

PAGER and MAP projects

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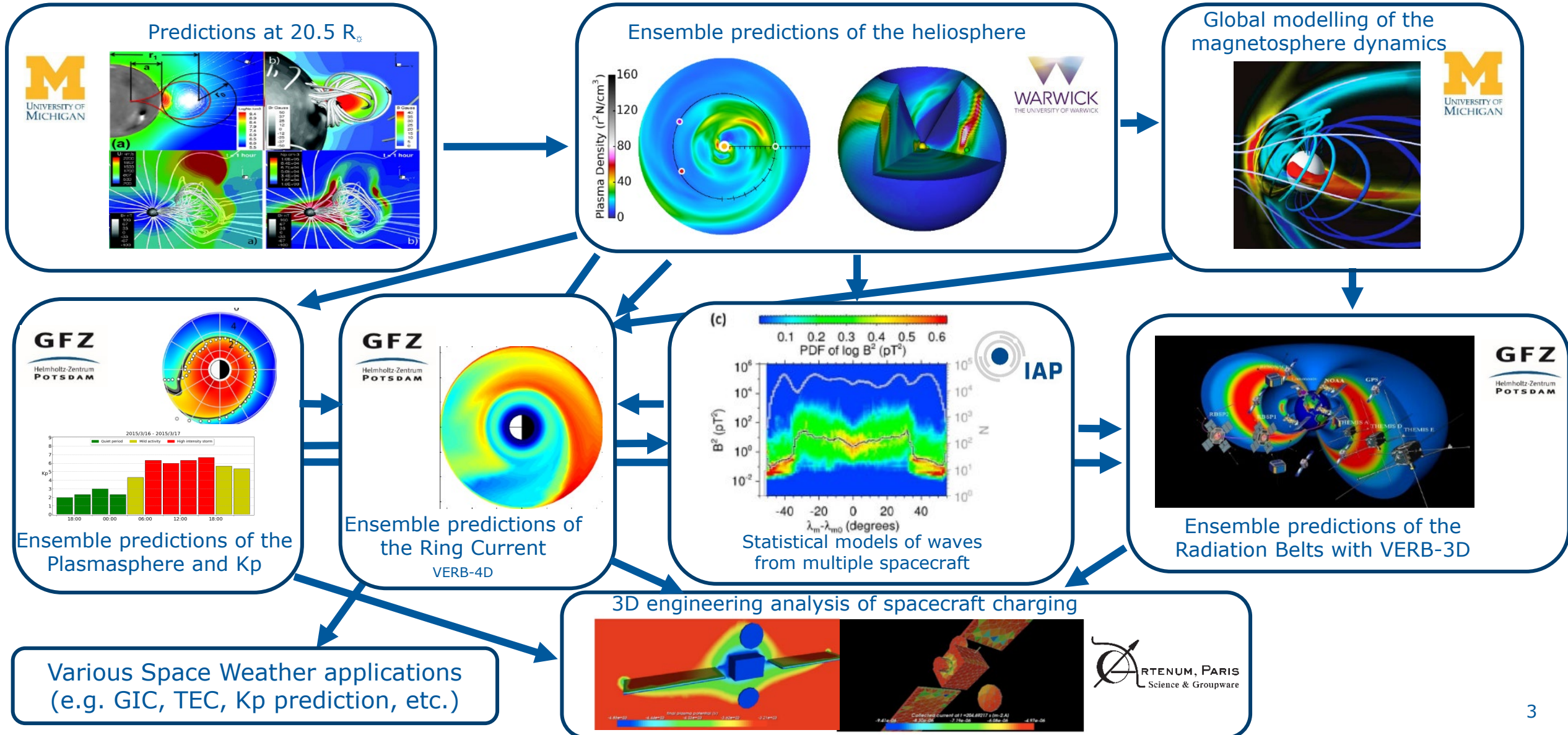
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Stakeholder Requirements



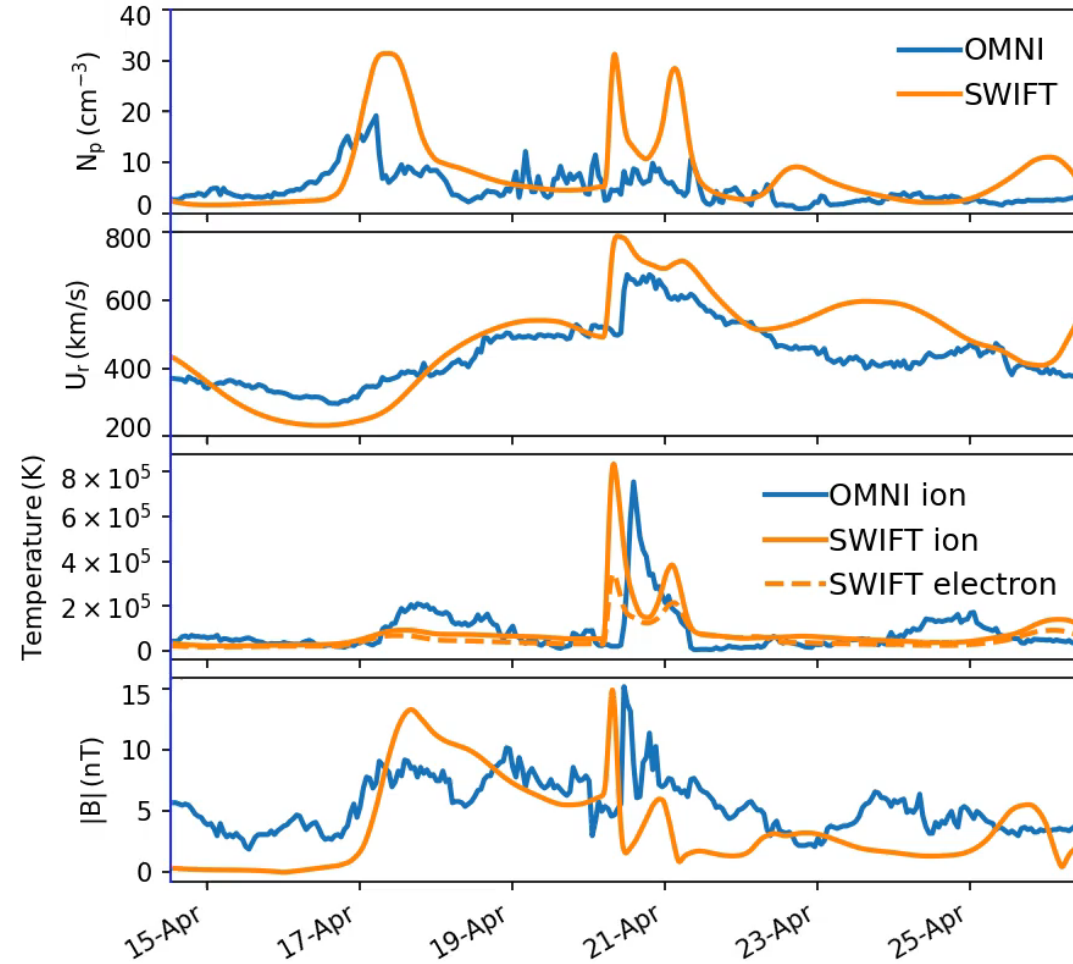
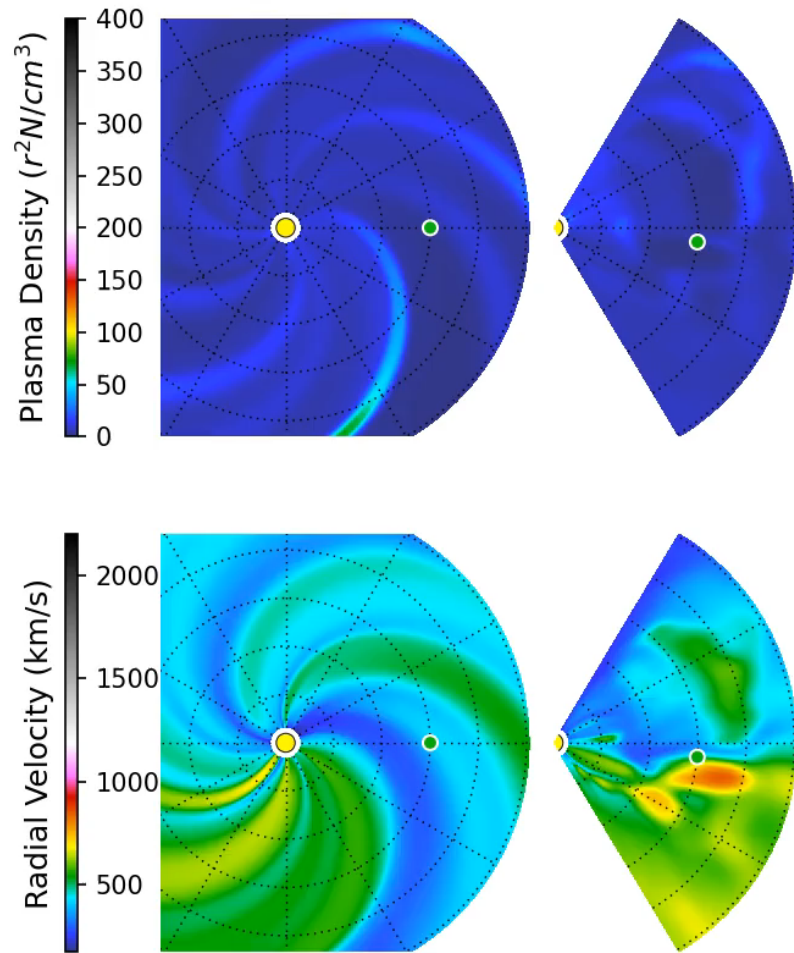
1. Predictions should be made with sufficient lead-time for the stakeholders to be able to respond to them
2. Predictions should be utilizing all available data and should be reliable
3. Predictions should provide confidence levels so that stakeholders can estimate risks and economic benefits/loss from reacting to the forecast
4. Forecasts should be clear and easy to understand and should provide variables that are usable for stakeholders, not just scientific output

