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Book of abstracts

Invited talks

Learning the Sun: Machine Learning and Physical Insight for Space Weather Forecasting

Sabrina Guastavino (Department of Mathematics, University of Genova), Edoardo Legnaro (Department of Mathematics, University of Genova), Michele Piana (Department of Mathematics, University of Genova), Anna Maria Massone (Department of Mathematics, University of Genova)

Understanding and forecasting solar eruptive events, such as solar flares, coronal mass ejections (CMEs), and the geomagnetic storms they can trigger, remains a core challenge in heliophysics, with far-reaching implications for space- and ground-based technological systems. These events are driven by complex processes originating in the solar atmosphere and extending through the heliosphere, and they can impact the Earth's environment. In recent years, Machine Learning (ML) has emerged as a powerful complement to traditional physics-based models, offering new pathways for real-time prediction, pattern recognition, and the discovery of hidden data relationships. This talk explores the integration of ML techniques with physical knowledge from solar and space physics to advance space weather forecasting. We present a range of applications, including: (1) forecasting solar flares from magnetograms of active regions; (2) predicting CME transit times from Sun to Earth using remote-sensing and in-situ observations; and (3) forecasting geomagnetic storms from solar wind and interplanetary magnetic field measurements acquired at L1. Emphasis is placed on the use of feature selection and ranking to identify key physical parameters, and on the incorporation of physics-guided constraints to enhance predictive performance and model interpretability. Results from recent events, including the May 2024 superstorm, highlight the potential of hybrid approaches that fuse data-driven techniques with physical insight, offering improvements in forecast lead time, robustness, and our scientific understanding of solar-terrestrial interactions.

Data-Driven Closures for Hybrid Plasma Models in Space Plasmas

George Miloshevich (CmPA, KU Leuven), Giuseppe Arrò (LANL), Luka Vranckx (KU Leuven), Francesco Pucci (ISTP-CNR), Pierre Henri (OCA)

Modeling multi-scale processes remains a fundamental challenge in collisionless space plasmas, impacting both predictive simulations and data-driven understanding of heliospheric environments. Fully kinetic simulations can resolve electron-scale dynamics, but their computational cost renders them impractical for large-scale or long-duration applications. Yet, kinetic processes critically influence the dynamics of energetic particles, which are central to the manifestation and impact of space weather phenomena.

In this study, we employ a system identification approach, utilizing neural network surrogates trained on high-fidelity kinetic simulations to extract data-driven equations of state for electrons. This approach enables closure of the moment hierarchy, facilitating the construction of efficient reduced-order models. Our analysis shows that accurately predicting Finite Larmor Radius (FLR) terms requires a non-local formulation, outperforming conventional analytic closures based on adiabatic invariants.

We demonstrate the generalization capability of the learned closure across varying turbulence regimes, recovering key energy transfer signatures, such as statistics of pressure-strain interaction, consistent with fully kinetic benchmarks. To provide explainability, we conduct ablation studies, revealing that electron pressure predictions depend not only on moments linked to adiabatic invariants but also on the parallel electric field, suggesting its possible role in plasma thermalization.

Finally, we couple the data-driven electron closure with kinetic ion dynamics, advancing toward hybrid kinetic simulations where electrons are represented via a neural network-based equation of state. This hybrid physics-informed machine learning framework offers a pathway to computationally efficient models with improved physical realism, potentially enabling both predictive simulations and parameter inference in heliospheric and magnetospheric applications.

The Sun in 3D: Bridging Gaps in Solar Observations with Physics-Informed Machine Learning

Robert Jarolim (High Altitude Observatory)

Despite the wealth of remote sensing data from multiple instruments and vantage points, a complete 3D picture of the solar atmosphere remains elusive. Line-of-sight integration, projection effects, and the limitation of magnetic field measurements to a single layer (typically the photosphere) pose major challenges to understanding the Sun's 3D magnetic and plasma structure from 2D observations.

In this talk, I will present recent advances in physics-informed machine learning that integrate physical models with observational data to address this gap. I will introduce neural representations for solar modeling, focusing on Physics-Informed Neural Networks (PINNs) and Neural Radiance Fields (NeRFs).

Using PINNs, we estimate the full 3D coronal magnetic field from 2D magnetogram data, demonstrating how both photospheric and chromospheric measurements can be leveraged to infer the complex magnetic topology of the solar atmosphere. I will then highlight how NeRFs enable 3D tomographic reconstructions of the solar corona by combining multi-viewpoint observations into coherent volumetric models. This approach offers new insights into the structure and evolution of the solar corona, including dynamic events such as coronal mass ejections.

Finally, I will discuss how integrating these machine learning approaches with multi-modal observations opens a new frontier in modeling the Sun's magnetic and plasma environment, andvancing our ability to interpret its dynamic behavior.

Bayesian Inference and Global Sensitivity Analysis for Ambient Solar Wind Prediction

Opal Issan (University of California San Diego)

The ambient solar wind plays a significant role in propagating interplanetary coronal mass ejections and is an important driver of space weather geomagnetic storms. A computationally efficient and widely used method to predict the ambient solar wind radial velocity near Earth involves coupling three models: Potential Field Source Surface, Wang-Sheeley-Arge (WSA), and Heliospheric Upwind eXtrapolation. However, the model chain has 11 uncertain parameters that are mainly non-physical due to empirical relations and simplified physics assumptions. We, therefore, propose a comprehensive uncertainty quantification (UQ) framework that is able to successfully quantify and reduce parametric uncertainties in the model chain. The UQ framework utilizes variance-based global sensitivity analysis followed by Bayesian inference via Markov chain Monte Carlo to learn the posterior densities of the most influential parameters. The sensitivity analysis results indicate that the five most influential parameters are all WSA parameters. Additionally, we show that the posterior densities of such influential parameters vary greatly from one Carrington rotation to the next. The influential parameters are trying to overcompensate for the missing physics in the model chain, highlighting the need to enhance the robustness of the model chain to the choice of WSA parameters. The ensemble predictions generated from the learned posterior densities significantly reduce the uncertainty in solar wind velocity predictions near Earth.

How to creatively account for the lack of an upstream monitor at planets other than Earth

Caitriona Jackman (Dublin Institute for Advanced Studies)

In this talk I overview the work of members of the DIAS Planetary Magnetospheres Group to utilise machine learning and data analytics to account for the lack of an upstream monitor at planets such as Mercury, Jupiter and Saturn. I will overview how we utilise available data to infer/predict/model the upstream solar wind and its likely influence on downstream magnetospheric dynamics.

Such work includes:

- application of a feedforward neural network to data from Mercury's magnetosheath to infer upstream solar wind velocities [Bowers et al., 2024]

- application of ensemble modelling, dynamic time warping, and Bayesian methods to track the solar wind out to Jupiter and model the shape of its magnetospheric boundaries [Rutala et al., 2024, 2025]

- Machine Learning for region classification (magnetosphere-magnetosheath-solar wind) at Mercury to locate all bow shock and magnetopause crossings from the MESSENGER era and illustrate the dynamic nature of solar wind influence there. [Hollman et al., 2025]

- U-Net semantic segmentation to find specific radio bursts at Saturn which may then be used as a proxy for solar wind compression dynamics [O'Dwyer et al., 2023; Jackman et al., 2025]

From Model to Impact: Engineering Machine Learning for Space Weather Forecasting

Paul Wright (University of Exeter)

Machine learning (ML) holds great promise for advancing space weather forecasting, but the path from research paper to operational impact is filled with challenges. Diverse datasets, inconsistent preprocessing, and varied evaluation methodologies make it difficult to compare models or establish true progress. Benchmark datasets and leaderboards, while useful, often encourage metric-chasing rather than readiness for real-world forecasting.

In this talk, I will highlight key pitfalls in current practice, including data leakage, imbalance, and lack of real-time validation, and outline best practices for moving ML models into production. Drawing on software and ML engineering principles, I will discuss how transparent data pipelines, experiment tracking, and open sharing can lay the groundwork for reproducibility and fair comparison. Ultimately, moving from model to impact depends on strong engineering foundations: versioned datasets and models, automated pipelines, reproducible packaging, and continuous monitoring on live data streams. With these in place, ML models can move beyond theory to become resilient, testable, and impactful in operational space weather forecasting.

Deep learning across multi-dimensional data

Henrik Eklund (ESA)

Neural networks can effectively identify patterns or weak signals that are challenging to detect through manual analysis. Through deep neural network implementation, essential signatures extraction from observational data can be effectively streamlined or automated. One powerful way to improve this extraction process is by increasing the input dimensionality of the dataset. For many imaging applications, adding the temporal or spectral domain enables a much richer interpretation of the underlying physical representation. One example of applications is how a spatio-temporal neural network architecture for deconvolution outperforms regular spatial image deconvolvers.

Similarly, treating a collection of data streams as artificial images and applying a similar neural network architecture, allows to find links between signatures across them.

TORAX: A Fast and Differentiable Tokamak Transport Simulator in JAX

Jonathan Citrin (Deepmind)

We introduce TORAX, an open-source differentiable transport simulator for tokamak fusion plasmas, targeting fast and accurate core-transport simulation for pulse planning and optimization, and unlocking broad capabilities for controller design and advanced surrogate physics. TORAX is written in Python using JAX, and solves coupled time-dependent 1D PDEs for core ion and electron heat transport, particle transport, and current diffusion. JAX's just-in-time compilation provides fast computation, while maintaining Python's ease of use and extensibility. JAX auto-differentiability enables gradient-based nonlinear PDE solvers, and gradient-based optimization techniques for wide applications such as data-driven parameter identification, and tokamak trajectory optimization. JAX's inherent support for neural network development and inference facilitates coupling ML-surrogates of constituent physics models in the multiphysics simulation, key for fast and accurate simulation. Code verification is obtained by comparison with the established multiphysics tokamak simulators on ITER-like and SPARC scenarios. TORAX is an open source tool, and aims to be a foundational component of wider workflows built by the wider community for future tokamak integrated simulations.

Contributed Talks (in order of presentation)

Monday

A New HOPE for Accurate Solar Flare Prediction

Anant Telikicherla (LASP / CU Boulder)*; Thomas Woods (LASP / CU Boulder); Bennet Schwab (SSL / UC Berkeley)

Solar flares are among the most powerful explosions in the solar system, releasing electromagnetic radiation across a broad spectrum, from gamma rays to radio waves. Despite decades of research, the physical mechanisms underlying solar flare initiation remain only partially understood. Predicting solar flares just minutes in advance, known as nowcasting, remains a major challenge in space weather research. In this presentation, we provide an update on our ongoing efforts to improve solar flare nowcasting through both data-driven analysis and novel instrumentation development. Our approach leverages the recently identified Hot Onset Precursor Event (HOPE), a subtle but statistically robust feature in Soft X-Ray (SXR) measurements that appears prior to most solar flares. We evaluate the utility of HOPE for early warning by analyzing SXR irradiance data from NASA's Miniature X-ray Solar Spectrometer-3 (MinXSS-3/DAXSS) alongside long-term observations from NOAA's GOES-XRS. We demonstrate that the HOPE effect consistently precedes flare onset by 10 - 15 minutes across a broad range of flare magnitudes. Building on this, we explore machine learning techniques, specifically LSTM and CNN-based models, for predicting flare peak flux and timing. The models are trained on decades of GOES-XRS data, and we present preliminary results that highlight the predictive power of incorporating HOPE-informed features. Finally, we introduce a new SXR imaging instrument currently in development to enhance HOPE-based flare detection. This payload is scheduled to fly aboard the Extreme-Ultraviolet Variability Experiment (EVE) calibration sounding rocket from White Sands Missile Range in April 2026. A successful demonstration would pave the way for future CubeSat or small-satellite deployments, offering valuable datasets for machine learning based flare nowcasting systems.

Interpretable Data-Driven Models for Solar Flare Forecasting through Deep Learning and Symbolic Regression

Youngjae Kim (Kyunghee university)*; Yongjae Moon (Kyunghee university); Jihyeon Son (Korea Astronomy & Space Science Institute)

In this study, we develop an interpretable data-driven solar flare forecasting model using time-series magnetic field parameters from active regions and flare catalogs. We first train deep learning models, then create interpretable surrogate models through symbolic regression. Our surrogate model achieves comparable performance to the original (TSS = 0.76) on 14 years of data while using 10,000 times fewer parameters in 5-fold cross-validation.

Our surrogate model reveals that flare productivity is high when both the total amount and asymmetry of current helicity are simultaneously elevated. We explore the physical interpretation of this relationship. This model successfully forecasts the first events of the most flare-productive active regions in solar cycles 24 and 25, where all empirical models in flare scoreboards we investigated failed. Our method can be applied to develop interpretable data-driven models across astronomy fields with time-series observations, potentially enabling new scientific discoveries from existing datasets.

Combining Physics-Derived and Machine-Learned Features for Probabilistic Solar Flare Forecasting

Ekaterina Dineva (KU Leuven, CmPA)*; George Miloshevich (KU Leuven, CmPA); Jasmina Magdalenić (KU Leuven, CmPA); Stefaan Poedts (KU Leuven, CmPA)

Operational solar flare forecasting requires computationally efficient and energy-optimal methods that maximize the use of available observational resources to deliver timely and reliable predictions. Synoptic full-disk observations from the Solar Dynamics Observatory (SDO) provide continuous monitoring of solar magnetic activity over more than one solar cycle, enabling detailed studies of solar variability and space weather impacts. The Space-weather HMI Active Region Patches (SHARP) vector magnetic field (VMF) maps and parameters, derived from the Helioseismic and Magnetic Imager (HMI), support investigations of active region evolution and flare triggering mechanisms. In this study, we use time series of SHARP VMF maps as input to a Disentangled Variational Autoencoder (VAE), a Disentangled Representation Learning (DRL) method that extracts low-dimensional features capturing the morphological and dynamic characteristics of active regions. These VAE-derived features exhibit temporal evolution patterns similar to, but not redundant with, certain SHARP parameters, indicating that their combination provides an enhanced

representation of solar magnetic activity. We construct a joint dataset merging human-curated SHARP parameters with machine-learned VAE features, resulting in a high-fidelity input for flare forecasting. Our forecasting pipeline utilizes this dataset to produce binary (Flare vs. No-Flare, Alert vs. No-Alert) and multi-class probabilistic predictions. The pipeline employs a Long Short-Term Memory (LSTM) network to learn the temporal evolution of the features for several time windows, followed by logistic regression to estimate probabilities for strategically labeled event classes. This integrated approach highlights the value of combining physics-derived and machine-learned representations to improve the accuracy and robustness of solar flare forecasting models.

