Research to Operations - Operations to Research

Friday May 17th, 2024

Dr. Thomas Berger
Executive Director
University of Colorado at Boulder
Space Weather Technology, Research, and Education Center

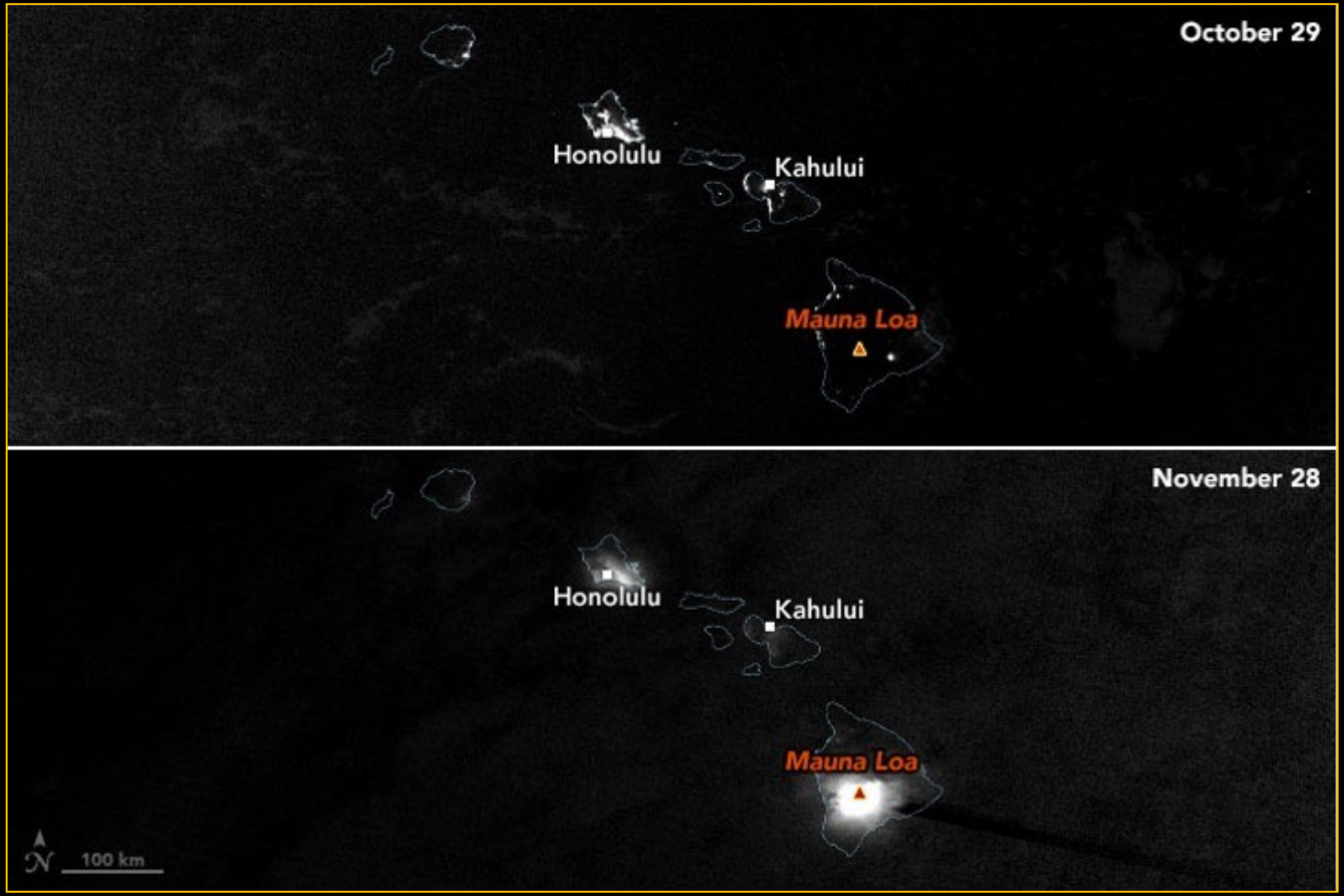
SWx TREC

University of Colorado Boulder
COLLEGE OF ENGINEERING AND APPLIED SCIENCE

Outline

1. Research vs. Operations and the definition of R2O–O2R
2. Operational space weather data and models
3. Predicting complex nonlinear systems.
4. Machine Learning to the rescue?
5. Recent developments from Space Weather TREC

Preface: it matters what you call things



Hawaiian Islands seen from space in 2022

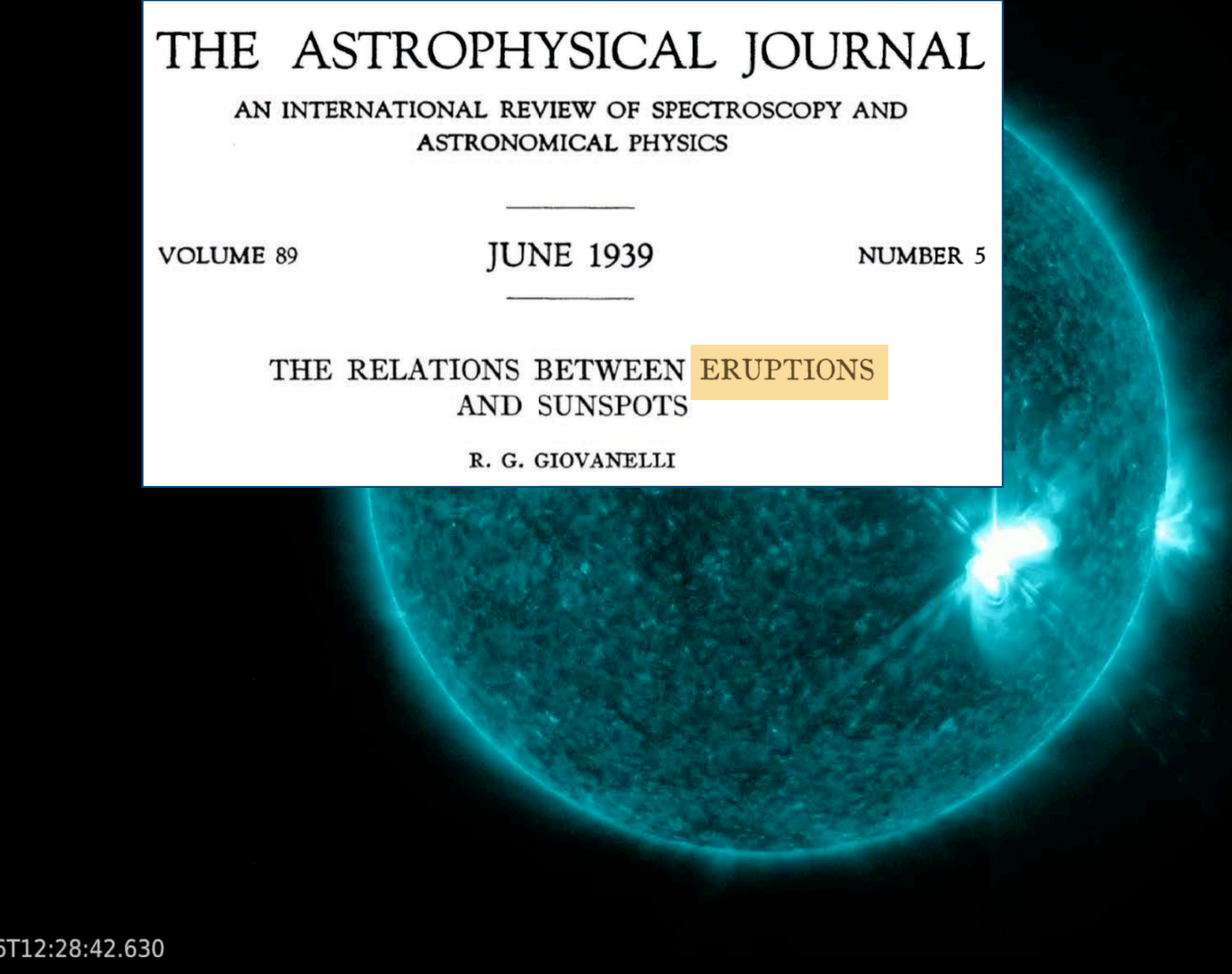
In 2022 there was a volcanic eruption on the island of Hawaii.

The event was observed telescopically by Martian space physicists and their conversation was secretly recorded by NASA.

The following text was translated by ChatGP8:

> "OMG! A bright spot is suddenly flaring from an island in the middle of the Pacific ocean!"
>
> "Wow! You're right!"
>
> "The spectral imager indicates temperatures of thousands of degrees!"
>
> "What could possibly cause such temperatures on the surface of the Earth??"
>
> "I have no idea…What should we call it?"
>
> "Let's call it an ***Earth Flare!***"
>
> "Awesome idea! I'll start the Overleaf."

Preface: it matters what you call things



THE ASTROPHYSICAL JOURNAL

AN INTERNATIONAL REVIEW OF SPECTROSCOPY AND ASTRONOMICAL PHYSICS

VOLUME 89 | JUNE 1939 | NUMBER 5

THE RELATIONS BETWEEN ERUPTIONS AND SUNSPOTS

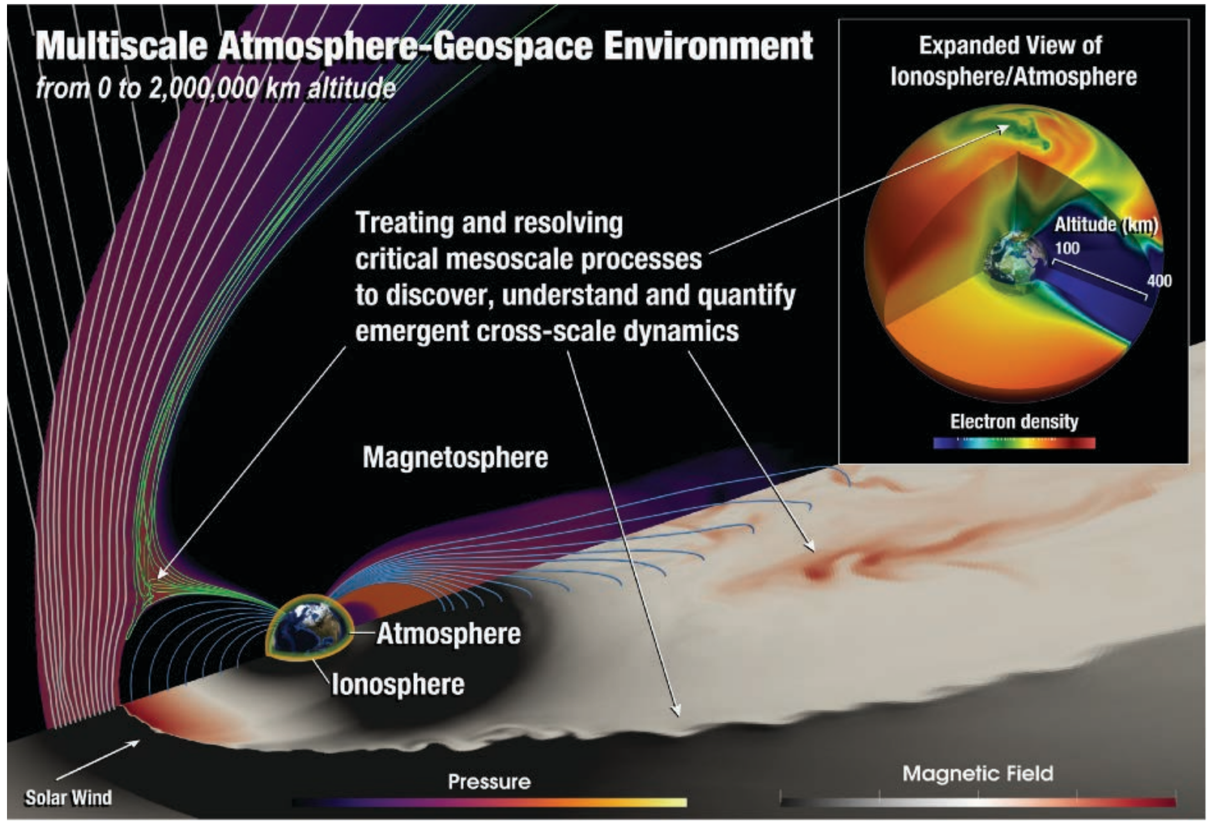
R. G. GIOVANELLI

- The root cause event is a magnetic explosion in the corona: aka, a **Solar Magnetic Eruption**
  - Solar magnetic eruptions can cause
    - **Solar Flares (photons)**
    - **Coronal Mass Ejections (plasma)**
    - **Radiation storms (energetic particles)**
  - Solar flares do **NOT** cause
    - CMEs
    - Geomagnetic storms or aurora
    - Radiation storms
    - Increased drag on LEO satellites
  - Solar flares **CAN** cause
    - Radio, radar, and GPS interference on the sunlit side of the Earth

1. Research vs. Operations and the definition of R2O-O2R

Definition of "R2O" and "O2R"

"Space Physics **Research**"



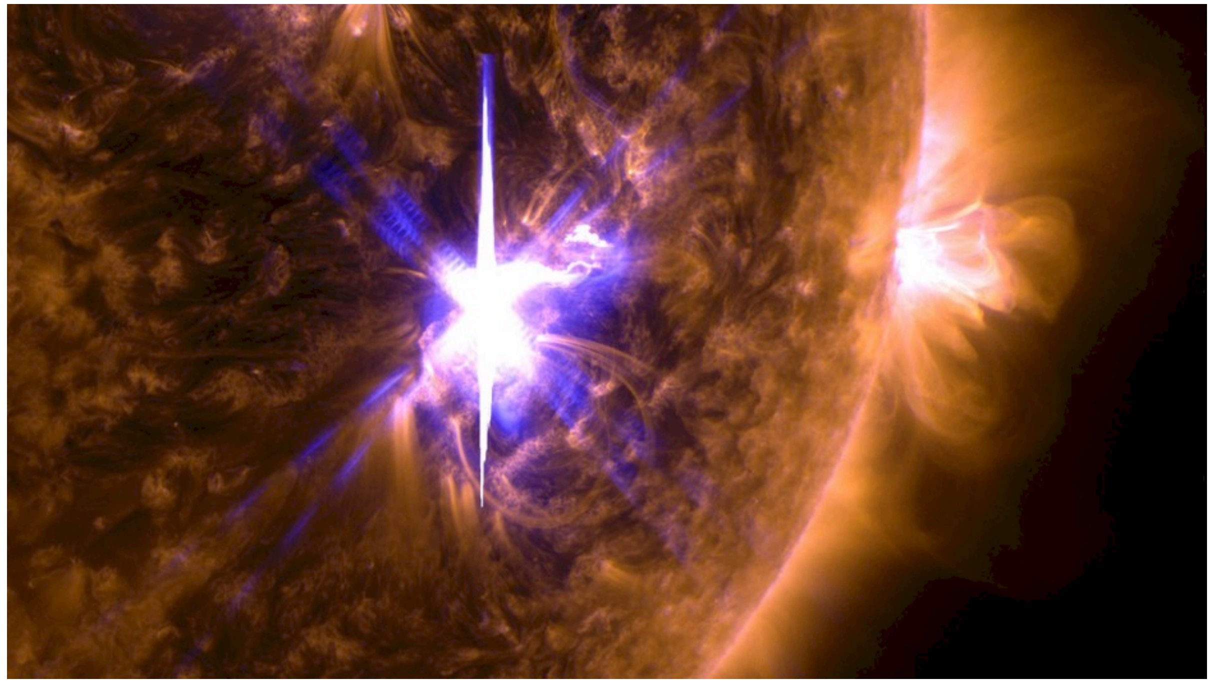
Physics-based models (i.e., PDEs)
to **UNDERSTAND**
causes and effects.