Ensemble forecast from the Sun will allow a long-term probabilistic prediction.



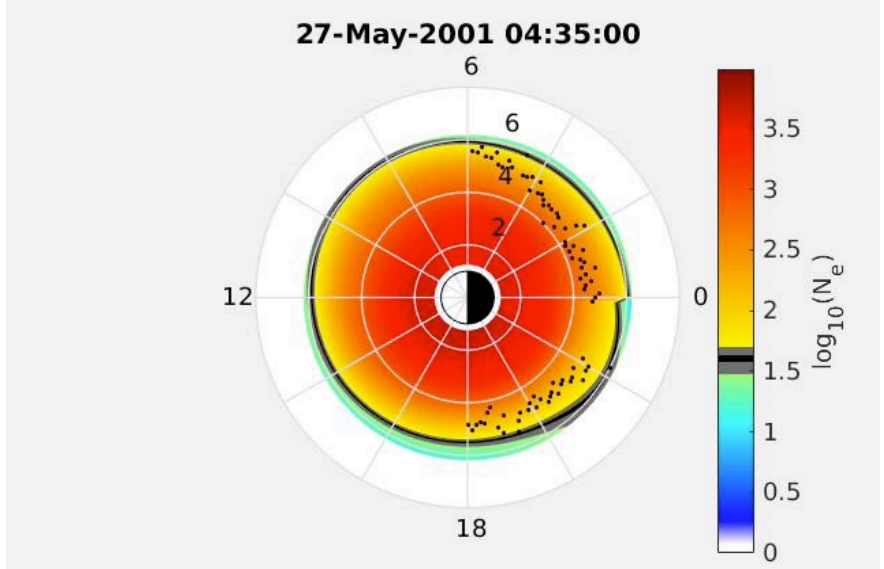
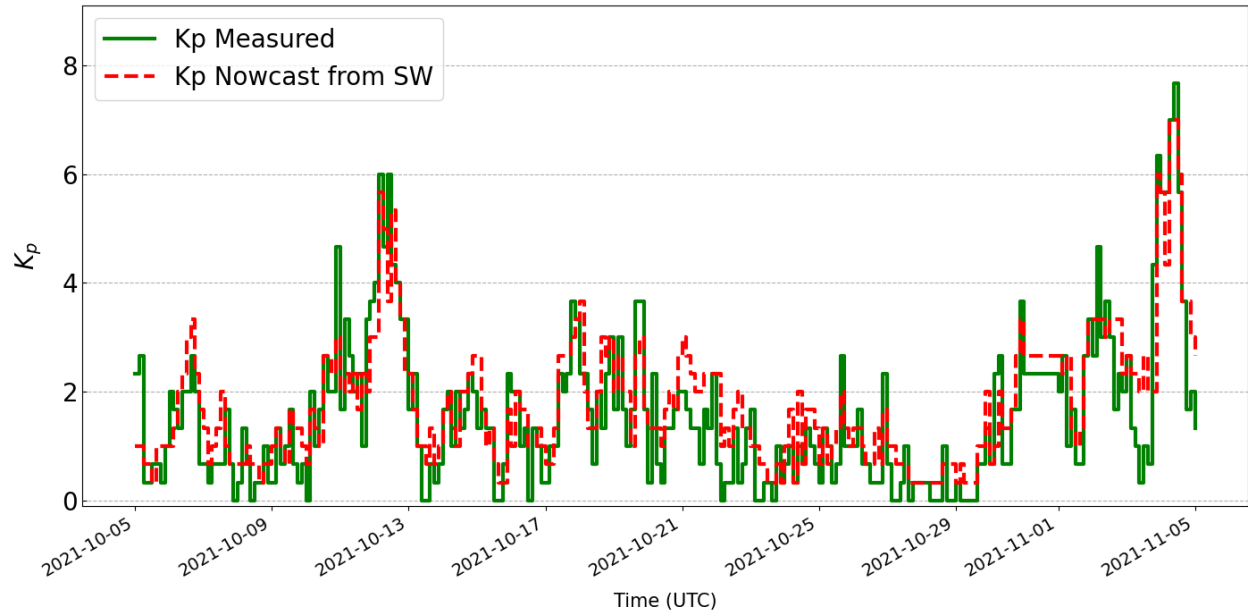
DEF-SWIFT CME Movie for Optimal Parameters

