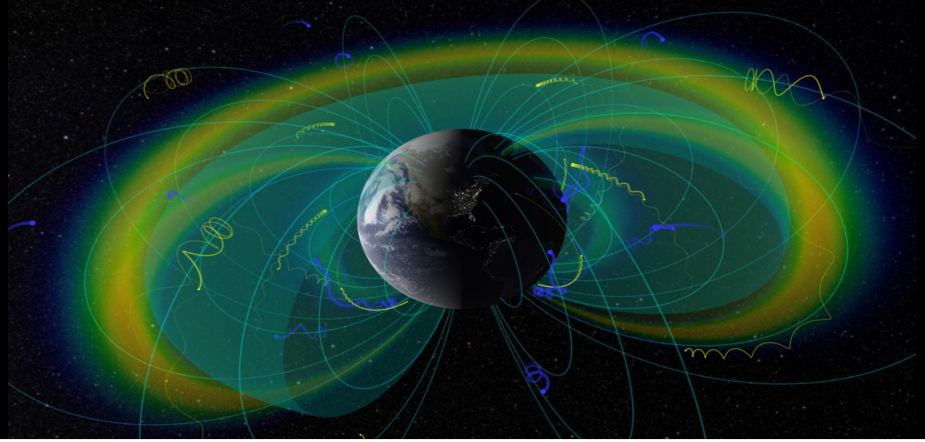


UNIVERSITÀ DEGLI STUDI DELL'AQUILA

EGU General Assembly 2022

Vienna, Austria & Online | 23–27 May 2022

ÉCOLE CENTRALE LYON

LMFA

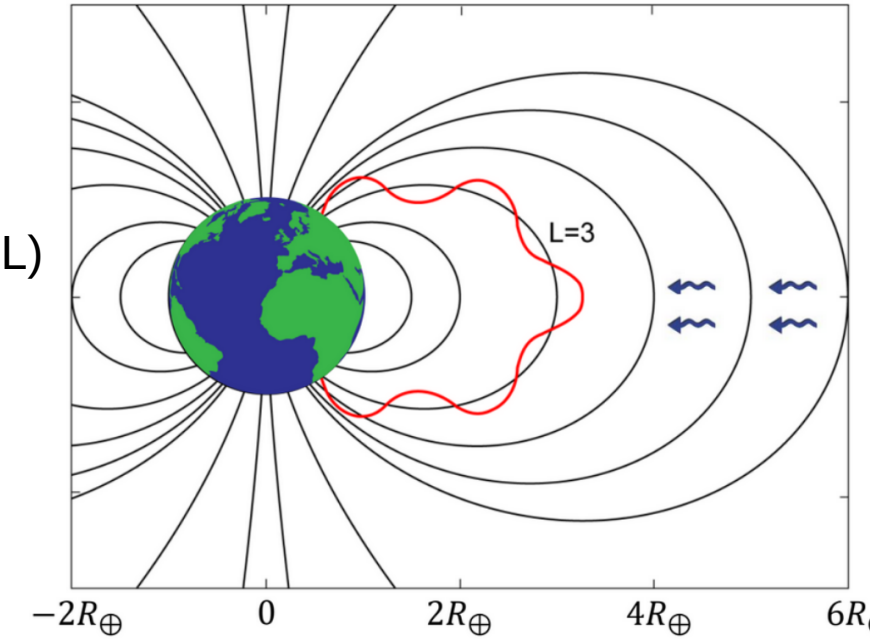
Automated tool for estimating Field Line Resonances (FLRs) using ground-based magnetometer measurements

E. Pietropaolo[1], Raffaello Foldes[1,2], A. Del Corpo[3], R. Marino[2] and M. Vellante[1]

[1] Università de L'Aquila, Dip. di Scienze Fisiche e Chimiche (Italy)
[2] École Centrale de Lyon – CNRS, Lab. de Méchanique des Fluides et d'Acoustique (France)
[3] Instituto di Geofisica e Vulcanologia, INGV (Italy)

Dynamics of the Earth's Plasmasphere via FLRs

Plasmasphere: - approx. between 1 and 6 R_E
- composed by dense and cool plasma (~1eV) of ionospheric origin
- surrounded by the *plasmapause* (PBL)