Operational Use of Deep Flare Net and AI techniques for Space Weather Forecasting

Naoto Nishizuka (National Institute of Information and Communications Technology (NICT))*; Yuki Kubo (National Institute of Information and Communications Technology (NICT)); Naoko Takahashi (National Institute of Information and Communications Technology (NICT)); Takuya Tsugawa (National Institute of Information and Communications Technology (NICT))

In this year, solar activity has reached the maximum and large-scale flares have frequently occurred. NICT has been operating space weather forecasting and developing forecasting models based on observational data, numerical simulations, and machine learning and AI techniques. We have developed an operational solar flare prediction model using deep neural networks, named Deep Flare Net (DeFN), which is used in daily space weather forecast meetings in NICT (Nishizuka et al. 2018 ApJ, 2021 EPS). The DeFN model can predict occurrence probabilities and the largest level of flares occurring within the next 24 hr, using magnetograms and EUV images taken by SDO during 2010-2015. DeFN can automatically detect active regions from magnetograms, extract 79 physical features from each region, and input them into deep neural networks to predict flares. We evaluated the prediction results by TSS, and we found that DeFN succeeded in predicting flares with TSS=0.80 (0.63) for >=M(C)-class flares, which is better than human forecasting. In addition, DeFN is operational from 2019 onwards and has been evaluated for accuracy every year. For example, in the 2019-2020 period, TSS=0.82 was achieved for the C-class flare prediction, and in the 2019-2023 period, TSS=0.70 (0.72) was achieved for the M(C)-class flare prediction. Failure analysis has also been used to clarify the characteristics of solar flares that are difficult to predict, and the model was extended to a Transformer model (Kaneda et al. 2022 ACCV). Furthermore, AI techniques are now beginning to be used in various ways for space weather forecasting in NICT, including the application of these methods to solar wind and geomagnetic storm forecasting, surrogate models applied to magnetospheric simulations, and automatic recognition of ionospheric observation ionograms. In this talk we will introduce DeFN in forecast operations and other AI applications in space weather forecasting.

Soft X-ray Flux Prediction for Onboard 24-Hour Solar Flare Forecasting Using CNNs and SDO/AIA Images

Panagiotis Gonidakis (Cmpa, KULeuven)*; George Miloshevich (Cmpa, KULeuven); Francesco Carella (Cmpa, KULeuven); Jasmina Magdalenić Zhukov (Cmpa, KULeuven); Stefaan Poedts (Cmpa, KULeuven)

Predicting solar flares is essential for safeguarding satellite operations, ensuring communication reliability, and protecting technological infrastructure. Most recent machine learning approaches have focused on classifying flares into discrete categories such as C, M and X. However, these discrete labels may fail to capture the underlying physical information X-ray flux, which is a continuous label. In parallel, there is growing interest in integrating AI algorithms onboard for future space missions which enables automation of key tasks, addresses communication delays due to the need for ground-based human intervention, intelligently activates instruments and filters out or prioritizes critical data for downlink.

In this work, we employ CNNs to perform regression and predict soft X-ray flux based on multi-modal image inputs from the SDO. Specifically, we combine images from several Atmospheric Imaging Assembly (AIA) wavelengths: 94 Å (flaring regions), 171 Å (quiet Sun), 193 Å (coronal structures), and 304 Å (chromosphere), to represent different layers of the solar atmosphere. All data are temporally aligned with corresponding GOES soft X-ray flux values, taking the 24-hour maximum as the regression target. To enable comparison with existing classification-based flare forecasting approaches, we post-process the continuous regression outputs to infer standard flare classes. We benchmark our method using metrics such as the TSS. Preliminary results show that using a weighted loss function which encourages the prediction of high-intensity values significantly improves performance over standard Mean Squared Error. Incorporating the 24-hour average flux as input significantly improves model performance. Finally, we ensure that the number of operations and trainable parameters remain relatively low to enable potential deployment onboard future space missions.

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Interpretable Deep Learning for Solar Flare Predictions

Linn Abraham (IUCAA)*; Vishal Upendran (The SETI Institute); Durgesh Tripathi (IUCAA); Ninan Philip (Artificial Intelligence Research and Intelligent Systems, Kerala, 689544); Nandita Srivastava (Udaipur Solar Observatory, Physical Research Laboratory, Udaipur 313001); Sreejith Padinhatteeri (Manipal Academy of Higher Education, Manipal 576104); Ramaprakash A. N. (IUCAA)

Solar flares are large impulsive releases of energy in the solar atmosphere, with significant impact on both the Earth's atmosphere and near-Earth space weather. Hence, mitigating the impact of solar flares on Earth requires a precise understanding and prediction of the trigger mechanisms of these flares, including the identification of pre-flare signatures. Traditional solar flare prediction models have relied primarily on features derived from photospheric magnetograms, typically using shallow and interpretable machine learning models. However, the chromospheric and coronal parts of the solar atmosphere are known to respond more clearly to pre-flare signatures than the photosphere. Hence, in this work, we attempt to understand pre-flare signatures in intensity images of the solar atmosphere, using deep learning. We train multiple models on data cubes of AIA active regions to classify image cubes into flaring or non-flaring active regions. We then apply several techniques to interpret regions in the AIA images mostly corresponding to the flaring class, including integrated gradients and Shapely values. We then perform a statistical study of these features to see how their distributions differ across the flaring and non-flaring classes. Additionally, we train a shallow and interpretable ML model on the same data and compare the performances of both the approaches. Through this analysis, we find that the features extracted from flaring and non-flaring patches show statistical differences and present distinct intensity patterns.

Generative Diffusion Models of the Solar Corona

Daniel da Silva (NASA/GSFC, UMBC)*; Andres Munoz (SWRI); Michael Kirk (NASA/GSFC); Nat Mathews (NASA/GSFC, UMD)

Diffusion models such as DeepMind's GenCast have demonstrated powerful performance in terrestrial weather forecasting, achieving results on-par and surpassing leading medium-range numerical weather simulations. We present our initial results to train a Denoising Diffusion Probabilistic Model (DDPM) of the solar corona, aimed as a first step at generating synthetic solar magnetic fields based on conditioning inputs. Conditioning inputs include multi-spectral imagery, magnetograms, and other measurements commonly used to frame coronal inverse problems.

Our initial experiment targets the generation of synthetic global magnetic field configurations of the solar coronal based on conditioning with the solar cycle phase. The model is trained on 10 years of WSA potential field source surface (PFSS) model runs, augmented with 15° to 345° azimuthal rotations to increase data diversity. Training is conducted in the spherical harmonics domain, leveraging concepts from Fourier Neural Operators (FNOs) and Spherical Fourier Neural Operators (SFNOs). A physics-informed loss function, built on a differentiable spherical harmonic expansion, is used to maximize generation of realistic 3D magnetic potentials.

In this presentation we introduce the theory and framework behind diffusion models, detail the training framework for our initial experiment, and discuss implications for Heliophysics applications. Our initial results suggest that diffusion-based generative models may provide a powerful approach to solving classical problems in Heliophysics such as inverse modeling, data assimilation, and forecasting.

Next-Generation MHD Modeling Of Solar Wind Using Neural Operators

Prateek Mayank (University of Colorado Boulder)

Traditional magnetohydrodynamic (MHD) solvers remain indispensable for modeling heliospheric plasma dynamics, yet their high computational cost and limited scalability hinder ensemble simulations and real-time forecasting. In this study, we propose a new framework employing neural operators to efficiently emulate 3D solar wind conditions learned directly from MHD simulation data. Our approach integrates observationally-derived multi-channel inputs and utilizes a hybrid training scheme, combining data-driven supervised learning with physics-informed constraints through embedded conservation laws. The neural operator demonstrates robust generalization capabilities, capturing complex heliospheric structures such as stream interaction regions and heliospheric current sheets.

By ensuring both physical consistency and fidelity to simulation data, our model offers a scalable and computationally efficient alternative to traditional MHD codes. This enables almost instantaneous generation of full 3D solar wind solutions with orders of magnitude faster than conventional codes. We will discuss challenges related to training stability, resolution of sharp structures, and ensuring physical realism, along with strategies such as coordinate-aware inputs and gradient-based diagnostics. This work demonstrates the transformative potential of neural operators as next-generation simulation tools in computational astrophysics and space weather forecasting.

Reconstruction of two-dimensional magnetohydrodynamic and Hall magnetohydrodynamic equilibria in space using physics-informed neural networks

Hiroshi Hasegawa (Institute of Space and Astronautical Science, JAXA)*; Eunjin Choi (Southwest Research Institute); Kyoung-Joo Hwang (Southwest Research Institute); Kyunghwan Dokgo (Southwest Research Institute)

We present a novel data analysis technique using physics-informed neural networks (PINNs) for reconstructing two-dimensional (2D), magnetohydrodynamic (MHD) and Hall MHD equilibria from single- or multi-spacecraft measurements in space of the magnetic field and plasma bulk parameters. Earlier reconstruction methods, as developed by Sonnerup et al. (JGR, 2006) and Sonnerup & Teh (JGR, 2008, 2009), rely on explicit spatial integration of the governing partial differential equations from spacecraft path(s), where measured data are available and initial conditions are set. Thus, their results are sensitive to measurement errors and violation of the underlying model assumptions, while our PINN-based approach can accommodate such errors and modest violation of the assumptions. We validate this method through benchmark tests by use of exact numerical solutions of 2D, ideal MHD and Hall MHD equations. By application to an extensively investigated magnetotail reconnection event seen by the Magnetospheric Multiscale mission (Torbert et al., Science, 2018), we demonstrate that reconnecting current-sheet geometry and structures, consistent with numerical simulations and comparable to earlier reports, can successfully be reconstructed. We also present a PINN-based empirical estimate of the reconnection rate and resistivity in the resistive MHD or Hall-MHD framework.

Physics-Informed Neural Networks for Modeling Geomagnetic Storm Dynamics

Manuel Lacal (University of Trento)*; Enrico Camporeale (Queen Mary University of London & University of Colorado); Giuseppe Consolini (INAF); Mirko Piersanti (University of L'Aquila); Mirko Piersanti (INAF)

Geomagnetic storms, driven by solar activity, pose a significant threat to modern technological infrastructure. Accurate prediction of these events hinges on robust physical models of the Sun-Earth system. This work introduces a novel framework that leverages Physics-Informed Neural Networks (PINNs) to systematically evaluate and refine such models. Our approach is founded on the well-established differential equation for ring current evolution by Burton et al. (1975). By employing PINNs, we solve the inverse problem: determining the optimal parameters for numerous candidate solar wind-magnetosphere coupling functions while enforcing physical consistency.

To enhance model fidelity and quantify uncertainties, we utilize an ensemble PINN approach and incorporate Random Fourier Features to mitigate the network's spectral bias, enabling the capture of high-frequency storm dynamics. As an initial application, we validate the framework using SMR and solar wind observations from the May 2024 "Gannon" storm. Our results quantify significant performance differences among the coupling functions, providing new insights into the physical mechanisms of solar wind-magnetosphere interaction.

This study demonstrates the capability of PINNs as a powerful tool for automated model discovery and validation in heliophysics. The findings have direct implications for advancing our understanding of magnetospheric dynamics and ultimately improving the predictive accuracy of Space Weather models.

Investigating Nonlinear Quenching Effects on Polar Field Buildup Using Physics-Informed Neural Networks

Jithu J Athalathil (Indian Institute of Technology Indore)*; M H Talafha (Research Institute of Science and Engineering, University of Sharjah); Bhargav Vaidya (Indian Institute of Technology Indore)

The evolution of the solar magnetic field is the key factor governing space weather drivers. Accurate forecasting of space weather requires precise modelling of the magnetic field's evolution on the solar surface using methods like Surface flux transport (SFT). Conventionally used SFT modelling techniques involve grid-based numerical schemes, making them computationally expensive. In this presentation, we present a novel, mesh-independent machine learning-based approach using Physics-Informed Neural Networks (PINNs) to simulate the temporal evolution of Bipolar Magnetic Regions (BMRs) on the solar photosphere. The ability of PINNs to solve advection-diffusion equations make it an efficient and accurate technique to simulate SFT equation. We employ this approach to study how nonlinear effects influence SFT models, with the broader goal of improving our understanding and constraints on solar dynamo processes. In particular, we focus on two mechanisms recently proposed to modulate solar cycle amplitudes: tilt quenching (TQ), representing a negative feedback between the cycle strength and the average tilt angle of active regions, and latitude quenching (LQ), indicating a positive relationship between cycle strength and the mean emergence latitude of active regions. Using PINNs within the SFT framework, we systematically examine the nonlinearities introduced by TQ, LQ, and their combined effects. Our study aims to clarify the distinct contributions of TQ and LQ to the solar dynamo. We find that the balance between LQ and TQ effects is closely linked to the ratio of meridional flow

speed to magnetic diffusivity in the SFT models. Given that LQ is better constrained through observations, it may offer a valuable benchmark for refining solar dynamo models to achieve closer alignment with solar observations.

Real-time Reconstruction of Coronal Magnetic Fields using a Physics-informed Neural Operator

Mingyu Jeon (Kyung Hee University)*; Hyun-Jin Jeong (KU Leuven); Yong-Jae Moon (Kyung Hee University); Jihye Kang (Kyung Hee University); Kanya Kusano (Institute for Space–Earth Environmental Research)

Solar coronal magnetic fields store the magnetic energy that drives solar eruptions, such as flares and coronal mass ejections, which significantly impact space weather. Nonlinear force-free fields (NLFFFs) are widely used to model the coronal magnetic fields. We present a physics-informed neural operator (PINO) model that learns the solution operator mapping from 2D photospheric vector magnetic fields to 3D NLFFFs. The model is trained using a combination of physics-based losses derived from the NLFFF partial differential equations and data-based losses from target NLFFF solutions. We first validate our approach using an analytical NLFFF model. Then, we train and evaluate the model on 2,327 numerically computed NLFFF samples from 211 active regions in the Institute for Space-Earth Environmental Research (ISEE) database. Our results demonstrate that the trained PINO model can reconstruct NLFFFs in under one second on a single consumer-grade GPU, enabling near real-time reconstruction of 3D coronal magnetic fields. For 30 selected active regions, the AI-generated NLFFFs exhibit both qualitative and quantitative agreement with the target NLFFFs. Furthermore, the magnetic energy evolution of the AI-generated NLFFFs for active region AR 11158 closely resembles that of the target NLFFFs and results obtained from existing methods. This model has the potential to be integrated into physics-based space weather forecasting frameworks, such as the flare prediction method proposed by Kusano et al. (2020).