Models are used to ***simulate*** reality.
Data are used to check (**validate**) models.

R2O

O2R

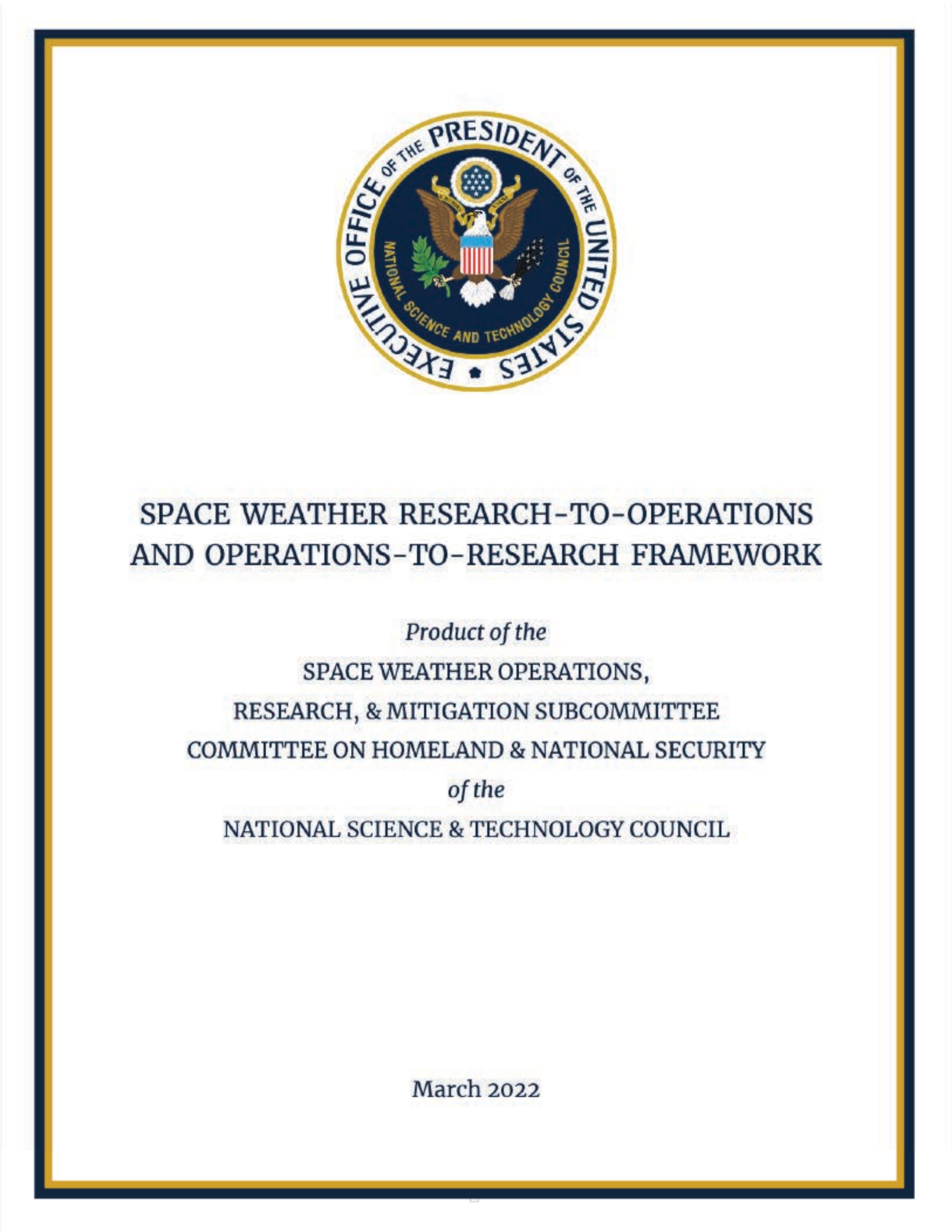
"Space Weather **Operations**"



Whatever models and data are available to run in real-time are used to **PREDICT** *phenomena and impacts*

Models+**data** are used to ***predict*** reality.

Government policy now exists on SWx R2O-O2R processes



SPACE WEATHER RESEARCH-TO-OPERATIONS AND OPERATIONS-TO-RESEARCH FRAMEWORK

Product of the

SPACE WEATHER OPERATIONS, RESEARCH, & MITIGATION SUBCOMMITTEE

COMMITTEE ON HOMELAND & NATIONAL SECURITY

of the

NATIONAL SCIENCE & TECHNOLOGY COUNCIL

March 2022

The Research-to-Operations Funnel

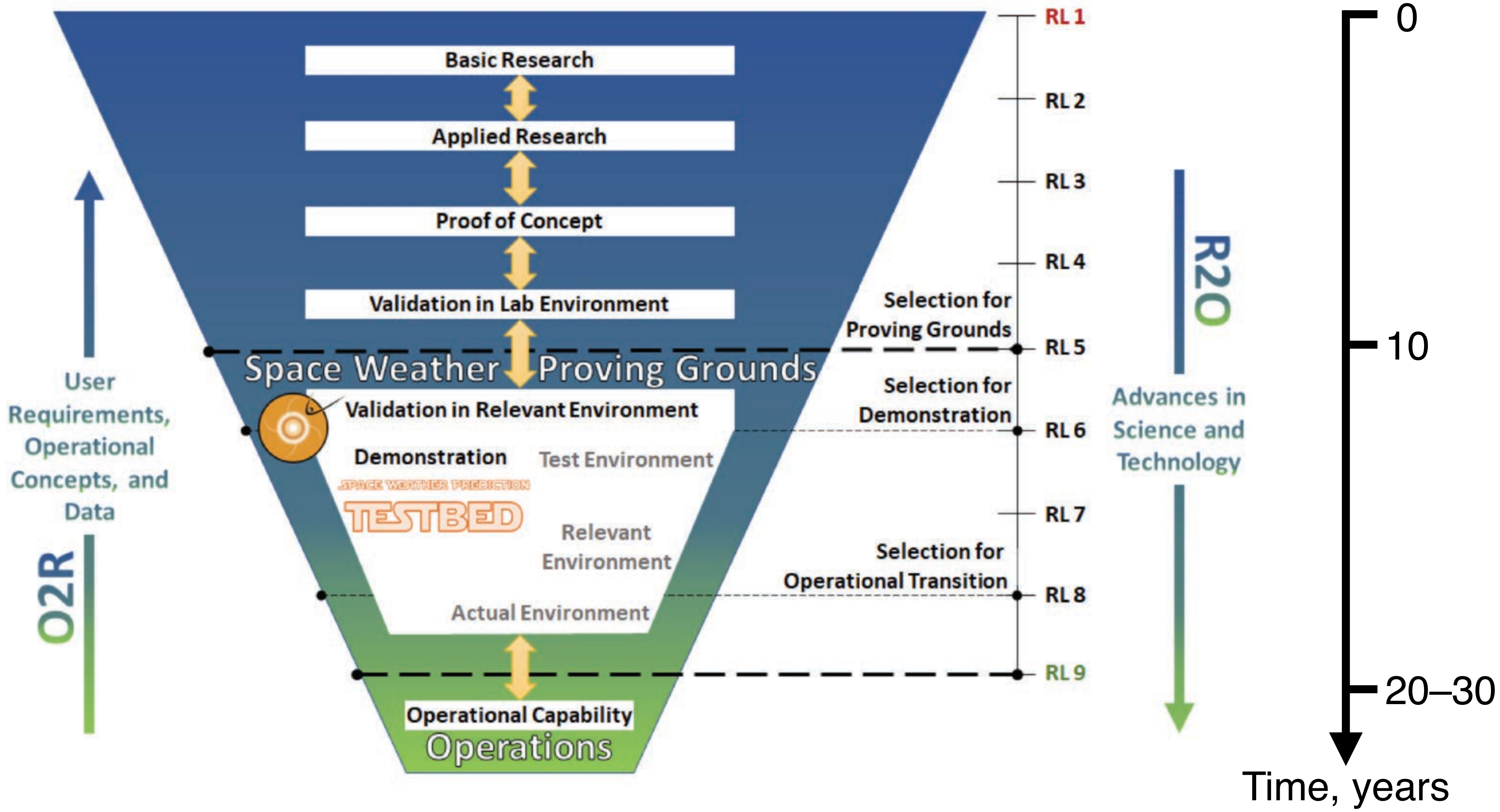


Figure 1: Research to Operations to Research Process (NOAA Example)

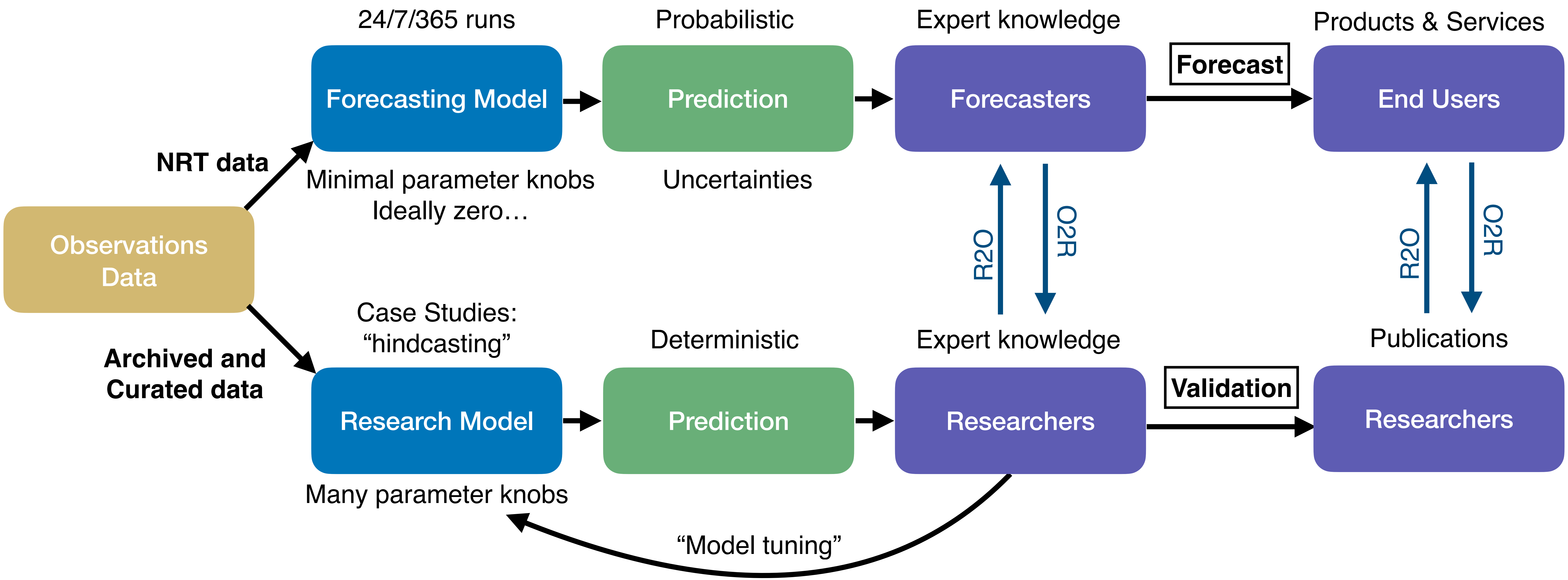
Definition of “Operations”

- **Near Real Time (NRT)**: observations and data are collected with latency measured in *seconds* or *minutes* (at most)
  - Very little time to clean up or eliminate bad data.
  - Observation systems have back-up systems in case of temporary or permanent failure.

- **No Fail:** people, data systems, models, and user interface tools must work **24/7/365**
  - All systems must have “hot-backups” that can be switched over in seconds or minutes.
  - If a model or tool crashes during operations and you are off-line for more than an hour, you get a call from the head of the National Weather Service…

- **Consequences:** the output of your models and tools are used by people in the real world to make **decisions** that can impact lives and $$$.
  - All forecasts must be extensively verified and have clear confidence levels attached.
  - Large number of false alarms and over-forecasting lead to people ignore you.

What is a Forecast vs. a Prediction?



"There is no value in a forecast. There is only value in how a forecast is used."
Tim Palmer, Royal Society Research Professor, Oxford

The ART of forecasting

"Forecasting is a necessary but not sufficient condition for success."
Sir Mark Walport, UK Chief Science Advisor

To be useful to anyone, a forecast must be

Accurate

Definition depends on application but is generally based on

Time - "how close can you get on arrival time?"

Magnitude - "how strong will it be?"

Reliable

Definition depends on application but is generally based on **consistency over time** and **low False Alarm Rate.**

Can systems operators take actions based on well-tested justifications of performance?

Timely

Definition is generally independent of application and is based on **time to deliver forecast** relative to time to impact.

Usually this is "As soon as possible" - ASAP.

Products: how forecasts & nowcast get communicated

Watch ⟶ Warning ⟶ Alert

Watch: "Something has been detected *or modeled* and *may* or *may not* cause an event."

- Generally issued on the basis of an observation that is consistently known to cause events, e.g., a CME leaving the Sun in the direction of Earth, or a large coronal hole rotating into the Sun-Earth line.
- Not a definitive prediction of occurrence - only stating a *possibility* of occurrence.
- Threshold for issuance is subjective, e.g., forecaster judges CME is Earth-directed from preliminary observations.

Warning: "Something has been detected or predicted and *will very likely* cause an event."

- Issued on the detection of an event at an upstream location, e.g. detection of a CME at the L1 Lagrangian point.
- Usually comes with a predicted magnitude, e.g., "G3 Warning", but is often updated as conditions/measurements change.

Alert: "An event is in progress."

- Based on measured levels of activity at the location of interest, e.g. ground-based magnetometers on Earth.
- The initial/provisional statement of the timing and magnitude of an event. May be refined after the fact.

Current space weather Watch, Warning, Alert capabilities

Event	Watch	Warning	Alert
Eruption (“Flare”)			*[1]
Radiation Storm		*[2]	*[3]
CME Geomagnetic Storm	*[4]	*[5]	*[6]

1. Based on passing M 1.0-level X-ray threshold in GOES XRS instrument.
2. 15—30 minutes based on flare magnitude and location.
3. Based on passing 10 MeV proton threshold in GOES SEISS instruments.
4. ±10 hours accuracy on CME arrival time, but this is not issued with the Watch. HSS and CIR events are not issued Watch products, only Warning on solar wind speed increase at DSCOVR at L1.
5. 15—45 minutes based on CME or HSS or CIR detection at DSCOVR at L1.
6. Based on detection of magnetic anomaly in USGS and Canadian ground-based magnetometer network.

What is a "nowcast"?

Specification of *current conditions* relevant to a particular operation or event.

Examples:

- 10 MeV proton flux at GEO during a Solar Energetic Particle event.
- Radio burst during a solar eruption event.
- Rate of change of TEC index over a geographical location.
- "Real-time" Kp index calculated from a magnetometer network.

Requirement: **Low-latency, "real-time", observations**.