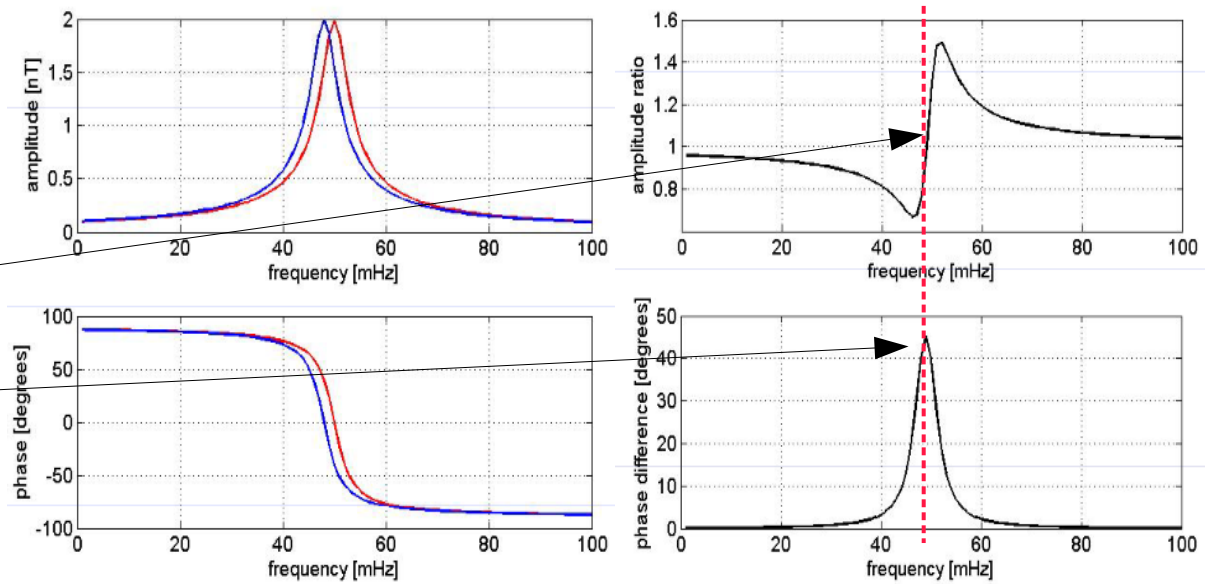


Field Line Resonances (**FLR**s), triggered by shear Alfvèn waves, are a key phenomenon to sound the plasmsphere dynamics and hence the the geomagnetic condition of near-Earth environment.

Gradient method (Waters et al., 1991) from pairs of ground-based magnetometer stations (ULF waves measurements)

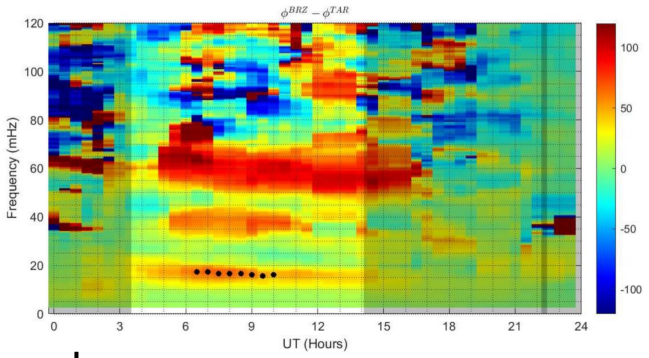
1) **Cross-Amplitude** crosses unity with positive (negative) slope
2) **Cross-Phase** has its maximum (minimum)

If a pair of stations crosses the PBL



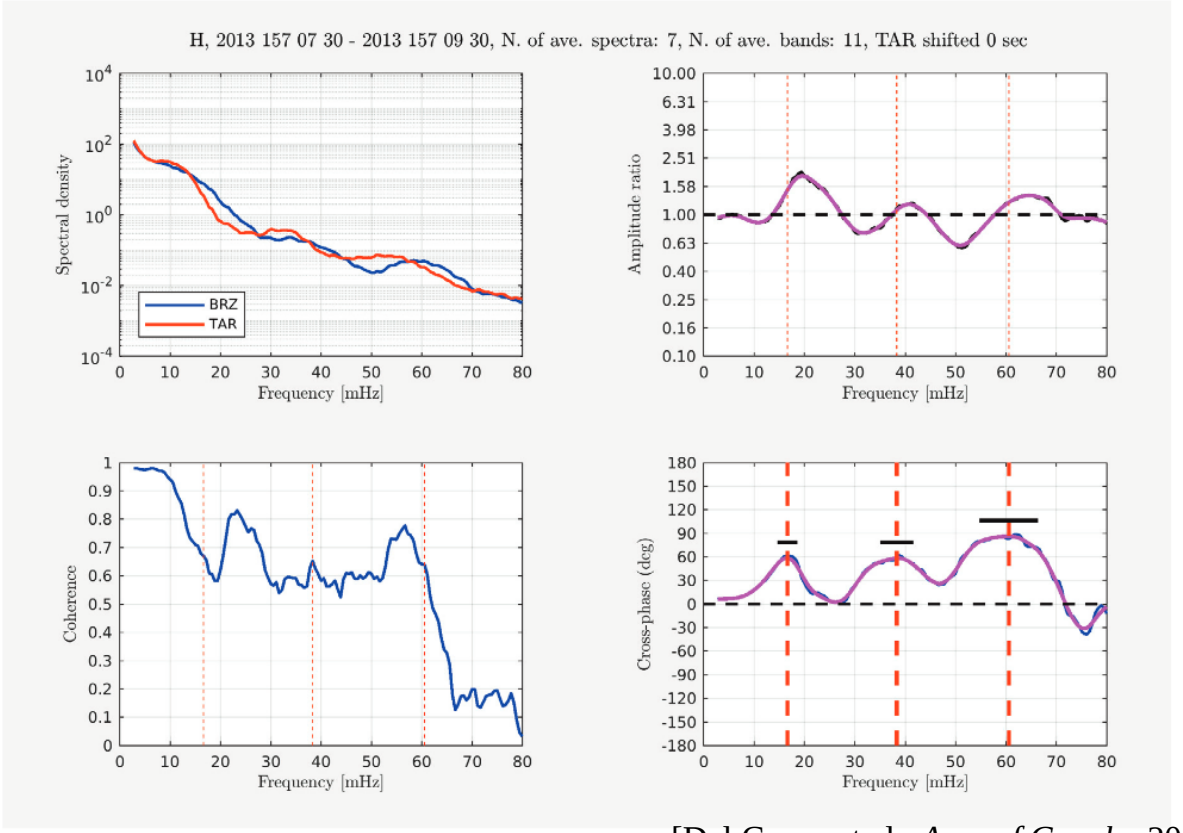
Ground-based magnetometer measurements → (Fourier Cross-Spectra) → **FLR frequencies** → (Singer wave-equation) → **Equatorial plasmaspheric mass density**

