

Reinventing Space Weather with Artificial Intelligence

Enrico Camporeale

CIRES / CU Boulder & NOAA Space Weather Prediction Center

We acknowledge NASA grants 80NSSC20K1580, 80NSSC21K1555, 80NSSC20K1275



University of Colorado
Boulder



Space Weather

Sunspots
Sunspots are comparatively cool areas at up to 7,700° F and show the location of strong magnetic fields protruding through what we would see as the Sun's surface. Large, complex sunspot groups are generally the source of significant space weather.

Coronal Mass Ejections (CMEs)
Large portions of the corona, or outer atmosphere of the Sun, can be explosively blown into space, sending billions of tons of plasma, or superheated gas, Earth's direction. These CMEs have their own magnetic field and can slam into and interact with Earth's magnetic field, resulting in geomagnetic storms. The fastest of these CMEs can reach Earth in under a day, with the slowest taking 4 or 5 days to reach Earth.

Solar Wind
The solar wind is a constant outflow of electrons and protons from the Sun, always present and buffeting Earth's magnetic field. The background solar wind flows at approximately one million miles per hour!

Solar Flares
Reconnection of the magnetic fields on the surface of the Sun drive the biggest explosions in our solar system. These solar flares release immense amounts of energy and result in electromagnetic emissions spanning the spectrum from gamma rays to radio waves. Traveling at the speed of light, these emissions make the 93 million mile trip to Earth in just 8 minutes.

Earth's Magnetic Field
Earth's magnetic field, largely like that of a bar magnet, gives the Earth some protection from the effects of the Sun. Earth's magnetic field is constantly compressed on the day side and stretched on the night side by the ever present solar wind. During geomagnetic storms, the disturbances to Earth's magnetic field can become extreme. In addition to some buffering by the atmosphere, this field also offers some shielding from the charged particles of a radiation storm.

Sun's Magnetic Field
Strong and ever-changing magnetic fields drive the life of the Sun and underlie sunspots. These strong magnetic fields are the energy source for space weather and their twisting, shearing, and reconnection lead to solar flares.

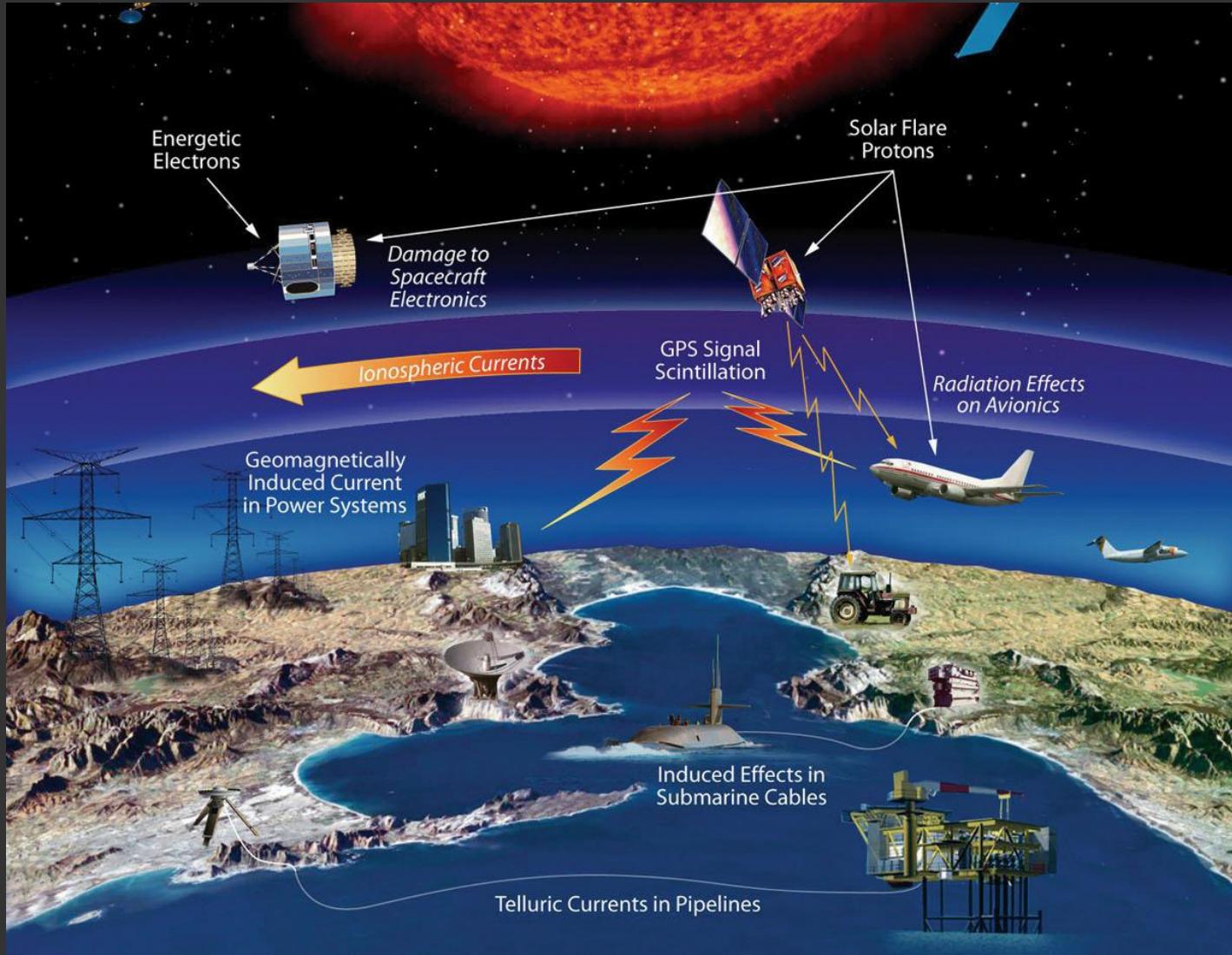
Solar Radiation Storms
Charged particles, including electrons and protons, can be accelerated by coronal mass ejections and solar flares. These particles bounce and gyrate their way through space, roughly following the magnetic field lines and ultimately bombarding Earth from every direction. The fastest of these particles can affect Earth tens of minutes after a solar flare.

Geomagnetic Storms
A geomagnetic storm is a temporary disturbance of Earth's magnetic field typically associated with enhancements in the solar wind. These storms are created when the solar wind and its magnetic field interacts with Earth's magnetic field. The primary source of geomagnetic storms is CMEs which stretch the magnetosphere on the nightside causing it to release energy through magnetic reconnection. Disturbances in the ionosphere (a region of Earth's upper atmosphere) are usually associated with geomagnetic storms.

Source images: NASA, NOAA.

NOAA
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
U.S. DEPARTMENT OF COMMERCE

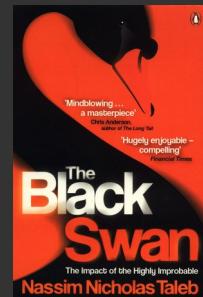
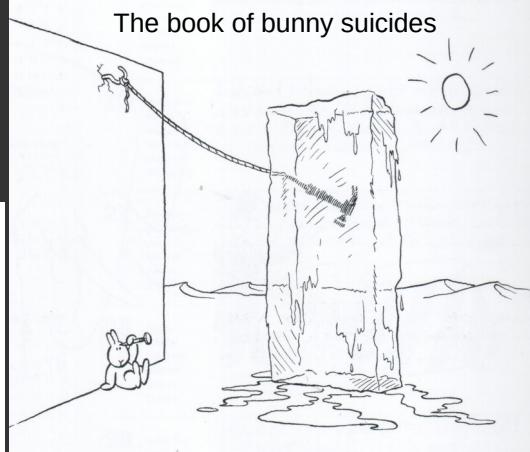
JOHN P. SPADE, SPACE WEATHER PREDICTION CENTER - www.spaceweather.gov



Credits:
NASA

A disaster waiting to happen...

- If a space weather event causes a power outage, we estimate costs to U.S. electricity consumers that may be ~\$400 million to ~\$10 billion for a moderate event and ~\$1 billion to ~\$20 billion for a more extreme event.
- The adverse impact of space weather is estimated to cost **\$200-\$400 million** per year;
- Losses to satellite companies range from thousands of dollars for temporary data outages up to **\$200 million** to replace a satellite
- Economists also estimate that timely warnings of geomagnetic storms to the electric power industry would save approximately **\$150 million** per year;
- a 1% gain in continuity and availability of GPS would be worth **\$180 million** per year.
- a “big one” would cause **\$2.6 trillion damage**



Space Weather

RESEARCH ARTICLE
10.1029/2018SW002003

Key Points:

- Physics-based frameworks are one way to model the economic impact of space weather for policy and risk management
- A methodology based on substorms, and including forecast quality, is presented to model space weather

Quantifying the Economic Value of Space Weather Forecasting for Power Grids: An Exploratory Study

J. P. Eastwood¹ , M. A. Haggood² , E. Biffis³, D. Benedetti³ , M. M. Bisi² , L. Green⁴, R. D. Bentley⁴, and C. Burnett⁵

¹The Blackett Laboratory, Imperial College London, London, UK, ²RAL Space, STFC Rutherford Appleton Laboratory, Didcot, UK, ³Department of Finance, Imperial College Business School, Imperial College London, London, UK, ⁴Mullard Space Science Laboratory, University College London, Dorking, UK, ⁵Space Weather Programme, Met Office, Exeter, UK

A disaster waiting to happen... and it does happen!