Merging Observational Data and Magnetohydrodynamics: A Variational Data Assimilation Approach for the Solar Wind

Jose Arnal (University of Toronto); Clinton Groth (University of Toronto)*

Over the last several decades, considerable effort has been dedicated to the computational modelling of space plasmas flows, with applications to heliospheric physics, the solar wind, and space weather science and forecasting. The space weather forecast models that have resulted from this effort are usually based on the global magnetohydrodynamics (MHD) modelling, an extension of conventional fluid dynamic descriptions to electrically conducting fluids. Despite the sophistication of these techniques, their accuracy in practice is very often limited by uncertainties in model input parameters. The application of data assimilation techniques in which observational measurements are incorporated to constrain model uncertainties offers a means of improving the predictions of global MHD models. To this end, this study presents a first application of a variational-based data assimilation strategy to boundary value problems for the three-dimensional ideal MHD equations, with a systematic treatment for the solenoidal constraint associated with the magnetic field. In the proposed approach, synthetic in-situ data for prototypical steady high-speed MHD outflows representative of the solar wind are considered and model-data mismatch is efficiently minimized via an optimization procedure that makes use of a discrete adjoint method in the evaluation of model parameter gradients. Details of the finite-volume solution method for the ideal MHD equations as well as the data assimilation algorithm for the inner boundary data of the MHD outflows are provided. Additionally, a number of observing system simulation experiments are presented, demonstrating the error-reduction capabilities of the proposed variational data assimilation framework.

Verification of Empirical and Deep Learning Models for Solar Wind Speed Forecasting

Seungwoo Ahn (Kyung Hee University)*; Jihyeon Son (Korea Astronomy and Space Science Institute); Yong-Jae Moon (Kyung Hee University); Hyun-Jin Jeong (KU Leuven)

In this study, we compare representative empirical models with a deep learning model (Son et al. 2023) for predicting solar wind speed at 1 AU. The empirical models are the Wang–Sheeley–Arge (WSA)–ENLIL model, which combines empirical methods with a magnetohydrodynamic model, and the empirical solar wind forecast (ESWF) model, which uses the relationship between the fractional coronal hole area and solar wind speed. Our deep learning model predicts solar wind speed over 3 days ahead using extreme–ultraviolet (EUV) images and up to 5 days of solar wind speed before the prediction date. We evaluate the models over the test period (October–December in each year from 2012 to 2020) in view of solar activity phases and the entire period. To validate the model's performance, we use two evaluation methods: a statistical approach and an event–based approach. For statistical verification during the entire period, our model outperforms the other empirical models, with a much lower mean absolute error (MAE) of 51.4 km/s and root mean squared error (RMSE) of 68.6 km/s, along with a much higher correlation coefficient (CC) of 0.69. For the event–based verification for high–speed solar wind streams, our model has superior performance in most of the six metrics evaluated within a ±1 day time window. In particular, it achieves a high success ratio of 0.82, emphasizing the model's stable performance and ability to minimize false alarms. These results show that our deep learning model has strong potential for practical application as a reliable tool for fast solar wind forecasting with its high accuracy and stability.

Extended Lead-Time Geomagnetic Storm Forecasting with Solar Wind Ensembles and Machine Learning

Matthew Billcliff (Northumbria University)*; Andy Smith (Northumbria University); Mathew Owens (University of Reading); Luke Barnard (University of Reading); Wai Lok Woo (Northumbria University); Nathaniel Edward-Inatimi (University of Reading); Jonathan Rae (Northumbria University)

Geomagnetic storms are major disturbances in Earth's magnetosphere that can disrupt satellites, communications, and power systems, leading to substantial economic and technological impacts. Existing forecasting methods typically rely on L1 satellite data, offering limited lead times of just a few hours—often too short for effective mitigation. This work explores how solar data can extend these lead times through ensemble modelling and machine learning.

We use the computationally efficient one-dimensional HUXt solar wind model to generate a large ensemble of solar wind profiles, capturing the spatial and propagation uncertainties inherent in solar observations. Unlike traditional 3D-MHD models, HUXt allows for rapid simulation of many possible scenarios. These simulated profiles are processed through regression-based machine learning models trained to predict the open-ended Hp30 geomagnetic index—a high-resolution (30-minute) alternative to the commonly used Kp index (3-hour resolution).

Each solar wind ensemble member is passed through a regression model to generate an Hp30 forecast, and these are aggregated into a final prediction. Forecast uncertainty is estimated using ensemble spread and historical correlations with observed solar wind (OMNI) data. The model is trained and tested on 30 years of historical data, with performance evaluated across lead times from 1 to 36 hours and varying storm intensities.

We assess different machine learning architectures and input features, with a focus on improving metrics such as Mean Absolute Error (MAE) and R-squared. This study highlights the potential of combining fast ensemble modelling with ML to enhance the accuracy and lead time of geomagnetic storm forecasts.

Long-Horizon Prediction of Solar Wind Events with Reinforcement Learning

Esraa Elelimy (University of Alberta)*; Jacob Adkins (University of Alberta); Adam White (University of Alberta); Abigail R. Azari (University of Alberta)

Space weather events such as geomagnetic storms and Coronal Mass Ejections (CMEs) affect Earth's space environment---including its ionosphere and magnetosphere---and disrupt technological systems both on Earth and in space. For example, geomagnetic storms and CMEs are known to interfere with power grids, telecommunications, and satellite operations. Advanced early warning of space weather events would allow for preventive measures that can mitigate these potentially harmful impacts. However, current approaches for geomagnetic storm and CME prediction are limited to large and often expensive computational systems. This limits the feasibility of early warning systems based on real-time solar wind data collected by spacecraft.

This presentation formulates the problem of making future predictions about solar wind data using General Value Functions (GVFs). GVFs are commonly used in reinforcement learning to formulate long-horizon predictions about the

future of time-dependent signals [Sutton et al., AAMAS, 2011]. GVFs encode information about the expected signal accumulation in the future, allowing us to answer questions such as \emph{what is the probability of an event happening in the future?}, unlike multi-step predictions in the time series literature that focus only on predicting the exact value of the signal. Using GVFs and recurrent neural networks, we develop a system that predicts geomagnetic storms and CMEs with a multi-hour lead time. We compare our results against NOAA's Space Weather Prediction Center alerts and the CMEs identified by the Richardson and Cane catalog [Richardson and Cane, Harvard Dataverse, 2024]. We focus on presenting the results of our system for the May 2025 G5 geomagnetic storm, and show that our prediction system would have been able to predict this event several hours before the first alert issued by NOAA. We conclude with a discussion of the potential of this predictive model for in situ operational space weather forecasting.

Gaussian Process forecast of strong geomagnetic storms using CME-ICME properties

Peter Wintoft (Swedish Institute of Space Physics), Magnus Wik (Swedish Institute of Space Physics), Per Danielsson (Swedish Institute of Space Physics), Ian Richarson (NASA)

In this work we develop a Gaussian Process (GP) model that target strong geomagnetic storms. The GP is chosen as it can be applied to small datasets and that it provides probabilistic forecast from which confidence intervals can be derived. Binary classification models are developed to forecast whether Kp >= 8- (G4 or G5) using CME-Earth transit time and minimum ICME Bz. The rationale for this is twofold: 1) except for a few events the G4/G5 storms are caused by CMEs, 2) Swedish power grid operator base their mitigation plan on levels of G4 or higher. The study is further expanded to classification and regression forecasts of Hp30 motivated by the fact that it is similar to Kp and extend beyond 9. For the classification model the limit is set at Hp30 >= 8+ as event maxima are biased upward by 2/3 compared to Kp. As Hp30 resolves different storms above 9 it is possible to also study regression models.

From a CME catalogue, transit times T and hourly minima Bz (GSM) are analysed together with maxima of Kp and Hp30 for each storm, in total 292 events over the years 1996 to 2023. The GP models are evaluated using leave-one-out cross validation. Models with just T and both T, Bz are developed, and unsurprisingly the T,Bz-models performs better than the T-models.

In realtime, typically only T is available from solar wind forecast models why it is useful to be able to forecast strong geomagnetic storms from only T. However, if some estimate of minimum Bz can be provided the forecast accuracy is greatly improved. The models are tested on the CCMC CME scoreboard data for the May 2024 storm.

ARCANE: An Operational Framework for Automatic Realtime ICME Detection in Solar Wind In Situ Data

Hannah Ruedisser (Austrian Space Weather Office, GeoSphere Austria)*; Gautier Nguyen (DPHY, ONERA, Toulouse, France); Ute V. Amerstorfer (Austrian Space Weather Office, GeoSphere Austria); Justin Le Louëdec (Austrian Space Weather Office, GeoSphere Austria); Eva Weiler (Austrian Space Weather Office, GeoSphere Austria); Emma E. Davies (Austrian Space Weather Office, GeoSphere Austria); Christian Möstl (Austrian Space Weather Office, GeoSphere Austria)

Interplanetary Coronal Mass Ejections (ICMEs) are the primary drivers of space weather disturbances, necessitating accurate and timely detection to mitigate their impact. While several methods have been proposed to identify these structures automatically, robust real-time detection remains a significant challenge.

We introduce ARCANE, an operational framework for the early detection of ICMEs in solar wind data under realistic operational constraints, enabling event identification without requiring observation of the full structure. This presentation outlines the methodology underlying ARCANE, highlights the challenges of adapting machine learning models for streaming data, and discusses the framework’s operational implementation at the Austrian Space Weather Office.

Furthermore, we showcase ARCANE's integration into a fully automated pipeline, capable of identifying the onset of an ICME’s magnetic obstacle in real-time and initiating immediate 3D modeling of its internal structure. This integration marks a promising step toward the operational combination of AI-based detection and physics-based modeling for improved space weather forecasting.

CAMEL-II: A 3D Coronal Mass Ejection Catalog Based on Coronal Mass Ejection Automatic Detection with Deep Learning

Jiahui Shan (Purple Mountain Observatory, Chinese Academy of Sciences)*; Li Feng (Purple Mountain Observatory, Chinese Academy of Sciences); Lei Lu (Purple Mountain Observatory, Chinese Academy of Sciences)

Coronal mass ejections (CMEs) are major drivers of geomagnetic storms, which may cause severe space weather effects. Automating the detection, tracking, and three-dimensional (3D) reconstruction of CMEs is important for operational predictions of CME arrivals. The COR1 coronagraphs on board the Solar Terrestrial Relations Observatory spacecraft have facilitated extensive polarization observations, which are very suitable for the establishment of a 3D CME system. We have developed such a 3D system comprising four modules: classification, segmentation, tracking, and 3D reconstructions. We generalize our previously pretrained classification model to classify COR1 coronagraph images. Subsequently, as there are no publicly available CME segmentation data sets, we manually annotate the structural regions of CMEs using Large Angle and Spectrometric Coronagraph C2 observations. Leveraging transformer-based models, we achieve state-of-the-art results in CME segmentation. Furthermore, we improve the tracking algorithm to solve the difficult separation task of multiple CMEs. In the final module, tracking results, combined with the polarization ratio technique, are used to develop the first single-view 3D CME catalog without requiring manual mask annotation. Our method provides higher precision in automatic 2D CME catalog and more reliable physical parameters of CMEs, including 3D propagation direction and speed. The aforementioned 3D CME system can be applied to any coronagraph data with the capability of polarization measurements. Our latest advancements in the segmentation and tracking modules will also be introduced.

Bayesian Inference for 3D CME Characterization and Uncertainty Quantification

Julio Hernandez Camero (University College London)*; Lucie Green (University College London)

Accurate three-dimensional (3D) characterization of coronal mass ejections (CMEs) is essential for modelling their propagation through interplanetary space and forecasting their arrival time at Earth. However, forecasting accuracy, assessed through platforms such as the Community Coordinated Modelling Center (CCMC) CME Scoreboard, has shown minimal improvement over the past decade, with persistent mean absolute errors around 13 hours. Several studies underscore fundamental issues in model inputs, notably uncertainties in CME parameter characterisation from coronagraph data as well as lack of knowledge of the solar wind conditions through which the CME propagates.

Current operational forecasting typically employs simplified morphological models, often relying on subjective manual fitting methods that underestimate true uncertainties, introduce user biases, and complicate statistically robust ensemble creation. Recent analyses reveal substantial variability in derived parameters depending on user input or viewpoint availability.

We introduce a 3D CME cone model fitting framework using Bayesian inference, reducing subjectivity by quantifying both observational and model uncertainties in the parameter space. Unlike traditional methods, Bayesian inference provides a comprehensive posterior distribution for CME parameters, quantifying uncertainties and parameter correlations.

Using our framework, we investigate how parameter uncertainties and correlations change when expanding from a single viewpoint to two viewpoints. Using our posterior distribution, we model ensembles of CMEs using the HUXt model and compare the forecasted time of arrival distributions to more ad-hoc methods that do not account for parameter correlations. Additionally, the posterior distributions offer informed priors crucial for data assimilation methods incorporating heliospheric imager (HI)-like observations, particularly valuable once missions such as Vigil become operational.

Data-driven, Probabilistic Solar Wind Reconstruction Beyond the Earth

Matthew Rutala (DIAS)*; Caitríona Jackman (DIAS); Mathew Owens (University of Reading); Luke Barnard (University of Reading); Abby Azari (University of Alberta)

Our perspective of the dynamic, three-dimensional solar wind beyond the Earth is considerably biased by a relative lack of available data and the high sensitivity of solar wind propagation models to the boundary conditions from which they are initialized. In particular, the solar wind is known to be highly

localized in heliolatitude, differing significantly over scales of $\sim 1^\circ$. This small-scale structure is relatively poorly measured in time: while spacecraft orbiting near 1 AU probe all heliolongitudes once every $\sim$27 day Carrington rotation, they sample each heliolatitude just over twice per year. Misspecification of the inner boundary directly leads to increased solar wind model errors in magnitude and arrival time, which reach $\sim$100 km/s and $\sim$days, respectively. Here we present a framework for probabilistically reconstructing the three-dimensional, time-varying solar wind based on the

HUXt solar wind propagation model and various data-assimilation techniques. We specify data-driven inner boundary conditions for the propagation model by back-mapping in-situ data from ≥1 AU to 0.1 AU. The longitudinal structure of this boundary is specified by corotation; the latitudinal structure is specified by Gaussian Process Regression (GPR), a non-parametric Bayesian method which allows us to estimate the boundary conditions while quantifying uncertainties. An ensemble of HUXt runs are driven from samples of this inner boundary and injected cone-model ICMEs with normally-varying parameters. As the reduced-physics HUXt model only propagates the solar wind flow speed and IMF polarity, model post-processing, in the form of Analog Ensemble (AE) and GPR modeling, is performed to add estimates of solar wind proton density and ram pressure. Ensemble members are compared to available in-situ data and re-weighted according to a Sequential Importance Resampling (SIR) setup to fine-tune the reconstructions of the ambient solar wind and transients embedded therein.