Estimating FLRs with Machine Learning methods



Several automated and semi-automated methods based on statistical tools (*Del Corpo et al., 2018; Wharton et. Al, 2018; Lichtenberger et al., 2013; Berube et al., 2003; Chi et al., 2003*).
All of them starts from **cross-phase** spectra.

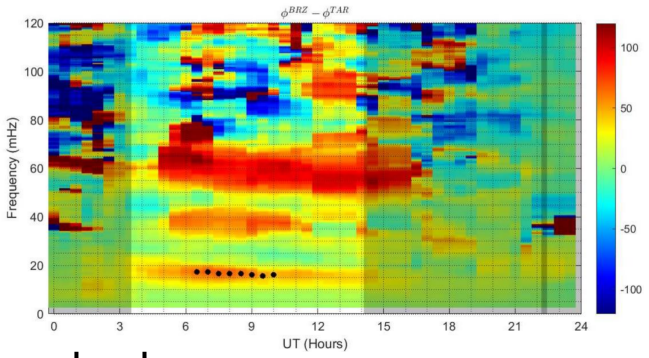
Semi-automated methods

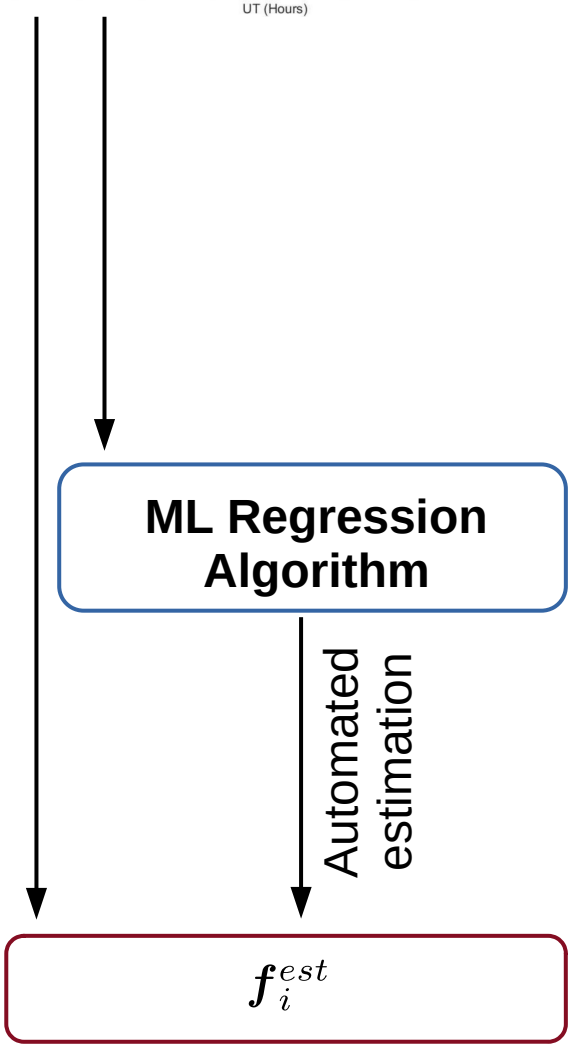


[Del Corpo et al., *Ann. of Geoph.*, 2018]

