A Next Generation Space Weather Particle Precipitation Model: Mature machine learning approaches, multiscale mesoscale prediction, and an open science framework for machine learning

An Open Science Community of Co-Creators

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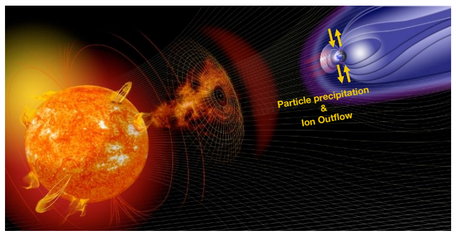
This poster in 30 seconds…

1. Demonstrate 'state-of-the-art' particle precipitation model capable of mesoscale prediction [*McGranaghan et al.,* 2021] and extension [*Ziegler and McGranaghan*, 2022]
2. Build trust in our artifacts and research products, we must design and adopt rigorous evaluation frameworks
3. Cultivate a sensibility of open science to understand how to create extensible foundations and usable artifacts

The Grand Challenge: Geospace Particle Transfer



The use case we focus on is Electron precipitation & Ion Outflow. Together they make up geospace particle transfer and are key components linking the ionosphere and the magnetosphere. They are among the most important and yet uncertain aspects of the geospace system

Open Science!

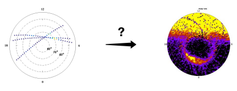
"*Open science is transparent and accessible knowledge that is shared and developed through collaborative networks*"

- Vicente-Saez & Martinez-Fuentes [2018]

Throughout this poster look for these icons for ways to use/contribute

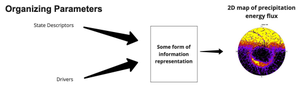
- Foundation to build on
- Usable artifact

The particle precipitation challenge



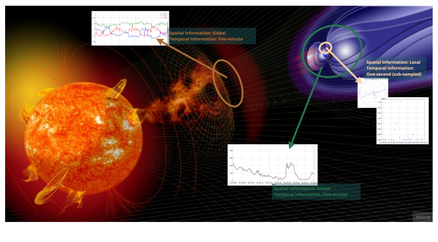
"The most important aspect of an auroral precipitation model…is the choice of organizing parameter."
–Newell et al., [2016]

Different sets of input parameters used in the particle precipitation models rely of a difference in philosophy of approach and lead to a difference in capabilities. Improvements must expand the organizing parameters used and find more expressive representations of the information



We present a new machine learning model (hereafter PrecipNet) that utilizes the expressive power of deep neural networks to incorporate both solar wind and magnetosphere-ionosphere (MI) state descriptors and to be capable of specifying substorm-scale (space and time) phenomena

Analysis Ready Data and Representativeness



Vital to AI/ML: understand the representativeness of your data!

See Figure 2 [McGranaghan et al., 2021]

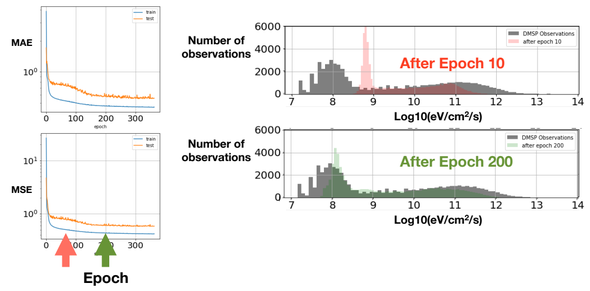
"DMSP Particle Precipitation AI-ready Data"
https://doi.org/10.5281/zenodo.4281122

Progress on the grand challenges of space physics in the digital age

Magnetosphere-Ionosphere particle transport at substorm-scale

A data-driven approach to the massive data and model design space

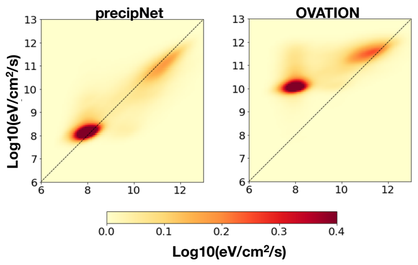
Training: Observing the learning process

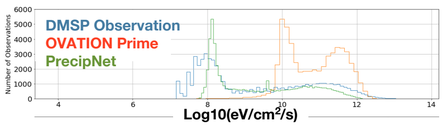


McGranaghan, R. M., et al. (2021). Toward a next generation particle precipitation model: Mesoscale prediction through machine learning (a case study and framework for progress). *Space Weather*, 19, e2020SW002684. https://doi.org/10.1029/2020SW002684

Ziegler, J. and McGranaghan, R.M. "Harnessing expressive capacity of Machine Learning modeling to represent complex coupling of Earth's auroral space weather regimes," *2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 2021, pp. 1189-1196, doi: 10.1109/ICMLA52953.2021.00193.