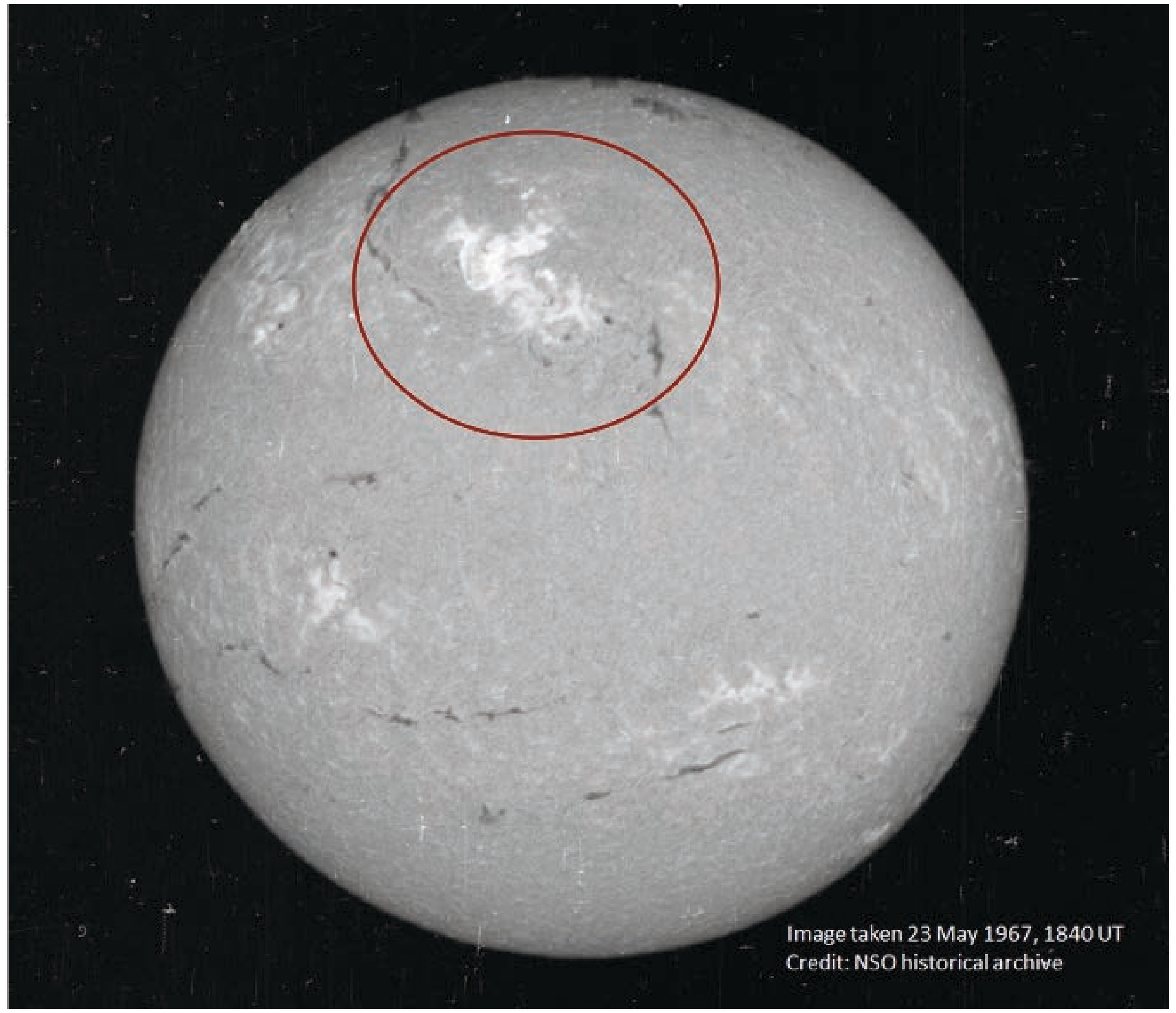
Latency requirements vary by mission, but are typically on the order of ***seconds or minutes***.
Example: GOES XRS (X-ray irradiance) and SEISS (proton flux) latency = ***3 seconds*** from ground-station to NOAA/SWCP forecast office.

Related: **All Clear** announcement — event termination and return of safe conditions.

Does not currently exist! There are customers who would like an "All Clear" product from operational forecasting offices. However, legal liability is a major issue: what happens if you declare "All Clear" and there is a major event?

The Value of Nowcasting

Ballistic Missile Early Warning System (BMEWS)
Over-the-Horizon radar system in Alaska
Sun was low in the Eastern sky at time of radio burst



23 May 1967 Solar Radio Flare
Signal was originally interpreted as Russian jamming prior to a nuclear attack

Knipp, D.J. *et al.* (2016) *Space Weather*, 14(9), pp. 614–633. doi:10.1002/2016SW001423.

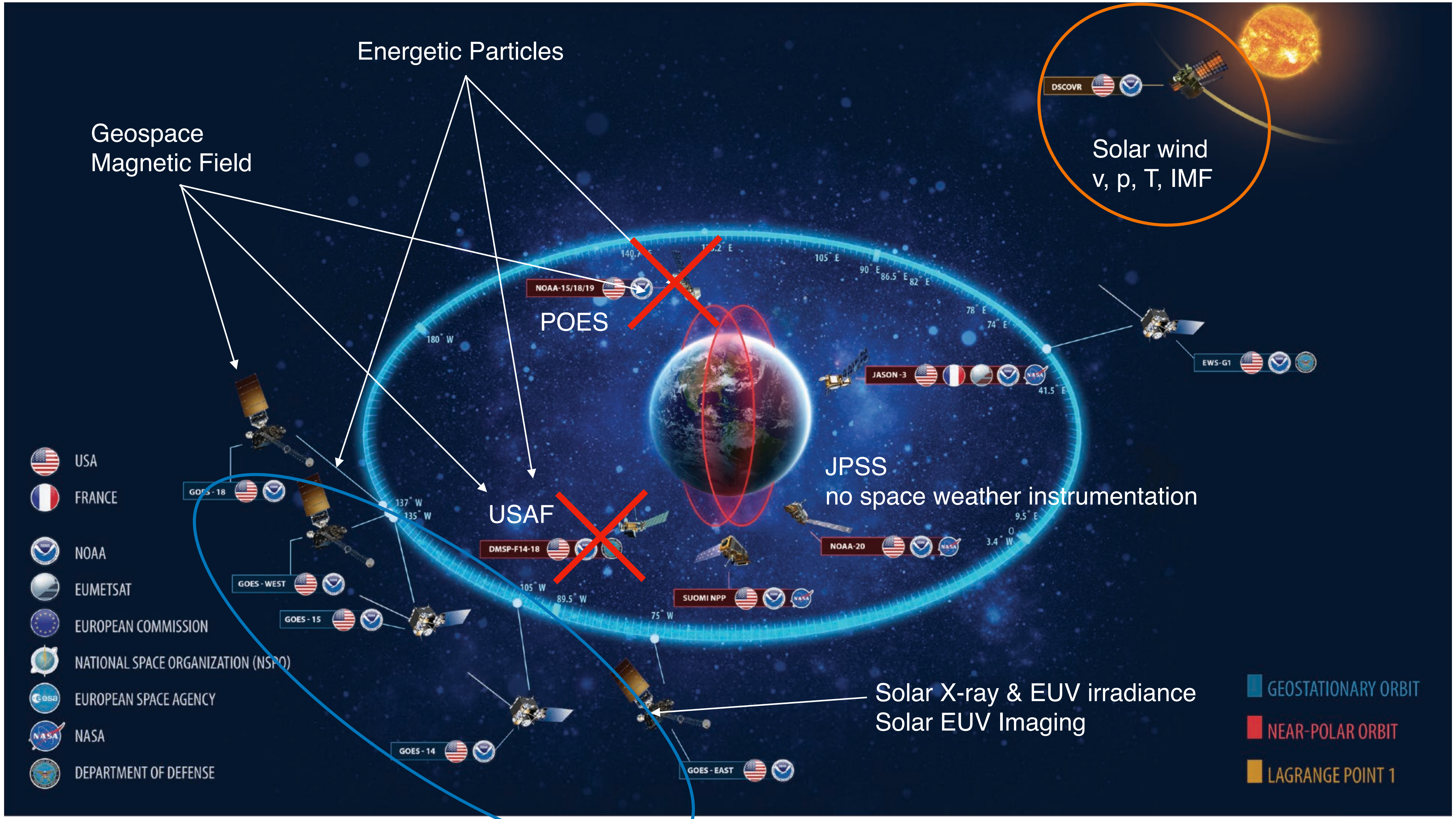
Model validation vs. Forecast verification

The final steps in determining model suitability for R2O transition to operations

- **Model Validation**:
  - The process of comparing model output to data from past events.
  - Does ***not*** measure success of model on NRT, noisy, data.
  - Can only be used to show that model is performing as expected in ***known conditions.***
  - ***Performed in "Proving Grounds" for validation in laboratory environment (RL 5–6)***
- **Forecast Verification:**
  - The process of comparing model output from runs on NRT, ***previously unseen***, inputs.
  - Model ***cannot be tuned*** during forecast verification.
  - Only way to show whether model is performing Accurate, Reliable, and Timely forecast***.***
  - ***Performed in independent "Testbed" environments at RL 7–8.***

2. Operational space weather data and models

NOAA Operational (space) weather observations



https://www.nesdis.noaa.gov/s3/2022-03/NOAASatelliteSystem_2022.03.14.png

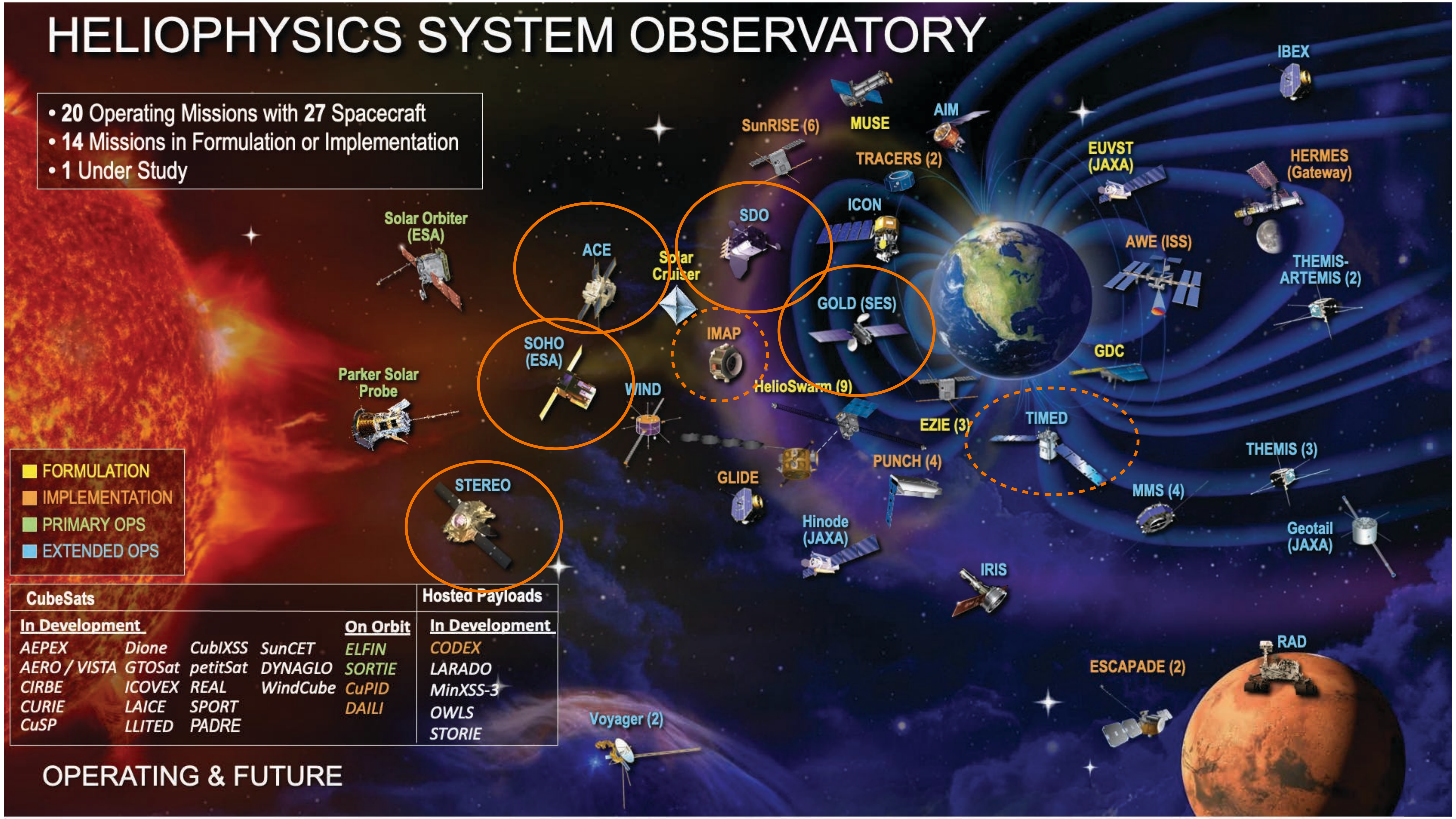
USSF operational space weather observations

- **DMSP polar-orbiting weather satellites (see previous slide)**
- **HASDM Calibration Objects for satellite drag modeling**
  - Not really an "observation system"
  - high repeat-rate tracking of known/steady Ballistic Coefficient satellites/objects.
- **Solar Optical Observation Network**
  - Hα telescope
- **Solar and Electro-Optic Network**
  - Ha full-Sun imaging
  - Solar radio monitoring
- **SCINDA Network**
  - GPS scintillation monitoring

Solar Optical Observation Network (SOON)
Hα Telescope
Kirtland AFB, NM

Solar & Electro-Optic Network (SEON)
Radio telescope
Sagamore Hill, MA

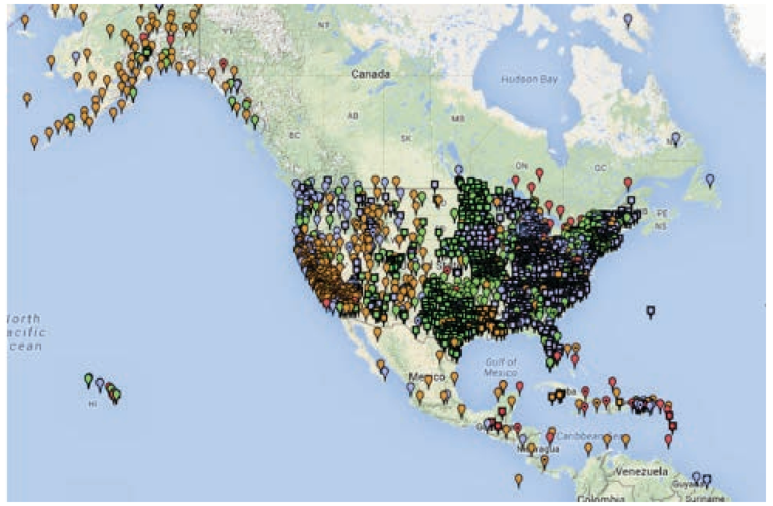
NASA missions that contribute space weather operations



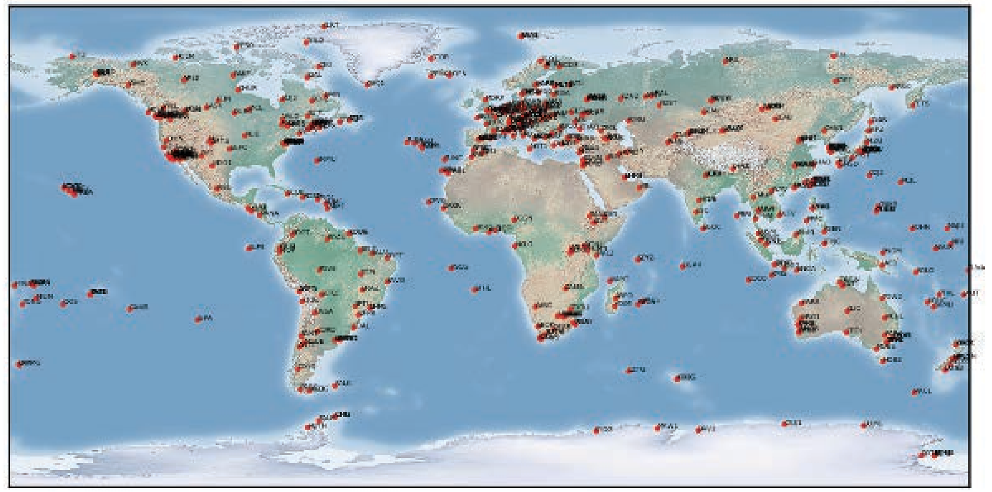
https://science.nasa.gov/heliophysics/mission-fleet-diagram

