SPARTAI: Solar PArticles Radiation Tool by AI

An AI-based forecasting pipeline for energetic electrons in Earth's radiation belts

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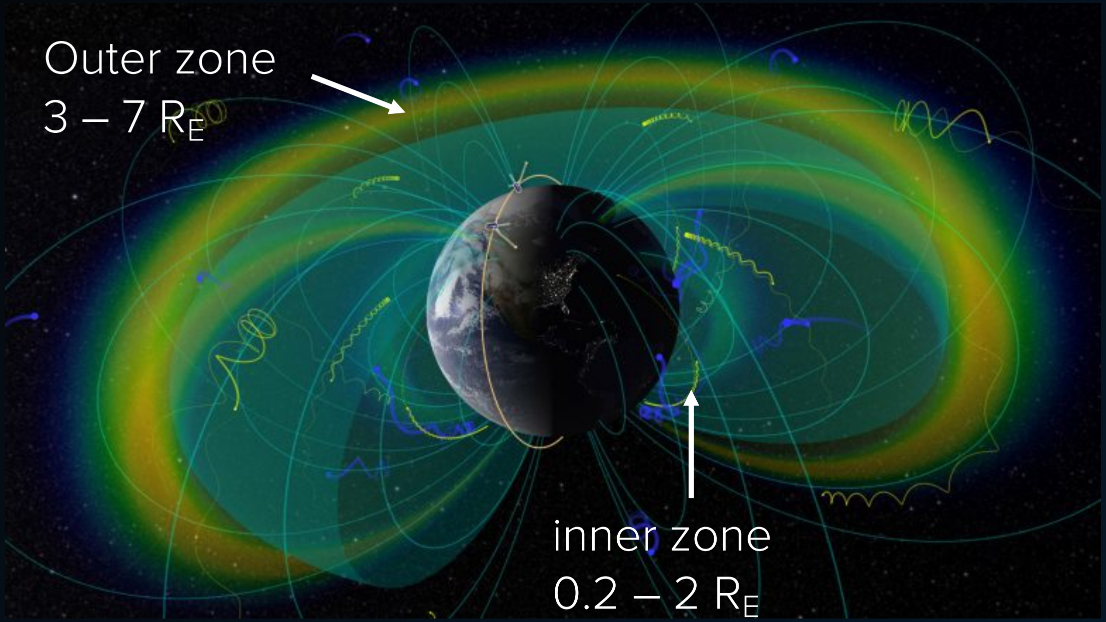
Research conducted at IRAP, UT, as part of the Augura Space project supported by Inria

Van Allen Radiation Zone

Region of space filled with energetic charged particles (e^-, p^+) that are captured by Earth's magnetic field.

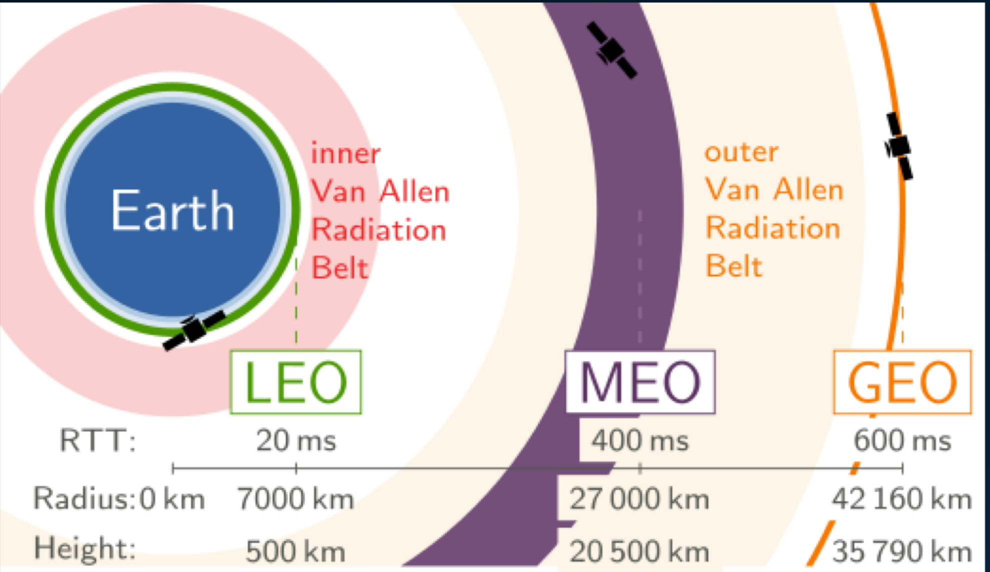


Its properties vary according to the solar activity.

Challenge: How the charged particles are accelerated to very high energies of several million e^- volt (MeV) ?

Radiation hazard for manmade space systems :

- Long-term electron dose effects
- Surface and deep-dielectric charging

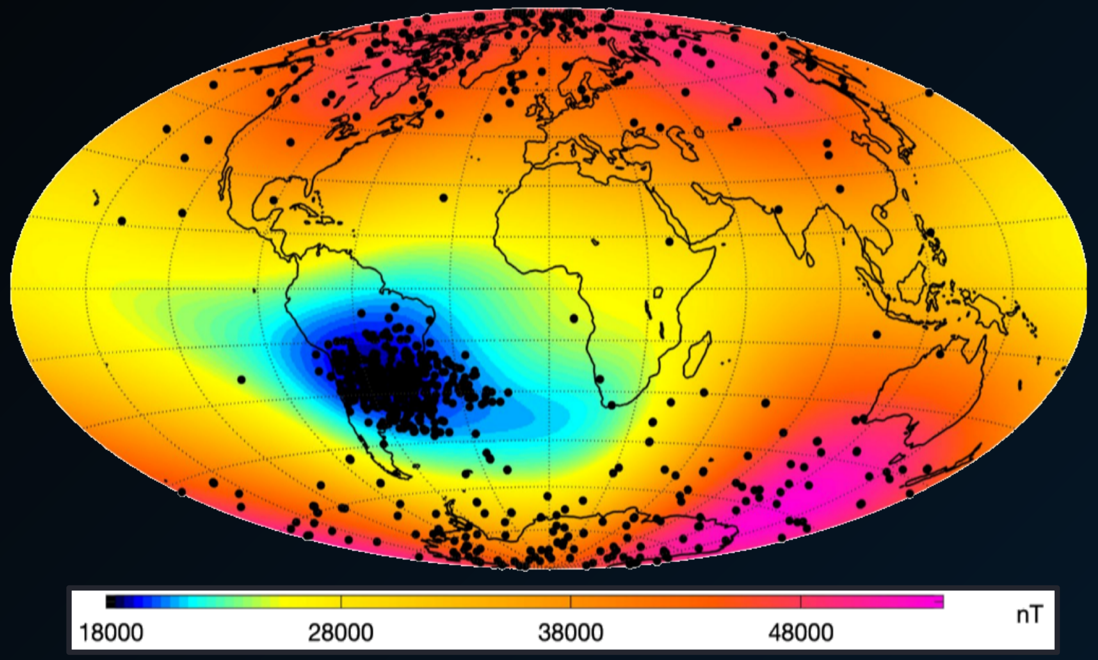


As of Oct 2025 (https://orbit.ing-now.com/)

~14000 space objects in orbit including 6961 in LEO, 521 in GEO, and 191 in MEO.

Satellite operational anomalies

Black dots: spacecraft anomalies registered onboard SWARM in 2013 – 2019. Colour: magnetic field strength



South Atlantic Anomaly: weakened magnetic field region pushing radiation belt particles towards the Earth.

ASTRONOMY

Software error doomed Japanese Hitomi spacecraft

Space agency declares the astronomy satellite a loss.

Nature, 2016

News

Orbital Blames Galaxy 15 Failure on Solar Storm

Intelsat, 2010

Predicting the variations of radiation belt energetic particle fluxes are thus critical

- NOAA: Linear Prediction Filter Analysis of Relativistic Electron at GEO orbit (Baker et al. 1990)
- ESA space weather demo product: Radiation Belt Forecast And Nowcast (RB-FAN) by ONERA.

