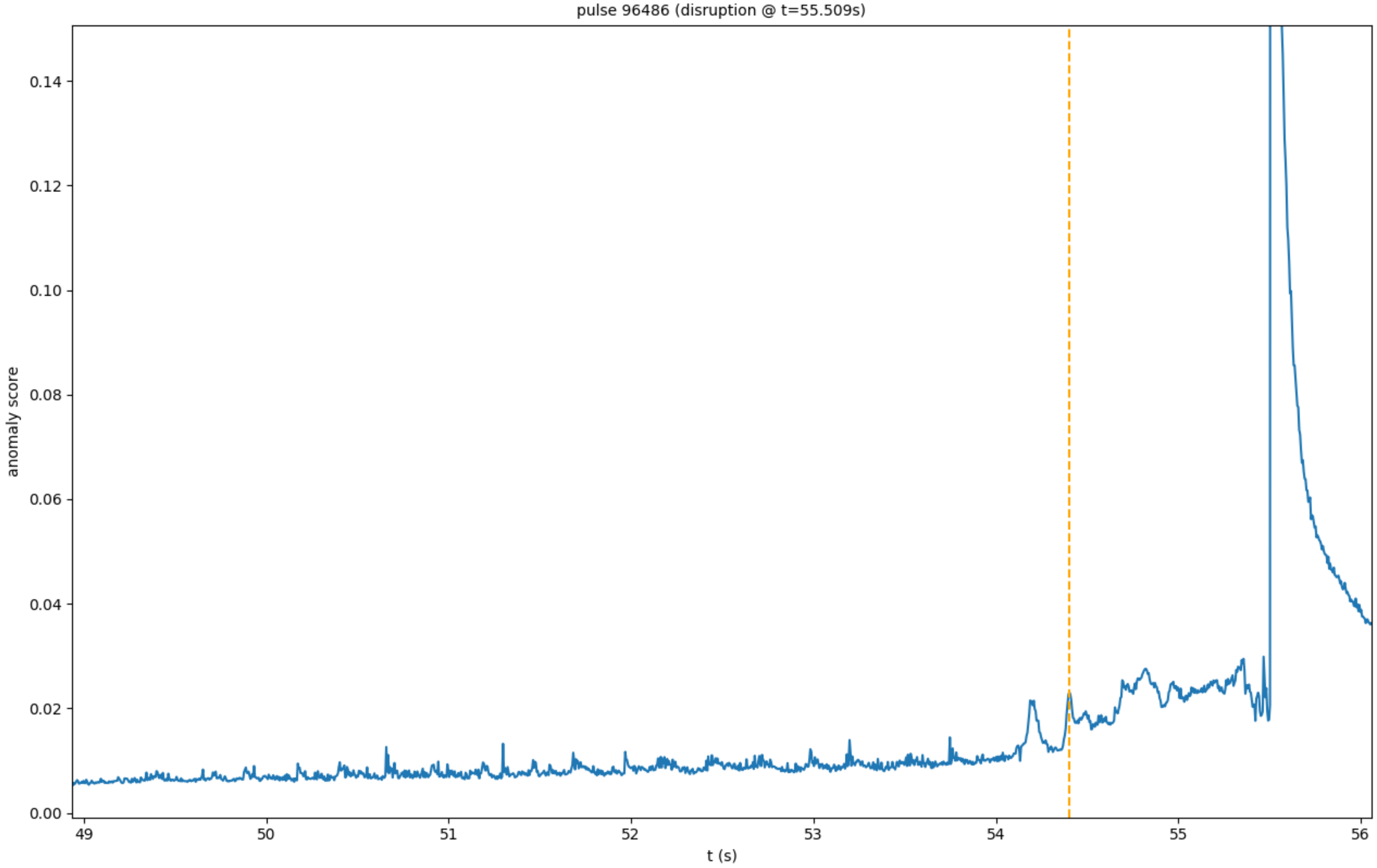

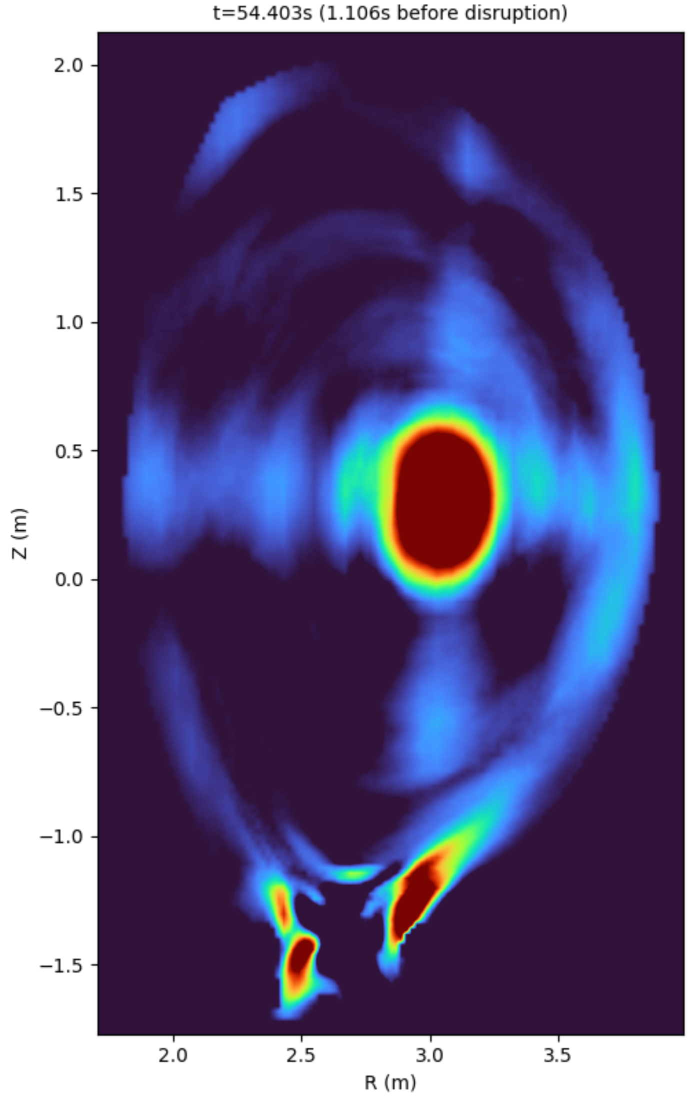

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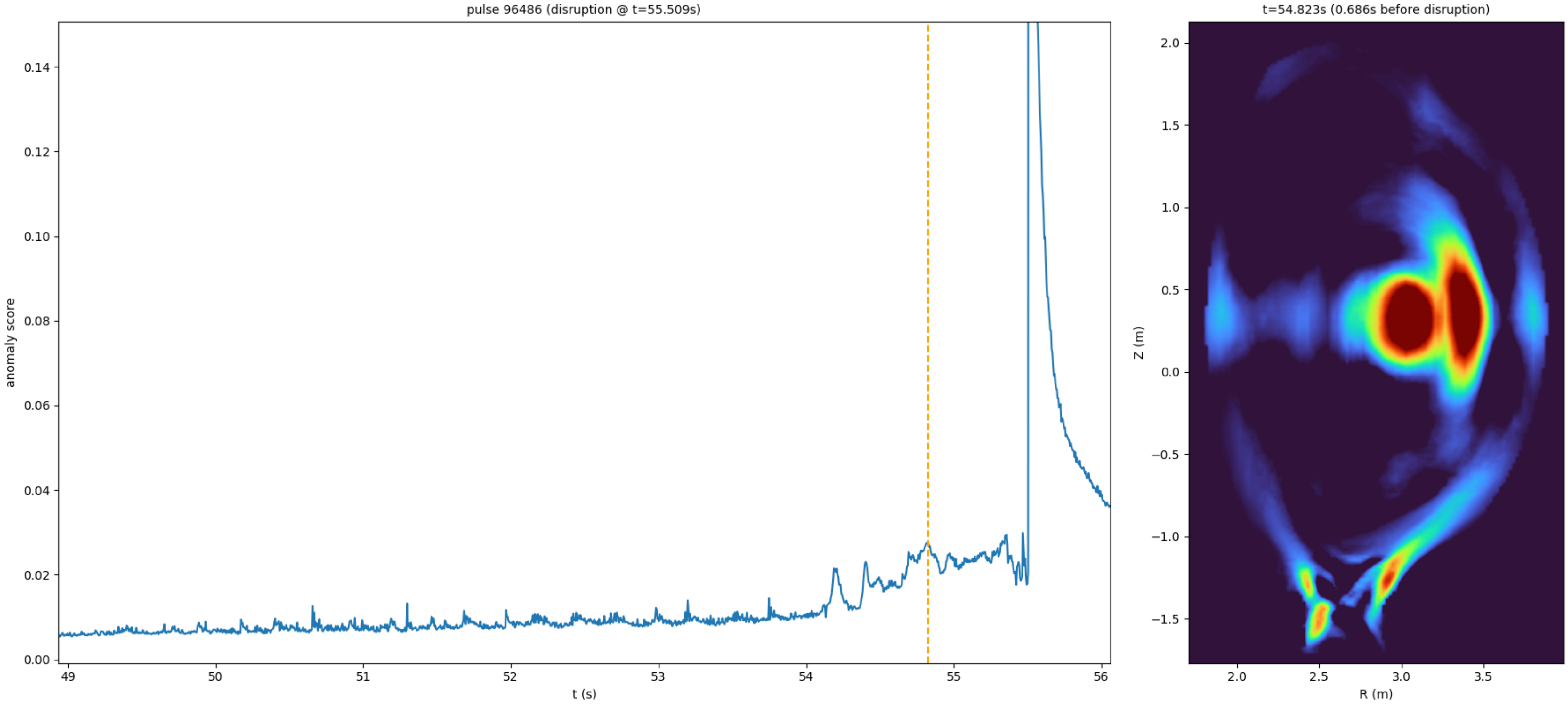

