



**2025 ITALIAN URSI ANNUAL MEETING**  
**26 JUNE 2025**

# **AI - POWERED IONOSPHERIC FORECASTING**



**ISTITUTO NAZIONALE  
DI GEOFISICA E VULCANOLOGIA**

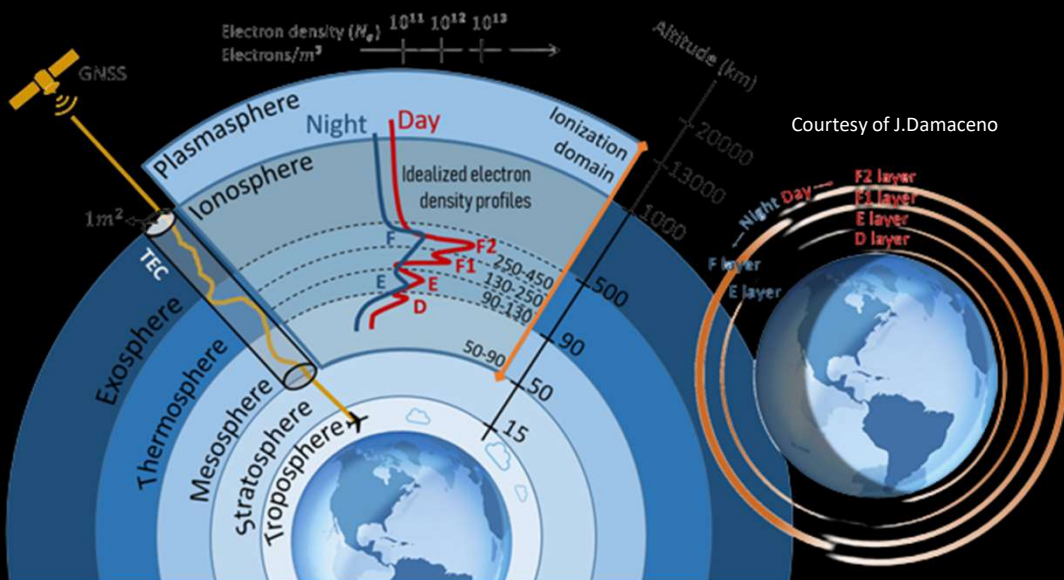
**Claudio Cesaroni, PhD**

Istituto Nazionale di Geofisica e Vulcanologia (INGV)  
Universidad Nacional de Tucumán (UNT)  
[claudio.cesaroni@ingv.it](mailto:claudio.cesaroni@ingv.it)

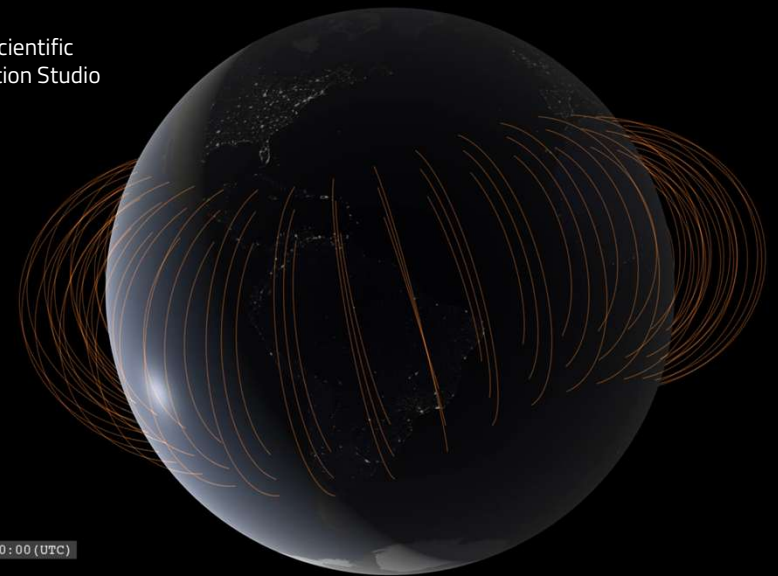


**UNIVERSIDAD  
NACIONAL  
DE TUCUMÁN**

# Making the ionosphere in one slide...

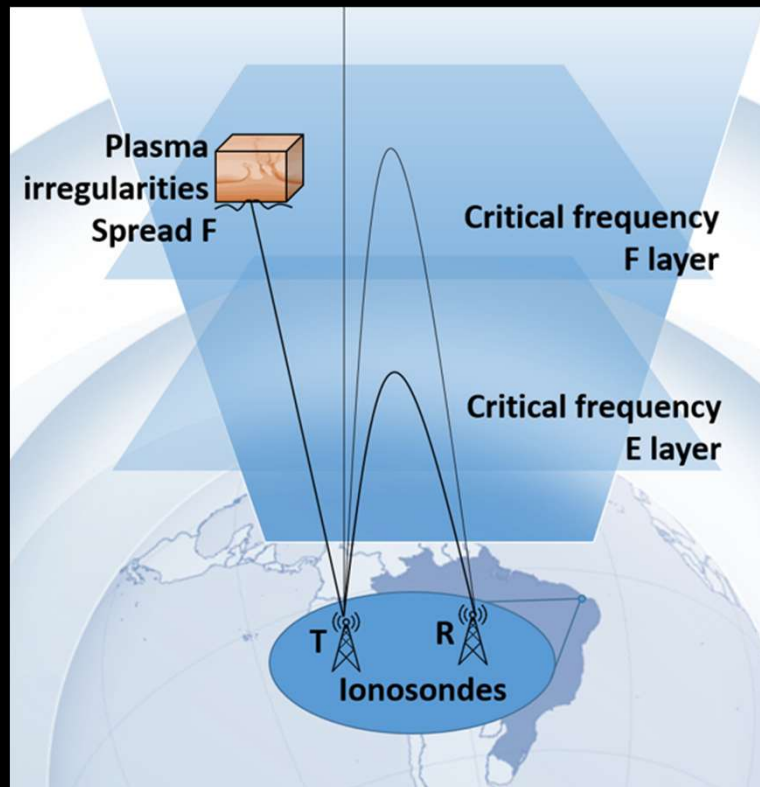


Credits:  
NASA's Scientific  
Visualization Studio



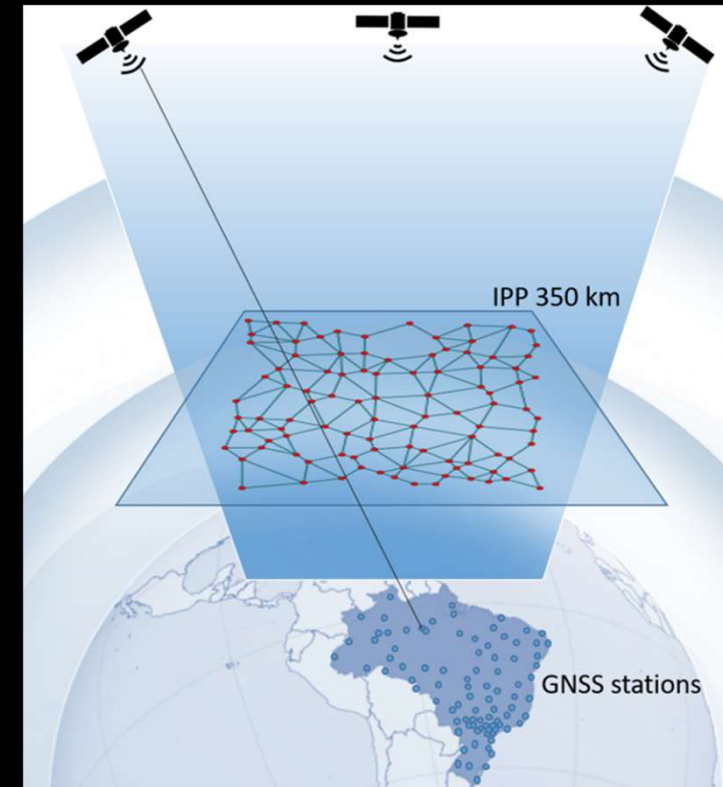
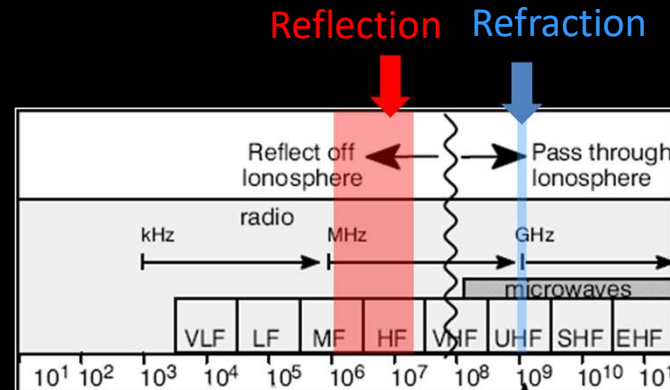
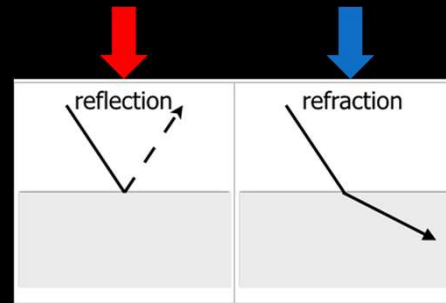


# Monitoring the ionosphere...



**Ionosondes**  
(HF remote soundings)

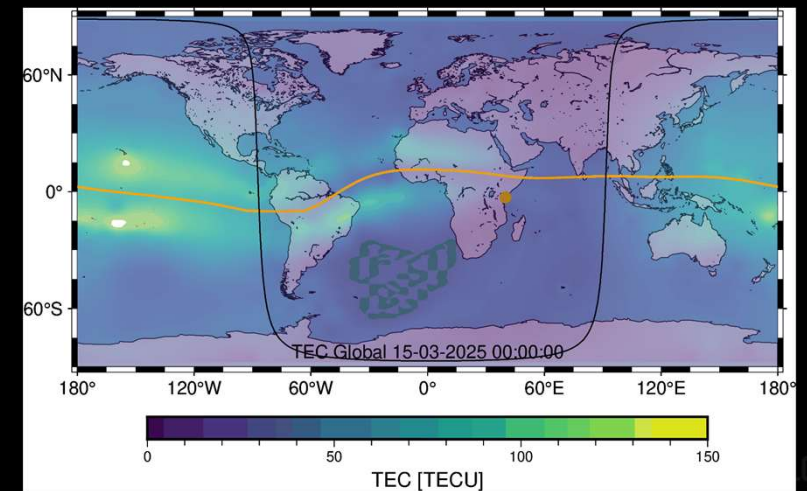
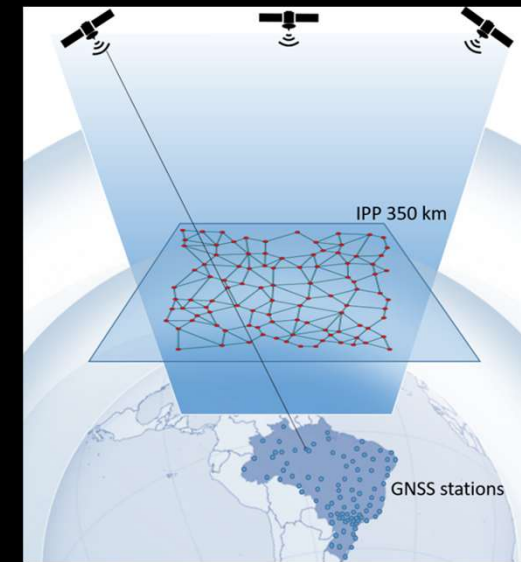
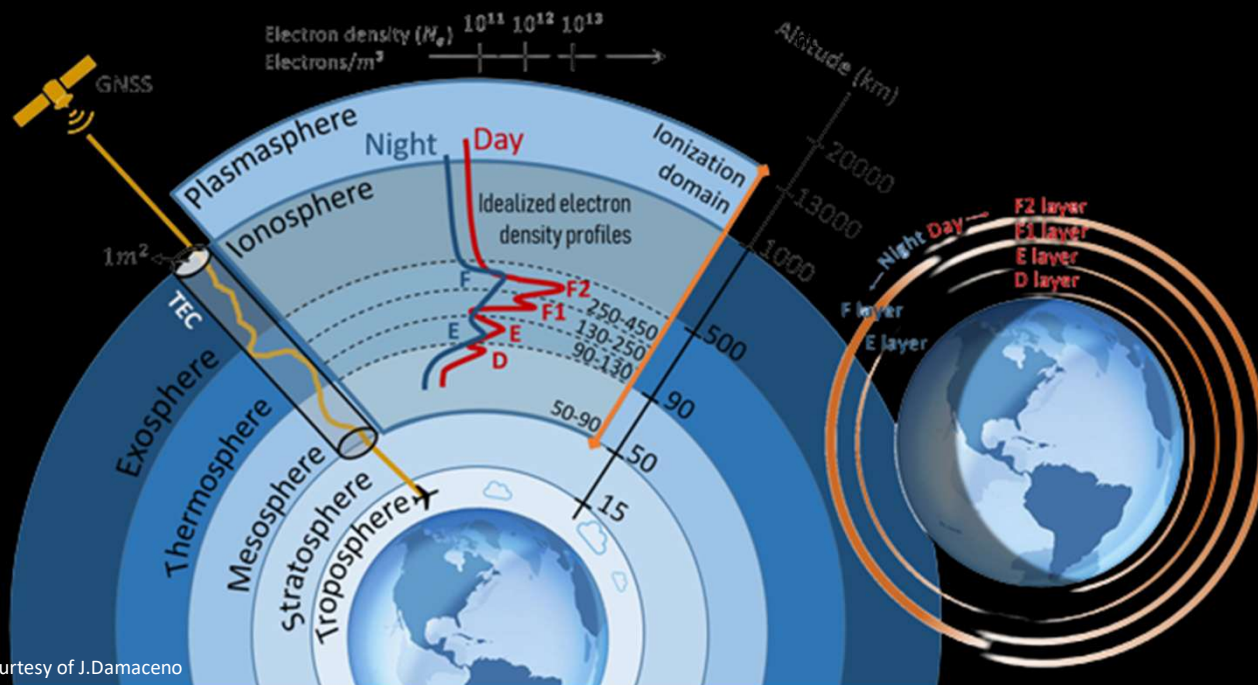
HF Sounding exploits reflection  
GNSS Sounding exploits refraction



**GNSS receivers**  
(L-band remote soundings)

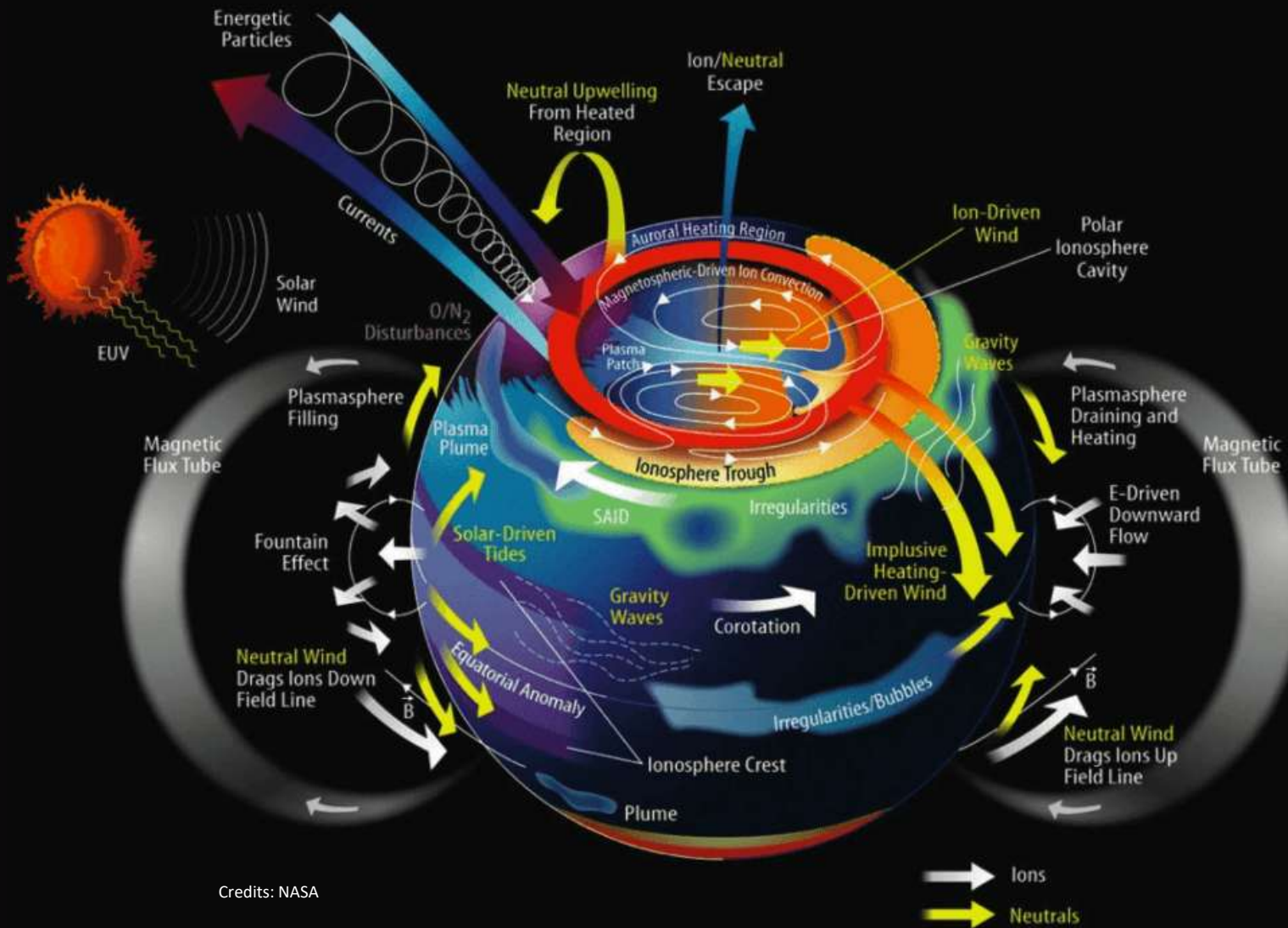
# Total Electron Content

Exploiting GNSS measurements to estimate the Ionospheric Total Electron Content (TEC)



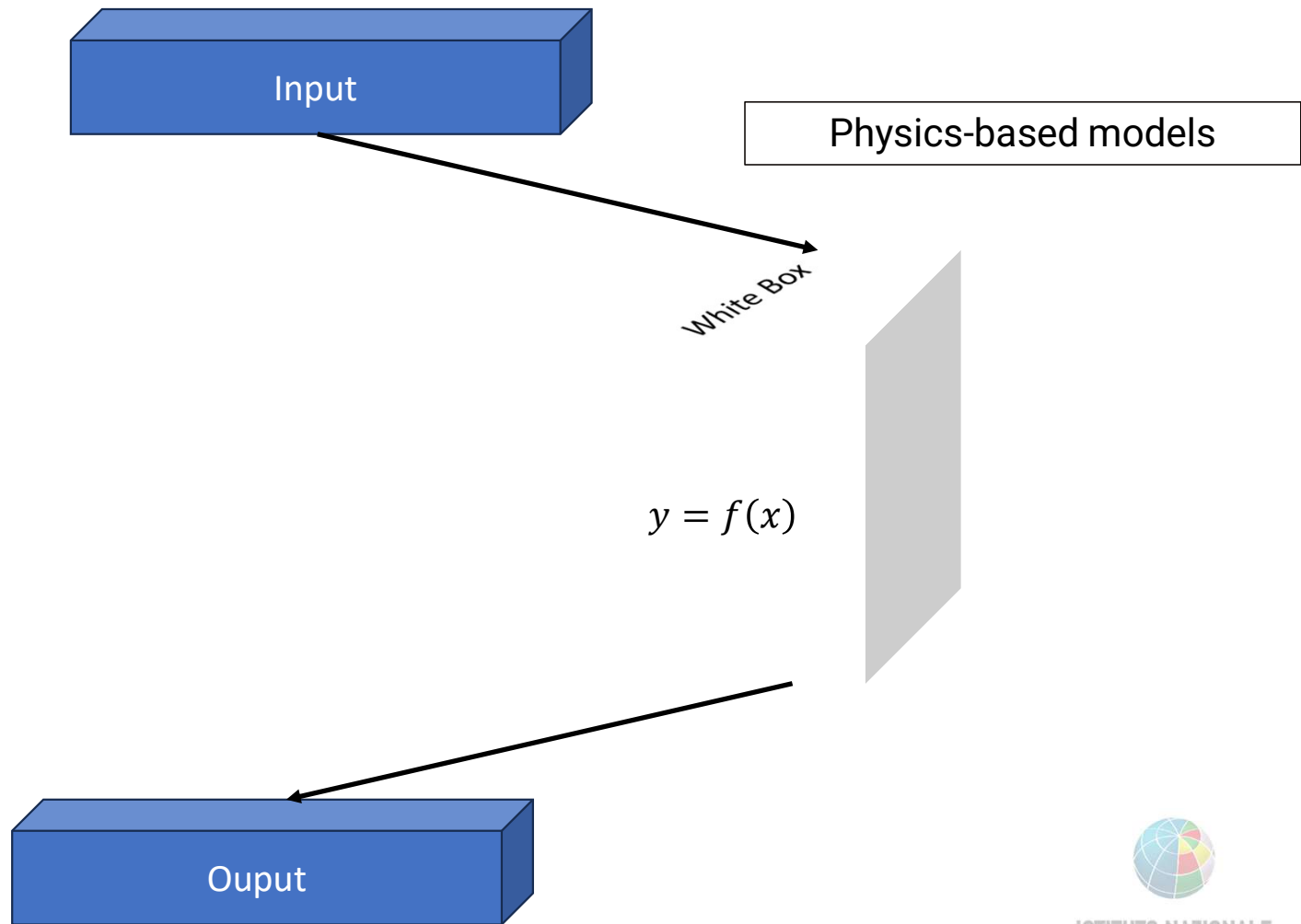


# A lot of external forcing...



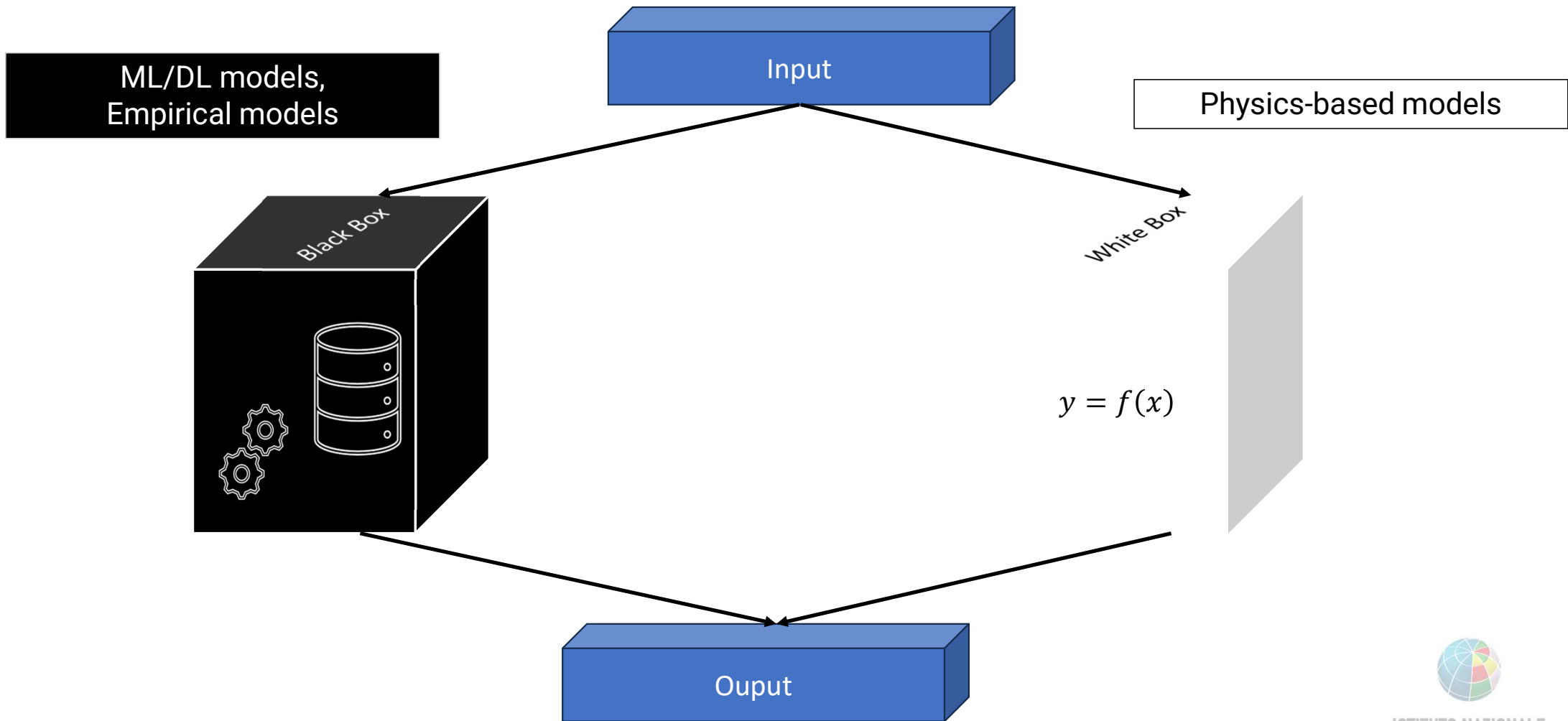
Credits: NASA

# How to model and forecast the ionospheric features?

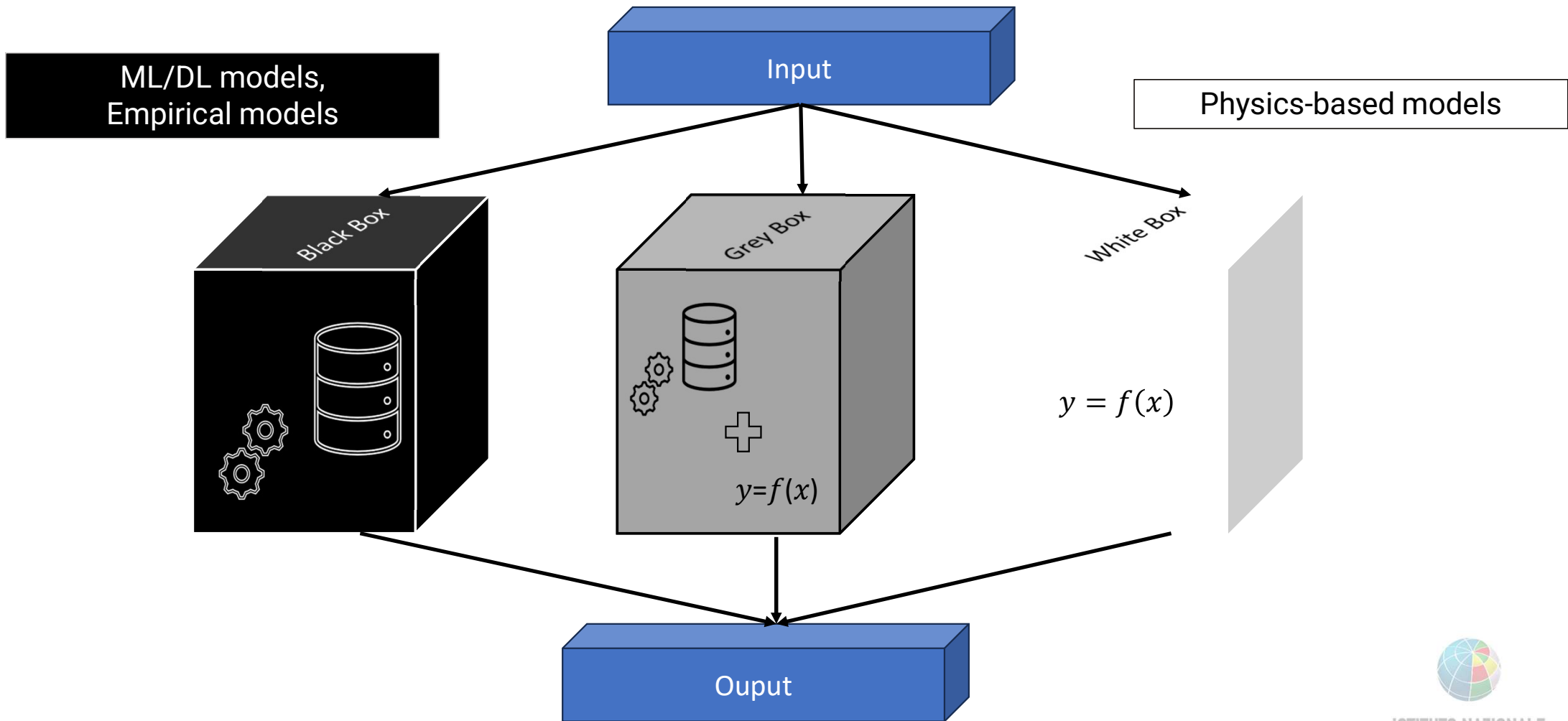




# How to model and forecast the ionospheric features?

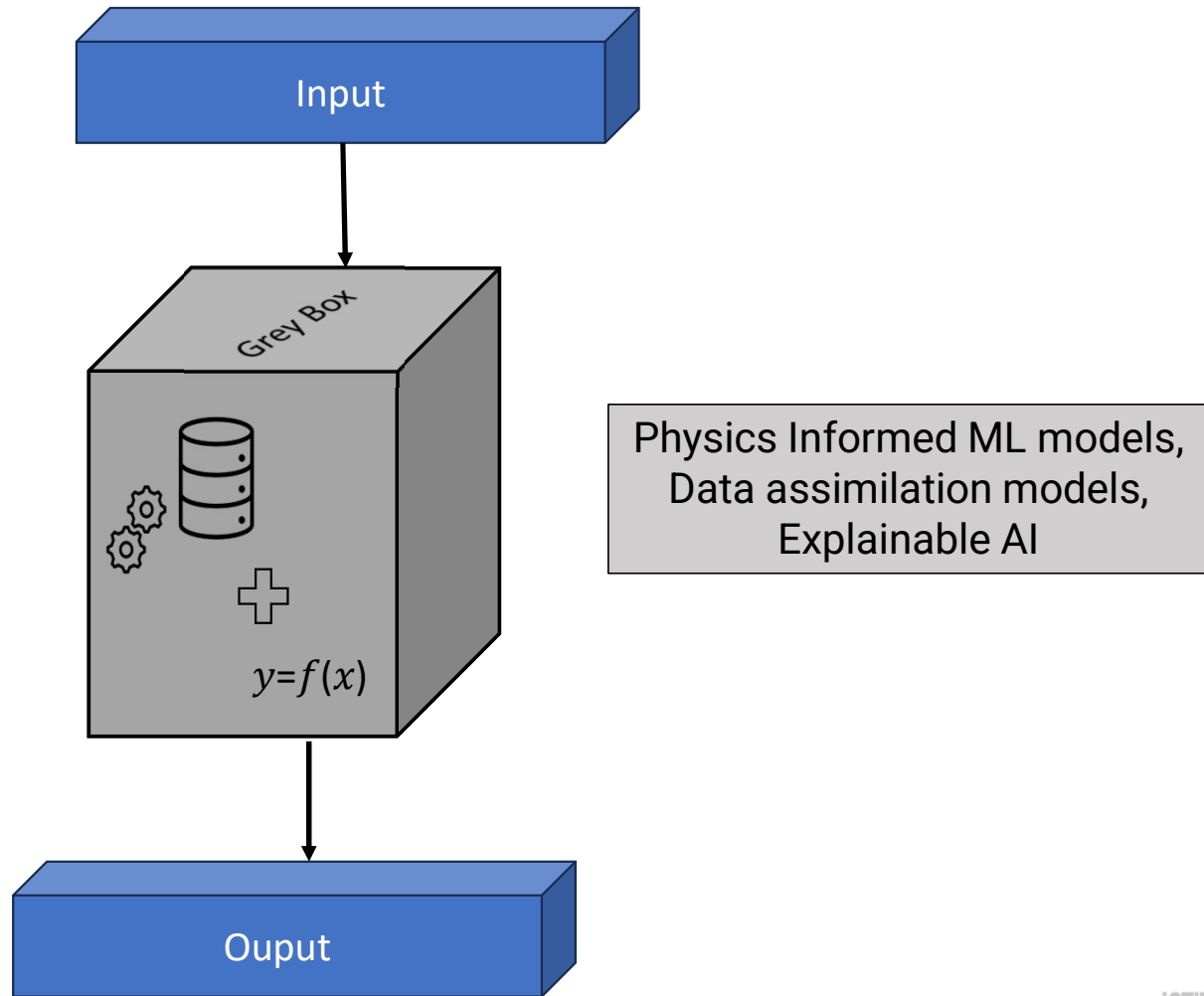


# How to model and forecast the ionospheric features?



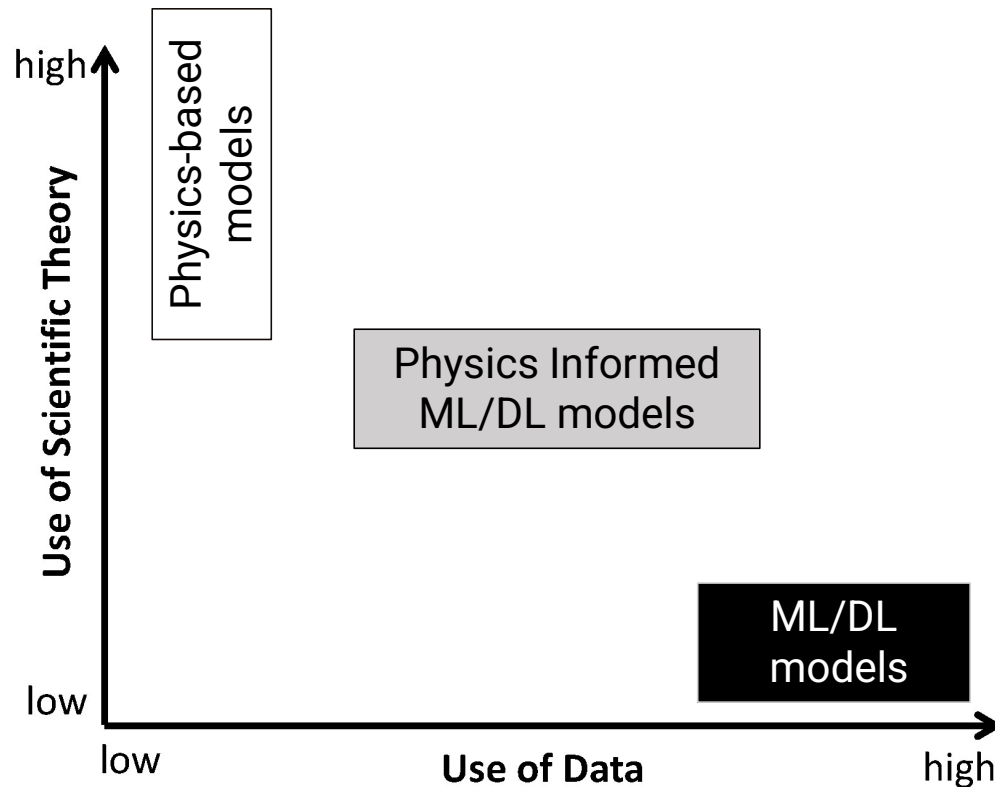


# How to model and forecast the ionospheric features?

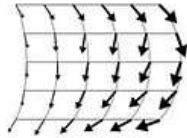
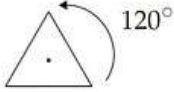
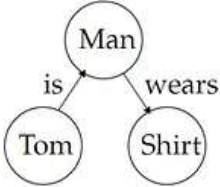
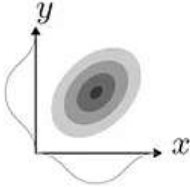



# Physics-informed Machine Learning (PIML)

Leverage physics to ease Machine Learning training task  
How to do it...