Predicting energetic radiation belt electrons with AI

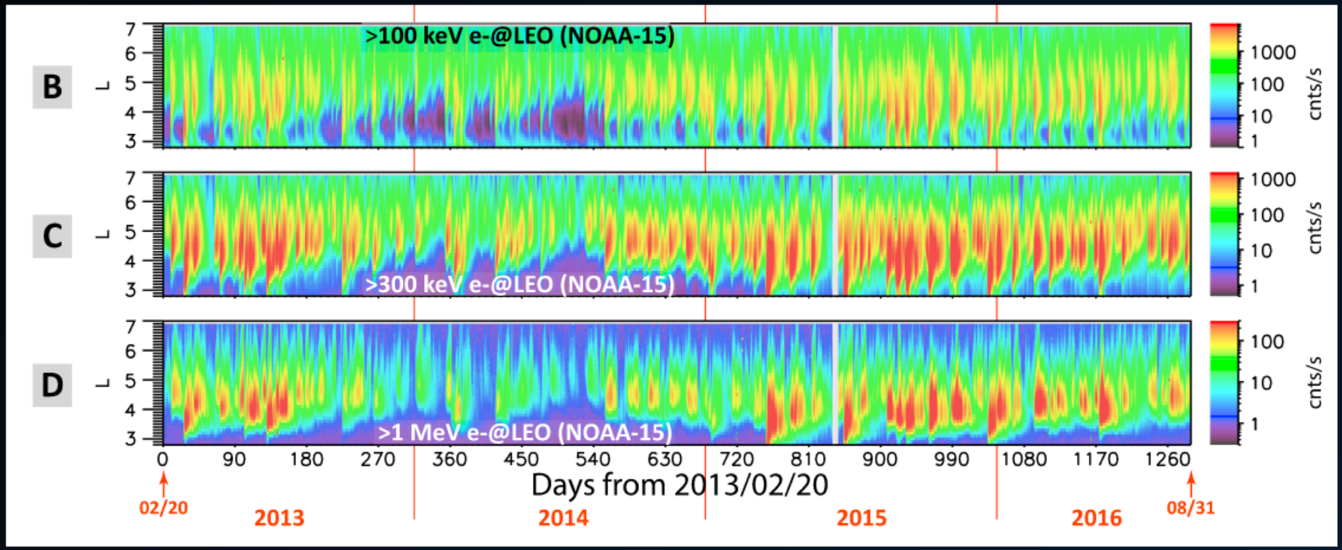
Space Weather

RESEARCH ARTICLE
10.1029/2018SW002095

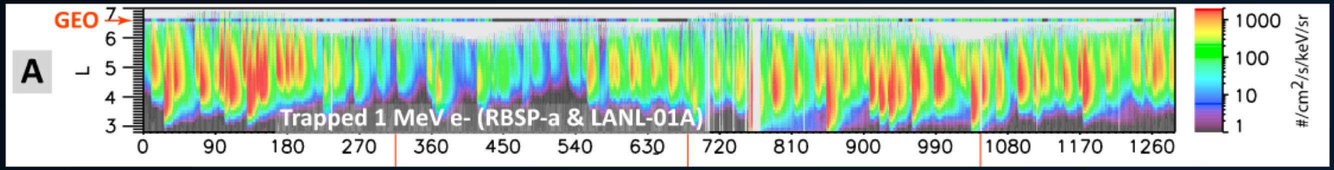
PreMevE: New Predictive Model for Megaelectron-Volt Electrons Inside Earth's Outer Radiation Belt

Modeling MeV electron fluxes from precipitating electrons

Inputs



Target



PreMeVE model series:

- Chen+2019: linear prediction filters
- Pires de Lima+2020: linear regression; neural networks: FNN, 1D-CNN, LSTM.
- Feng+2024: CNN with Transformer layers

Data

- NOAA-15 Polar Operational Environmental Satellite (POES):
  - e^- flux measurements

+ solar wind speed upstream of Earth

Benchmarked with the **Van Allen probe** (2013-2016) and **LANL's GEO** satellite.

SPARTAI – developing our own pipeline

(similar to PreMeVE) **POES** at $t\text{-}\delta t$, ... $t\text{-}1$

(equivalent to LANL s/c) **GOES** at $t\text{-}\delta t$, ... $t\text{-}1$

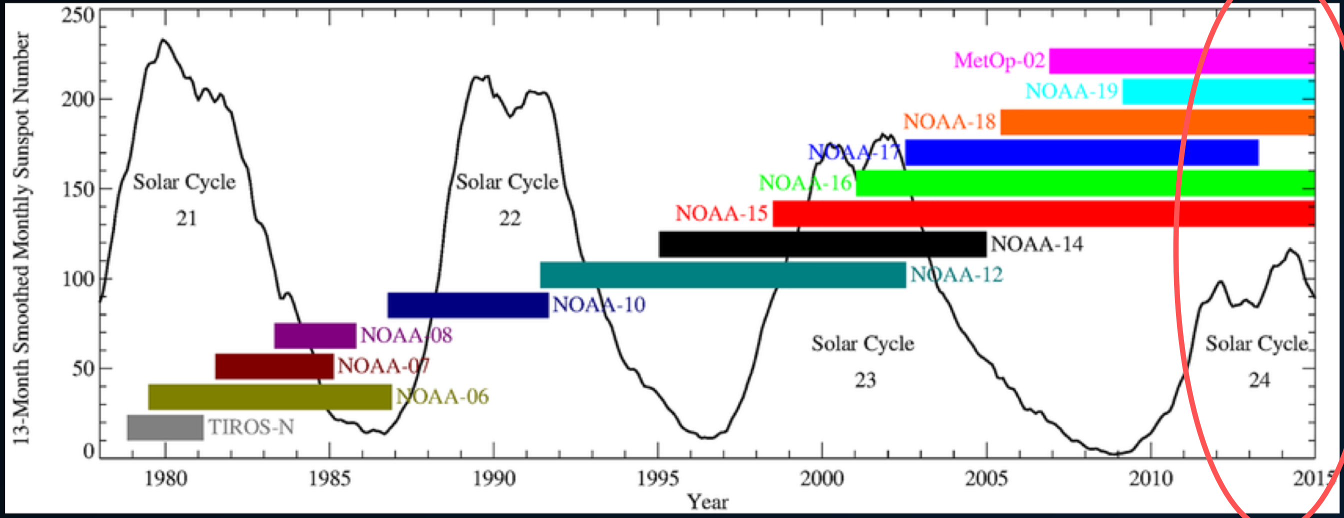
$\mathbf{V_{sw}}$, ..., at $t\text{-}\delta t$, ... $t\text{-}1$

ML algorithms

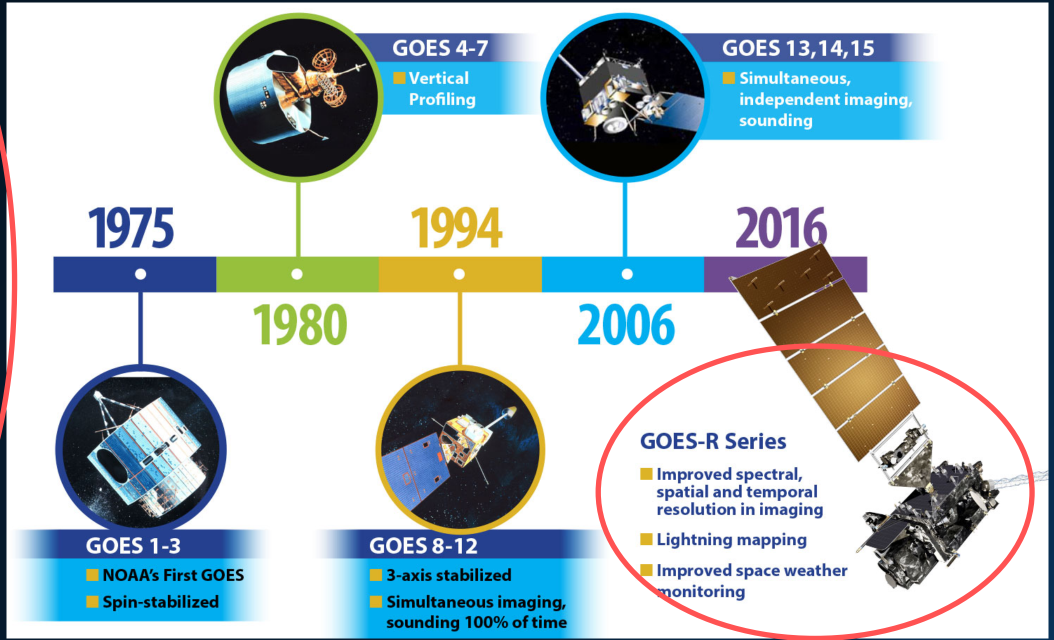
POES 1-MeV at t, $t{+}\Delta t$ (equivalent to the Van Allen probe)

