Current status and possible paths forward for ML-enhanced Space Weather predictions

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CIRES / CU Boulder & NOAA Space Weather Prediction Center

Thanks to: H. Singer, M. Cash, C. Balch, E. Adamson, G. Toth, Z. Huang, J. Bortnik, G. Wilkie, A. Drozdov, M. Gruet, M. Chandorkar, A. Care', J. Borovsky, G. Lapenta, X. Chu, R. McGranaghan, …, and probably others

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University of Colorado Boulder

CIRES

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NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

U.S. DEPARTMENT OF COMMERCE

What is Space Weather?

Space weather

From Wikipedia, the free encyclopedia

Not to be confused with Space Weather (journal).

Space weather is a branch of space physics and aeronomy, or heliophysics, concerned with the time varying conditions within the Solar System, including the solar wind, emphasizing the space surrounding the Earth, including conditions in the magnetosphere, ionosphere, thermosphere, and exosphere.[1] Space weather is distinct from but conceptually related to the terrestrial weather of the atmosphere of Earth (troposphere and stratosphere). The term *space weather* was first used in the 1950s and came into common usage in the 1990s.[2]

The study of plasma within the Solar System (i.e. not astronomy, not astrophysics)

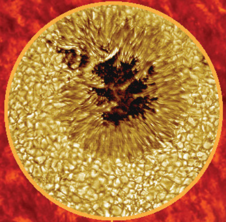
Upper atmosphere

Space Weather

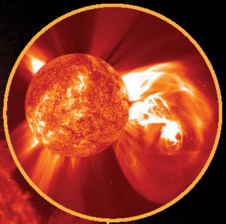
Space weather refers to the variable conditions on the Sun and in the space environment that can influence the performance and reliability of space-based and ground-based technological systems, as well as endanger life or health. Just like weather on Earth, space weather has its seasons, with solar activity rising and falling over an approximate 11 year cycle.

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.



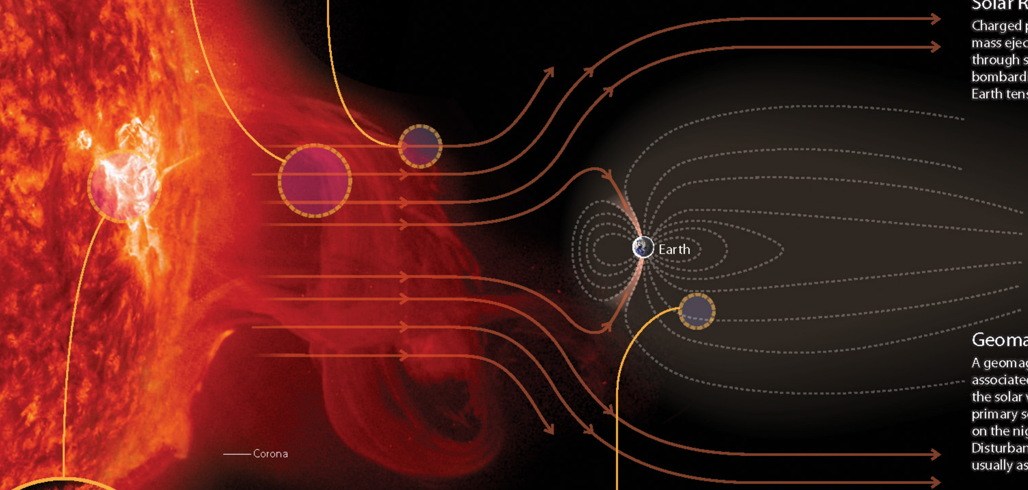
Coronal Mass Ejections (CMEs)



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!

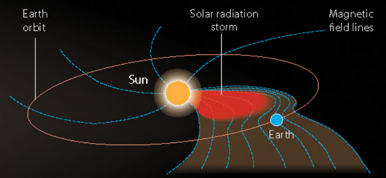


Sun's Magnetic Field

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.

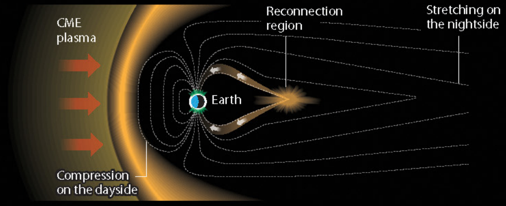
Solar Radiation Storms

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.