Civil ground-based space weather measurements

USGS Magnetometer Network
Geomagnetic storm data

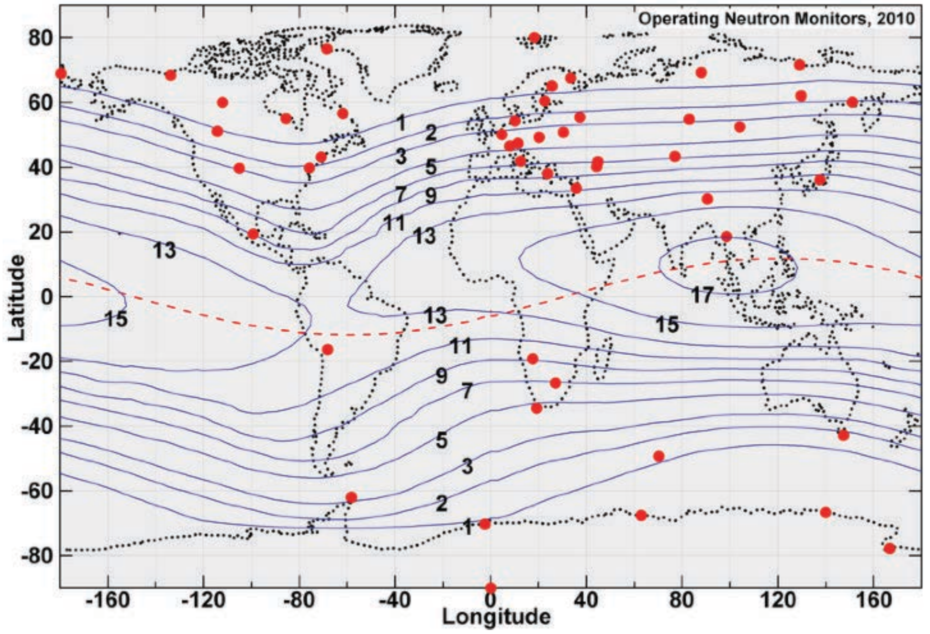


USCG CORS GPS Network
Ionospheric TEC data



IGS RTIG GPS Network
Ionospheric TEC data

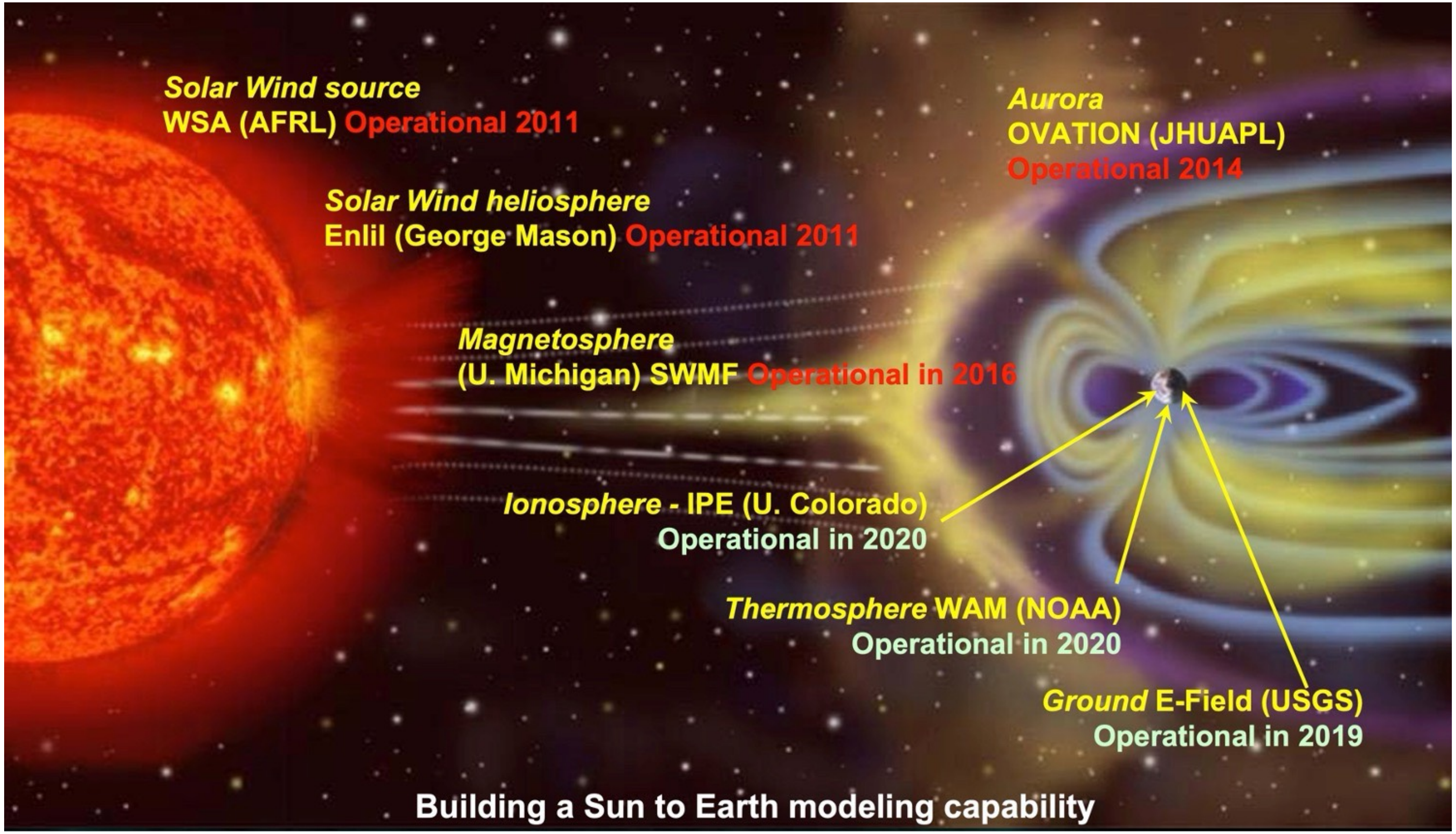
NSF Global Oscillations Network Group (GONG)
Solar magnetograms and Hα images



Neutron monitor network
SEP event aviation radiation dose calibration

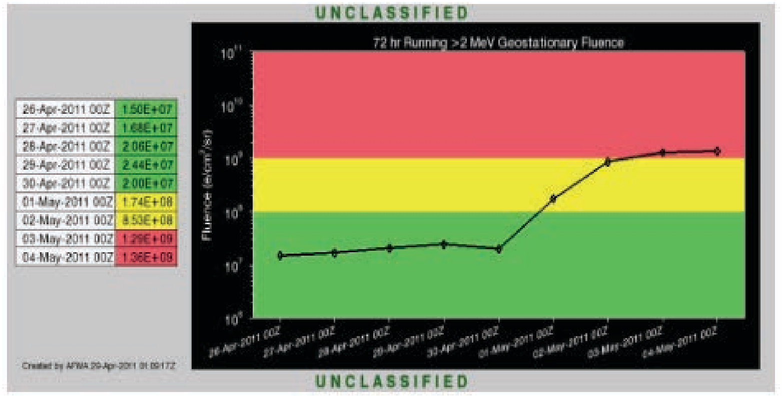
NOAA operational space weather models/products

Adapted from E. Talaat, NAS SWx Infrastructure Workshop I, 16-June-2020

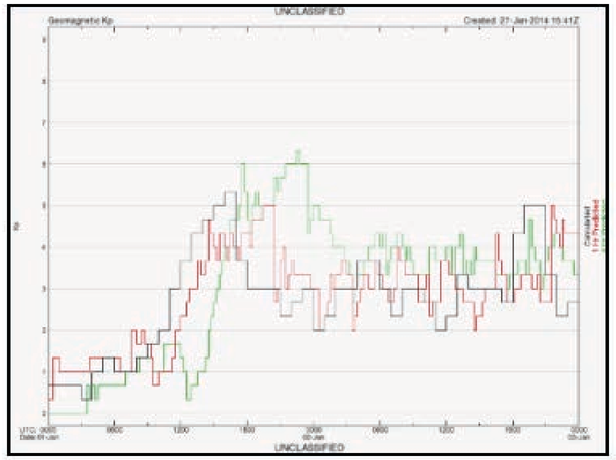


DOD operational space weather models/products

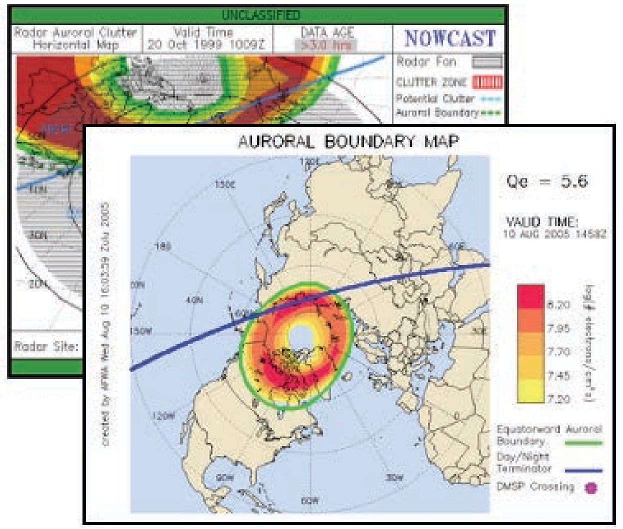
Concentration on communications and orbital systems



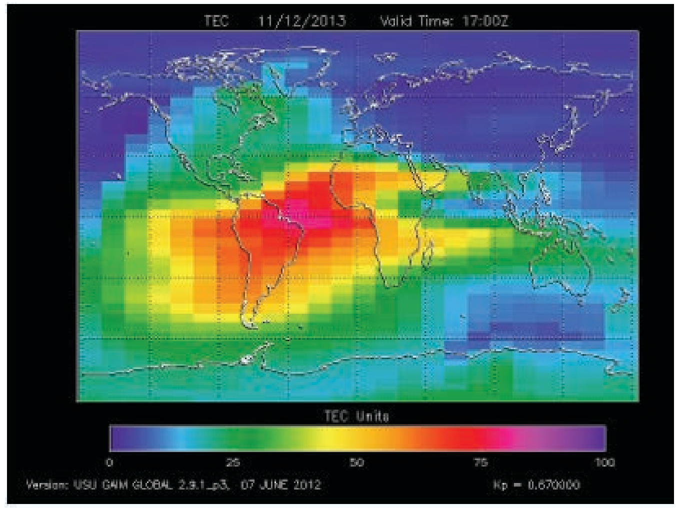
Magnetosphere – GEO radiation hazard



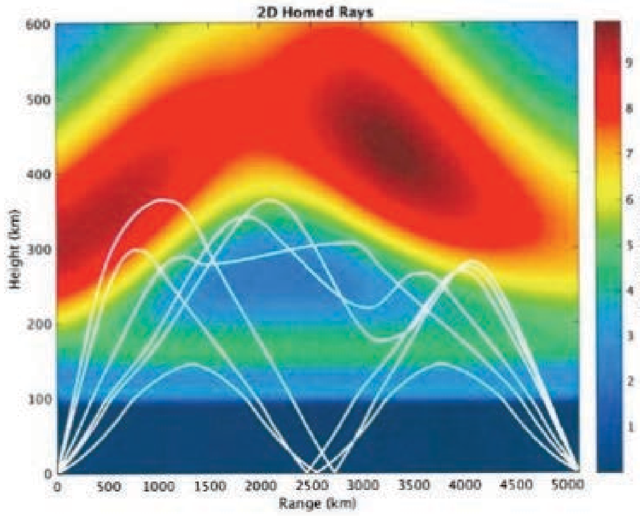
Magnetosphere – Wing Kp model



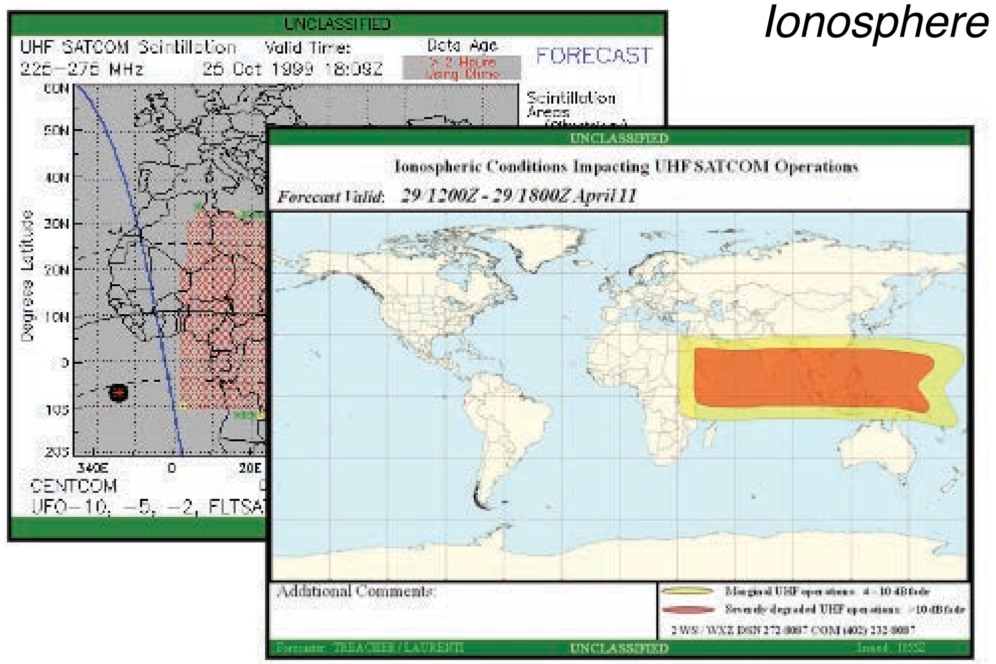
Magnetosphere – Auroral location
Ionosphere