Markets Tech Media Success Perspectives Videos

LIVE TV

CNN+



SpaceX will lose up to 40 satellites it just launched due to a solar storm



By [Jackie Wattles](#), CNN Business

Updated 7:44 PM ET, Wed February 9, 2022

SPACE



News

Tech

Spaceflight

Science & Astronomy

Search For Life

[Home](#) > [News](#) > [Spaceflight](#)

Solar geomagnetic storms could threaten more satellites after Elon Musk's Starlink

By [Chelsea Gohd](#) published 28 days ago

"That is a drag," NOAA's Bill Murtagh said.

NOAA Space Weather Prediction Center

NOAA SPACE WEATHER PREDICTION CENTER
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

Wednesday, September 15, 2021 18:59:55 UTC

HOME ABOUT SPACE WEATHER PRODUCTS AND DATA DASHBOARDS MEDIA AND RESOURCES SUBSCRIBE ANNUAL MEETING FEEDBACK Search

SPACE WEATHER CONDITIONS on NOAA Scales

24-Hour Observed Maximums Latest Observed Predicted 2021-09-15 UTC

R none S none G none R none S none G none R1-R2 1% S1 or greater 1% G none

Solar Wind Speed: 340 km/sec Solar Wind Magnetic Fields: Bt 5 nT, Bz -1 nT Noon 10.7cm Radio Flux: 78 sfu

Global Ionosphere Valid at: Jul 21 2021 03:10 UTC NOAA Announces Appointees to New Space Weather Advisory Group

Total Electron Content (TEC) Maximum Usable Frequency (MUF)

The WAM-IPE space weather forecast model is now operational! GONG Space Weather Data Processing Transitioned to SWPC

Total Electron Content (TEC) Anomaly Maximum Usable Frequency (MUF) Anomaly

Space Weather Educational Video

SERVING ESSENTIAL SPACE WEATHER COMMUNITIES

Aviation Electric Power Emergency Management Global Positioning System (GPS)
Radio Communications Satellites Space Weather Enthusiasts

THE SUN (EUV)

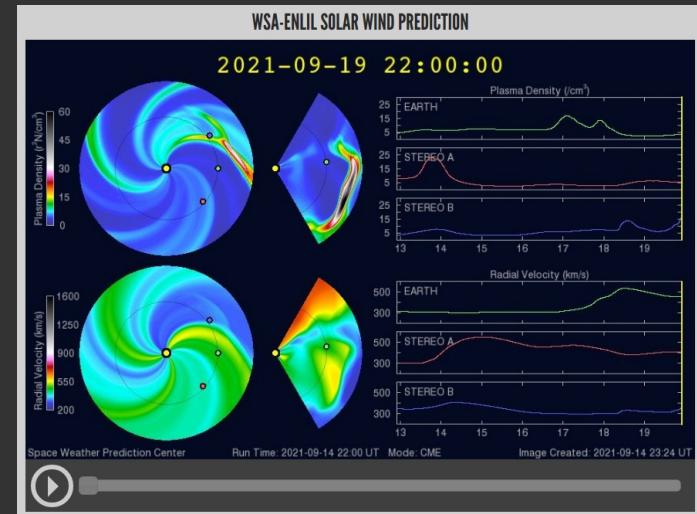
CORONAL MASS EJECTIONS

THE AURORA

NOAA Space Weather Prediction Center Aurora Forecast
For 2021-09-15 20:05 (UTC) Forecast Lead Time: 70 minutes
HF: 13.2 GW (Range 5 to 200)

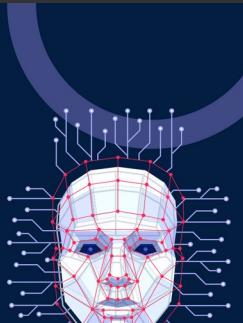
SWPC mission:

*Safeguarding society with
actionable space weather
information*



AI is changing the landscape (every landscape)

How AI is changing
the landscape of
SEO



How Machine Learning is
Changing the Landscape of

CLINICAL
DECISION
SUPPORT
SYSTEMS?



AI: Changing the Landscape of Accounting



HOW AI IS CHANGING
THE LANDSCAPE OF
BUSINESS AND
MARKETING

www.learnitguid.net

HOME > TECH & INNOVATION

How AI is Changing the GIS Landscape

Ernest Hamilton Jun 14, 2021 10:43 AM EDT



How AI is changing the
business landscape

A Future With AI Writing
Companions:
Changing the Landscape for
Writers



How AI is changing the
landscape of the
entertainment industry

September 16, 2022

Playing with ChatGPT

E

write a comment on the future of AI in space weather forecasting models



AI has the potential to greatly improve space weather forecasting models. By utilizing machine learning algorithms, AI can analyze vast amounts of data and identify patterns that may not be easily visible to the human eye. This can lead to more accurate predictions of space weather events, such as solar flares and geomagnetic storms, which can have significant impacts on satellites, power grids, and communication systems. Additionally, AI can process data in real-time, allowing for faster and more efficient forecasting. However, it's important to note that AI in space weather forecasting is still an emerging field, and more research and development is needed to fully realize its potential.



Playing with ChatGPT

E

write a comment on the future of AI in space weather forecasting models



AI has the potential to greatly improve space weather forecasting models. By utilizing machine learning algorithms, AI can analyze vast amounts of data and identify patterns that may not be easily visible to the human eye. This can lead to more accurate predictions of space weather events, such as solar flares and geomagnetic storms, which can have significant impacts on satellites, power grids, and communication systems. Additionally, AI can process data in real-time, allowing for faster and more efficient forecasting. However, it's important to note that AI in space weather forecasting is still an emerging field, and more research and development is needed to fully realize its potential.



(Couldn't agree more!!)

E

Can you mention some examples where AI has already proven successful in space weather prediction, possibly outperforming physics-based models?



Yes, AI has already shown promise in improving space weather predictions. Here are a few examples:

1. Solar Flare Prediction: AI algorithms have been used to analyze solar images and predict solar flares with high accuracy. In some cases, AI models have outperformed physics-based models in terms of prediction accuracy.
2. Geomagnetic Storm Forecasting: AI has also been used to forecast geomagnetic storms, which can disrupt communication systems and power grids on Earth. Machine learning algorithms have been trained on historical data to identify patterns and make predictions, which have been shown to be more accurate than traditional physics-based models.
3. Ionosphere Modelling: AI has been used to model the ionosphere, which is a layer of the Earth's atmosphere that is strongly influenced by space weather. By using AI algorithms to analyze large amounts of data, it is possible to create more accurate models of the ionosphere and better understand the impact of space weather on communication systems.

These are just a few examples of the potential of AI in space weather prediction. As the field continues to evolve and AI algorithms become more sophisticated, it's likely that we'll see even greater improvements in space weather forecasting.

E

Please reference some scientific literature



Certainly, here are some relevant scientific papers on the use of AI in space weather prediction:



1. "A deep learning approach for the prediction of solar flares" by K. Shi et al., published in the Journal of Atmospheric and Solar-Terrestrial Physics in 2019.
2. "Geomagnetic storm forecasting using machine learning algorithms" by X. Zhang et al., published in the Journal of Space Weather and Space Climate in 2018.
3. "Ionosphere modeling with deep neural networks" by S. Chen et al., published in the Journal of Geophysical Research: Space Physics in 2020.
4. "Solar wind prediction using deep neural networks" by Y. Zhang et al., published in the Journal of Geophysical Research: Space Physics in 2019.

These papers provide a good starting point for understanding the use of AI in space weather prediction, and highlight some of the successes and challenges in this field.

E

Is there any good review paper on using machine learning in space weather?



Yes, there are many review papers that discuss the use of machine learning in space weather forecasting. Here are a few that you may find useful:



1. "Machine Learning in Space Weather: A Review" by J. Kim, et al., published in *Space Science Reviews* (2019)

This paper provides an overview of the use of machine learning in various aspects of space weather research, including solar flare prediction, geomagnetic storm forecasting, and ionosphere modeling.

2. "Deep Learning in Space Weather: A Review" by Y. Zhang, et al., published in *Frontiers in Astronomy and Space Sciences* (2019)

This paper focuses on the use of deep learning in space weather forecasting and discusses the advantages and limitations of this approach. It also provides an overview of recent advances in deep learning algorithms for space weather applications.