Start time 2014-04-14 12:11



Machine Learning Model of Kp and Plasma Density

Example output

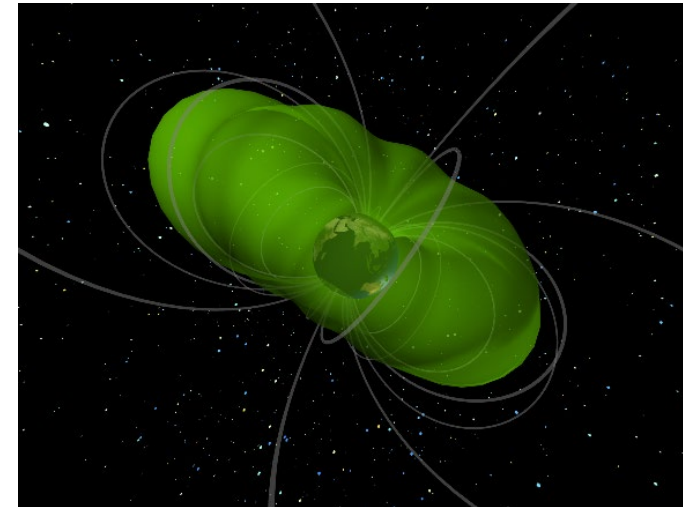
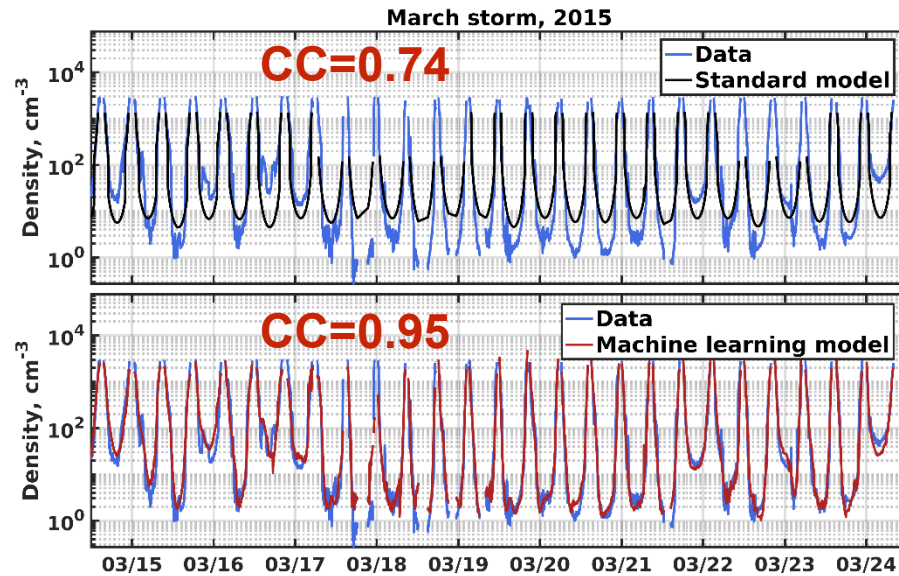


Zhelavskaya et al., 2017

The model trained on single point measurements from 2012 to 2016 reproduces the global dynamics observed in 2001

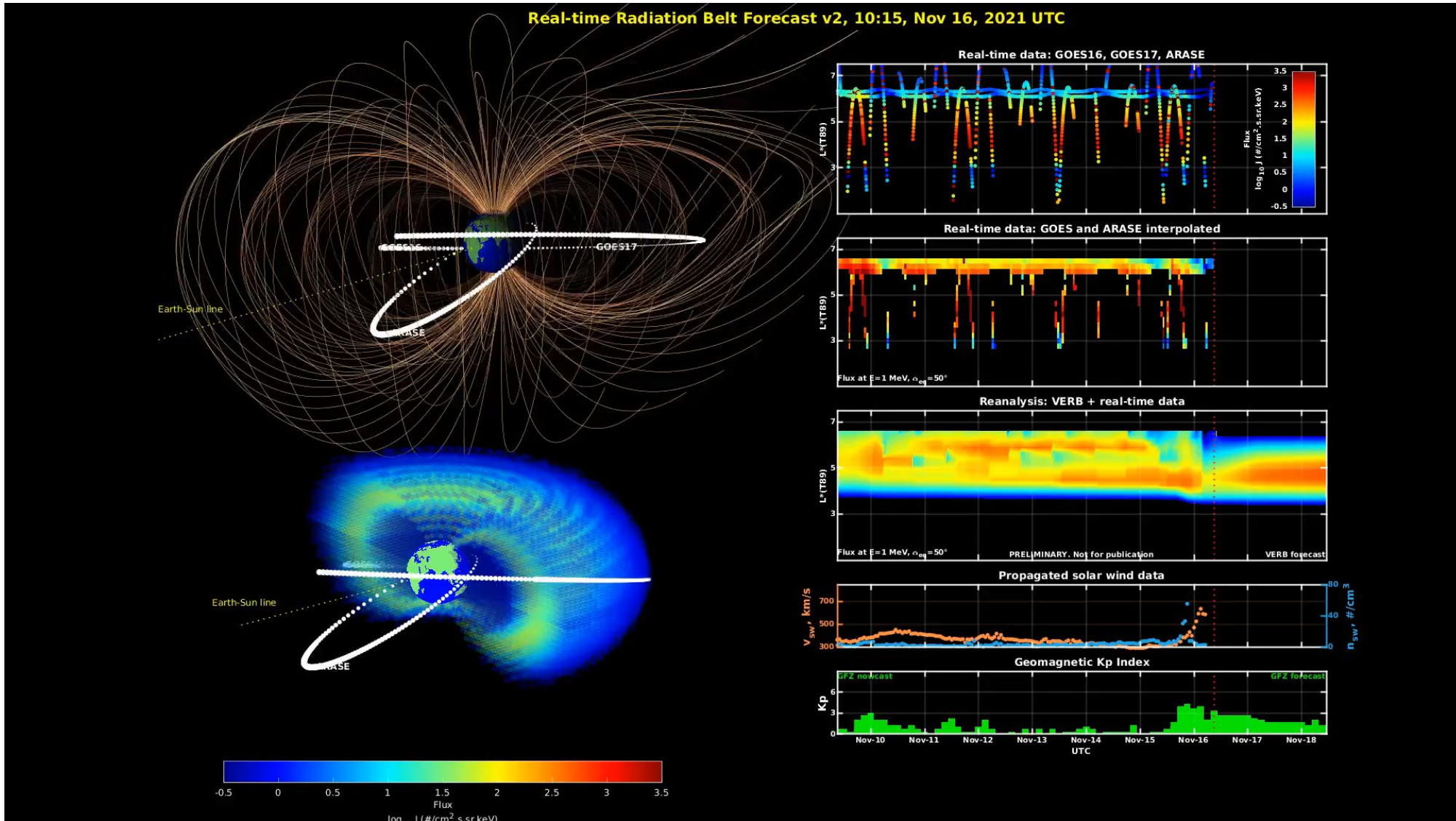
Empirical Models Using Machine Learning

Plasmaspheric modelling is important for GPS navigation and satellite charging



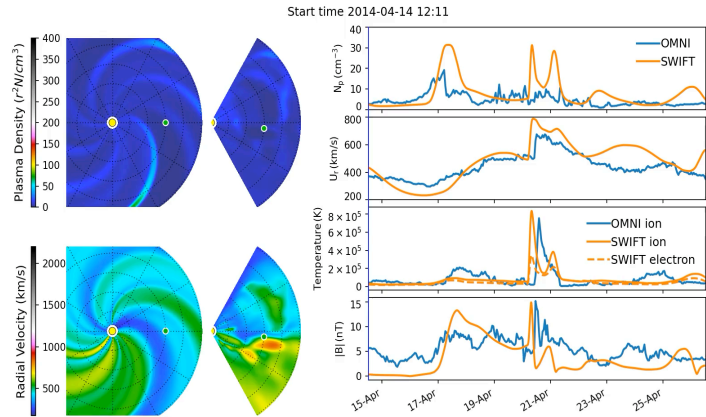
Reconstruction of plasma density along the satellite orbit