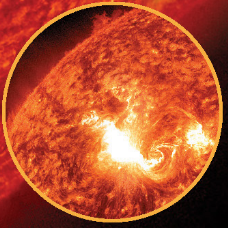


Geomagnetic Storms

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 atomosphere) are usually associated with geomagnetic storms.



Solar Flares



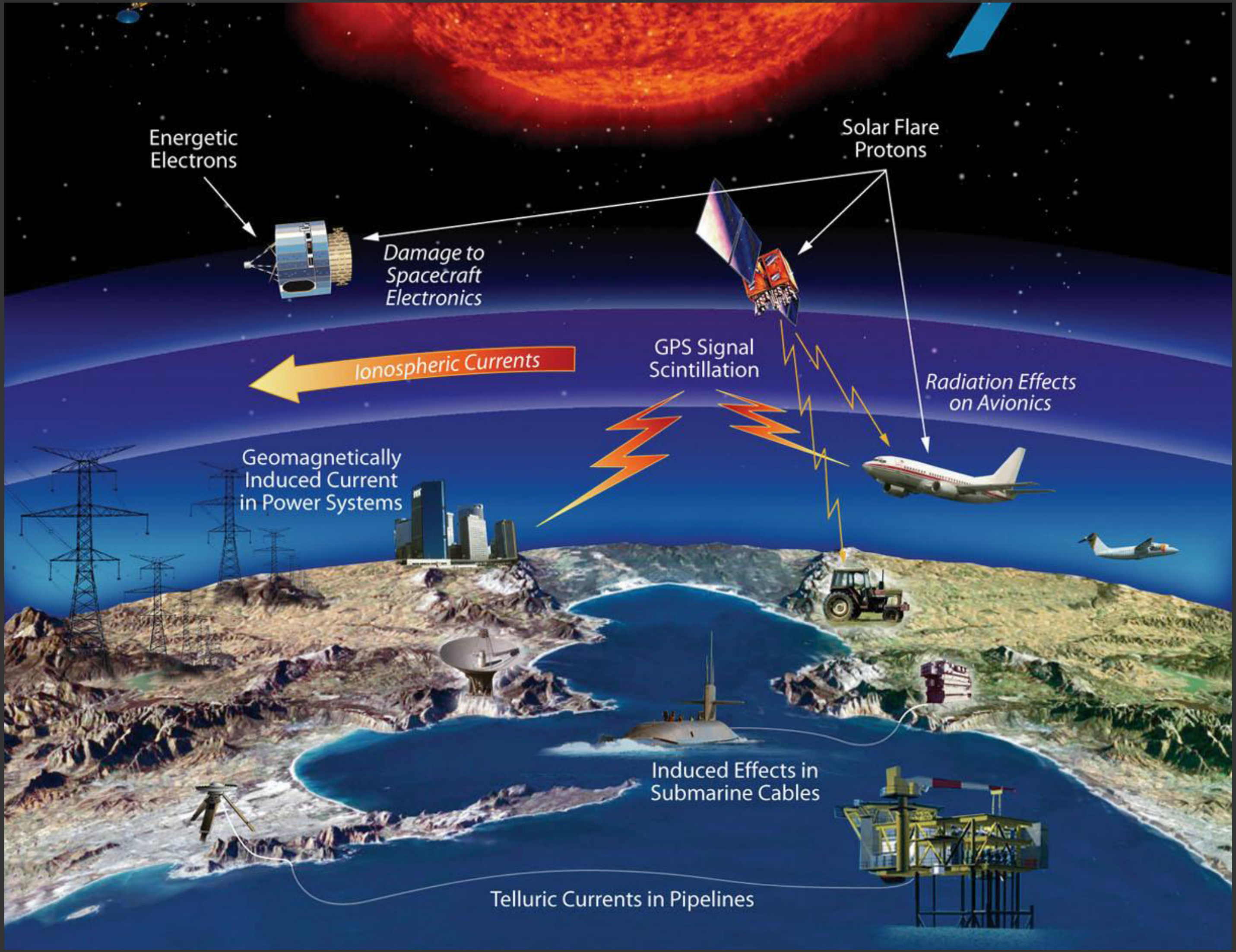
Reconnection of the magnetic fields on the surface of the Sun drive the biggest explosions in our solar system. These solar flares release immense amounts of energy and result in electromagnetic emissions spanning the spectrum from gamma rays to radio waves. Traveling at the speed of light, these emissions 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.