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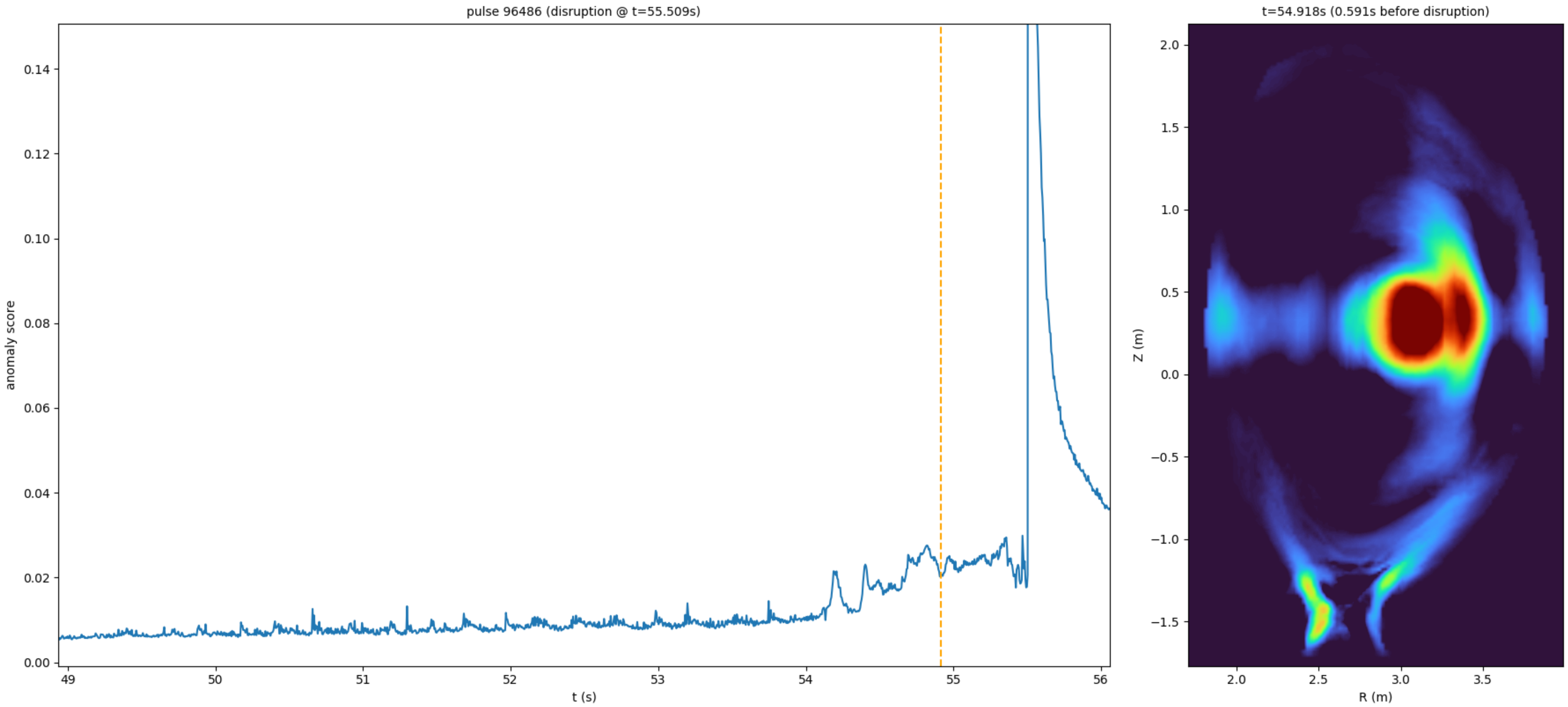

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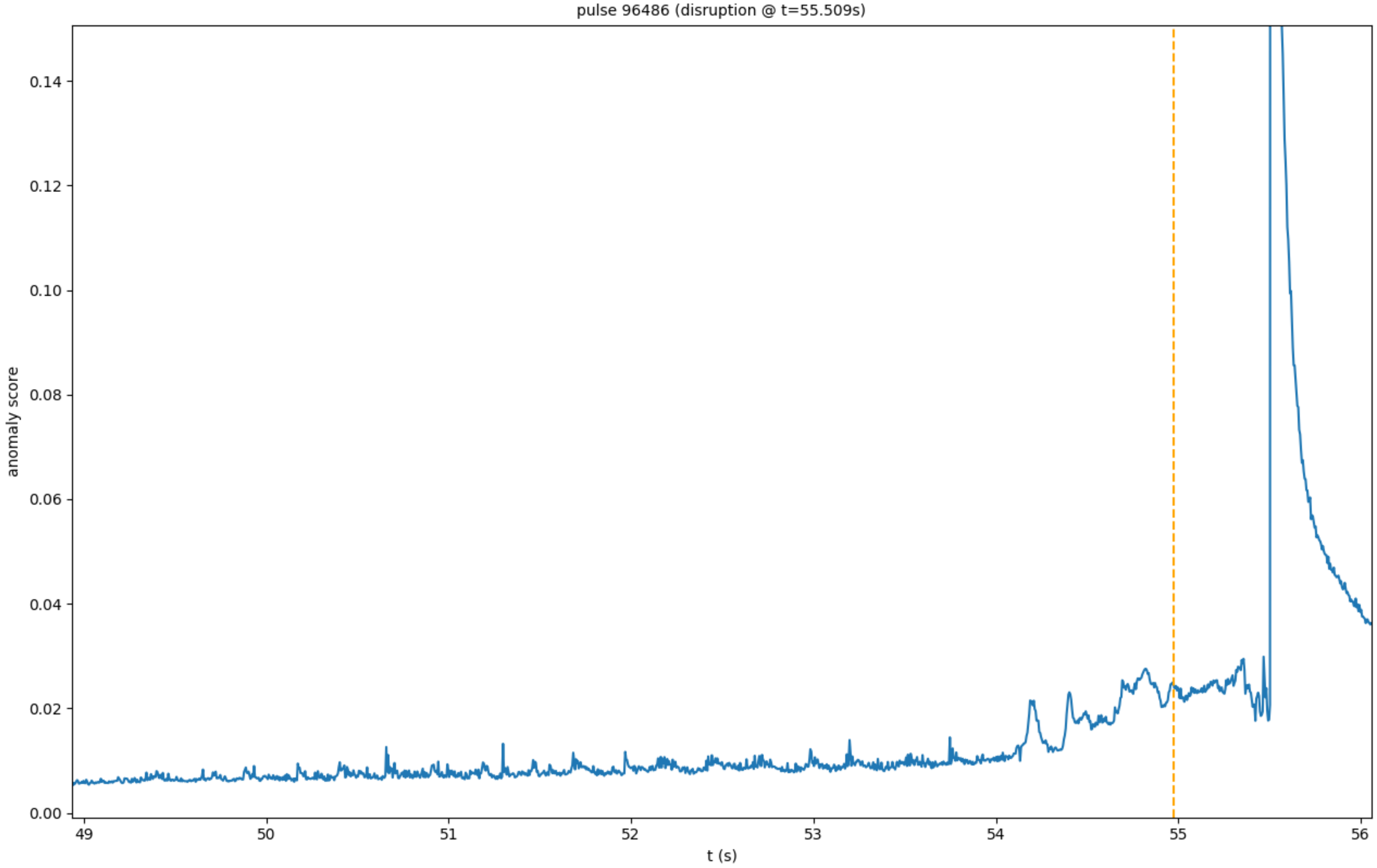