Kp Prediction from Solar Wind Parameters Using Sparse Library Regression

Sadaf Shahsavani (GFZ Helmholtz Centre for Geosciences)*; Yuri Shprits (GFZ Helmholtz Centre for Geosciences); James Edmond (GFZ Helmholtz Centre for Geosciences)

Accurate forecasting of the Kp index, a global measure of geomagnetic activity, is critical for space weather applications. In this study, we investigate the use of sparse library regression techniques to develop data-driven models for both short-term and long-term Kp prediction. Leveraging high-resolution OMNI solar wind parameters, including IMF Bz, solar wind speed, and proton density along with their historical averages, we construct a comprehensive library of nonlinear features. Using Orthogonal Matching Pursuit (OMP), we identify a compact, physically meaningful model that captures the dominant drivers of geomagnetic variability. Model performance is evaluated across multiple test intervals and benchmarked against a neural network baseline. Our results show that the proposed approach achieves competitive predictive accuracy with significantly reduced computational cost. This work underscores the potential of sparse regression frameworks in heliophysics, particularly given their ability to reflect the inherent sparsity of the governing physical processes when represented in an appropriate feature space.

Wednesday

Towards Operational Planetary Space Weather with A Virtual Solar Wind Monitor at Mars

Abigail Azari (University of Alberta)*

Unlike Earth, Mars does not possess an upstream solar wind monitor. This lack of continuous solar wind observations has fundamentally limited scientific studies that investigate solar wind impacts on the Mars space environment, and with increasing relevance, operational tasks for predicting space weather at the planet. Previous estimates of the solar wind have been pursued through physics-based modeling (e.g. magnetohydrodynamic models) or empirical (e.g. assuming statistical relationships with downstream observations) proxies. Proxies are often based on downstream observations from multiple orbiting spacecraft. These spacecraft pass in and out of the bow shock providing a semi-regularly sampling of the pristine solar wind. The most complete, and ongoing, set of the solar wind’s magnetic field and plasma parameters is from the NASA MAVEN spacecraft. MAVEN has orbited Mars since 2014, but additional assets add resolution to this dataset such as including ESA’s MEX mission which has been in orbit since 2003, and the CNSA’s Tianwen-1 orbiter since 2021.

In this presentation I will summarize a prior effort to create a continuous solar wind estimation upstream from Mars. This virtual solar wind monitor, or vSWIM (see Azari, Abrahams, Sapienza, Halekas, Biersteker, Mitchell, Pérez et al., 2024, doi: 10.1029/2024JH000155) was trained and assessed on MAVEN data with Gaussian process regression. Gaussian process regression, a type of machine learning, was used to provide predictions, and uncertainties on these predictions, at various temporal resolutions. vSWIM currently enables informed solar wind estimation at Mars for the majority time periods since 2014. I will summarize the prior operational aspects of this work, including required GPU acceleration, as well as assessment of uncertainty quantification. I will extend to an outlook for vSWIM’s multi-spacecraft integration for operational space weather prediction efforts.

Classifying MESSENGER Magnetospheric Boundary Crossings Using a Random Forest Model

Daragh Hollman (Dublin Institute for Advanced Studies)*; Caitriona Jackman (Dublin Institute for Advanced Studies); Katarina Domijan (Maynooth University); Charles Bowers (Dublin Institute for Advanced Studies, University of Michigan); Simon Walker (Dublin Institute for Advanced Studies); Matthew Rutala (Dublin Institute for Advanced Studies); Alexandra Fogg (Dublin Institute for Advanced Studies)

We present a new list of magnetopause and bow shock crossings based on automated region classification for the MESSENGER (Mercury Surface, Space Environment, Geochemistry and Ranging) mission. We fit a random forest model to magnetometer and ephemeris data to classify the solar wind, magnetosheath, and magnetosphere regions surrounding Mercury. The random forest was highly accurate when predicting the testing dataset, with an accuracy of 0.984 ± 0.0008. We apply this model to the orbital phase (March 2011 to April 2015) of the MESSENGER mission, and determine crossings automatically where changes in region classification occur. We compare the spatial distribution of these new crossings against existing datasets of boundary crossing intervals, observing that the average spatial distributions of individual crossings are skewed further towards the flanks of the magnetosphere, indicating increased boundary variability there. Additionally, we find the number of individual bow shock crossings increases linearly with heliocentric distance, suggesting an increase in boundary variability at larger heliocentric distances. This is in agreement with the labelling of crossing intervals in previous works, which show an average increase in duration at large heliocentric distances.

Auto-encoder based reduced order emulation of the Earth electron radiation belt modeling

Gautier Nguyen (ONERA)*; Guillerme Bernoux (ONERA); Antoine Brunet (ONERA); Maria Tahtouh (ONERA); Ingmar Sandberg (SPARC)

Reduced Order models (ROMs) aim at approaching the solutions of traditional high-fidelity physics-based models with a reasonable accuracy and at a reduced computational cost. This by projecting project highly non-linear features onto a latent space of reduced dimension which dynamics could be driven by external variables. Thanks to the ever-growing amount of in-situ data, Auto-Encoders (AE) and their variants have become a widely used dimensionality reduction technique for ROM development. The key challenge for this application stands in the obtention of disentangled, interpretable and information intensive latent variables, this to ensure a modeling of their dynamics and a reconstruction back in the physical space that are consistent with the temporal evolution of external variables.

In this study, we focus on the first step of ROM development, reducing the dimensionality of the Earth electron radiation belt dimensionality with AEs or one of its variants. Using long-term simulations of the electron belts between 2001 and 2019, we evaluate the strengths and limitations of different AE types to produce independent and interpretable latent variables while ensuring an efficient reconstruction of electron fluxes.

We then couple our best model with a Long Short-Term Memory (LSTM) network to design a preliminary Earth electron radiation belt ROMs driven by geomagnetic external parameters.

Finally, we benefit from the availability of geomagnetic indices during periods without spacecraft data to provide a global, long-term reconstruction of the electron belt state over several past solar cycles.

This work was supported by both the "Event-Based Electron Belt Radiation Storm Environments Modelling" Activity led by the Space Applications & Research Consultancy (SPARC) under ESA Contract 4000141351/23/UK/EG and ONERA internal fundings, through the federated research project PRF-FIRSTS.

SPARTAI – an AI-based forecasting pipeline for energetic electrons in the Earth's radiation belts

François Ginisty (Augura Space)*; Rungployphan Kieokaew (Inria/Augura Space); Ryad Guezzi (Inria/Augura Space); Hadrien Mariaccia (Inria/Augura Space); Alexandre Suteau (Inria/Augura Space)

Highly energetic electrons (at the MeV level) in the vicinity of the Earth's radiation belts pose significant risks on satellites through single event effects and long-term radiation damage, in GEO, MEO, and LEO orbits. Accurate forecasting of electron fluxes in this environment is essential for risk mitigation and spacecraft operations. Over the past few decades, several physics-based models have been developed to forecast radiation belt conditions. Here, we develop an AI-based forecasting pipeline for MeV-level electron fluxes a few days in advance using data from NOAA's space weather instruments and NASA-NOAA's Geostationary Operational Environmental Satellites (GOES). We tested and benchmarked several architectures of machine learning and neural network architectures (e.g., CNN, LSTM, and Transformers), as well as several combinations of these to address data sparsity while optimising performance. Our preliminary results are rather promising, with an $R2$ score over 80 % for all L-shells (McIlwain L-parameter). Using data covering for at least one complete solar cycle, we will present our findings during extreme events. We will also consider European-based and the ESA's space weather data for model training and for the development of the future operational forecasting pipeline. This work is a prototype product demonstration co-developed by Inria for Augura Space, a deep tech startup that delivers AI-powered space weather intelligence

A threshold-based random forest forecasting model for the Outer Radiation Belt

Dylan Weston (Northumbria University)*; I. Jonathan Rae (Northumbria University); Andy Smith (Northumbria University); Clare Watt (Northumbria University)

The Van Allen Radiation belts are highly dynamic in both strength and location, meaning that the belts are difficult to predict for spacecraft operators. Forecasting models exist, in part, to minimise any additional damage caused by this natural hazard. Both physics-based and machine learning models already exist; physics-based models allow for a deeper understanding of the system, and machine learning models offer a computationally cheap way to make a forecast but do not necessarily provide physical insight.

We present a collection of machine learning models capable of predicting if the Outer Radiation Belt crosses set percentile thresholds with considerable skill up to 3-days in advance, and some skill up to 6-days in advance. We use a Random Forest classification model to predict if the daily ~2MeV electron flux level across the Outer Radiation Belt exceeds thresholds from the 60th to the 95th percentiles. Each model shows a high level of accuracy at nowcasting and skill at forecasting up to 6 days in advance, a longer forecast than current operational models. Using feature importance, we determine the key inputs into each model in order to gain an insight into which drivers are important in driving increasing flux levels and over what timescales they have an impact. Crucially, we find that only a small number of geomagnetic indices are required to be able to forecast radiation belt fluxes with good skill, meaning that models such as these could be operationally viable for space weather stakeholders.

Thursday

Dataset Creation for ML Applications in Heliophysics - Lessons from ARCAFF

Daniel Gass (Dublin Institute of Advanced Studies)*; Shane Maloney (Dublin Institute of Advanced Studies); Paul Wright (University of Exeter); Eduardo Legnaro (University of Genova)

The handling and processing of training data is one of the most important steps for any machine learning project relating to heliophysics. No matter how sophisticated the model architecture, the quality and scientific validity of the output of these models is implicitly related to decisions made during dataset design.

The challenge of meaningfully exploiting the high volume of data delivered from instruments such as Solar Orbiter, the Solar Dynamics Observatory (SDO), and others is central to observational heliophysics. ML and broader data science concepts adopted from Astroinformatics are helping to access the fundamental physical processes captured by such instruments as a greater understanding of ML in heliophysics is attained.

Unfortunately, the importance of well curated, reproducible datasets in ML heliophysics projects has historically been overlooked. Dataset creation is often performed ad-hoc, sometimes lacking in sufficient documentation and version histories. Reproducibility and transparency are essential, required for both validation of presented science results and development by other researchers for future work.

This talk will outline past work and discuss the necessary change from understanding datasets as finished semi-black box products to dataset preparation packages as open source software, which can constantly be improved, updated, and extended to cover wider and more robust use cases by many users.

Though it is not the intention of this talk to advocate for one particular format or package of software, work created for the Active Region Classification And Flare Forecasting (ARCAFF) project will be presented to provide an example of the application of the aforementioned principles to a real world example within a research project with applied ML heliophysics. It will also address common dataset pitfalls such as physicality and class imbalances, and how to manage (sometimes undocumented) issues within source datasets such as the SDO.

Cross-Calibrated Video Super-Resolution for Solar Dopplergrams

Bhishek Manek (Laboratory for Atmospheric and Space Physics, University of Colorado Boulder)*; Andrés Muñoz Jaramillo (Southwest Research Institute)

Solar Dopplergrams capture oscillatory patterns on the Sun’s surface driven by pressure waves from the interior—most notably the 5-minute p-mode oscillations. These time-resolved signals are critical for helioseismology and long-term studies of solar dynamics. However, Dopplergram data collected across different observatories—such as HMI (high-resolution, high-cadence, space-based), MDI (space-based, moderate resolution), and GONG (ground-based, lower resolution)—suffer from non-uniform spatial and temporal resolution, cadence mismatches, and instrument-specific systematic biases. These discrepancies hinder joint analysis and scientific continuity across solar cycles.

We present OpenDopp, an open-source, AI-powered infrastructure for video super-resolution and cross-calibration of multi-instrument Dopplergram sequences. Our framework is built on Vision Transformers (ViTs) with cross-frame attention, enabling it to reconstruct high-resolution sequences by modeling the temporal coherence of solar oscillations. Unlike traditional calibration pipelines that rely on heuristic preprocessing or static transfer functions, OpenDopp learns instrument-specific degradations and corrections directly from the data. It operates across diverse domains—space- and ground-based Dopplergrams—and bridges resolution gaps while preserving the physical integrity of the oscillatory signal.

This work demonstrates that transformer-based architectures, trained on large-scale solar datasets, can serve as a foundation for both enhancement and calibration of scientific imaging sequences. We evaluate performance using conventional perceptual metrics (e.g., PSNR, SSIM) as well as physically grounded loss functions. By harmonizing disparate datasets, OpenDopp enables opportunities for cross-mission science and long-term solar interior studies, and offers a transferable paradigm for applying modern ML techniques to complex, heterogeneous scientific datasets.

MLOps for Reproducible Machine Learning in Space Science: Insights from ESAC

Léa Zuili (ESA)

Machine learning (ML) is becoming an increasingly valuable tool in heliophysics and other space sciences, especially as data volumes grow. Science platforms like ESA Datalabs, along with next-generation large-scale surveys, further enhance ML's potential by facilitating access to heterogeneous, high-resolution datasets.

However, this also brings a key challenge: reproducibility. A 2022 Nature article suggested that "ML could fuel a reproducibility crisis in science." Indeed studies across disciplines show that many ML models are difficult to reproduce or reuse - even when code and data are available. Inadequate evaluation practices, missing implementation details, and lack of standardisation often make it impractical to replicate results or adapt models for new applications. This poses a major challenge for Open Science, where reproducibility is essential for building on prior work.

To better understand this issue in our context, we interviewed researchers at ESAC. We identified major obstacles to model reuse: difficulties running shared models (e.g., missing dependencies, opaque errors), retraining or fine-tuning them. Some researchers also express skepticism toward ML results, especially when compared to established physics-based methods.

As a potential solution, we explore MLOps - a set of practices and tools designed to improve the reproducibility, traceability, and reusability of ML workflows through versioning, ML-specific logging, and structured sharing.

We tested this approach during a hackathon carried on ESA datalabs at ESAC, where participants attempted to reproduce ML-based scientific results - with and without access to an MLOps framework. We present key findings of this experiment and share tools and recommendations based on participant feedback. Finally, we highlight the complementary role of explainable AI (XAI) in improving model interpretability and scientific trust.