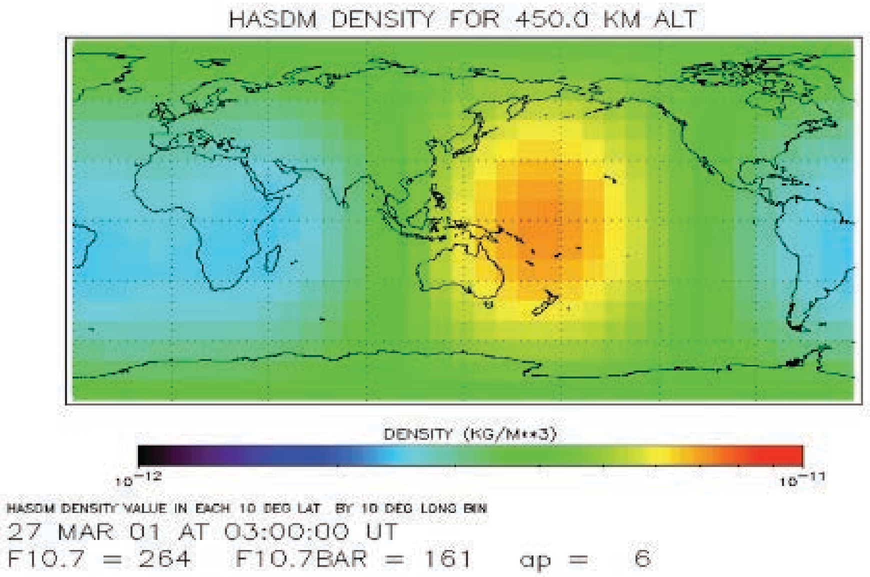
Ionosphere – GAIM model



Ionosphere – HF propagation tool



Ionosphere – scintillation alerts



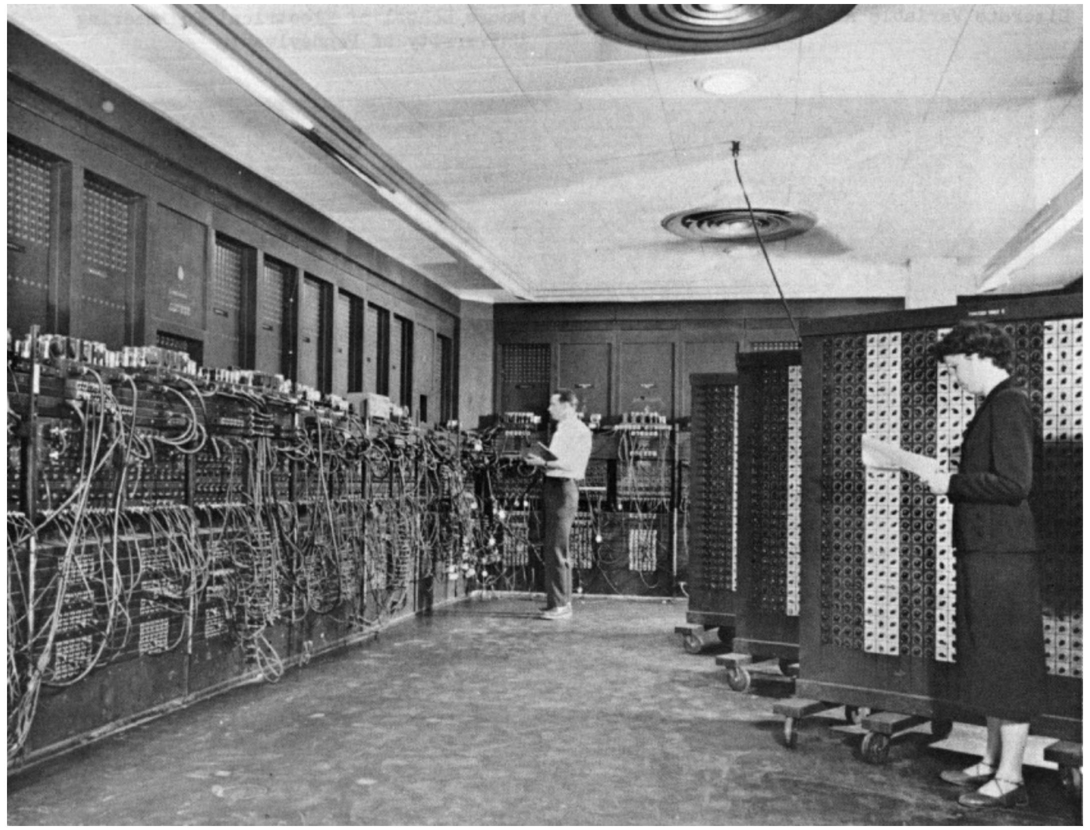
Thermosphere – HASDM model

3. Predicting complex nonlinear systems

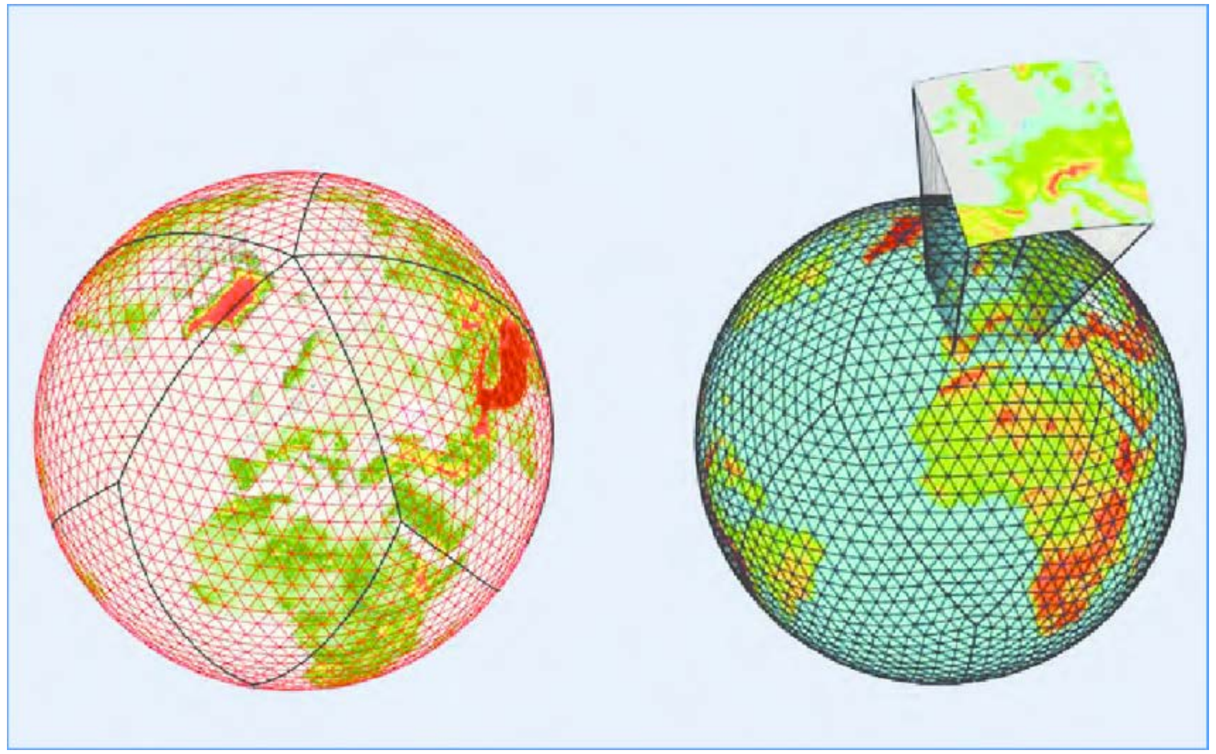
The von Neumann prediction paradigm

Predictive model = physics-based PDEs solved on grids using computers

E. von Neumann
c. 1940



ENIAC I ~1947
40 OPS



Physics-based weather models solved with finite difference methods on gridded domains

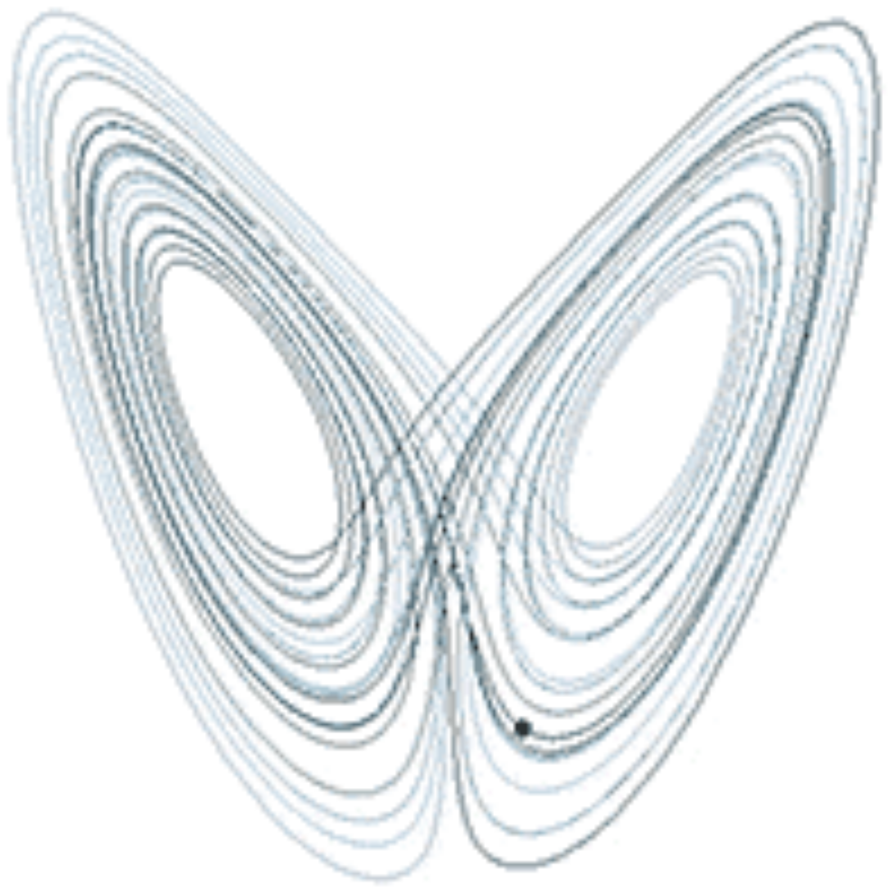
Two problems served as the driving motivators: design of the hydrogen bomb and weather prediction

Lorenz 1963: “Chaos” and unpredictability

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$

$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$



Phase space diagram

Solution traces out a “trajectory” in n-dimensional space

$$\frac{d\mathbf{x}}{dt} = f(\mathbf{x}, t)$$

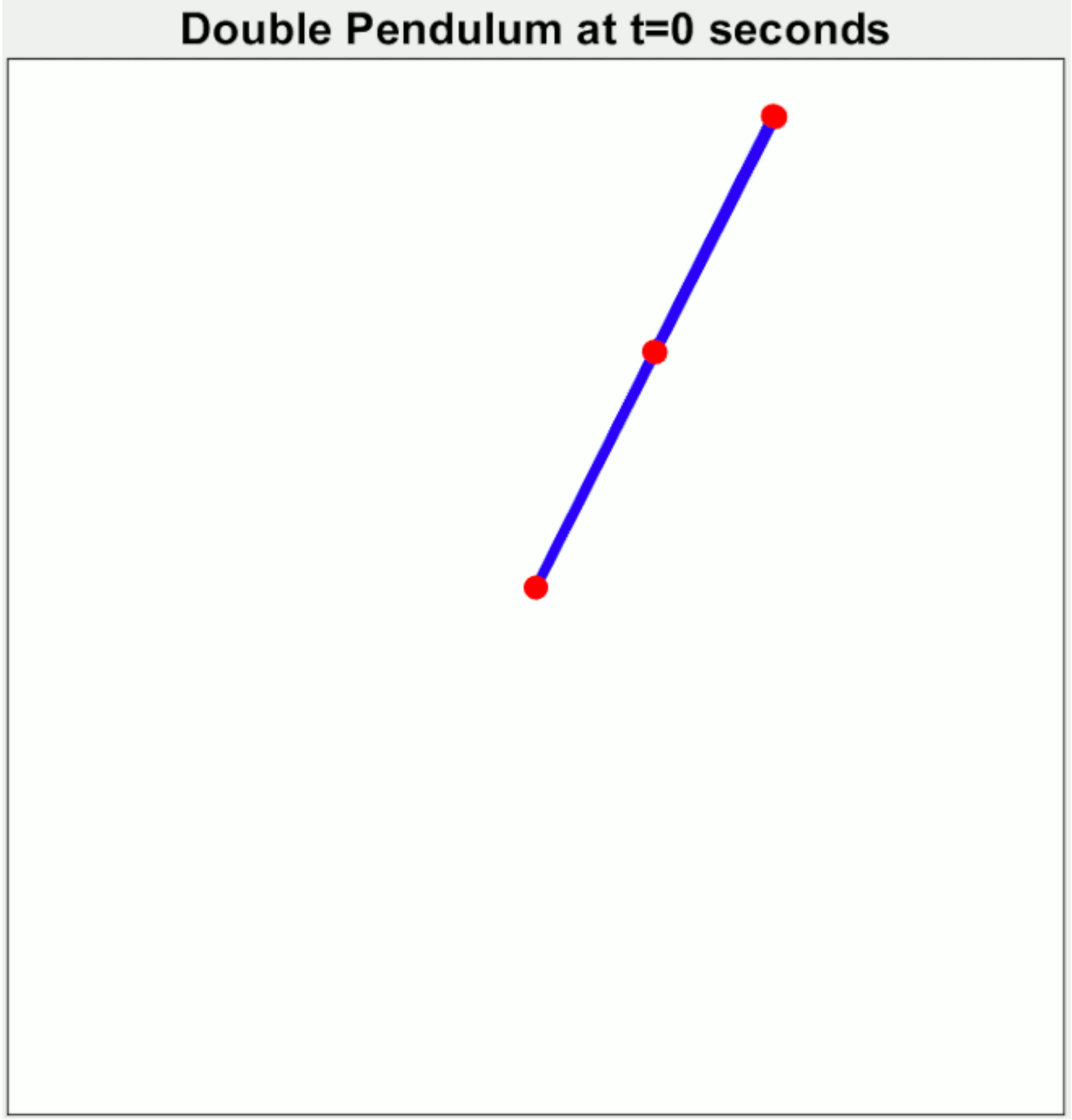
General form of dynamical system model

System of nonlinear ODEs

No analytic solution - numerical solutions only

Small perturbations in initial conditions lead to very different trajectory through phase space

Even very simple systems can be chaotic



Simple Newtonian system with analytical solution

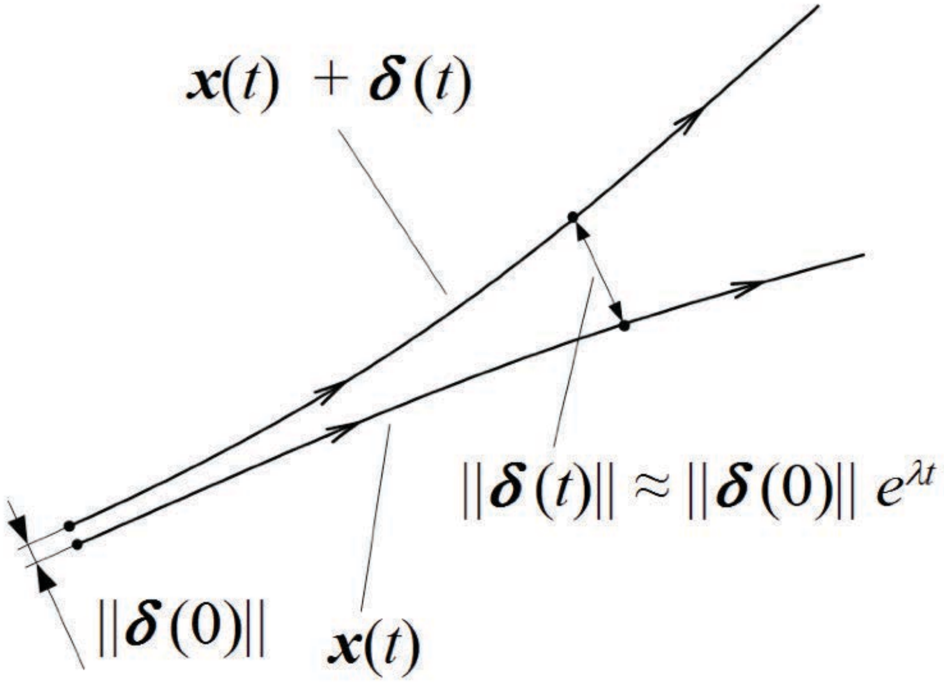
Tiny differences in initial conditions lead to rapid divergence of trajectories

Computational round-off error is enough to produce different trajectories

Are chaotic systems completely unpredictable?