Di et al., 2023

Algebraic Equations	Differential Equations	Simulation Results	Spatial Invariances
$E = m \cdot c^2$ $v \leq c$	$\frac{\partial u}{\partial t} = \alpha \frac{\partial^2 u}{\partial x^2}$ $F(x) = m \frac{d^2 x}{dt^2}$		
Logic Rules	Knowledge Graphs	Probabilistic Relations	Human Feedback
$A \wedge B \Rightarrow C$			

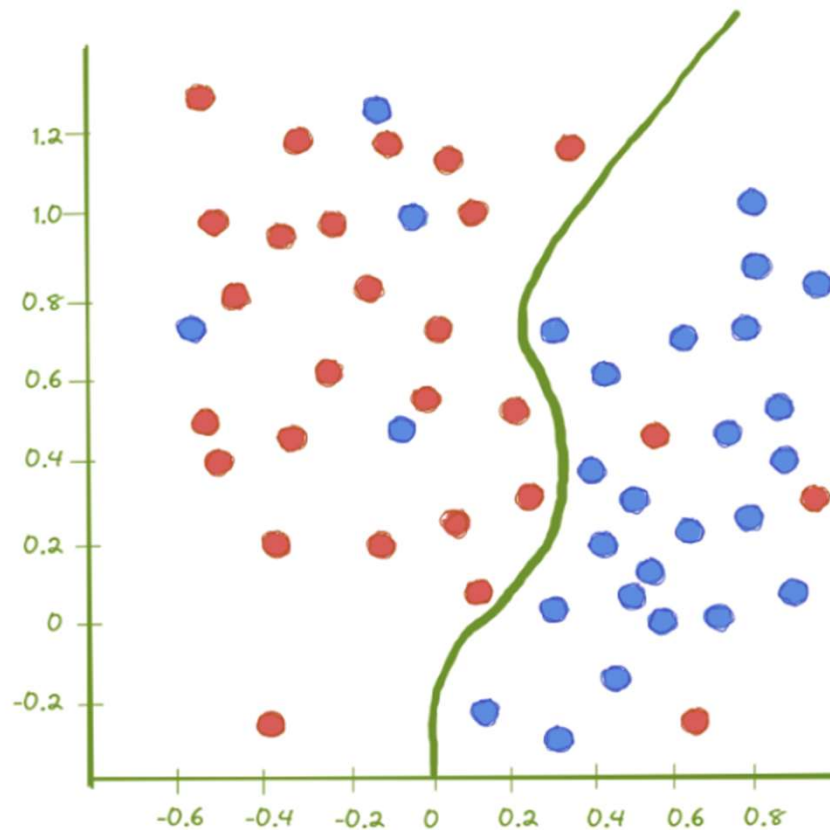
Hamilton et al., 2022



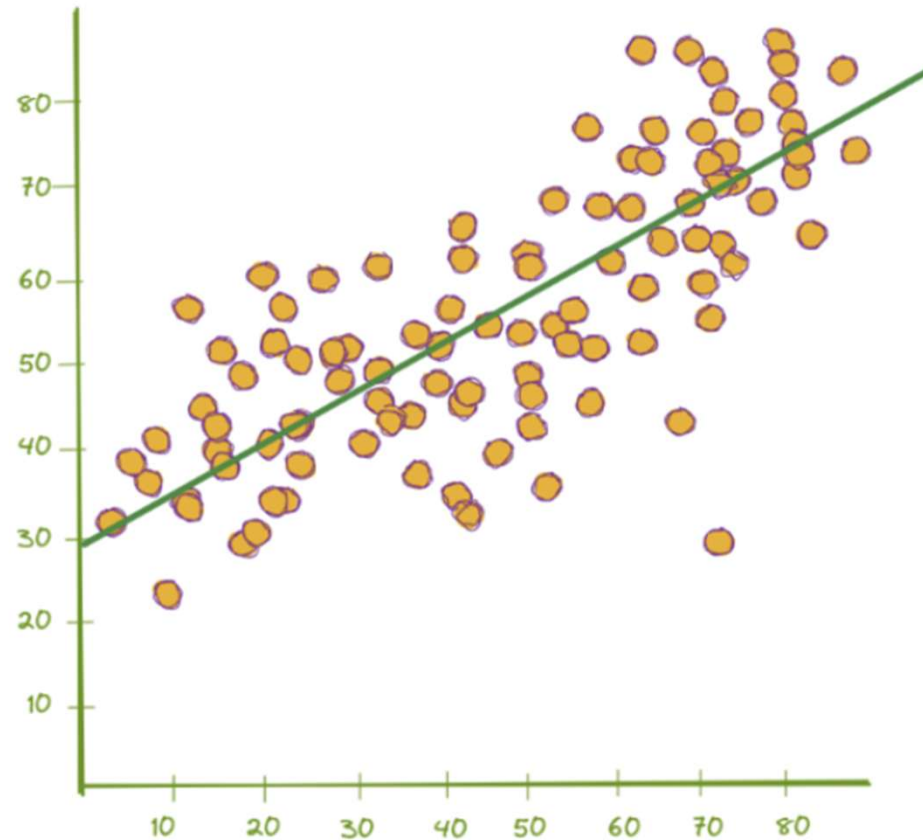
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# Regression vs Classification



classification

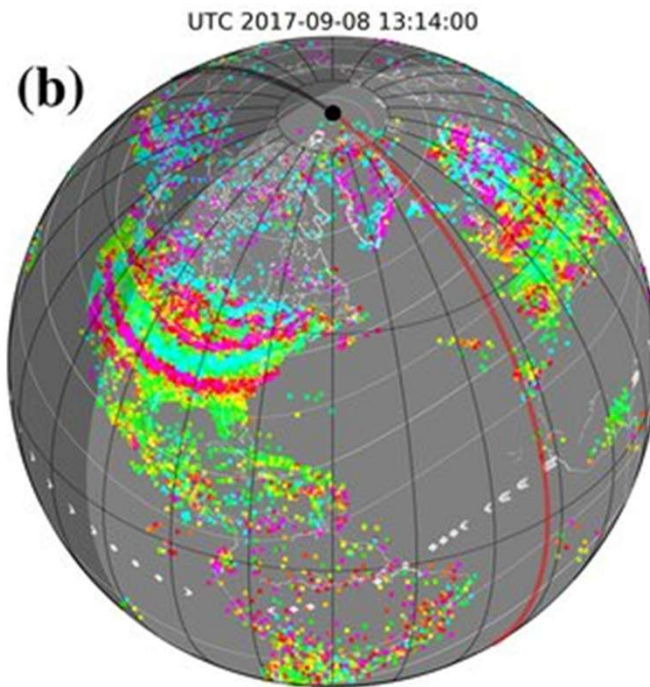


regression



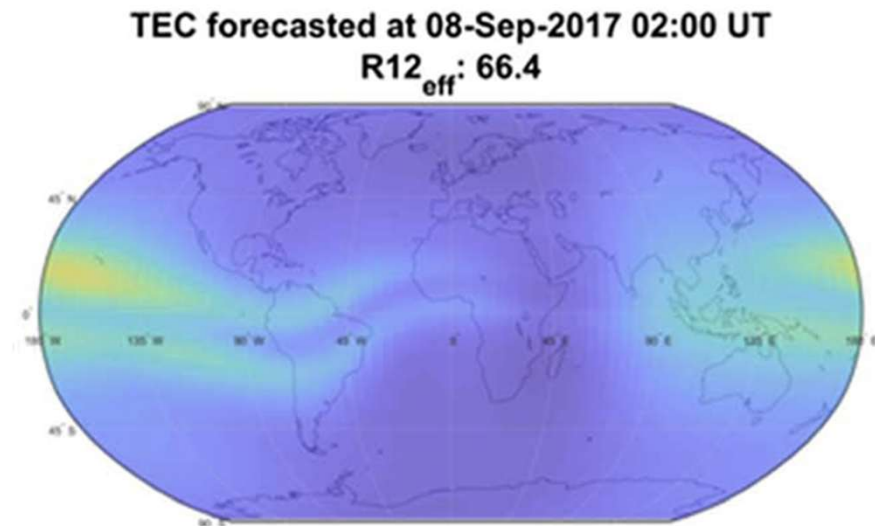
# Regression vs Classification

LSTID occurrence



classification

Global TEC forecasting

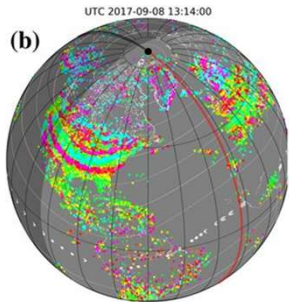


regression



# How will the Global TEC change in the next 24 hours?

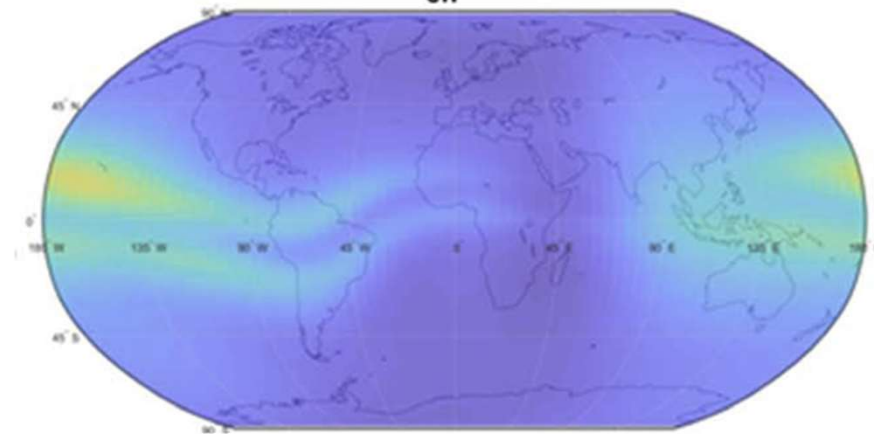
LSTID occurrence



classification

## Global TEC forecasting

TEC forecasted at 08-Sep-2017 02:00 UT  
 $R12_{\text{eff}}: 66.4$



regression



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# What the ionospheric community did so far for TEC forecasting?

*The extensive application of ML techniques in ionospheric modeling the recent years demonstrate relevant forecasting efficiency. The benefits may be greater through the coupling of physics-based models with ML.*

Tsagouri et al., 2023

## Temporal domain



- Short-term

(Up to a few hours)

Zhang et al., 2023

Huang et al., 2015

Sivavaraprasad et al., 2020

- Long-term

(Up to a couple of days)

Oruz et al., 2019

Muslim et al., 2021

## Spatial domain



- Local

Tebabal et al., 2018

Hang et al., 2014

Kharakhashyan et al., 2021

- Regional

Xiong et al., 2021

Ferreira et al., 2017

- Global

Cesaroni et al., 2020

Liu et al., 2020

## ML/DL techniques



- RNN (NARX, LSTM, GRU)

Tebabal et al., 2018

Hang et al., 2014

Kharakhashyan et al., 2021

- CNN/CRNN

Cherrier et al., 2017

Gao et al., 2023

- GAN/Transformer

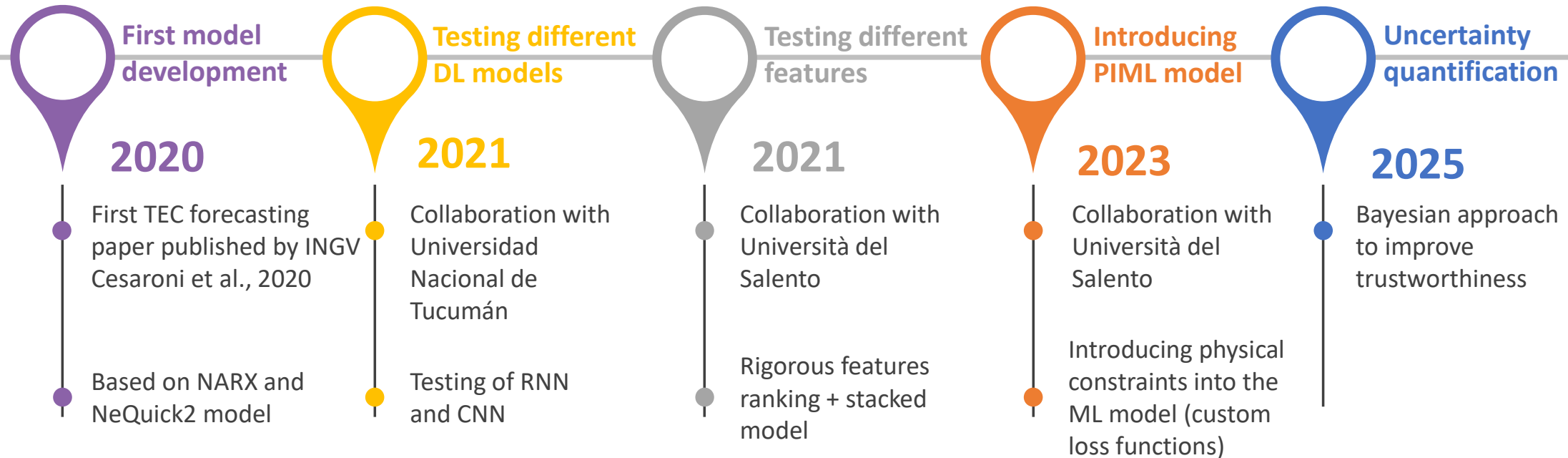
Yang et al., 2022

Yuan et al., 2023



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# Our roadmap toward a Physics-Informed forecasting TEC model



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# Our roadmap toward a Physics-Informed forecasting TEC model



First model  
development

2020

First TEC forecasting  
paper published by INGV  
Cesaroni et al., 2020

Based on NARX and  
NeQuick2 model

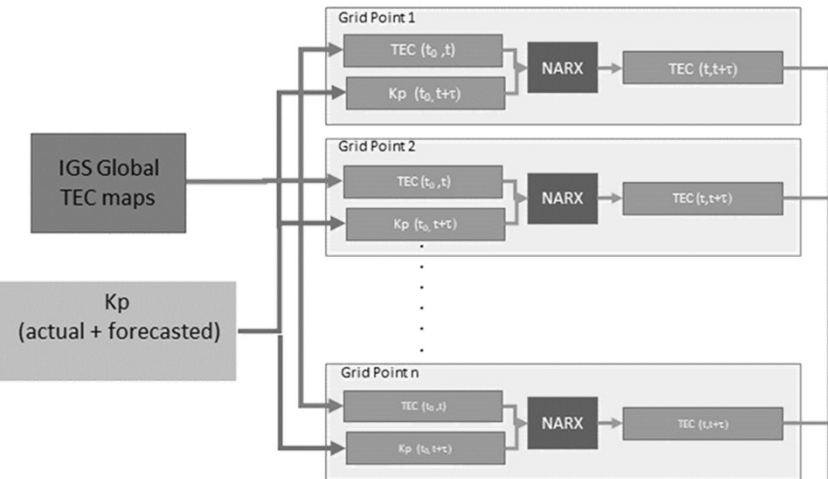


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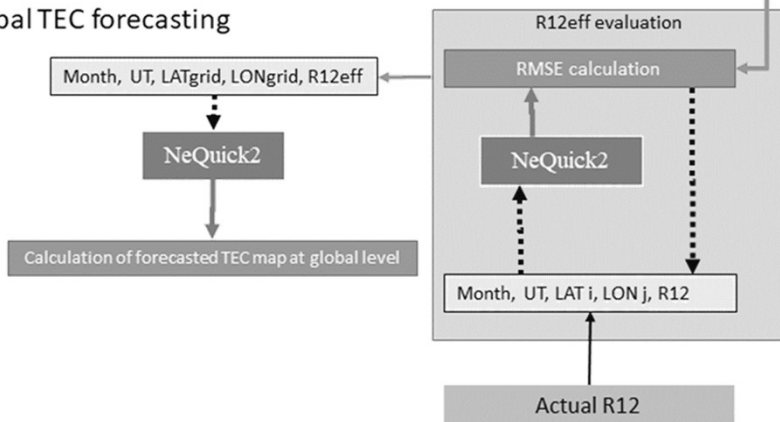


# NARX model for TEC forecasting

## Single Point TEC forecasting



## Global TEC forecasting

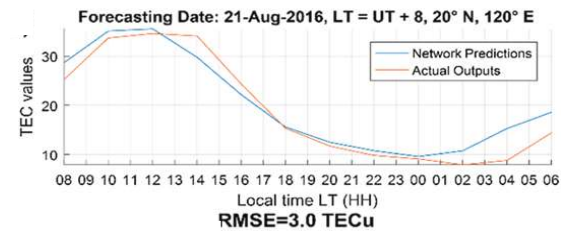
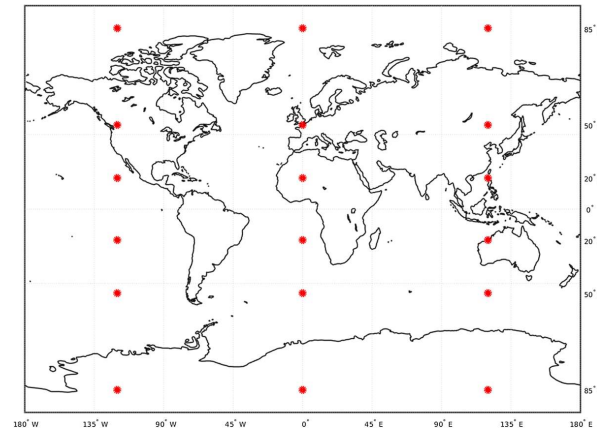
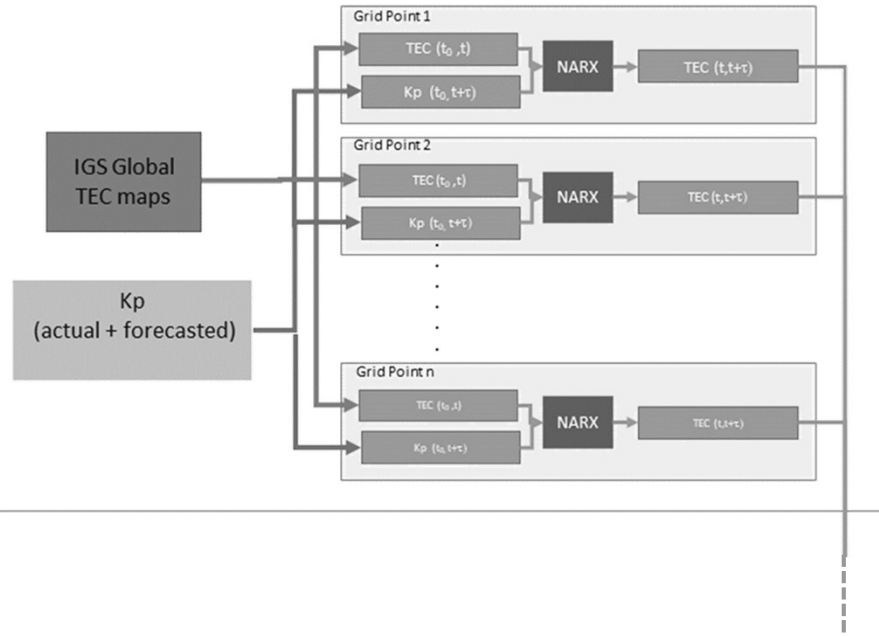


Cesaroni, C., Spogli, L., Aragon-Angel, A., Fiocca, M., Dear, V., De Franceschi, G., & Romano, V. (2020). Neural network based model for global Total Electron Content forecasting. *Journal of space weather and space climate*, 10, 11.



# NARX model for TEC forecasting

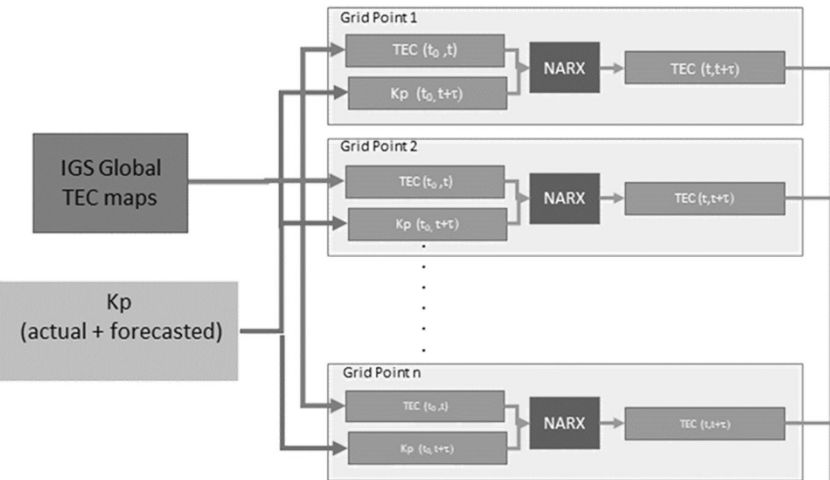
## Single Point TEC forecasting



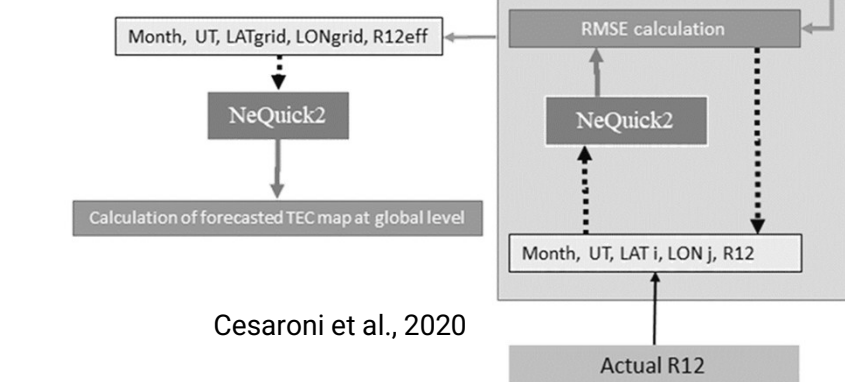
Cesaroni et al., 2020

# NARX model for TEC forecasting

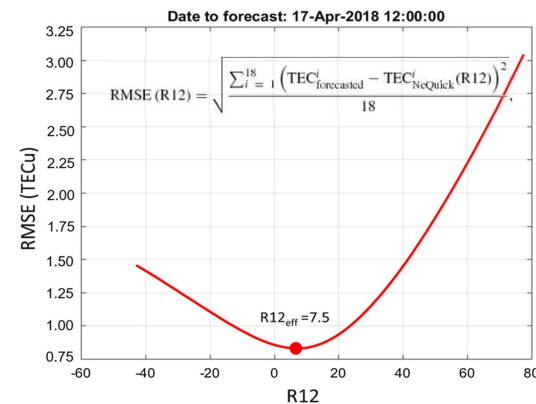
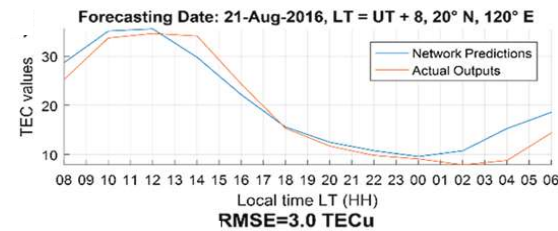
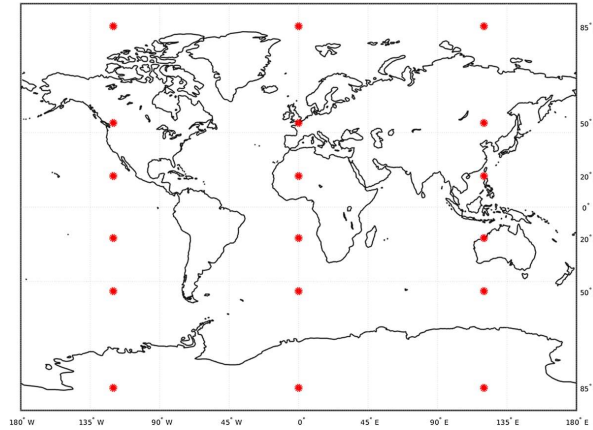
## Single Point TEC forecasting



## Global TEC forecasting

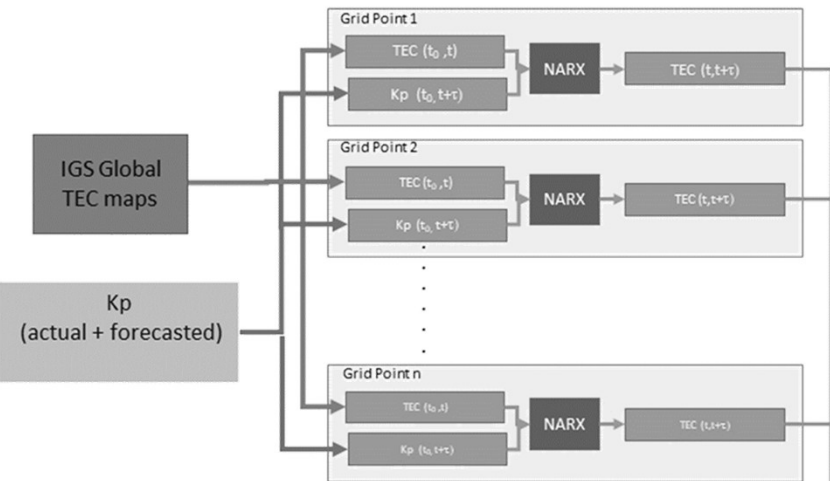


Cesaroni et al., 2020

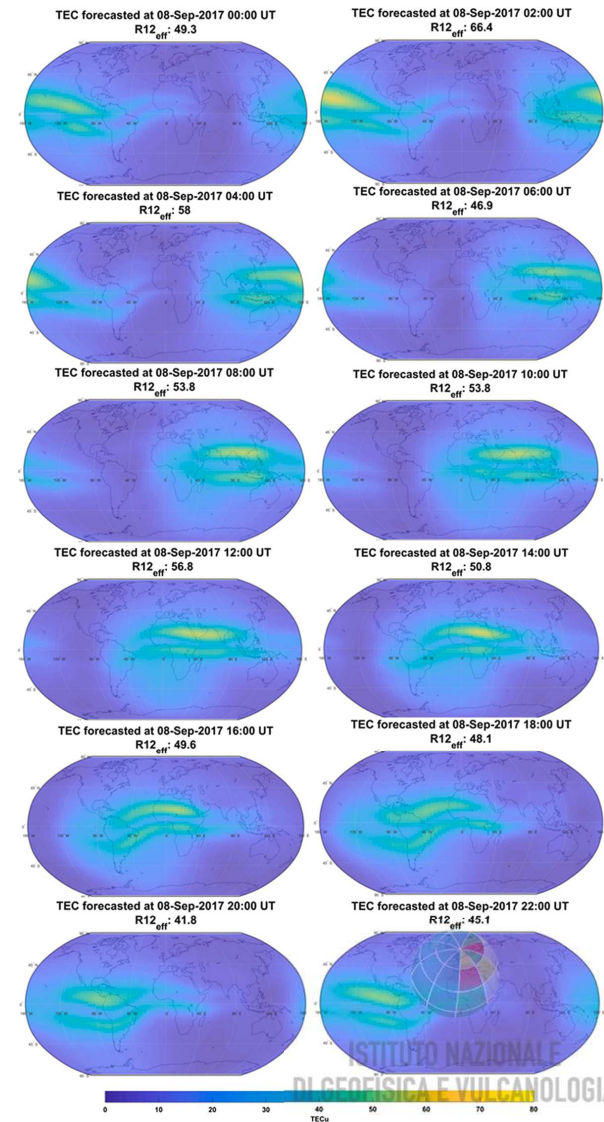
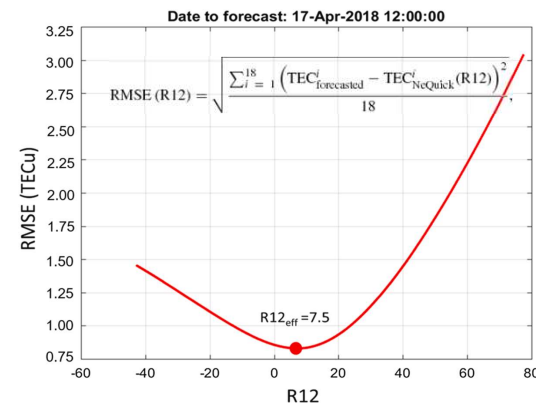
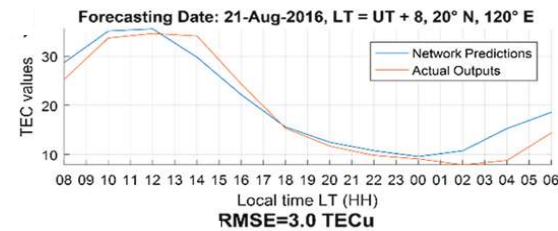
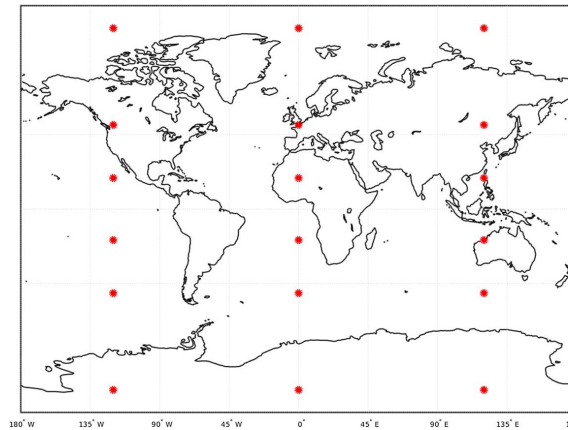
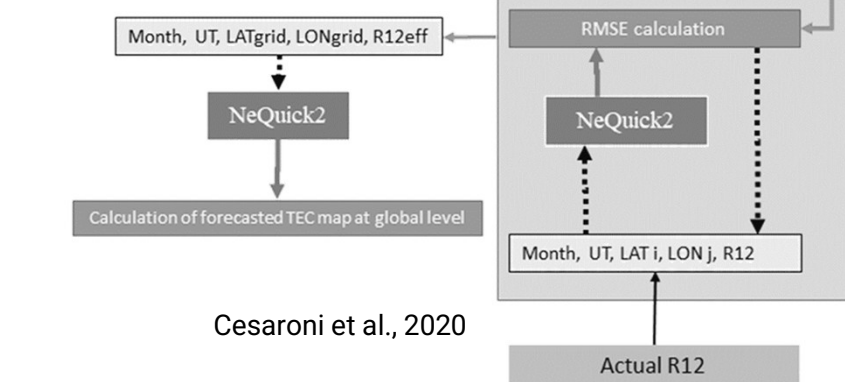


