Ionospheric Modelling

with Machine Learning_

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The International Reference Ionosphere and NeQuick – Improving the Representation of the Real-Time Ionosphere
Trieste, Italy 29 September -10 October, 2025

Outline_

01 Introduction

02 Case Studies

03 Challenges & Data

04 Quick ML Demo

“Die Physik ist für die Physiker eigentlich viel zu schwer.”

-David Hilbert

The Big Challenge: Complexity & Data_

- The system is **highly complex**: driven by the sun from above and the lower atmosphere from below.
- **Traditional models** are physics-based or empirical (e.g. GITM, SAMI3, IRI, NeQuick).
- **The Data Surge**: millions of data from satellites, ground-based radars, and GPS receivers.

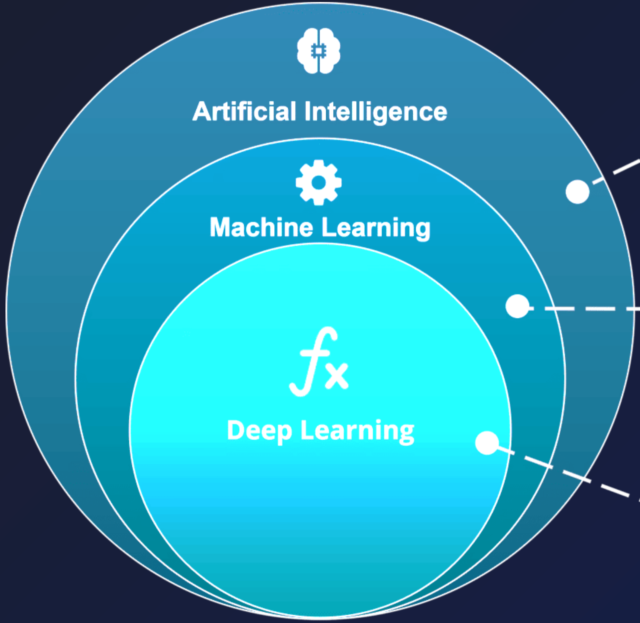
The Problem: How do we make sense of all this data for ionospheric studies?

This is where ML shines!