It depends on your accuracy requirements and time horizon

Lyapunov Exponents



$$\lambda = \lim_{t\to\infty} \lim_{\|\delta(0)\|\to 0} \frac{1}{t} \ln \frac{\|\delta(t)\|}{\|\delta(0)\|}$$

A chaotic nonlinear system can be predicted to some accuracy $\delta(t)$ for a limited time $t(\lambda, \delta)$.
This is why a "free running" weather model can give a pretty good forecast for ~2 days.

"We need to understand the system in order to predict it"

Sorry, no. ***Understanding*** is neither necessary nor sufficient for prediction

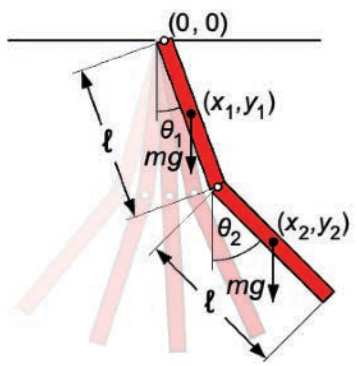
Not necessary

$$i\hbar\gamma^{\mu}\partial_{\mu}\Psi - mc\Psi = 0$$

Quantum Electrodynamics

- Completely non-understandable.
- Extremely accurate predictions, e.g. e^- anomalous magnetic moment.

Not sufficient



Nonlinear dynamics

- Completely understandable: classical Newtonian physics.
- Unpredictable using first principles models due to inherent errors in measurement and calculation.

But…scientific understanding *is* necessary to accurately ***simulate*** complex systems

What is necessary for prediction?

Data!

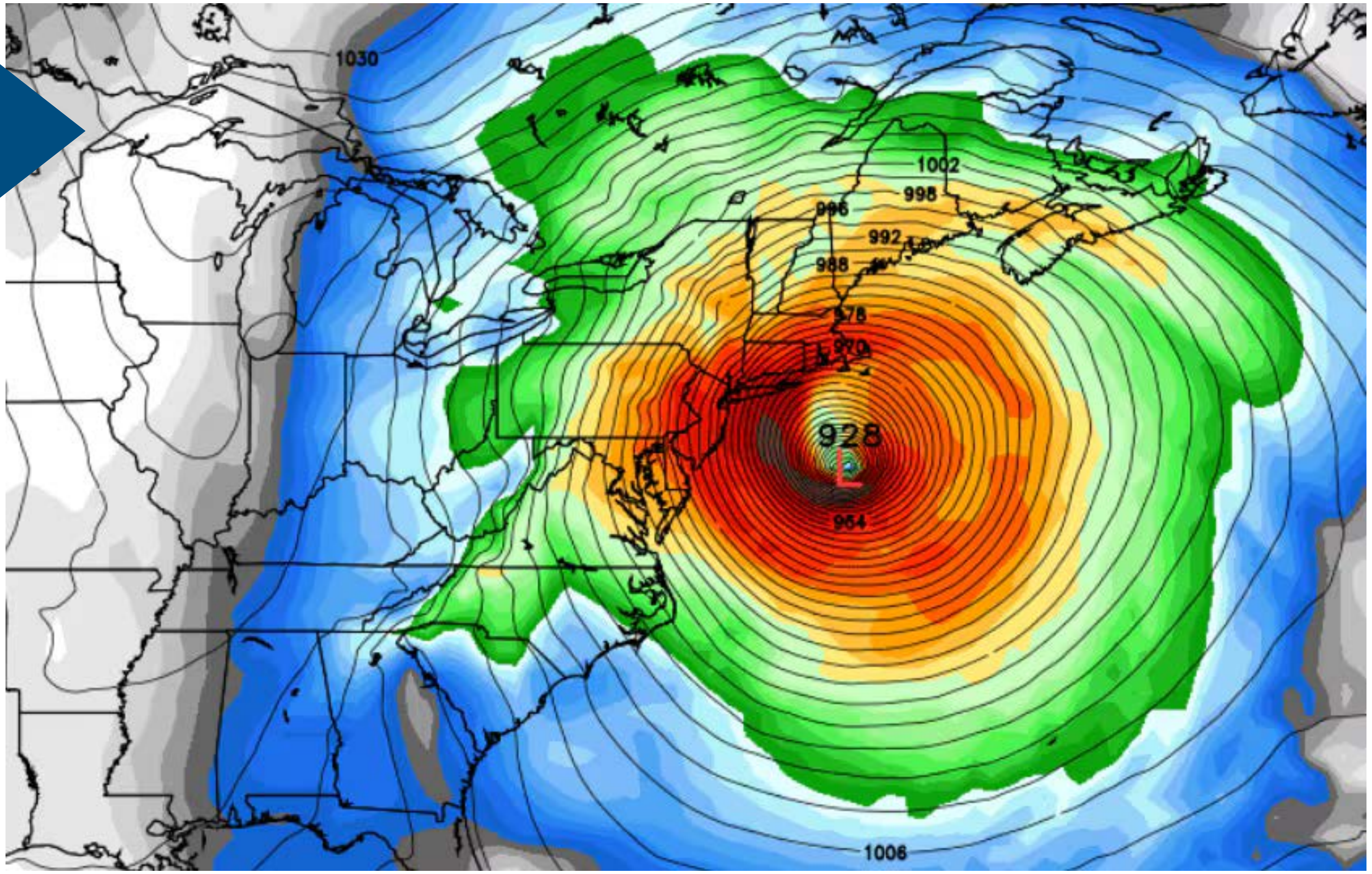
Data Assimilation (DA)

The only reason you get an accurate and reliable 3–5 day weather forecast!

~100 million global measurements from sea level to 60 km
every 6 hours

WCOSS supercomputer system: 14.5 PetaFLOPS

(Recall ENIAC = 40 OPS: 15 orders of magnitude in 80 years!)



Data Assimilation (DA)

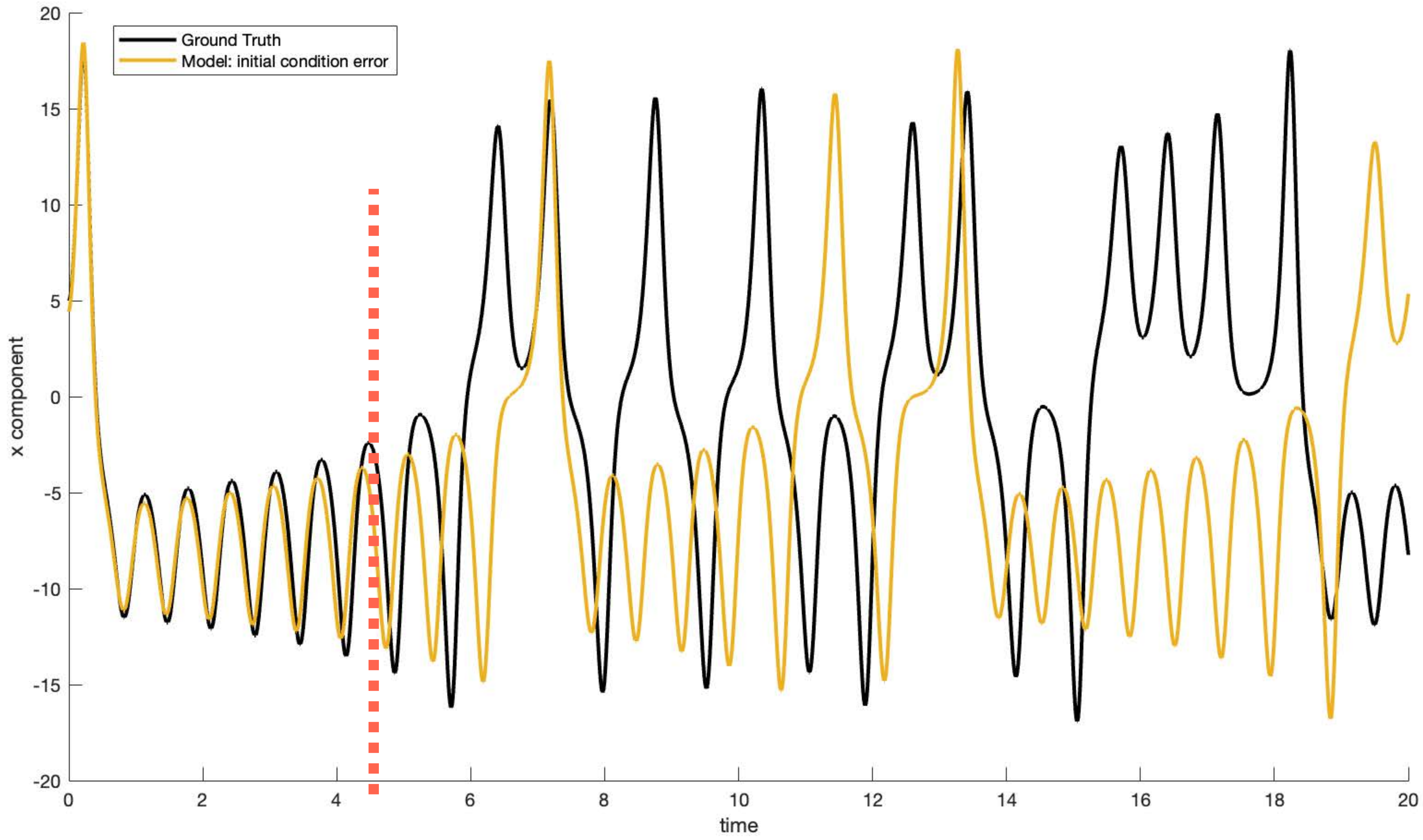
The case of **imperfect model** (initial condition noise)

Lorenz63 model

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$

$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$



Data Assimilation (DA)

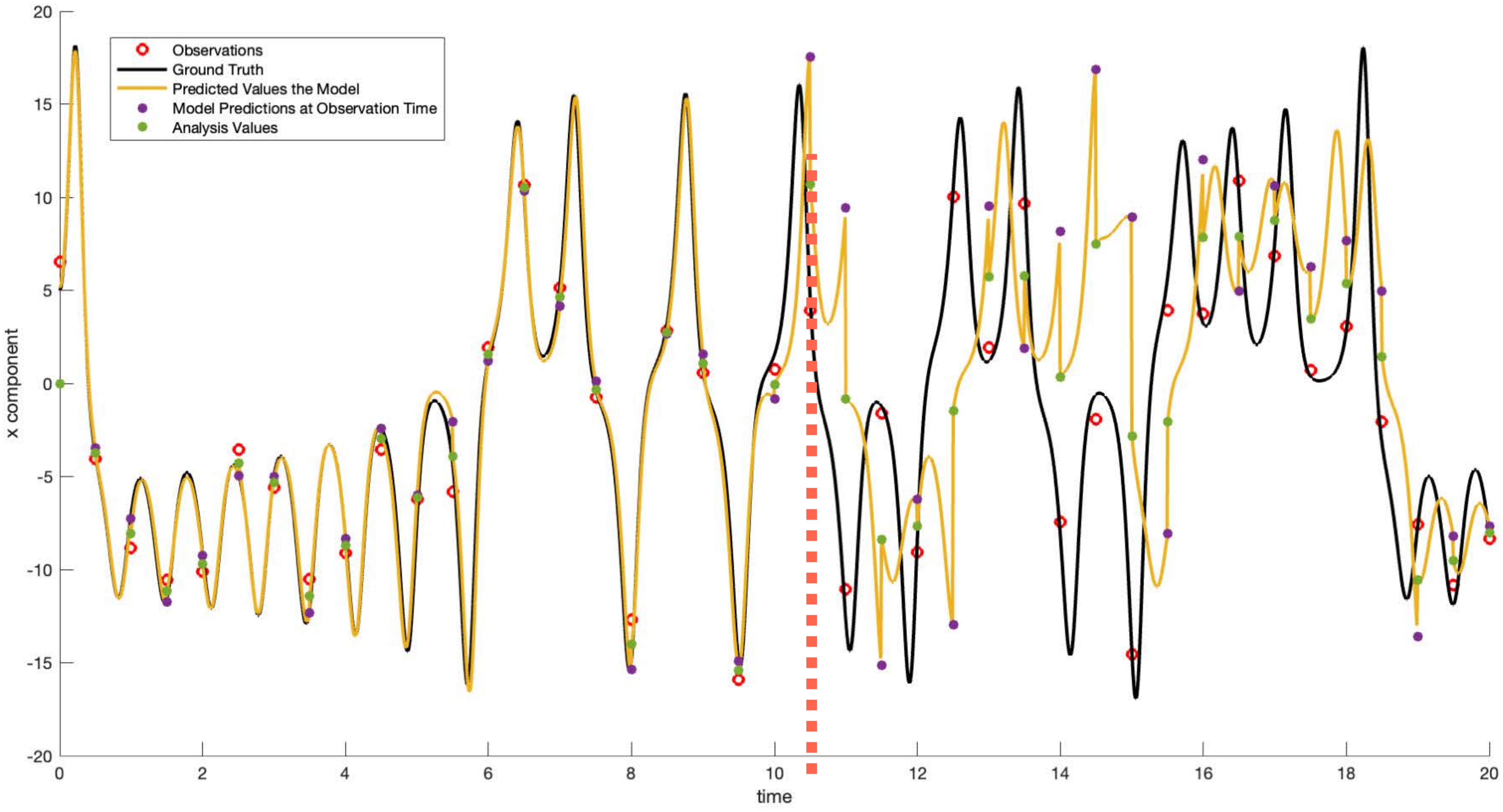
Kalman filter balance of **imperfect model** and **noisy observations**

Lorenz63 model

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$

$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$



4. Machine Learning to the rescue?

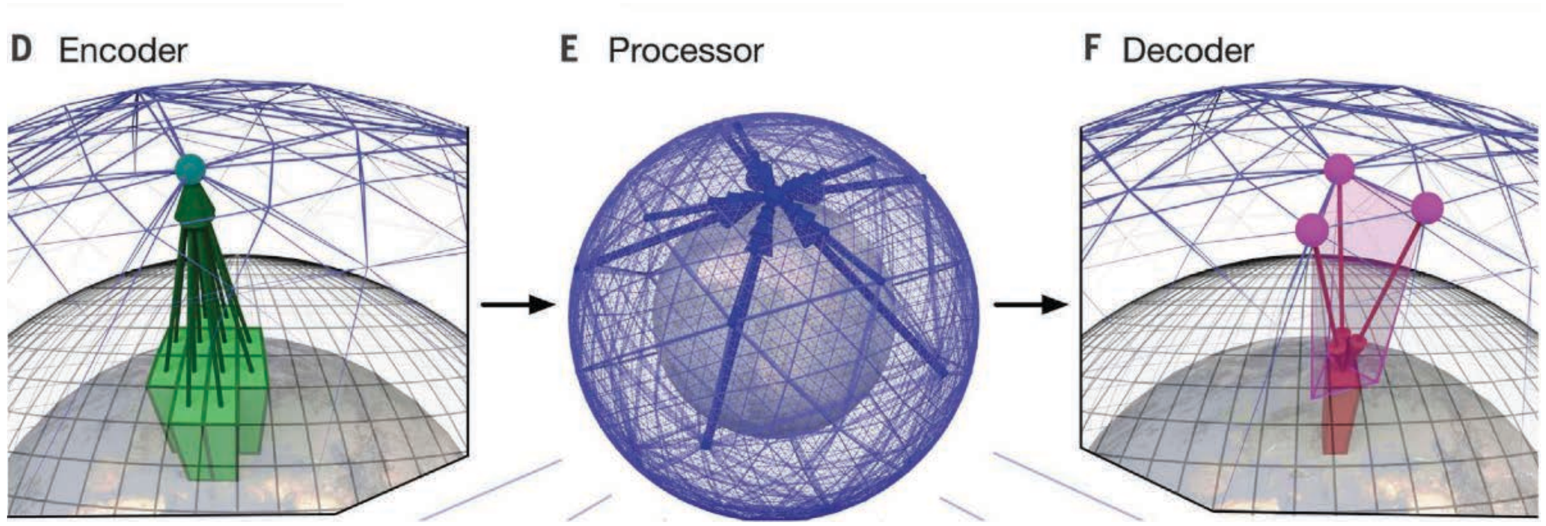
The data science revolution: no physics needed…