VERB-DA Radiation Belt Model

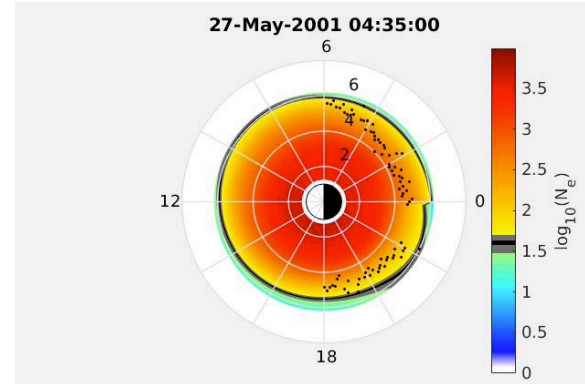


PAGER models

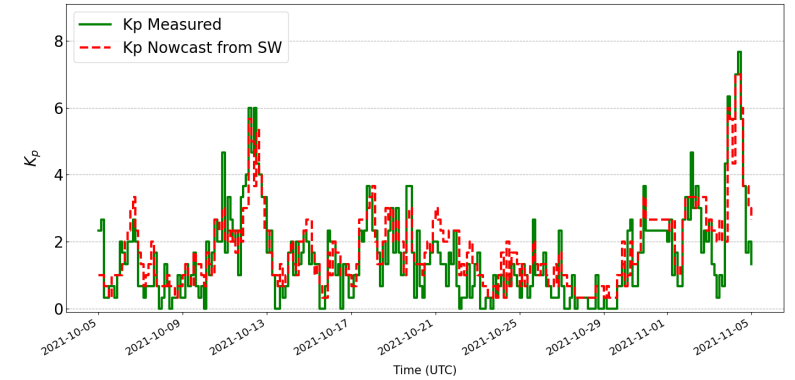
SWIFT model



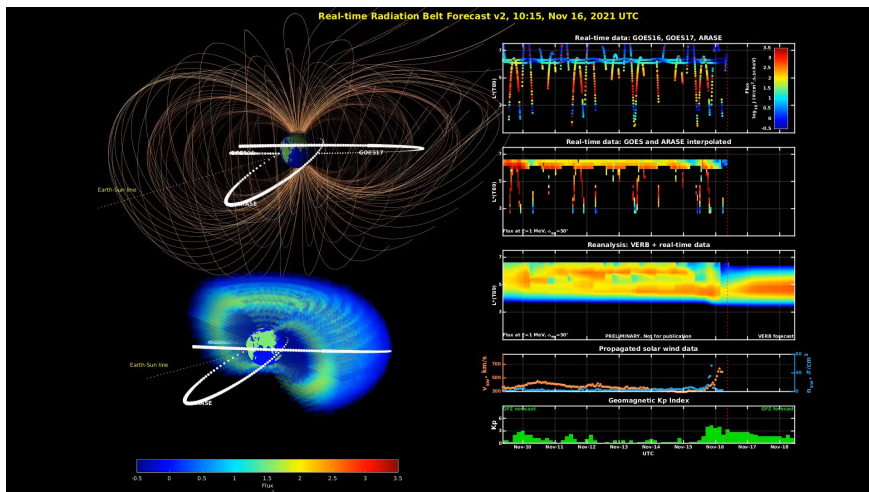
PINE model



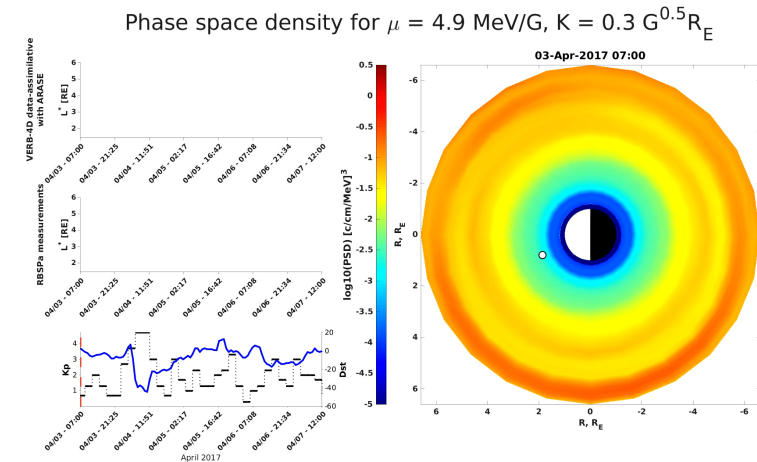
AI Kp model



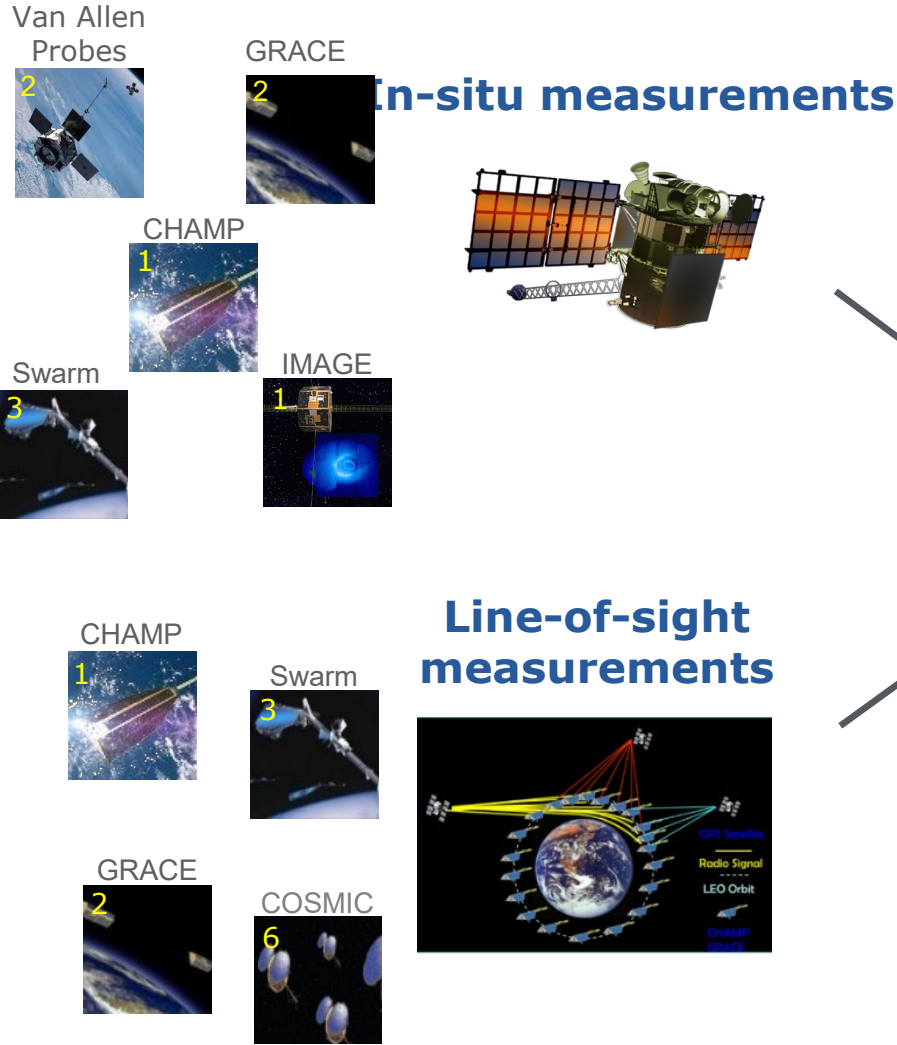
Data assimilative VERB-3D



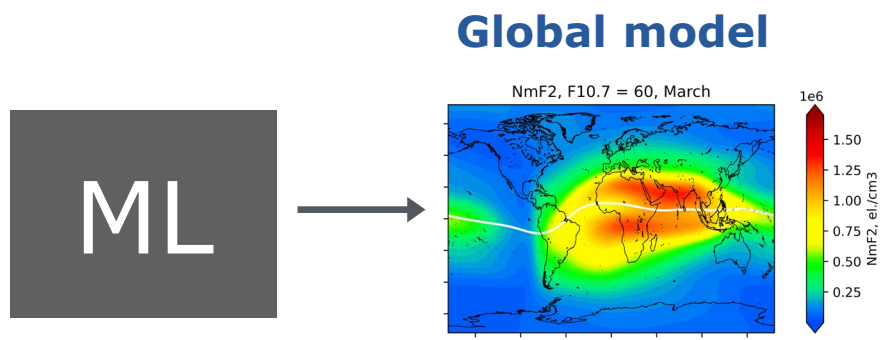
Data assimilative VERB-4D



Methodology



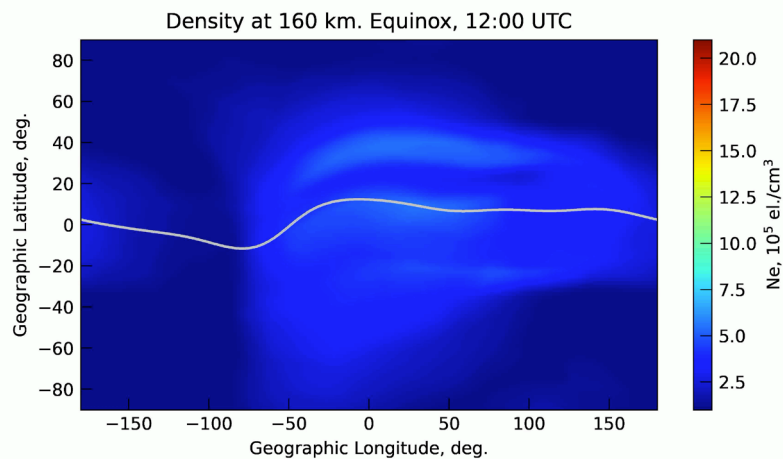
The entire training data set contains ~2 billion measurements