Why ML is a Perfect Fit for Ionospheric Studies?_

- Big Data handling
- Learns non-linearity
- Speed
- Complementary Tool

Rudiments of Machine Learning_

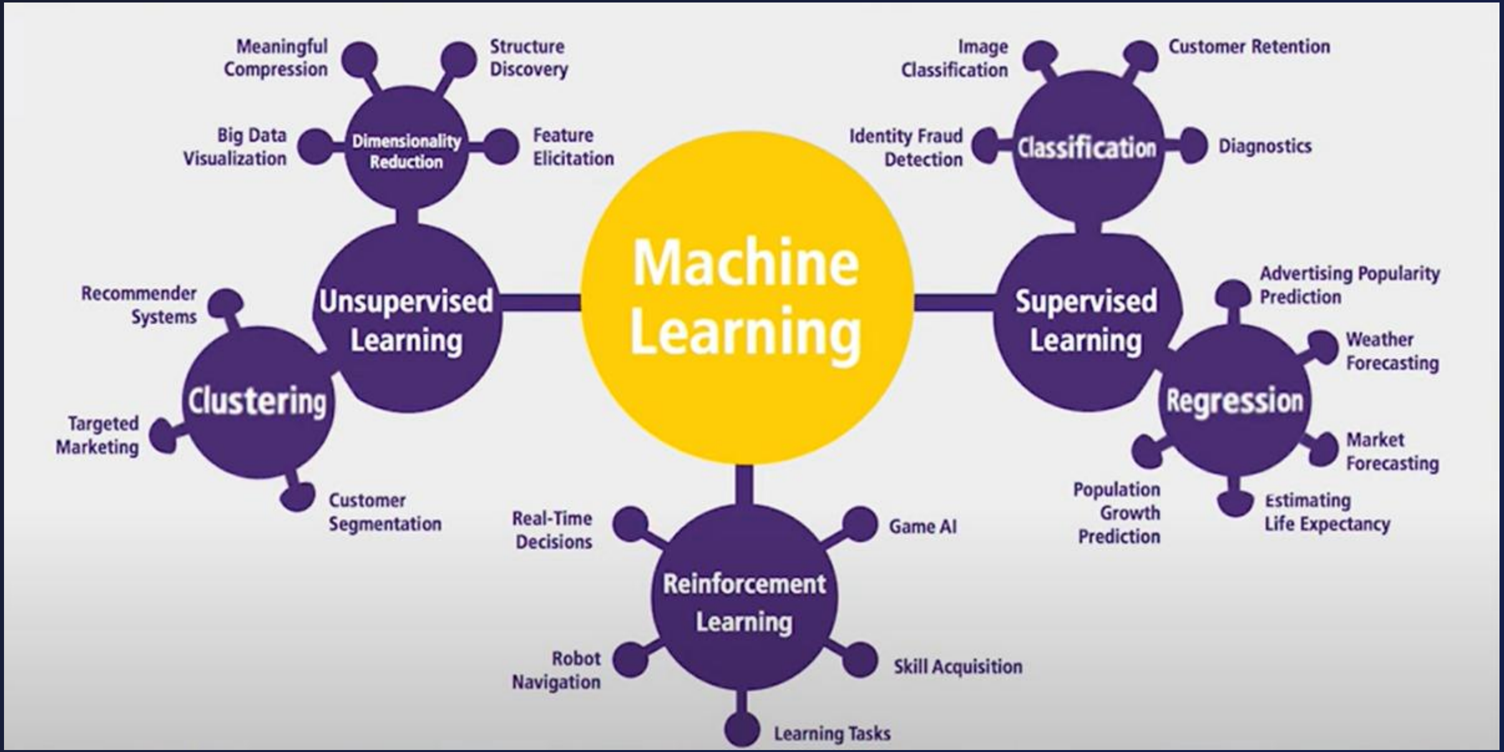


ARTIFICIAL INTELLIGENCE
A technique which enables machines to mimic human behaviour

MACHINE LEARNING
Subset of AI technique which use statistical methods to enable machines to improve with experience

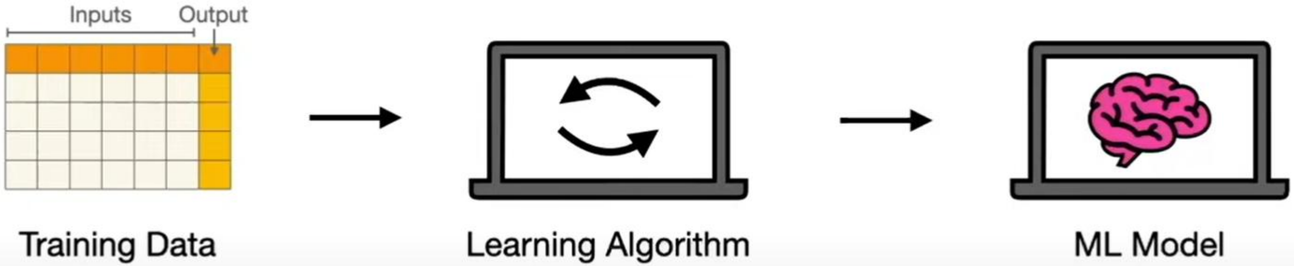
DEEP LEARNING
Subset of ML which make the computation of multi-layer neural network feasible

Categories of ML_

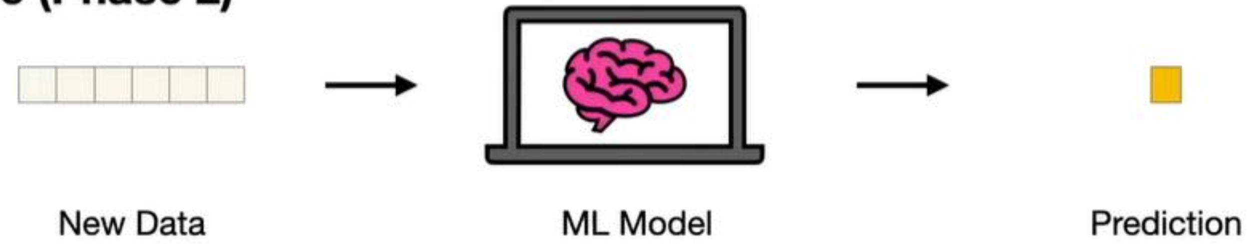


Training (Phase 1)