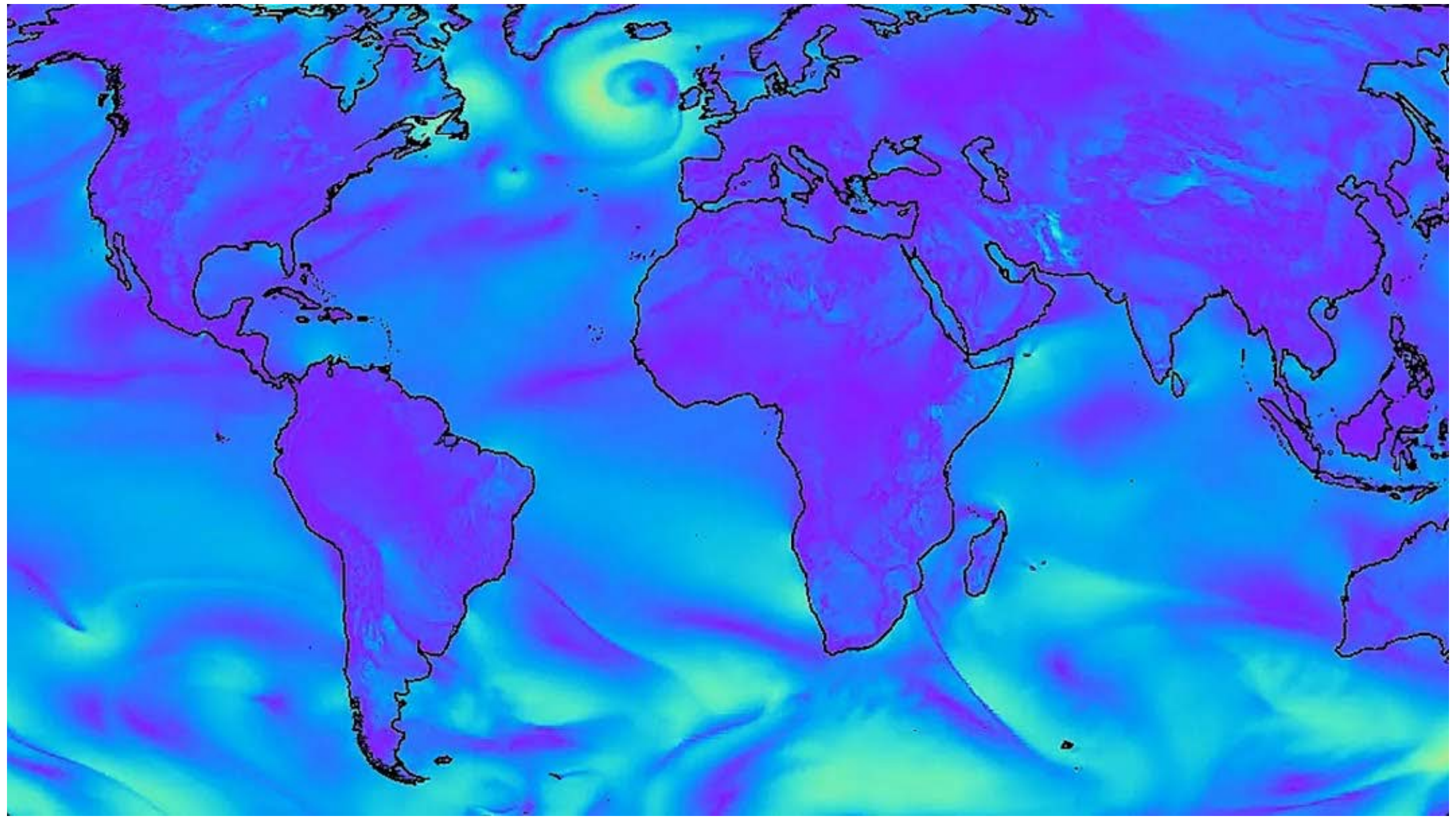
WEATHER FORECASTING

Learning skillful medium-range global weather forecasting

Remi Lam[1]*†, Alvaro Sanchez-Gonzalez[1]*†, Matthew Willson[1]*†, Peter Wirnsberger[1]†, Meire Fortunato[1]†, Ferran Alet[1]†, Suman Ravuri[1]†, Timo Ewalds[1], Zach Eaton-Rosen[1], Weihua Hu[1], Alexander Merose[2], Stephan Hoyer[2], George Holland[1], Oriol Vinyals[1], Jacklynn Stott[1], Alexander Pritzel[1], Shakir Mohamed[1]*, Peter Battaglia[1]*

Global medium-range weather forecasting is critical to decision-making across many social and economic domains. Traditional numerical weather prediction uses increased compute resources to improve forecast accuracy but does not directly use historical weather data to improve the underlying model. Here, we introduce GraphCast, a machine learning–based method trained directly from reanalysis data. It predicts hundreds of weather variables for the next 10 days at 0.25° resolution globally in under 1 minute. GraphCast significantly outperforms the most accurate operational deterministic systems on 90% of 1380 verification targets, and its forecasts support better severe event prediction, including tropical cyclone tracking, atmospheric rivers, and extreme temperatures. GraphCast is a key advance in accurate and efficient weather forecasting and helps realize the promise of machine learning for modeling complex dynamical systems.





GraphCast - trained on 30 years of “reanalysis” data

Pattern recognition machine: no physics in the model at all

As skillful at prediction as the ECMWF physics-based model

https://www.science.org/doi/10.1126/science.adi2336


LiveDst
Geomagnetic storm prediction
SWx TREC
Dst model
Model description
Data API
Current time (UTC): 2024-05-16 10:39
Selected Date Range 2024-05-15 10:00 to 2024-05-16 17:00
SET DATE RANGE
2024-05-15T20:00:00 UTC
Kyoto Dst
dst (nT) :
-43
2024-05-15T19:45:00 UTC
LiveDst model predictions
T+1 (nT) :
-34 ± 2
2024-05-16T10:30:00 UTC
LiveDst model run at 24-05-16T10:30
6-hr prediction (nT) :
-92 ± 0
-35
-40
-45
-50
-55
-60
-65
-70
-75
-80
-85
-90
-95
-100
-105
2024-05-15 10:00:00
2024-05-15 12:00:00
2024-05-15 14:00:00
2024-05-15 16:00:00
2024-05-15 18:00:00
2024-05-15 20:00:00
2024-05-15 22:00:00
2024-05-16 00:00:00
2024-05-16 02:00:00
2024-05-16 04:00:00
2024-05-16 06:00:00
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2024-05-16 10:00:00
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09:00:00
12:00:00
15:00:00
Highcharts.com
ADD PLOTS
DOWNLOAD DATA

LiveWire
Geoelectric field prediction

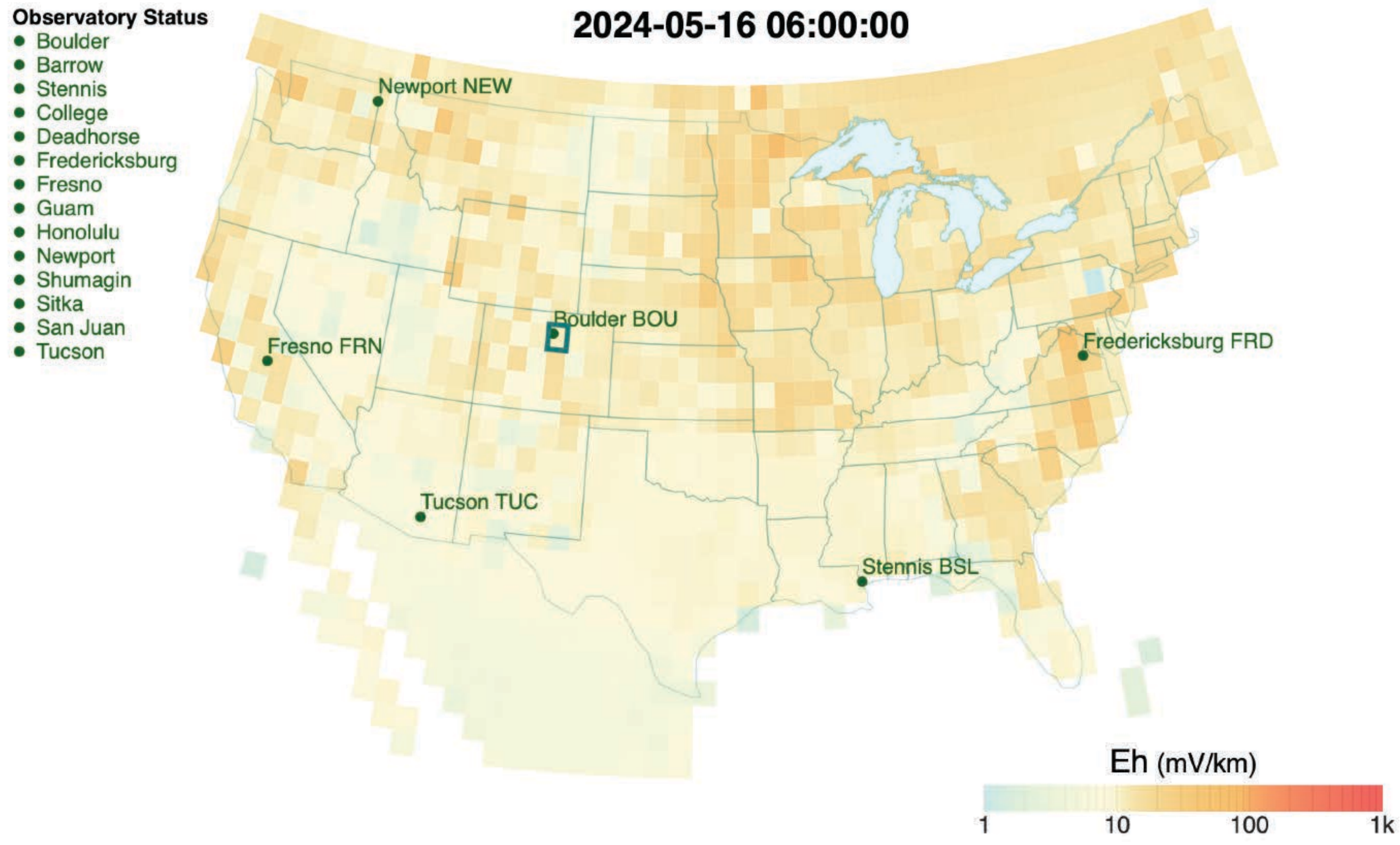
SWx TREC

Map | Documentation

Select a variable

Eh: Horizontal electric field magnitude

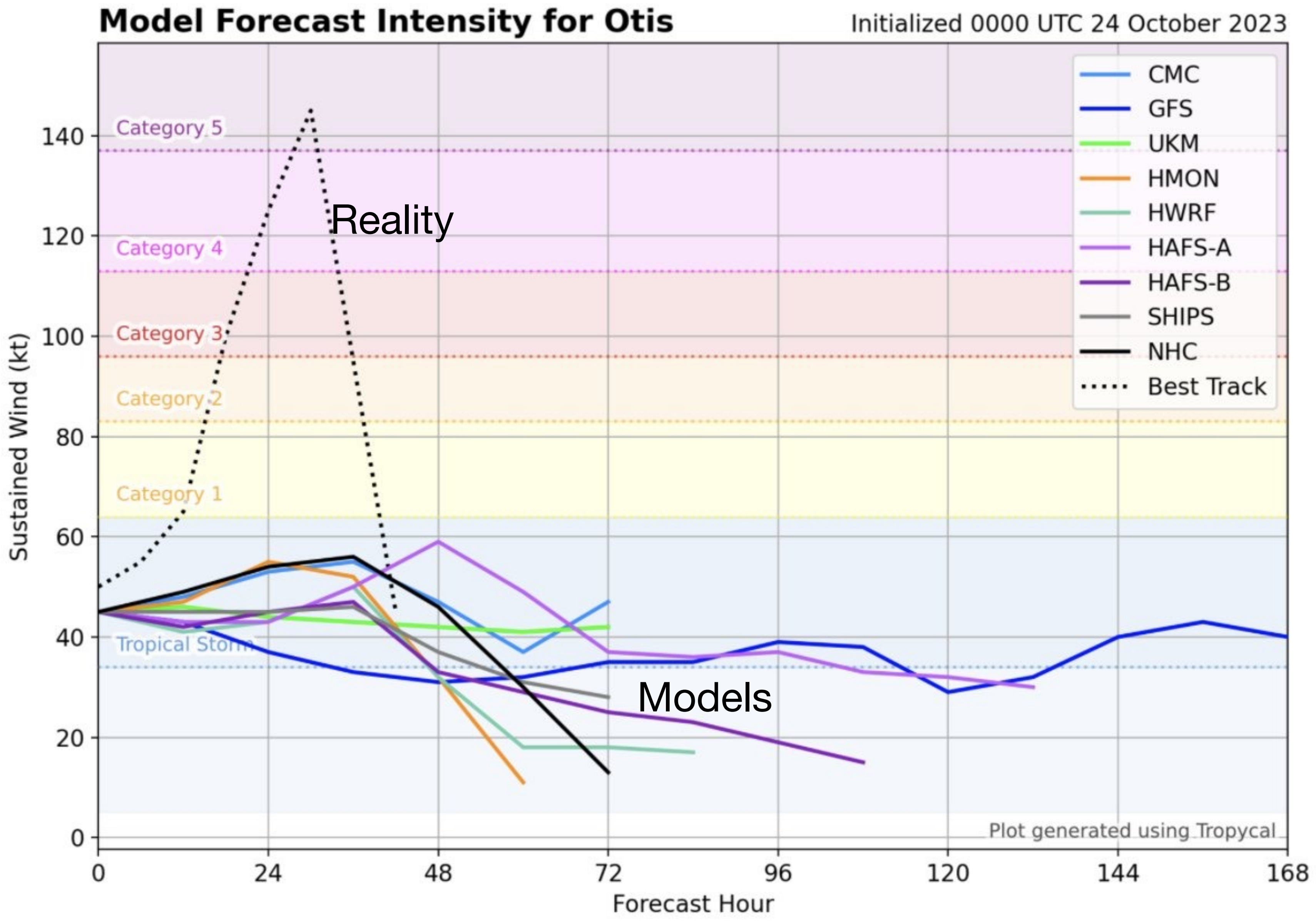
Current Time
2024-05-16 12:52 UTC



Physics-based models, even with DA, can also fail to generalize

Hurricane Otis: Acapulco, Mexico, October 25, 2023

- No physics-based NWP models predicted the rapid intensification of Tropical Storm Otis – *even with data assimilation*
- Largest predicted wind speed = 60 kt (Tropical Storm)
- Actual wind speed at landfall = 145 kt (Category 5 hurricane)



Sources: National Oceanic and Atmospheric Administration, UK Met Office, Canadian Meteorological Centre • By John Keefe