Prediction Center – www.spaceweather.gov

Source images: NASA, NOAA.



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**

FINAL REPORT

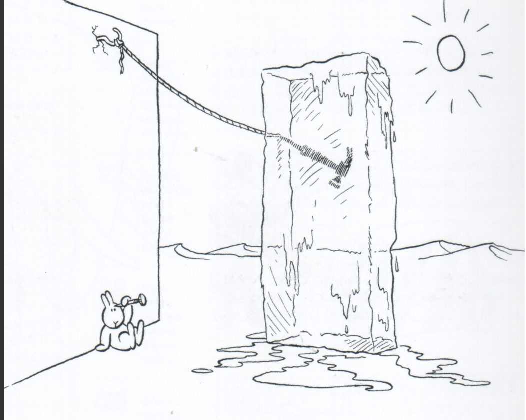
Social and Economic Impacts of Space Weather in the United States

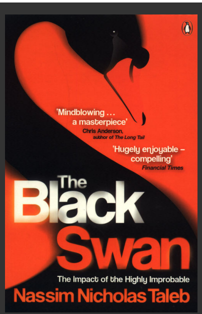
September 2017

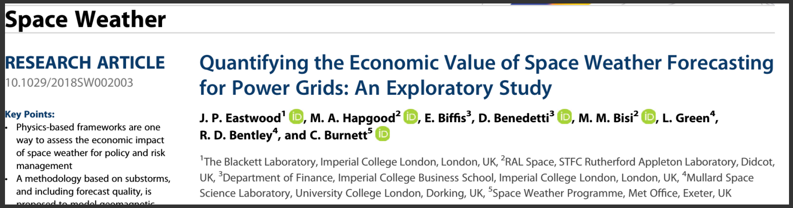
Abt Associates
Bethesda, Maryland

Written under contract for the
NOAA National Weather Service

The book of bunny suicides







Space Weather

RESEARCH ARTICLE
10.1029/2018SW002003

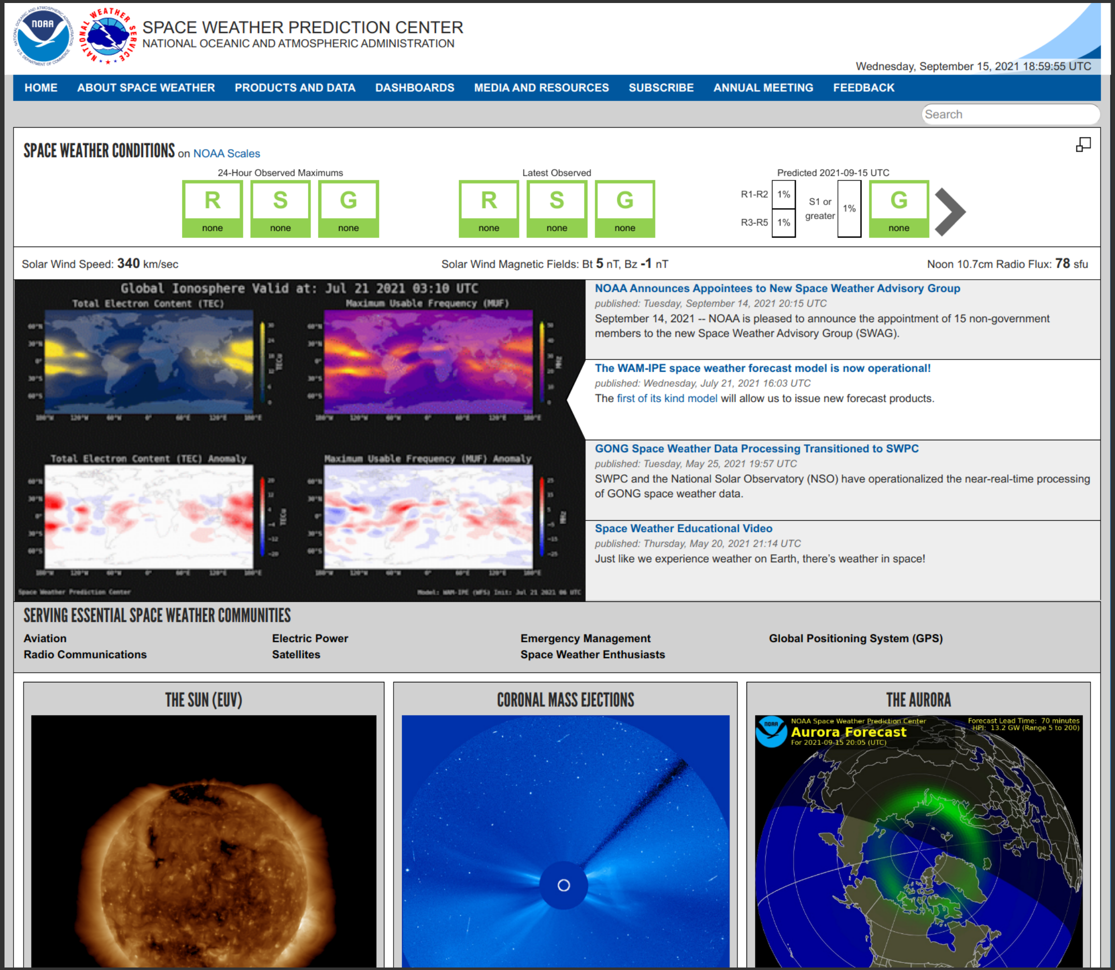
Quantifying the Economic Value of Space Weather Forecasting for Power Grids: An Exploratory Study