- Taking advantage of large datasets from **Space Environment Monitor (SEM)** onboard weather satellites

Polar Operational Environmental Satellite (POES) / MetOp



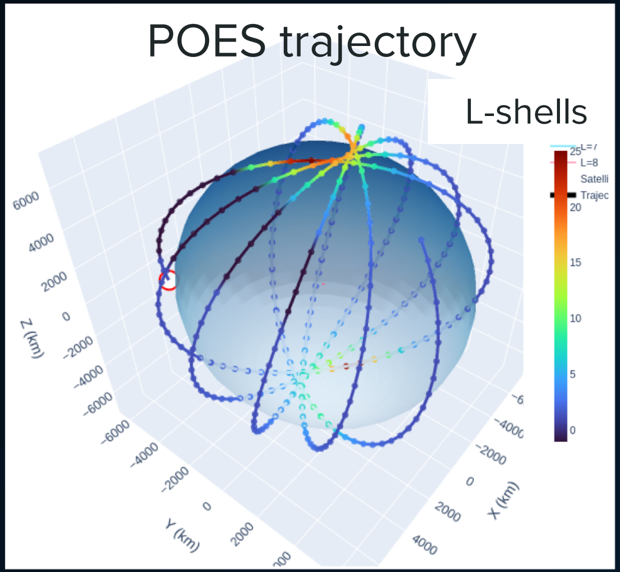
Geostationary Operational Environmental Satellite: GOES



SPARTAI – data preparation

Inputs (inspired by PreMeVE2.0):

- Solar wind speed (**V**) upstream of Earth
- GOES-15 SEM:
  - **E1** (> 0.8 MeV) e^- flux
- POES-15 SEM-2:
  - **E2** (> 100 keV) & **E3** (> 300 keV) e^- fluxes
  - **P6** (> 1 MeV) flux, designed for p^+ but mostly contaminated by 1-MeV e^- flux (Chen+2019).

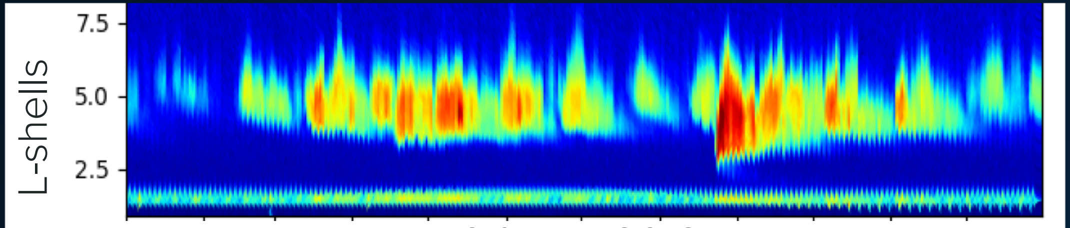


Data processing

Original SEM 2s data: **F** (time, lat, lon, …, fluxes)

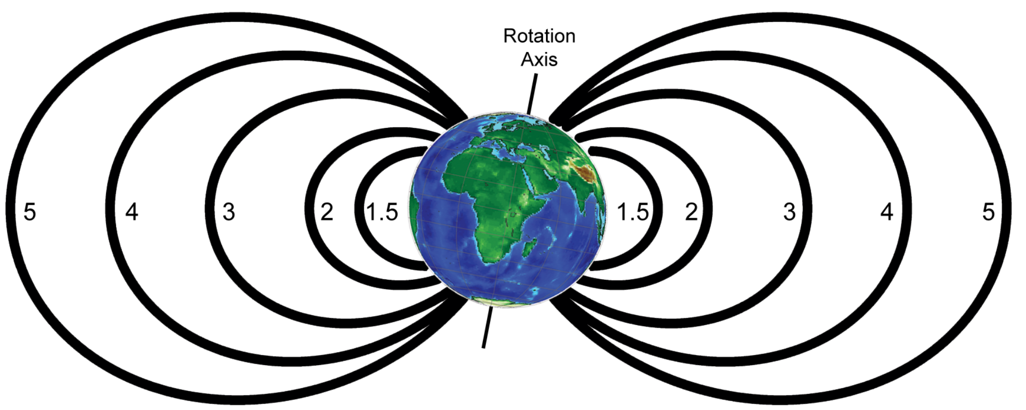
Round, group by time and L-value using average

Tabular data: temporal flux variation for each L



ex: P6 flux in 2018

Coordinates L-value: the set of magnetic field lines which cross the magnetic equator at a number of R_E



L-shells between 2.8 and 6.0, then at 6.6

Benchmarking against PreMeVE2.0

- Modeling 1-MeV e^- flux, **L by L**, using linear regression and neural networks
  - **Train** Feb 2013 – June 2015 (67%); **Validate** July – Dec 2015 (14%); Test: Jan – Aug 2016 (19%).