# NARX model for TEC forecasting

## Single Point TEC forecasting

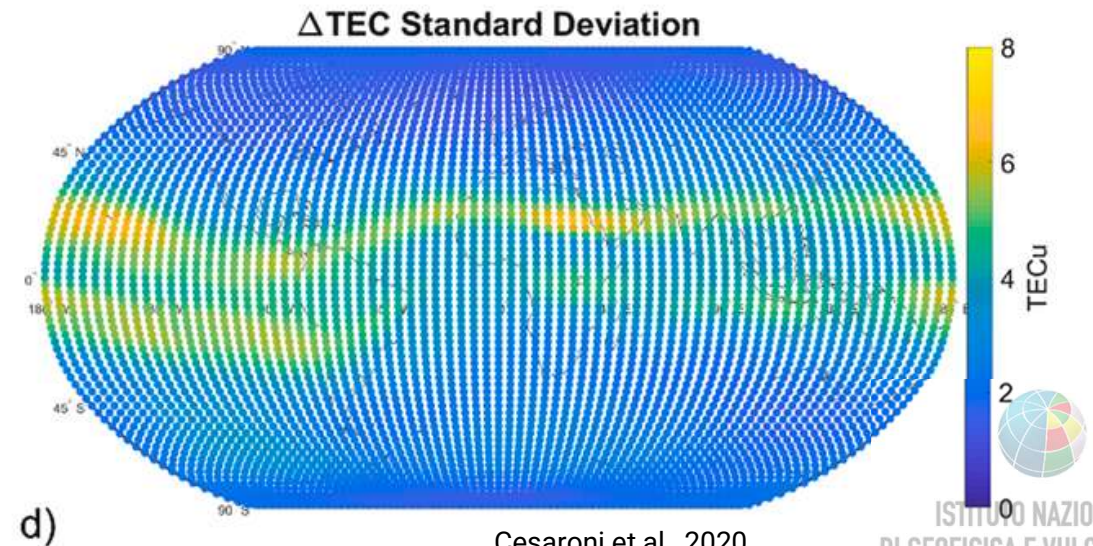
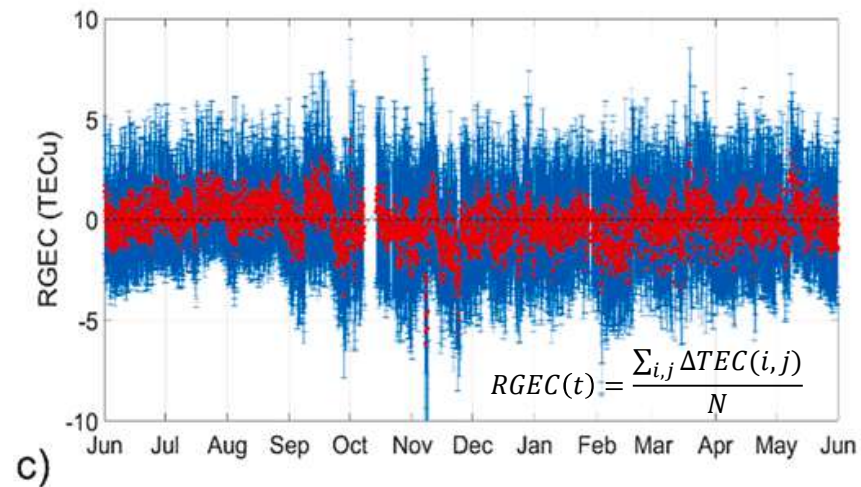
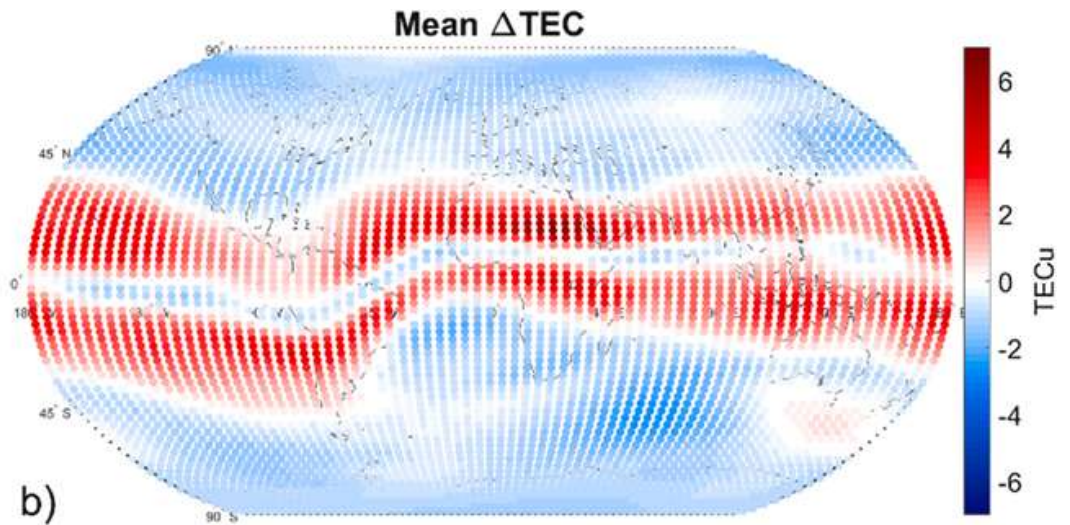
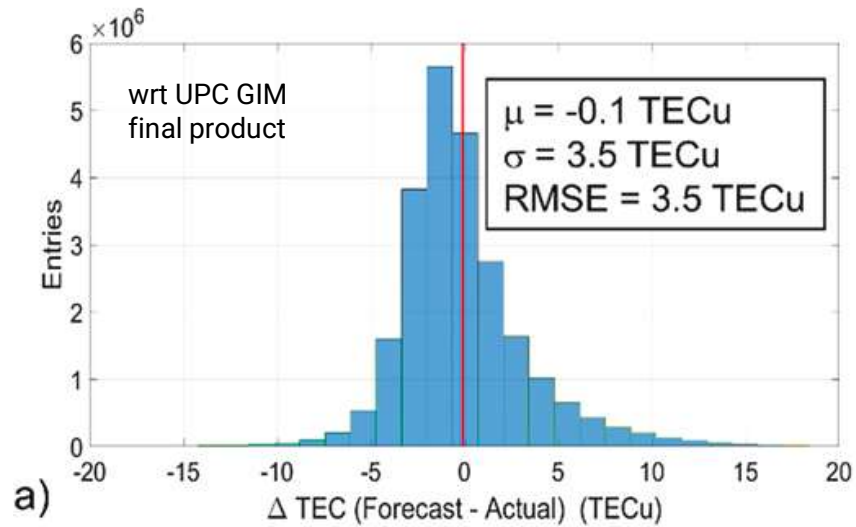


## Global TEC forecasting





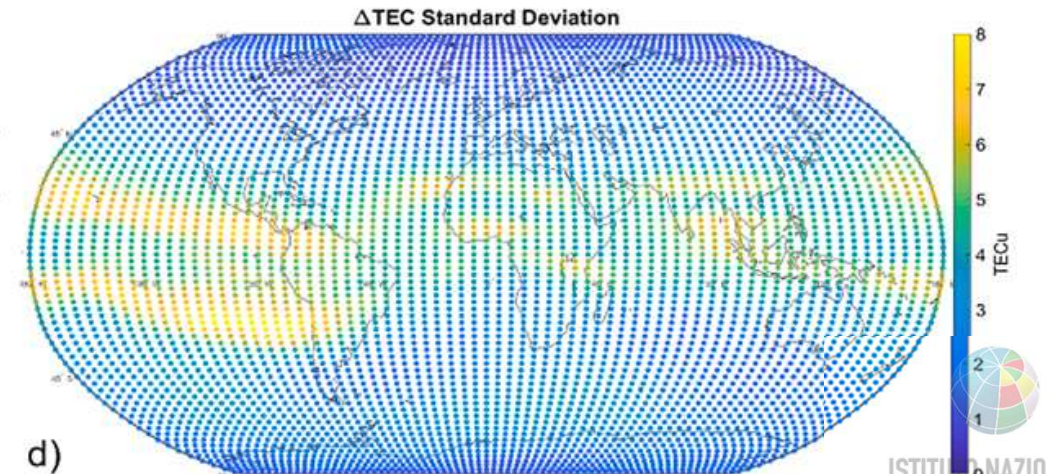
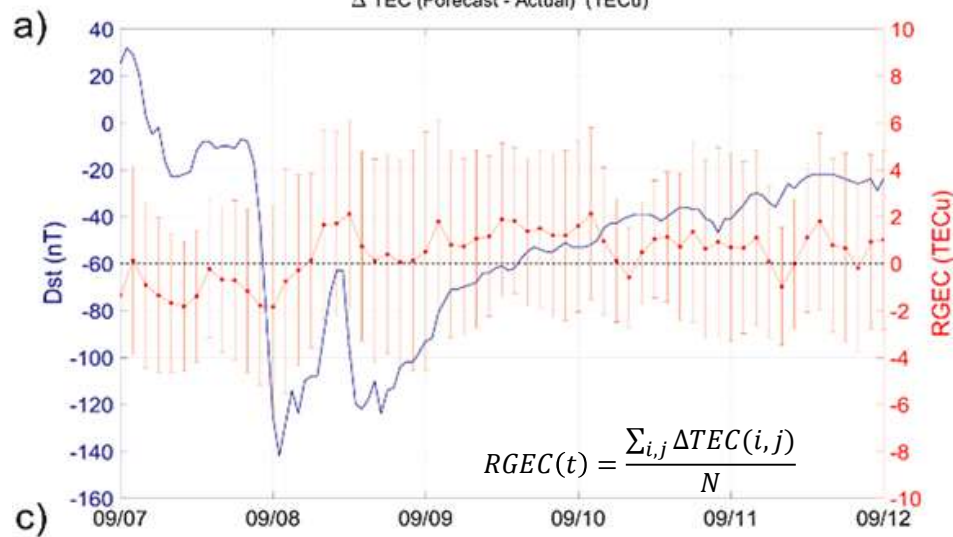
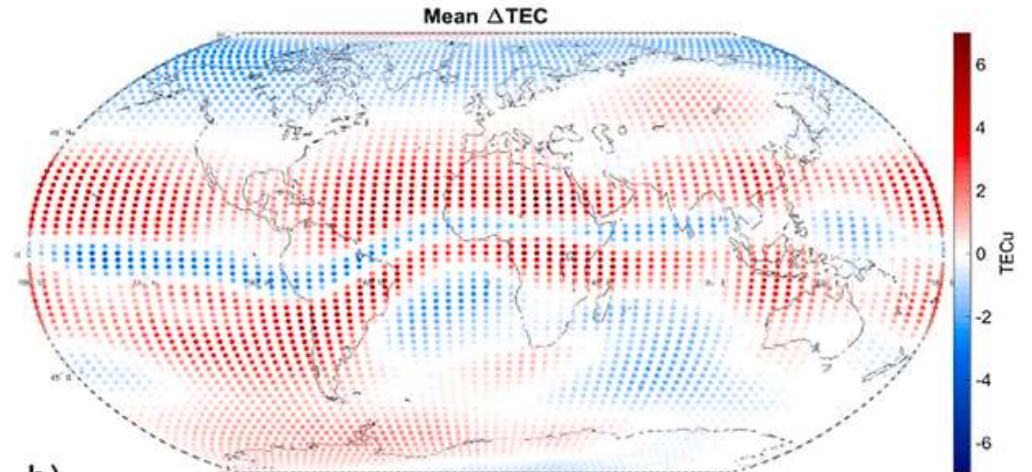
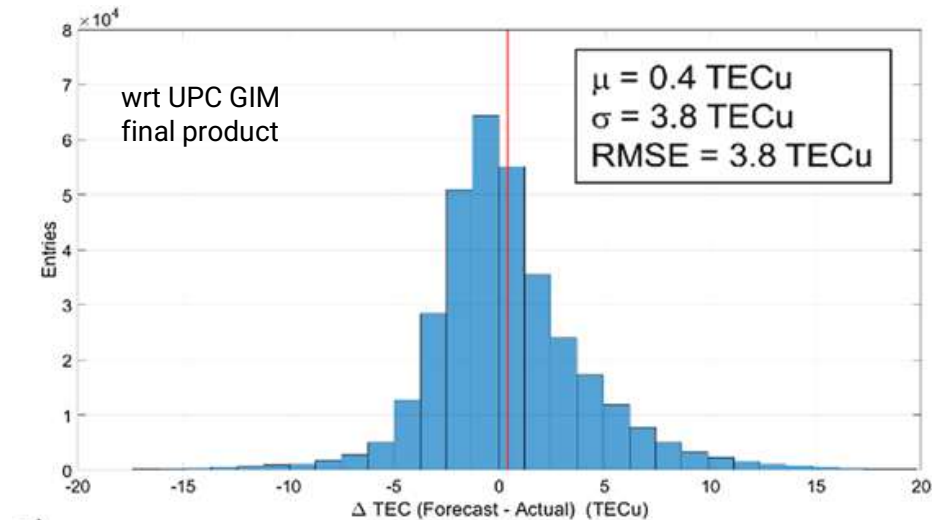
# NARX model validation - Overall



Cesaroni et al., 2020

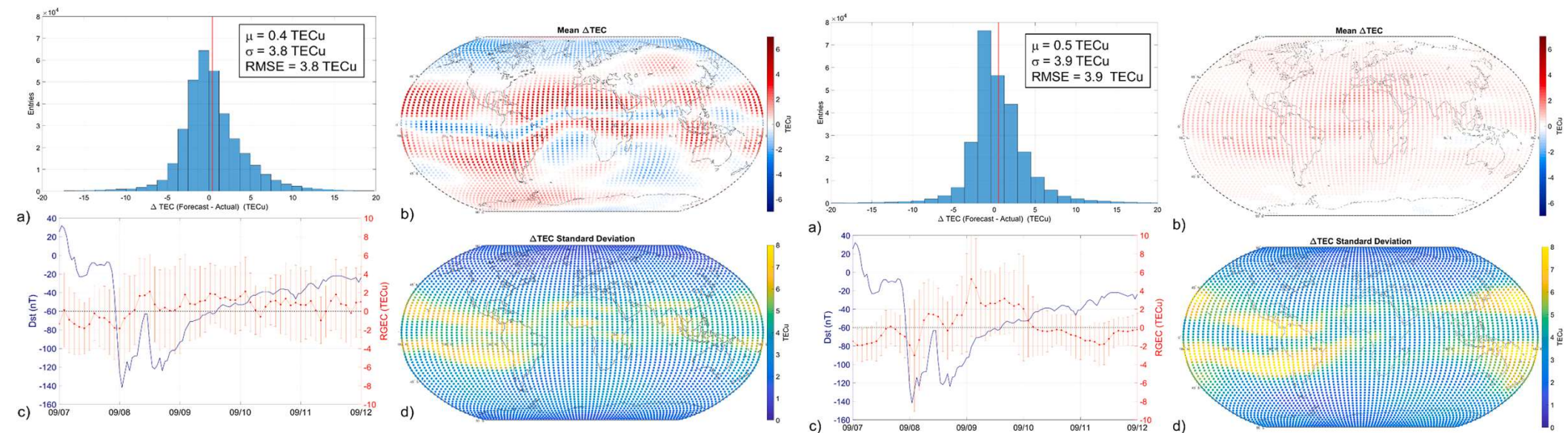


# NARX model validation - September 2017 storm



Cesaroni et al., 2020

# NARX model validation - September 2017 storm

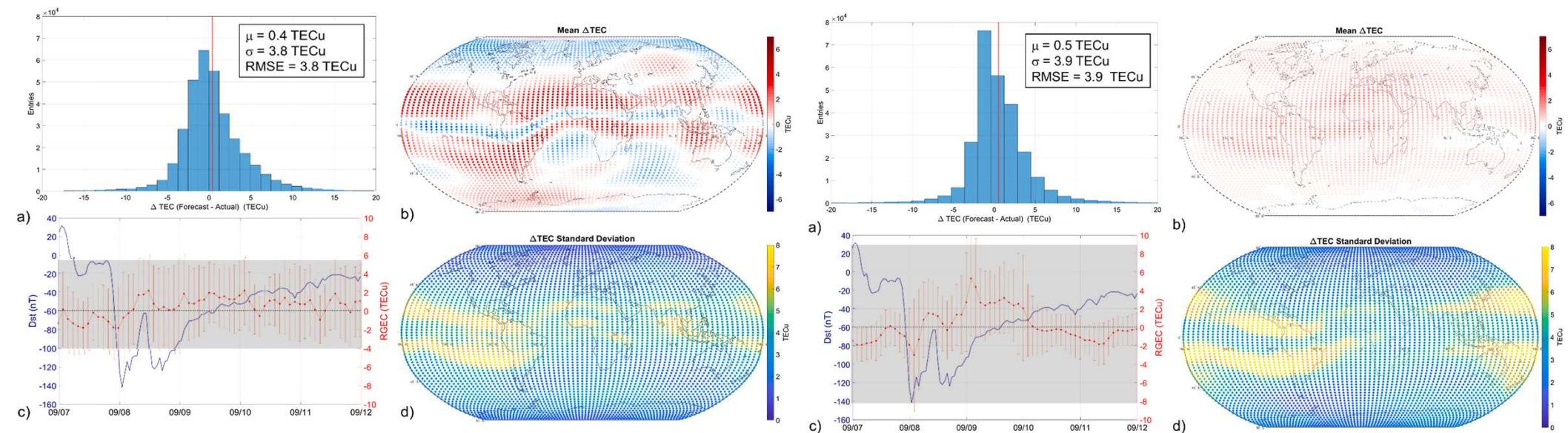


Model

«Frozen» Ionosphere (Naive model)



# NARX model validation - September 2017 storm

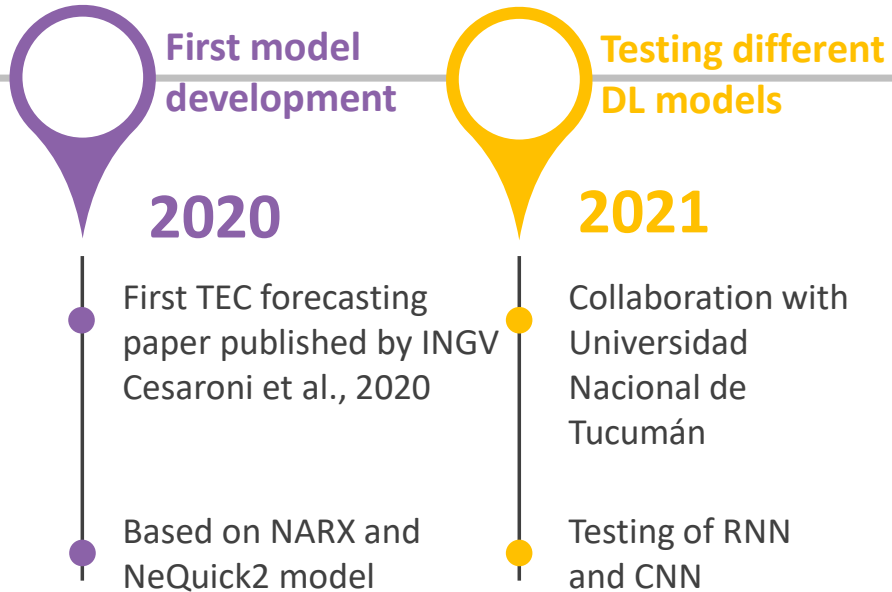


Model

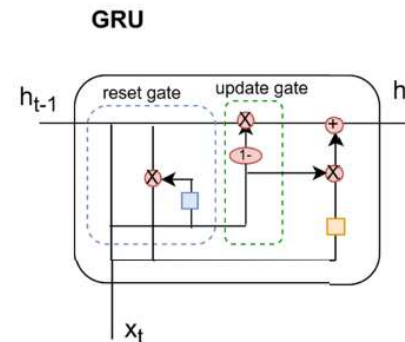
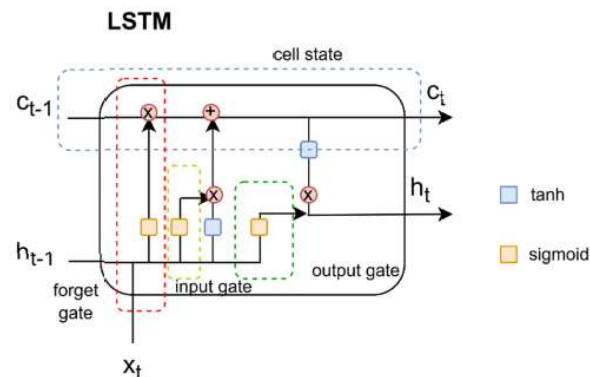
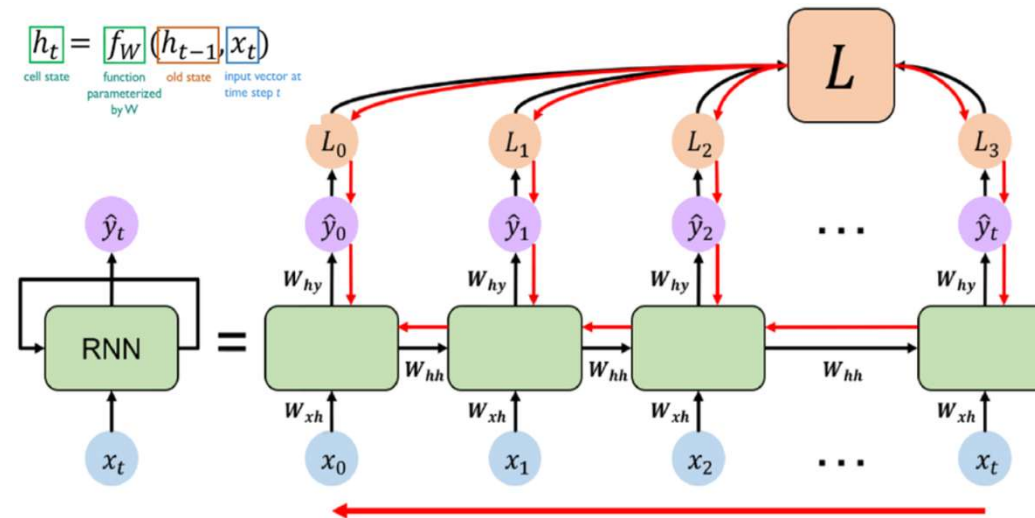
«Frozen» Ionosphere (Naive model)



# Our roadmap toward a Physics-Informed forecasting model



# Recursive NN vs Convolutional NN

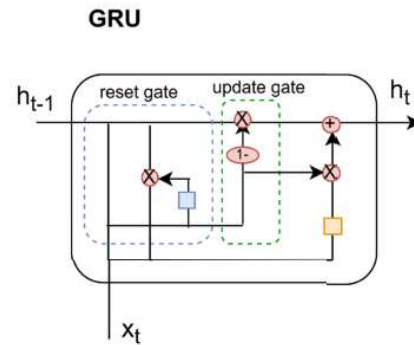
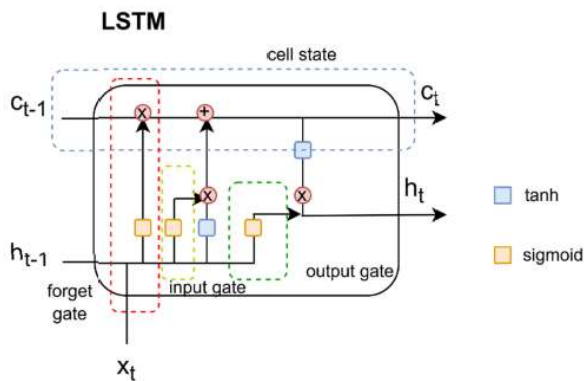
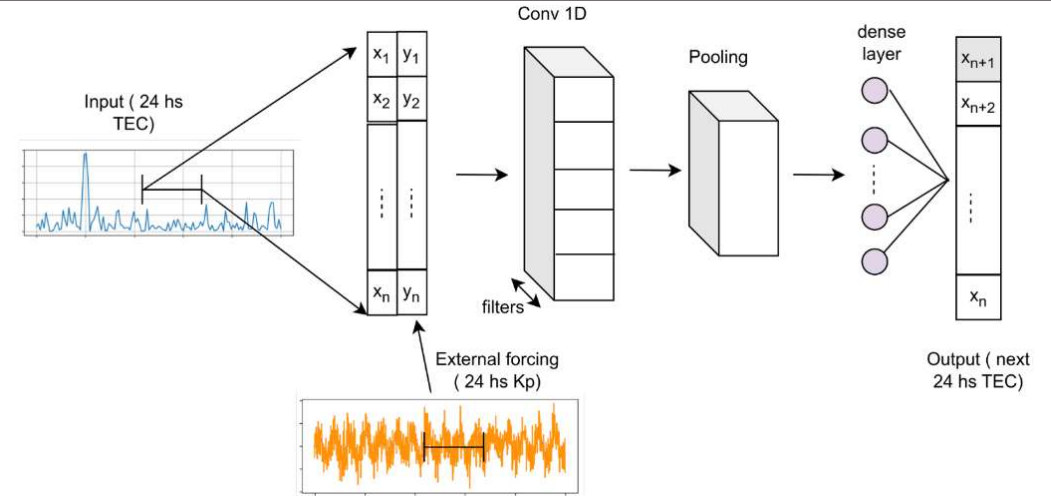
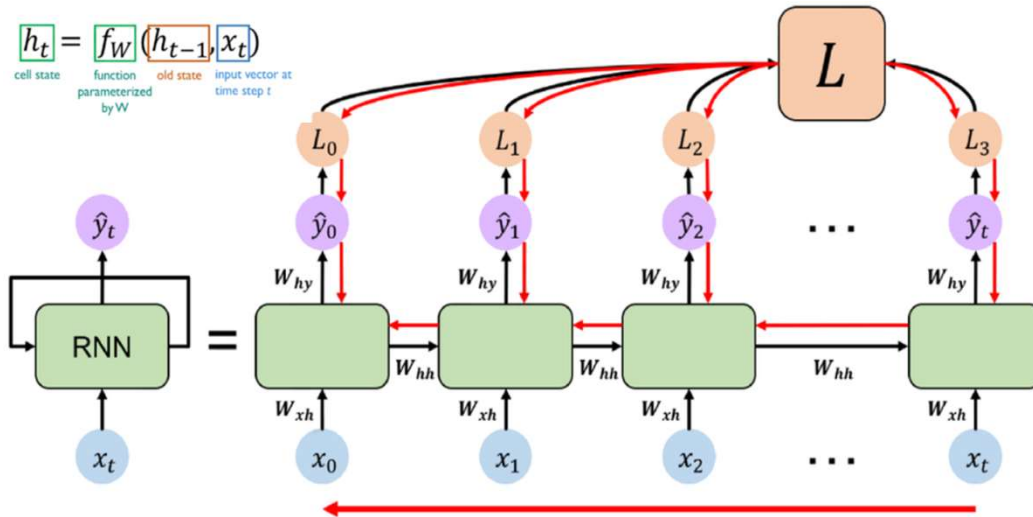


Molina, M. G., Namour, J. H., Cesaroni, C., Spogli, L., Argüelles, N. B., & Asamoah, E. N. (2025). Boosting total electron content forecasting based on deep learning toward an operational service. *Journal of Atmospheric and Solar-Terrestrial Physics*, 268, 106427.