Fit a model's predictions to reality



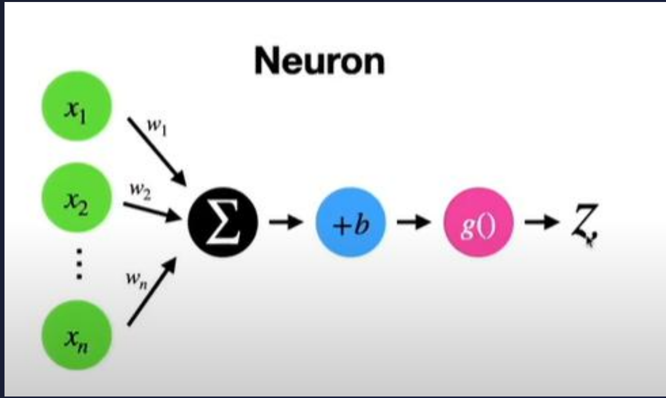
Inference (Phase 2)

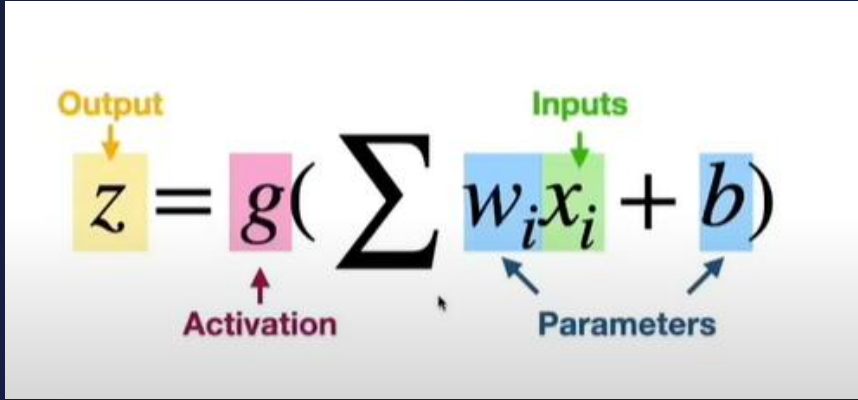


Popular ML techniques_

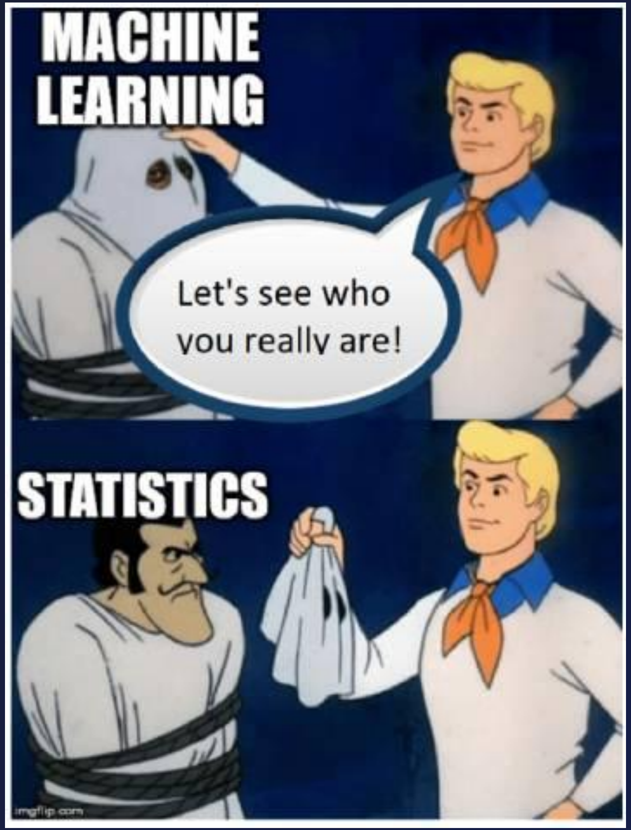
Name	Description	Loss Function	Type
Linear Regression	Predicts continuous output by fitting a linear relationship between inputs and output	Mean Squared Error (MSE)	Regression
Logistic Regression	Models the probability of a binary outcome using a logistic (sigmoid) function	Binary Cross-Entropy (Log Loss)	Classification
Decision Tree	Splits data into branches based on feature values to make predictions	Impurity measures (e.g., Gini, Entropy, MSE)	Both
Random Forest	Ensemble of decision trees averaged (regression) or voted (classification)	Same as Decision Tree	Both
XGBoost	Gradient boosting framework that builds trees sequentially to correct prior errors	Customizable; often Log Loss or MSE	Both
SVM (Support Vector Machine)	Finds the optimal hyperplane that separates classes or fits data	Hinge loss (classification), Epsilon-insensitive loss (regression)	Both