Short-Term Solar Energetic Proton Flux Forecasting using Transformer Architectures

Mohamed Nedal (Dublin Institute for Advanced Studies (DIAS))*; Peter Gallagher (Dublin Institute for Advanced Studies (DIAS)); David Long (Dublin City University); Shane Maloney (Dublin Institute for Advanced Studies (DIAS)); Kamen Kozarev (Institute of Astronomy and National Astronomical Observatory, Bulgarian Academy of Sciences); Oleg Stepanyuk (Institute of Astronomy and National Astronomical Observatory, Bulgarian Academy of Sciences)

Accurate short-term forecasting of Solar Energetic Proton (SEP) flux is critical for mitigating the effects of space weather on satellite operations, telecommunications, and human spaceflight. In this work, we present a novel Transformer-based deep learning architecture for predicting hourly-averaged SEP integral flux across three standard GOES channels. Our model incorporates key input features—such as the F10.7 index, sunspot number, solar wind speed, and interplanetary magnetic field strength—collected from NASA's OMNIWeb database and GOES satellite observations, spanning four solar cycles. Additionally, we include active region characteristics from NOAA daily reports, thereby providing a more comprehensive depiction of solar activity.

The Transformer architecture leverages the self-attention mechanism to capture long-range dependencies in solar activity patterns, potentially improving upon traditional recurrent neural network approaches. This work builds upon our previous SEP forecasting efforts (Nedal et al., 2023), extending the methodology through advanced deep learning architectures and refined data partitioning strategies.

Our research focuses on developing a robust framework for capturing complex temporal relationships in SEP events, with particular emphasis on the model's ability to generalize across various solar conditions and forecasting horizons. The Transformer architecture's capacity to process sequential data in parallel while maintaining long-term memory makes it well-suited for this challenging space weather prediction task. We will benchmark our approach against existing methods to establish performance baselines and demonstrate the potential advantages of attention-based models in this domain.

Ultimately, these efforts advance our understanding of SEP behavior and enhance operational space weather monitoring and risk mitigation strategies through state-of-the-art deep learning techniques.

Automatic Identification of Magnetic Reconnection to Assess its Role in Collisionless Turbulent Plasmas Using Unsupervised Machine Learning

Paulina Quijia Pilapana (Northumbria University)*; Julia Stawarz (Northumbria University); Andy Smith (Northumbria University)

Within collisionless turbulent plasmas, intense thin current sheets can undergo magnetic reconnection, potentially influencing turbulence dynamics and facilitating energy dissipation. The Magnetospheric MultiScale (MMS) mission provides high-resolution, multi-point observations of Earth's magnetosheath that are ideal for studying these "turbulence-driven" reconnection sites. However, identifying magnetic reconnection events within observations is challenging and time-consuming due to their localised nature, complex magnetic topologies, and the wide range of scales. We present an unsupervised machine learning framework to systematically identify magnetic reconnection in turbulent plasma observations. This approach requires key physical features that highlight reconnection sites as input. It begins with the Toeplitz Inverse Covariance-Based Clustering (TICC) algorithm, which segments time series into clusters represented as time-invariant correlation networks, enabling the detection of complex turbulent patterns. TICC is trained and evaluated using intervals with previously identified reconnection events. It successfully recovers known reconnection events and also suggests new candidates. To validate candidate events, each structure is rotated into its local coordinate system relative to any reconnection present, where reconnection signatures become clearer and can be quantitatively characterised by fitting to approximate templates of the expected temporal profiles of reconnection even encounters. The resulting fit parameters are then used as input to a second layer of unsupervised machine learning based on KMeans clustering, which distinguishes true reconnection events from false positives. This automated algorithm will allow the creation of a larger, statistically robust catalogue of turbulence-driven reconnection events that will support studies on how turbulence properties influence the prevalence of reconnection and its role in the dissipation of energy.

Koopman Operator Theory and new Data-Driven Approach to Modeling and Signal Processing of Spatiotemporal Data

Joanna Slawinska (Dartmouth College)*; Dimitrios Giannakis (Dartmouth College)

We present a method combining ideas from the theory of vector-valued kernels with delay-coordinate embedding techniques in dynamical systems capable of identifying spatiotemporal patterns, without prior knowledge of the state space or the dynamical laws of the system generating the data. The approach is particularly powerful for systems in which characteristic patterns cannot be readily decomposed into temporal and spatial coordinates and are characterized by wide range of scales, potentially coupled with each other. We show our approach reveals coherent patterns of intermittent character with significantly higher skill than conventional analytical methods based on decomposing signals into separable spatial and temporal patterns. Our approach employs Koopman operator theory and its data-driven approximation with novel machine learning approaches. Extensions of our techniques to nonparameteric predictions, including data-assimilation and subgrid-scale modeling, will be presented as well. Applications in heliophysics and astrophysics will be discussed in the end.

Aurora Detection in Sequential e-POP/FAI Images Using Deep Learning and Explainable AI

Junmu Youn(Kyung Hee University)*; Serin Jeon (Chungnam University); Woong Jeon (Kyung Hee University); Se-Heon Jeong (Korea Astronomy and Space Science Institute); Jeong-Heon Kim (Korea Astronomy and Space Science Institute); Yong-Jae Moon (Kyung Hee University); Wookyoung Lee (Korea Astronomy and Space Science Institute); Hyosub Kil (Korea Astronomy and Space Science Institute)

In this study, we employ a deep learning approach to detect auroras from sequential image observations captured by the Enhanced Polar Outflow Probe (e-POP)/Fast Auroral Imager (FAI). Estimating the auroral oval boundary is crucial for predicting changes in the Earth’s upper atmosphere. Observing the polar region with a satellite provides valuable datasets for estimating this boundary. The e-POP/FAI captures auroral emissions in the near-infrared range (650–1100 nm) at a one-second cadence. However, detecting auroras using a single-channel approach is challenging, as it is difficult to distinguish them from other features such as clouds and city lights. To overcome this problem, we employ a CNN-based ResNeXt-50 deep learning model to automatically detect auroras and discriminate them from non-auroral features, in e-POP/FAI images. The input of our model consists of three frames captured at two second intervals over a total duration of five seconds. Output of the model predicts whether auroras are present in the sequence. Additionally, we utilize the Eigen Class Activation Mapping (Eigen-CAM) and GradCAM method, which is an explainable AI, to highlight the location of auroral emissions. For our study, we used images from 2015 to 2017 for training and testing.

Our model demonstrates high performance, achieving an accuracy of 0.83. For further work, we will develop a pipeline for estimating the auroral oval using this deep learning method.

An AI-powered Surface Flux Transport model to measure high-resolution velocity fields and forecast magnetic flux emergence

Nina Bonaventura (Steward Observatory, University of Arizona); Plinio Guzmán (Fused.io); Nishu Karna (Center for Astrophysics | Harvard and Smithsonian); Katherine Keegan (Emory University)*; Shea Hess-Weber (Hansen Experimental Physics Lab, Stanford University); Spiridon Kasapis (Space Physics Group, Department of Astrophysical Sciences, Princeton University); Bhibuti Jha (Southwest Research Institute); Anthony Yeates (Durham University); Andrés Muñoz-Jaramillo (Southwest Research Institute)

Solar magnetism is the main driver of solar and interplanetary variability. The evolution of the solar magnetic field is driven largely by the emergence of complex magnetic regions into the solar photosphere and corona, and their subsequent evolution as they interact with plasma flows and existing magnetic fields. Surface flux transport (SFT) models are the main tool we use to understand the evolution of surface magnetism; they work by driving the evolution of surface magnetic fields through the prescription of surface velocity fields and flux emergence. Two of the main limitations we aim to address in this work are: 1. Their low-resolution and 2. Their limited ability to use data to estimate and forecast the flows and flux emergence that drive short-term (hours to days) evolution of the surface magnetic field. We present the ARCADE (Active Region Characterization and Analysis of Evolution) model: A hybrid model that uses data driven AI estimation of flux emergence and velocity fields and integrates the surface flux transport equation using PyTorch. We discuss the power of combining numerical integration into a PyTorch framework, how our model performs in comparison to state-of-the-art SFT models, provide an overview of estimated velocity fields and flux emergence patterns, and discuss how it can be used to improve space weather forecasts.

Transient-Oriented Clustering of Solar Wind Observations at 1 AU

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Solar wind is a stream of magnetized plasma composed primarily of protons, electrons, and alpha particles. Traditionally, the solar wind has been categorized as slow and fast according to the proton speed at 1 AU. Recent studies and new observations led to more refined classification schemes, such as the three-parameter plasma scheme of Xu and Borovsky (2015), which aims at distinguishing between coronal hole, sector reversal, streamer belt origin, and ejecta wind, later extended by Camporeale et al. (2017) with a supervised learning technique.

In addition to the steady-state wind, interplanetary space is characterized by transients, such as Interplanetary Coronal Mass Ejections (ICMEs) and Stream or Corotating Interaction Regions (SIRs/CIRs), which are among the primary drivers of space weather effects. The solar wind is also characterized by small-scale phenomena such as magnetic reconnection. Eriksson et al. (2022) provide a valuable resource for studying the occurrence of reconnection in the solar wind.

Heidrich-Meisner & Wimmer-Schweingruber (2018) used K-means clustering to classify solar wind data from the ACE spacecraft data set. They showed the importance of the combination of the magnetic field strength and the lower-order moments of the proton velocity distribution function, such as proton density, temperature, and speed, while excluding ICMEs from their data set. In this work, we apply unsupervised techniques to cluster solar wind in situ observations at 1 AU, using time series data from the Wind spacecraft and the OMNI dataset, including periods with solar wind transients. We compare the resulting clusters with the established Xu and Borovsky (2015) classification and investigate how different temporal cadences (3s and 1min) affect the clustering results. Finally, we evaluate our results against transient events catalogues, such as Koller et al. (2022), to assess correspondences with ICMEs, SIRs/CIRs, and reconnection exhausts.

Friday

Bayes in Space: A Bayesian Deep Learning approach for Coronal Temperature estimation

Nikita Balodhi (Northumbria University)*; Richard Morton (Northumbria University)

The Corona, the outermost layer of the Sun, is a region of intense activity and showcases various solar phenomena that affects the thermal distribution of its constituting plasma. The study of the temperature distribution across the corona is essential in understanding different heating mechanisms that lead to the strikingly high temperatures reached by the corona. This distribution can be estimated using photometric observations in multiple bandpasses by imaging surveys like the Atmospheric Imaging Assembly onboard the Solar Dynamics Observatory. However, each bandpass covers a range of plasma temperatures and cannot be estimated directly through these observations. The temperatures can be estimated by inverting the intensity or number of photons hitting the detector through the channel passband. We propose an uncertainty based deep learning approach to generate Differential Emission Measure (DEM) maps from solar images, that contain information of the amount of thermal plasma emitted by the solar corona along a line-of-sight at a certain temperature. A machine learning approach consists of training a neural network to read AIA images from multiple bandpasses and develop their DEM maps across a range of temperatures as output. While this network can be designed to provide real, non-negative DEM value for each input intensity, it can disrupt the DEM map if it is unsure of its predictions and gives out a wrong output. We introduce an uncertainty in deep learning methods for obtaining the DEM maps from AIA images by and evaluate our results.

HelioFM a foundation model in heliophysics

Andrés Muñoz-Jaramillo (Southwest Research Institute)*

Artificial Intelligence (AI) has emerged as a transformative tool for establishing connections between data and acting as a tool that empowers humans to solve a wide variety of problems for which there were no easy solutions. In heliophysics, AI has been applied to a wide variety of problems including space weather forecast, data calibration and homogenization, computer vision (i.e. segmentation), coronal field extrapolation, etc.

However, compared to other communities, the scientific community is nearly a decade behind in terms of taking advantage of AI. There are many factors behind this lag, including (but not limited to) access to computational resources, lack of expertise, lack of explainability, difficulty validating results, etc. This presentation is about HelioFM: a multi-purpose large AI foundation model, built with an extensive subset of SDO data and a complementary infrastructure to make it usable and useful to the heliophysics community.

Here we'll discuss what Foundation models are, how are we building HelioFM, preliminary results on our pretext task and downstream applications, and the steps we are taking to ensure that this foundation model is both usable and useful.

Toward Uncertainty-Aware Thermospheric Drag Forecasting via Time Series Foundation Models

Sergio Sánchez Hurtado (Universidad Politécnica de Madrid)*, Victor Rodriguez-Fernandez (Universidad Politécnica de Madrid)

Deep learning has rapidly reshaped the space-weather community, motivating a thorough re-examination of how we forecast the thermospheric drivers that govern drag and thus orbit determination for objects in Low-Earth Orbit. Current operations usually predict solar and geomagnetic indices that are passed to empirical or physics-based atmosphere models whose densities feed propagators for short-term trajectory updates, yet error accumulates at every stage of this pipeline, especially during geomagnetic disturbances. Building on recent progress in large pretrained networks, we investigate whether emerging time-series foundation models (TSFMs) can act as data-driven surrogate models that map heterogeneous heliospheric observations directly to drag-relevant quantities, thereby reducing compounded error while enabling rapid, uncertainty-aware updates. This approach recasts drag prediction as an inverse problem solved end-to-end, permits automatic identification of storm-time features, and supports tracking of rapid transitions in the upper atmosphere. Prior studies have demonstrated the feasibility of uncertainty-aware trajectory frameworks and storm-time drag-perturbation modelling. We outline data-curation and benchmarking strategies for adapting TSFMs to drag forecasting, quantify skill improvements over an NRLMSISE-based baseline, and show that properly adapted TSFMs preserve accuracy through the severe storms of March 2024 and February 2025. The resulting framework combines physics insight with modern machine learning, delivering real-time, uncertainty-quantified orbital products, supporting autonomous catalogue maintenance and collision avoidance, and when fine-tuned to individual catalogue objects, offering object-specific precision that meets the most stringent operational requirements.

Posters

Poster Session 1 (Tuesday)

A Multi-Stage Self Organizing Map-Autoencoder-LSTM Model for Total Solar Irradiance Prediction

Idowu Raji (Brazilian National Institute for Space Research)*; Rafael Duarte Coelho dos Santos (Brazilian National Institute for Space Research); Luis Vieira (Brazilian National Institute for Space Research); Frery Alejandro (Victoria University of Wellington, Newzealand)

Predicting total and spectral solar irradiance is a fast-growing area of research, driven by advances in machine learning approaches and their vital roles in climate modeling and space weather forecasting. Important factors influencing the prediction of solar irradiance include continuum, magnetogram, humidity, temperature, time of day and date, cloudiness index, latitude, longitude, outer atmospheric images, F10.7(proxy), among others. It is noted that the utilization of various ML techniques for computing, forecasting, and predicting solar irradiance is a result of advances in the physical models' techniques for predicting solar irradiance. This study will explore the application of multi-stage machine learning techniques to enhance the solar irradiance prediction, focusing specifically on predicting total solar irradiance (TSI). This study will explore a self-organizing map for clustering and grouping solar images. The model will generate a feature map, which will then be employed as input to an autoencoder for further representation learning. The encoder part of the autoencoder will be employed to reduce the feature dimension and to extract the compressed features, and the decoding part will reconstruct the images grouped by SOM. However, the output of the encoder will represent the input for the long-short-term model to perform the TSI forecast. The space-based data considered for this experiment include the data set from the phase before and after solar cycle 24 maximum, to understand the physical mechanism of these two distinct phases. The model considered for this experiment will be trained and evaluated using the mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), correlation coefficient (R), coefficient of determination (R2), and the mean absolute percentage error (MAPE) as performance metrics. Keywords: Total Solar Irradiance. Self-Organizing Map-Autoencoder-LSTM.