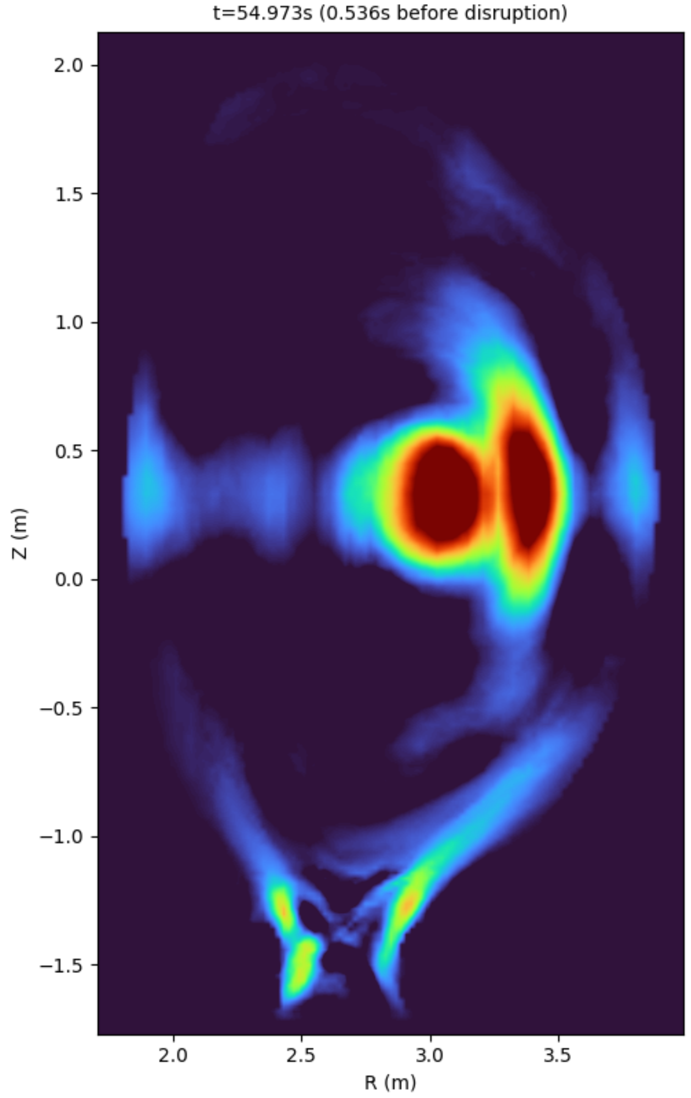

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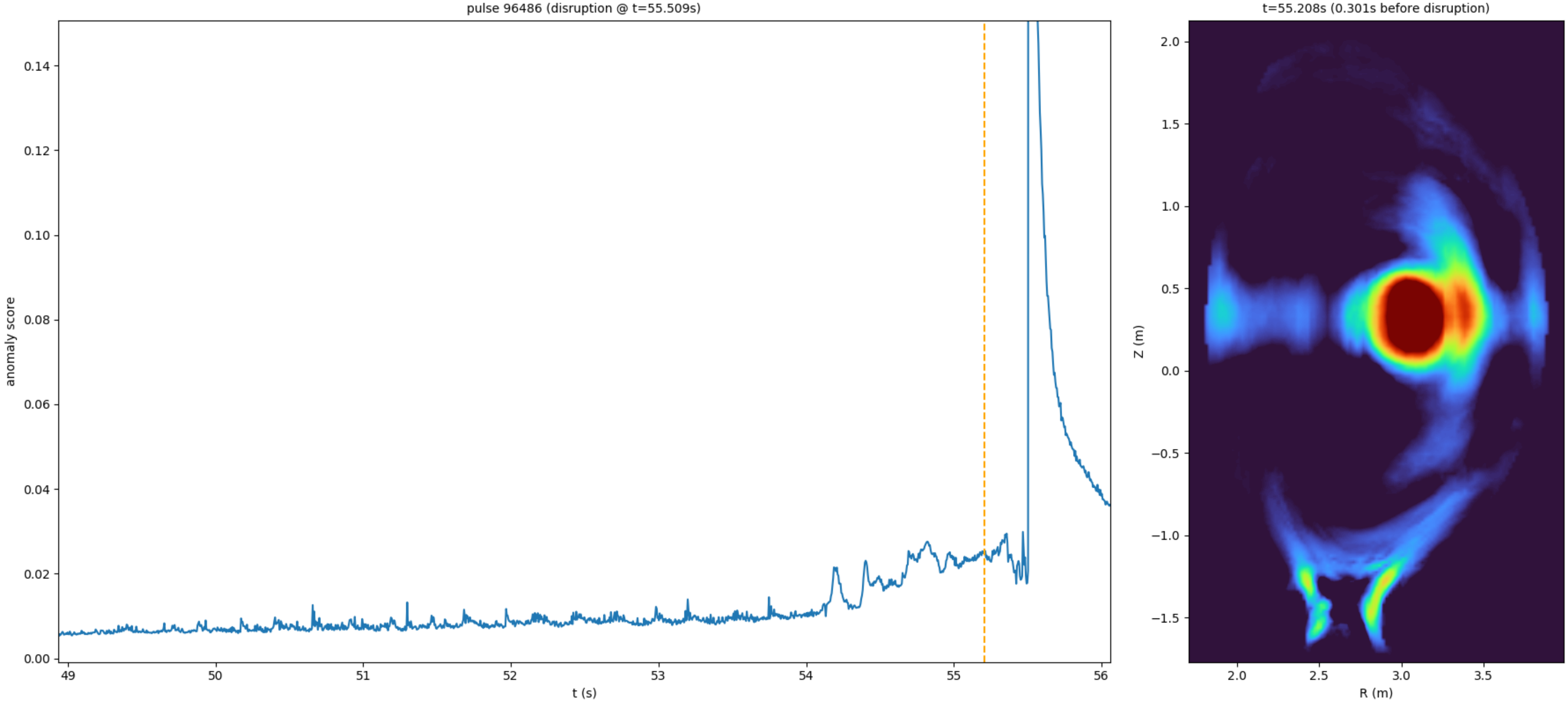