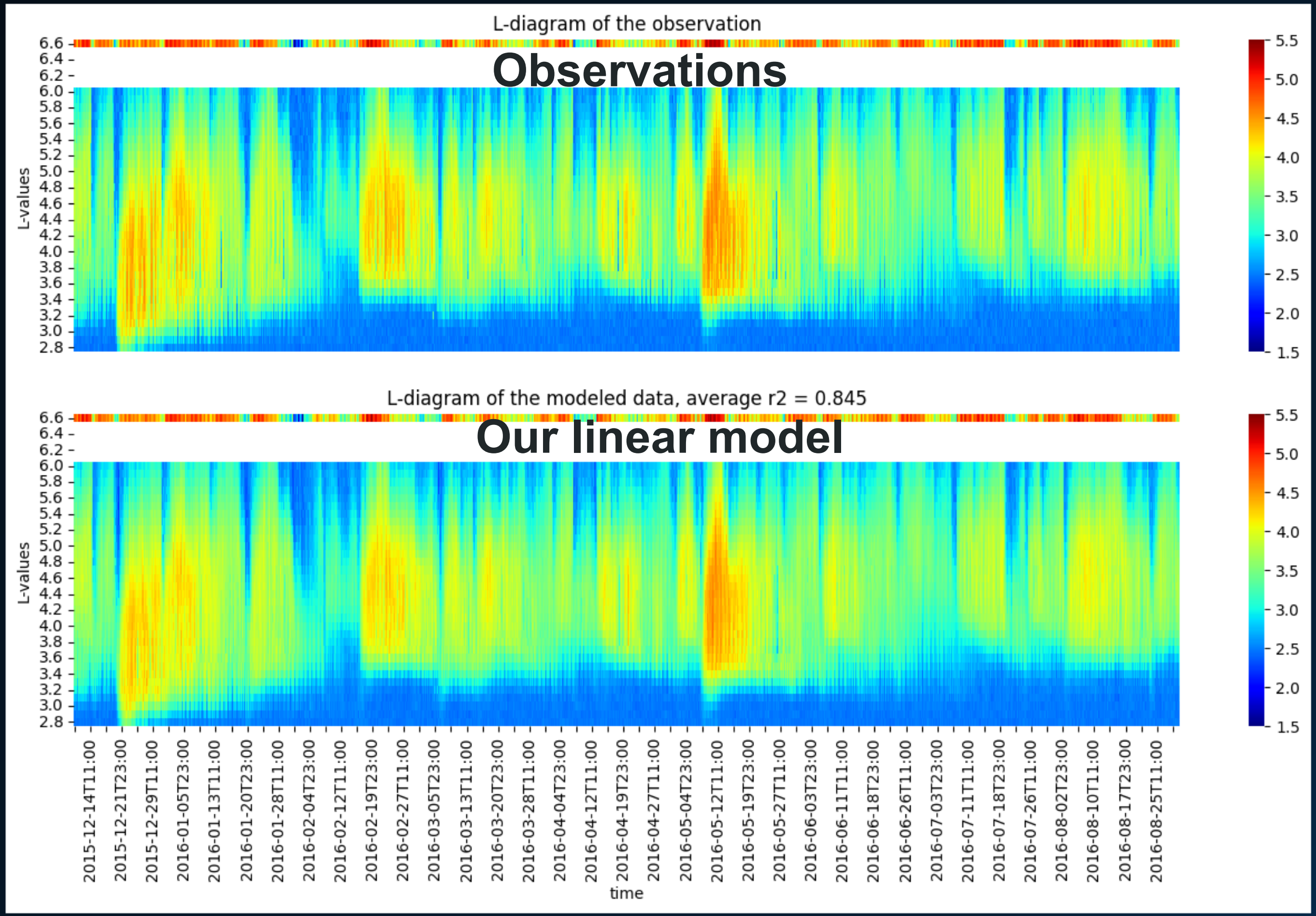
SPARTAI – benchmarking results

Average R^2 of the test data

Model	PreMeV-E 2.0 $2.8 \leq L \leq 6.0$	**SPARTAI $2.8 \leq L \leq 6.0$**
Linear Reg	0.887	**0.845**
FNN-64-32-elu	0.879	**0.841**
LSTM-128	0.886	**0.844**
CNN-64-relu	0.890	**0.828**

Model	PreMeV-E 2.0 L = 6.6 (GEO)	**SPARTAI L = 6.6 (GEO)**
Linear Reg	0.587	**0.861**
FNN-64-32-elu	0.524	**0.821**
LSTM-128	0.589	**0.768**
CNN-64-relu	0.363	**0.601**

Our models are about 5% worse on average, but they are 40% better for GEO.

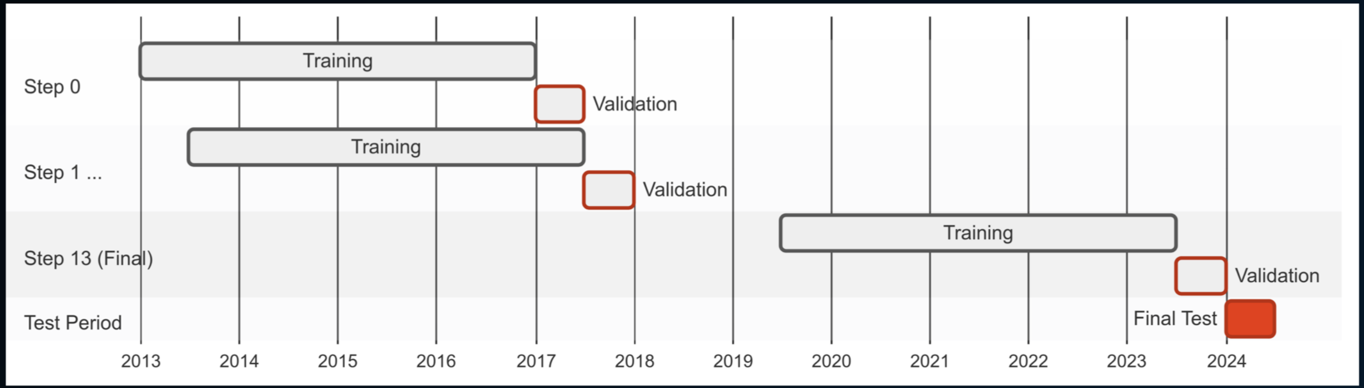


The 1-MeV e⁻ flux variation during geomagnetic storms (e⁻ penetration to low L) are reproduced, despite some different details.

SPARTAI – development

Data Train + validate: 2013 – 2023 (11 years); test: Jan – June 2024

Training strategy: Walk forward validation



i. A model is trained from scratch and then validated.

ii. The training is **resumed** from previous step **with the shifted window**, and then validated with the adjacent data.

iii. Repeat until arriving at the test data.

A model is saved at every step. The best model is chosen for "test".

More solar & geomagnetic activity indicators:

SW speed (V), density (N), magnetic field (Bz), storm disturbance index (Dst), Kp

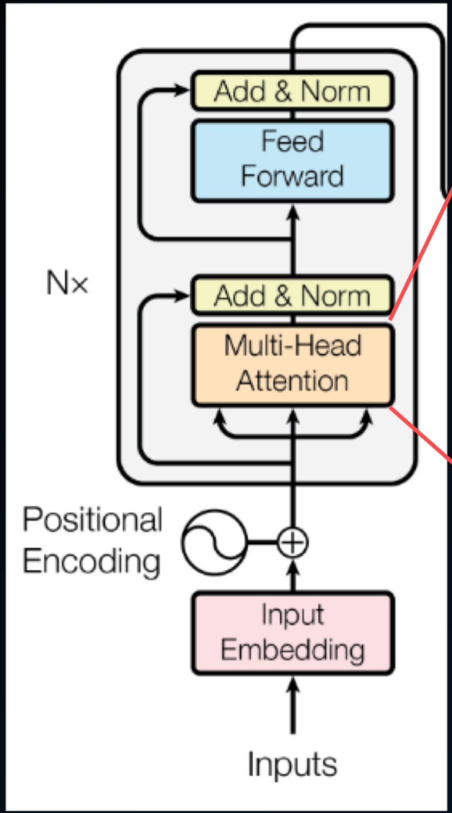
More AI models

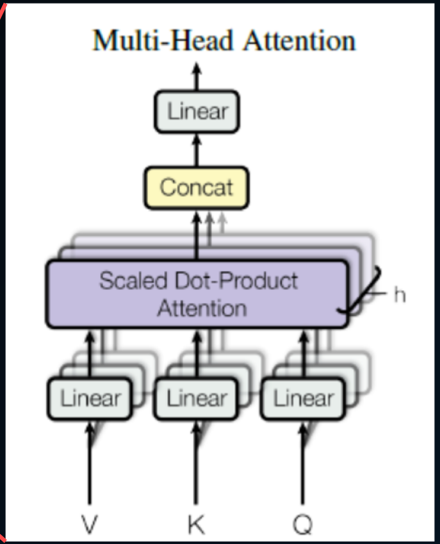
- Ridge regression
- XGBoost
- Transformer Encoder
- Time series foundation model (decoder only).

The Transformer – model architecture

[Vaswani et al. 2017: Attention is All You Need]

Encoder maps an input sequence $(x_1, \ldots, x_n)$ to $(z_1, \ldots, z_n)$





Scaled dot-product attention

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

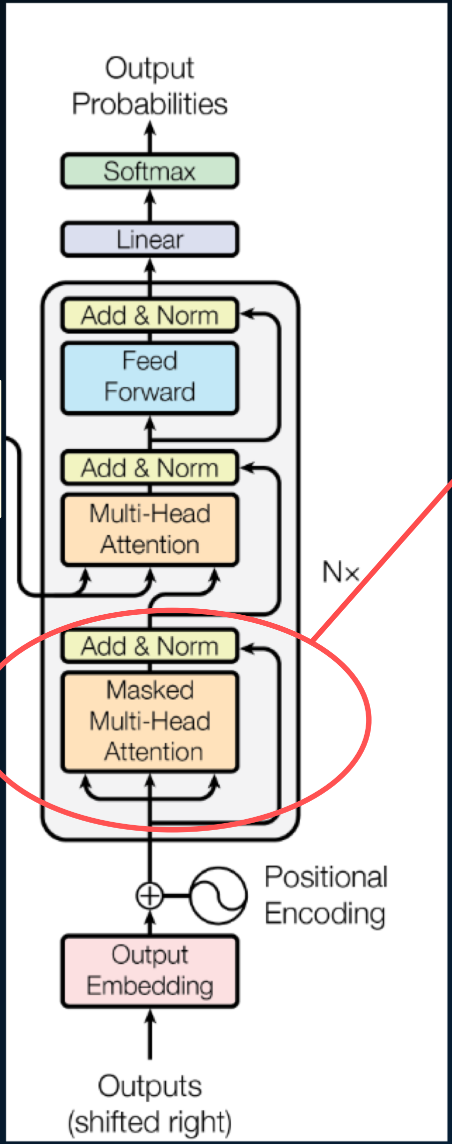
Query (Q): the element seeking info, e.g., each word