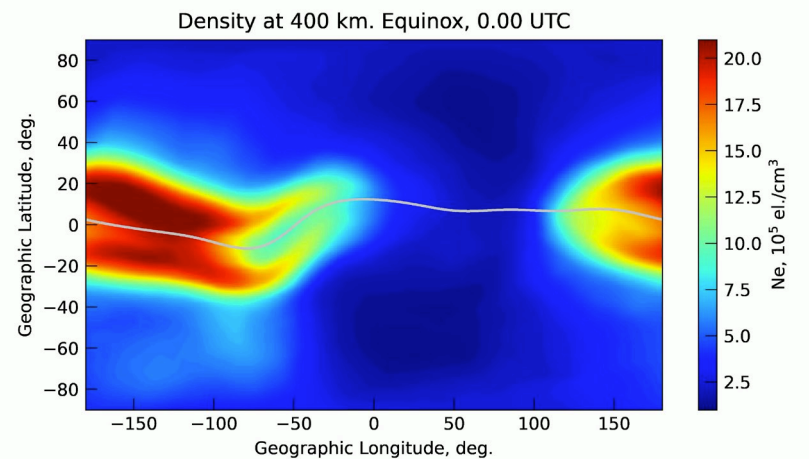
Data is provided by DLR NZ, data management is by DLR Jena, GFZ leads the modeling efforts

Global Density Model

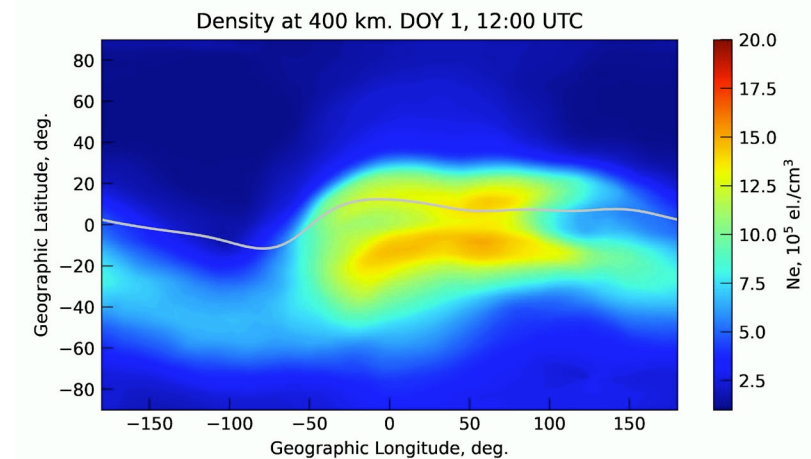
The model predicts 3D distribution of electron density and its variability on daily and annual timescales



Electron density variation with altitude



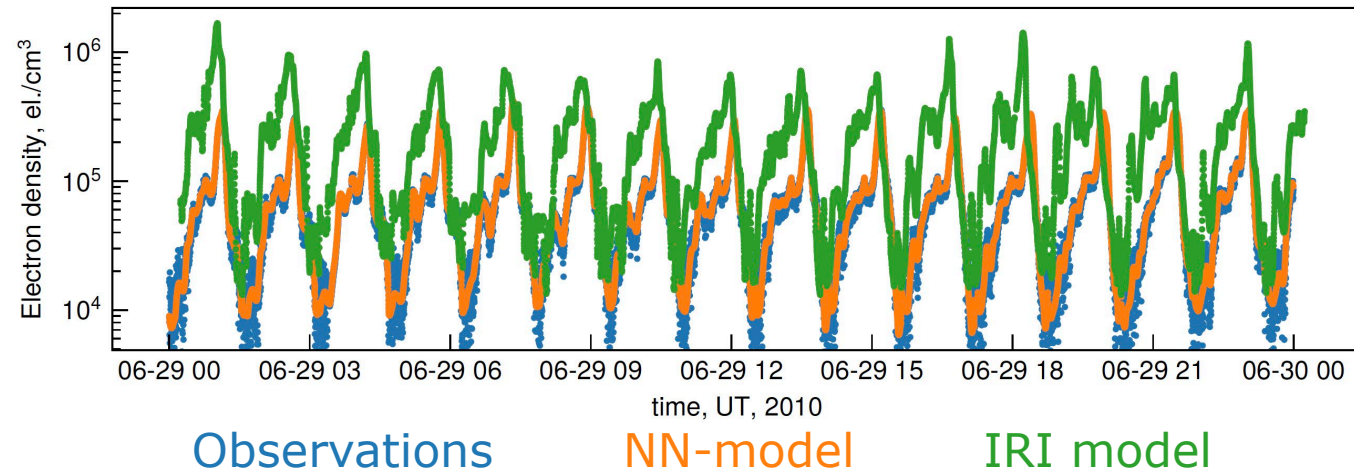
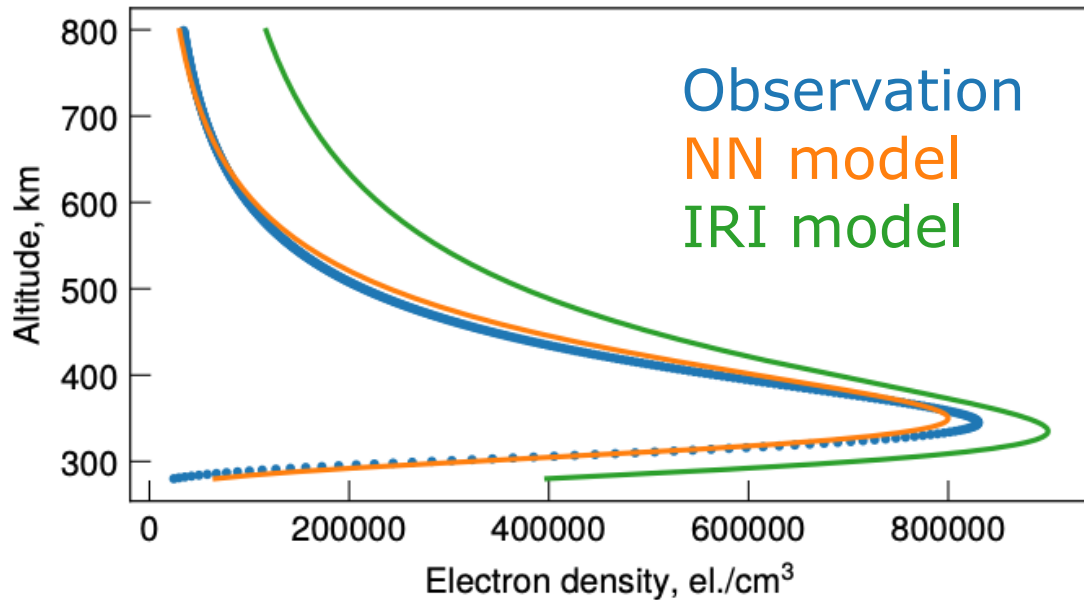
Daily variation of electron density at 400 km altitude