3. "Space Weather Forecasting Using Machine Learning: A Review" by J. K. Lee, et al., published in *Advances in Space Research* (2019)

This paper provides a comprehensive review of the use of machine learning in space weather forecasting, including solar flare prediction, geomagnetic storm forecasting, and ionosphere modeling. It also discusses the challenges and future directions for the field.

These are just a few examples of the many review papers that are available on the topic. I hope these references will help you find the information you need.

E

Is there any good review paper on using machine learning in space weather?



Yes, here's a review paper on the use of machine learning in space weather forecasting:



- "Machine Learning Approaches to Space Weather Forecasting: A Review" by S. Li, et al., published in *Journal of Geophysical Research: Space Physics* (2019).

This paper provides an overview of the various machine learning techniques that have been applied to space weather forecasting, including neural networks, support vector machines, decision trees, and others. It also discusses the challenges and limitations of using machine learning in space weather forecasting, as well as future directions for research in this field. This paper provides a comprehensive overview of the current state of the field and is a good starting point for anyone interested in using machine learning for space weather forecasting.

Take home message #1: AI needs to be Trustworthy

E

Did you just make this reference up? Are you sure it actually exists?



I apologize if the reference is incorrect. As a language model, I don't have the capability to verify the existence of every scientific paper I mention. I strive to provide accurate information based on the training data I have been provided. If you would like, you can search for the paper online to verify its existence and obtain a copy if it is available.



E

That's OK, don't feel too bad. Do you know what is the most highly cited review paper on machine learning in space weather?



I apologize but I am not aware of the most highly cited review paper on machine learning in space weather. The field is rapidly evolving, and new papers are being published all the time. A good way to find the most highly cited review paper would be to search online databases, such as Google Scholar or the Web of Science, using keywords such as "machine learning in space weather" and "review paper." These databases allow you to sort papers by their citation count, so you can identify the most highly cited ones. Additionally, you can also check the reference lists of recent papers in the field to see which review papers are being cited frequently.

E

Have you read a review paper by Enrico Camporeale?



Yes, I am aware of a review paper by Enrico Camporeale on the use of machine learning in space weather forecasting. Enrico Camporeale is a well-known researcher in the field of space weather and has published several papers on the topic.

The paper you are referring to is likely:

- "Machine learning in space physics" by E. Camporeale, published in Living Reviews in Solar Physics (2018).

Take home message #2:

AI needs to know what it doesn't know

Space Weather

FEATURE ARTICLE

10.1029/2018SW002061



The Challenge of Machine Learning in Space Weather: Nowcasting and Forecasting

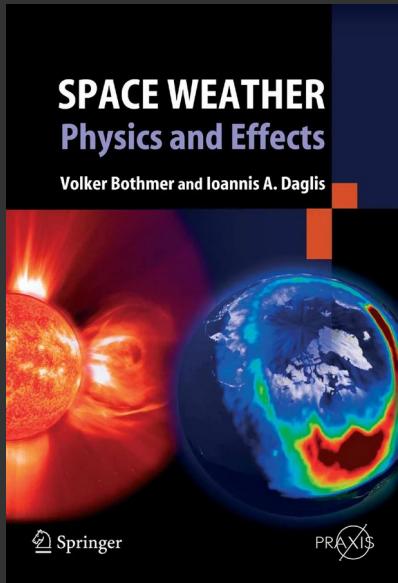
E. Camporeale^{1,2} 

¹CIRES, University of Colorado Boulder, Boulder, CO, USA, ²Centrum Wiskunde & Informatica, Amsterdam, The Netherlands

Abstract The numerous recent breakthroughs in machine learning make imperative to carefully ponder how the scientific community can benefit from a technology that, although not necessarily new, is

**Camporeale, E. (2019). The challenge of machine learning in space weather:
Nowcasting and forecasting. *Space Weather*, 17(8), 1166-1207.**

How did we get where we are? The myth of the analogy with meteorology



Published in 2007

Space weather forecasting historically viewed through the lens of meteorology

George Siscoe

The history of progress in the effectiveness of meteorological forecasting can be divided into ten stages: (1) recognition of societal need; (2) development of rules for forecasts based on visual observations; (3) quantification of storm parameters through instrument observations; (4) development of retrospective synoptic weather maps; (5) institution of forecast centers after the technological means of forecasting (the telegraph and instrument-based weather maps) came into being; (6) development of models of storm structure; (7) subjective analysis based on weather chart analysis; (8) objective analysis based on empirical formulas; (9) numerical predictions based on integrating the equations of atmospheric motion; and (10) storm tracking by radar and satellites. A parallel division of the history of space weather forecasting is here recounted. Whereas the effectiveness of meteorological forecasting dramatically increased with the advent of the numerical forecasting (stage 9), space weather forecasting is presently making progress through massively expanding its repertoire of objective forecast algorithms (stage 8). The advent of physics-based numerical space weather predictions (the stage of dramatic improvement in forecast effectiveness in meteorology, stage 9) is still in the future for space weather, although codes to achieve such predictions are under development. The crucial role that teaching forecasting in core meteorology courses has played in producing researchers motivated to improve forecasting effectiveness (and its absence in space weather curricula) is emphasized.

How did we get where we are? The myth of the analogy with meteorology

REVIEW

doi:10.1038/nature14956

The quiet revolution of numerical weather prediction

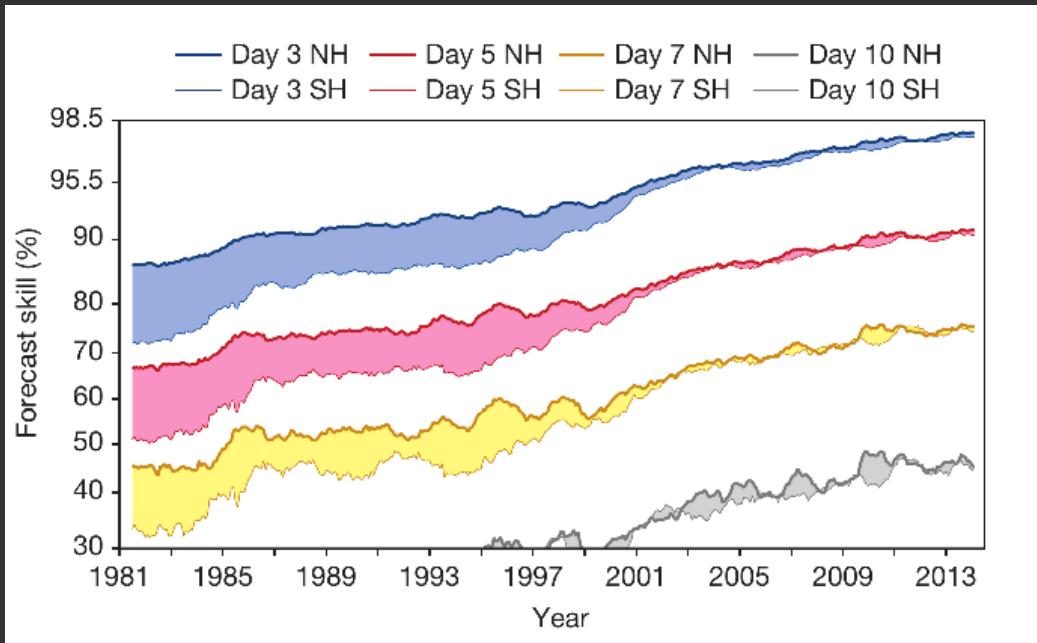
Peter Bauer¹, Alan Thorpe¹ & Gilbert Brunet²

Advances in numerical weather prediction represent a quiet revolution because they have resulted from a steady accumulation of scientific knowledge and technological advances over many years that, with only a few exceptions, have not been associated with the aura of fundamental physics breakthroughs. Nonetheless, the impact of numerical weather prediction is among the greatest of any area of physical science. As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe, and it is performed every day at major operational centres across the world.

This Review explains the fundamental scientific basis of numerical weather prediction (NWP) before highlighting three areas from which the largest benefit in predictive skill has been obtained in the past—physical process representation, ensemble forecasting and model initialization.

Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature*, 525(7567), 47-55.

How did we get where we are? The myth of the analogy with meteorology



A measure of forecast skill at three-, five-, seven- and ten-day ranges, computed over the extra-tropical northern and southern hemispheres.

How did we get where we are?

The myth of the analogy with meteorology

- For the last 20 years the accepted narrative in the space weather community has been that SWx is a ‘younger sibling’ of terrestrial weather.
- As such, the hope has always been that SWx will soon achieve the same level of extraordinary success witnessed in numerical weather predictions.
 - As a consequence the majority of effort (and funding) has been spent in developing physics-based models.