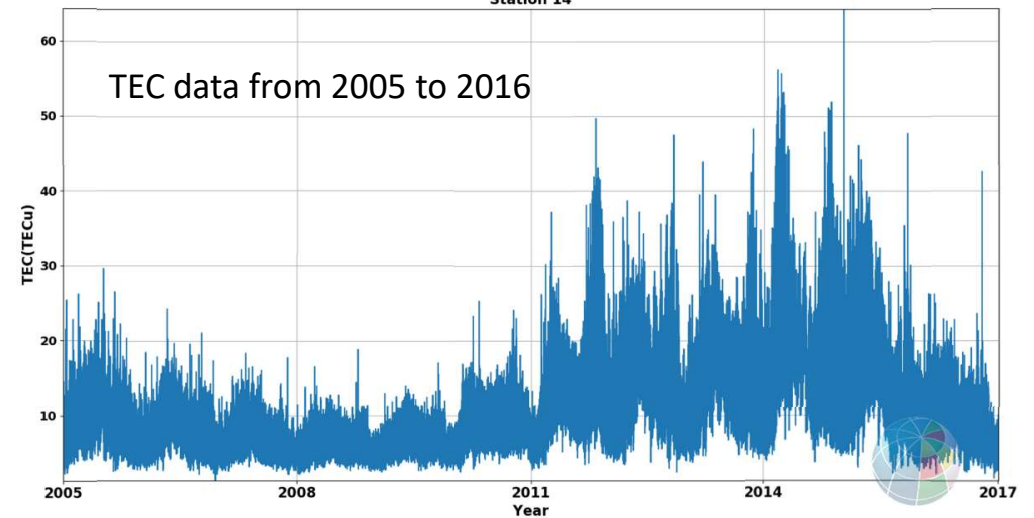
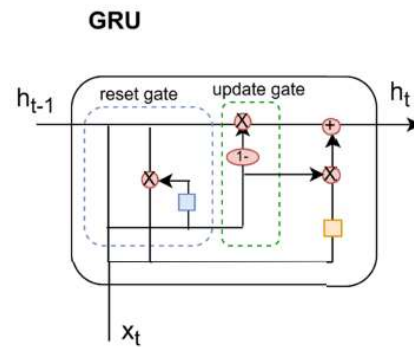
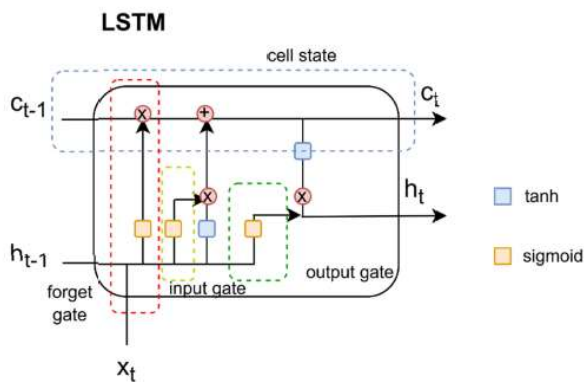
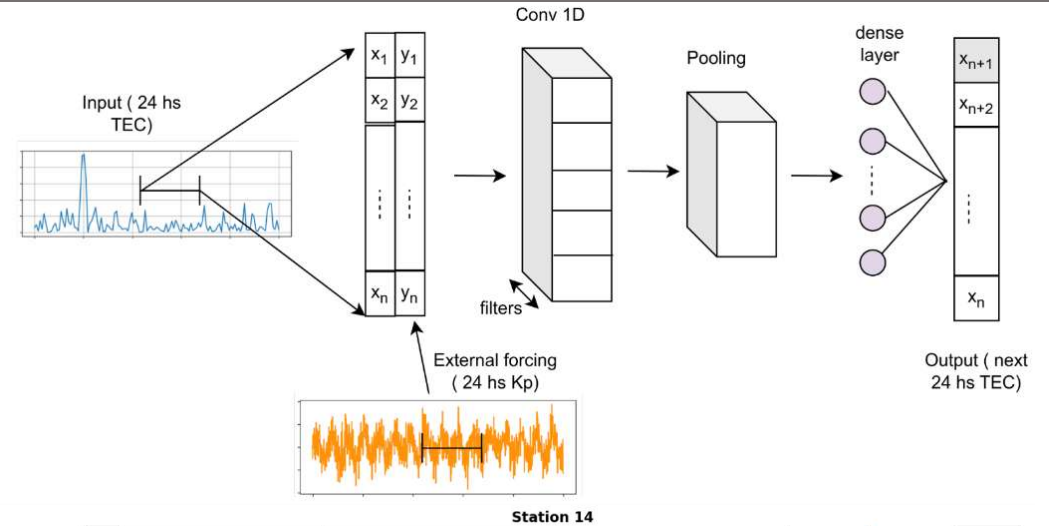
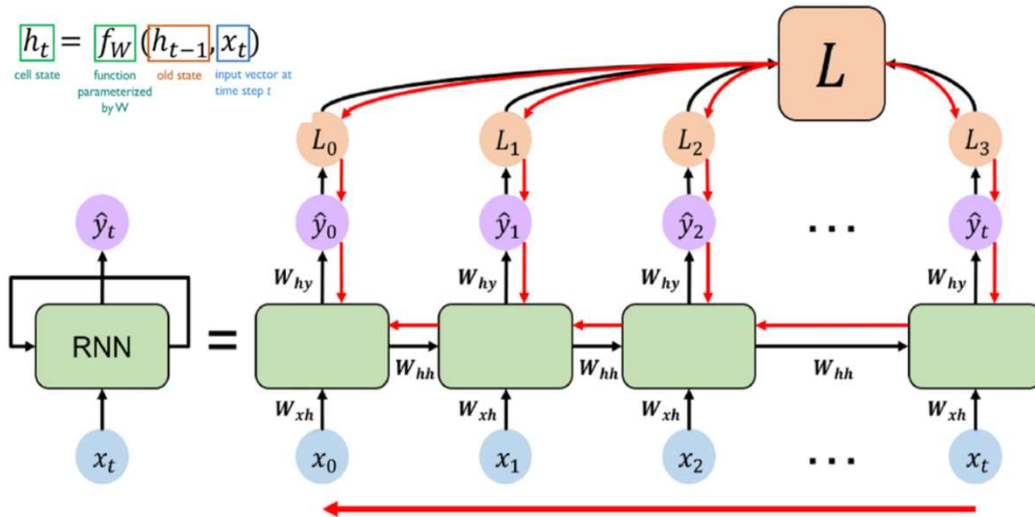


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# Recursive NN vs Convolutional NN



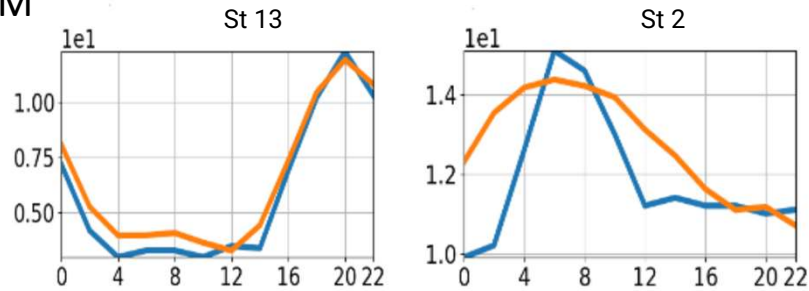
# Recursive NN vs Convolutional NN



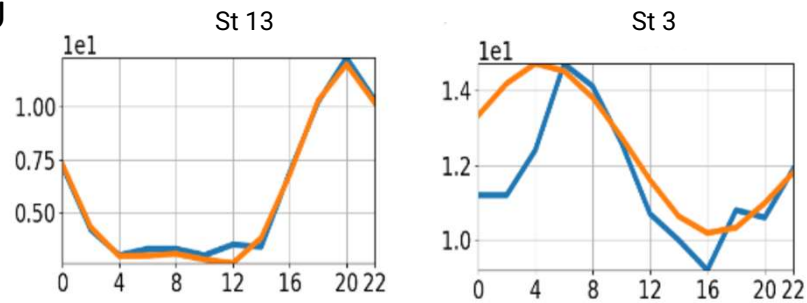


# RNN and CNN results

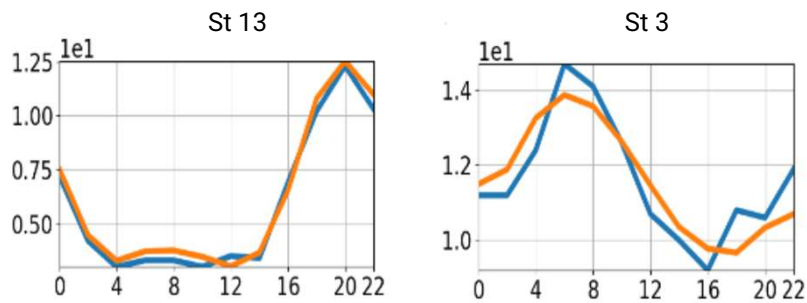
LSTM



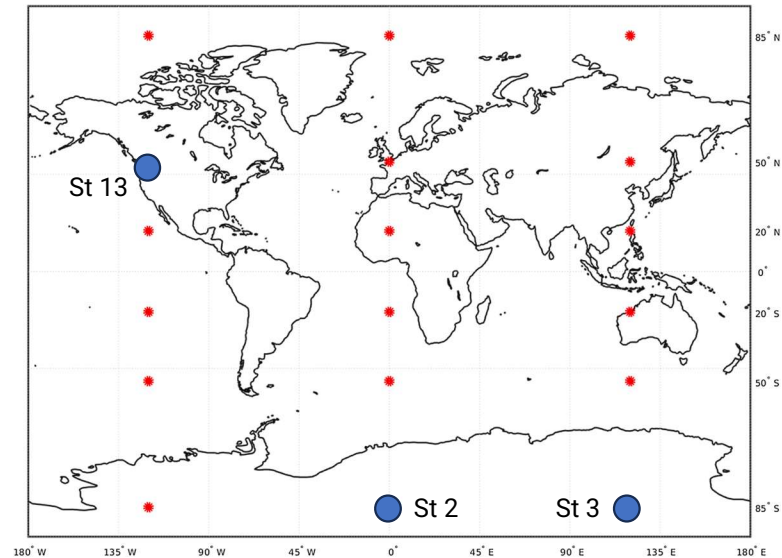
GRU



CNN



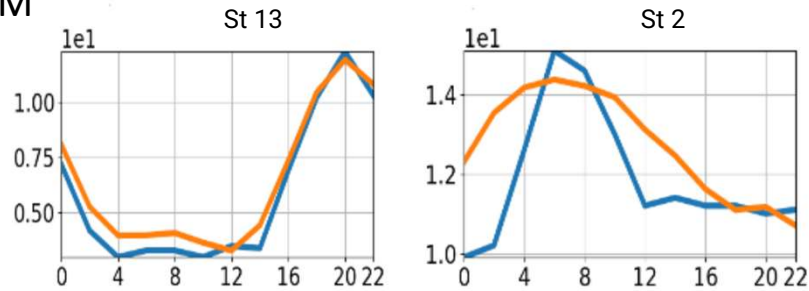
Molina et al., 2025



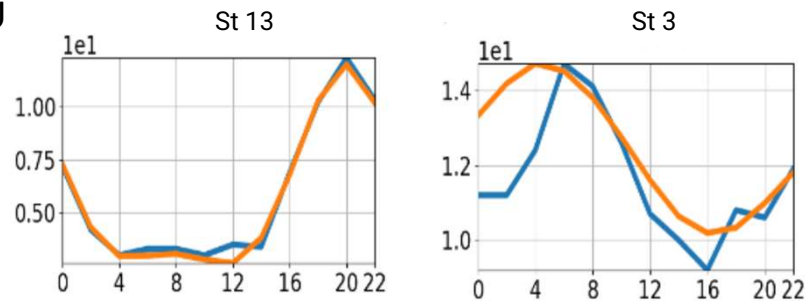
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# RNN and CNN results

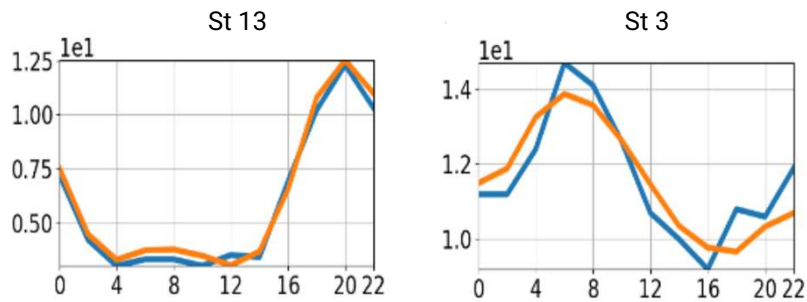
## LSTM



## GRU

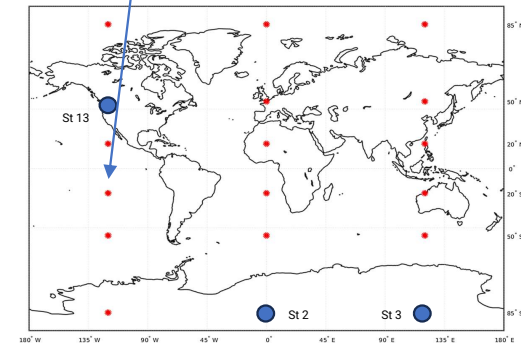
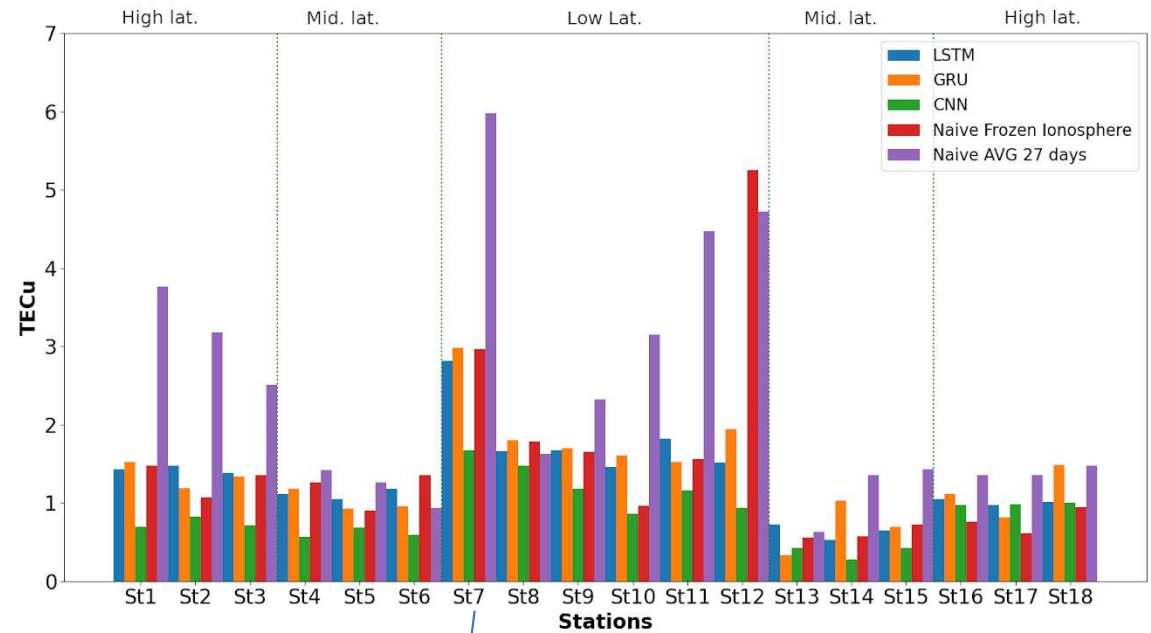


## CNN

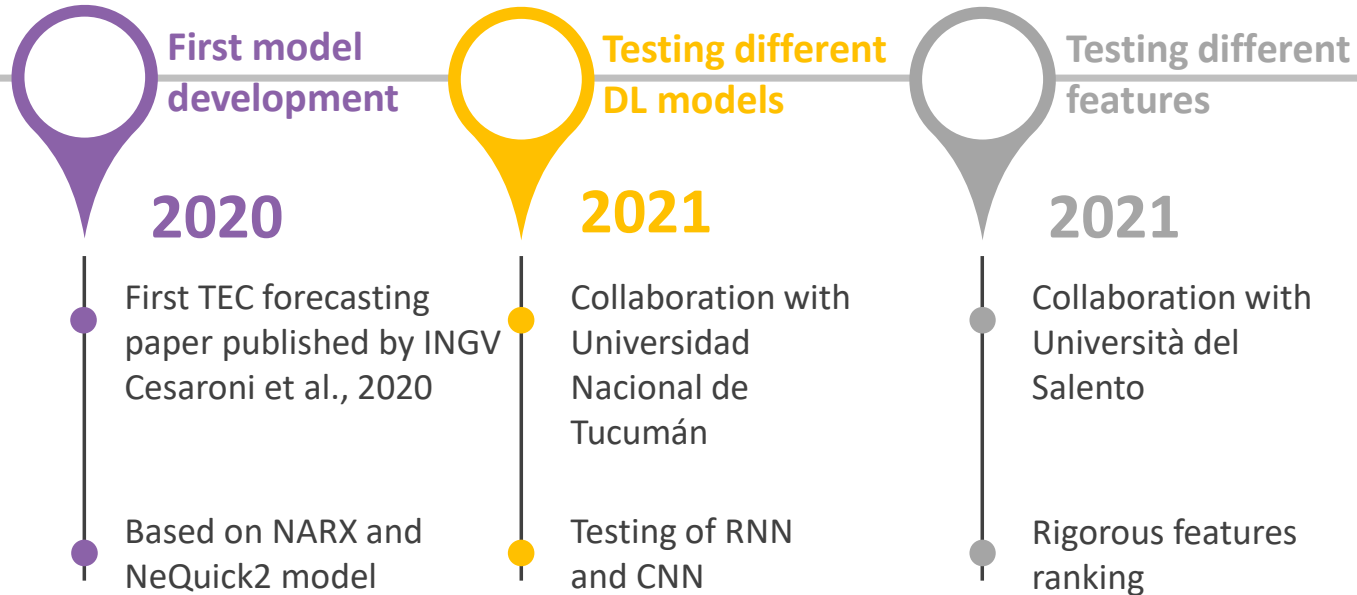


Molina et al., 2025

## RMSE for each modeling technique

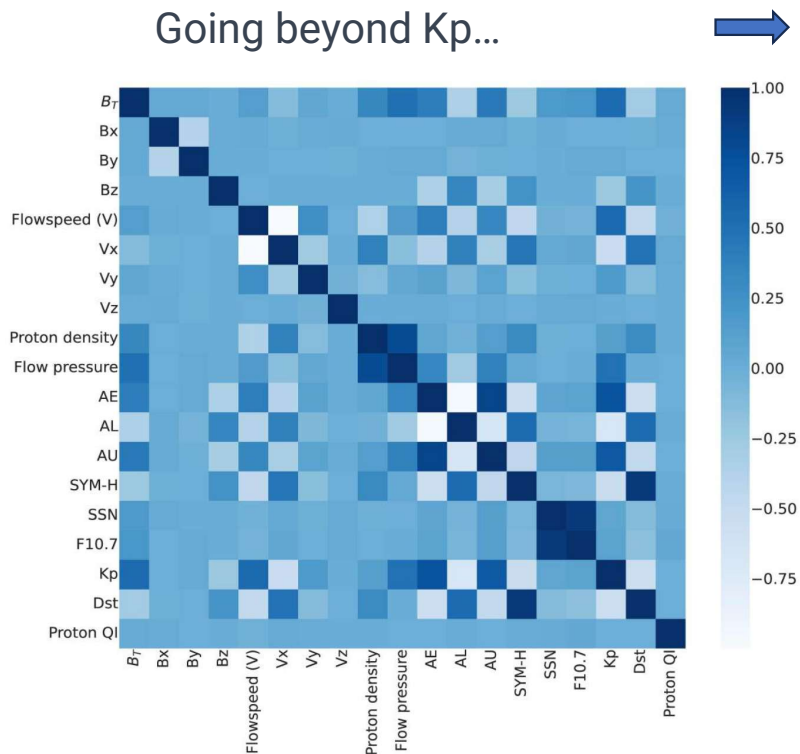


# Our roadmap toward a Physics-Informed forecasting model



# Features ranking

Going beyond Kp...



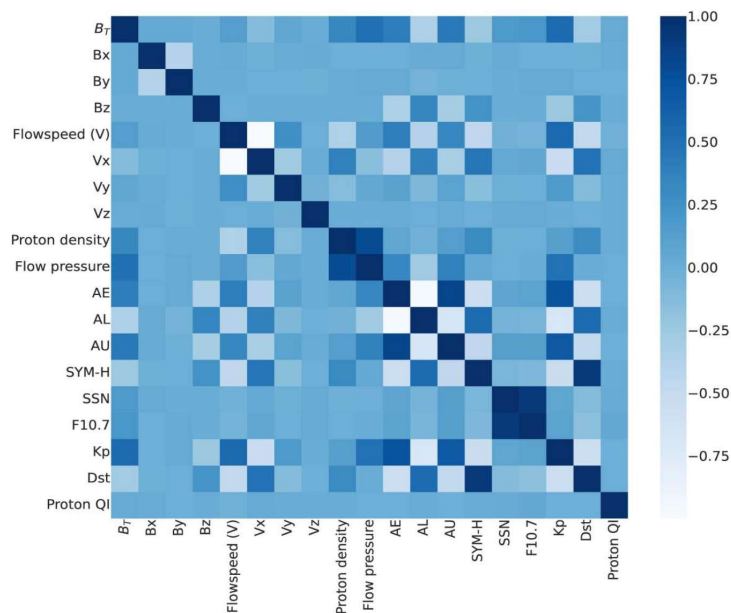
Indices	Parameters
Aurora Electrojet	AU, AL, AE
Geomagnetic	Dst, SYM/H, Kp
Magnetic and Solar	F10.7, SSN, proton density, flow pressure, solar wind (Proton QI), magnitude of average field vector (nT), vector components ( $B_x$ , $B_y$ , $B_z$ ), velocity ( $V_x$ , $V_y$ , $V_z$ )(km/s)

← Pearson correlation coefficient among external driver

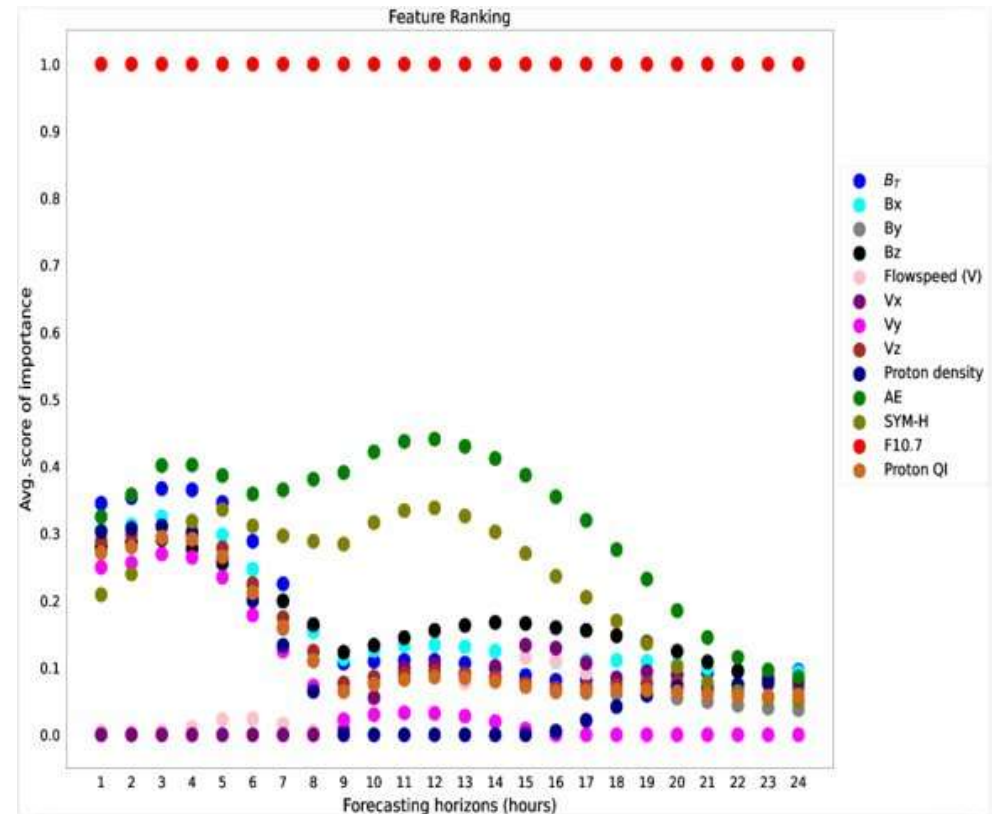
Asamoah, E. N., Cafaro, M., Epicoco, I., De Franceschi, G., & Cesaroni, C. (2024). A stacked machine learning model for the vertical total electron content forecasting. *Advances in Space Research*, 74(1), 223-242.

# Features ranking

Indices	Parameters
Aurora Electrojet	AU, AL, AE
Geomagnetic	Dst, SYM/H, Kp
Magnetic and Solar	F10.7, SSN, proton density, flow pressure, solar wind (Proton QI), magnitude of average field vector (nT), vector components (Bx, By, Bz), velocity (Vx, Vy , Vz)(km/s)



Nana Asamoah et al, 2024a

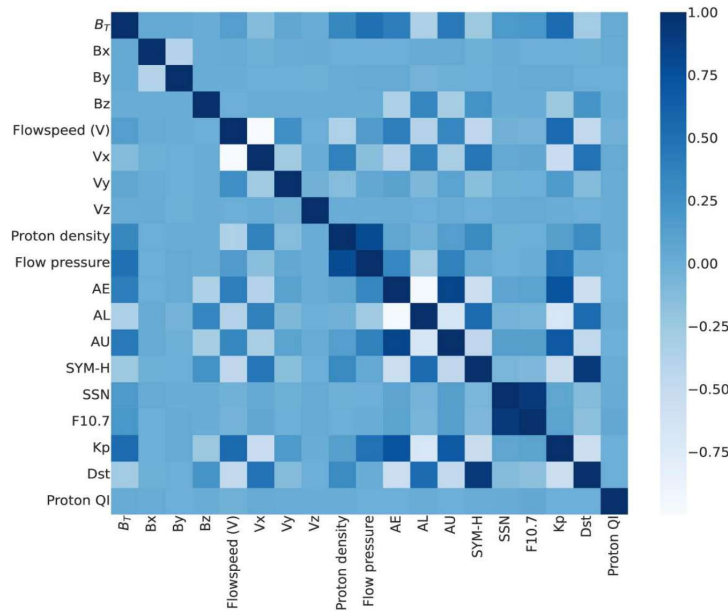


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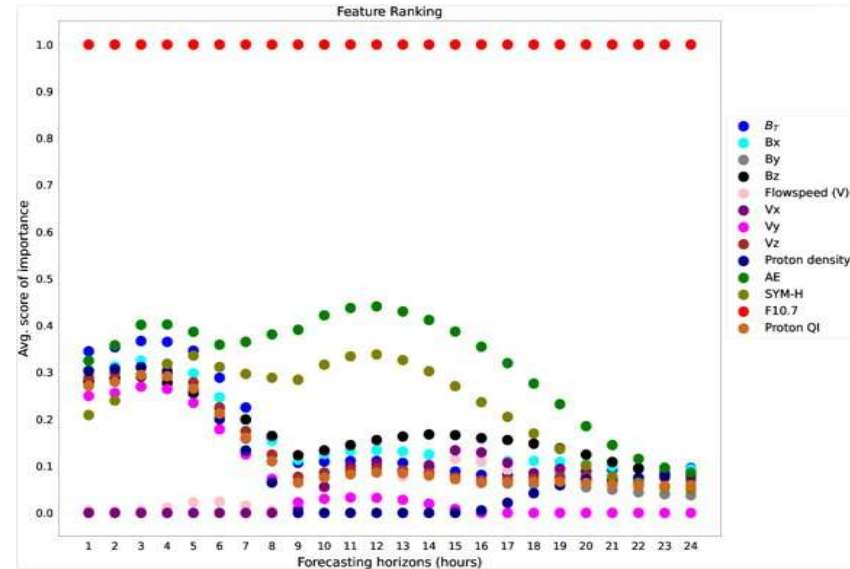
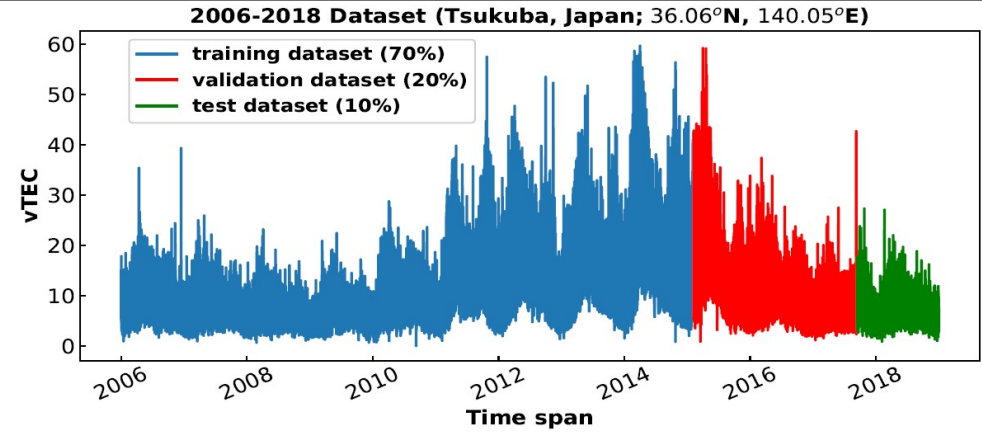


# Features ranking

Indices	Parameters
Aurora Electrojet	AU, AL, AE
Geomagnetic	Dst, SYM/H, Kp
Magnetic and Solar	F10.7, SSN, proton density, flow pressure, solar wind (Proton QI), magnitude of average field vector (nT), vector components (Bx, By, Bz), velocity (Vx, Vy , Vz)(km/s)