$$\boldsymbol{f}_i^{est}$$

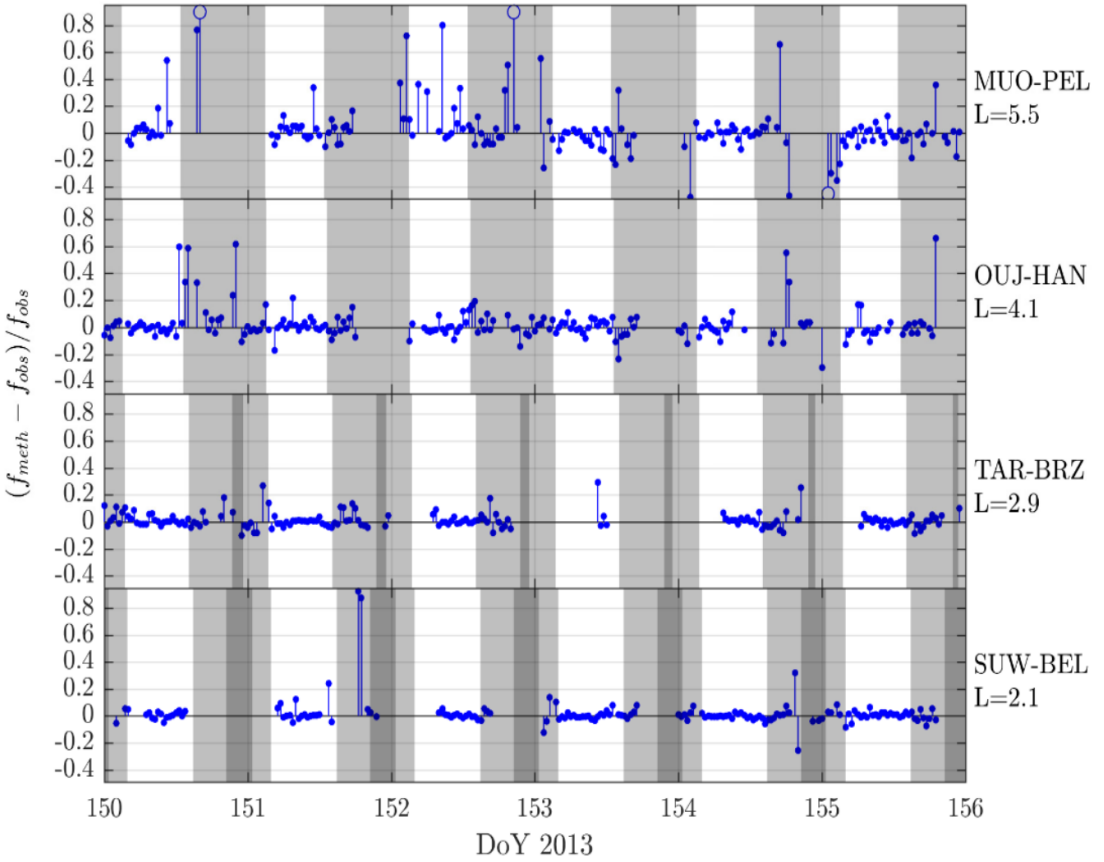
Estimating FLRs with Machine Learning methods





ML regression algorithm:

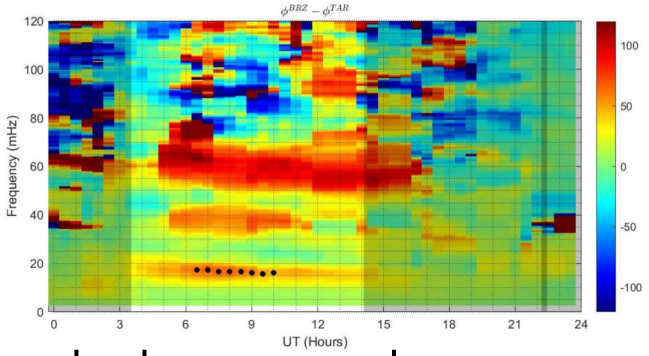
Input: 2-hr. cross-phase spectra (30-min. time step)
Output: Estimated resonance frequency



[Foldes et al., *JGR: Space Physics*, 2021]

But this approach assumes that there exists a FLR at any given time (not true in principle).