How did we get where we are? The myth of the analogy with meteorology

- It is now time for revisiting that narrative and to admit that physics-based models have not delivered what was it was expected ~20 years ago, and probably will never do.

How did we get where we are? The myth of the analogy with meteorology

- It is now time for revisiting that narrative and to admit that physics-based models have not delivered what was it was expected ~20 years ago, and probably will never do.
- The fundamental reason is that in the Sun-Earth system, we will never reach the required level of accuracy/detail in:
 - Physical processes representation (i.e. kinetic vs fluid physics and small-scale instabilities)
 - Ensemble modeling (lack of in-situ observations of space weather drivers)
 - Model initialization/data assimilation (lack of observations to be assimilated – in NWP on the order of 10M observations)

State-of-the-art operational physics-based models

	Lead-time	Actionable (lead-time + Uncertainty Quantification)	Accuracy	Cost
WSA/ENLIL	1 – 3 days ahead prediction	No uncertainty	No better than zero-cost models	~ 50,000 CPU-hours/year Approximately \$2,000/year (excluding storage, RAM, etc)
SWMF (Geospace)	20 – 60 mins ahead	No uncertainty	No better than persistence	~ 420,000 CPU-hours/year Approx. \$15,000/year (excluding storage, RAM, etc)
WAM/IPE	2 days ahead prediction	No uncertainty	Not sure about validation	~320,000 CPU-hours/year Approx. \$10,000/year (excluding storage, RAM, etc)

Take home message #3: ML will become the standard way of SWx forecasting by the end of the decade

	Lead-time	Actionable (lead-time + Uncertainty Quantification)	Accuracy	Cost
Machine Learning	1 hour – 3 days	Ensemble or built-in UQ	Typically better than physics-based equivalent	Example: LiveDst (a forecast every 15 minutes) ~ 250 CPU-hours/year costs <\$10/year (including everything: storage, I/O time, RAM, etc.)

What can ML do for Space Weather? (a non-comprehensive list)

Geomagnetic indices

Space Weather

RESEARCH ARTICLE

10.1029/2018SW001898

Key Points:

- First use of a Long Short-Term Memory network to provide single-point prediction of the Dst index, up to 6 hr ahead
- Development of a method that combines neural network and

Multiple-Hour-Ahead Forecast of the Dst Index Using a Combination of Long Short-Term Memory Neural Network and Gaussian Process

M. A. Gruet¹ , M. Chandorkar² , A. Sicard¹, and E. Camporeale² 

¹ONERA, The French Aerospace Lab, Toulouse, France, ²Center for Mathematics and Computer Science (CWI), Amsterdam, Netherlands

manuscript submitted to *Space Weather*

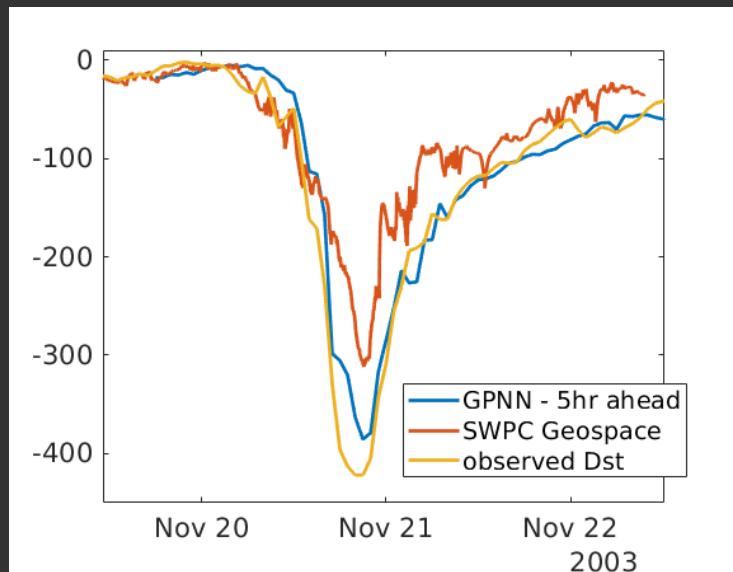
Multi-Hour Ahead Dst Index Prediction Using Multi-Fidelity Boosted Neural Networks

A. Hu¹, E. Camporeale^{1,2}, B. Swiger^{1,2}

¹CIRES, University of Colorado, Boulder, CO, USA

²NOAA Space Weather Prediction Center, Boulder, CO, USA

The Dst (Disturbance storm time) index is an index of magnetic activity derived from a network of near-equatorial geomagnetic observatories



Geomagnetic indices

Space Weather®

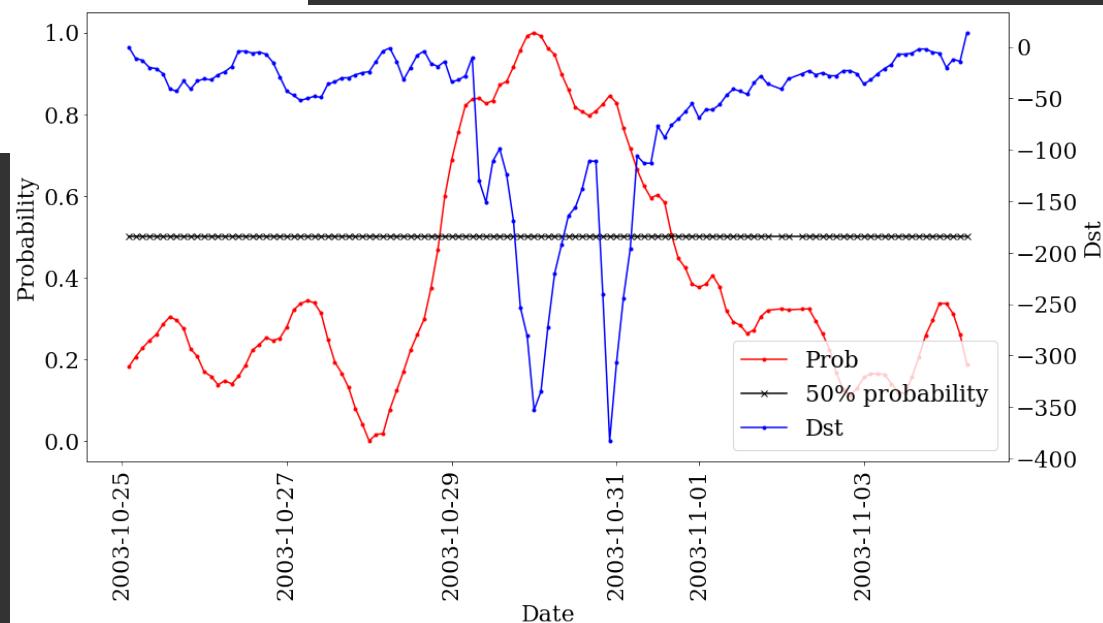
Research Article | Open Access | CC BY \$

Probabilistic Prediction of *Dst* Storms One-Day-Ahead Using Full-Disk SoHO Images

A. Hu✉, C. Schneider, A. Tiwari, E. Camporeale

First published: 23 May 2022 | <https://doi.org/10.1029/2022SW003064>

The *Dst* (Disturbance storm time) index is an index of magnetic activity derived from a network of near-equatorial geomagnetic observatories



Geomagnetic indices

Space Weather®



RESEARCH ARTICLE

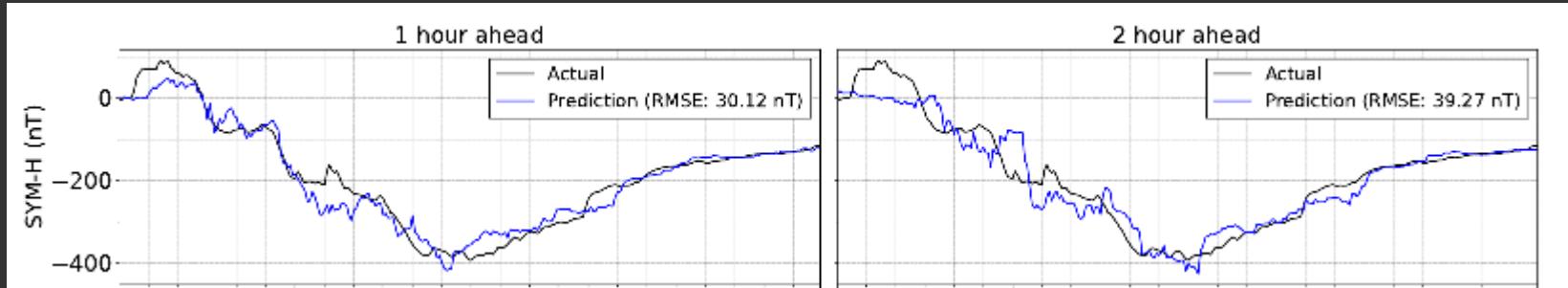
10.1029/2021SW002928

Key Points:

- We adapt gradient boosting machines for forecasting the SYM-H index

New Findings From Explainable SYM-H Forecasting Using Gradient Boosting Machines

Daniel Iong¹ , Yang Chen¹ , Gabor Toth² , Shasha Zou² , Tuija Pulkkinen² , Jiaen Ren² , Enrico Camporeale^{3,4} , and Tamas Gombosi²



Geomagnetic indices

Space Weather®



RESEARCH ARTICLE

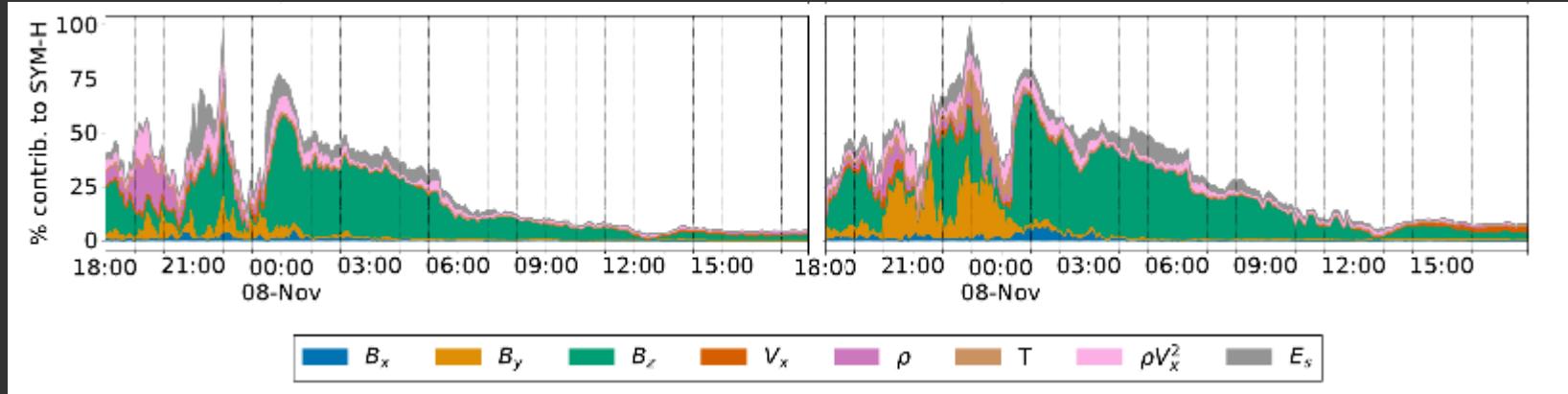
10.1029/2021SW002928

Key Points:

- We adapt gradient boosting machines for forecasting the SYM-H index

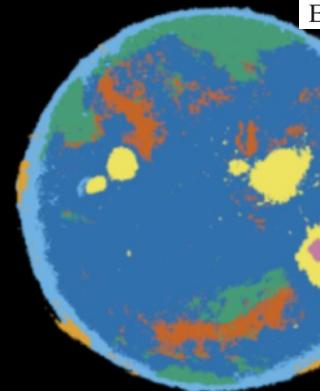
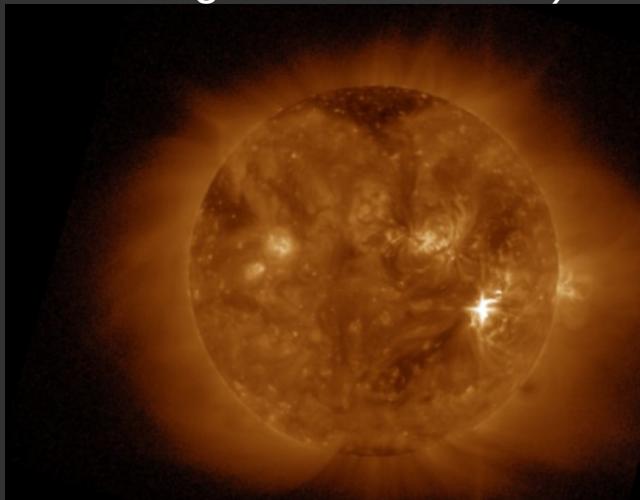
New Findings From Explainable SYM-H Forecasting Using Gradient Boosting Machines

Daniel Iong¹ , Yang Chen¹ , Gabor Toth² , Shasha Zou² , Tuija Pulkkinen² , Jiaen Ren² , Enrico Camporeale^{3,4} , and Tamas Gombosi²



Segmentation of coronal holes in solar disk images

- Segmentation of solar disk images (supervised or unsupervised):
 - Automatically extract different solar regions (that are associated with different solar wind/geoeffectiveness)



Monthly Notices
of the
ROYAL ASTRONOMICAL SOCIETY
MNRAS 481, 5014–5021 (2018)
Advance Access publication 2018 October 1

doi:10.1093/mnras/sty2628

Segmentation of coronal holes in solar disc images with a convolutional neural network

Egor A. Illarionov^{1,2}★ and Andrey G. Tlatov^{2,3}

Solar Phys (2019) 294:117
<https://doi.org/10.1007/s11207-019-1517-4>

Solar Filament Recognition Based on Deep Learning

Gaofei Zhu^{1,2,3} · Ganghua Lin^{1,3} ·
Dongguang Wang^{1,3} · Suo Liu^{1,3,4} · Xiao Yang^{1,3}

Courtesy of Dan Seaton and J. Marcus Hughes, NCEI, CIRES, and University of Colorado Boulder

Solar flare prediction

- Possibly the most active research area in ML for space weather!

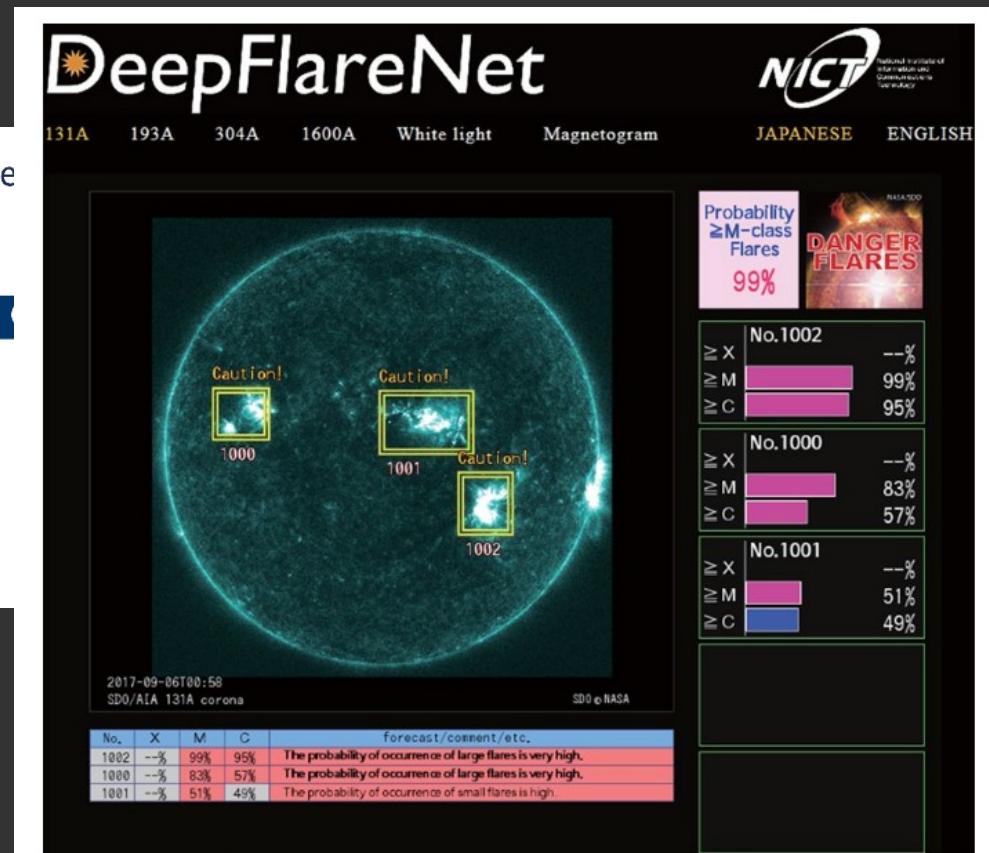
Nishizuka et al. *Earth, Planets and Space* (2021) 73:64
<https://doi.org/10.1186/s40623-021-01381-9>

FULL PAPER

Operational solar flare prediction model using Deep Flare Net

Naoto Nishizuka^{1*}, Yuki Kubo¹, Komei Sugiura², Mitsue Den¹ and Mamoru Ishii¹

Earth, Plane



Solar flare prediction

SOLAR FLARE PREDICTION USING *SDO/HMI* VECTOR MAGNETIC FIELD DATA WITH A MACHINE-LEARNING ALGORITHM

M. G. BOBRA AND S. COVIDAT

W. W. Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA 94305, USA; couvidat@stanford.edu

Received 2014 August 1; accepted 2014 November 1; published 2015 January 8



Predicting Solar Flares with Machine Learning: Investigating Solar Cycle Dependence