Neural Networks (NN)_

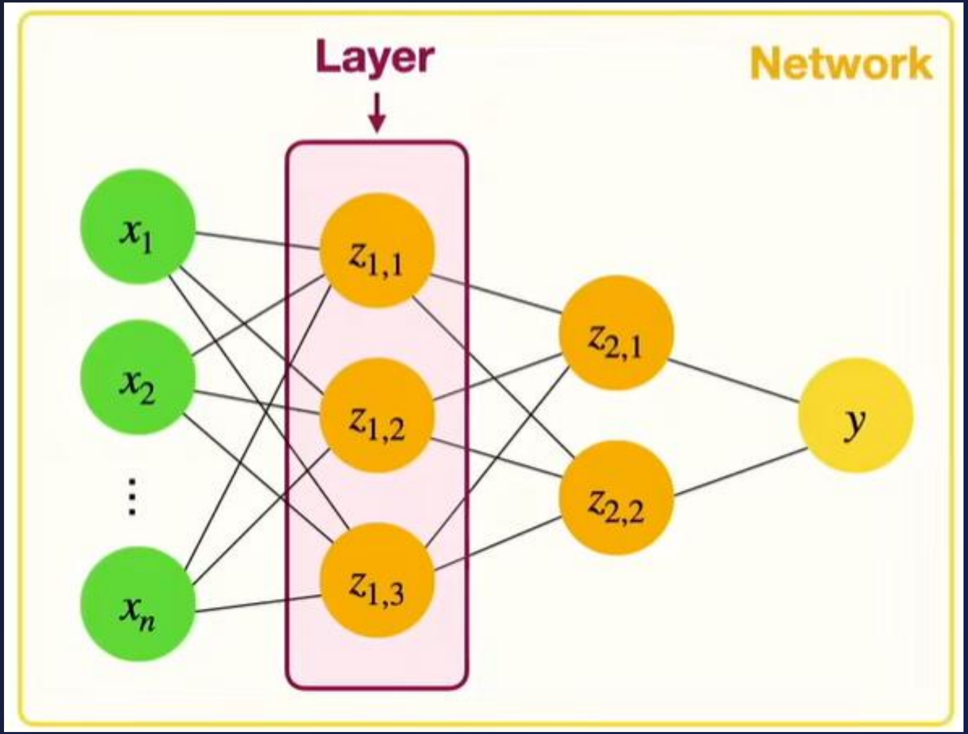




Let’s see who you really are, ML?



Neural Networks (NN)_

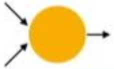


Neural Networks (NN)_

But wait there's more…

Zoo of NN components and architectures

Neurons



Name	Description
Vanilla	Basic unit computing weighted sum + activation; used in FFNNs and CNNs
LSTM	Advanced neuron with memory and gates for long-term dependencies in sequences

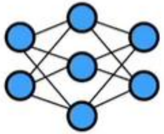
Activations

Name	Description
ReLU	max(0, x); fast, widely used in deep networks
Sigmoid	S-shaped, output in (0, 1); used in binary classification
Tanh	Like sigmoid but centered at 0; output in (-1, 1)
Softmax	Outputs a probability distribution; used in final layer of multi-class classification

Layers

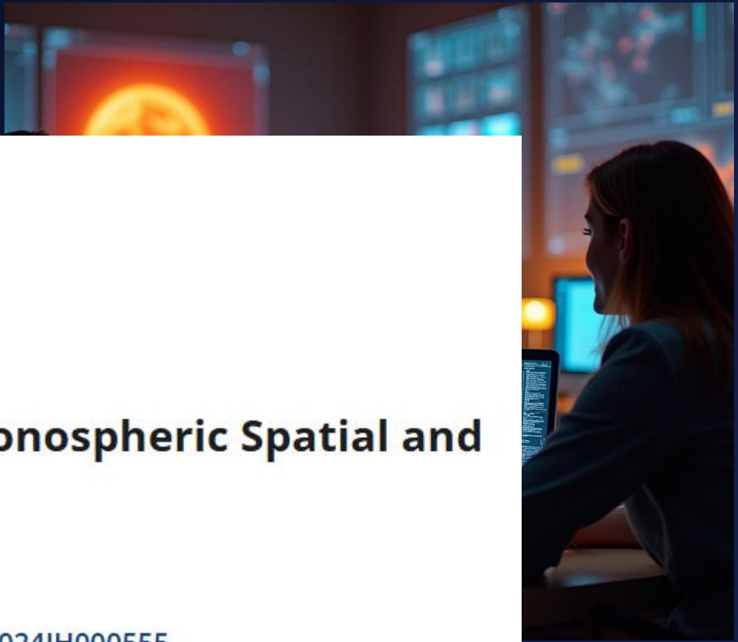
Name	Description
Fully Connected	Standard layer where each neuron connects to all inputs
Recurrent	Maintains memory across timesteps; used in RNNs, LSTMs
Convolutional	Extracts spatial features using filters; used in image data
Attention	Computes weighted importance of different inputs; key in Transformers
Pooling	Downsamples spatial data; used in CNNs to reduce size and noise
Normalization	Stabilizes training by normalizing activations; includes BatchNorm, LayerNorm
Dropout	Randomly deactivates neurons during training to prevent overfitting