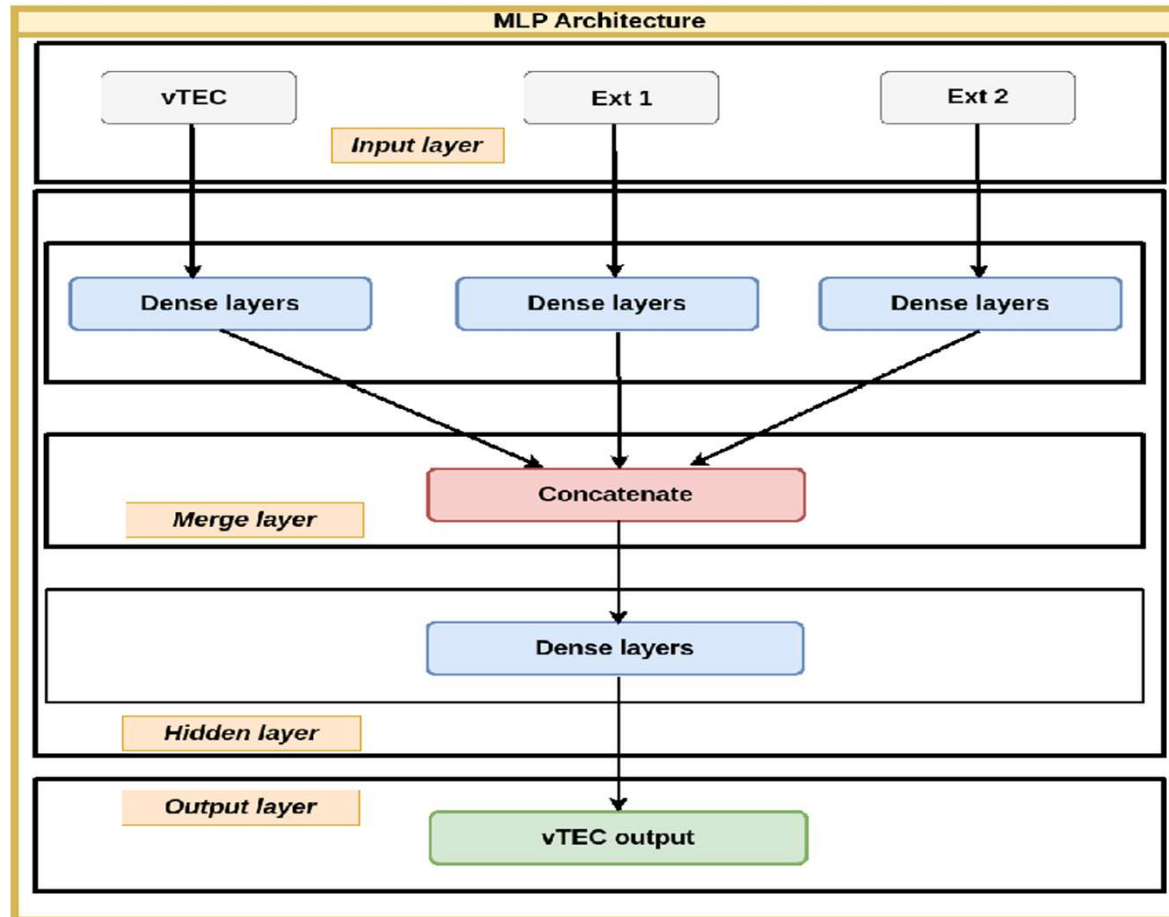


Nana Asamoah et al, 2024a



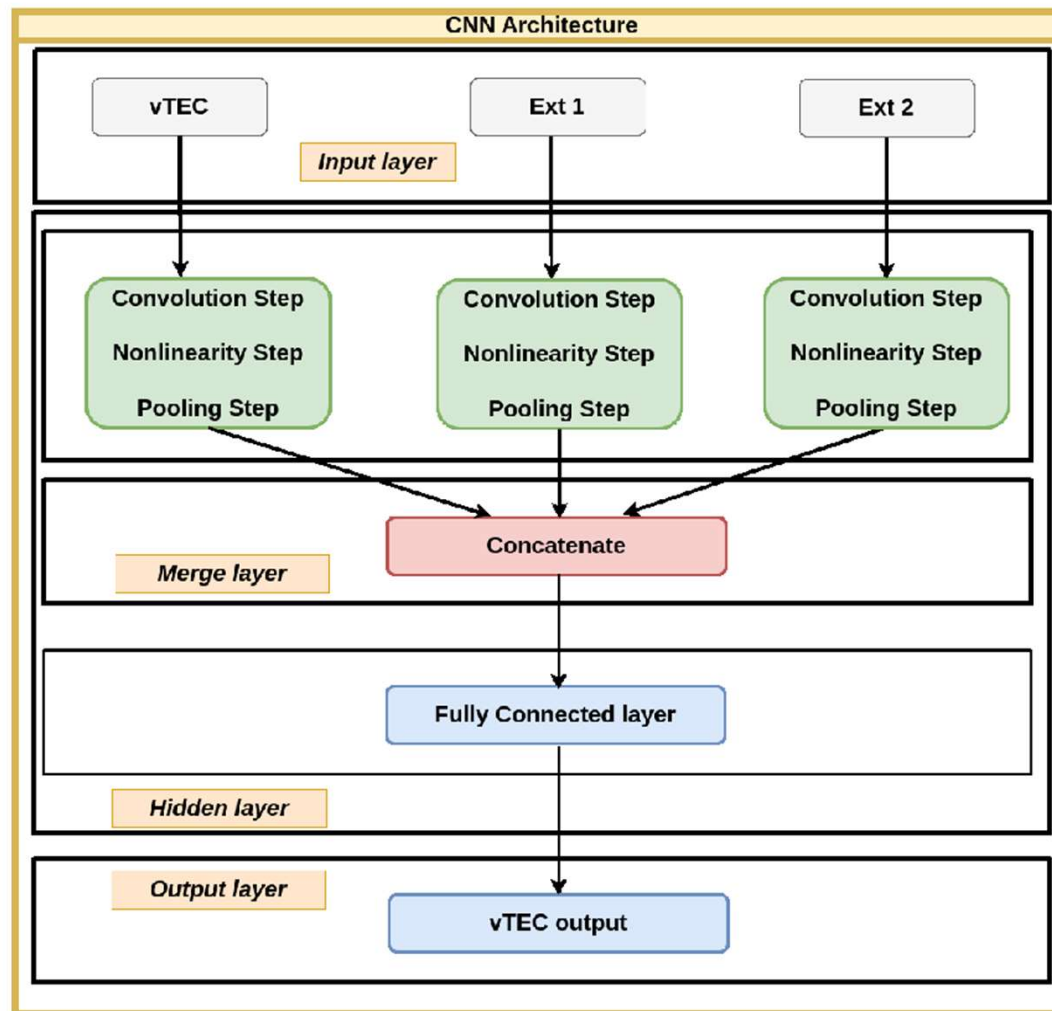
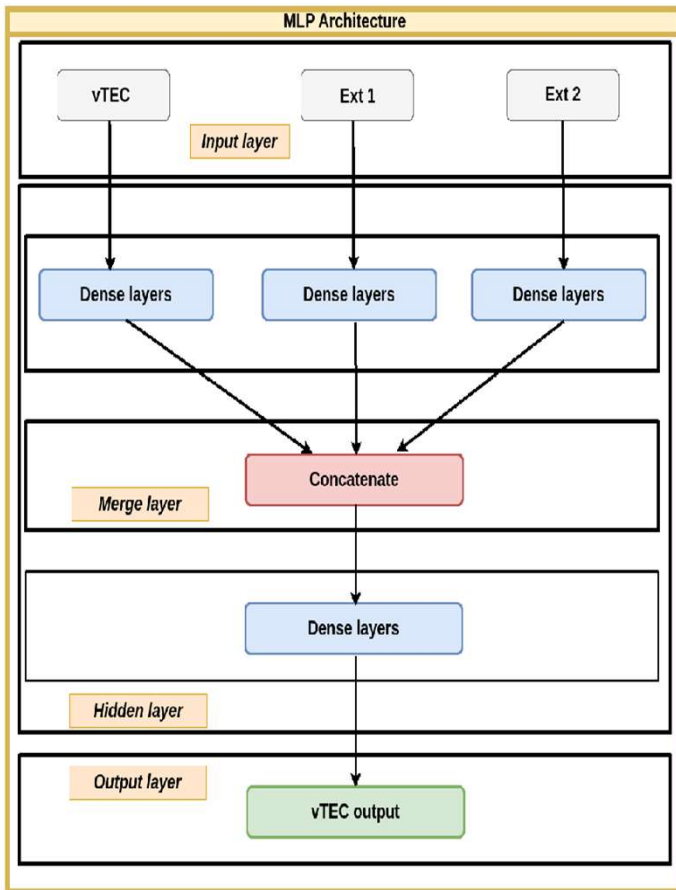
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# Base Learners



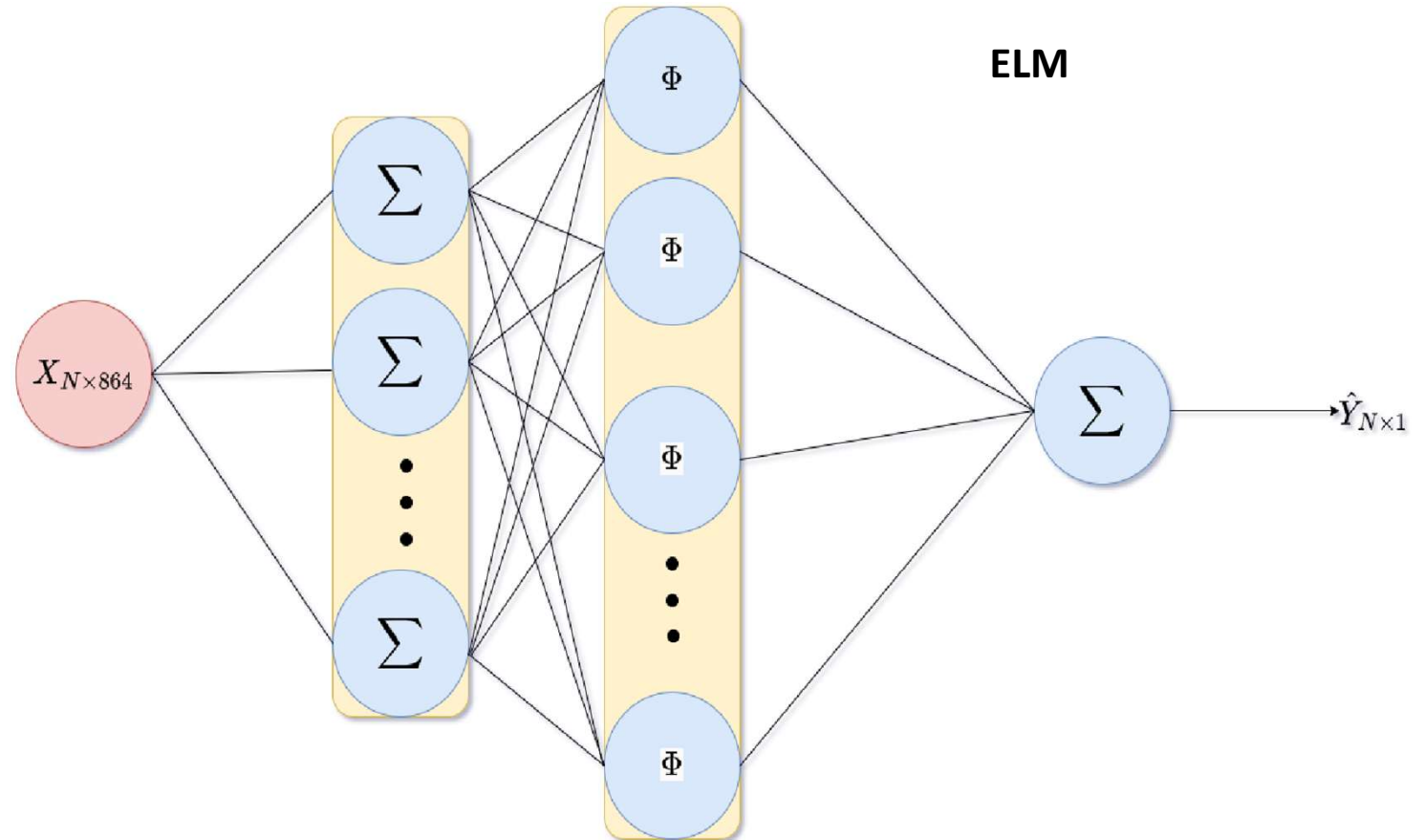
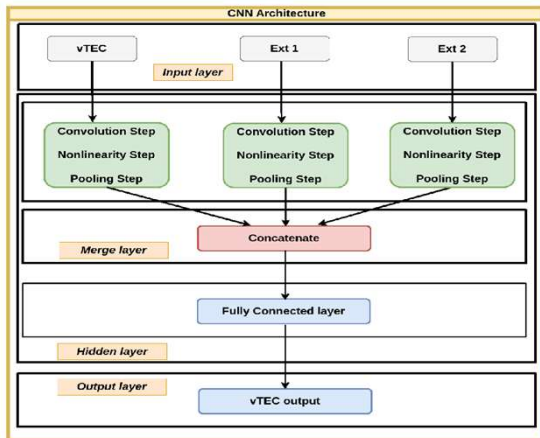
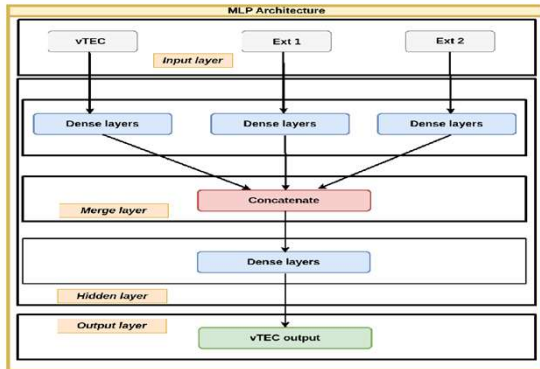
Nana Asamoah et al, 2024a

# Base Learners



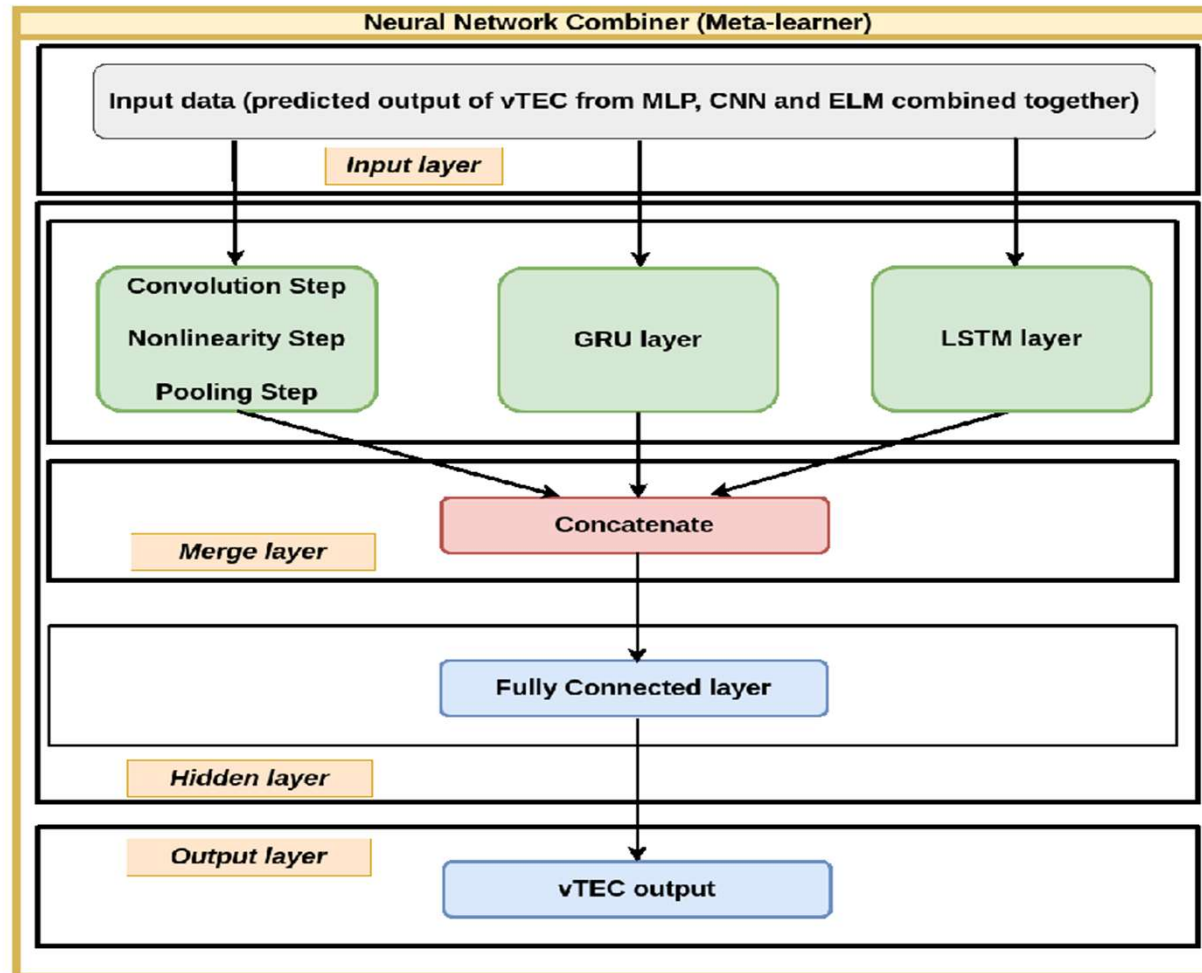
Nana Asamoah et al, 2024a

# Base Learners



Nana Asamoah et al, 2024a

# Stacked model



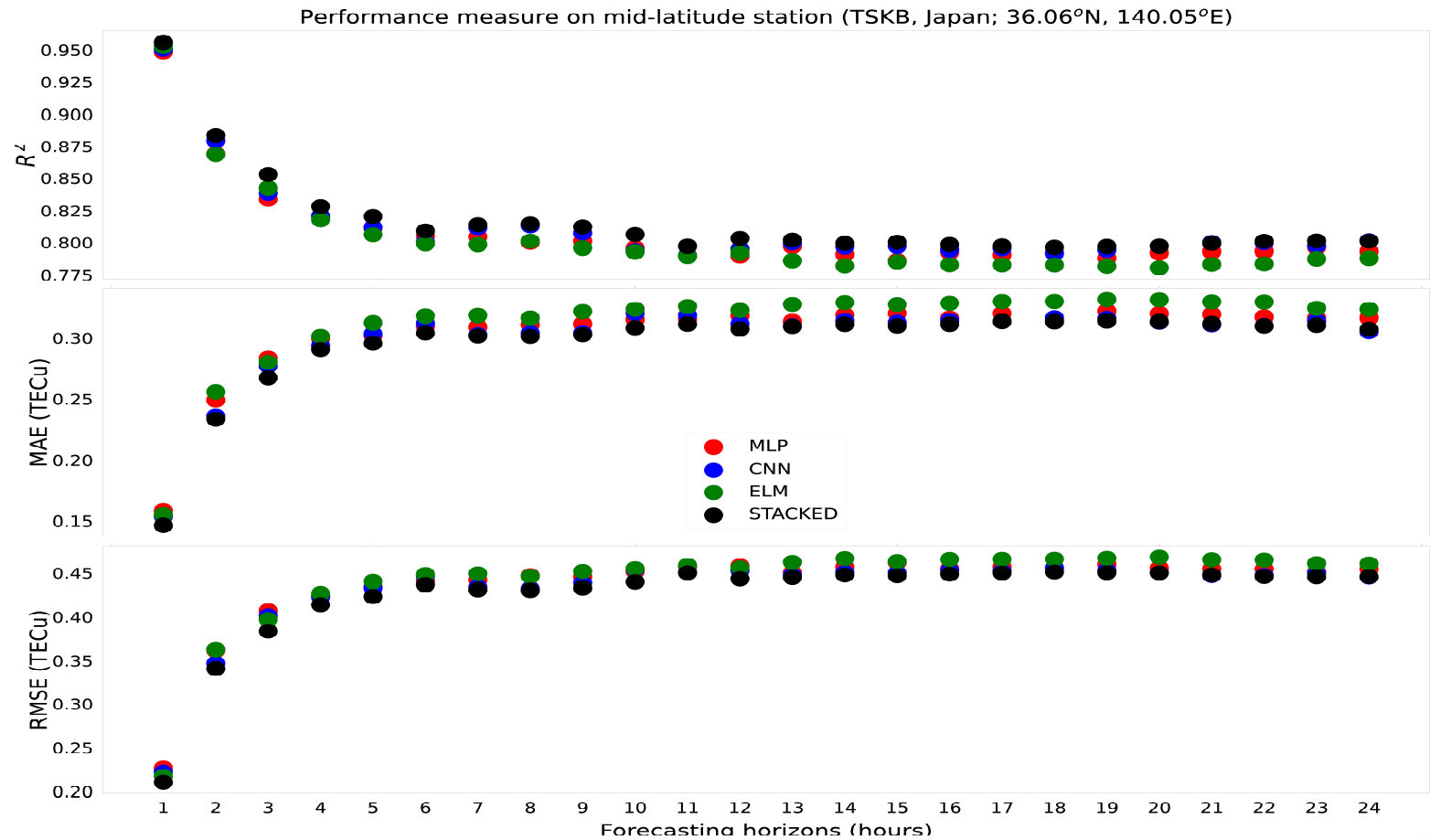
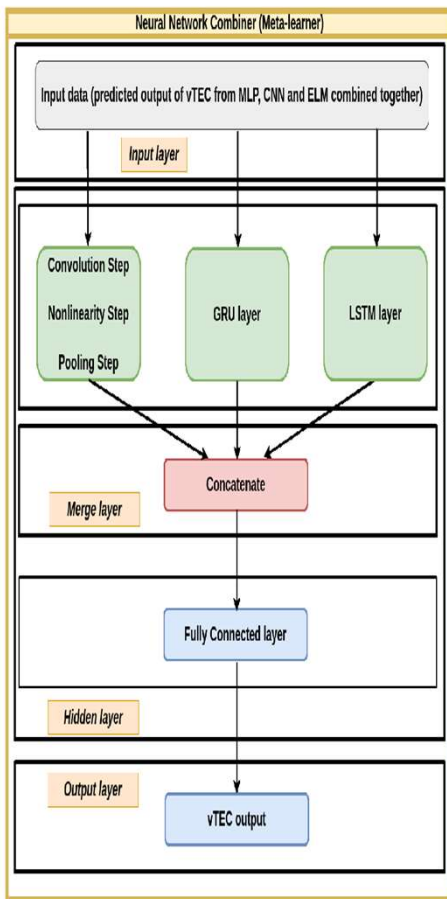
Nana Asamoah et al, 2024a



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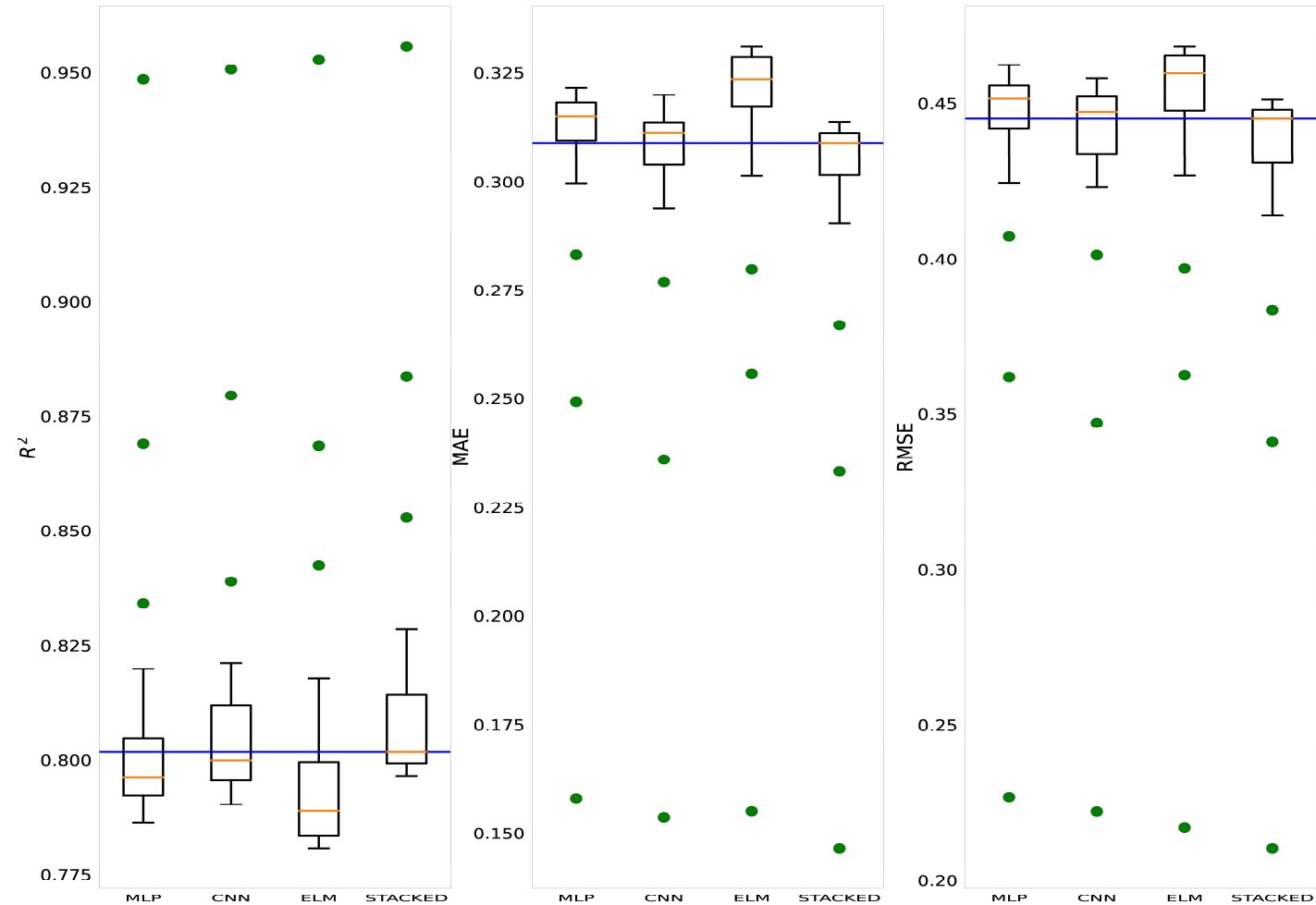
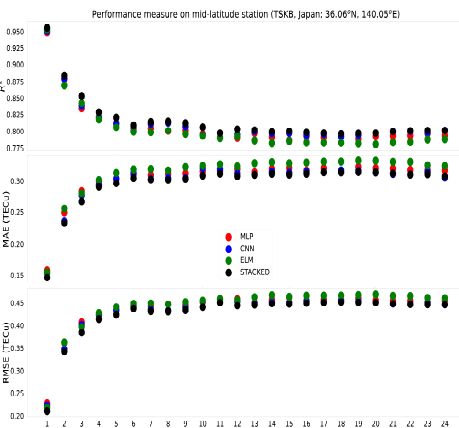
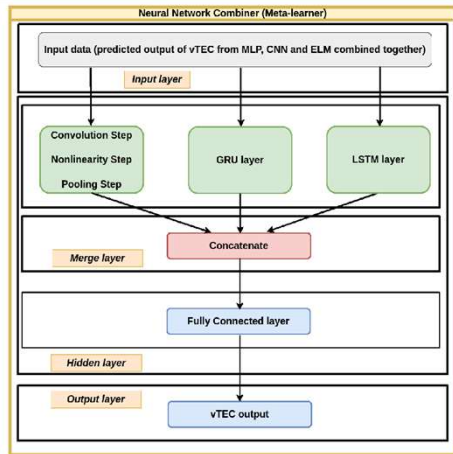


# Stacked model



Nana Asamoah et al, 2024a

# Stacked model

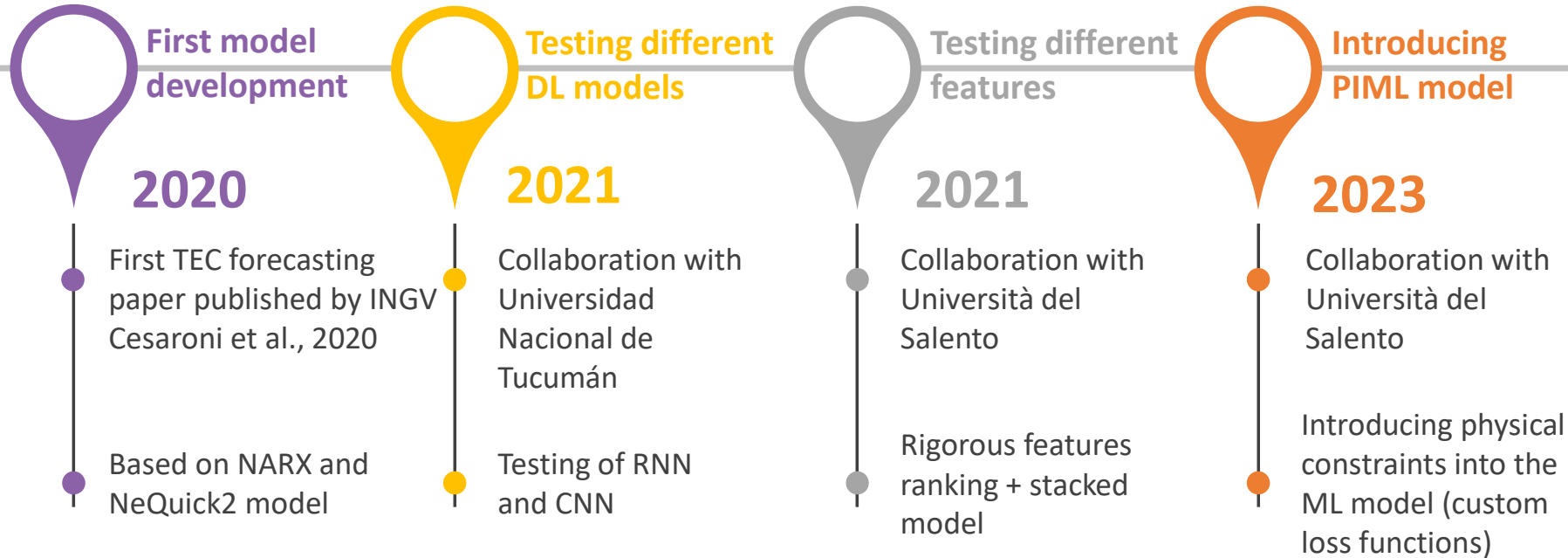


Nana Asamoah et al, 2024a



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# Our roadmap toward a Physics-Informed forecasting model



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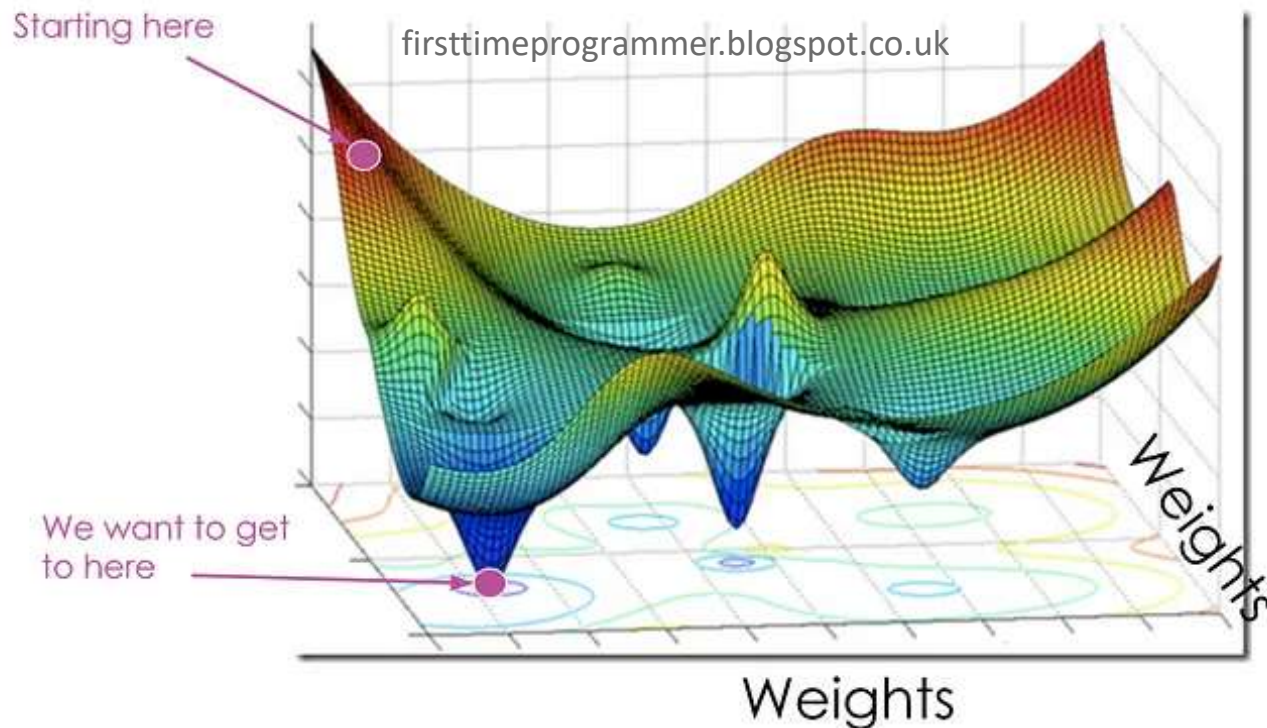


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# Loss Function for regression problems

The loss function is the bread and butter of modern machine learning; it takes your algorithm from theoretical to practical and transforms neural networks from glorified matrix multiplication into deep learning.