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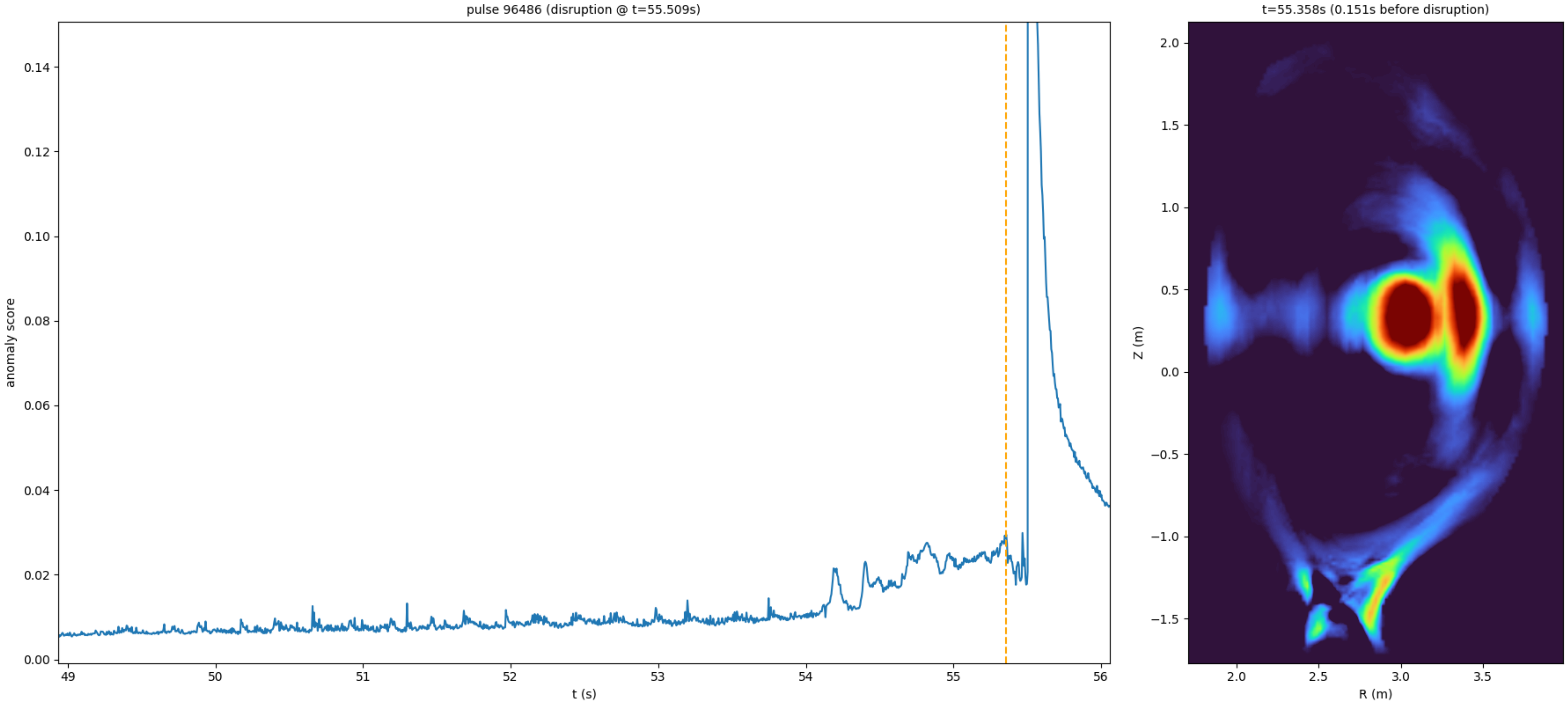

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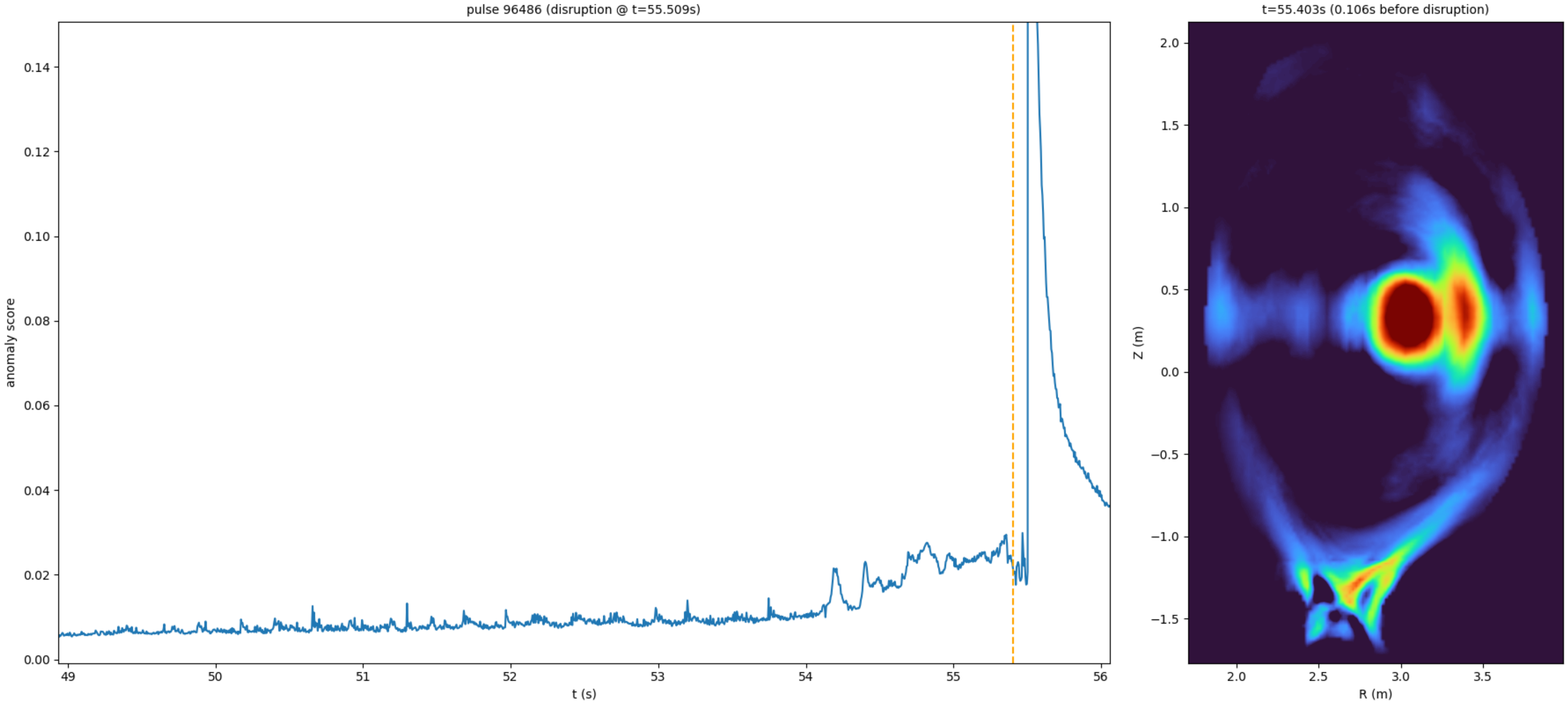