Networks



Name	Description
Feedforward (FFNN)	Basic architecture with no loops; used for static input-output tasks
RNN	Handles sequential data using recurrence; remembers previous inputs
CNN	Uses convolutions to process grid-like data such as images
Transformer	Uses self-attention to model sequences without recurrence; state-of-the-art in NLP & beyond

Case Studies



JGR Machine Learning and Computation

Review Article | Open Access

A Review of Machine Learning-Based Ionospheric Spatial and Temporal Modeling

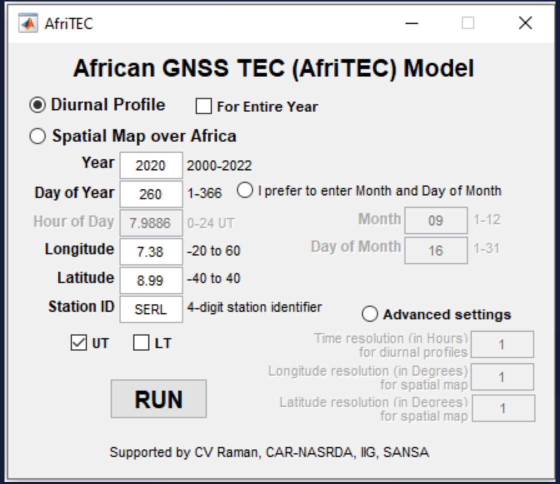
Shuyin Mao, Manuel Hernández-Pajares, Benedikt Soja

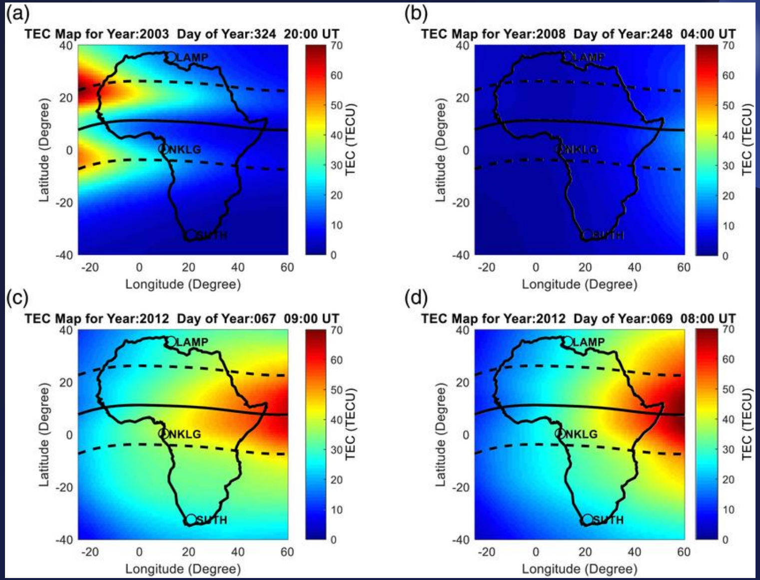
First published: 23 September 2025 | https://doi.org/10.1029/2024JH000555

Mao, S., Hernández-Pajares, M., & Soja, B. (2025). A Review of Machine Learning-Based Ionospheric Spatial and Temporal Modeling. *Journal of Geophysical Research: Machine Learning and Computation*, *2*(3), e2024JH000555. https://doi.org/10.1029/2024JH000555

The AfriTEC model

The AfriTEC model is the first ionospheric TEC model over the entire African region (25° degree West to 60° East, 40° latitude South to 40° North). It was built with an ANN trained with GNSS and COSMIC data.
The model can be used to obtain the ionospheric GNSS TEC at all locations over the African continent.