<https://www.datarobot.com/>



MSE 
$$J(\theta) = \frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2$$

RMSE 
$$J(\theta) = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2}$$

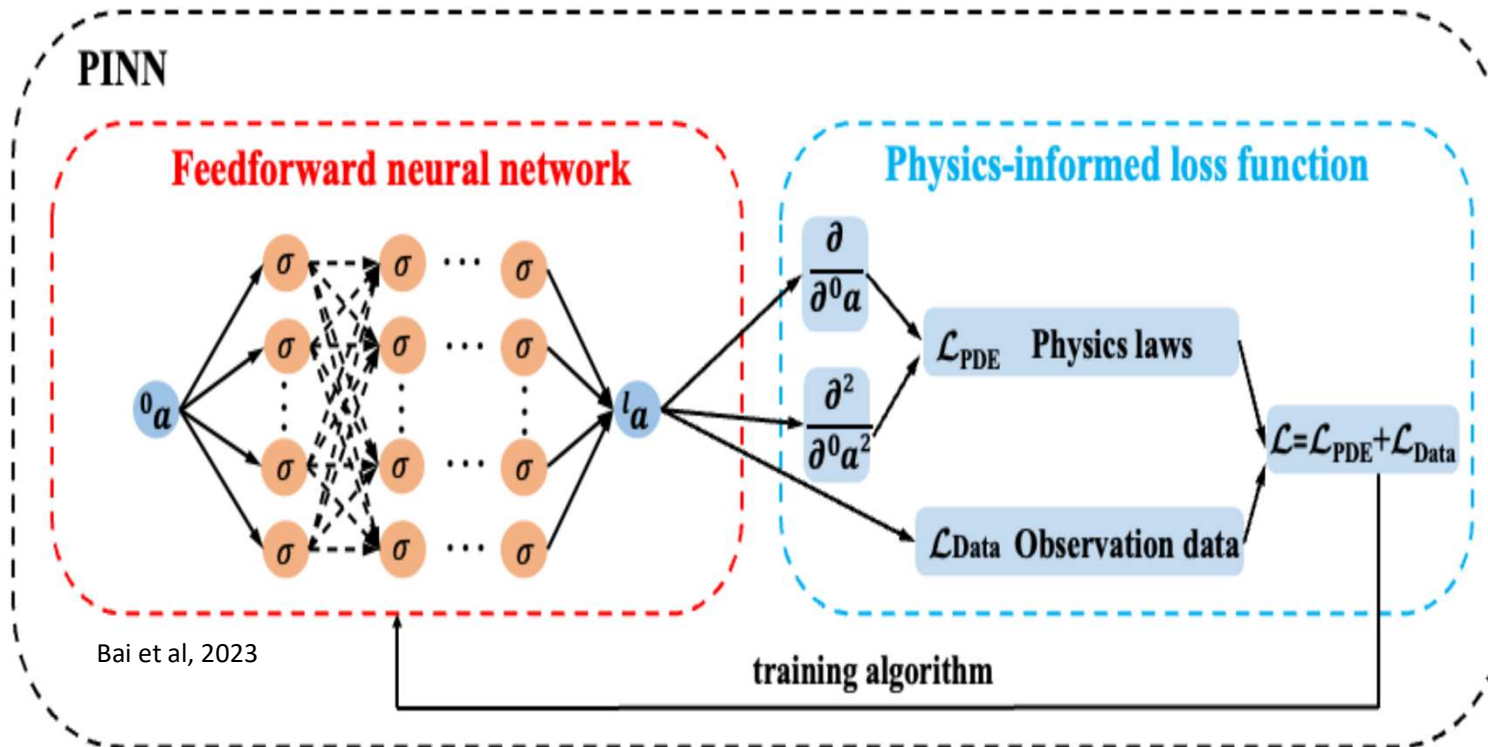
MAE 
$$J(\theta) = \frac{1}{N} \sum_{n=1}^N |y_n - \hat{y}_n|$$



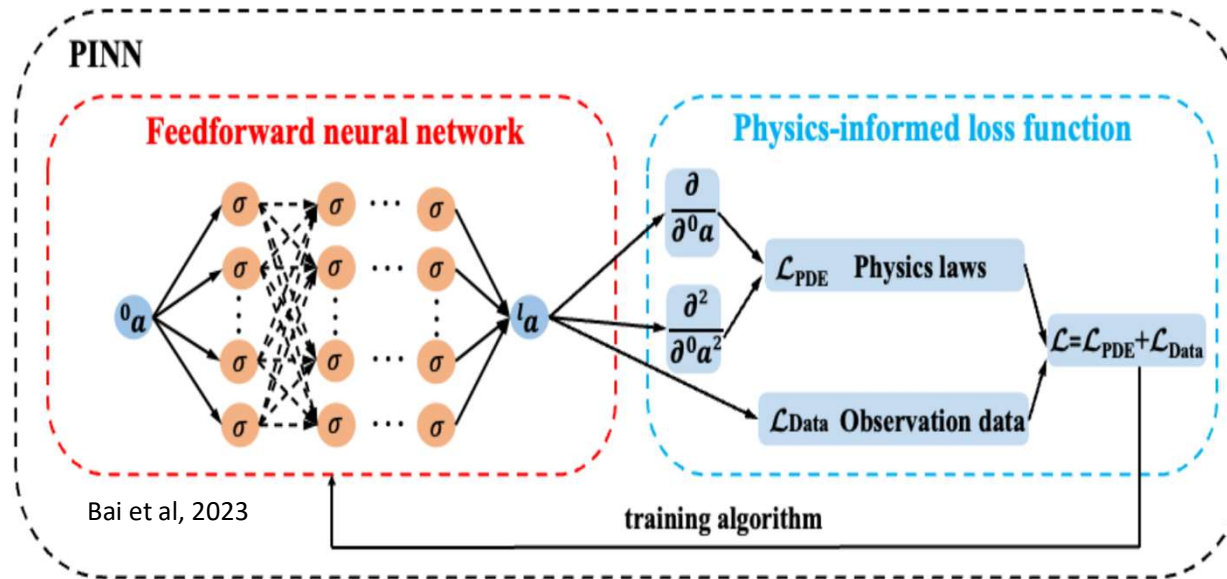
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# Custom Loss Functions



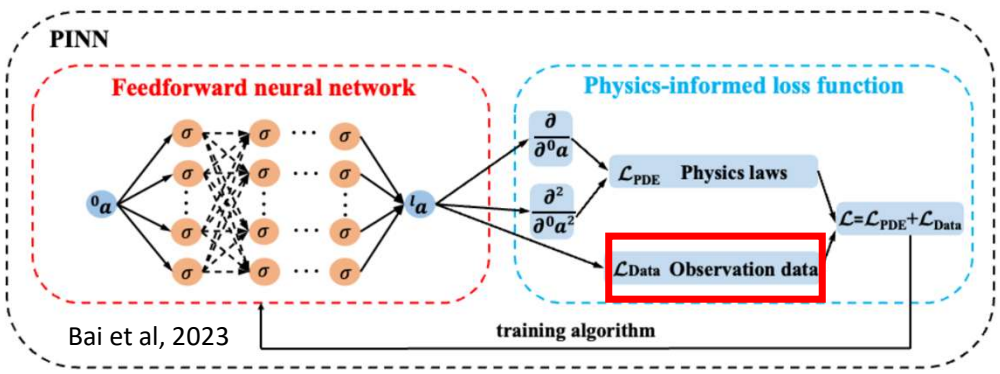
# Custom Loss Functions



<i>Parameter (<math>P_i</math>)</i>	<i>Unit</i>	<i>Symbol</i>
<i>Disturbance Storm Time index</i>	$nT$	$Dst$
<i>Solar Wind Speed</i>	$km\ s^{-1}$	$v$
<i>IMF <math>B_y</math></i>	$nT$	$B_y$
<i>IMF <math>B_z</math></i>	$nT$	$B_z$
<i>Akasofu coupling function</i>	$erg\ s^{-1}$	$\epsilon$



# Custom Loss Functions



Parameter ( $P_i$ )	Unit	Symbol
Disturbance Storm Time index	nT	Dst
Solar Wind Speed	km s <sup>-1</sup>	v
IMF B <sub>y</sub>	nT	B <sub>y</sub>
IMF B <sub>z</sub>	nT	B <sub>z</sub>
Akasofu coupling function	erg s <sup>-1</sup>	ε

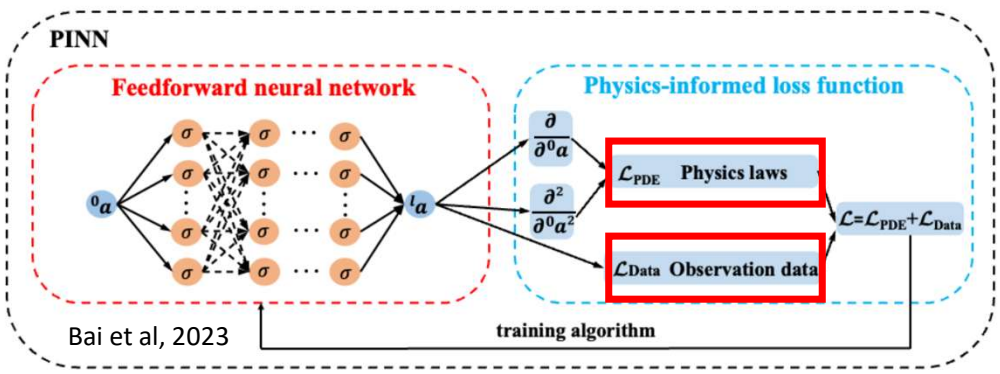
$$J(\theta, \lambda_1, \lambda_2) = \frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2 +$$

Custom loss function

Mean Square Error

Asamoah, E. N., Cafaro, M., Epicoco, I., De Franceschi, G., & Cesaroni, C. (2024). Physics-informed loss functions for vertical total electron content forecast. *Earth Science Informatics*, 17(3), 2569-2586.

# Custom Loss Functions



Parameter ( $P_i$ )	Unit	Symbol
Disturbance Storm Time index	$nT$	$Dst$
Solar Wind Speed	$km\ s^{-1}$	$v$
IMF $B_y$	$nT$	$B_y$
IMF $B_z$	$nT$	$B_z$
Akasofu coupling function	$erg\ s^{-1}$	$\epsilon$

$$J(\theta, \lambda_1, \lambda_2) = \underbrace{\frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2}_{\text{Mean Square Error}} + \underbrace{\left\{ - \left( \sum_{n=1}^N \lambda_1 \sum_{t=1}^T x_{nt,Dst} * Dst + \sum_{n=1}^N \lambda_2 \sum_{t=1}^T x_{nt,B_z} * B_z \right), \frac{dB_z}{dt} < 0 \right.}_{\text{Huber-like loss function}} \left. 0, otherwise \right\}$$

Custom  
loss  
function

Mean  
Square  
Error

Huber-like loss function

$$x_{nt,Dst} = \begin{cases} 1, Dst < -50\ nT \\ 0 \end{cases}$$

$$x_{nt,B_z} = \begin{cases} 1, B_z < -5\ nT \\ 0 \end{cases}$$

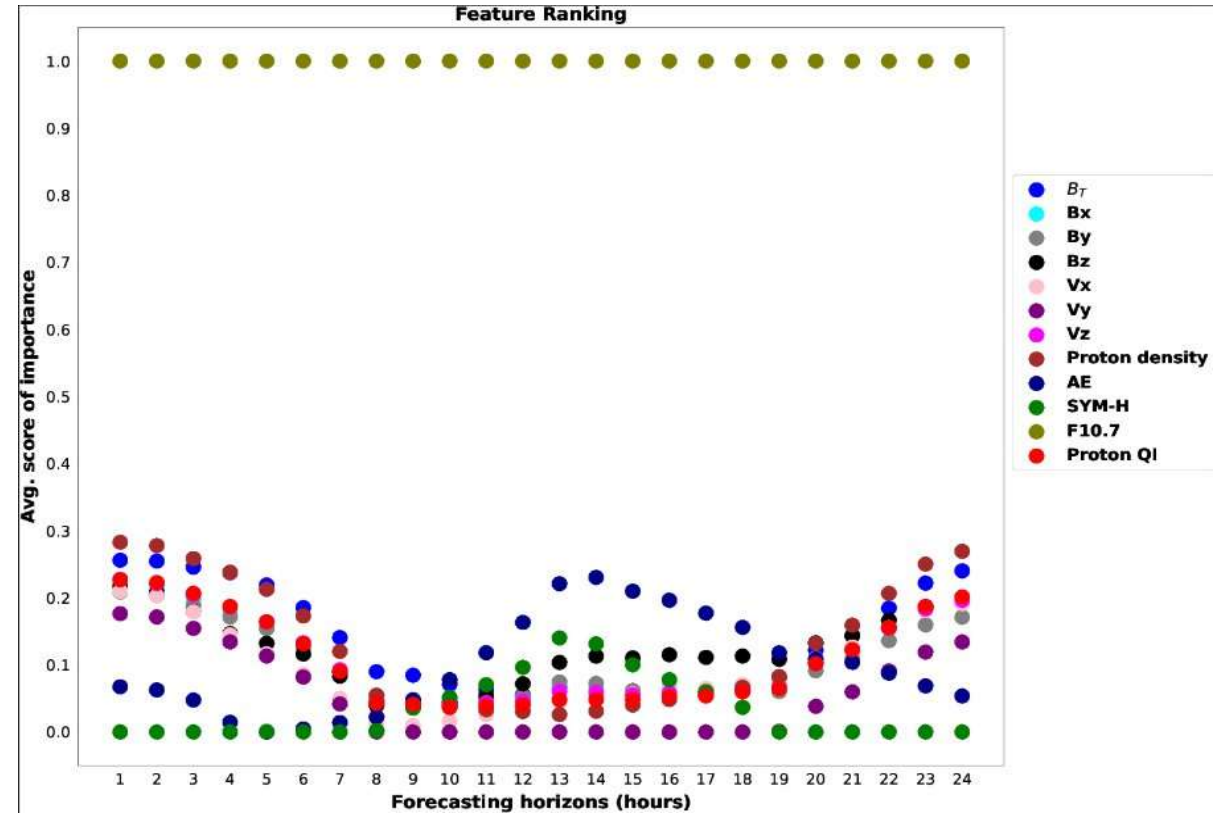
“Storm time” definition

Nana Asamoah et al, 2024b



# Custom Loss Functions: some results...

<i>Loss function</i>	<i>Quantities involved</i>
<i>mse_v0</i>	
<i>mse_v1</i>	$Dst, B_z$
<i>mse_v2</i>	$Dst, B_z, dB_z/dt$
<i>mse_v3</i>	$\epsilon$
<i>mse_v4</i>	$\epsilon, Dst, B_z$
<i>mse_v5</i>	$\epsilon, Dst, B_z, dB_z/dt$

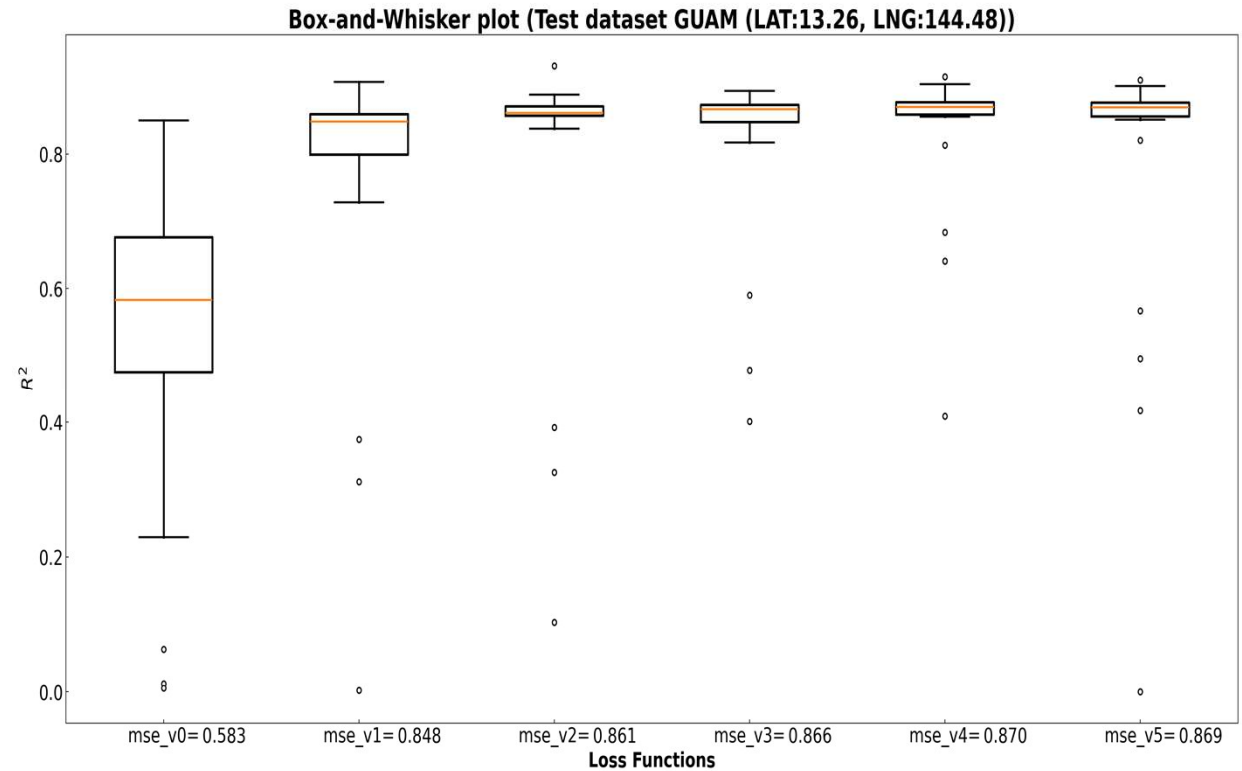
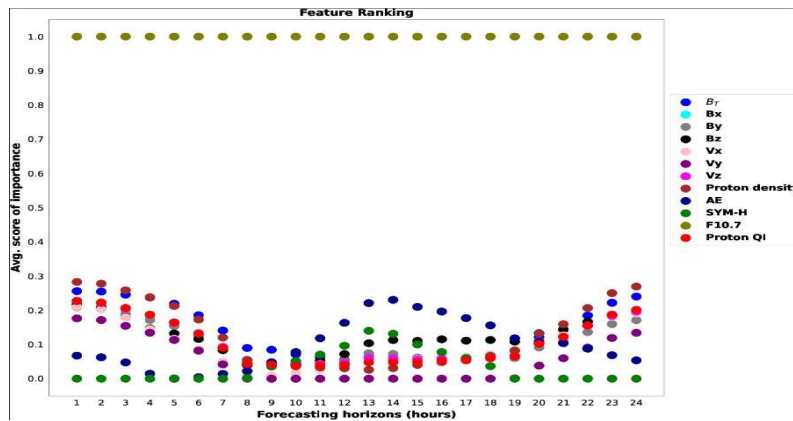


Guam Dataset

Nana Asamoah et al, 2024b

# Custom Loss Functions: some results...

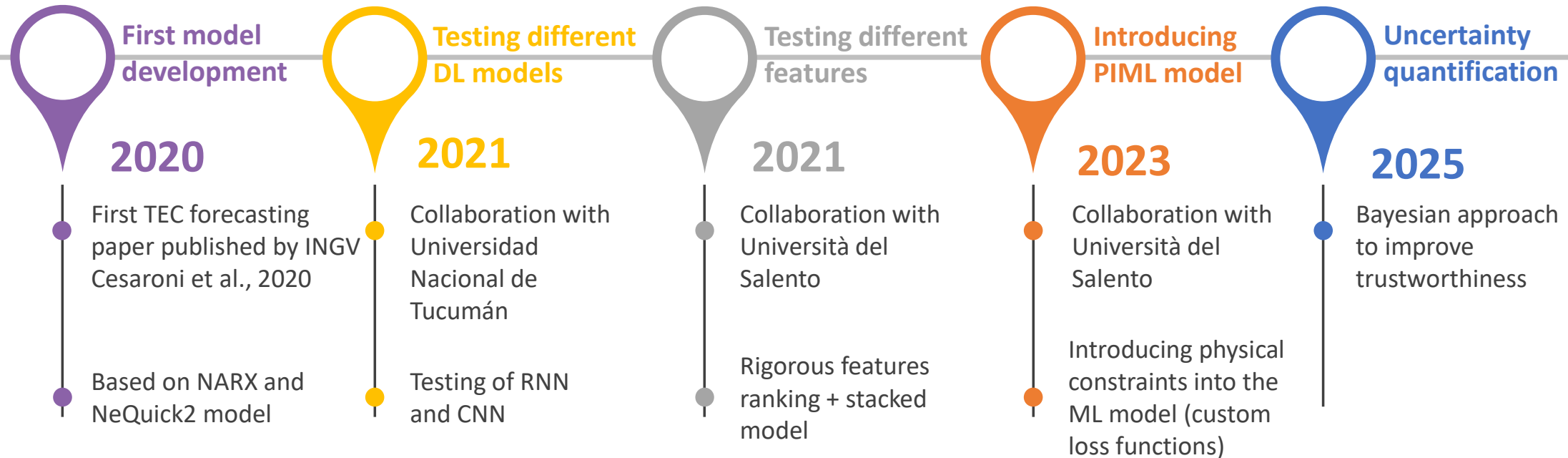
Loss function	Quantities involved
$mse\_v0$	
$mse\_v1$	$Dst, B_z$
$mse\_v2$	$Dst, B_z, dB_z/dt$
$mse\_v3$	$\epsilon$
$mse\_v4$	$\epsilon, Dst, B_z$
$mse\_v5$	$\epsilon, Dst, B_z, dB_z/dt$



Guam Dataset

Nana Asamoah et al, 2024b

# Our roadmap toward a Physics-Informed forecasting model



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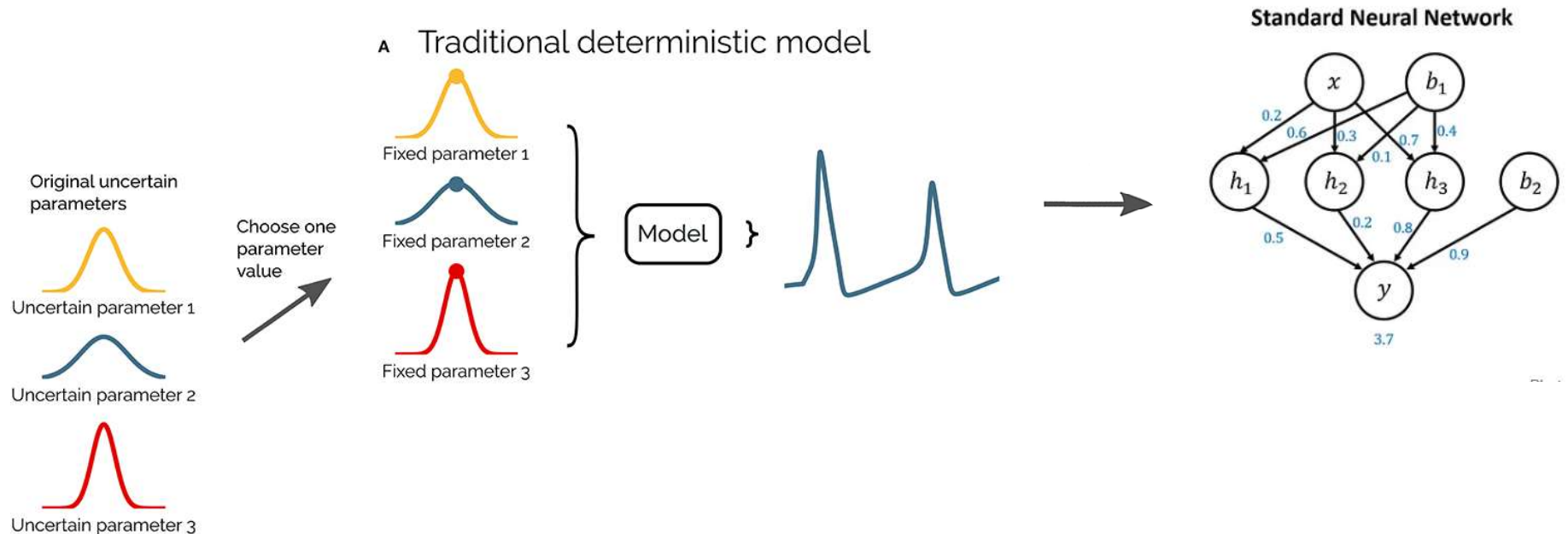
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# Uncertainty quantification: Bayesian NN

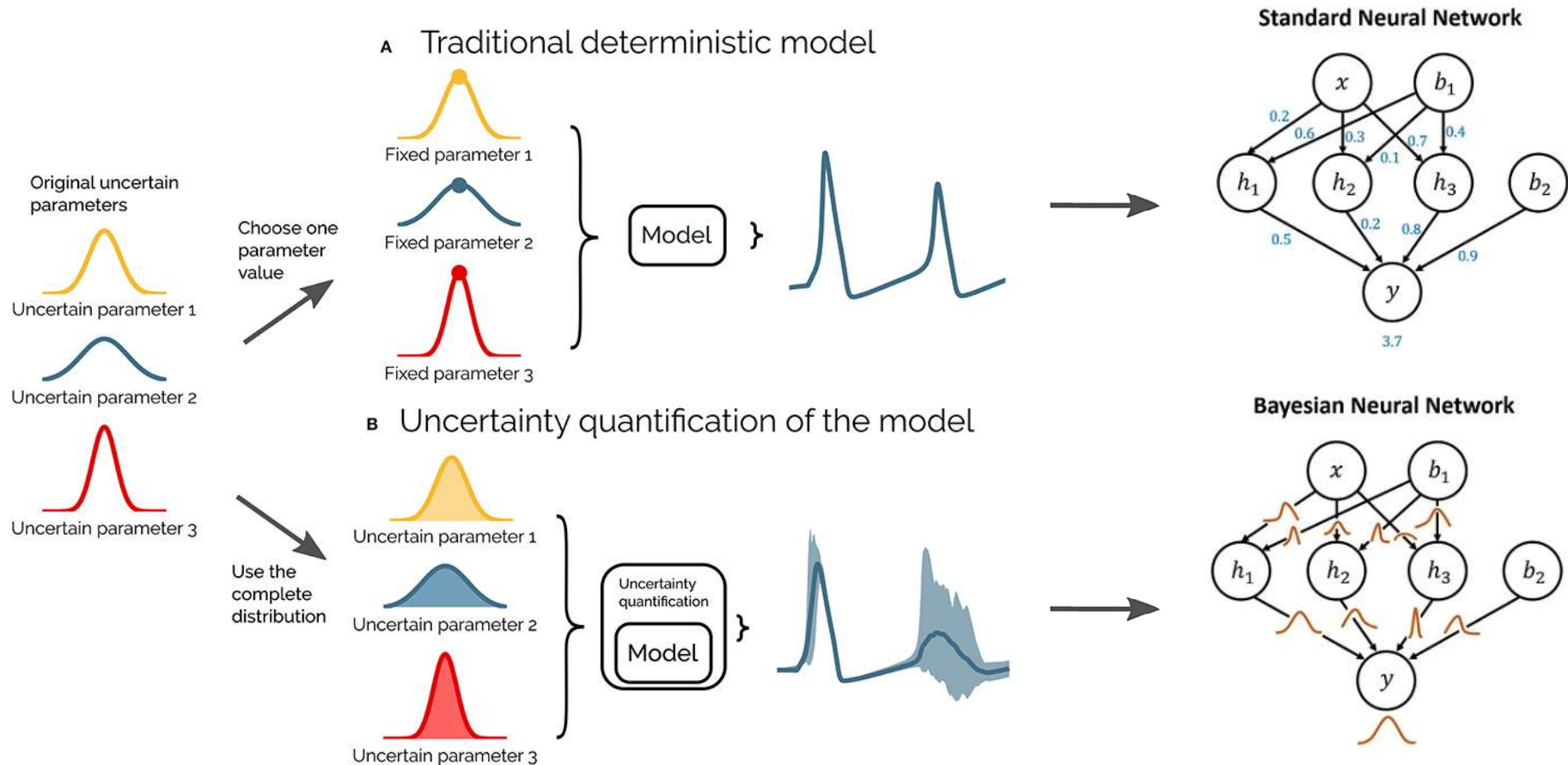
The measurements and modeling of the ionosphere are particularly challenging due to its complexity and variability, both regular and irregular. This complexity increases the uncertainty of results when forecasting future instances. Therefore, it is necessary to quantify these uncertainties in order to obtain reliable forecasts.





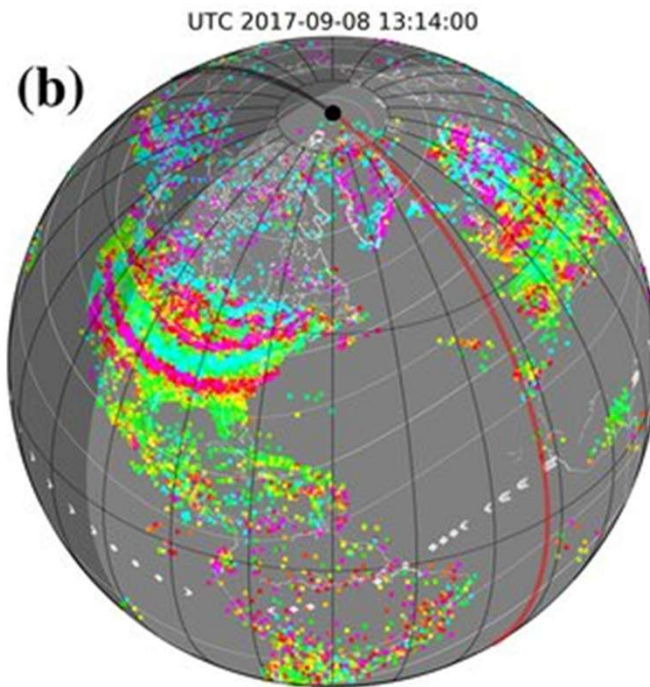
# Uncertainty quantification: Bayesian NN

The measurements and modeling of the ionosphere are particularly challenging due to its complexity and variability, both regular and irregular. This complexity increases the uncertainty of results when forecasting future instances. Therefore, it is necessary to quantify these uncertainties in order to obtain reliable forecasts.