J. P. Eastwood[1], M. A. Hapgood[2], E. Biffis[3], D. Benedetti[3], M. M. Bisi[2], L. Green[4], R. D. Bentley[4], and C. Burnett[5]

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

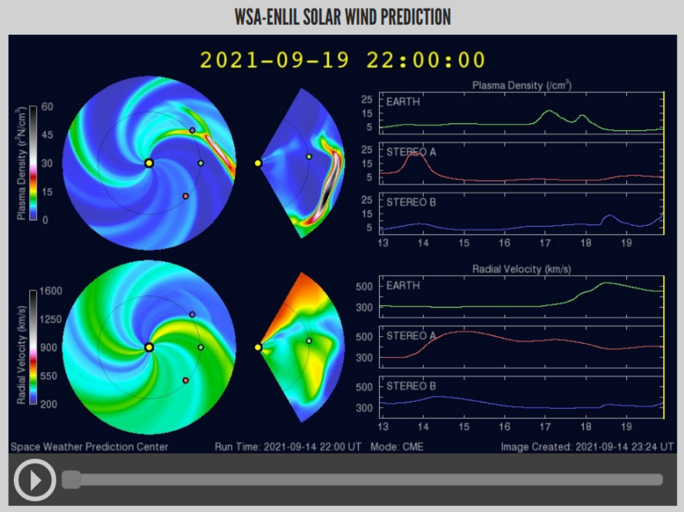
Key Points:
- Physics-based frameworks are one way to assess the economic impact of space weather for policy and risk management
- A methodology based on substorms, and including forecast quality, is

NOAA Space Weather Prediction Center



SWPC mission:

Safeguarding society with actionable space weather information



ML in Space Weather

“It is commonly said that space weather prediction is around 50 years behind terrestrial weather predictions” [1]*:*

- Lack of fundamental understanding
(plasma vs fluid physics)
- Sparsity of observations (temporal and spatial)
- Lack of standardization of metrics, user needs, etc.

[1] Chairwoman Johnson’s opening statement for space weather hearing titled “Space Weather: Advancing Research: Monitoring, and Forecasting Capabilities.”

ML in Space Weather

"It is commonly said that space weather prediction is around 50 years behind terrestrial weather predictions" [1]*:*

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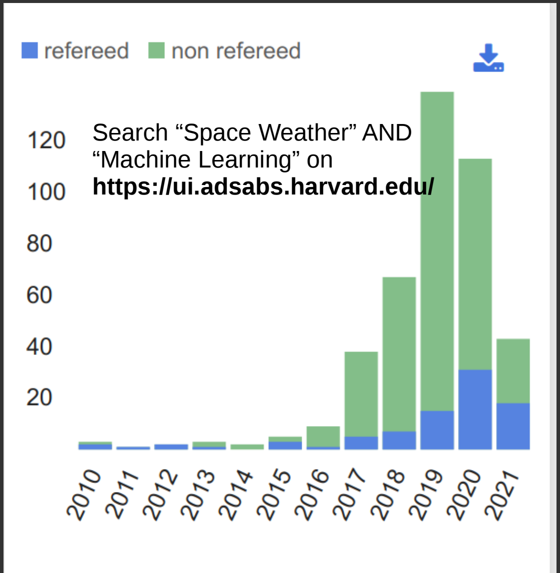