Results: Validation data: F16 for all of 2010 (>50k data samples, >1500 satellite passes)
Comparison: OVATION Prime (considered 'state of the art', eval'ed at validation data locations)





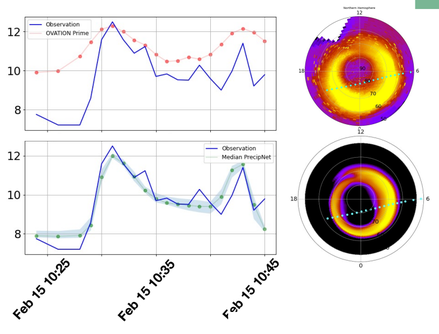
Evaluation Level #1: Standard metrics

Over full validation data set

Metric	precipNet*	OVATION Prime
R^2	0.752 +/- 0.02	-0.512
Slope of linear fit	0.722 +/ 0.04	0.348
Intercept of linear fit	2.583 +/- 0.42	7.588
Root mean squared error	0.762 +/- 0.03	1.887
Mean absolute error	0.556 +/- 0.04	1.574

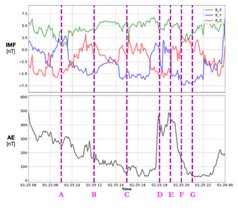
*10-fold cross validation

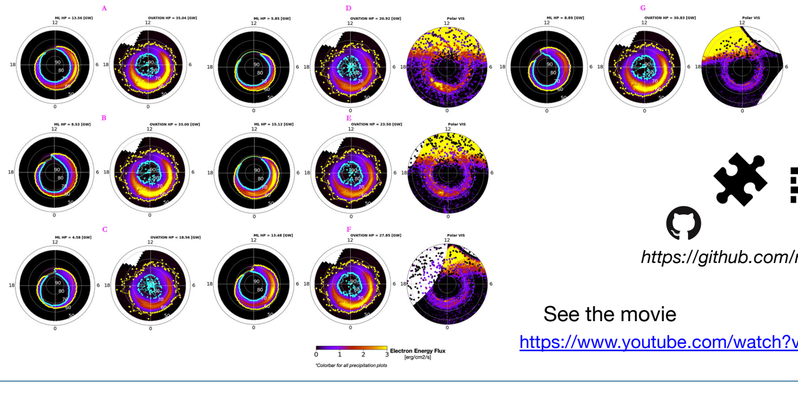
Evaluation Level #2: Against the state-of-the-art



Demonstration over one validation data set high-latitude crossing

Evaluation Level #3: Over known phenomena



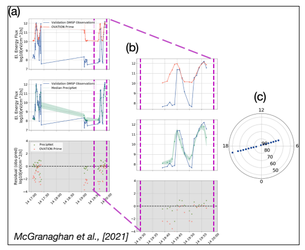


https://github.com/rmcgranaghan/precipNet

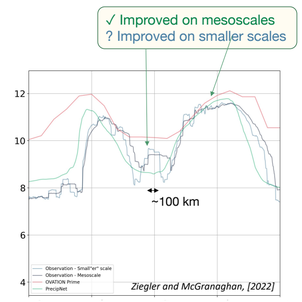
See the movie
https://www.youtube.com/watch?v=26HomytBL7Y

What's next?

Extension: Mutliscale understanding and honest assessment: Looking across scales



We have shown that PrecipNet better captures mesoscales (100-500 km scale sizes), but how do we understand the smaller scales?



With these models and **the tools we provide with it** we can seamlessly look across scales to explore the true multiscale behavior and interrogate our understanding of it

Active Directions

Loss function engineering

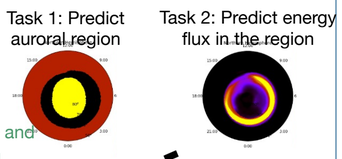
Tail loss function

$$\left[\frac{1}{N}\sum_{i=1}^{N}(obs-pred)^2\right] * \left[1+\sum_{j}^{M}\gamma_j\right]$$

Where $\gamma_j(obs, pred) = w$ if obs > tail threshold & pred < tail threshold
$\gamma_j(obs, pred) = 0$ otherwise

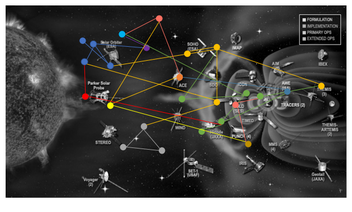
Multi-task learning
Ruder [2017]

Add auxiliary task to classify the auroral region in addition to energy and number flux target – new paradigm obtained from learning theory



The Heliophysics KNOWledge Network (Helio-KNOW) and an Earth and Space Science Knowledge Commons

Transcending this talk: The Earth and Space Science *Knowledge Commons*



Robust, responsive, responsible AI/ML requires deep integration of knowledge. The first step is to change how we organize our data and ourselves.The future of Heliophysics depends on the schema we develop for our data, the flexibility of that schema to changing needs, and the platform on which to provide the information so that the community can interact with it, thus transforming the information into knowledge.

The Heliophysics KNOWledge Netowrk (Helio-KNOW; https://github.com/rmcgranaghan/Helio-KNOW) is the collection of software and systems for improved information representation in Heliophysics, and the digital commons for the community to use and collaborate through them.

See a full talk on the Knowledge Commons

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