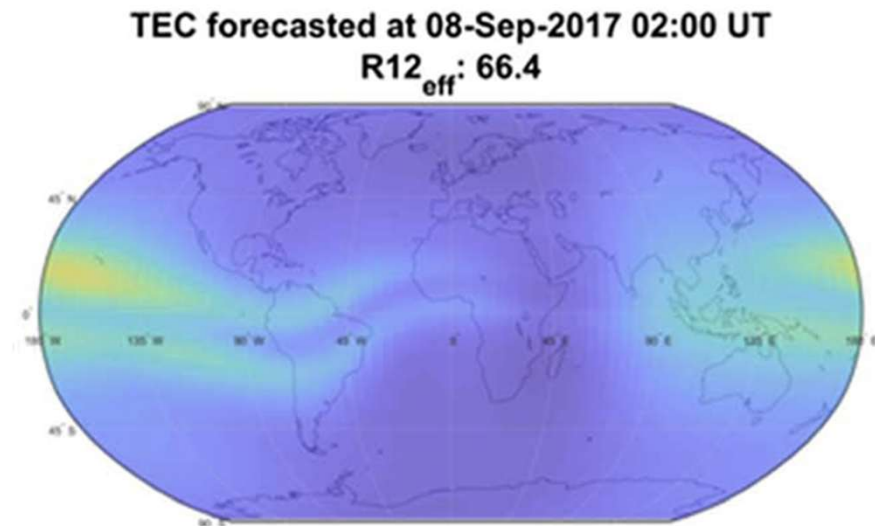
# Regression vs Classification

LSTID occurrence



classification

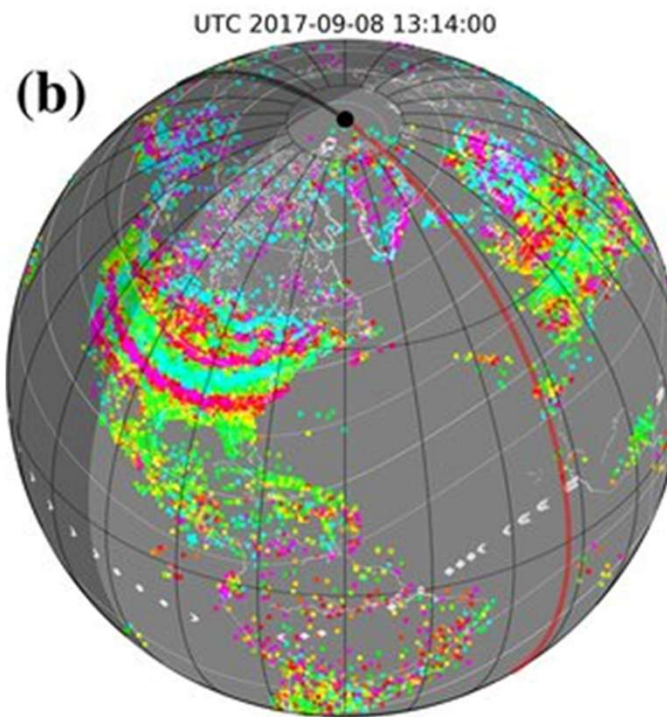
Global TEC forecasting



regression

# Will there be a LSTID in the next 3 hours?

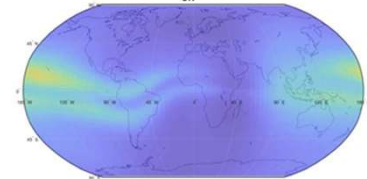
LSTID occurrence



classification

Global TEC forecasting

TEC forecasted at 08-Sep-2017 02:00 UT  
 $R12_{off} = 66.4$



regression



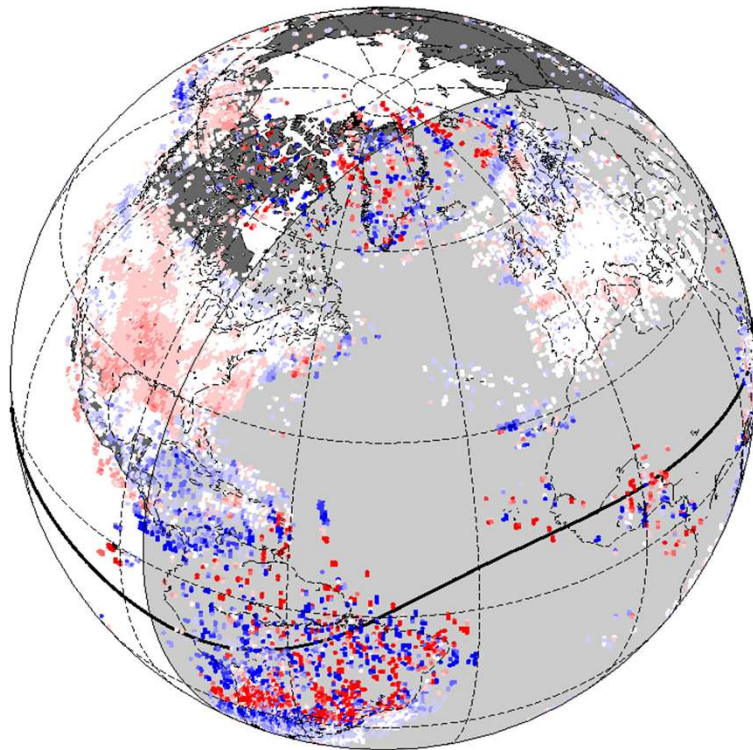
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# LSTID in a nutshell

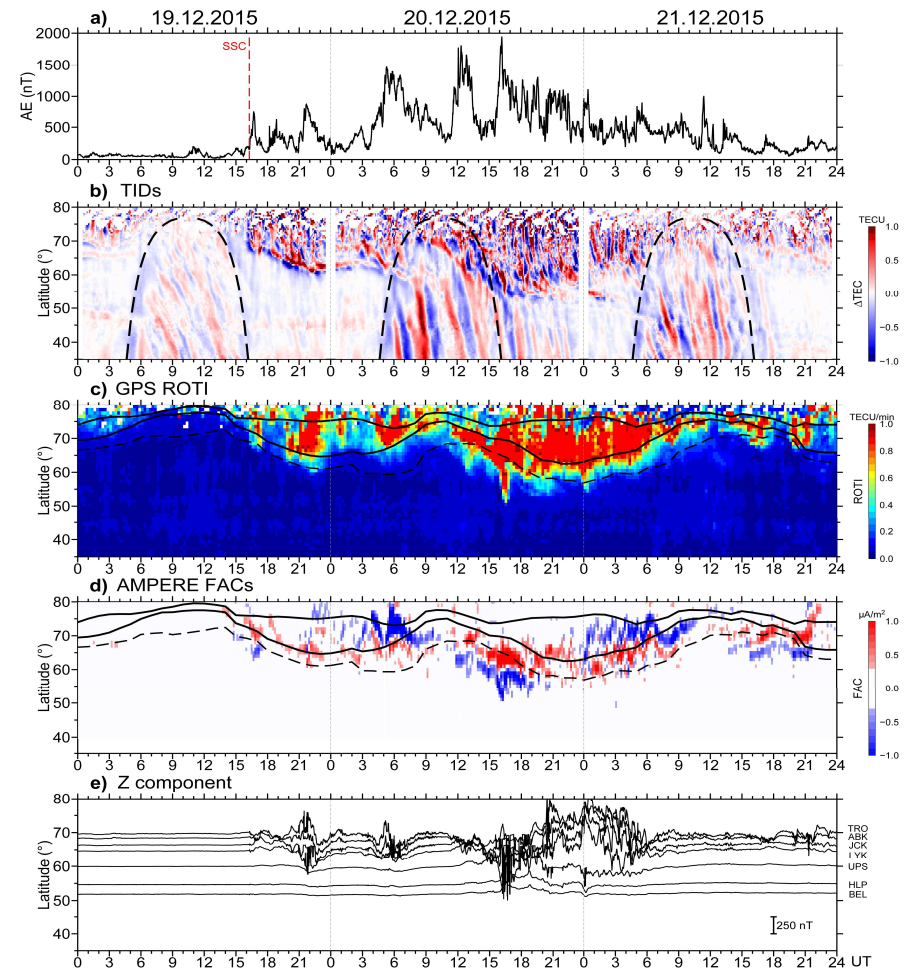
## Large-scale Travelling Ionospheric Disturbances

17/03/2015 00:30 UT



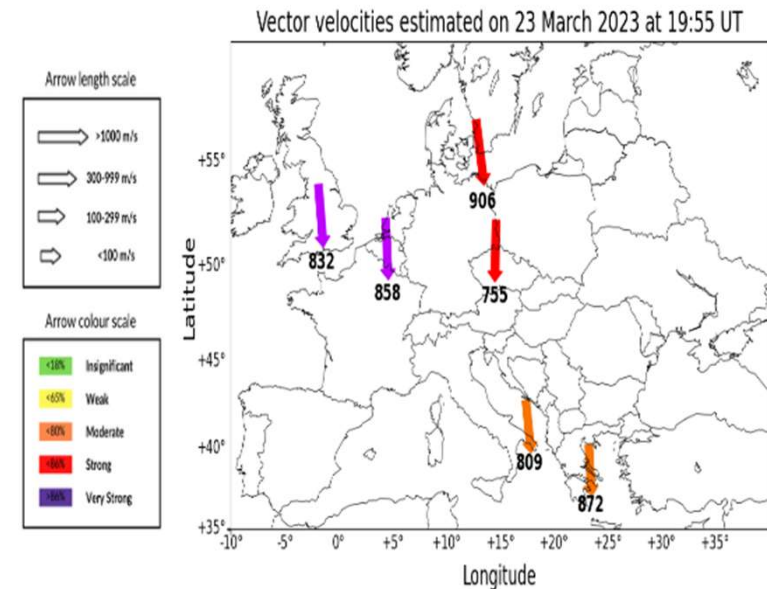
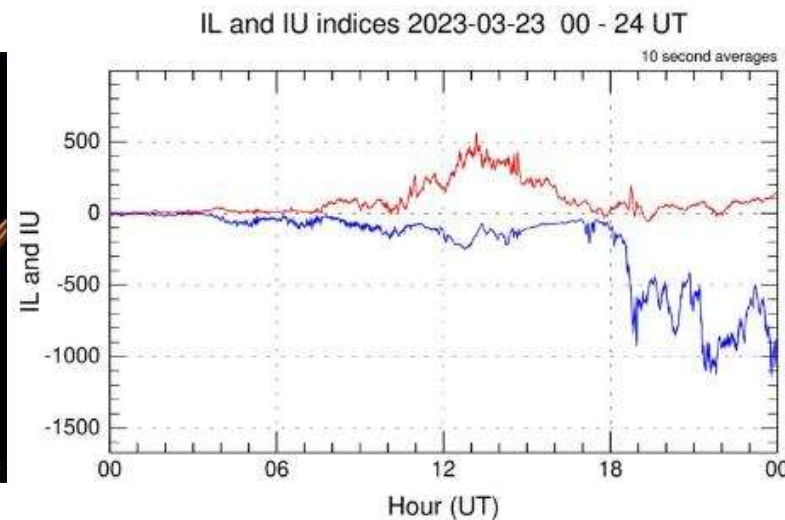
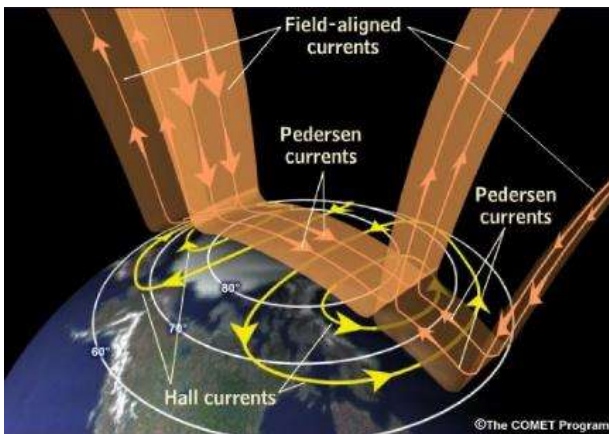
$\Delta\text{TEC}$   
-1.0 -0.5 0.0 0.5 1.0

Zakharenkova et al., 2016



# LSTID in a nutshell

## LSTIDs occurrence chain of events from the auroral oval to middle latitudes

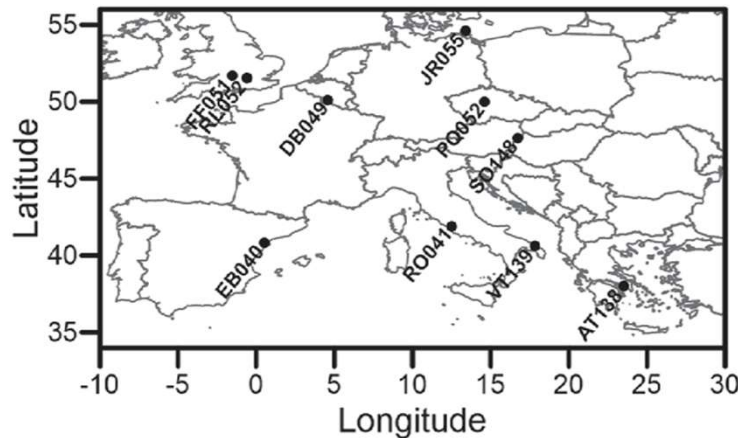




# LSTID detection (HF)

## The Detection method: HF-Interferometry

### INPUT



- Characteristics from VI Ionospheric sounding (**MUF(3000)F2**).
- Network of DPS4D with stations working **synchronized**.
- GIRO DIDBase Fast Chars database <http://giro.uml.edu/didbase/scaled.php>

### - Detection of TID-like variation

Detect coherent TID-like variations by spectral analysis.

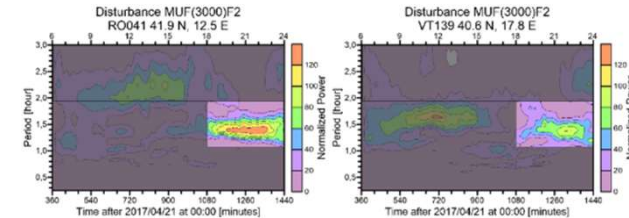
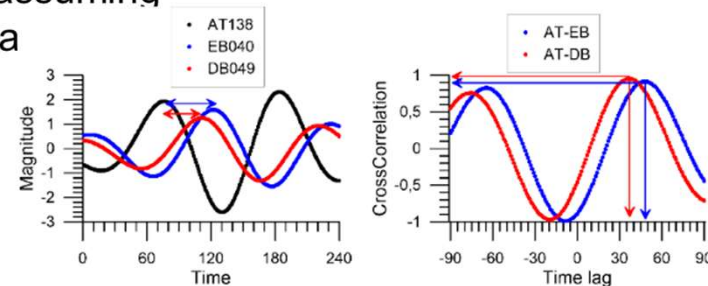
### - TIDs contribution to data variability.

Application of the Parseval's relation [ $A(\omega)$  vs  $A(T)$ ]

$$SPCont(\%) = \frac{\sum_{T=T_{TID_S}}^{T=T_{TID_E}} A(T)^2}{\sum_{T=T_S}^{T=T_E} A(T)^2}$$

### - Estimation of the velocity and azimuth of the TID

Estimate time delays for different sites by cross-correlation,  $\Delta TM_i$ . Estimate velocity of disturbance  $\vec{v}$  assuming planar propaga



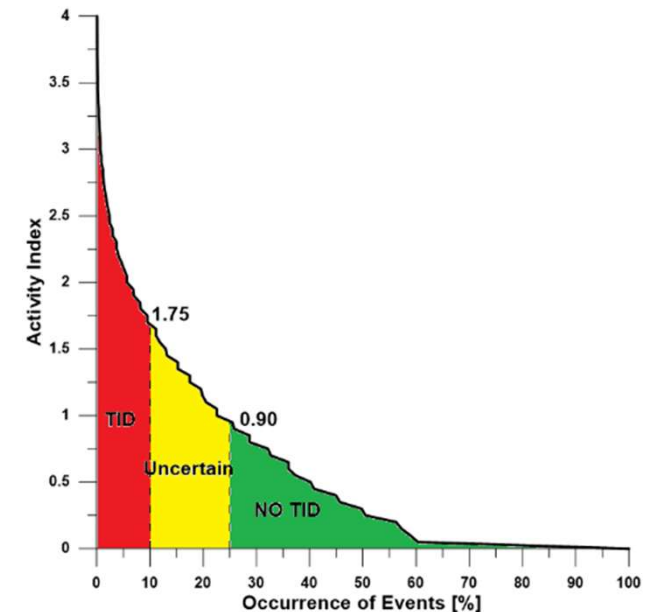
# LSTID detection (HF)

## • HF-EU index

OE\_HFI\_YYYYMMDDHHmm\_COND.log files every 5 minutes

```
EU 201701271330 TrL AV= 3.00 Area= 66.00% ActivityIndex= 1.98 TID  
SA 201701271330 TrL AV= 0.00 Area= 0.00% ActivityIndex= 0.00 NO TID
```

- One index for the whole network.
  - It is the product of the average intensity of the TID (related to the spectral contribution) multiplied by the area affected (number of stations).
  - The thresholds have been established by statistics
    - 0 means no data
    - 0.1 means nothing detected



# LSTID detection (HF)

## HF-INT: Catalogue of events

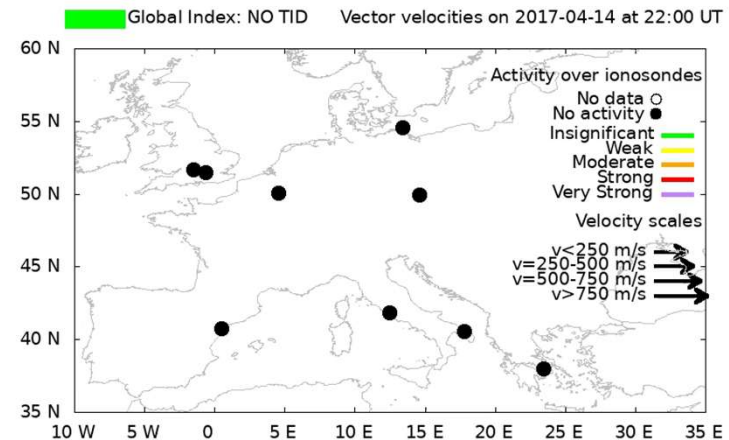
- **Visual inspection to determine LSTIDs events**

- Looking for coherent velocity propagation
- 1604 LSTIDs events detected and recorded above Europe between 01/2014 and 12/2022

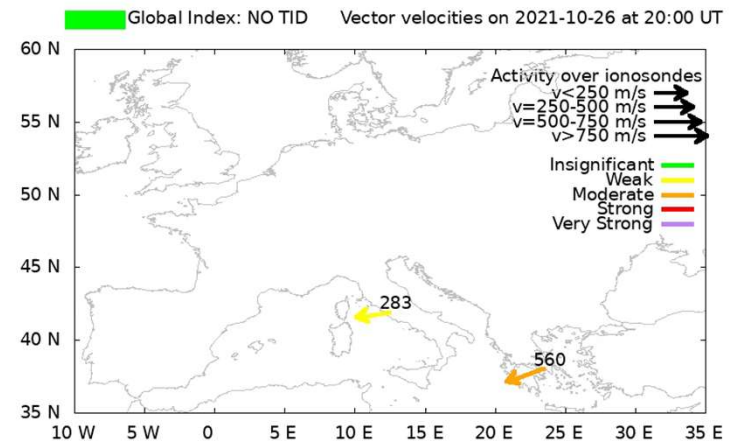
- **Determination of onset time and duration**

- Approximative

- **Average of the main characteristics of the TID for all stations and during the whole event.**



Included  
in the  
catalogue



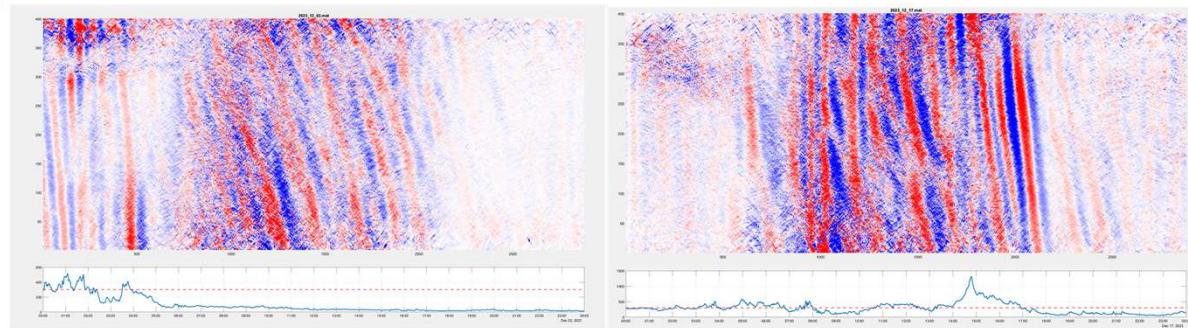
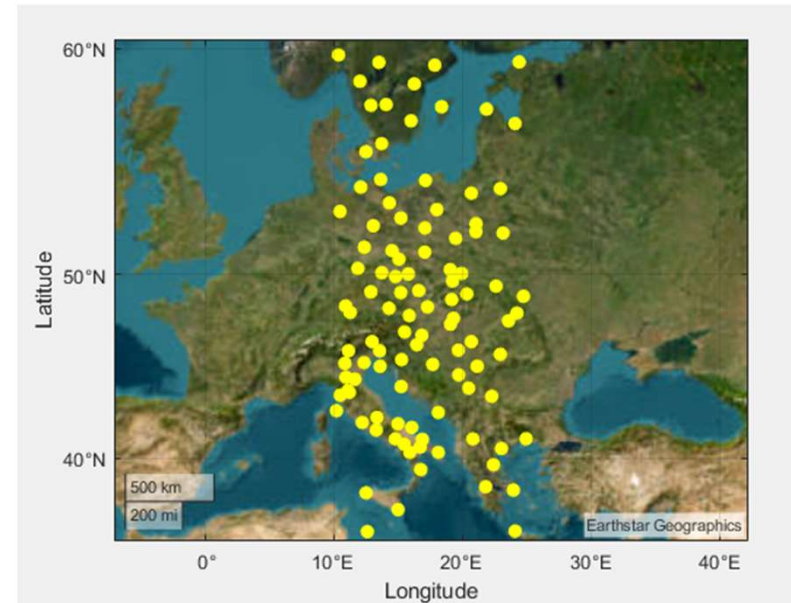
Not included  
in the  
catalogue

# LSTID detection (GNSS)

- Keograms are latitude-time plots, optimal to highlight NS propagation of LSTID
- Data gathered from EUREF Permanent GNSS Network
- Stations belonging to 10-25 Longitude
- Reduction of stations with KNN for optimal coverage
- GFLC of phase measurements for GPS, GLONASS, Galileo and BeiDou
- Verticalization of zero-averaged GFLC
- Detrended with 3<sup>rd</sup> order Savitzky-Golay filter on a 1.5-hour window
- dTEC median on bins of 5km NS and 1 minute in time

MATLAB code for GFLC and IPP computation is available here:

<https://github.com/mquerra96/MyIonosphere.git>



(Bottom panels are showing IE index)



# LSTID detection (GNSS)

## Unsupervised LSTID Extraction from Keograms

- **Preprocessing**

- Adjust dTEC values based on solar zenith angle.

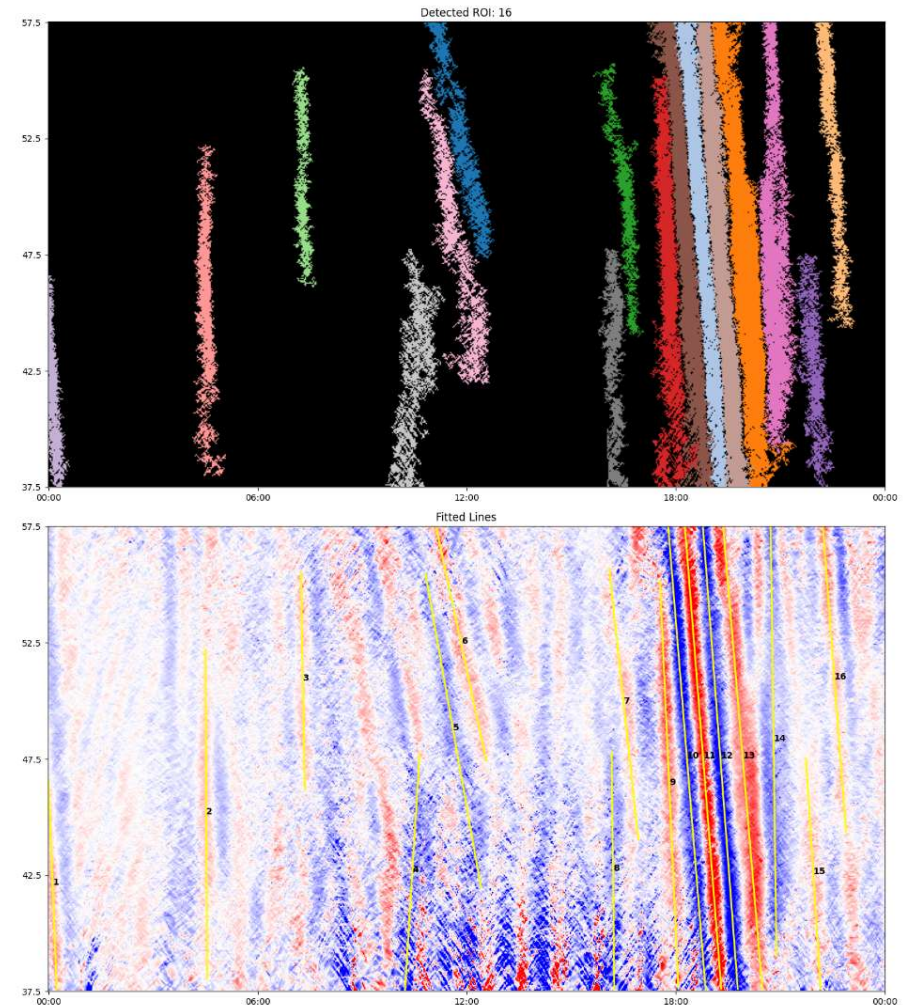
- **Segmentation**

- Define ROI as connected regions in the keogram.
- Refine ROI using a clustering algorithm.

- **Feature Extraction**

- Use RANSAC (Random Sample Consensus) algorithm to estimate ROI speeds.

M.A. Fischler and R.C. Bolles. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM, 24(6):381–395, 1981.

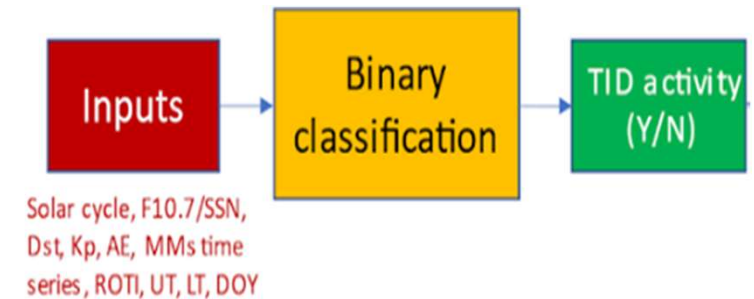




# LSTID forecasting

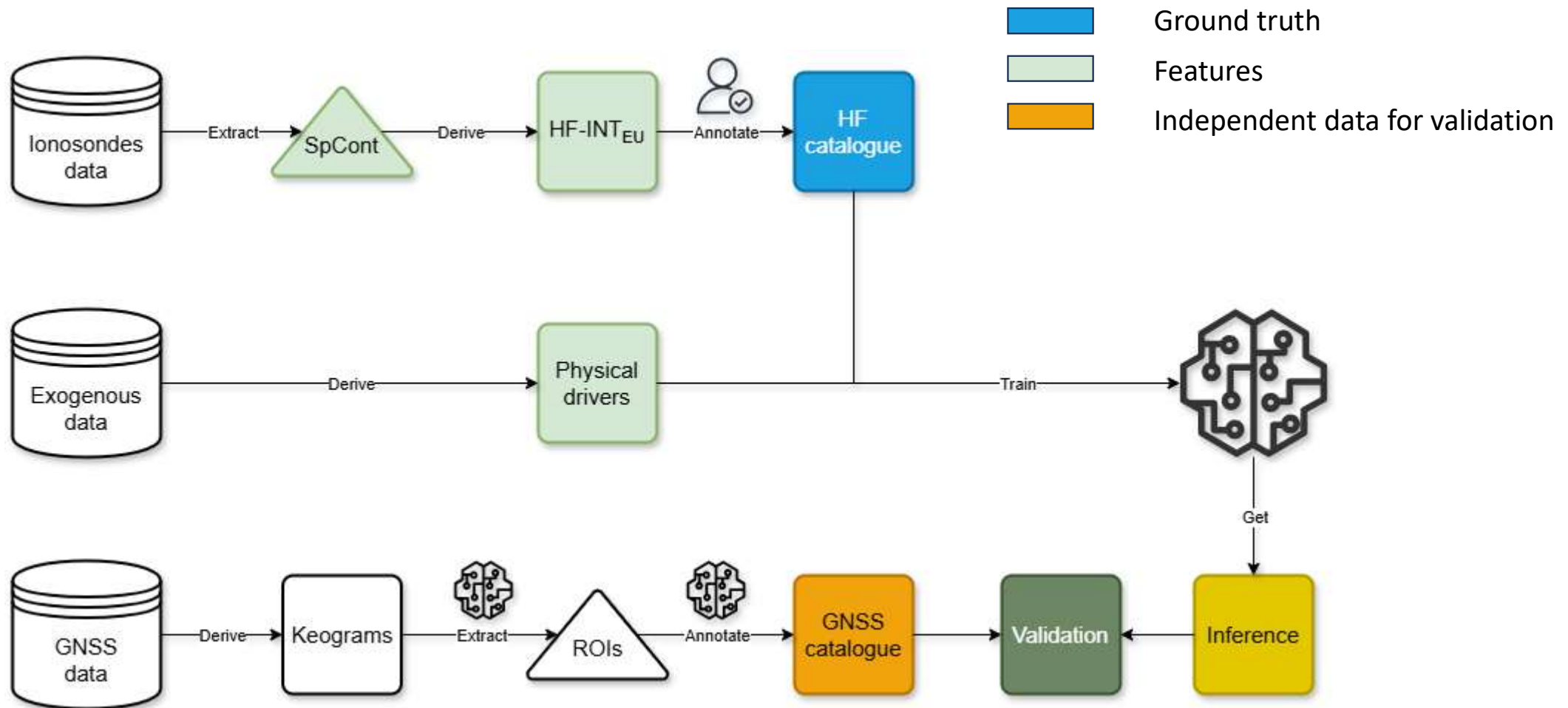
## Developing the ML models: catalogue-based forecasting

- The problem is framed as a **multivariate time-series binary classification**
- We employed the HF-INT refined LSTID catalogue provided by Ebro Observatory, consisting of **1604 LSTID events** detected above Europe between 01/2014 and 12/2022
- The database is generated by leveraging a network of ionosondes covering the European sector



Parameter	Example
Start time	2022 01 11 21:00
Duration	2.0 hrs
Period	119.74 min
Amplitude	0.72 MHz
Velocity	597.47 m/s
Azimuth	202.39°

# LSTID forecasting approach

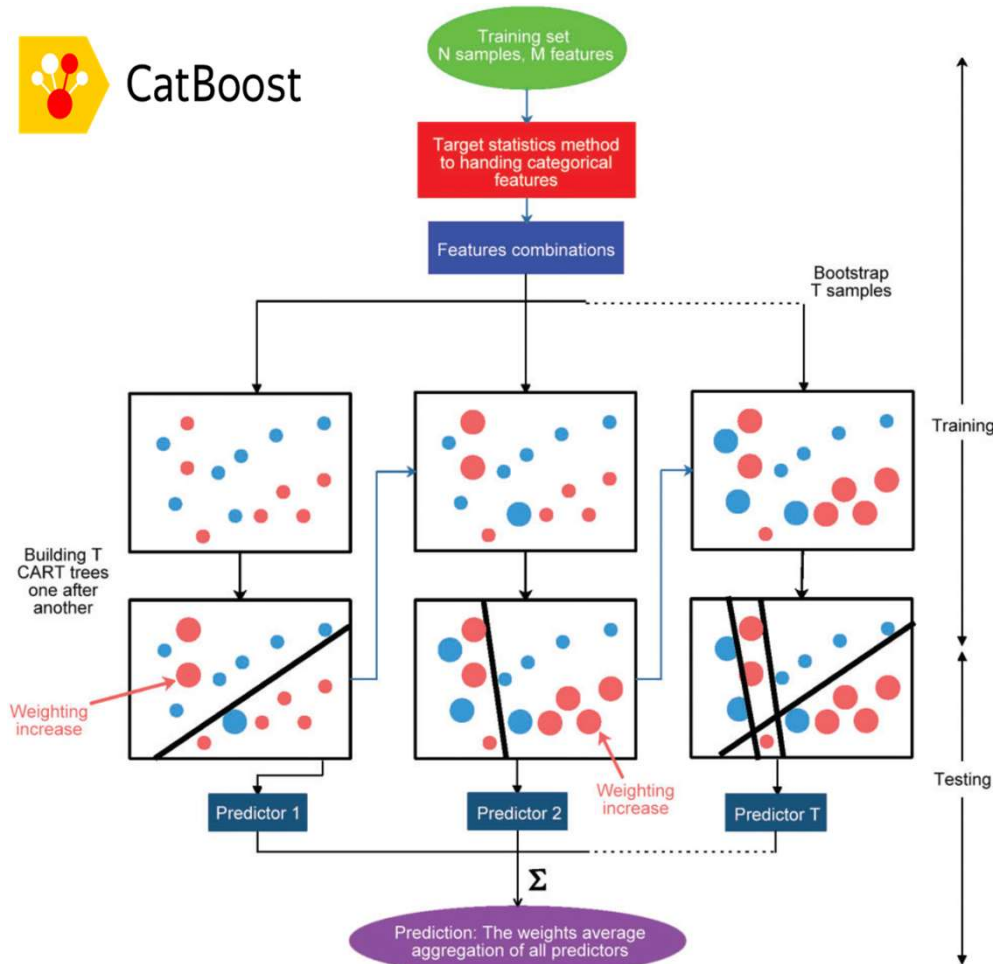


# Our ML Stack

- Easily understandable and adaptable syntax
- One of the top languages for training ML models
- **Category & Boosting** (gradient boosting on decision trees)
- A symmetric balanced tree architecture leads to an efficient CPU implementation, decreases prediction time (great for real-time inference) and controls overfitting
- Categorical and missing values are handled natively
- Integrates SHAP to break predictions into features' contributions
- Efficient optimisation framework for model hyper-parameters tuning
- **Machine Learning Operations** (MLOps) to organise and manage ML experiments
- The **SHapley Additive exPlanation** (SHAP) framework allows to test features influence on the model output from both global and local aspects
- Enhancement for interpretability and explainability of the model – very desirable features in potentially high-risk settings