Challenges to prediction of non-linear systems

Modeling challenges

- Unknown physics (e.g., initial lack of waves in radiation belt models)
- Simplified physics (e.g., parameterized turbulence or chemistry)
- Lack of generalization (events outside of previous experience)

Data challenges

- Insufficient measurements at boundary and/or initial conditions (lack of data)
- Inaccurate and/or imprecision measurements (noisy/bad data)
- Insufficient cadence of data

Computational challenges

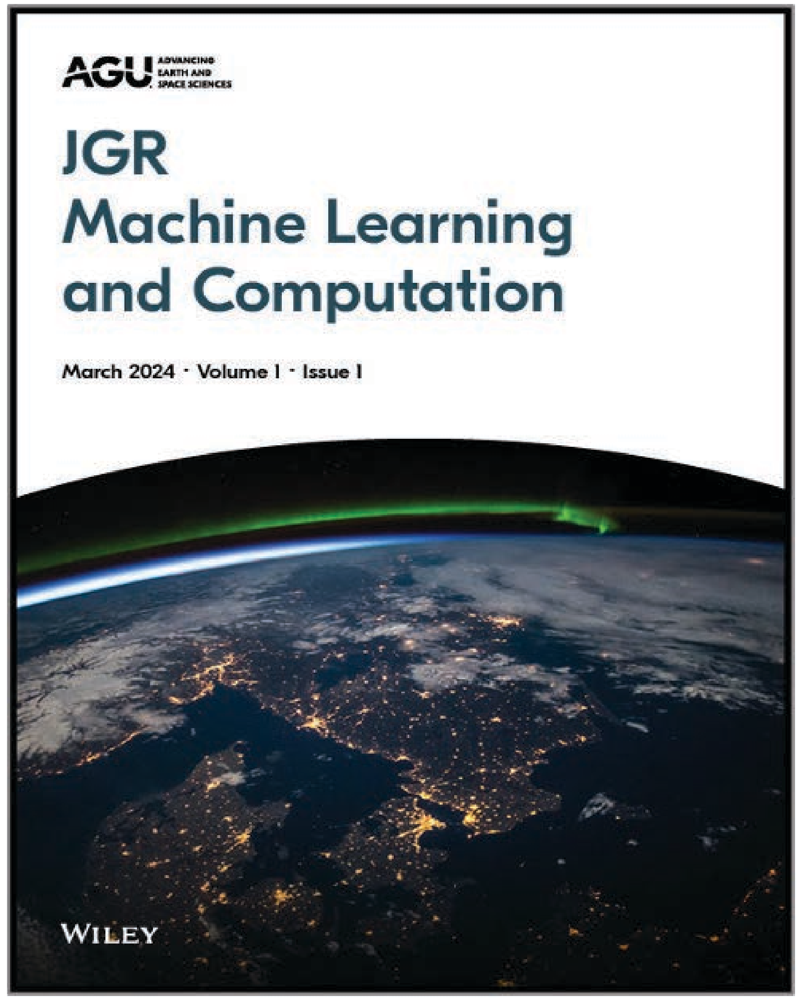
- Accumulating computational round-off errors
- Courant-Friedrichs condition violations
- Grid topology issues

Publish your space weather ML research in JGR-ML!

An AGU publication dedicated to Machine Learning and computational methods in Earth and space sciences.

Enrico Camporeale
CU/SWx TREC
Founding Editor in Chief

JGR: Machine Learning and Computation fills a crucial gap for researchers utilizing machine learning or artificial intelligence in the Earth and space sciences. With this journal, we now have a dedicated platform for rigorous peer review of our research."

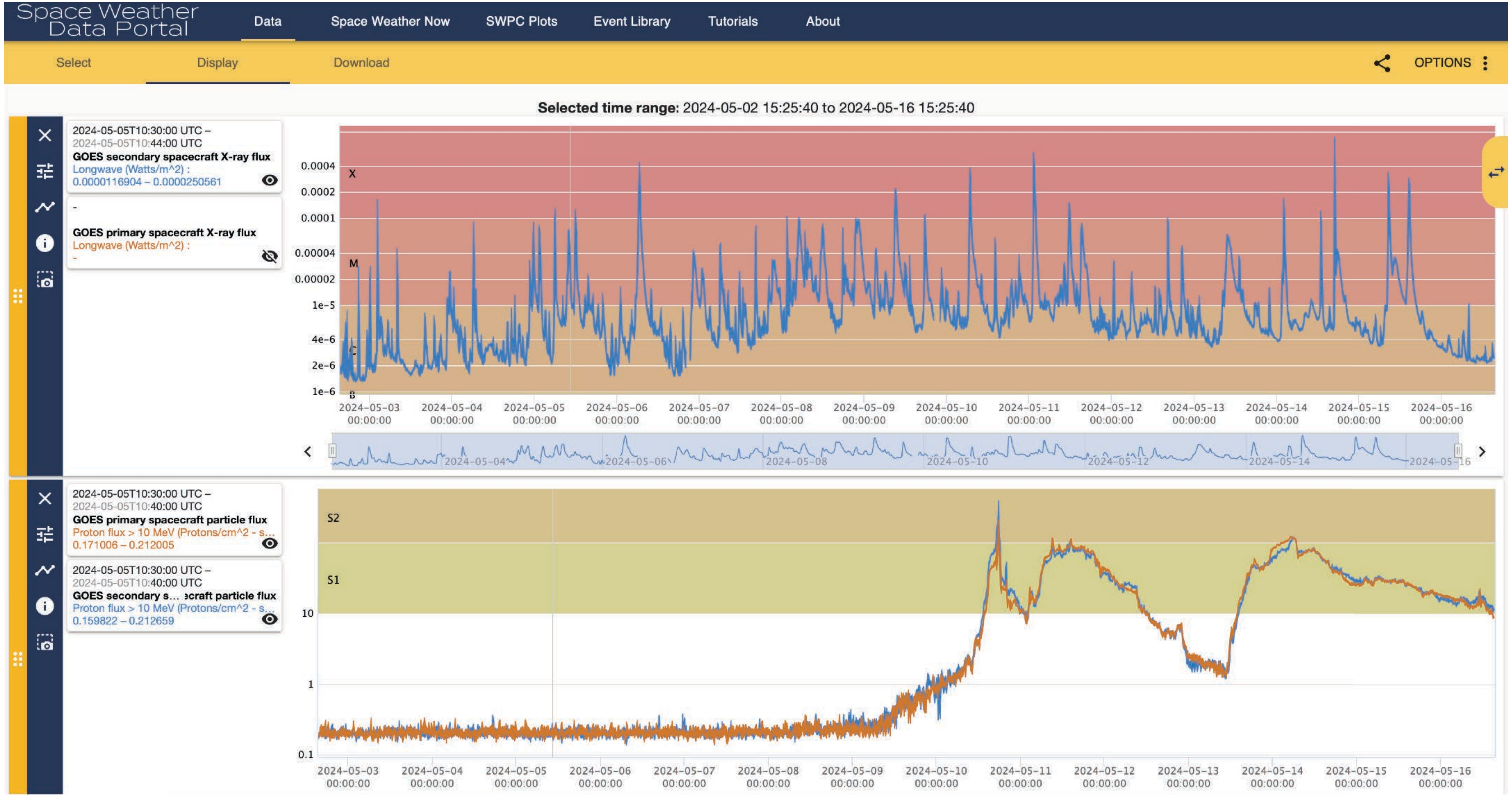


Contact JGR-MachineLearning@agu.org

5. Recent developments from SWx TREC

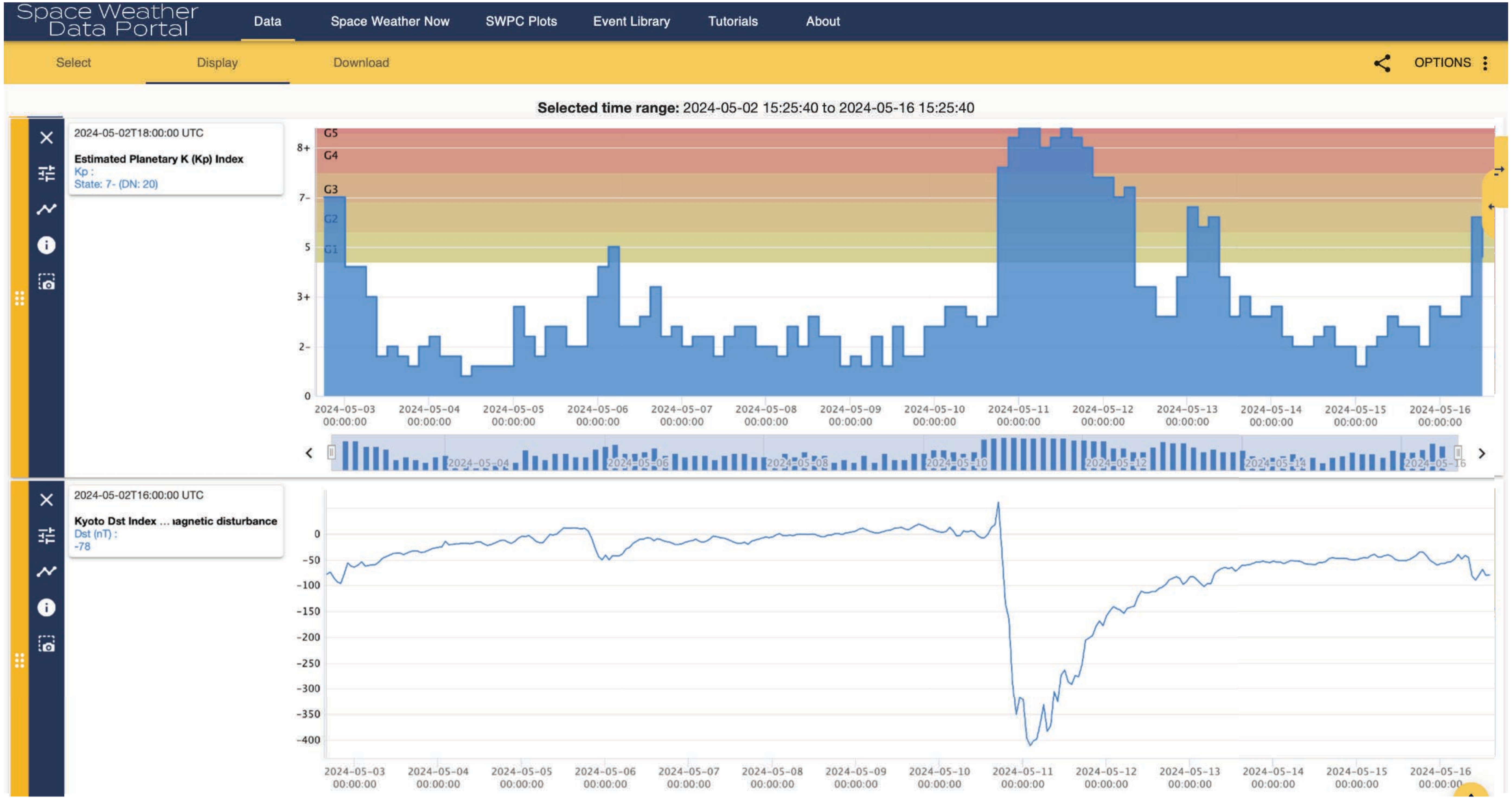
SWx TREC space weather data portal

Fast web-based platform for current and archival space weather data



SWx TREC space weather data portal

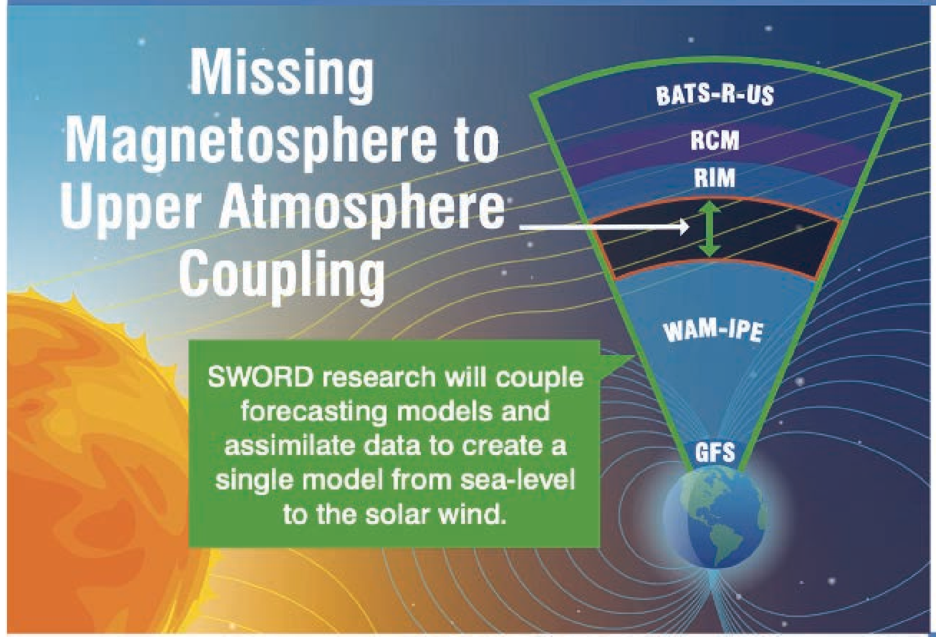
Fast web-based platform for current and archival space weather data



NASA SWORM SWx Center of Excellence

Addressing the challenge of orbital space weather forecasting

SWORD: Space Weather Operational Readiness Development Center



Benefits

Improved understanding of the magnetosphere –ITM system, leading to better forecasting and nowcasting of geomagnetic storm impacts on LEO satellite operations, airline navigation and communications and more.

Novel data science and machine learning methodologies for data-driven discovery, ensemble modeling, and uncertainty quantification.

Advanced cloud-based R2O-O2R platform based on AWS partner technology for acceleration of transitions to NOAA. JEDI data assimilation integration to assure compatibility with future NOAA Unified Forecast System models.

Wider Impacts

Education and mentoring in modeling, data science, and operational forecasting via an active Visiting Scientist program.

Direct benefits to operational space weather forecasting, space traffic management, satellite operations, and the aviation industry.

Vision

The SWORD Center is an international, multi-disciplinary, focal point where researchers, operational forecasters, and the space weather user community work collaboratively to improve forecasts and nowcasts of the orbital and cis-lunar space environment.

5-year Research and Transition Goals

Next-generation physics-based modeling for geospace forecasting, coupling two operational forecasting models (SWMF/Geospace and WAM/IPE) for improved physics description.

A data assimilation system exploiting existing neutral density, ionospheric, and mesospheric data for the operational WAM/IPE ionosphere/thermosphere/mesosphere (ITM) model.

Advanced machine learning models for accelerated ensemble calculations, model calibration, and uncertainty quantification in magnetospheric and geospace system forecasts.

Team Role	Members	Organizations
PI	T. Berger	Univ. of Colorado (CU)
PM	J. Putt	CU Boulder
Co-Is	T. Pulkkinen, Y. Chen, T. Gombosi, Z. Huang, A. Ridley, I. Sokolov, S. Zou	University of Michigan
	D. Baker, E. Camporeale, P. Chamberlin, F. Laskar, G. Lucas, N. Maruyama, M. Miesch, E. Sutton	CU Boulder
	A. Jaynes	University of Iowa
	D. Ozturk	University of Alaska
	N. Pedatella, L. Qian	NCAR/HAO
	M. Mlynczak	NASA/LaRC
Collaborations	NASA/CARA, CGS DRIVE Center at JHU/APL	
International	UK MetOffice, SANSA	Commercial Partners: SpaceX, GeoOptics, Amazon, LeoLabs, Global Aerospace Corp., Muon Space, Flyer Research, MAVerick