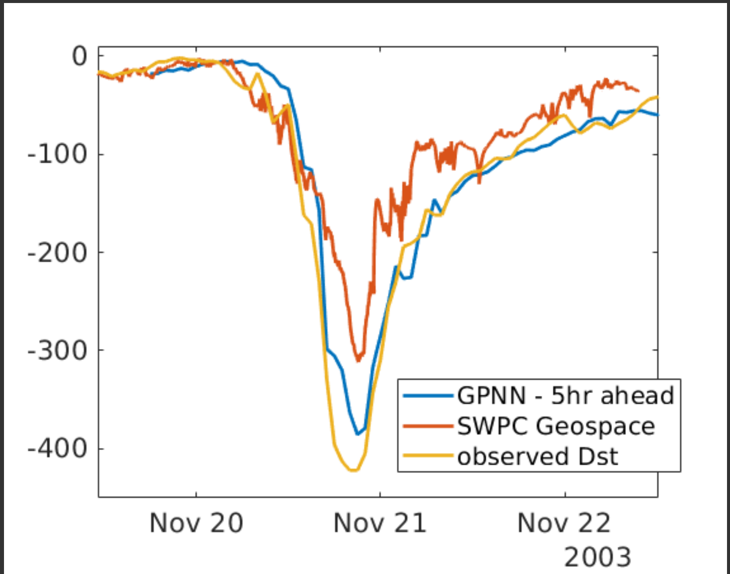
However, the niche of ML within Space Weather is catching up rapidly (10 years behind weather?)
In 2020, 7% of papers published in SWx journals used ML

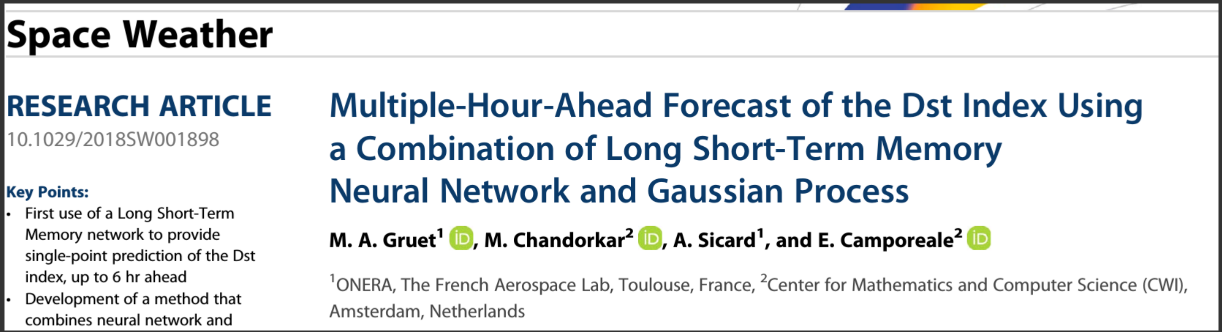
[1] Chairwoman Johnson's opening statement for space weather hearing titled "Space Weather: Advancing Research: Monitoring, and Forecasting Capabilities."

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

- ML works better than physics-based simulations to forecast global/average indexes such as Dst
  - Why? Because in a physics-based approach of a complex system you need to get ‘every single piece right’

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





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. Gruet[1], M. Chandorkar[2], A. Sicard[1], and E. Camporeale[2]