Key (K): signposts to locate important elements

Value (V): values carry the info, determining importance

Decoder

"Generation of the outputs"



Encoder stack

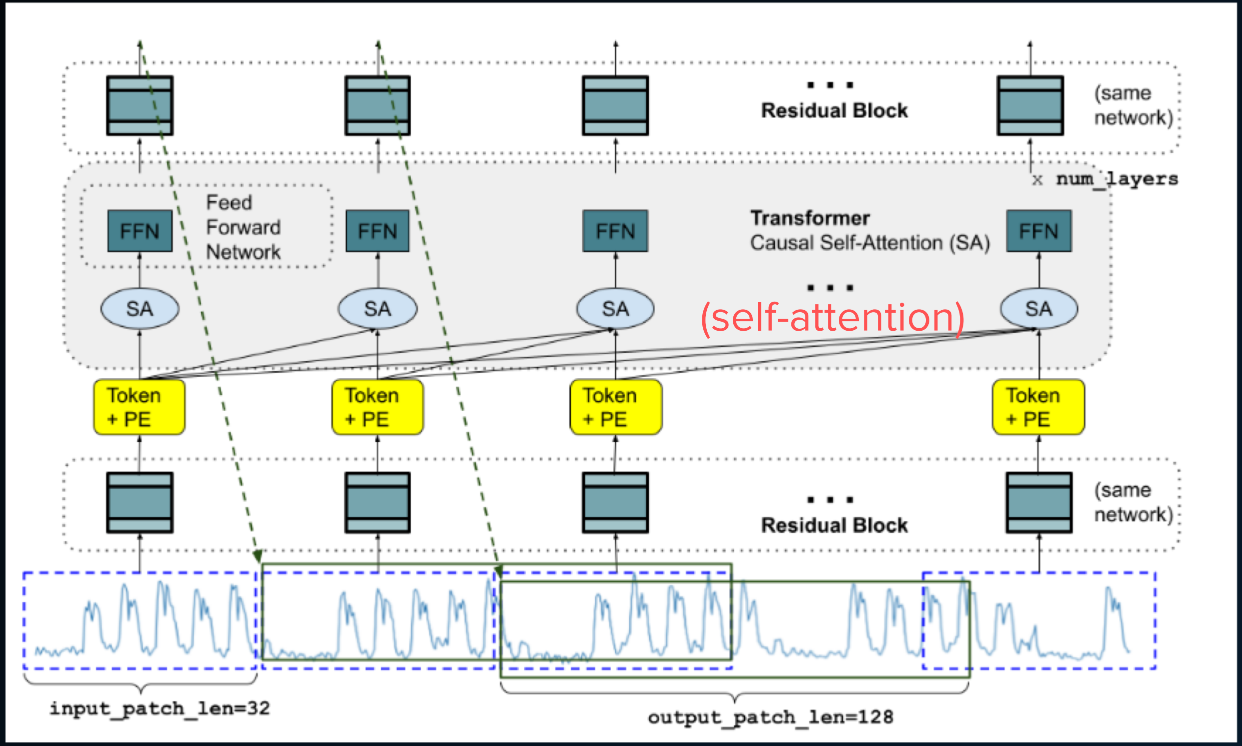
This masking ensures that the predictions for position i can depend only on the known outputs at positions < i.

The output embeddings are offset by one position

Time series foundation model

A DECODER-ONLY FOUNDATION MODEL FOR TIME-SERIES FORECASTING *Das+2024, ArXiv*

Decoder style attention model with **input patching** (similar to a token in language models)



Pretrained using a large time-series corpus, e.g., Google Trends (https://trends.google.com), Wiki pageviews, traffic, weather, electricity, synthetic, M4, …, with different granularities from hourly to monthly.

SPARTAI - our application (TimesFM 2.4)

- Zero-shot (default) forecast
- Linear regression on covariates (our input variables, shifted in time), then we apply the foundation model on the residual

SPARTAI – our development results

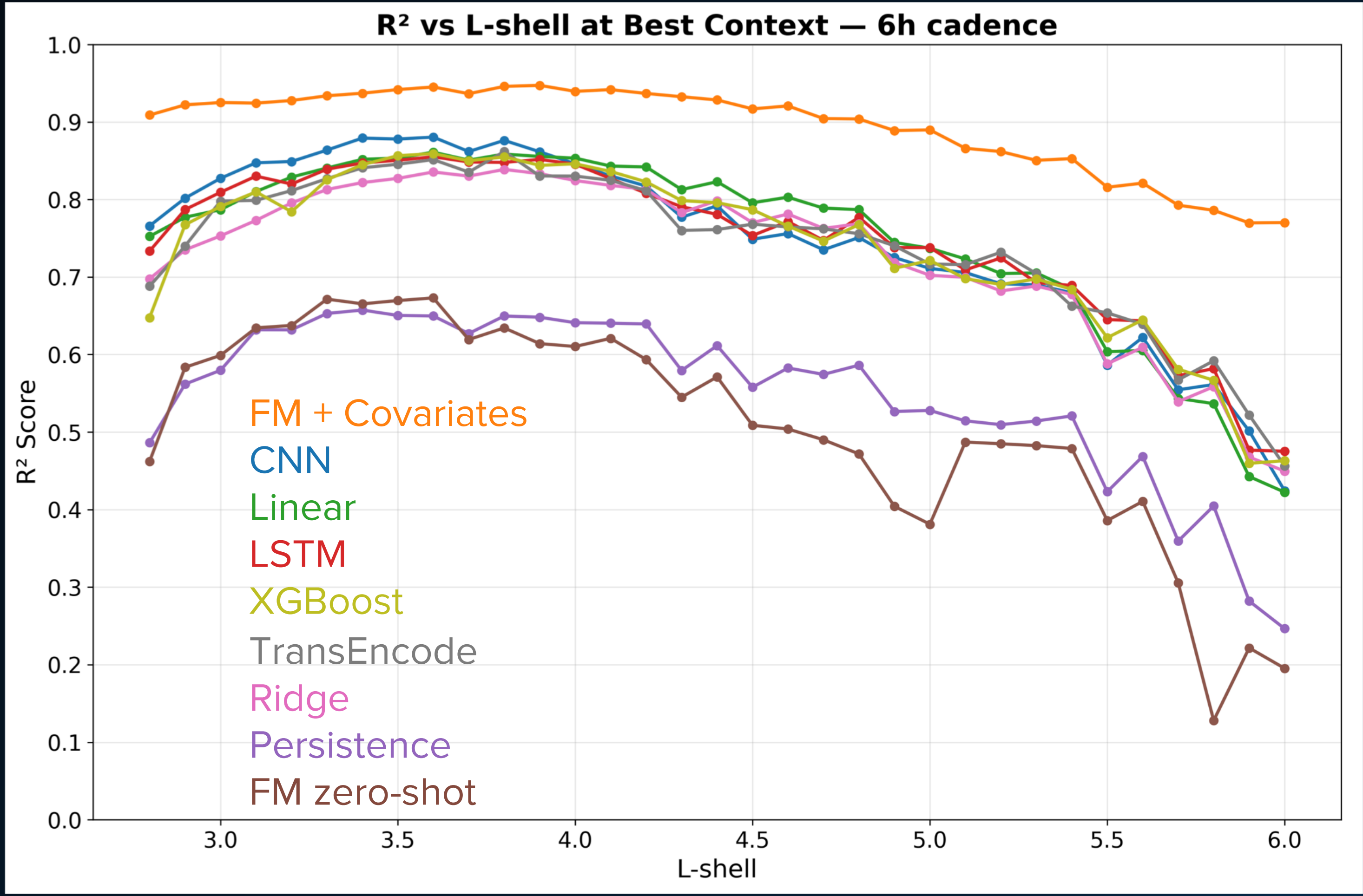
Linear, CNN, LSTM are identical to the benchmarking experiment.

Persistence: use last value as prediction.

Other models: simplest working architectures with no fine-tuning.

We performed experiments to find best context length (history length used for prediction). No R^2 improvement for > 24 hours.