Estimating FLRs with Machine Learning methods



ML Classification Algorithm

Fully-automated algorithm

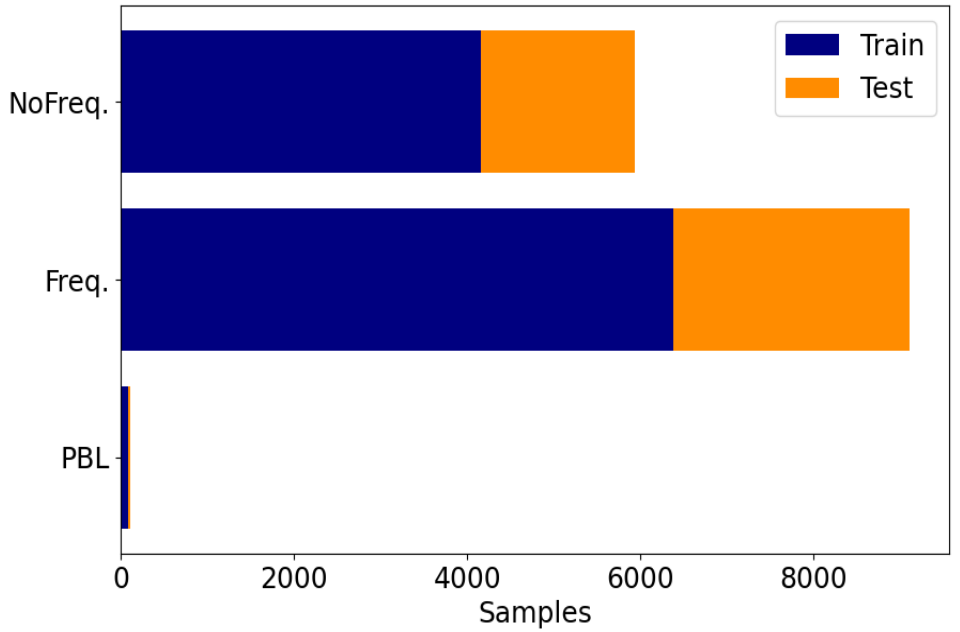
ML Regression Algorithm

Automated estimation

f_i^{est}

~15,000 samples from TAR-BRZ between 2012 and 2018 (from Equatorial quasi-Meridional Magnetometer Array, EMMA)

Input: 2-hr. cross-phase spectra (30-min. time step)
Output: Belonging Class

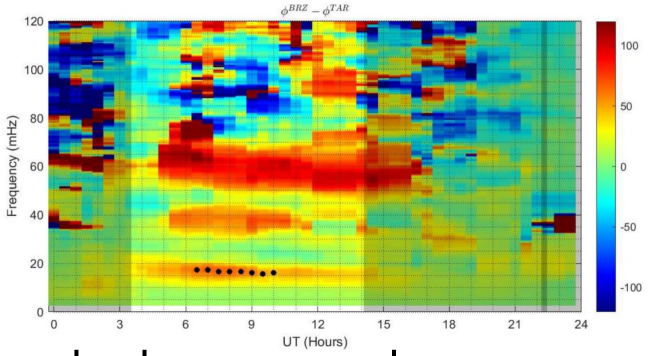


38.1%

61.1%

0.8%

Estimating FLRs with Machine Learning methods



ML Classification Algorithm

Fully-automated algorithm

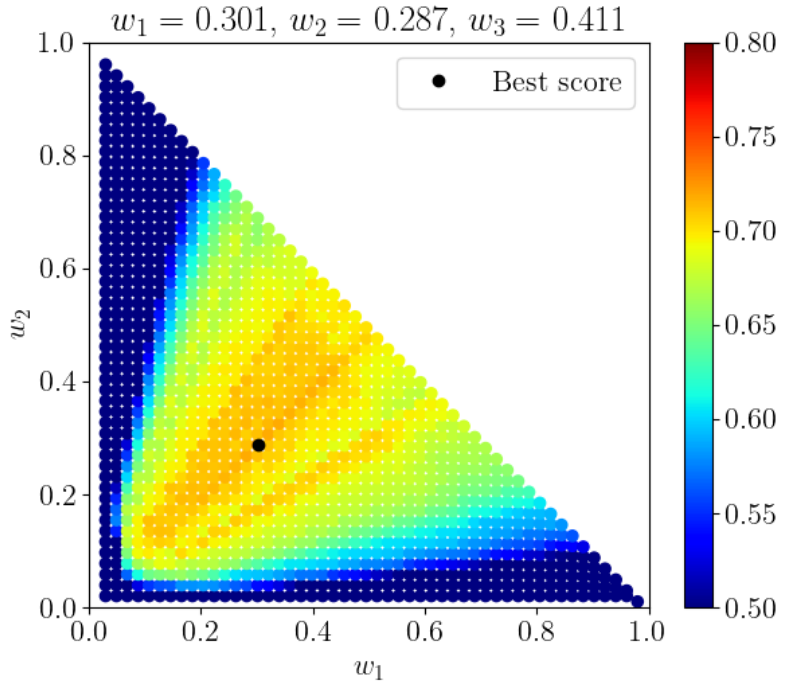
ML Regression Algorithm

Automated estimation

f_i^{est}

~15,000 samples from TAR-BRZ between 2012 and 2018 (from Equatorial quasi-Meridional Magnetometer Array, EMMA)