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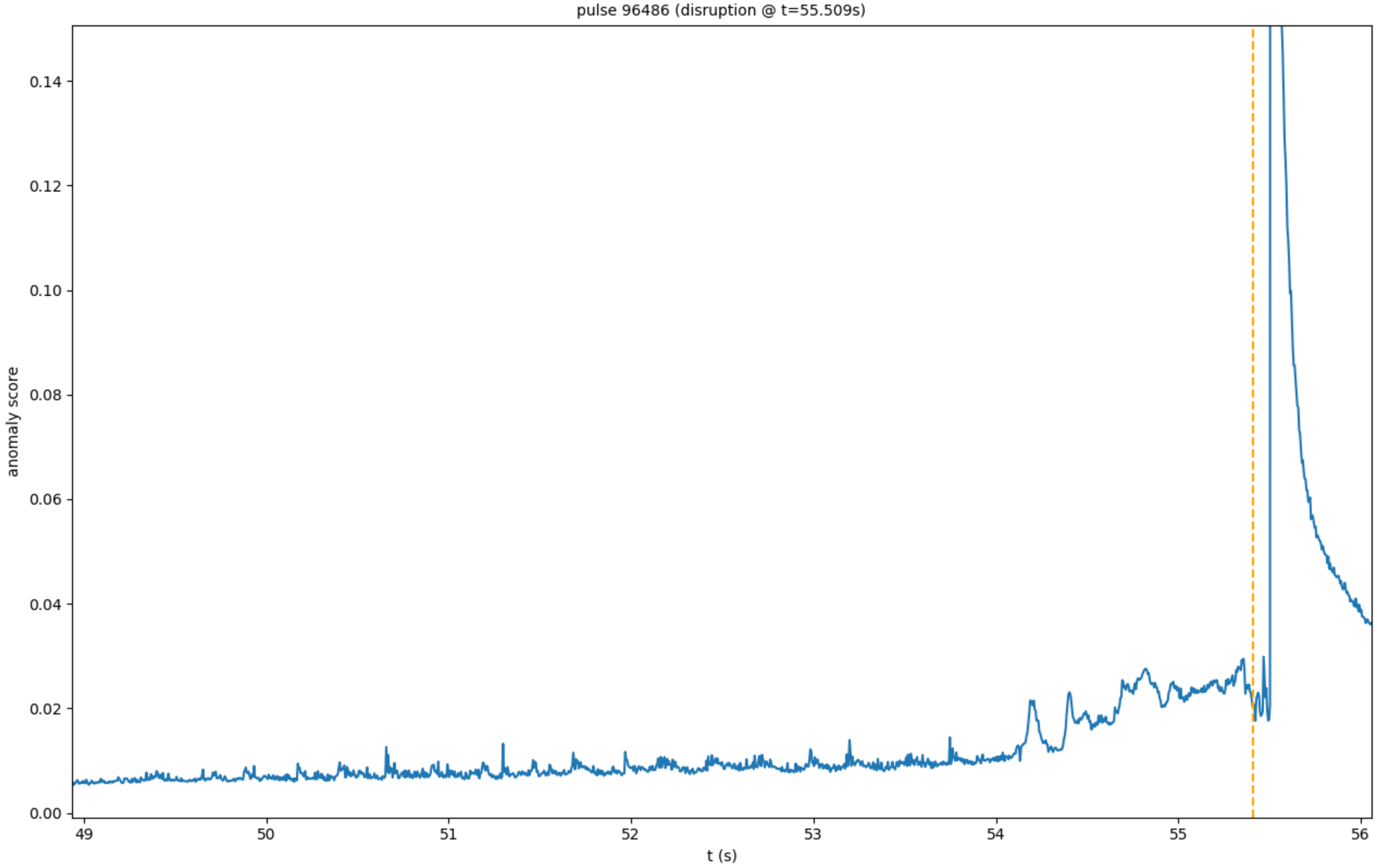

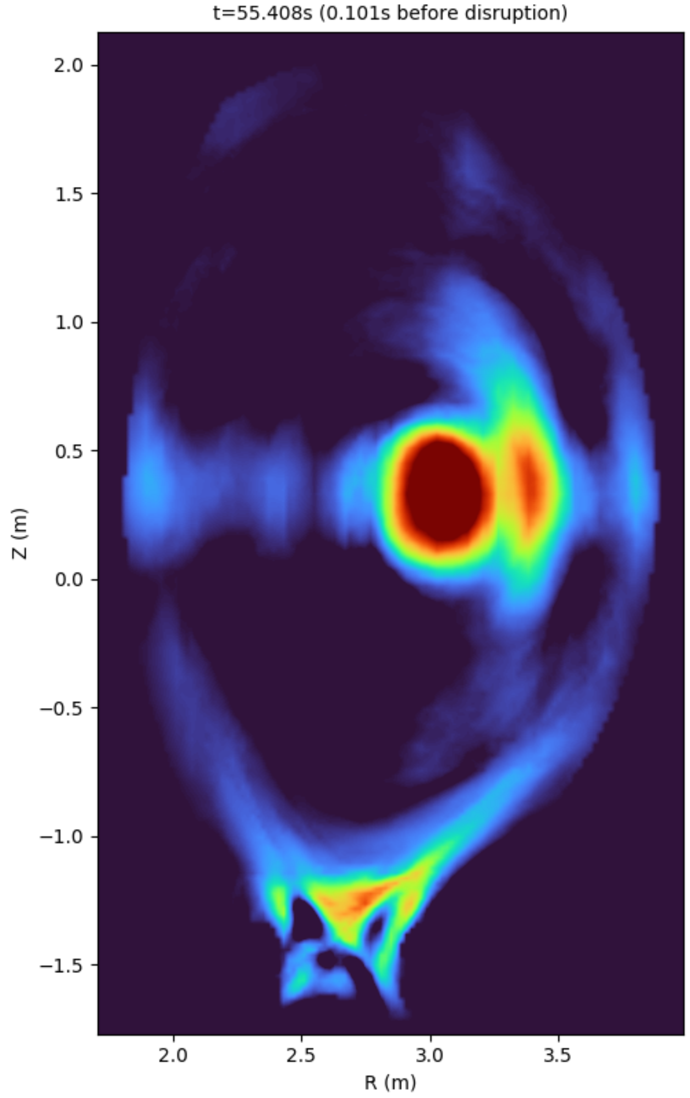

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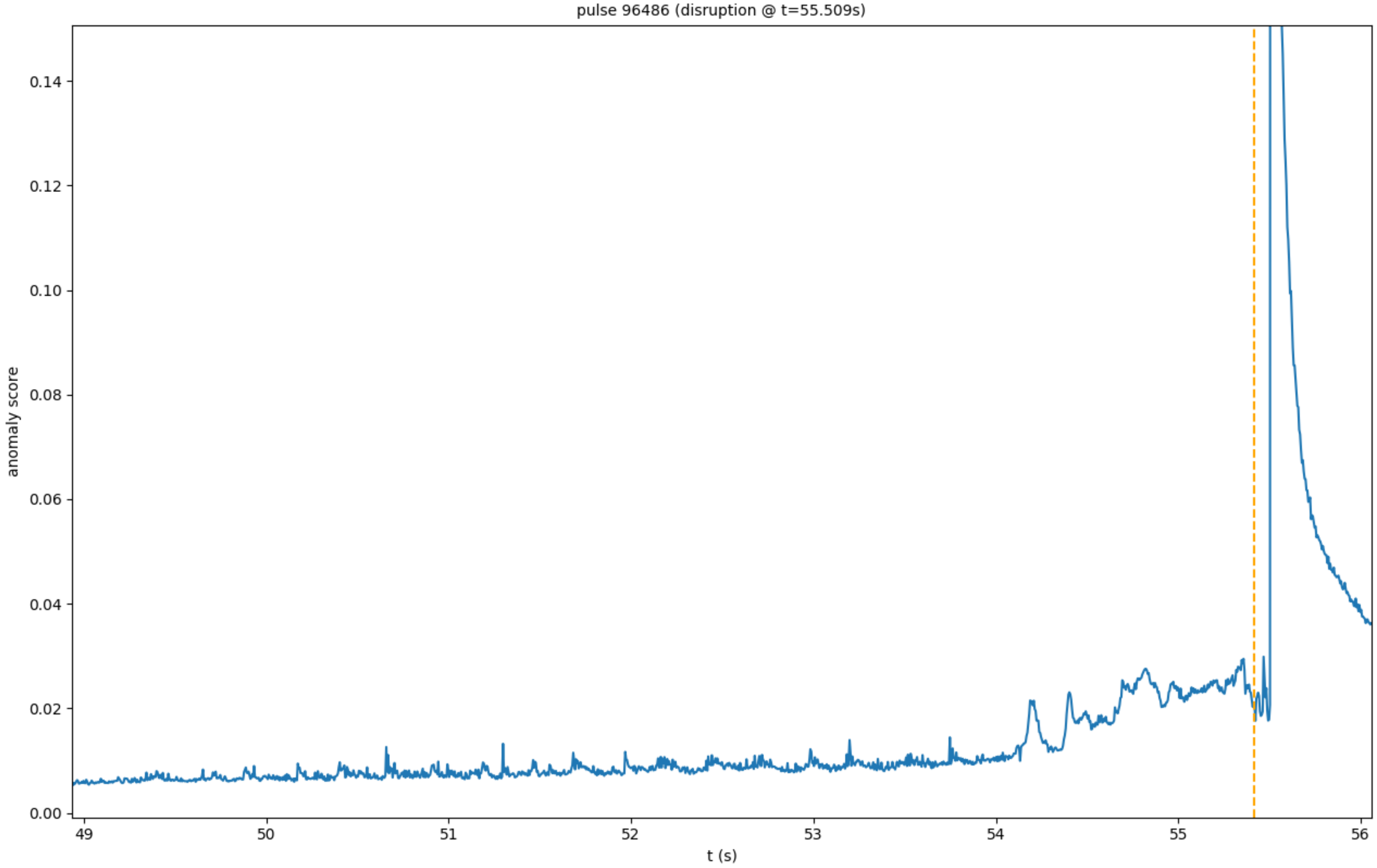