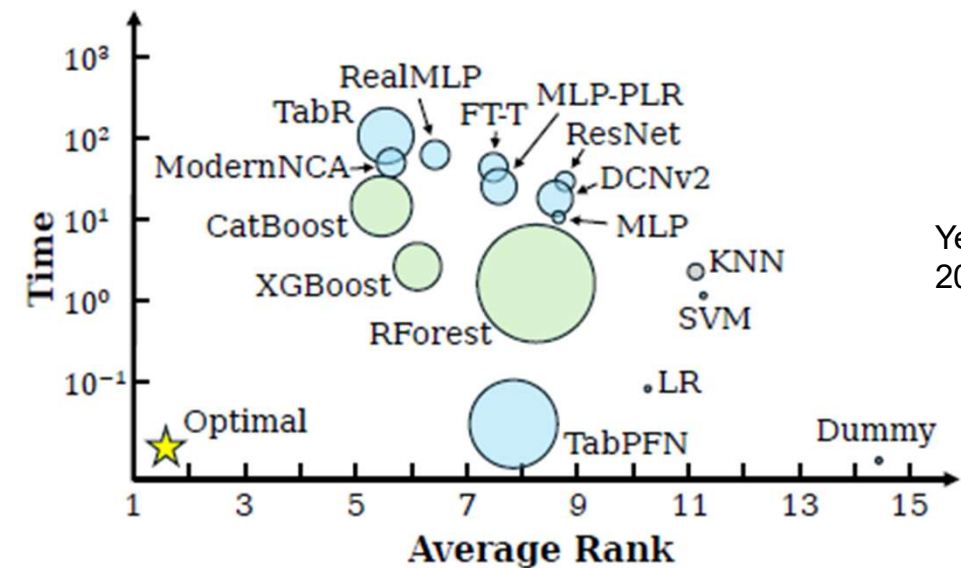
# CatBoost



Yao et al.,  
2021

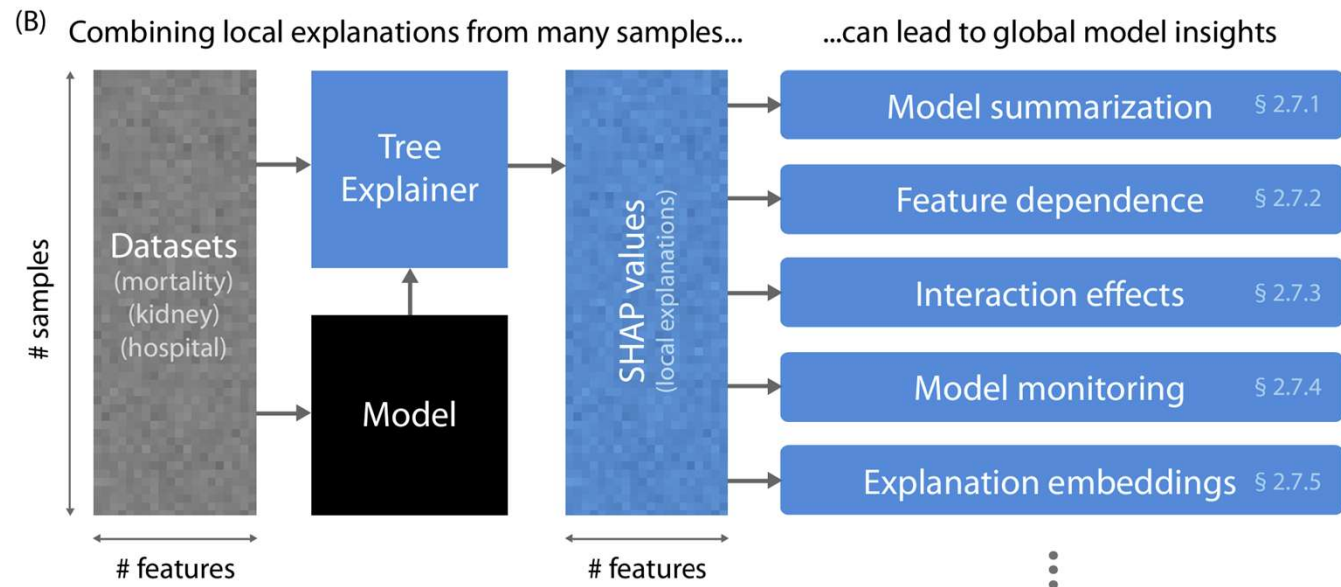
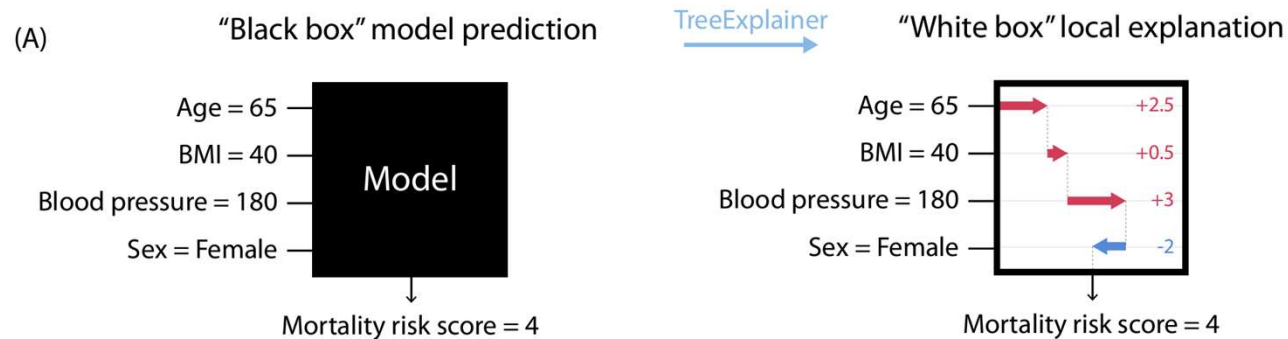
Here's how CatBoost works in simple terms:

- 1. Boosting with Trees:** CatBoost builds a series of decision trees (weak learners) one after another. Each tree aims to fix the errors made by the previous trees, gradually improving the overall model's accuracy.
- 2. Handling Categorical Data:** A unique feature of CatBoost is its ability to handle categorical data (like "color: red, blue, green") without needing to convert these categories into numbers manually.
- 3. Order of Rows:** Unlike other boosting algorithms, CatBoost takes the order of training data rows into account. It randomly shuffles data to make the predictions more stable and less sensitive to data order.



Ye et al.,  
2025

# How we can explain the model?



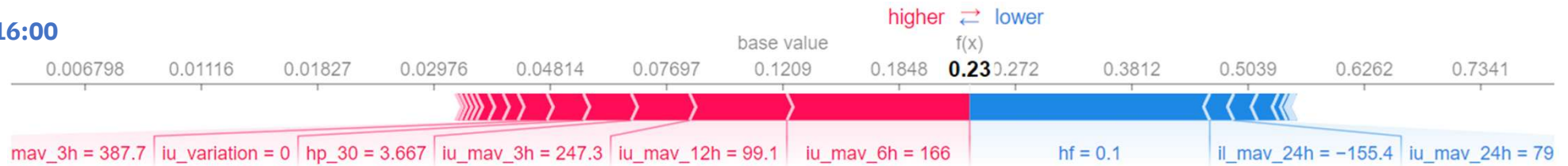


# SHAP values: local interpretation

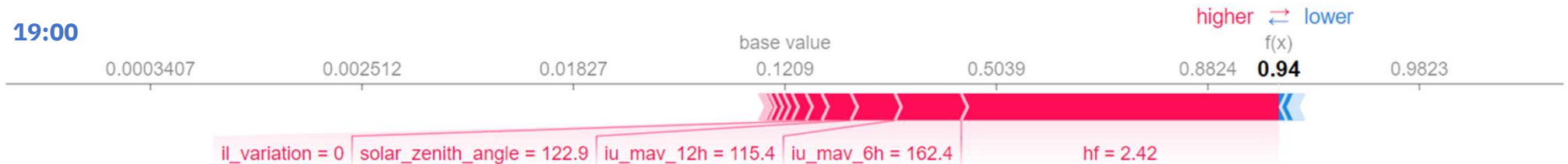
23/12/2022 22:20, LSTID lasted 1.5h

Threshold=0.5

16:00



19:00



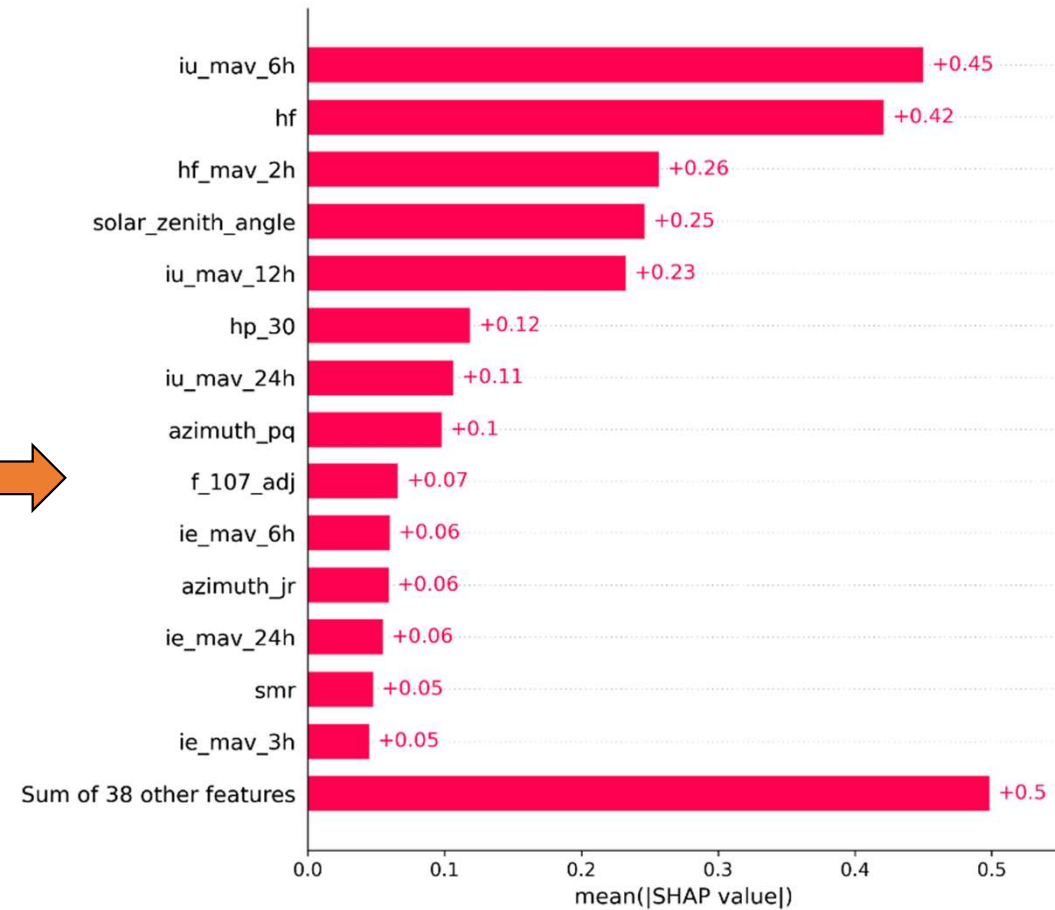
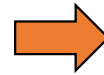
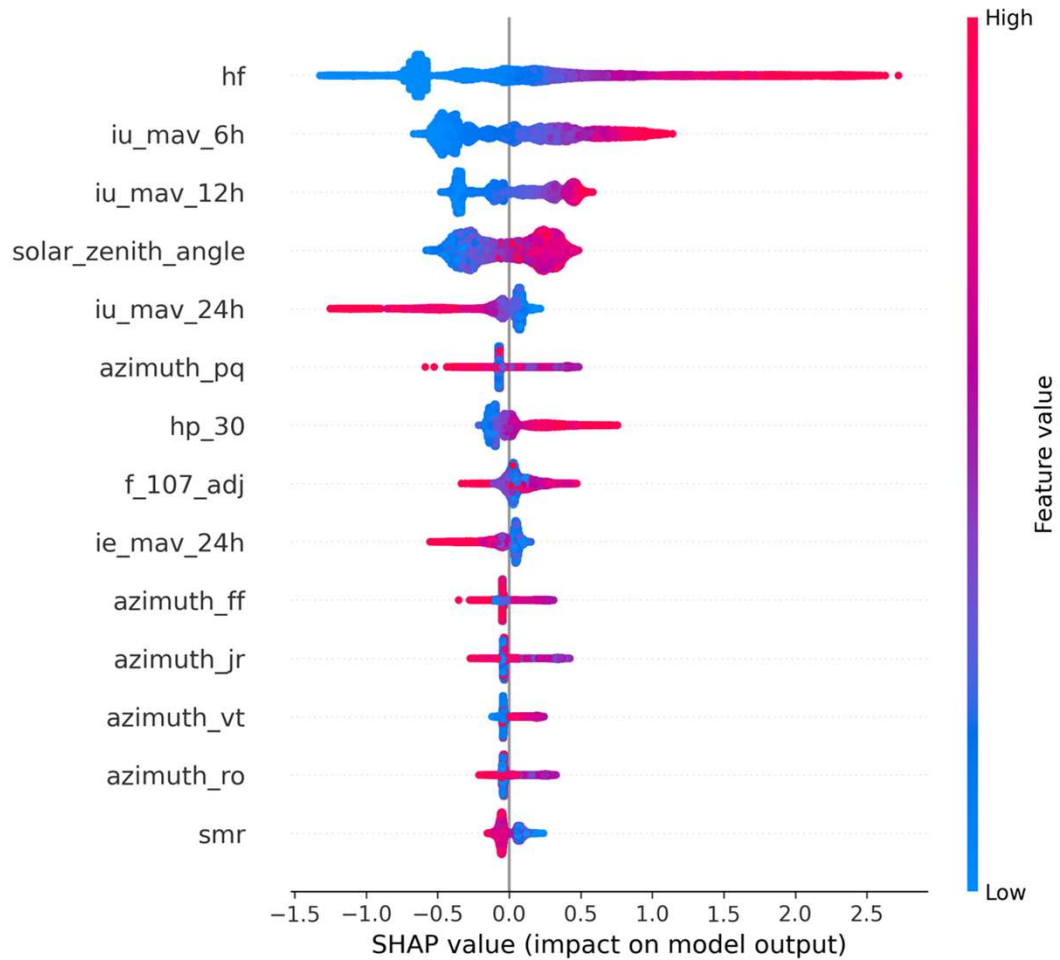
22:00



00:30



# Local to Global interpretation



# How to evaluate the performance?

TID doesn't occur	True Negative	False Positive
TID occurs	False Negative	True Positive
	TID not predicted	TID predicted

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$F_1 = \frac{P * R}{P + R}$$

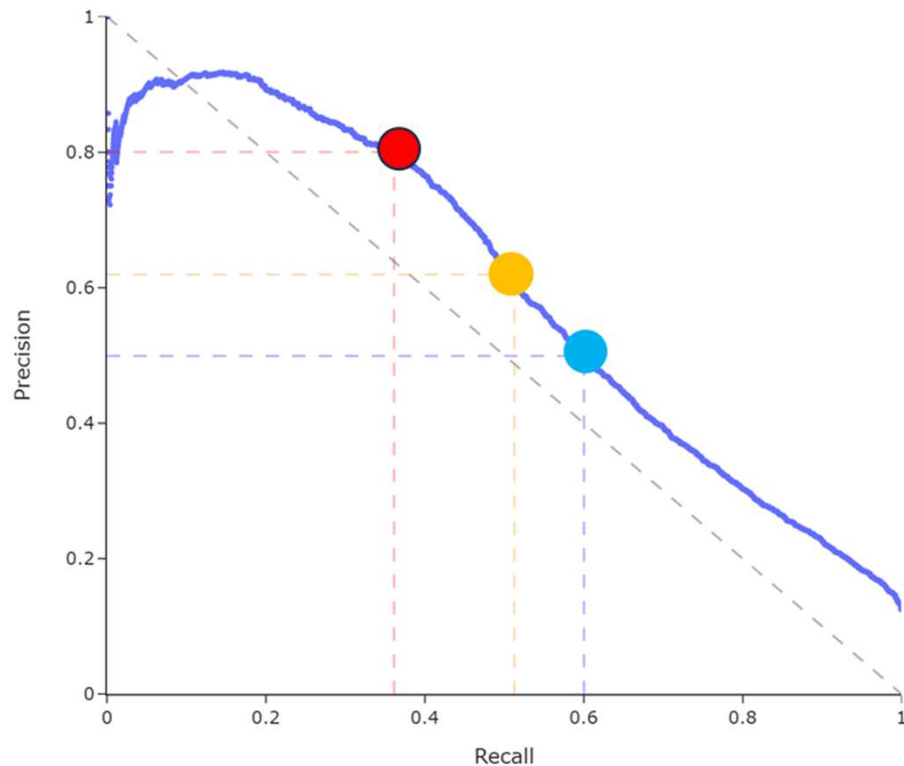
**Precision** is a good measure to determine, when the costs of False Positive is high

**Recall** actually calculates how many of the Actual Positives our model capture through labeling it as Positive (True Positive)

**F1 Score** might be a better measure to use if we need to seek a balance between Precision and Recall AND there is an uneven class distribution (large number of Actual Negatives).

# Model Operational Modes

The model results in **3 distinct operating modes**, tailored for scenarios with varying relative costs of false positives/negatives



## High-precision

**Great** when the cost of false positives is the most significant  
**But** not all the events are predicted, or prediction can be “intermittent”

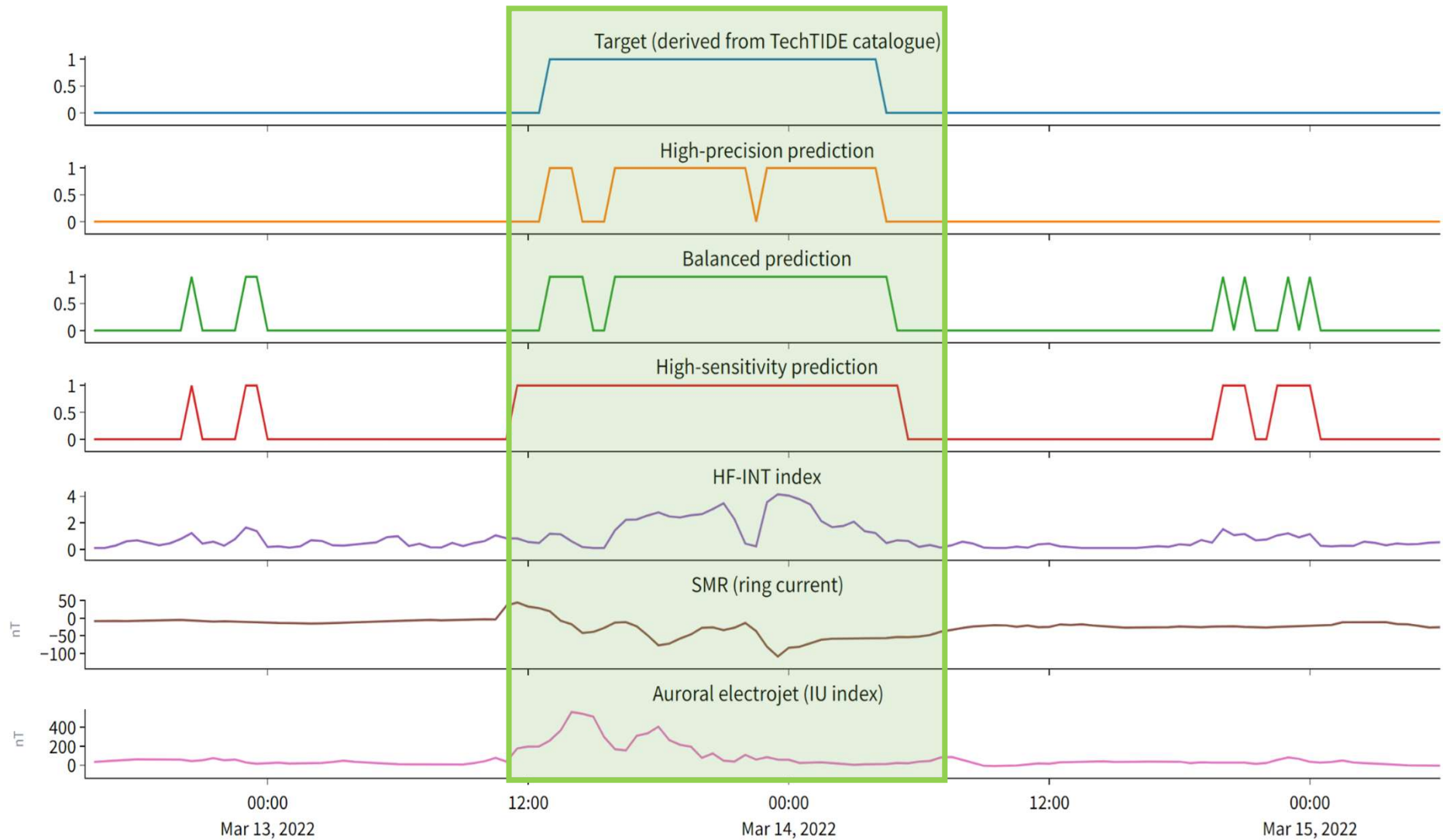
## Balanced

**Great** to strike a balance between precision and sensitivity  
**But** does not take into account the relative cost of false positives and false negatives

## High-sensitivity

**Great** when the cost of false negatives is the most significant  
**But** the user can get a great deal of alerts (alert fatigue)

# Validation on case events: 13-14/03/2022

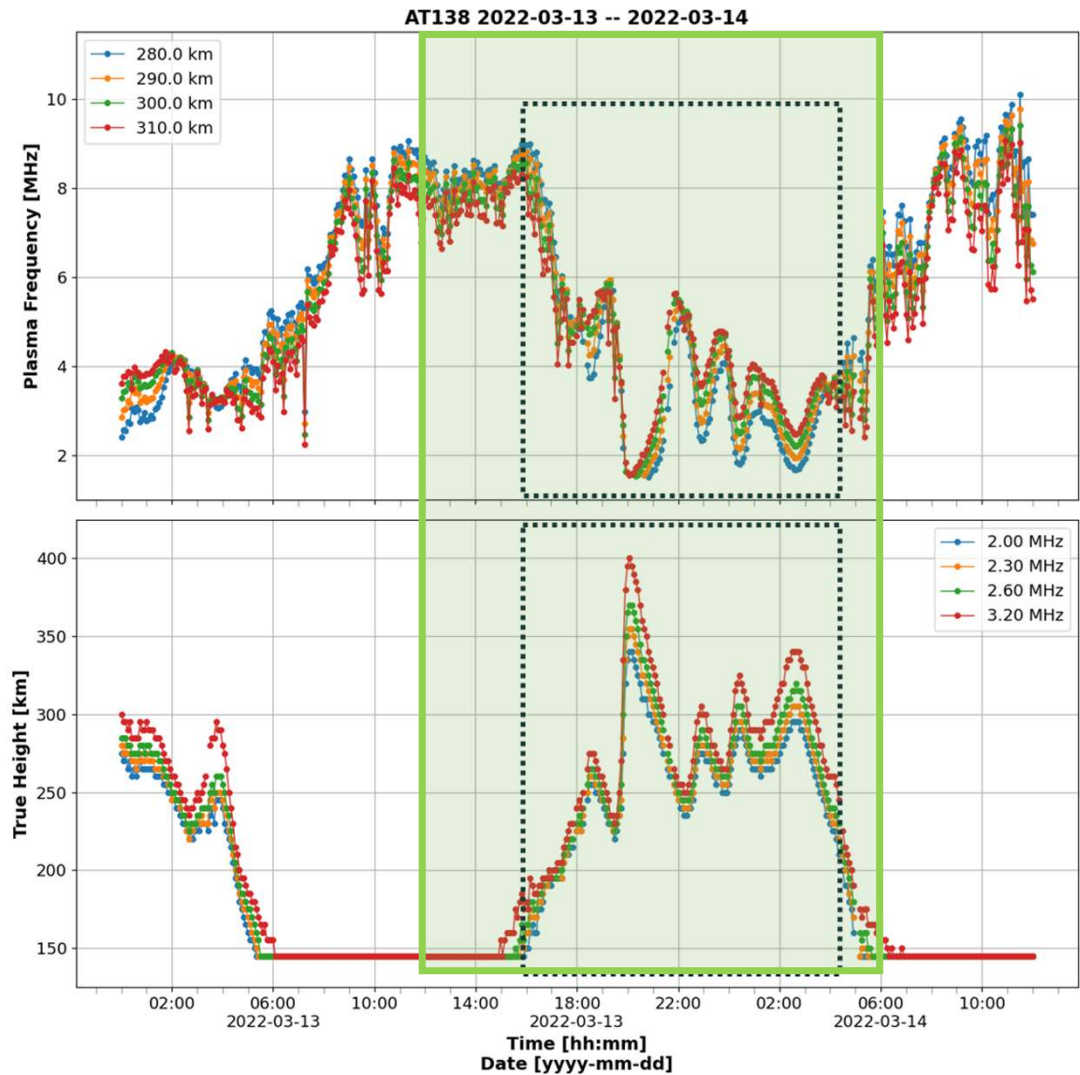
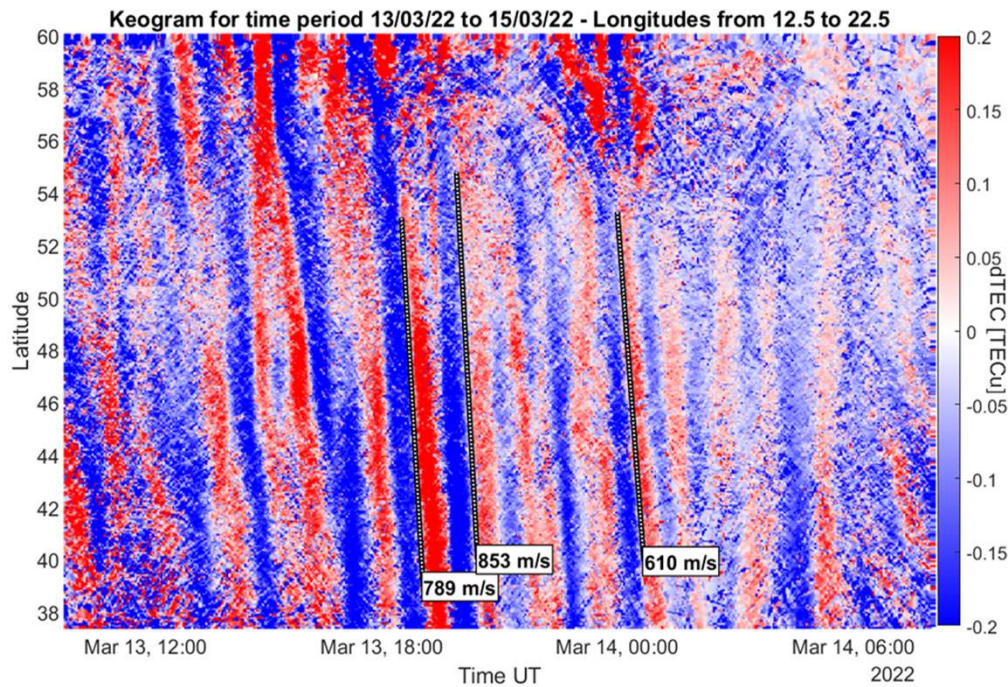




# Validation on case events: 13-14/03/2022

HF measurements from Athens (Greece)

GNSS measurements over Europe



# Take home message

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**ML/DL can support the forecasting of the ionospheric features but...**

- Select the proper algorithms is not an easy task
- Features to be used as input to the models should be accurately selected by means of proper features importance evaluation tools (e.g. SHAP values)

**To go beyond the state-of-the-art modelling capabilities, we (probably) need to...**

- Use several ML/DL algorithms in an ensemble modelling approach
- Include physical constraints to properly guide the ML/DL models during the training phase

**To move towards operational models, we need to...**

- Be able to estimate the reliability of our outputs (Bayesian NN could be the answer)



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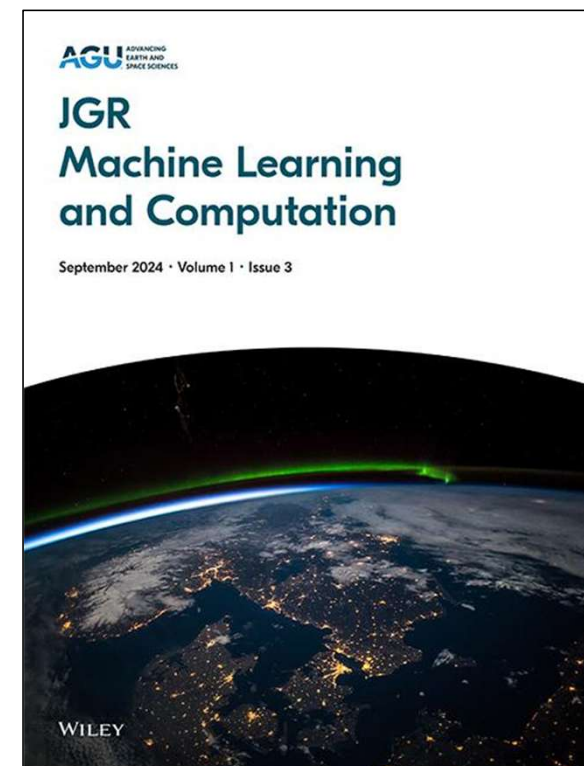
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- Enrico Camporeale, founding editor-in-chief and research scientist at the University of Colorado Boulder



**Contact [JGR-MachineLearning@agu.org](mailto:JGR-MachineLearning@agu.org)**





**Beacon Satellite**  
SYMPOSIUM 2025

# ABSTRACT SUBMISSION IS NOW OPEN

DEADLINE HAS BEEN EXTENDED TO **JUNE 29TH 2025**



ISTITUTO NAZIONALE  
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**2025 ITALIAN URSI ANNUAL MEETING**  
**26 JUNE 2025**



**THANK YOU!**

**Claudio Cesaroni, PhD**

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