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

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

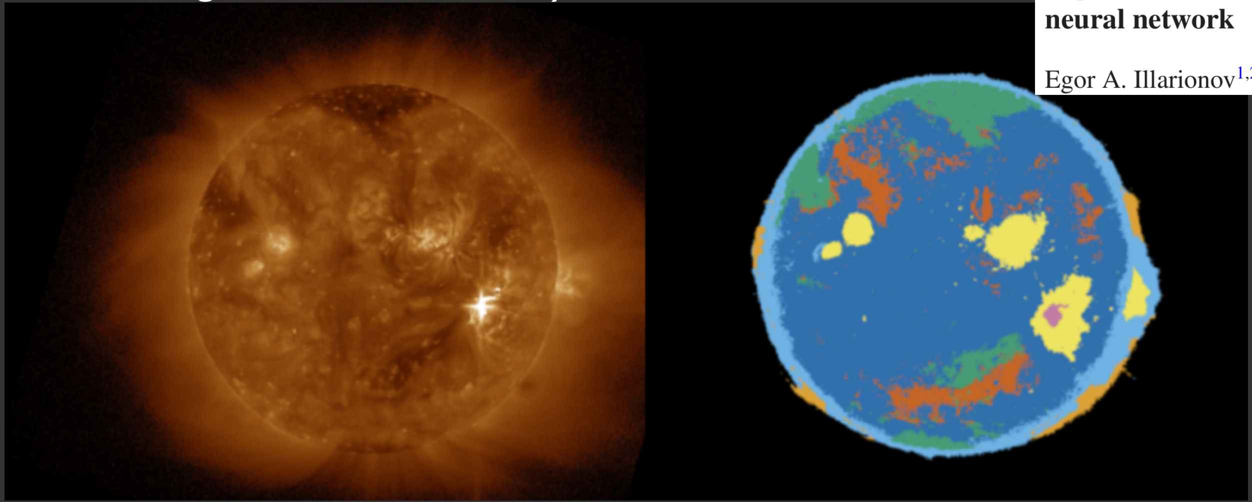
- Segmentation of solar disk images (supervised or unsupervised):
  - Automatically extract different solar regions (that are associated with different solar wind/geoeffectiveness)

Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY

MNRAS **481,** 5014–5021 (2018) doi:10.1093/mnras/sty2628
Advance Access publication 2018 October 1

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

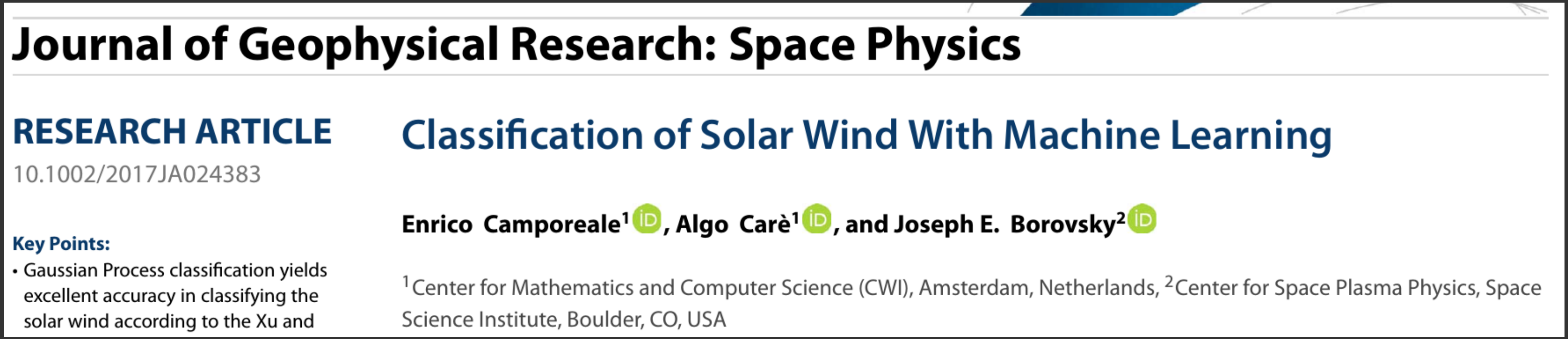
Egor A. Illarionov[1,2★] and Andrey G. Tlatov[2,3]



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

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

- Solar wind classification (supervised):
  - Extending human labeled database from 8000 hrs (<1 year) to 40+ years


Journal of Geophysical Research: Space Physics

RESEARCH ARTICLE
10.1002/2017JA024383

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

Classification of Solar Wind With Machine Learning

Enrico Camporeale[1], Algo Carè[1], and Joseph E. Borovsky[2]

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

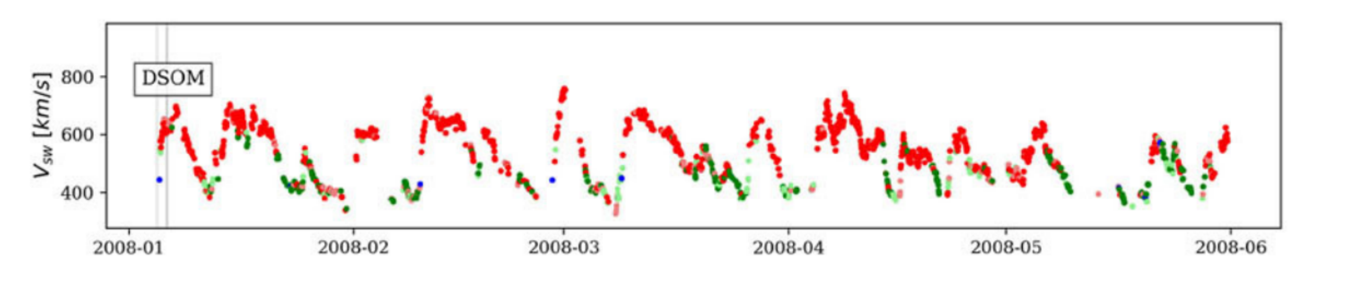
What can ML do for Space Weather?
(a non-comprehensive list)