Revealing the Martian ionosphere using AI and 20 years of Mars Express data

Simon Joyce (University of Leicester)*

The ionosphere is a region of plasma in the atmosphere which has important effects on radio transmissions. For Mars, knowledge of the ionosphere is particularly important for the interpretation of ground penetrating radar data, which is used to search for sub-surface water and ice deposits. It is also potentially a factor affecting communications with ground rovers and will be an important consideration for future human exploration. The ionospheric region forms mainly due to the photoionization of the neutral atmosphere into ions and electrons. Solar EUV irradiation and solar wind are the key energy inputs to the Martian ionosphere. The Mars Express orbiter has been observing the ionosphere since 2005 and produced a large dataset of ionograms. Over 2.3 million ionogram images have been recorded to date, and only a small fraction of them have been fully analysed. We present an AI classifier which has been developed to enable improved exploitation of the complete dataset. Testing shows that the classifier, based on a Convolutional Neural Network, is 97% accurate. Preliminary results of applying the classifier to the complete dataset have revealed the Martian ionosphere as never seen before. The long duration of the dataset enables analysis of the effects of solar cycles, seasonal variability and space weather events on the Martian ionosphere.

Information theory based system level Babcock-Leighton flux transport model-data comparisons

Simon Wing (Johns Hopkins University)*; Jay Johnson (Andrews University); Mausumi Dikpati (UCAR HAO)

System level Babcock-Leighton flux transport model-data comparisons are performed using information theory. The model is run with maximum meridional flow speed of 16.5 m/s with the flow speed systematically varied by 20\% (BLFT20) and 50\% (BLFT50). Overall, the comparisons show that the models qualitatively capture much of the information flows among the toroidal field (sunspot number), polar field, and meridional flow. BLFT20 generally compares better than BLFT50 suggesting that meridional flow variation of 20\% may be more realistic than 50\%. However, the information flow from the meridional flow to the polar field is captured better in BLFT50. There is more information flow from the sunspot number to the polar field than the other way around in BLFT20 and observations.

The information flow from the polar field to the sunspot number peaks at lag times (τ) $\sim$ 2 year and 7-9 years. The results can shed light to the nature of the Sun's magnetic memory, and the diffusive/dissipative processes and advection in the turbulent flux transport at the Sun.

Dst Forecasting with REDst: Pushing the Limits of Real-Time L1 Data

Armando Collado-Villaverde (Universidad de Alcalá)*; Pablo Muñoz (Universidad de Alcalá); Consuelo Cid (Universidad de Alcalá)

Provide timely geomagnetic storms forecasts using indices like the Dst could help to improve resilience of technological systems against Space Weather events. In this direction we present REDst, a Deep Learning model designed for real-time operation that provides forecasts up to 6-hours ahead. To improve its accuracy and usability we rely on three pillars: the output provides a forecast for each hour, including a prediction confidence interval; the usage of ACE stream data, avoiding OMNI temporal inconsistencies and; a training process based on curriculum learning with value dependent loss function. REDst is trained on 69 storms (from the period 1998-2017) and evaluated on 22 recent storms (from 2017 to 2024) using preliminary ACE MAG and SWEPAM measurements, the closest archive to the real-time products distributed by NOAA/SWPC. Based on the results, we can have determined that the accuracy is operationally viable up to 3 hours for the main phase of a geomagnetic storm and up to 6 hours for the recovery phase or disturbances derived from high speed streams. Repository is available at: https://github.com/Redxgit/REDst Realtime product is available at: https://www.senmes.es/pub/ISG/dst_forecast.png

Automatic Detection of Lyman-alpha Solar Flares Based on GOES/EUVS Flux and ASO-S/SDI Images

Rong Sun (Purple Mountain Observatory, Chinese Academy of Sciences)*; Lei Lu (Purple Mountain Observatory, Chinese Academy of Sciences); Li Feng (Purple Mountain Observatory, Chinese Academy of Sciences)

This study presents automated algorithms for detecting Lyman-alpha (Lyα) solar flares by integrating two complementary datasets. For GOES/EUVS Lyα flux, the automatic detection program identifies solar flares by tracking the light curve slope and generates a flare list containing start time, peak time, end time, significance, and other relevant parameters. For ASO-S/SDI Lyα full-disk images, the program detects and tracks flares, finally compiling an event catalog. The basic characteristics (e.g., temporal and spatial information) are determined using a triple-threshold scheme. Statistical analyses of Lyα flares are also discussed. This algorithm facilitates quantitative scientific analysis and real-time space weather forecasting applications.

Unsupervised analysis of dangerous space weather: Combining ground and space-based measurement

Maria Hasler (Northumbria University)*

Understanding space weather is essential for mitigating risks and protecting both ground-based and space-based infrastructure. This is particularly critical in the case of extreme events, which are difficult to predict due to their non-periodic nature. A specific aspect of space weather that remains poorly understood is the exchange of information from space to the ground through the ionosphere. A central component of this process involves understanding how current systems such as field-aligned currents transfer energy and momentum between the magnetosphere and the ionosphere. However, the non-linear behaviour of these current systems poses significant challenges for identifying the drivers of ionospheric currents and understanding the inner dynamics of the ionosphere itself. To tackle these complexities and their effects on the ground, we adopt a data-driven approach that integrates both ground-based (SuperMAG) and space-based (AMPERE) observations. Specifically, we focus on gaining insights into extreme events by leveraging the power of unsupervised machine learning techniques, which have proven useful in finding patterns in unlabelled observational data. A combination of Variational Autoencoders and clustering methods is used to determine trends and behaviours of the data in lower-dimensional space while also creating a labelled dataset for further study.

Automatic Identification of CMEs images using synthetically trained neural networks

Yasmin Machuca (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza, CONICET)*; Florencia Cisterna (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza); Francisco Iglesias (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza, CONICET, Max Planck Institute for Solar System Research, Gottingen, Germany); Diego Lloveras (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza, CONICET); Mariano Sanchez (Grupo de Estudios en

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Coronal mass ejections (CMEs) are major drivers of space weather, with significant technological and societal impacts. To evaluate their geoeffectiveness once expelled, it is crucial to promptly identify them in coronagraph images and characterize their kinematics. Deep Neural Networks (DNNs) have recently achieved remarkable success in image recognition and segmentation. However, applying these models to CME segmentation is hindered by the lack of large, curated datasets for supervised training. We address this by generating a synthetic dataset composed of real coronagraph backgrounds (without CME) combined with synthetic CME brightness images produced using the Graduated Cylindrical Shell (GCS) model and ray tracing. We present preliminary results using a DNN model to identify and segment the outer envelope of CMEs. Specifically, we fine-tune the Mask R-CNN model to produce a GCS-like mask from a single input differential coronagraph image. We quantify the model error in a testing sample of synthetic images and evaluate its performance on real coronographic images. The latter is done by comparing basic morphological CME parameters (central position angle, angular width, etc.) with results from widely used automatic CME detection catalogs, and with the projected masks obtained from 3D GCS reconstructions based on three simultaneous viewpoints of the same event.

Automated Detection of Foreshock Transients Using Machine Learning Techniques

Shi Tao (University of Helsinki)*; Lucile Turc (University of Helsinki); Souhail Dahani (University of Helsinki); Milla Kalliokoski (University of Helsinki); Veera Lipsanen (University of Helsinki); Nicolas Aunai (Laboratoire de Physique des Plasmas (LPP)); Savvas Raptis (Johns Hopkins University); Shan Wang (Peking University); Hui Zhang (Shandong University)

Foreshock transients (FTs) are mesoscale, transient phenomena near the Earth’s bow shock that play an important role in solar wind-magnetosphere interactions. Although a number of statistical studies have been conducted to characterize their features, there is to date no comprehensive and automated catalog of FTs. In this study, we employ machine learning techniques to identify FTs from satellite observational data, aiming to construct a more complete FT catalog. Specifically, we utilize a list of FT events detected by Cluster 1 from 2003 to 2009 (Wang, 2012) as the training set and evaluate three different identification approaches: (1) a convolutional neural network (CNN) trained on the entire catalog of FT events labeled as class 1, with separate solar wind intervals (from the catalog by Michotte de Welle et al.) labeled as class 0; (2) a traditional machine learning model (Gradient Boosting) trained exclusively on the FT catalog, with internal segmentation labeling the core, boundary, and background solar wind regions; and (3) a window-based CNN using the same segmented labeling strategy as method two. While all models perform well on the validation set, they exhibit high false positive rates when tested on the Cluster 1 solar wind data from 2010, which was not included in the training or validation sets. These results show that the machine learning methods have potential in FT detection but warrant future improvements.

Discovering heat flux closures using machine learning methods

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In computational plasma physics, kinetic models are used to simulate plasma phenomena where small-scale physics is expected to be of importance. These models contain the full information of the particle velocity distribution function, but are computationally expensive. Therefore, computationally cheaper models are utilized, which can then be deployed to larger scales e. g. 10-moment fluid models or magnetohydrodynamics (MHD). However, the large-scale behavior is critically influenced by small-scale behavior. For example, solar wind observations show that ion- and electron-scale instabilities constrain the solar wind temperature anisotropy over the entire heliosphere (Matteini et al., 2013) and observations and fully kinetic simulations have recently demonstrated the nontrivial link between the small and the large scales in heat flux regulation in the solar wind (Cattell et al., 2021; Micera et al., 2021). Thus, models are required that can include kinetic processes, in reduced form, into large-scale simulations. At the moment, analytical closures are used to close the hierarchy of fluid equations, but these closures are strictly valid only in certain regimes. For example, Landau fluid closures (Hunana et al., 2019) assume that the plasma is close to the Local Thermodynamic Equilibrium, which is not the case for most space plasmas. Finding suitable closure equations is an ongoing research topic that is becoming increasingly more difficult in complex systems (e.g. Allmann-Rahn et al., 2018; Ng et al., 2020). In this study, we try to improve fluid models by learning a suitable symbolic closure for the heat flux by applying machine learning methods (Alves & Fiuza, 2022) to data from fully kinetic simulations. We start validating the learned closure

equation on ten-moment simulations of electrostatic and -magnetic instabilities with the final aim of turbulence simulations.

Augura Space Nowcast Platform: A Research-Focused, Open Demonstrator for Space Weather Data Integration and Visualization

François Ginisty (Augura Space)*; Alexandre Suteau (Inria/Augura Space); Hadrien Mariaccia (Augura Space); Rungployphan Kieokaew (Inria/Augura Space)

Augura Space has developed the Augura Space Nowcast Platform, an open-access, research-oriented tool designed to support the space weather scientific community by providing centralized access to key space environment parameters in near-real time. The platform consolidates publicly available data from European and international providers focusing on solar wind, interplanetary magnetic field, energetic particle fluxes, geomagnetic indices, ionospheric parameters, and solar imagery. Its objective is to offer a complete and user-friendly demonstrator, facilitating rapid situational awareness, cross-disciplinary studies, and data exploration by broad users including researchers, students, and engineers. The development addressed several technical challenges: Harmonizing multi-source data streams with diverse formats and cadences. Implementing a robust, modular infrastructure for data ingestion, archiving, and visualization. Ensuring traceability, transparency, and systematic referencing of data sources in line with FAIR data principles. The platform complements ongoing efforts by offering a research-oriented, freely accessible environment to foster scientific use, training, and collaboration, as well as enhance its accessibility towards new potential users. It also provides a testbed for future evolutions toward more sector-specific applications.

Physics-Informed Deep Learning for the characterization of the electron radiation belts dynamics

Emerick Laborde (ONERA)*; Gautier Nguyen (ONERA); Antoine Brunet (ONERA); Robert Ecoffet (CNES)

The application of Physics-Informed Neural Networks (PINNs), for both forward and inverse modeling in physical systems, has been flourishing over the past recent years. Applied to radiation belt modeling (Camporeale et al. 2022), this methodology has proven its capacity to reconstruct, to some extent, the diffusion and sink coefficients that drive the dynamics of the radiation belts from in-situ observations of particle fluxes. However, due to the specificities of this physical system—including a very large temporal and spatial dynamics of the state, as well as very inhomogeneous and anisotropic coefficients—and the ill-posed nature of the inverse problem, PINNs can sometimes fail to accurately capture the dynamics of the physical coefficients. Therefore, a proper evaluation of the method is required before its application in an operational context. In this study, we present a quantitative evaluation of PINNs for the 1D Fokker-Planck equation, which corresponds to a simplified model of electron radiation belt dynamics. Using the framework of twin experiments, we investigate when PINNs are able to reconstruct accurately the physical parameters of the system and when they fail to do so. Using various scenarios representative of the radiation belts dynamics, we analyze the capabilities and limitations of PINNs in this context.

Transition to a Critical State of Active Regions: Identifying Solar Flare Precursors

Daniele Telloni (National Institute for Astrophysics - Astrophysical Observatory of Torino)*; Sabrina Guastavino (Department of Mathematics - University of Genova); Anna Maria Massone (Department of Mathematics - University of Genova); Michele Piana (Department of Mathematics - University of Genova)

In the context of space-weather forecasting, particularly under the theme of automatic event identification, we present a novel adaptation of the Natural Time Analysis (NTA) framework to solar Active Regions (ARs) for reliable flare-precursor detection. In recent decades, diverse catastrophic phenomena - from earthquakes and landslides to structural collapses and myocardial infarctions - have been framed as critical transitions in complex systems, marked by a sudden, irreversible shift from equilibrium to an unstable state. Here, we extend NTA for the first time to solar ARs by processing time series of magnetograms from the Helioseismic and Magnetic Imager onboard the Solar Dynamics Observatory and their corresponding SHARP indices (total magnetic flux, magnetic shear angle, current helicity, etc.). We construct energy-weighted event sequences that capture the evolving dynamics of each region. Case studies of M-flare-productive ARs reveal pronounced changes in NTA parameters - most notably in current helicity - immediately before flare onset, while a control set of non-flaring regions shows no analogous critical signatures. These results validate NTA as a powerful, data-driven tool for solar flare nowcasting and highlight current helicity as a key feature for tracking the approach to criticality. This novel application enriches our understanding of flare-triggering mechanisms within the theory of critical phenomena and offers a promising operational technique for short-term space-weather forecasting and automated event detection.