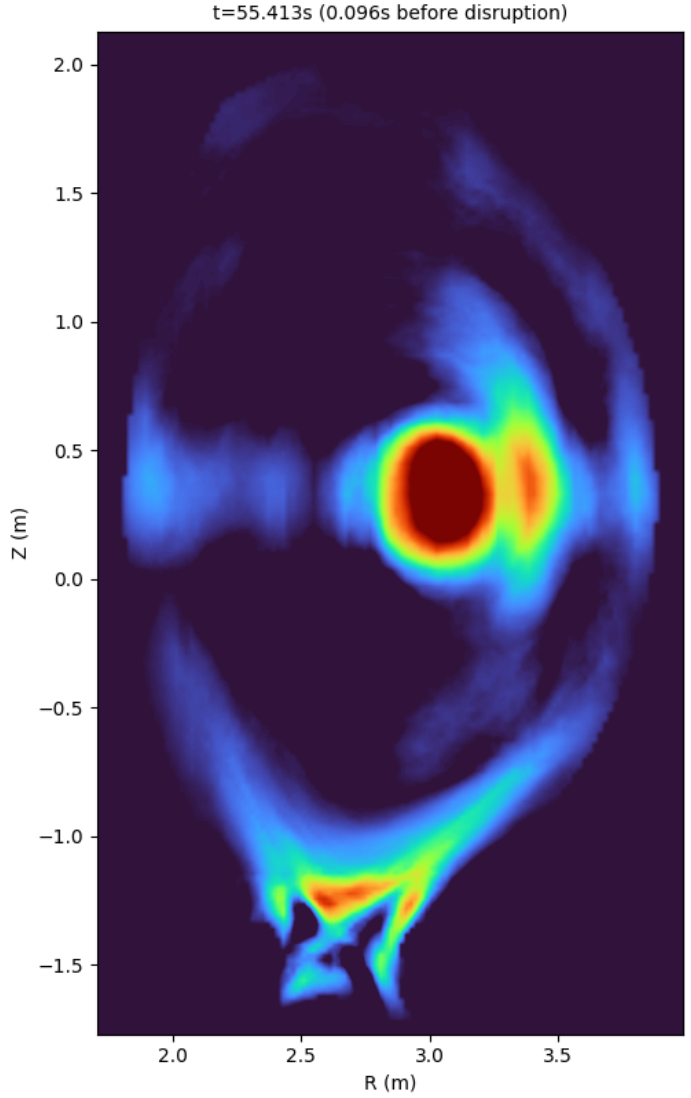

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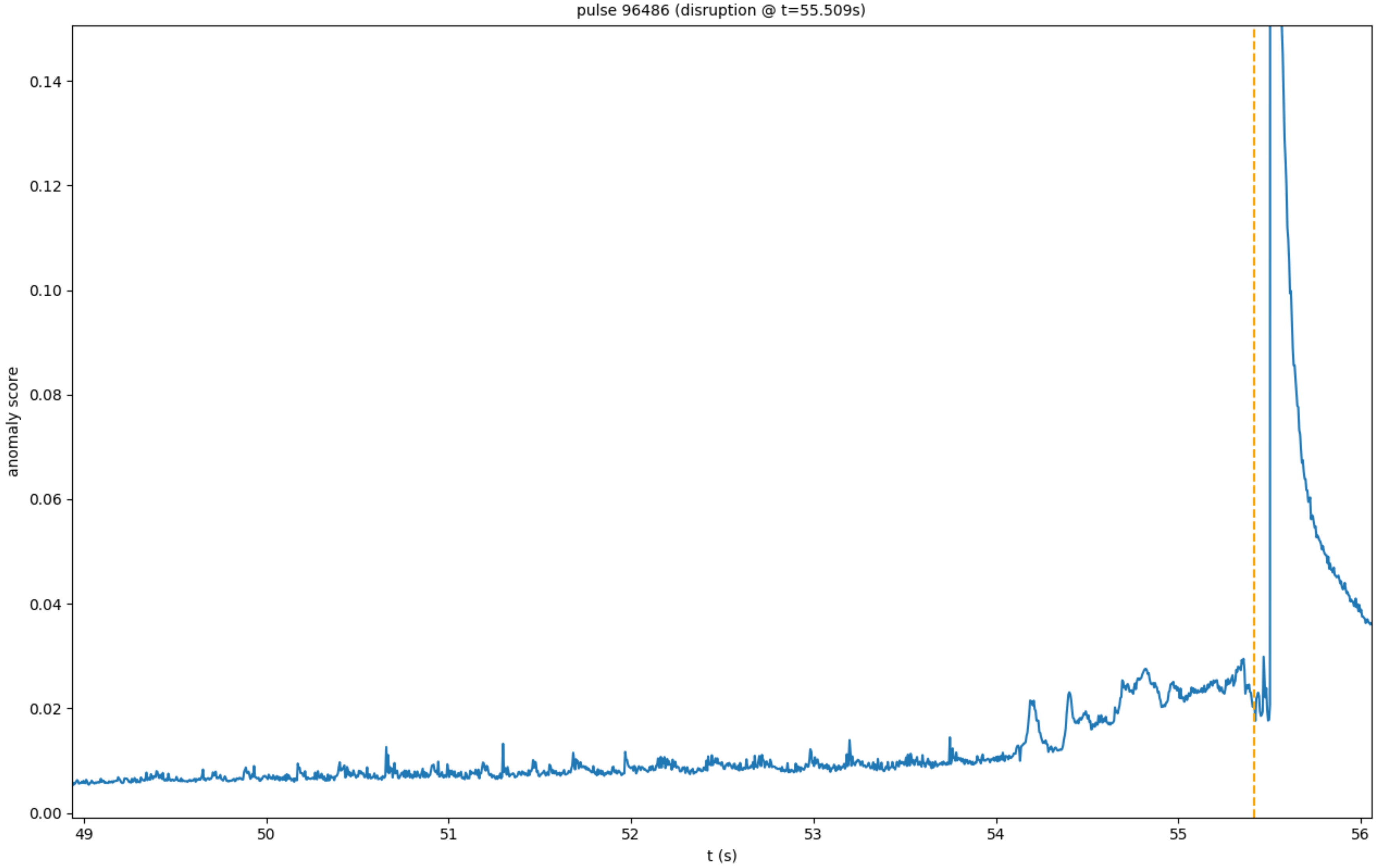