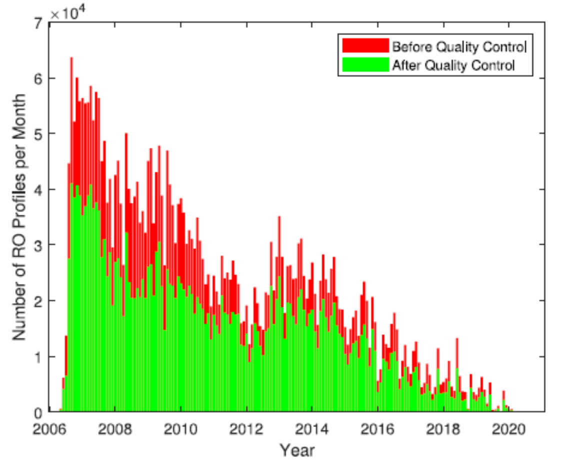
Okoh et al, 2019, https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JA027065

3D NN Model

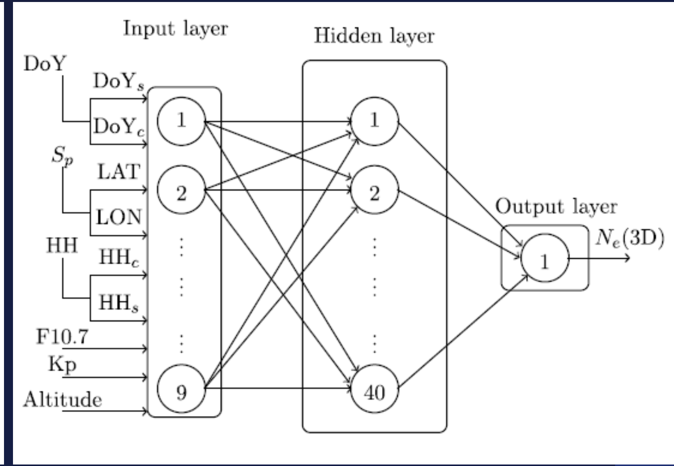
- 3D-NN model *(Habarulema et al, 2021)*

  ANN, RO COSMIC (2006-2019) data

3D NN Model



Data availability before and after data QC



NN architecture for one sub-model

$$DoY_s = sin\left(\frac{2\pi \times DoY}{365.25}\right), \quad DoY_c = cos\left(\frac{2\pi \times DoY}{365.25}\right)$$

$$HH_s = sin\left(\frac{2\pi \times HH}{24}\right), \quad HH_c = cos\left(\frac{2\pi \times HH}{24}\right)$$