Input: 2-hr. cross-phase spectra (30-min. time step)
Output: Belonging Class

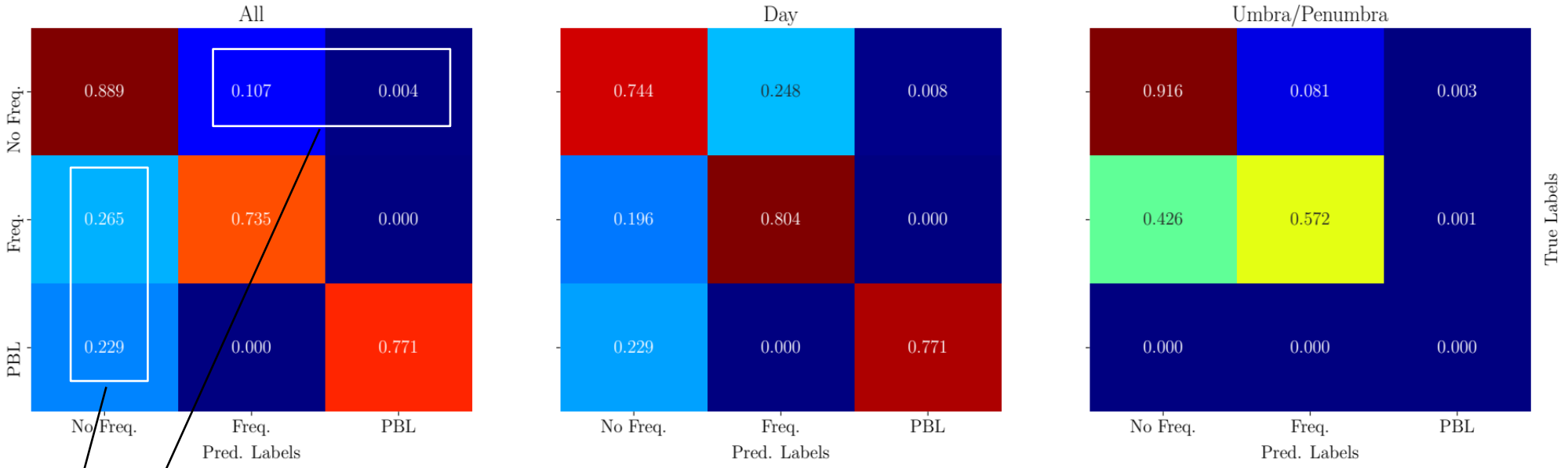


Unbalanced Data Set

Moving Threshold: (Validation set)
maximize $F(w_1, w_2) \rightarrow$ Score

with $0 \leq w_1 + w_2 \leq 1 - w_3$