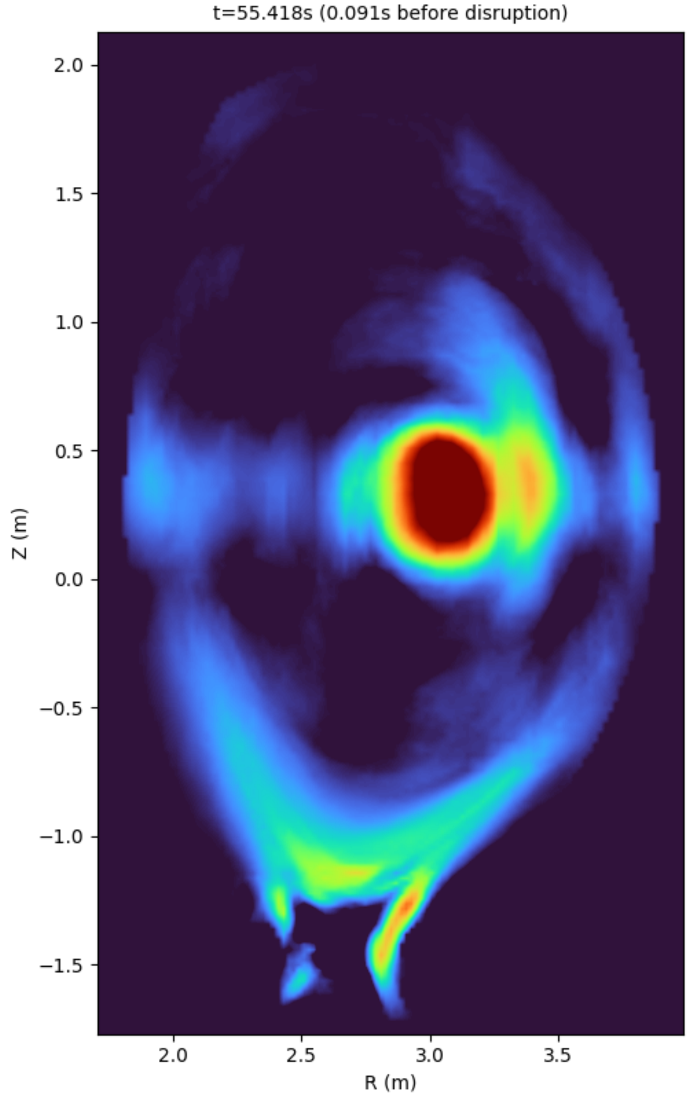

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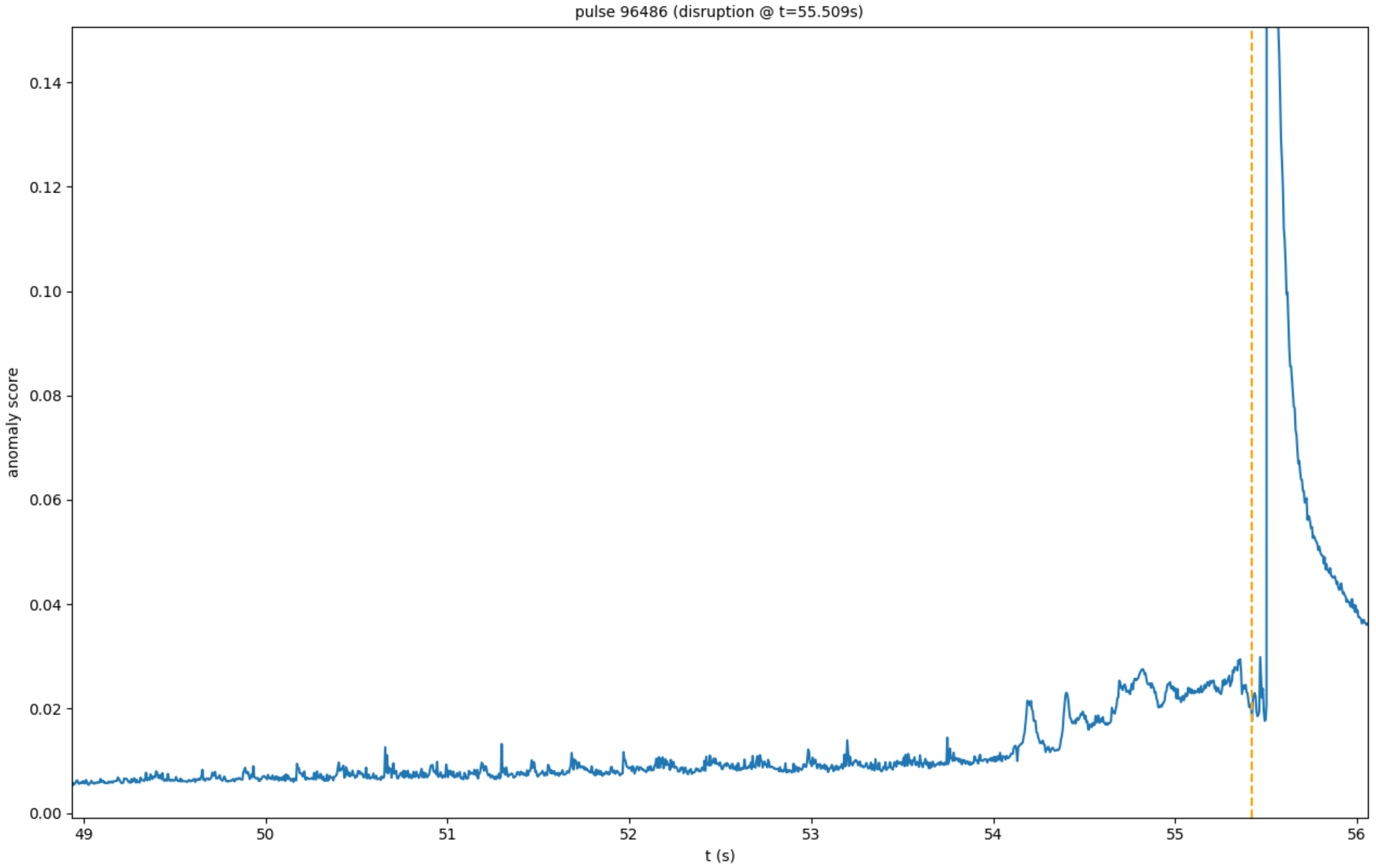