Xiantong Wang¹ , Yang Chen², Gabor Toth¹ , Ward B. Manchester¹ , Tamas I. Gombosi¹ , Alfred O. Hero³, Zhenbang Jiao², Hu Sun², Meng Jin^{4,5} , and Yang Liu⁶

¹ Department of Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, USA; xtwang@umich.edu

² Department of Statistics, University of Michigan, Ann Arbor, MI, USA

³ Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI, USA; [Solar Phys \(2018\) 293:28](https://doi.org/10.1007/s11207-018-1250-4)

⁴ Lockheed Martin Solar and Astrophysics Laboratory, Palo Alto, CA, USA

<https://doi.org/10.1007/s11207-018-1250-4>

⁵ SETI Institute, Mountain View, CA 94043, USA

⁶ Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA 94305, USA

Received 2020 January 22; revised 2020 April 13; accepted 2020 April 14; published 2020 May

Decreasing False-alarm Rates in CNN-based Solar Flare Prediction Using *SDO/HMI* Data

Varad Deshmukh¹ , Natasha Flyer², Kiera van der Sande³, and Thomas Berger⁴

¹ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

² Department of Mathematics, Colorado School of Mines, Boulder, CO 80303, USA

³ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

⁴ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

Forecasting Solar Flares Using Magnetogram-based Predictors and Machine Learning

Kostas Florios^{1,2} , Ioannis Kontogiannis¹ , Sung-Hong Park³ , Jordan A. Guerra³ , Federico Benvenuto⁴ , D. Shaun Bloomfield⁵ , Manolis K. Georgoulis¹

¹ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

² Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

³ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

⁴ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

⁵ Department of Geosciences, Colorado School of Mines, Boulder, CO 80303, USA

Solar wind classification

- The geoeffectiveness of solar wind is related to its source region
- Xu & Borovsky (2015) introduced a 4-category solar wind: ejecta, coronal holes, sector reversal, streamer belts
- 40 years of OMNI data have been automatically categorized (based on a training set of ~9,000 hours covering 1995-2008)

Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE

10.1002/2017JA024383

Classification of Solar Wind With Machine Learning

Key Points:

- Gaussian Process classification yields excellent accuracy in classifying the solar wind according to the Xu and

Enrico Camporeale¹ , Algo Carè¹ , and Joseph E. Borovsky² 

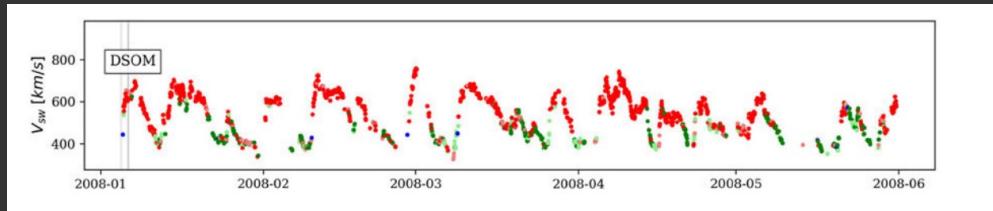
¹Center for Mathematics and Computer Science (CWI), Amsterdam, Netherlands, ²Center for Space Plasma Physics, Space Science Institute, Boulder, CO, USA

Unsupervised classification

Visualizing and Interpreting Unsupervised Solar Wind Classifications

Jorge Amaya*, Romain Dupuis, Maria Elena Innocenti and Giovanni Lapenta

Mathematics Department, Centre for Mathematical Plasma-Astrophysics, KU Leuven, Leuven, Belgium



Data-Driven Classification of Coronal Hole and Streamer Belt Solar Wind

Téo Bloch¹  · Clare Watt¹  · Mathew Owens¹  ·
Leland McInnes²  · Allan R. Macneil¹ 

Objectively Determining States of the Solar Wind Using Machine Learning

D. Aaron Roberts¹ , Homa Karimabadi² , Tamara Sipes³ , Yuan-Kuen Ko⁴ , and Susan Lepri⁵ 

Solar wind speed

Space Weather*

RESEARCH ARTICLE

10.1029/2021SW002976

Special Section:
Heliophysics and Space Weather
Solar Wind Speed Forecasting

Attention-Based Machine Vision Models and Techniques for Solar Wind Speed Forecasting Using Solar EUV Images

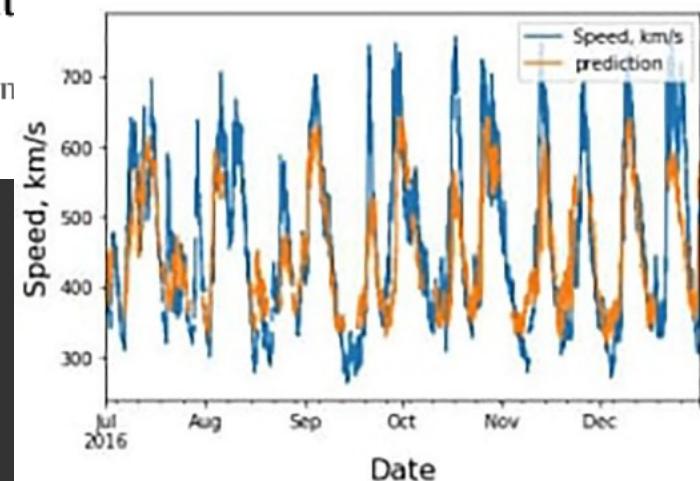


Edward J. E. Brown^{1,2,3} , Filip Svoboda¹, Nigel P. Meredith² , Nicholas Lane^{1,4}, and Richard B. Horne²

Solar Wind Speed Prediction via Graph Attention Network

Yanru Sun¹, Zongxia Xie¹ , Haocheng Wang¹, Xin Huang², and Qinghua Hu

¹College of Intelligence and Computing, Tianjin University, Tianjin, China, ²National Astronomical Observatory of Sciences
Published as a conference paper at ICLR 2020



DYNAMIC TIME LAG REGRESSION: PREDICTING WHAT & WHEN

Mandar Chandorkar
Centrum Wiskunde en Informatica
Amsterdam 1098XG

Cyril Furtlechner
INRIA-Saclay

Bala Poduval
University of New Hampshire
Durham, NH 03824

Enrico Camporeale
CIRES, University of Colorado
Boulder, CO

Michèle Sebag
CNRS – Univ. Paris-Saclay

Ionospheric scintillation and thermosphere

Space Weather®

DETECTION OF GNSS IONOSPHERIC SCINTILLATIONS BASED ON MACHINE LEARNING DECISION TREE

LE

top
sets

Science Through Machine Learning: Quantification of Post-Storm Thermospheric Cooling

Richard J. Licata¹ , Piyush M. Mehta¹ , Daniel R. Weimer² , Douglas P. Drob³ , W. Kent Tobiska⁴ , and Jean Yoshii⁴

Space Weather®

NICOLA LINTY , Member, IEEE

Department of Electronics and Telecommunications Pol
Torino Italy

ALESSANDRO FARASIN 

ALFREDO FAVENZA 
Istituto Superiore Mario Boella, Torino Italy

FABIO DOVIS 

Department of Electronics and Telecommunications Politecnico di Torino,
Torino Italy

RESEARCH ARTICLE

10.1029/2021SW002918

Key Points:

- We develop a nonlinear global model

Improved Neutral Density Predictions Through Machine Learning Enabled Exospheric Temperature Model

Richard J. Licata¹ , Piyush M. Mehta¹ , Daniel R. Weimer² , and W. Kent Tobiska³ 

Radiation belts' electron flux

Space Weather®

RESEARCH ARTICLE

10.1029/2021SW002808

Key Points:

- A neural network model was developed to forecast relativistic electron fluxes with energies



Relativistic Electron Model in the Outer Radiation Belt Using a Neural Network Approach

Xiangning Chu¹ , Donglai Ma² , Jacob Bortnik² , W. Kent Tobiska³ , Alfredo Cruz³ , S. Dave Bouwer³, Hong Zhao⁴ , Qianli Ma^{2,5} , Kun Zhang⁶ , Daniel N. Baker¹ , Xinlin Li¹ , Harlan Spence⁷ , and Geoff Reeves⁸

Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE

10.1002/2017JA024406

Empirical Modeling of the Plasmasphere Dynamics Using Neural Networks

Key Points:

- We developed a dynamic plasmasphere density model by

Irina S. Zhelavskaya^{1,2} , Yuri Y. Shprits^{1,2,3} , and Maria Spasojević⁴

Radiation belts' electron flux

JGR Space Physics

RESEARCH ARTICLE

10.1029/2022JA030377

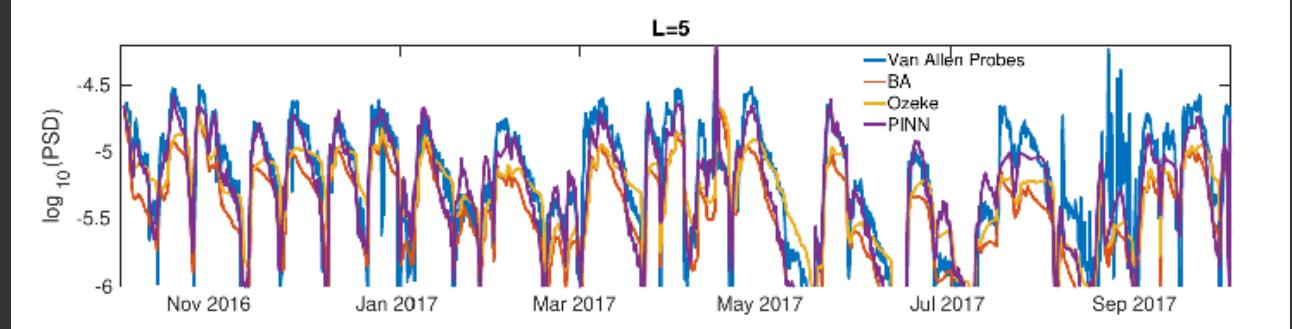
Special Section:

Machine Learning in
Heliophysics

Data-Driven Discovery of Fokker-Planck Equation for the Earth's Radiation Belts Electrons Using Physics-Informed Neural Networks

E. Camporeale^{1,2} , George J. Wilkie³ , Alexander Y. Drozdov⁴ , and Jacob Bortnik⁴ 

**Data-driven discovery
of physics laws with
Machine Learning!**

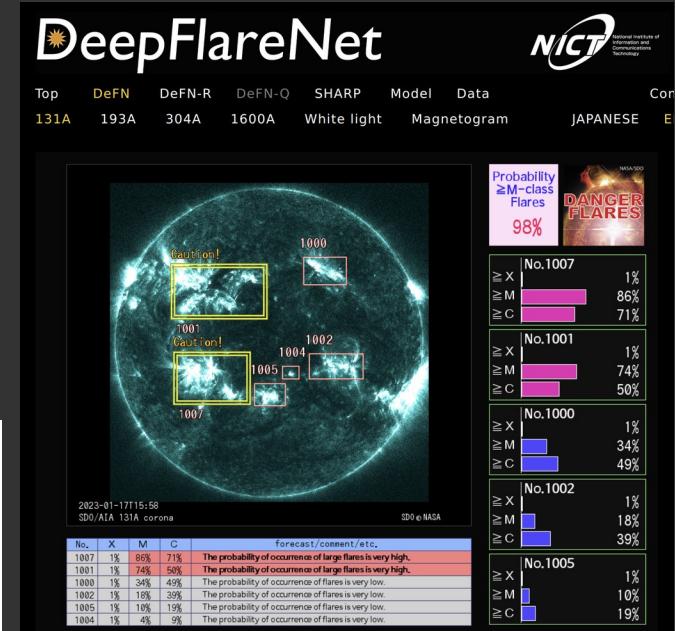
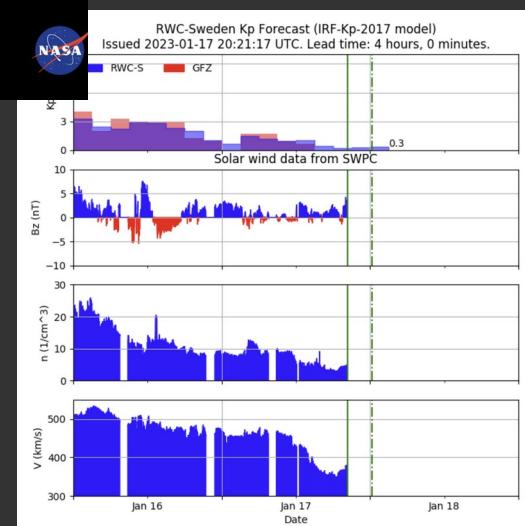


Operational ML models



<https://swx-trec.com/dst/>

<https://swe.ssa.esa.int/irf-federated>



https://defn.nict.go.jp/top_eng.html

See also:

<https://spaceweather.gfz-potsdam.de/products-data/forecasts/>

Path forward for ML in SWx

Freely adapted from:

Space Weather

FEATURE ARTICLE

10.1029/2018SW002061



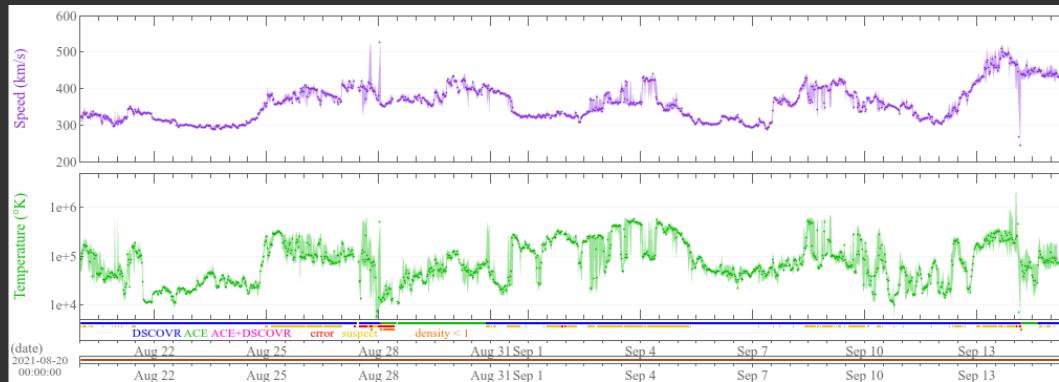
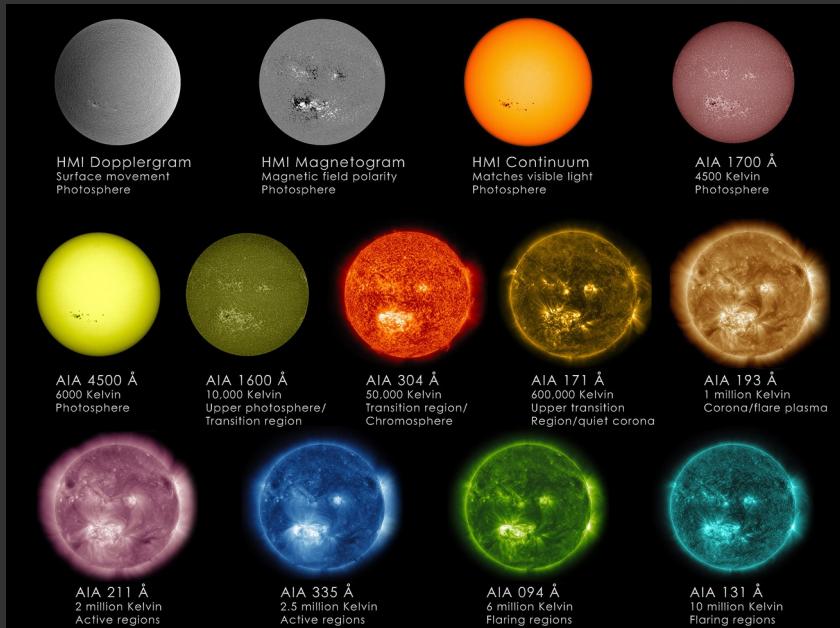
The Challenge of Machine Learning in Space Weather: Nowcasting and Forecasting

E. Camporeale^{1,2} 

¹CIRES, University of Colorado Boulder, Boulder, CO, USA, ²Centrum Wiskunde & Informatica, Amsterdam, The Netherlands

Path forward for ML in SWx

- *The information problem:* What is the minimal physical information required to make a forecast?



200M pixels → 1 scalar value

Path forward for ML in SWx

- *The gray-box problem:* What is the best way to make an optimal use of both our physical understanding and our large amount of data in the Sun-Earth system?