Seasonal variation of electron density at 400 km altitude

Neural network-based model of Electron density in the Topside ionosphere (NET)

An example of COSMIC profile, 24 June 2010 GRACE-KBR (~400 km altitude), 29 June 2010



- The NN model reproduces electron density profiles provided by the COSMIC mission well

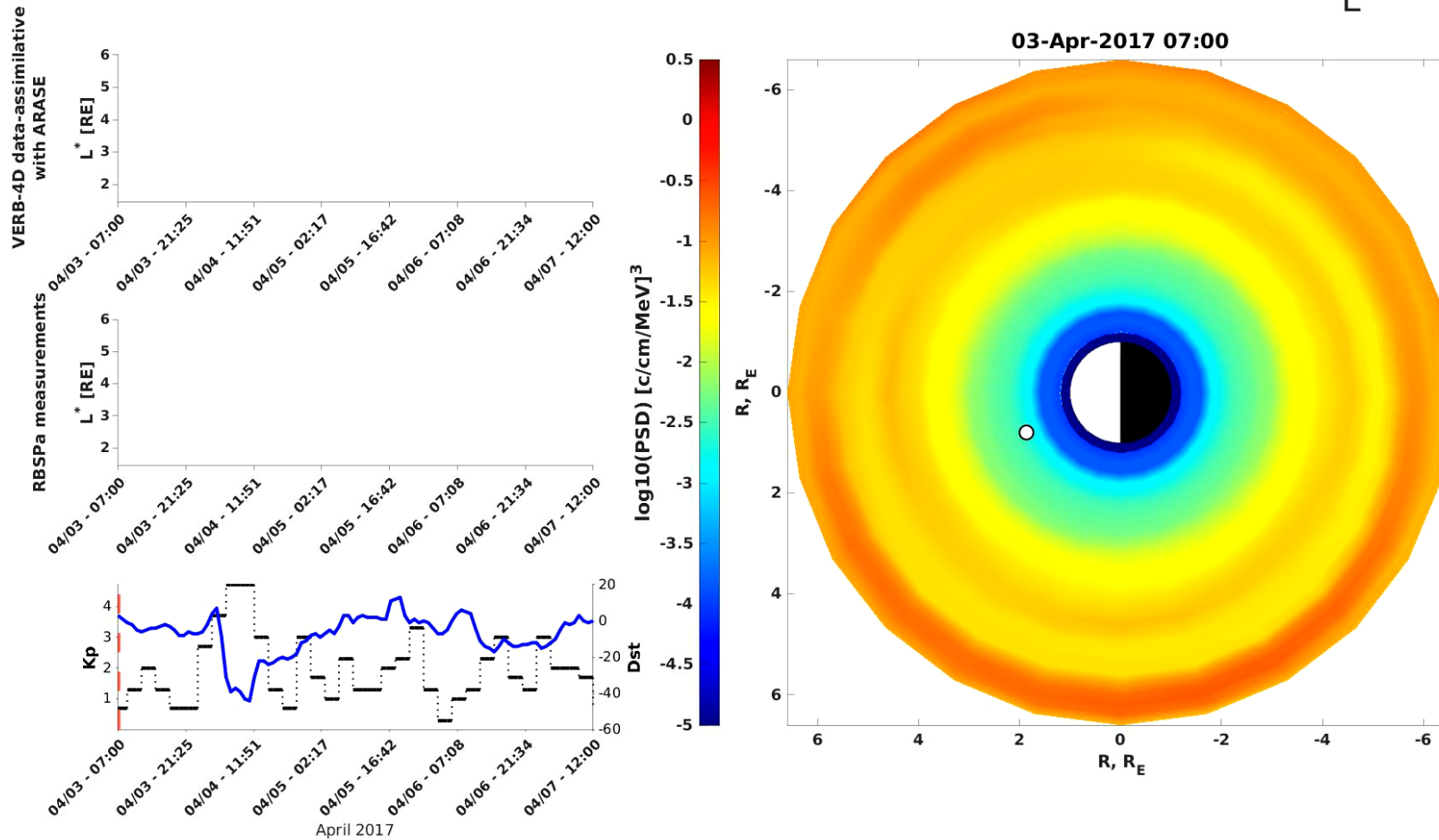
- The IRI also has an overestimation of density during low solar activity in 2010.
- The NN-based model captures electron densities observed by the GRACE mission well.
- The NN-based model outperforms IRI on average by 46%

Summary



- PAGER project responds to stakeholder requirements by: providing coupled simulations, performing ensemble simulations, using data assimilation in the solar wind and in the inner magnetosphere and providing simple indicators of radiation in space
- Predictions of Kp, Plasmasphere conditions, radiation belt fluxes, and ring current are already available at www.spacepager.eu
- A new 4D data-driven model of electron density based on 19 years of measurements from COSMIC, GRACE, CNOFS, and CHAMP allows to reconstruct plasma density in the ionosphere in terms of longitude, latitude, altitude, and time.
- Data Assimilation and Machine Learning provide new tools for utilizing various types of data and combining observations from different missions. These tools will help answer most compelling science question.
- Careful inter-calibration of the instruments requires science mission quality golden standard data.

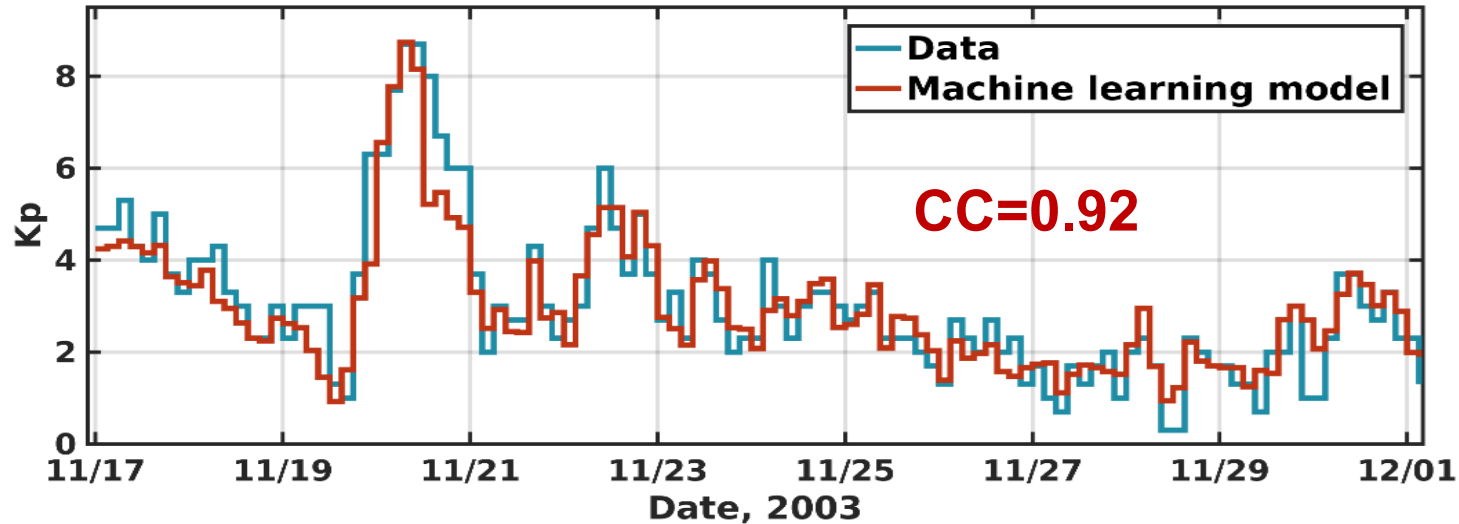
Phase space density for $\mu = 4.9 \text{ MeV/G}$, $K = 0.3 \text{ G}^{0.5} R_E$