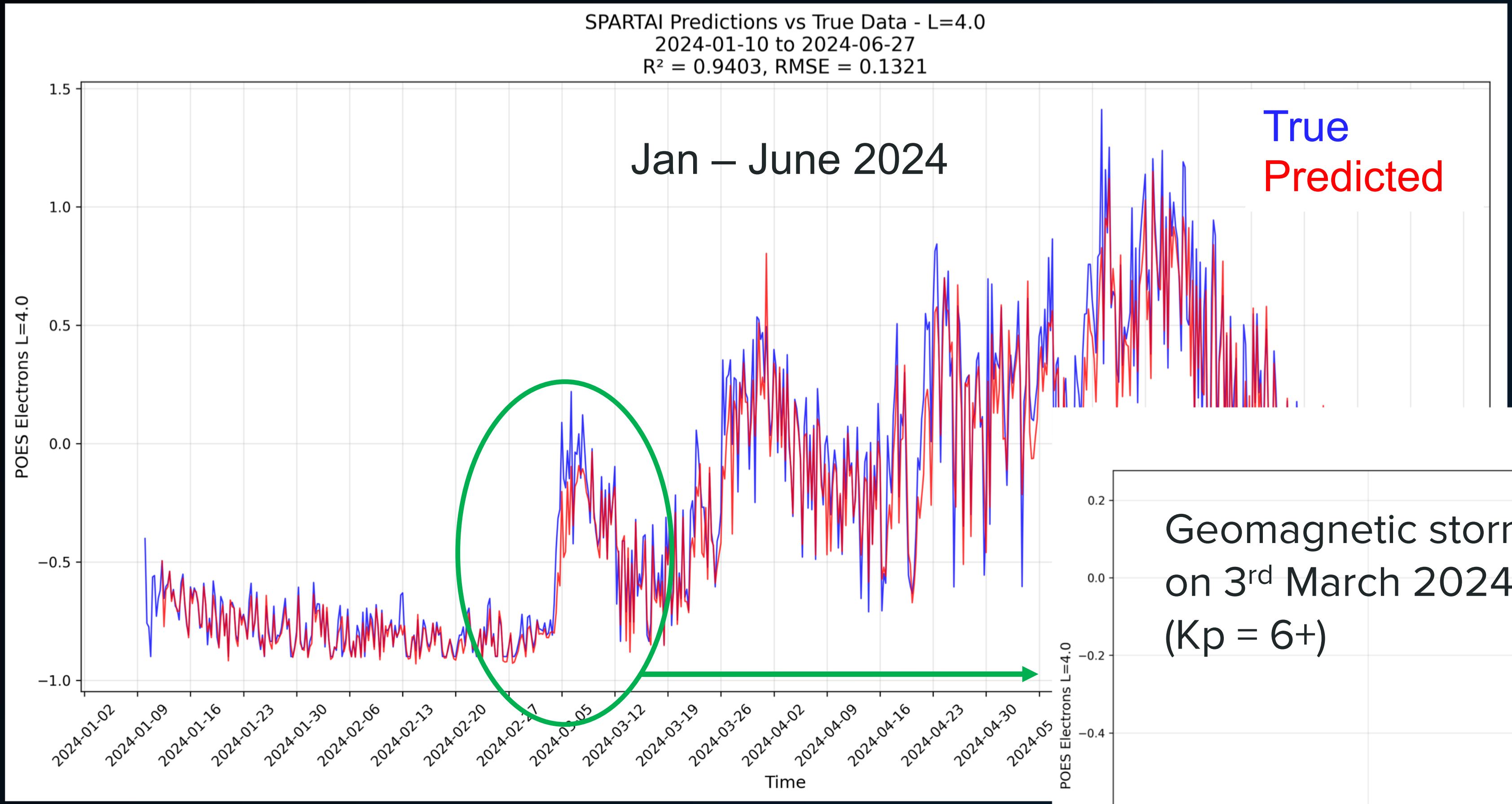
R^2 score for 6h forecast (Jan – June 2024)

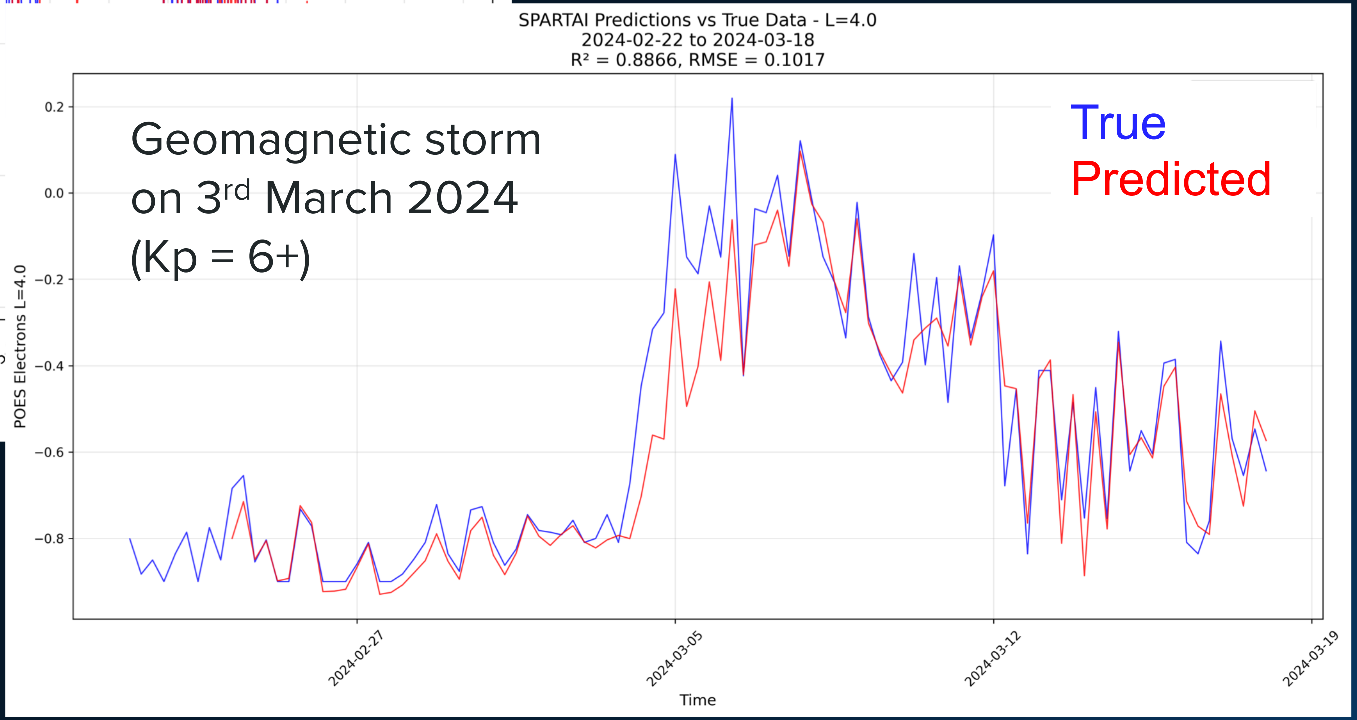


*The **TimesFM + covariates** outperforms all models for all L-shells, reaching R^2 over 0.9 for L < 4.6.*