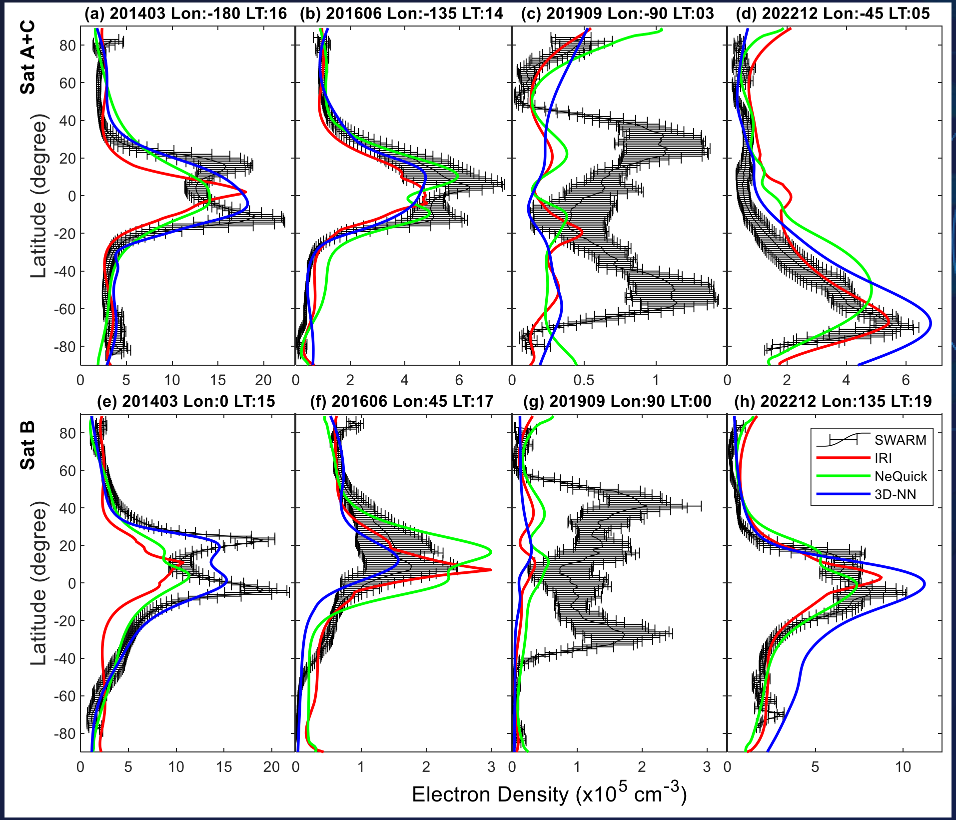
DOY and HH cyclic components

Habarulema, J. B., Okoh, D., Burešová, D., Rabiu, B., et al, (2021). A global 3-D electron density reconstruction model based on radio occultation data and neural networks. Journal of Atmospheric and Solar-Terrestrial Physics, 221, 105702.

Comparison 3D NN, IRI 2020, NeQuick 2

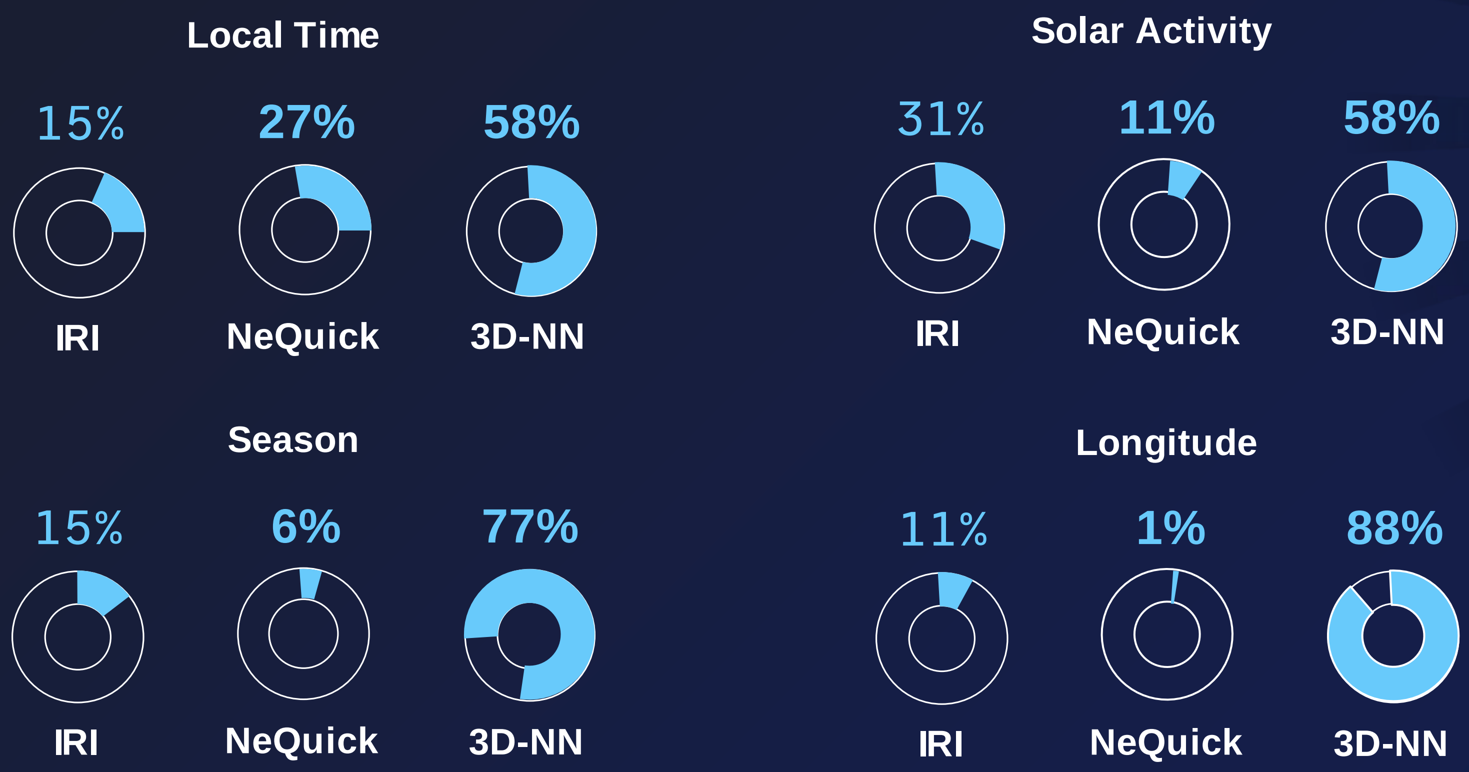
	YYYYMM	Long Band	LT	RMSD (10^5 cm^{-3})		
				IRI 2020	NeQuick 2	3D-NN
Sat A+C	201403	-180	16	3.32	2.28	**1.77**
	201606	-135	14	0.76	**0.50**	0.53
	201909	-90	03	**0.46**	0.47	0.47
	202212	-45	05	**0.70**	1.03	1.23
Sat B	201403	0	15	3.90	2.95	**1.57**
	201606	45	17	0.27	0.51	**0.23**
	201909	90	00	0.82	**0.73**	0.86
	202212	135	19	0.91	**0.67**	1.83