Assimilation of RBSP Hope and MagEIS, validated with ARASE MEPE and HEP, April 2017

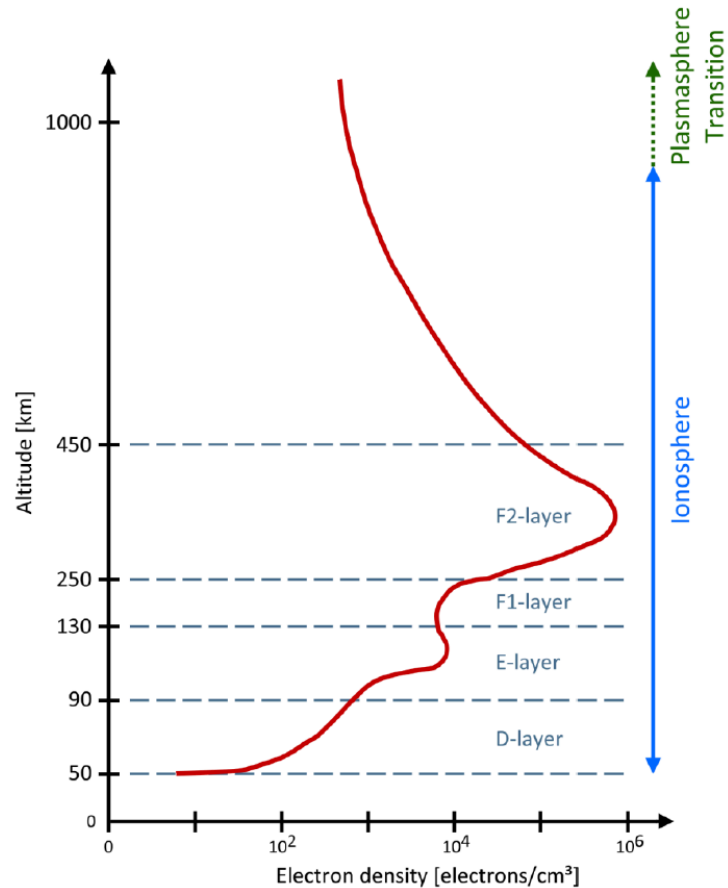
Planetary Geomagnetic Index Kp Predicted by ML

Kp index is derived from the observations of magnetic field provided by GFZ-Potsdam. It can be predicted using ML from the solar wind data



- Kp is used by the power grid operators to determine when power shortages may occur.
- Kp is used to determine when satellite anomalies may occur in space.
- Kp is used to calculate the drag on satellites and determine the time and location of the vehicle reentry.

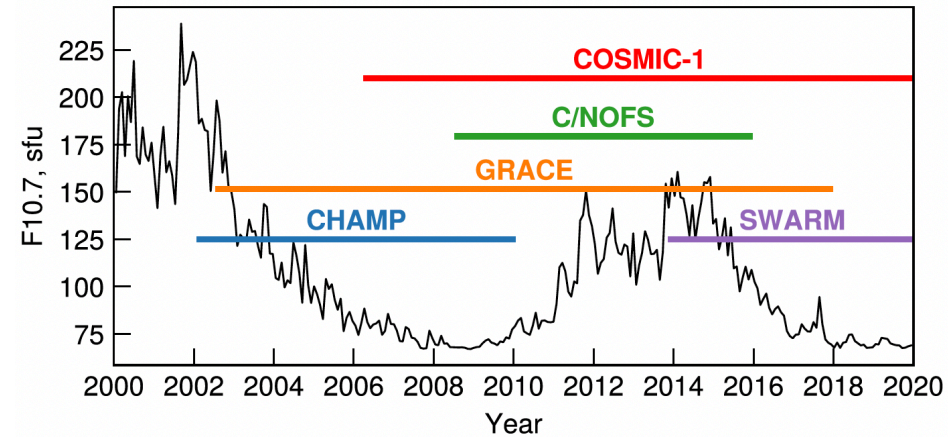
Data Intercalibration



Limberger (2015)

An example of the ionospheric profile

We collected electron density observations from 5 satellite missions covering more than 19 years



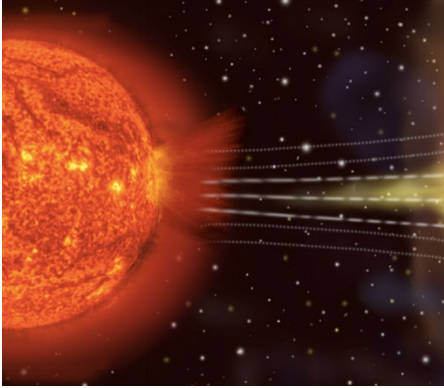
[Smirnov et al., 2021], JGR Space Physics

- In order to use these data for modelling, it is necessary to remove systematic biases between them
- The data sets and our calibration factors are publicly available and can be used by the community

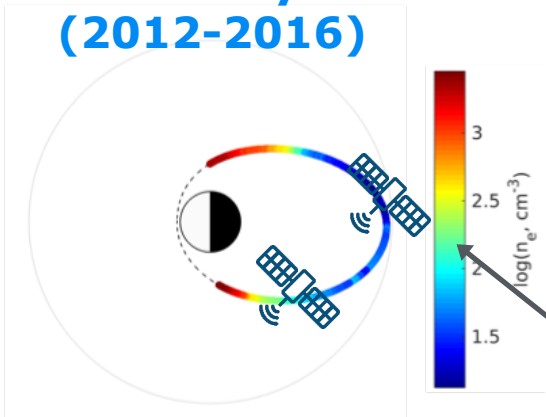
Thank you

Machine Learning Model of the Plasma Density

Input: Solar wind



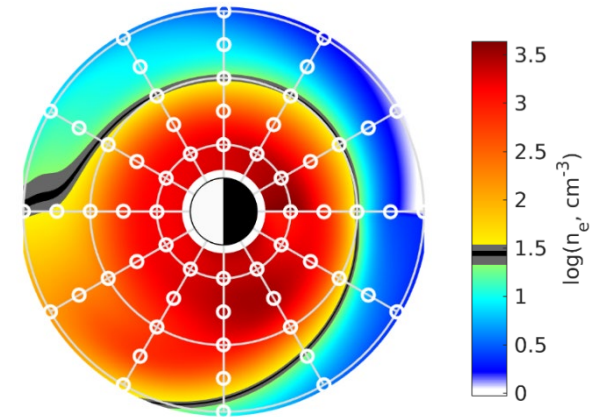
Training dataset: Plasma density (2012-2016)