- Solar wind classification (unsupervised):

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



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

- Regression problems, i.e. predict:
  - The value of a geomagnetic index (Dst, Kp, etc.);
  - The arrival time of a Coronal Mass Ejection;
  - Global Total Electron Content (TEC) maps;
  - Solar wind speed;
  - Relativistic electrons at GEO;
  - Ground magnetic field (dB/dt)
  - Electron precipitation

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

- Classification problems, i.e. what is the probability that:
  - An active region will flare in the next 24 hours?
  - dB/dt will exceed a given value?
  - The solar wind is originated by coronal holes/ejecta, etc.
  - A region of the Sun belongs to a coronal hole

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]

[a]Computational Neurobiology Laboratory, Salk Institute for Biological Studies, La Jolla, CA 92037; and [b]Division 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!**

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

CrossMark

Why Does Deep and Cheap Learning Work So Well?

Henry W. Lin[1] · Max Tegmark[2] · David Rolnick[3]

Path forward for ML in SWx

Freely adapted from:

Space Weather

FEATURE ARTICLE
10.1029/2018SW002061

GRAND CHALLENGES
CENTENNIAL COLLECTION

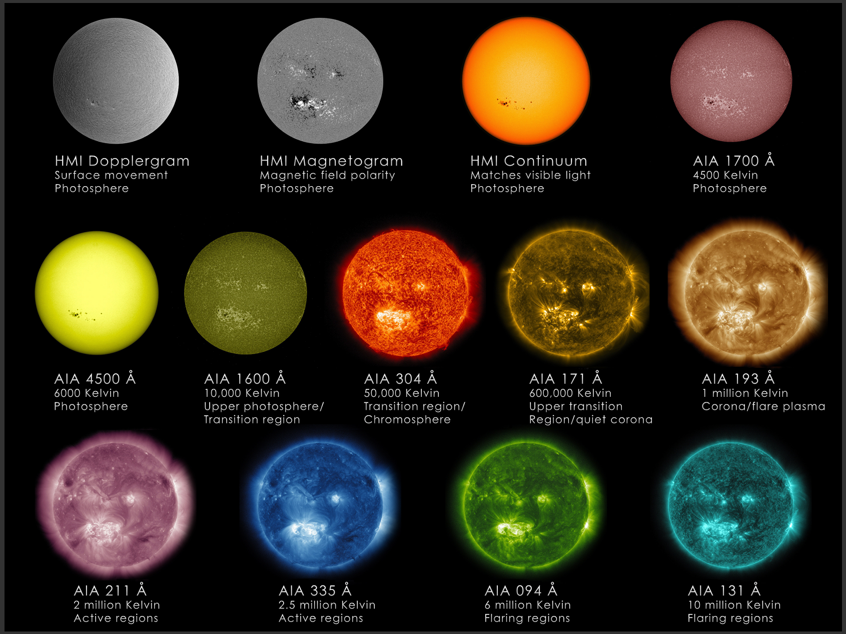
The Challenge of Machine Learning in Space Weather: Nowcasting and Forecasting