Neural Network-Based Detection of Plages in Historical Solar Drawings

Dibya Mishra(ARIES)*; Subhamoy Chatterjee (Southwest Research Institute); Bibhuti Kumar Jha (Southwest Research Institute); Dipankar Banerjee (Indian Institute of Space Science and Technology)

Kodaikanal Solar Observatory (KoSO) hosts a unique, century-spanning archive of multi-wavelength solar observations, including rare hand-drawn “suncharts” (1904–2022) that document solar features such as sunspots, plages, and filaments using the Stonyhurst grid. These annotated drawings, recently digitized at 6k × 6k resolution, present an untapped resource for long-term solar activity studies but remain largely unquantified due to their manual nature. In this work, we present the first fully automated pipeline for plage detection in these historical solar drawings using supervised deep learning. A Convolutional Neural Network (CNN) model, trained on a single solar cycle using manually annotated plage masks, is employed to segment plage regions across nearly 100 years (1909–2007) of digitized charts. A companion CNN-based model was also developed to detect solar limb parameters (center, radius, and P-angle) for spatial alignment and projection correction. To validate our approach, the CNN-derived plage area series is compared against co-temporal Ca II K full-disk image observations. Our results demonstrate strong agreement and fill historical data gaps in earlier plage catalogues. This study not only enables the generation of consistent, long-term solar activity maps but also highlights how modern deep learning techniques can unlock scientific insights from legacy, analogue data sources.

DeepHelio - Predicting Solar Wind Speed at L1 Using Solar Imagery and Deep Learning

Alexandre Suteau (Augura Space)*; Hadrien Mariaccia (Augura Space); François Ginisty (Augura Space); Rungployphan Kieokaew (Augura Space); Ryad Guezzi (Augura Space)

Forecasting solar wind conditions at the Lagrange L1 point is determinant for mitigating space weather risks caused by high-speed solar wind streams. As stated in several recent papers, the variation of the solar wind velocity is a key proxy for space weather events like solar storms and geomagnetic perturbations. In the light of Augura Space's mission to make AI driven space weather forecasting operational, we are developing DeepHelio, a project investigating deep learning approaches to predict solar wind speed at L1. Our pipeline combines AIA solar images and HMI magnetograms from the Solar Dynamics Observatory (SDO), OMNI in-situ measurements of the solar wind and geomagnetic indices to train a multimodal deep learning regression model. In this poster, we present our studies on novel model architectures - combining traditional neural networks, CNNs and transformers - and the results we obtained. Augura Space’s DeepHelio project seeks to fill the gap between state-of-the-art computer vision models and heliophysics.

Data-Driven Plasma Closure Relation for Landau Damping in One Dimension

Samuel Burles (Queen Mary University of London)*, Enrico Camporeale (Queen Mary University of London & University of Colorado, USA)

Space and laboratory plasmas exhibit complex dynamics across many spatio-temporal scales. Global MHD simulations are typically used for large-scale modelling of the Earth’s magnetosphere, as kinetic simulations are too computationally demanding. However, reduced models, such as MHD, cannot resolve the small-scale kinetic physics, which is required for certain phenomena, such as magnetic reconnection in the magnetotail. Reduced fluid models of plasma are obtained from the kinetic theory by closing the hierarchy of velocity moments of the Vlasov equation, requiring some simplifying approximations. We propose a data-driven closure relation trained on fully kinetic simulation data, which is then integrated into a fluid solver. We train a neural network to learn the closure relating the heat flux to the lower-order moments, trained on data generated from high-resolution Vlasov simulations. Benchmarks for textbook phenomena such as linear Landau damping and comparison against the analytic Hammett-Perkins closure are presented.

Automatic GCS reconstruction of CMEs using synthetically-trained neural networks

Mariano Sanchez Toledo (Grupo de Estudio de Heliofísica en Mendoza)*; Francisco Iglesias (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza, CONICET, Max Planck Institute for Solar System Research, Gottingen, Germany); Florencia Cisterna (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza); Yasmin Machuca (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de Mendoza, CONICET); Diego Lloveras (Grupo de Estudios en HeliofÍsica de Mendoza, Universidad de

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Coronal Mass Ejections (CMEs) are key drivers of space weather with significant technological and social impacts. Since they cannot be predicted, assessing their geoeffectiveness after ejection is crucial, particularly their 3D direction and kinematics. However, reconstructing their 3D structure from up to three simultaneous 2D coronagraphic views is an ill-posed problem. The Graduated Cylindrical Shell (GCS) geometric model is widely used for this purpose, but its application is manual and highly dependent on operator expertise. In recent years, Deep Neural Networks (DNNs) have achieved great success in image recognition and segmentation tasks. A challenge in applying DNNs to CME 3D reconstruction is the lack of large, labeled datasets for supervised training. To address this, we generated a multi-view synthetic dataset by combining actual quiet (no CME) coronagraph backgrounds with synthetic CMEs created using the GCS model and raytracing. We present preliminary results of a DNN that automatically reconstructs the 3D CME outer envelope from three simultaneous differential coronagraph images taken from different viewpoints. The model uses a deep convolutional backbone with a fully connected head and is trained on our synthetic dataset to predict the GCS parameters that best describe the CME’s outer envelope.

DeepSDO: A Deep Learning-Based Approach for Automated Detection and Visualization of Solar Events

Ji-Hye Baek (KASI)*; Sujin Kim (KASI); Seonghwan Choi (KASI); Jongyeob Park (KASI); Jihun Kim (KASI); Wonkeun Jo (InnoWithus); Dongil Kim (Ewha Womans University); Suwoon Lee (InnoWithus)

Solar event detection has been a subject of long-standing research, with increasing interest in leveraging deep learning and data-driven techniques in recent years. In this work, we introduce an automated approach to identifying key solar features—coronal holes, sunspots, and prominences—by applying deep learning-based object detection models to solar imagery. The DeepSDO dataset was created using data from the Solar Dynamics Observatory (SDO), with bounding box annotations provided for the three target features. Utilizing this dataset, we trained two well-known object detection algorithms: the Single Shot MultiBox Detector (SSD) and the Faster Region-based Convolutional Neural Network (Faster R-CNN). Evaluation results indicate that both models show strong performance in detecting coronal holes and sunspots, while their accuracy in detecting prominences was relatively limited. Furthermore, a web-based visualization tool was developed to display detection outcomes, and the service is currently available on the Korea Data Center for SDO platform. Looking ahead, we aim to integrate this system with Helioviewer and the Heliophysics Event Knowledgebase (HEK) to establish a more comprehensive and effective solar observation framework. The dataset will also be made publicly available to support further research in solar physics and deep learning-based object detection.

Flare forecasting using Fully Convolutional Network to gain insight into active regions

Paloma Jol (Northumbria University)*

Solar flares are large eruptions of electromagnetic radiation from the Sun that can affect Earth's atmosphere and our technologies (e.g., radio communications). Flares are identified by the arrival of their energetic photons at Earth, meaning that their space-weather effects occur at the same time we become aware that a flare is in progress - this makes it essential for us to forecast them in advance. This work aims to predict solar flares within a 24-hour window using a Deep Learning model. We use 3D vectormagnetic images obtained from the Solar Dynamics Observatory (SDO) Space-weather HMI Active Region Patch (SHARP) data series, specifically the solar-radial component of the magnetic field. By using whole active region full-resolution images as input we want to improve our understanding of the physics leading up to flares and aiming to use feature importance to locate areas of interest in the active region images. We use radial-field images from 2013 to 2023, inclusive, at a cadence of 24 hours along with the corresponding Geostationary Operational Environmental Satellites (GOES) X-ray flare events in the next 24 hours to create the image and flare-outcome label pairs. Filtering is performed to limit our data set to images containing single NOAA-numbered active region within ±75° longitude. With HARP separated data sets for training and testing, we implement a Fully Convolutional Network (FCN) for the binary classification of flare events with GOES X-ray flare class above C1. We present a statistical evaluation of the model’s predictive performance using various classification metrics, assessing its ability to distinguish between flare and non-flare events.

Anomaly detection applied to solar wind composition measured by SOHO/CELIAS/CTOF and ACE/SWICS

Verena Heidrich-Meisner (CAU Kiel)*

The charge state and elemental composition of the solar wind are sensitive tracers of the conditions in different heights in the solar corona. Both are typically measured with time-of-flight mass spectrometers. The data analysis for this type of instruments tends to be time-consuming and often sensitively depends on specific instrumental properties. Here, we utilize anomaly detection, namely Isolation Forest and One-Class Support Vector Machines (SWMs), trained on measurements of the Charge Time-Of-Flight (CTOF) onboard the SOlar and Heliospheric Observatory (SOHO) and the Solar Wind Ion Composition Spectrometer (SWICS) onboard the Advanced Composition Explorer (ACE), to identify unusual observations for the purpose of (1) analyzing rare but interesting physical phenomena in the solar wind that tend to be overlooked by traditional approaches and (2) marking data affected by instrumental effects.

Stereoscopic DEM Analysis Using Solar Orbiter/EUI and AI-Generated Data

Junmu Youn (Kyung Hee University)*; Harim Lee (New Jersey Institute of Technology); Hyun-Jin Jeong (KU Leuven); Jin-Yi Lee (Kyung Hee University); Eunsu Park (New Jersey Institute of Technology); Yong-Jae Moon (Kyung Hee University)

In this study, we determine the differential emission measures (DEMs) using data from the Solar Orbiter/Extreme Ultraviolet Imager (EUI)/Full Sun Imager (FSI) and AI-generated EUV images. The FSI observes only two full-disk extreme ultraviolet (EUV) channels (174 and 304 Å), which poses a limitation for accurately determining DEMs. To address this issue, we use deep learning models based on Pix2PixCC, trained on the Solar Dynamics Observatory (SDO)/Atmospheric Imaging Assembly (AIA) dataset. These models successfully generate five-channel (94, 131, 193, 211, and 335 Å) EUV data from 174 and 304 Å EUV observations, achieving high correlation coefficients. We then apply the trained models to the Solar Orbiter/EUI/FSI dataset and generate the five EUV channels that the FSI cannot observe. We use a regularized inversion method to compare the DEMs derived from the SDO/AIA dataset with those from the Solar Orbiter/EUI/FSI data supplemented by the AI-generated channels. First, we demonstrate that when SDO and Solar Orbiter are at inferior conjunction, the main peaks and widths of the DEMs are highly consistent for the same coronal structures. These results show that deep learning enables accurate DEM determination using Solar Orbiter/EUI/FSI data combined with AI-generated EUV images. Additionally, we determine the DEMs when the two instruments are at various angular separations, such as 60 degrees (L4 and L5) and 180 degrees apart. Here, we present stereoscopic study examples of coronal features enabled by our approach.

SuperSynthia LOS: Learning to Estimate Photospheric Vector Fields from Line-of-Sight Magnetograms

David Fouhey (New York University); KD Leka (NorthWest Research Associates)*

Solar photospheric line-of-sight magnetograms are easier to estimate than full vector magnetograms since the line-of-sight component (Blos) can be obtained from total intensity and circular polarization signals, unlike the perpendicular component, which depends on harder-to-measure linear polarization. However, the line of sight component is not physically meaningful. To produce an estimate of the radial component (Br) a common "correction" is often applied that includes an assumption which is nearly always false. We present a method to estimate the full vector-field information from Blos by building on the recent SuperSynthIA approach that was originally used with Stokes vectors as input for simultaneous inversion and disambiguation. As input, SSLOS accepts one or more line-of-sight magnetograms and associated metadata; as output, our method estimates full vector field in heliographic components, meaning that the physically-relevant vector components are returned without need for further disambiguation steps or component transforms. We demonstrate estimates of the full vector field on unseen examples from both HMI and GONG, including examples that predate the Solar Dynamics Observatory mission. Our results show that learning is not a replacement for a dedicated vector-field observing facilities, but may serve to unlock information from past data and, at the very least, provide more accurate Br maps from Blos than are created using the simple viewing angle assumption.

Self Supervised Encoding to Find Similar Observations

Andy Smith (Northumbria University)*; Jonny Rae (Northumbria University); Julia Stawarz (Northumbria University); Weijie Sun (University of California, Berkeley); Sarah Bentley (Northumbria University)

We often have large, unlabelled datasets in space physics, where the phenomenon of interest only appears rarely. Understanding the underlying physics of the system from rare observations is a challenge, and locating complementary, similar observations in large datasets can be prohibitively time consuming. We present an automated, self-supervised method by which the key information from two-dimensional data can be encoded into a vector representation. This representation (encoding/embedding) contains the key information describing the data; we can then use the distance between vectors to assess the similarity of the observations. We show the potential of this method with two example datasets (~ five thousand images): spacecraft in situ electron velocity distributions and auroral all sky images. In the case of the electron distributions, we test a "seed" image of a rare phenomena – corresponding to the region of space near the site of magnetic reconnection. We can then extract the closest partners of this image, using the distance between the embedding vectors. The two closest neighbours of the seed image represent two "new" observations close to the site of magnetic reconnection. This method promises to be a useful tool in locating interesting phenomena in large datasets, providing an efficient method for moving from case studies to thorough statistical surveys.

Enhancing image resolution of solar magnetograms: A latent diffusion model approach

Francesco Ramunno (University of Applied Sciences North Western Switzerland (FHNW))*; Paolo Massa (University of Applied Sciences North Western Switzerland (FHNW)); Vitaliy Kinakh (University of Geneva); Brandon Panos (University of Applied Sciences North Western Switzerland (FHNW)); André Csillaghy (University of Applied Sciences North Western Switzerland (FHNW)); Svyatoslav Voloshynovskiy (University of Geneva)

The spatial properties of the solar magnetic field are crucial to decoding the physical processes in the solar interior and their interplanetary effects. However, observations from older instruments, such as the Michelson Doppler Imager (MDI), have limited spatial or temporal resolution, which hinders the ability to study small-scale solar features in detail. Super-resolving these older datasets is essential for uniform analysis across different solar cycles, enabling better characterization of solar flares, active regions, and magnetic network dynamics. In this work, we introduce a novel diffusion model approach for super-resolution and we applied it to MDI magnetograms to match the higher-resolution capabilities of the Helioseismic and Magnetic Imager (HMI). By training a latent diffusion model (LDM) with residuals on downscaled HMI data and fine-tuning it with paired MDI/HMI data, we could enhance the resolution of MDI observations from 2″/pixel to 0.5″/pixel. We evaluated the quality of the reconstructed images by means of classical metrics, such as peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), Fréchet inception distance (FID), and learned perceptual image patch similarity (LPIPS) and we checked if physical properties, such as the unsigned magnetic flux or the size of an active region, are preserved. We compare our model with different variations of LDM and denoising diffusion probabilistic models (DDPMs), but also with two deterministic architectures already used in the past for performing the super-resolution task. Furthermore, we show with an analysis in the Fourier domain that the LDM with residuals can resolve features smaller than 2″, and due to the probabilistic nature of the LDM, we can assess their reliability, in contrast with the deterministic models. Future studies aim to super-resolve the temporal scale of the solar MDI instrument so that we can also have a better overview of the dynamics of the old events.