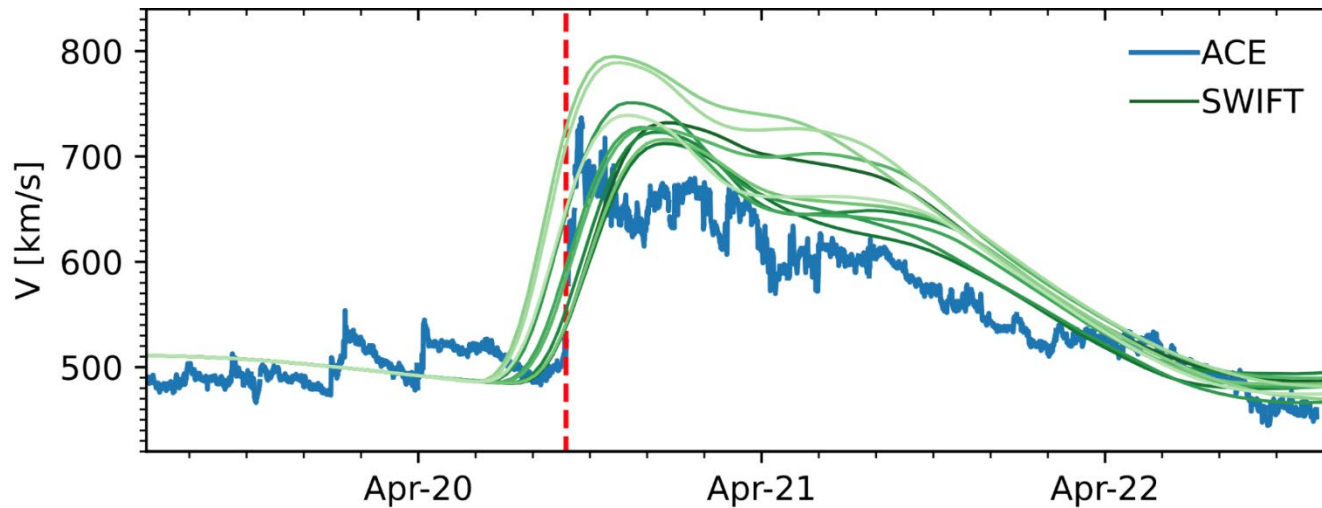
NASA's Van Allen Probes

ML

Global model of the plasmasphere



Zhelavskaya et al., 2017



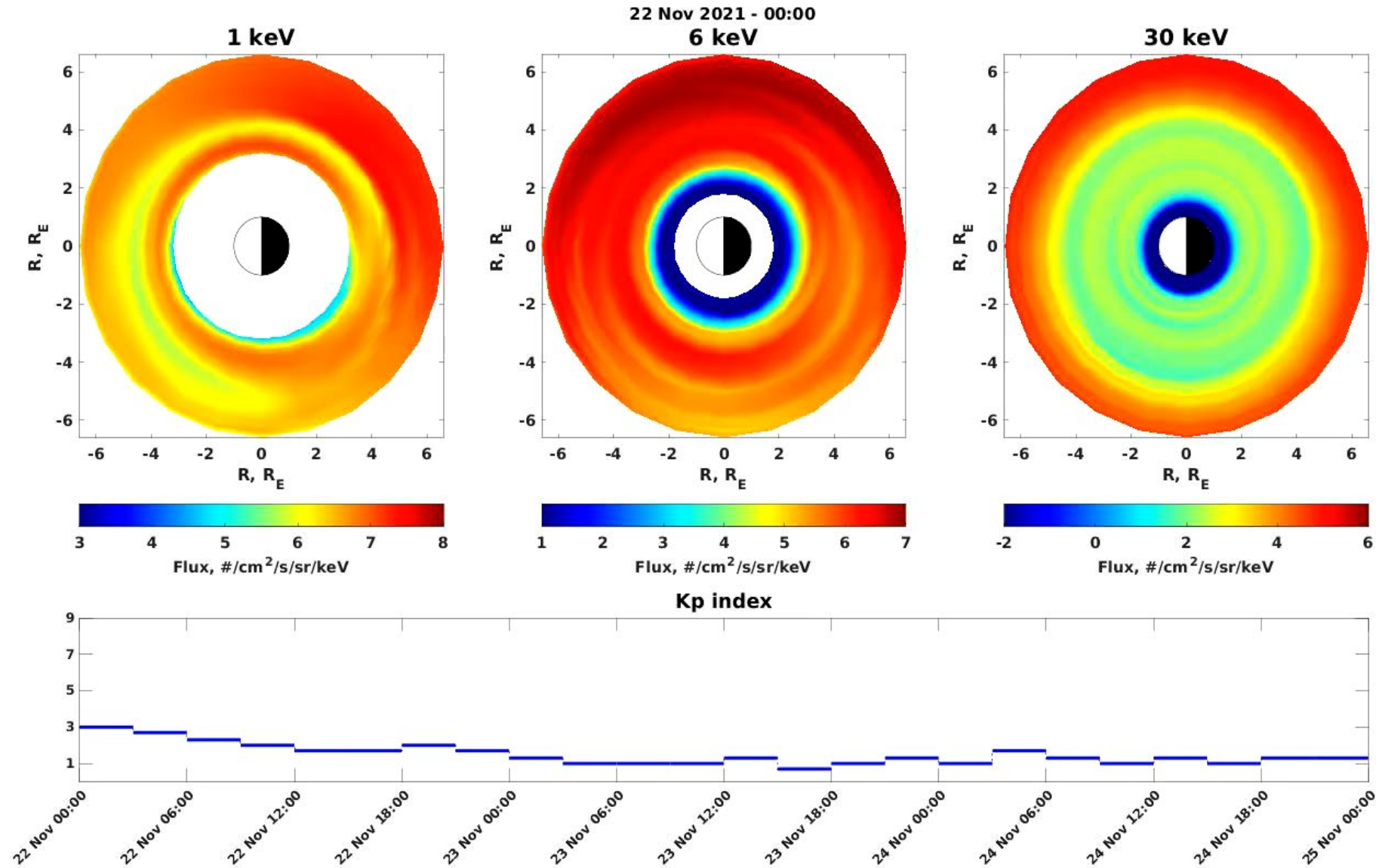
Blue is ACE data

Green the ensemble

These ensembles use PAGER's cone example Gibson-Low CME from SWMG

This has been rotated and parameters adjusted for a best fit against SW speed only

Not a prediction as this would require a database of Gibson-Low CME candidates to select from based on CME alerts

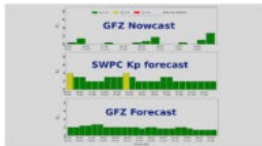




PAGER Data Products

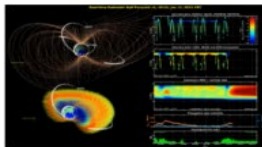
The following products are available:

- Forecast of the Kp Index
- Data assimilative forecast of the near-Earth radiation belts
- Electron Ring Current forecast
- Ensemble predictions of the Solar Wind at L1
- Forecast of plasma density



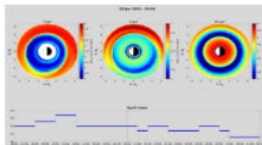
Forecast of the Kp Index

Prediction of Kp forecast. Neural network is trained to predict Kp values using historical solar wind and interplanetary magnetic field data.



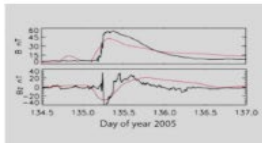
Data assimilative forecast of the near Earth radiation belts

Two-day radiation belt forecast of 1 MeV electrons using the data-assimilative VERB code, real-time ARASE, ACE, GOES and POES data.

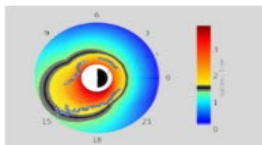


Electron ring current forecast

Three days forecast of ring current electron flux for 1keV, 6keV and 30keV particles at 85° pitch angle using the VERB-4D code.



Ensemble predictions of the Solar Wind at L1



Forecast of plasma density

The visualization and result of real-time predictions for plasmaspheric PINE model, data assimilative ring current simulations with VERB-4D, data assimilative radiation belts forecast with VERB-3D, solar wind predictions with SWIFT and predictions of Kp are already available on our web site at www.spacepager.eu.