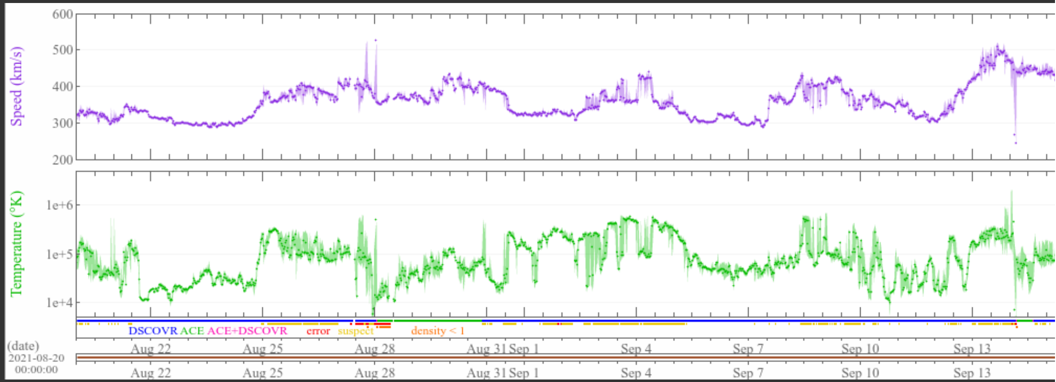
E. Camporeale[1,2]

[1]CIRES, University of Colorado Boulder, Boulder, CO, USA, [2]Centrum 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

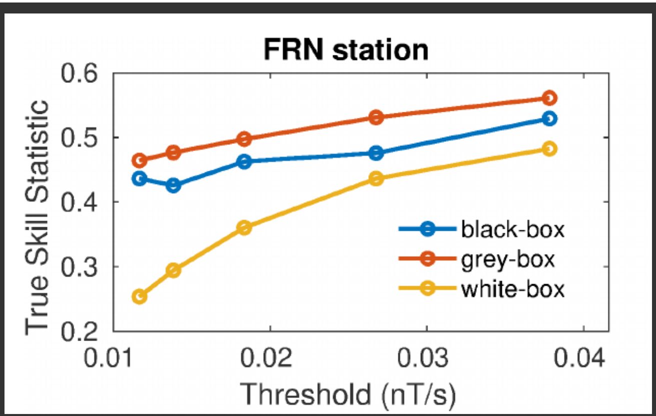
10.1029/2019JA027684

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. Cash[3], H. J. Singer[3], C. C. Balch[3], Z. Huang[4], and G. Toth[4]



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?

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

On the Generation of Probabilistic Forecasts From Deterministic Models

E. Camporeale[1,2], X. Chu[3], O. V. Agapitov[4], and J. Bortnik[5]

Key Points:

- We introduce a new method to estimate the uncertainties associated

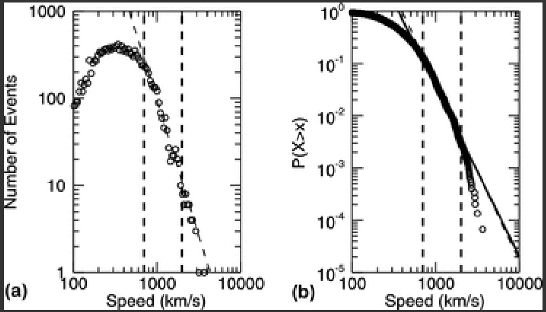
International Journal for Uncertainty Quantification, 11(4):81–94 (2021)

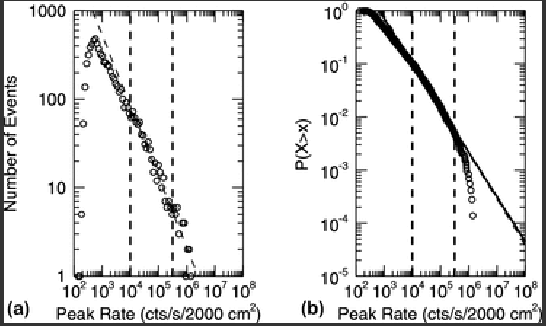
ACCRUE: ACCURATE AND RELIABLE UNCERTAINTY ESTIMATE IN DETERMINISTIC MODELS

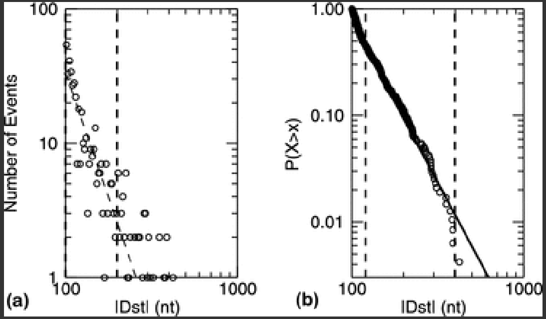
Enrico Camporeale[1,] & Algo Carè[2]*

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 Riley[1]

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

None of the examples mentioned in this presentation are operational at SWPC. All of them outperform current operational models (or claim to do so)

- *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*

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