JGR Space Physics

RESEARCH ARTICLE

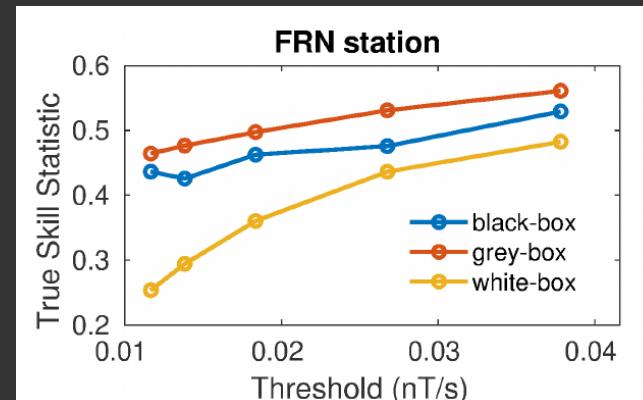
10.1029/2019JA027684

Key Points:

- We present a new model to forecast the maximum value of dB/dt over 20-min intervals at specific locations

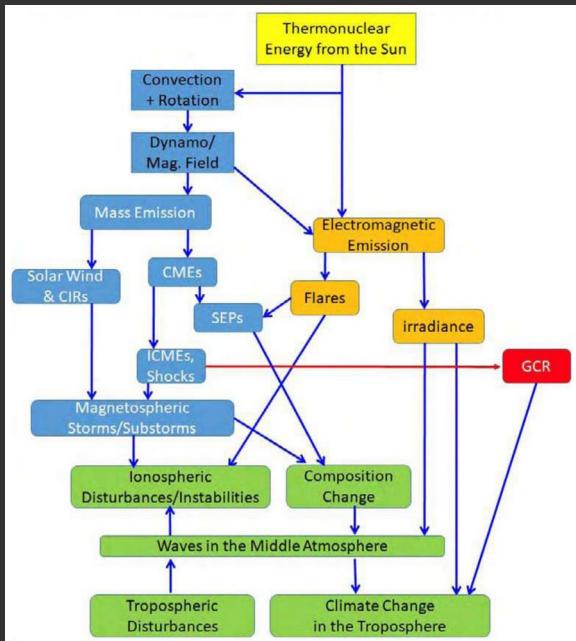
A Gray-Box Model for a Probabilistic Estimate of Regional Ground Magnetic Perturbations: Enhancing the NOAA Operational Geospace Model With Machine Learning

E. Camporeale^{1,2} , M. D. Cash³, H. J. Singer³ , C. C. Balch³ , Z. Huang⁴, and G. Toth⁴ 



Path forward for ML in SWx

- *The surrogate problem:* What components in the Space Weather chain can be replaced by an approximated black-box surrogate model? What is an acceptable trade-off between lost of accuracy and speed-up?



Review

Physics of Space Weather Phenomena: A Review

Ashok Kumar Singh ^{1,*}, Asheesh Bhargawa ¹, Devendraa Siingh ² and Ram Pal Singh ³

Path forward for ML in SWx

- *The uncertainty problem:* Most Space Weather services provide forecast in terms of single-point predictions. There is a clear need of understanding and assessing the uncertainty associated to these predictions. Propagating uncertainties through the Space Weather chain from solar images to magnetospheric and ground-based observations is a complex task that is computationally demanding.

Space Weather

RESEARCH ARTICLE

10.1029/2018SW002026

Key Points:

- We introduce a new method to estimate the uncertainties associated

On the Generation of Probabilistic Forecasts From Deterministic Models

E. Camporeale^{1,2} , X. Chu³ , O. V. Agapitov⁴ , and J. Bortnik⁵ 

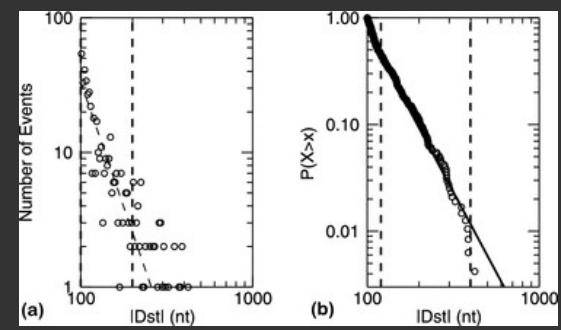
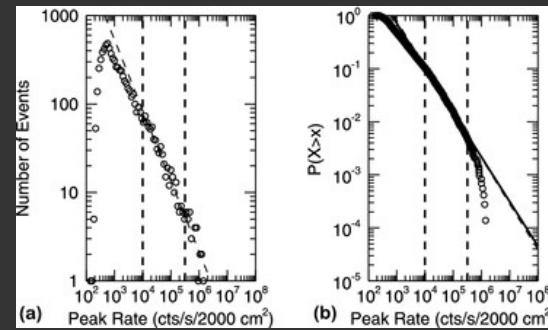
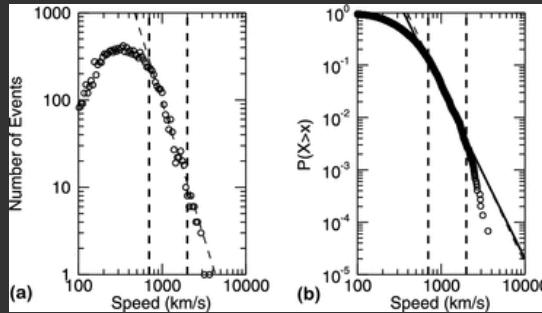
International Journal for Uncertainty Quantification, 11(4):81–94 (2021)

ACCRUE: ACCURATE AND RELIABLE UNCERTAINTY ESTIMATE IN DETERMINISTIC MODELS

Enrico Camporeale^{1,} & Algo Care²*

Path forward for ML in SWx

- *The too often too quiet problem:* Space weather data sets are typically imbalanced: many days of quiet conditions and a few hours of storms. This poses a serious problem for any machine learning algorithm. It is also problematic for defining meaningful metrics that actually assess the ability of a model to predict interesting but rare events.



SPACE WEATHER, VOL. 10, S02012, doi:10.1029/2011SW000734, 2012

On the probability of occurrence of extreme space weather events

Pete Riley¹

SynWind: Synthetic Solar Wind Generator

Enrico Camporeale, Andong Hu, Brian Swiger

CIRES, University of Colorado at Boulder & NOAA Space Weather Prediction Center

Path forward for ML in SWx

- *The knowledge discovery and explainability problem:* How do we distill some knowledge from a machine learning model and improve our understanding of a given system? How do we open the black-box and reverse-engineer a machine learning algorithm?

arXiv.org > physics > arXiv:2107.14322

Physics > Space Physics

[Submitted on 29 Jul 2021]

Machine-learning based discovery of missing physical processes in radiation belt modeling

Enrico Camporeale, George J. Wilkie, Alexander Drozdov, Jacob Bortnik

Summary

ML 4 SWx is the quintessential interdisciplinary field.

**These 6 problems not only hinder progress in Space Weather,
but pose fundamental challenges in the fields of AI and UQ.**

- *The information problem*
- *The gray-box problem*
- *The surrogate problem*
- *The uncertainty problem*
- *The too often too quiet (rare events) problem*
- *The knowledge discovery and explainability problem*

Back-up slides

Why does it work (so well) ?

A short digression

Why does it work (so well) ?

A short digression

The Unreasonable Effectiveness of Mathematics in the Natural Sciences

Richard Courant Lecture in Mathematical Sciences delivered at New York University,
May 11, 1959

EUGENE P. WIGNER

Princeton University

“The miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics is a wonderful gift which we neither understand nor deserve.”

Why does it work (so well) ?

The Unreasonable Effectiveness of Data

Alon Halevy, Peter Norvig, and Fernando Pereira, Google

The unreasonable effectiveness of deep learning in artificial intelligence

Terrence J. Sejnowski^{a,b,1} 

^aComputational Neurobiology Laboratory, Salk Institute for Biological Studies, La Jolla, CA 92037; and ^bDivision of Biological Sciences, University of California San Diego, La Jolla, CA 92093

We are not in the same boat with image and text recognition, self-driving, or recommendation systems!

Why does it work (so well) ?

Physics to the rescue!

- Physical properties such as invariance, symmetry, conservation laws, etc. reduce drastically the ‘search space’ of parameters
- Any system that follows ‘laws of physics’ should be learnable by Machine Learning
- Any simulation can be emulated by ML
- The major hurdle is **Data Quality & Quantity!**

SCIENCE ADVANCES | RESEARCH ARTICLE

COMPUTER SCIENCE

AI Feynman: A physics-inspired method for symbolic regression

Silviu-Marian Udrescu¹ and Max Tegmark^{1,2*}

A core challenge for both physics and artificial intelligence (AI) is symbolic regression: finding a symbolic expression that matches data from an unknown function. Although this problem is likely to be NP-hard in principle, functions of practical interest often exhibit symmetries, separability, compositionality, and other simplifying properties. In this spirit, we develop a recursive multidimensional symbolic regression algorithm that combines neural network fitting with a suite of physics-inspired techniques. We apply it to 100 equations from the *Feynman Lectures on Physics*, and it discovers all of them, while previous publicly available software cracks only 71; for a more difficult physics-based test set, we improve the state-of-the-art success rate from 15 to 90%.

J Stat Phys (2017) 168:1223–1247
DOI 10.1007/s10955-017-1836-5



Why Does Deep and Cheap Learning Work So Well?

Henry W. Lin¹ · Max Tegmark² · David Rolnick³