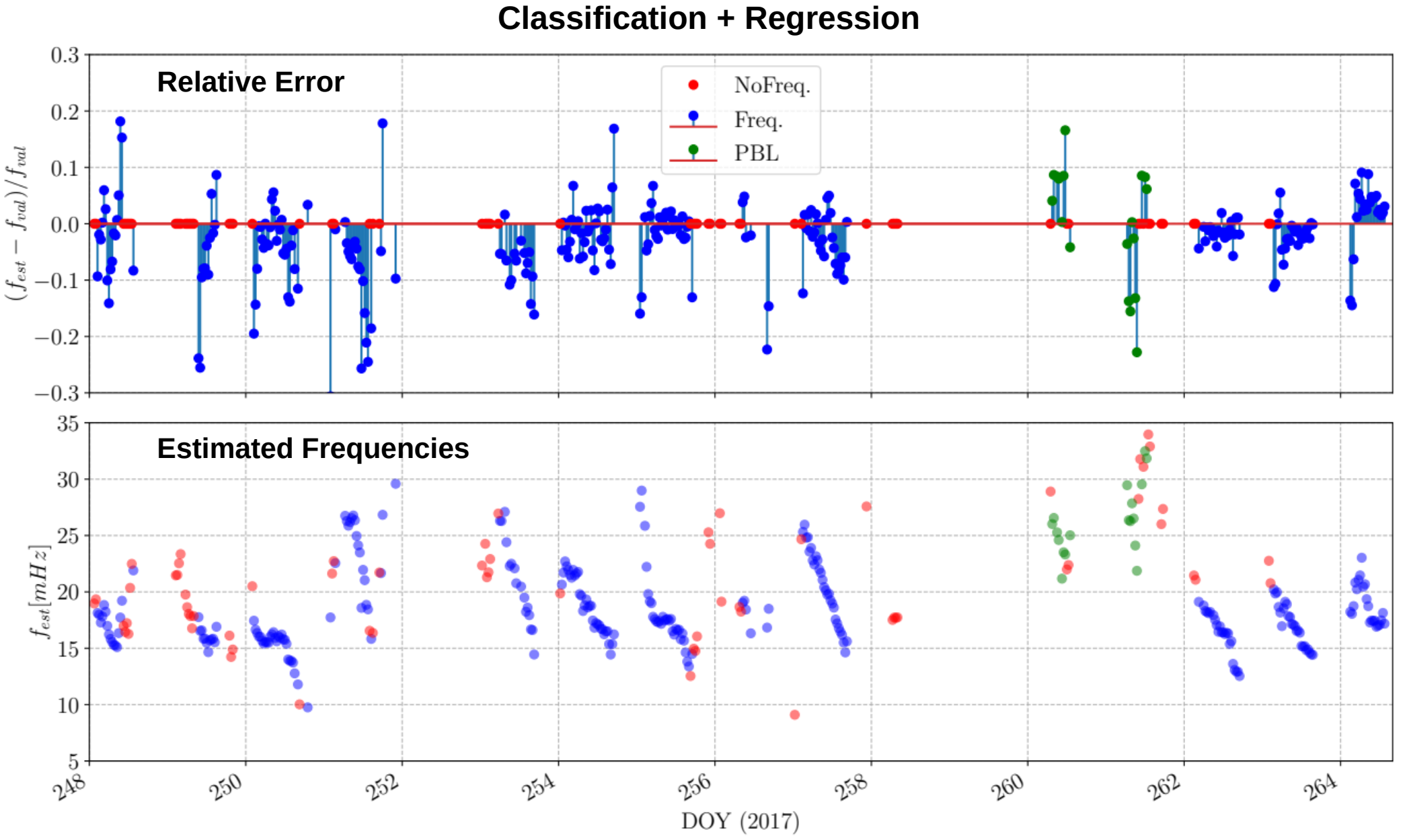
ML Classification of Effective FLRs



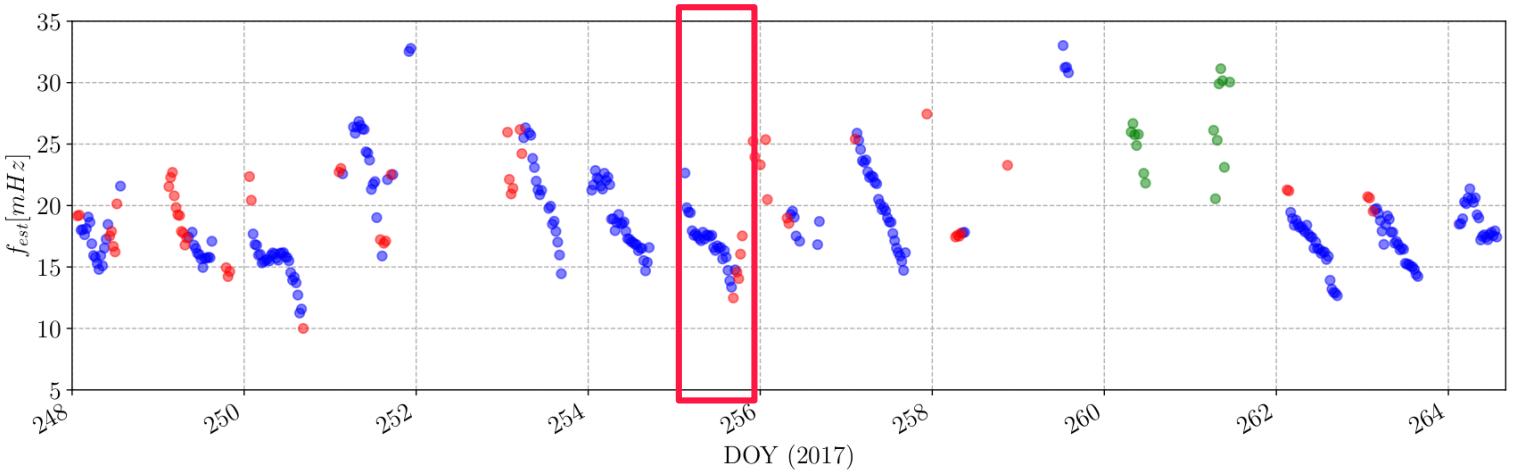
- **Wrong Information ~10.7%** : NoFreq classified as Freq/PBL (as low as possible)
- **Information Loss ~ 26.5%**: Freq/PBL classified as NoFreq