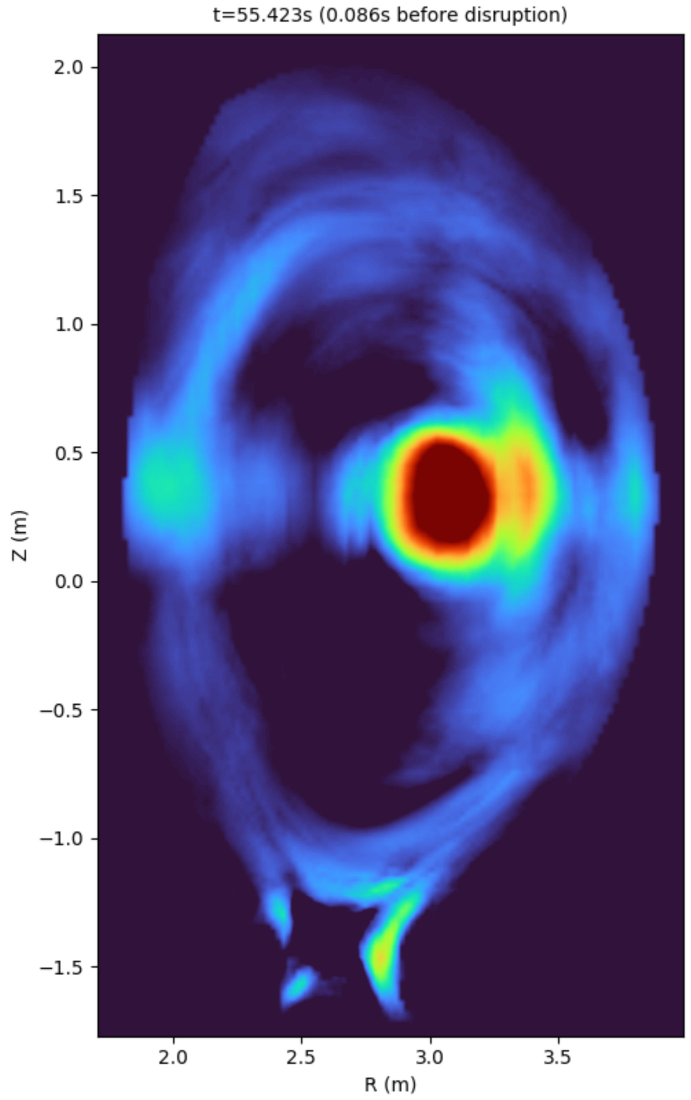

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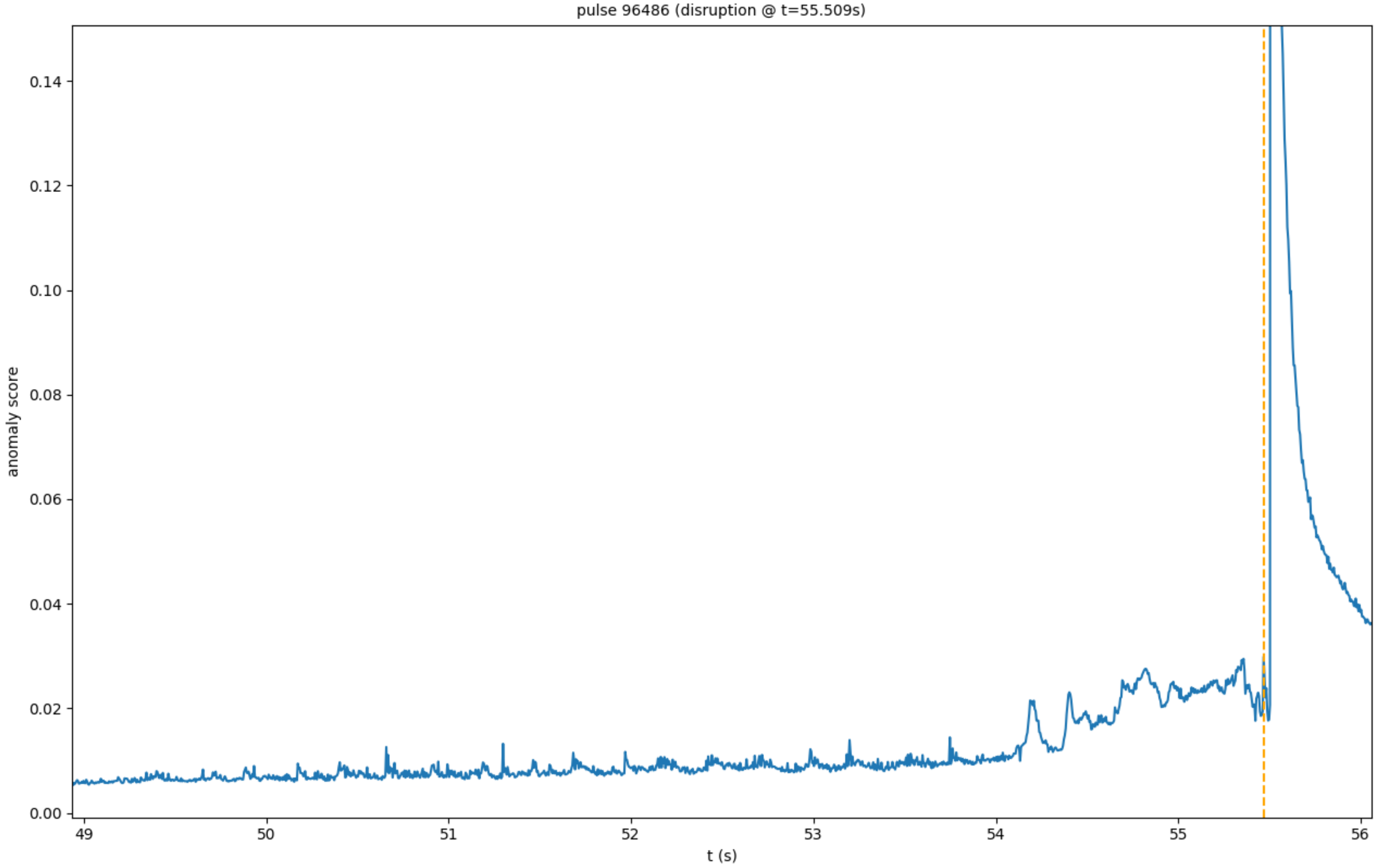

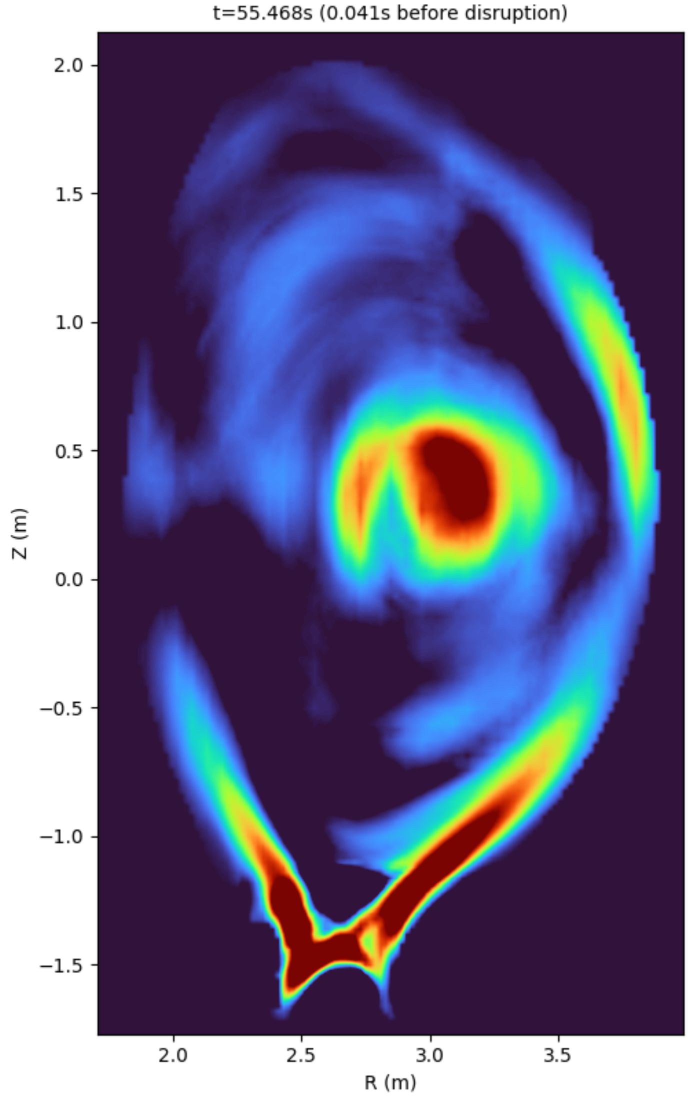

Conclusion

- Multiple physics phenomena at play in baseline pulses
  - e.g. 92213: core radiation build-up + instabilities driven by MARFEs[1]
  - e.g. 96486: core radiation + core dynamics + MARFEs + divertor event
  - other anomalies related to outboard radiation, UFOs[2], sawteeth[3], etc.
- Different time frames of disruption precursors
  - core radiation appears long before disruption, relevant for disruption avoidance
  - MARFE-like behaviour appears much closer to disruption, disruption mitigation only
  - other markers such as ELMs[4], UFOs, divertor events are signalled by the anomaly score
- Possible criticisms and future work
  - nothing new in here, everything was already in the data
  - extend to other pulses beyond baseline, e.g. hybrid scenario
  - idea of applying to every pulse hits upon computational limits

Acknowledgments: CCFE/UKAEA Advanced Computing; EUROfusion HPC MARCONI-FUSION at CINECA, Italy

[1] B. Lipschultz et al, “Marfe: an edge plasma phenomenon”, Nucl. Fusion, vol. 24, no. 8, 1984
[2] A. Murari et al, “Algorithms for the Automatic Identification of MARFEs and UFOs in JET Database of Visible Camera Videos”, IEEE Trans. Plasma Sci., vol. 38, no. 12, 2010
[3] S. von Goeler et al, “Studies of Internal Disruptions and *m*=1 Oscillations in Tokamak Discharges with Soft–X-Ray Techniques”, Phys. Rev. Lett., vol. 33, no. 20, 1974
[4] H. Zohm, “Edge localized modes (ELMs)”, Plasma Phys. Control. Fusion, vol. 38, no. 2, 1996