SPARTAI – inference example

TimesFM + covariates 1-MeV e⁻ flux prediction for L=4.0





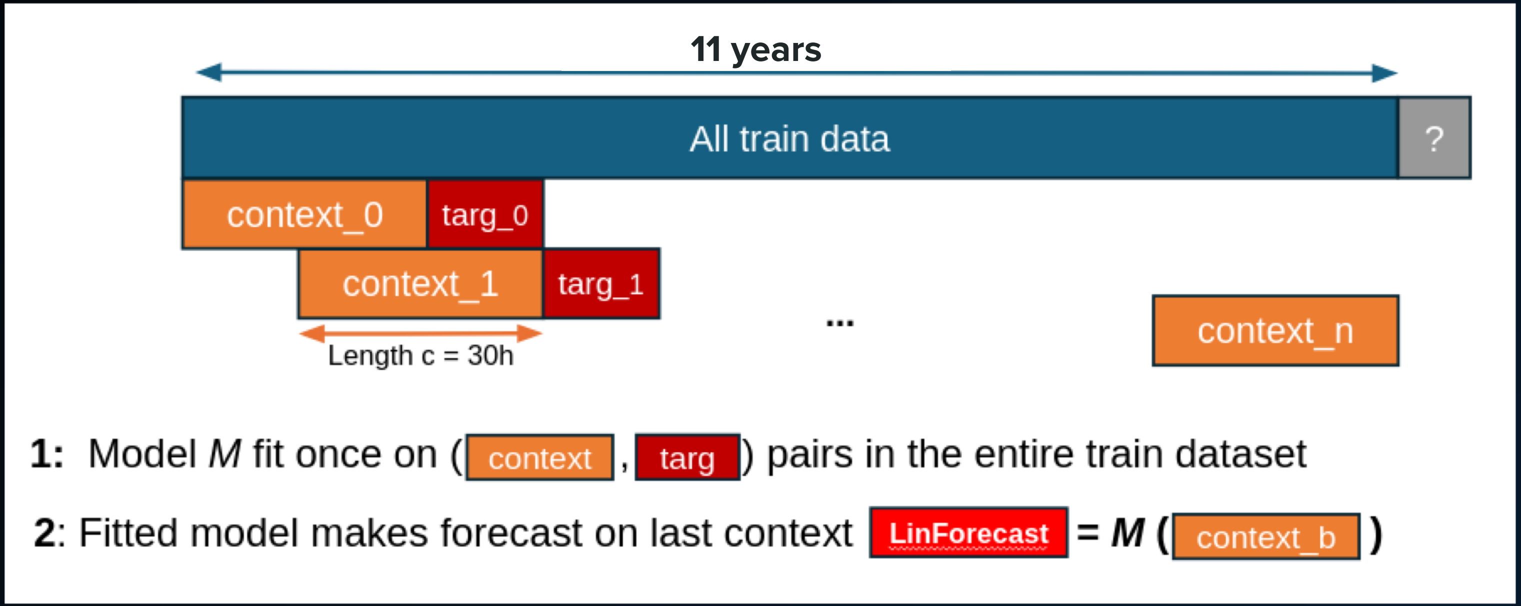
Some underestimated peaks and delay during 1-MeV e⁻ flux enhancement during the storm

Large-scale variations including 1-MeV e⁻ flux enhancements during storms are reproduced

Classic ML approaches vs FM application

Similar to PreMeVE, we find that the **linear regression** model is the most successful. => The relationship between dynamics of **trapped 1-MeV e^-** and the **precipitation e^-** is dominated by **linear components**.

Classic approach



- The training is done on the 11 years of data (with walk forward validation). Model is used with the latest context for a prediction.

Introduction of FM model

- Zero-short prediction yields very poor results
  - ➢ We handle the linear part first, then compute the residuals

R(i) = M(context_i) - targ_i for i< b

- ➢ The pretrained model is used to estimate the residuals (nonlinear).

Summary and perspectives

We develop a prototype pipeline for 1-MeV electron flux prediction for the outer radiation belt.

Benchmarking:

- We develop our own equivalent models (Linear, FNN, CNN, LSTM) to PreMeVE 2.0.
- We train, validate, and test with our defined (equivalent) dataset
  - Slightly poorer results to PreMeVE 2.0 (poorer data quality?)
  - Linear regression works best.

Development:

- We add more models (Ridge, XGBoost, Transformer Encoder), as well as apply TimesFM.
- We train and validate with more data (1 solar cycle), and test in Jan – June 2024 (solar max)

✓ Linear fitting on latest context + nonlinear fitting with TimesFM works best

How do we explain this physically?

Perspectives: improve time cadence and forecast horizons, produce derived products.

Back-up slides

Data processing

Original POES data (2s): geographical coordinates (lat, lon, alt), L-value, magnetic local time, flux measurements

shape: (118_953_997, 9)

time --- str	lat --- f64	lon --- f64	L --- f64	MLT --- f64	alt --- f64	e2 --- f64	e3 --- f64	p6 --- f64
2013-01-01 00:02:39	48.373	80.639	2.07	5.34	819.2	69.44444	null	487.80487
2013-01-01 00:02:43	48.142	80.541	2.05	5.33	819.1	69.44444	null	731.70734
2013-01-01 00:02:45	48.027	80.493	2.05	5.33	819.1	69.44444	null	null
2013-01-01 00:02:53	47.564	80.301	2.01	5.31	818.9	69.44444	null	243.90244
2013-01-01 00:02:55	47.448	80.254	2.01	5.31	818.9	138.88889	133.33333	null
…	…	…	…	…	…	…	…	…
2025-06-03 07:22:39	81.07	105.081	18.78	14.12	811.7	486.11108	533.3333	null
2025-06-03 07:22:41	81.106	104.344	18.87	14.09	811.7	694.4444	533.3333	243.90244
2025-06-03 07:22:43	81.14	103.601	18.96	14.06	811.7	416.66666	400.0	null
2025-06-03 07:22:45	81.173	102.852	19.06	14.03	811.7	763.88885	1066.6666	null
2025-06-03 07:22:47	81.205	102.098	19.15	14.0	811.7	694.4444	1066.6666	null

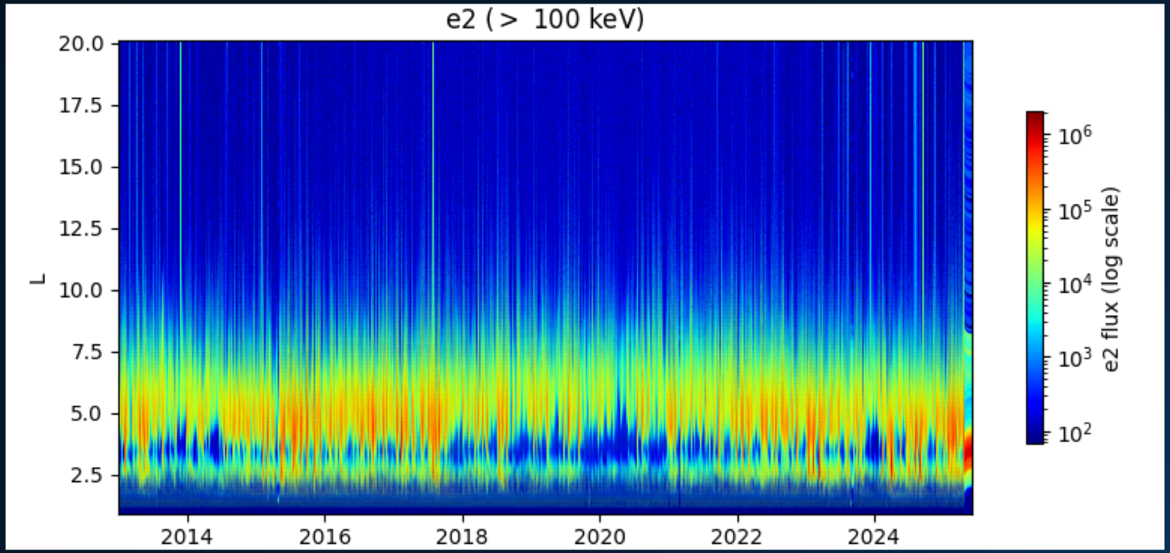
- ➢ Round from 2s to 1h; round L-value to one decimal place
- ➢ Limit 1.0 ≤ L≤ 20. Group by time and L using mean

Processed POES data: hourly averaged flux at each L for each energy channel (191 * 3 = 573 columns)