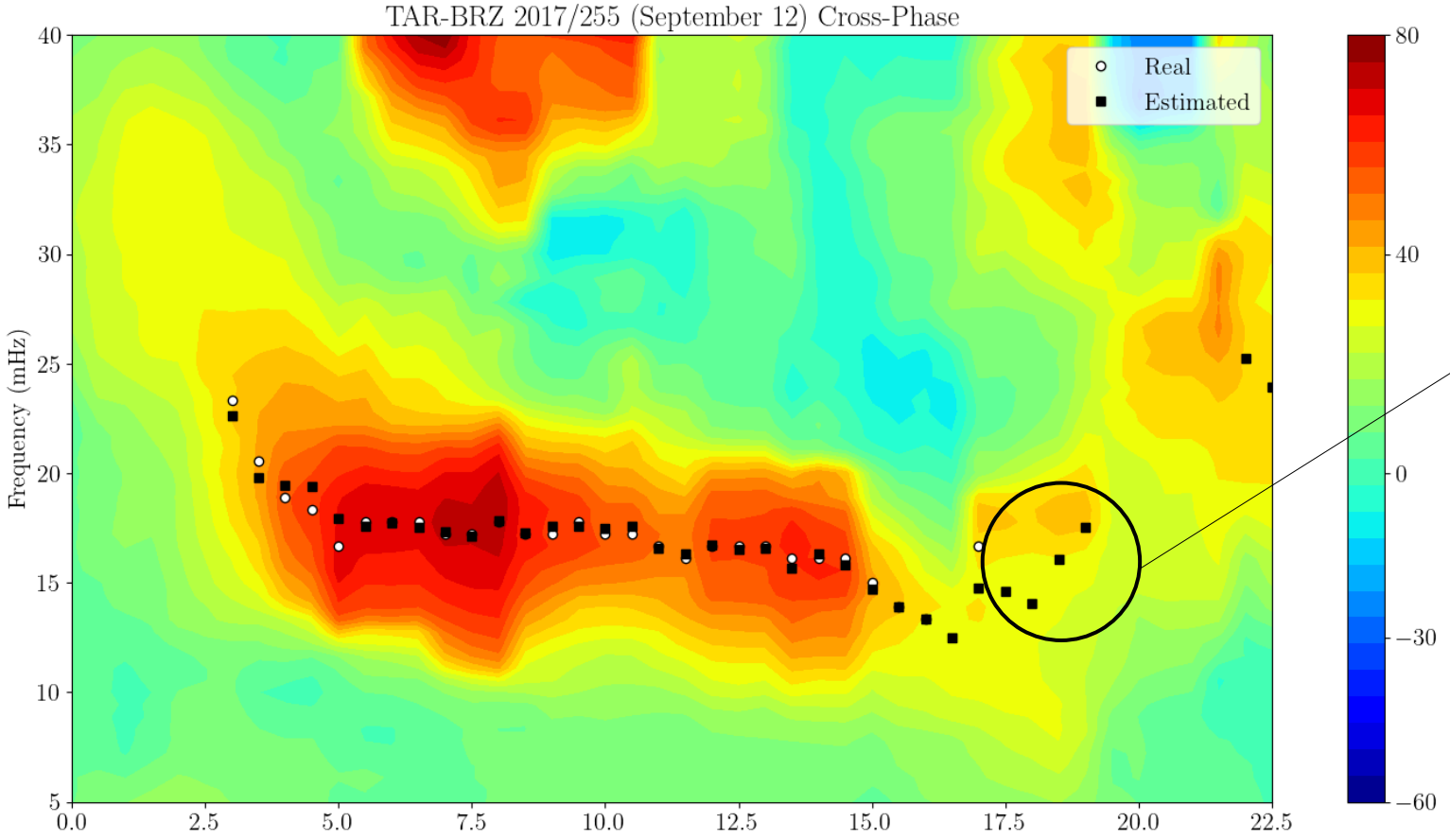
- For an operational tool we are trying to minimize the amount of "**wrong information**" (NoFreq. → Freq./PBL)
- Considering only *daytime samples* **drastically changes** the class balance.
- **Binary classification** (no PBL samples) could improve the results.

Automated estimation of FLRs with ML



Automated estimation of FLRs with ML





As expected, the ML regression algorithm looks for peaks (maxima) in the cross-phase spectrum

Conclusions and Future Perspectives

- Machine Learning methods (both **regression** and **classification**) represent a valuable tool for the *automated* estimation of FLRs starting from cross-phase spectra computed from ground-based measurements (ULF waves).
- The results show a small “loss of information” (~25%) and a minimal amount of “wrong information” (~10%).
- The procedure could be improved by considering only *daytime* samples and/or implementing a **binary classification** (PBL samples included into the NoFreq. Class).
- The analysis will be extended to other pairs of stations along the EMMA network in order to have a more robust and reliable algorithm.

Thank you for your attention

CÆSAR Comprehensive sPAce wEather Studies for the ASPIS prototype Realization

UNIVERSITÀ DEGLI STUDI DELL'AQUILA

INGV terremoti vulcani ambiente

ISTITUTO NAZIONALE DI GEOFISICA E VULCANOLOGIA

ÉCOLE CENTRALE LYON

LMFA