Okoh D., Cesaroni C., Habarulema, J., Migoya-Orué Y., et al. (2024). Investigation of the global climatologic performance of ionospheric models utilizing in-situ Swarm satellite electron density measurements, *Advances in Space Research*, 2024, https://doi.org/10.1016/j.asr.2024.08.052



Monthly mean SWARM measurements vs IRI, NeQuick and 3D-NN model predictions.
Error bars on SWARM indicate the standard deviations of the averaged values for each 1° latitude bin.

Comparison 3D NN, IRI 2020, NeQuick 2



ML: Challenges & Pitfalls_

- “Black box” nature (XAI, SHAP)
- Extrapolation issue
- Data Availability

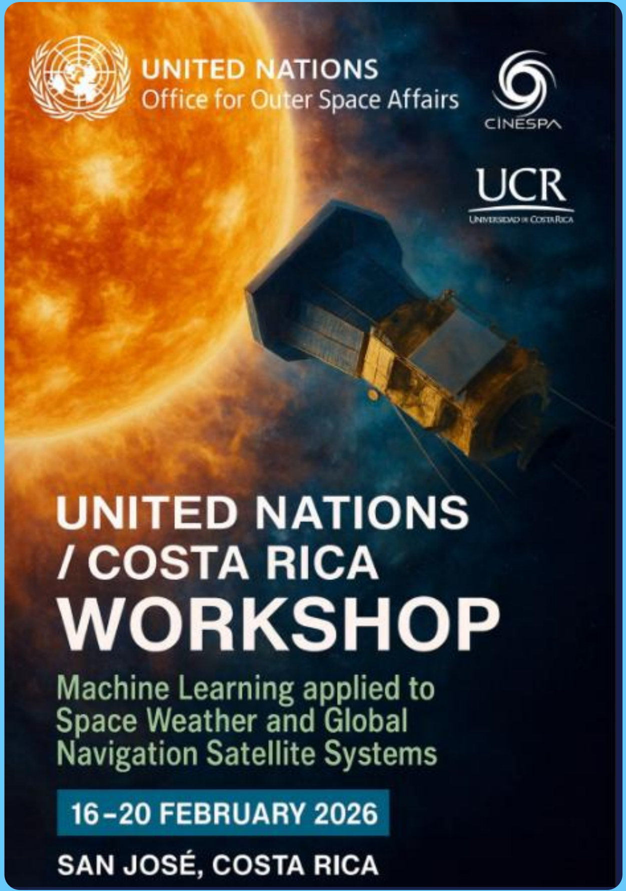
ML: Challenges & Data_

- Data Scarcity/ Quality
- Data Imbalance
- Data labeling

UN/COSTA RICA Workshop on ML for SW & GNSS

https://www.unoosa.org/oosa/en/ourwork/psa/schedule/2026/united-nations-costa-rica-workshop-2026.html

Deadline: 30/09



Quick Demo_

https://tinyurl.com/yenkML

Thanks_

yenca@ictp.it