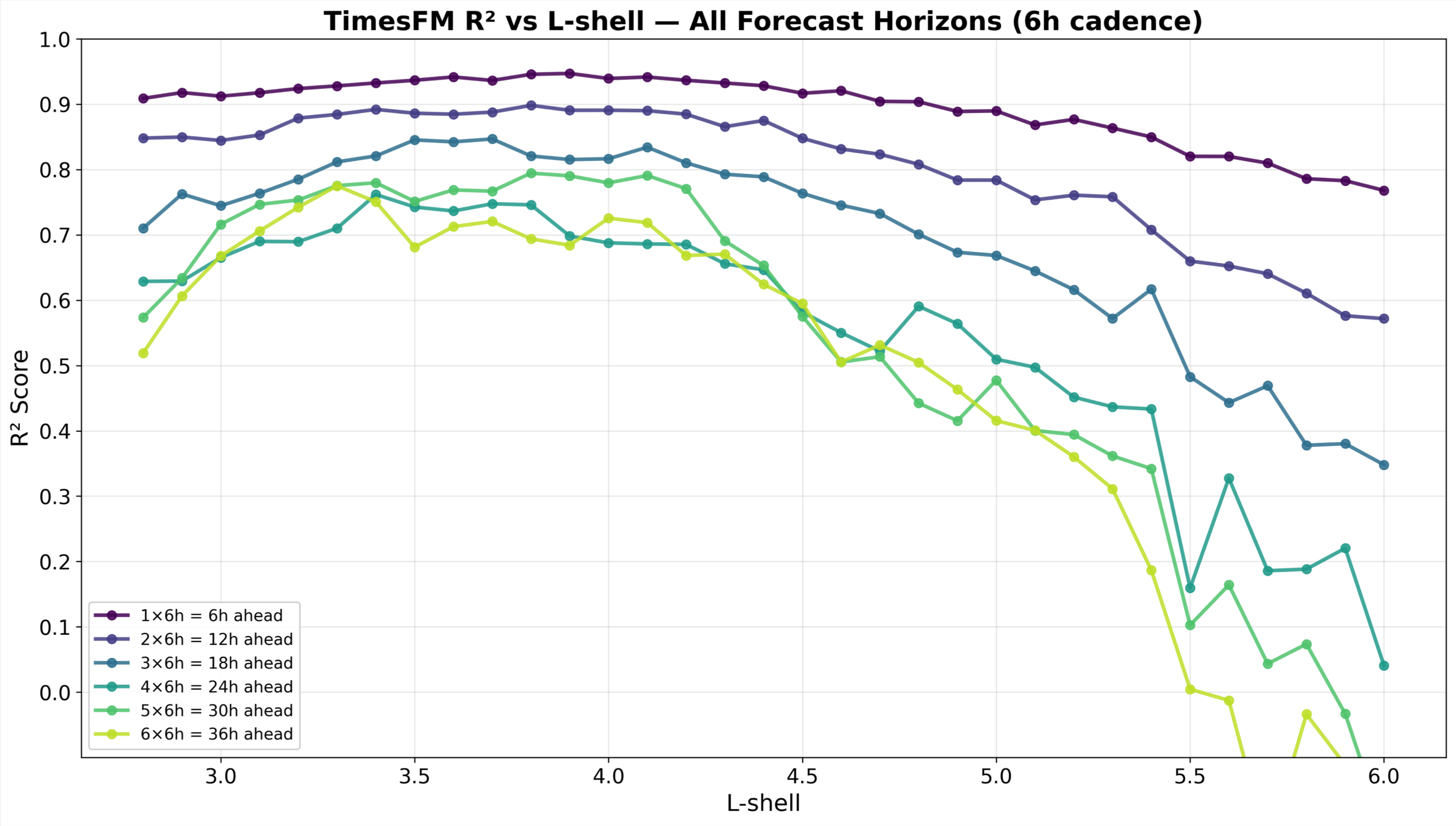
shape: (107_063, 574)

time --- datetime[μs]	e2_2.1 --- f64	e2_2.0 --- f64	e2_1.9 --- f64	…	p6_19.9 --- f64	p6_20.0 --- f64	p6_18.8 --- f64	p6_19.3 --- f64
2013-01-01 00:00:00	77.16049	89.285711	92.59259	…	null	null	null	null
2013-01-01 01:00:00	1192.63282	515.232953	261.99494	…	null	null	null	null
2013-01-01 02:00:00	3780.864051	3671.874833	1436.965754	…	null	null	null	null
2013-01-01 03:00:00	154.671713	120.192305	217.803024	…	null	null	null	null
2013-01-01 04:00:00	146.604934	138.888885	123.456789	…	null	null	null	null
…	…	…	…	…	…	…	…	…
2025-06-03 03:00:00	47611.349072	48069.055736	50791.01229	…	null	null	null	null
2025-06-03 04:00:00	7165.798437	3281.249985	86.805553	…	null	null	487.80489	243.90244
2025-06-03 05:00:00	32385.543852	28527.92126	10938.977039	…	null	null	null	null
2025-06-03 06:00:00	102150.460167	156109.7208	191520.826	…	325.20325	null	243.90244	243.90244
2025-06-03 07:00:00	17253.924391	9978.718239	7723.765115	…	null	null	null	null

Visualization of L-time diagram of e2 flux



Performance of model forecasting with TimesFM + covariates



Particles access to the Earth's magnetic field

Kallenrode, 1998
D. A. Bryant 1993

Rigidity measures momentum of the particle. It refers to the fact that a higher momentum particle will have a higher resistance to deflection by a magnetic field.

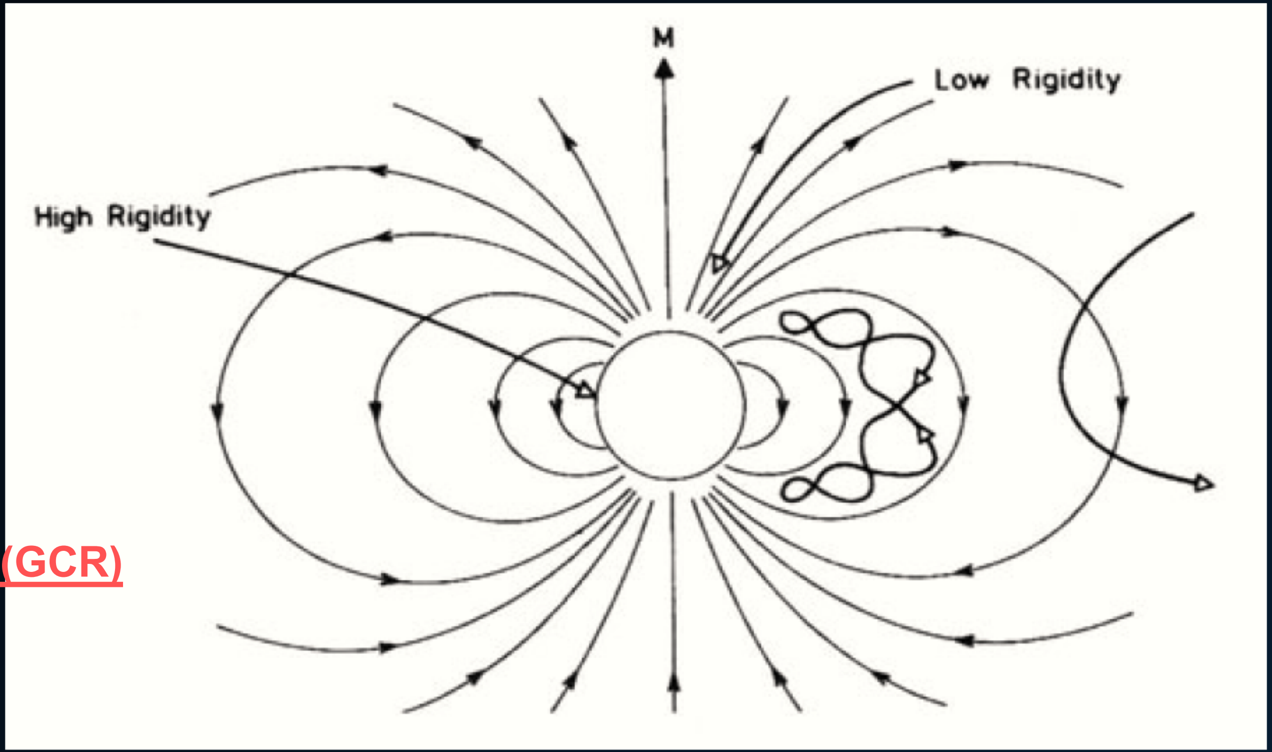
High-rigidity particles

- able to traverse the magnetosphere
- no long-lived trapped particle components with high rigidities exists

Galactic cosmic rays (GCR)

Depending on their direction of incidence, they either

- penetrate deep into the magnetosphere and interact with the upper atmosphere
- deflected back into space.



Low-rigidity particles

Only at the polar cusps can these particles penetrate into the magnetosphere

Particles hitting the low-latitude magnetosphere from the outside perform half a gyro-orbit inside the magnetosphere and then are reflected back into space.

Long-lived component: particles are trapped inside the radiation belts. Their motion is regulated by the adiabatic invariants.