Poster Session 2 (Wednesday)

Comparison of automatic and machine-learning detections of EMIC waves

Benjamin Grison (Institute of Atmospheric Physics)*; Vavrinec Kavan (Institute of Atmospheric Physics)

Density gradients, as observed at the plasmapause, and temperature anisotropies, as observed in the ring current, have been known for a long time to enhance growth of ElectroMagnetic Ion Cyclotron (EMIC) waves. EMIC waves play an important role in the dynamic of the radiation belt population. Large database of EMIC waves are helpful to properly model their occurrence. The EMIC wave distribution is analyzed in term of location (Magnetic local time, L-shell, magnetic latitude, distance to the magnetopause), frequency (absolute in Hz or normalized to the local proton gyrofrequency), and polarizations (including also wave normal angle, planarity and coherence). Statistical properties of EMIC emissions needs to be studied on large dataset that can be built up by visual selections, automatic detection or machine-learning selections. This study gathers observations of EMIC waves observed by the Cluster spacecraft, THEMIS spacecraft and Van Allen Probes whose datasets supplement each other. Cluster orbit is polar and its apogee is at almost 20 Earth Radii (perigee above 4 Earth radii). Van Allen Probes and THEMIS orbits are designed to probe the inner magnetosphere equatorial region (from about 2 to 6 Re for Van Allen Probes and beyond the magnetopause for THEMIS). We first compare the datasets obtained for each mission based on an empirical detection procedure (adapted from Bortnik et al.) and based on a machine-learning procedure developed from scratch. This helps to identify potential bias of each selection. After reviewing the EMIC properties of the dataset, we analyze the distribution of subset of EMIC waves called EMIC triggered emissions Ref: Bortnik, J., Cutler, J. W., Dunson, C., & Bleier, T. E. (2007). An automatic wave detection algorithm applied to Pc1 pulsations. Journal of Geophysical Research, 112, A04204. https://doi.org/10.1029/2006JA011900 We acknowledge funding from Czech Science Foundation (GA ČR) project 25-19511L (RADIANCE)

Modeling Ring Current Ion Distribution using MLP, CNN, LSTM, and Transformer Networks

Qiushuo Wang (UCLA)*

The ring current is an important component of the Earth's near-space environment, as its variations are the direct driver of geomagnetic storms that can disrupt power grids, satellite communications, and navigation systems, thereby impacting a wide range of technological and human activities. Oxygen ions (O+) are one of the major components of the ring current and play a significant role in both the enhancement and decay of the ring current during geomagnetic storms. We employed the neural network technique to construct a global ring current O+ ion model based on the Van Allen Probes observations. Through optimization of the combination of input geomagnetic indices and their respective time history lengths, the model demonstrates remarkable statistical results and effectively reconstructs the spatiotemporal variation of ring current O+ ions, providing a comprehensive and dynamic representation of the global ring current O+ ion distribution during geomagnetic storm time.

On timescale of geomagnetic storm recovery phase.

Giuseppe Consolini (Istituto Nazionale di Astrofisica (INAF-IAPS), Roma, Italy)*; Manuel Lacal (University of Trento, Department of Physics, Trento, Italy); Paola De Michelis (Istituto Nazionale di Geofisica e Vulcanologia, Roma, Italy); Simone Benella (Istituto Nazionale di Astrofisica (INAF-IAPS), Roma, Italy); Elettra Consolini (University of Rome Tor Vergata, Department of Physics, Roma, Italy); Mirko Piersanti (University of L’Aquila, Department of Physical and Chemical Sciences, L’Aquila, Italy)

Geomagnetic storms are a comprise of different processes occurring in the near Earth environment due to the Sun-Earth interaction. The monitoring of the dynamics of geomagnetic storms can be done using the DST or equivalent geomagnetic indices as Sym−H and SMR, which are associated with the dynamics of the magnetospheric equatorial ring-current. Here, we investigate the dynamics of the geomagnetic storm recovery phase using SuperMag SMR index. In detail, we characterize the multiscale character of the recovery phase moving from a stochastic-Langevin description approach, discussing its implications in developing a more reliable differential equation which could take into account of the multiscale features. We will, indeed, show that recovery phase cannot be simply described in terms of a single relaxation time, but involves a dependence on the value of SMR on time. Physical implications are discussed in the framework of ordinary differential equations and physics informed neural networks (PINNs) modeling of geomagnetic storms dynamics. This study was carried out within the Space-It Up project funded by the Italian Space Agency, ASI, and the Ministry of University and Research, MUR, under contract n.2024-5-E.0 - CUP n. I53D24000060005

Revisiting the cold-dense plasma sheet formation mechanism using causal inference and information-theoretic analysis

Hiroshi Hasegawa (Institute of Space and Astronautical Science, JAXA)*; Chih-Ping Wang (University of California, Los Angeles); Katariina Nykyri (NASA, Goddard Space Flight Center); Philippe Escoubet (European Space Agency); Kyoung-Joo Hwang (Southwest Research Institute); Sae Aizawa (Laboratoire de Physique des Plasmas); Fuishan Fu (Beihang University); Shiva Kavosi (University of New Mexico); Hyangpyo Kim (Space Research Institute); Viacheslav Merkin (Applied Physics Laboratory); Rumi Nakamura (Space Research Institute); Adriana Settino (Space Research Institute)

The cold-dense plasma sheet (CDPS), characterized by low-temperature and high-density plasmas, is known to form through efficient solar wind entry into Earth’s magnetosphere, particularly under northward interplanetary magnetic field (IMF) conditions. The CDPS has been identified as a potential preconditioning factor for intense geomagnetic storms that are not well predicted by conventional models. Several formation mechanisms have been proposed—including double poleward-of-the-cusp magnetopause reconnection, Kelvin-Helmholtz instability (KHI), and kinetic Alfvén wave turbulence—each supported by various observational signatures. However, their relative contributions remain uncertain due to the inherent limitations of local measurements in revealing their global impact. In this study, we revisit the CDPS formation mechanism through the lens of causal inference, a methodology for identifying and quantifying cause-and-effect relationships, in combination with information-theoretic analysis to assess nonlinear correlations among relevant variables. By examining the causal relationships between solar wind/IMF parameters and

plasma sheet properties, we identify the solar wind Alfvén Mach number (MA) as a key factor in disentangling the effects of the proposed mechanisms. Specifically, we pay attention to theoretical expectations that as MA increases, the efficiency of magnetic reconnection decreases while the KHI becomes more readily excited and grows more rapidly. Our results indicate that the KHI alone cannot account for the CDPS formation. Instead, we suggest that fast solar wind entry via poleward-of-the-cusp reconnection plays a critical role, followed by slower plasma transport into the plasma sheet mediated by the KHI or KHI-induced processes.

Solar EUV Channel Selection with Magnetogram via Multi-domain image Translation

Daeil Kim (Kyung Hee University)*; Yong-Jae Moon (Kyung Hee University); Junmu Youn (Kyung Hee University)

In this study, we present the selection of one Extreme Ultraviolet (EUV) channel along with solar magnetogram using a deep learning model based on multi-domain image translation. For this study, we use 3,425 paired data from the Solar Dynamics Observatory (SDO) Atmospheric Imaging Assembly (AIA) and the Helioseismic and Magnetic Imager (HMI) magnetogram. Among these, we use 2,891 pairs for training, while the others are used to test our model. We successfully generate the other five EUV images from one input image using a single generator. Our main results are as follows. First, the overall generation performance of our model shows a good correlation coefficient (CC) value of 0.92, ranging from 0.90 to 0.93. Second, among the six combinations of inputs, HMI + 94Å and HMI + 131Å show the best performance for generating other EUV channels, as the average CC reaches 0.93. Third, our model shows the lowest performance for generating 131Å, with a CC of 0.88. Furthermore, a differential emission measure (DEM) analysis confirms that our model can reproduce thermal structures that are physically consistent with the observations. Our study may be a complementary tool for the selection of imaging instruments for deep space missions such as L4.

Reconstructing Historical Solar Activity Indices to Model Past Space Weather Events

Poshan Belbase (Catholic University of America)*; Denny Oliveira (NASA/GSFC); Gangkai Poh (NASA/GSFC); Theodosios Chatzistergos (Max Planck institute for solar system research); Matthew Finley (NASA/GSFC); Eftyhia Zesta (NASA/GSFC); Hisashi Hayakawa (Nagoya University)

Solar indices are critical inputs for modeling and forecasting the near-Earth space environment, particularly the thermosphere, which directly influences the motion of objects in low-Earth orbit through atmospheric drag. Among the most widely used solar proxies in this context are F10.7, S10.7, M10.7, and Y10.7, which serve as drivers for thermospheric density models such as Jacchia-Bowman 2008 (JB2008) model. Accurate representation of these indices is essential for reliable thermospheric density predictions, especially during periods of high solar activity that can significantly increase atmospheric drag on satellites and space debris. However, our knowledge of atmospheric drag during extreme events is quite limited partly due to the relative scarceness of observations. Thus, to evaluate the robustness and reliability of thermospheric models, it is important to assess their performance during major historical solar events. However, such validation requires long-term datasets of solar drivers extending well into the past, far beyond the availability of direct measurements. In this study, we present a method to reconstruct the four key solar proxies back to the early 1800s using an artificial intelligence (AI) approach. The reconstruction is based on three long-standing solar activity parameters: the sunspot number, sunspot area, and solar plage. These parameters have been systematically recorded over the past two centuries and serve as strong indicators of solar output. Initially, we trained a multiple AI model using the overlapping periods of modern observations where both the target proxies and the input solar activity indices are available. The model was evaluated for its accuracy in reproducing existing proxy data. Following the validation, we will reconstruct a continuous time series of all indices back to the 1800s. The complete dataset will be made publicly available via Zenodo to support the broader space weather and atmospheric science community.

Solar Active Region Classification with Deep Learning

Edoardo Legnaro (Università di Genova)*; Sabrina Guastavino (Università di Genova); Michele Piana (Università di Genova); Anna Maria Massone (Università di Genova); Paul Wright (University of Exeter); Shane Maloney (Dublin Institute for Advanced Studies)

In this talk, we will present our results in leveraging deep learning techniques for the automatic classification of solar active regions, for both the Mount Wilson and the McIntosh classification schemes. For this latter one, we consider a hierarchical multitask learning approach that mirrors the dependency structure inherent in the McIntosh system, which decomposes sunspot morphology into three components: the modified Zurich class (Z), penumbral class (p), and compactness class (c). We will present advanced model training techniques, including the teacher forcing method applied in the McIntosh classification. This method proves useful for enhancing training stability and convergence

speed while mitigating error propagation by incorporating ground truth labels as input for subsequent tasks, with its influence gradually decreasing throughout the training process.

Mitigating hallucination with non-adversarial strategies for image-to-image translation in solar physics

Veronique Delouille (Royal Observatory of Belgium)*; Niels Sayez (UCLouvain); Christophe De Vleeschouwer (UCLouvain); Laure Lefevre (Royal Observatory of Belgium); Sabrina Bechet (Royal Observatory of Belgium)

Image-to-image translation using generative adversarial networks (GANs) has become a standard approach across numerous scientific domains. In solar physics, GANs have become popular to reconstruct some unavailable modalities from physically related modalities that are available at the time of interest. However, the scientific validity of GANs generated outputs has so far been largely overlooked. In particular, it is known that generative deep learning models have a tendency to produce visually and statistically convincing outputs that may nevertheless be physically inconsistent with the input data. In this work, we measure the discrepancy between GAN-generated solar images and real observations in two applications: the generation of chromospheric images from photospheric images, and the generation of magnetograms from Extreme Ultraviolet images. Next, we investigate non-adversarial training strategies and network architectures whose behavior may adapt to the input at hand. Specifically, we propose an architecture that modulates the generative model's internal feature maps with input-related information, thereby favoring the transfer of input/output mutual information to the output. Our results show that GANs consistently fall short of non-adversarial U-net translation models in physics-constrained applications due to the generation of visually appealing features, termed as 'hallucinations', that do not have any physical correspondance. Additional conditioning the U-net model based on modulation of internal feature maps significantly enhances cross-modal image-to-image translation.

High resolution TEC forecasting using transformers models

Atuel Villegas (Tucuman Space Weather Center)*; Noelia Arguelles (Tucuman Space Weather Center); Eric Asamoah (Istituto Nazionale di Geofisca e Vulcanologia (INGV)); Claudio Cesaroni (Istituto Nazionale di Geofisica e Vulcanologia (INGV)); Maria Graciela Molina (Tucuman Space Weather Center)

The Total Electron Content (TEC) is a key parameter for studying the ionospheric conditions, with major impacts on telecommunications and other technologies using radio propagation. Many efforts have been made to predict the ionosphere’s status, with machine learning (ML) being one of the main techniques with significantly good results. However, TEC forecasting models using ML predominantly focus on global predictions with hourly or lower resolutions. In this study, we focus on low-latitude single-station forecasting of TEC with a time resolution of 10 minutes, using a deep learning technique based on the concept of self-attention. The high resolution allows us to capture different time scales in the ionospheric conditions. In order to find the best model for this task, we implemented an automated feature selection pipeline. The process starts with a large number of features, and iteratively removes the least important ones. The feature importance is computed using feature permutation and the optimum set of features is selected based on the best root mean squared error (RMSE) over the validation dataset. The architecture proposed for the forecasting is the so-called ‘transformers’ based on the self-attention mechanism to retrieve the more relevant past information for the forecasting. The results are very promising showing a good fit for the test set and for particular case studies of geomagnetic storms.

AIA2STIX: Bridging the gap between UV and X-ray in solar imaging

Francesco Ramunno (University of Applied Sciences North Western Switzerland (FHNW))*; Muriel Stiefel (University of Applied Sciences North Western Switzerland (FHNW) and ETH); André Csillaghy (University of Applied Sciences North Western Switzerland (FHNW)); Samuel Krucker (University of Applied Sciences North Western Switzerland (FHNW))

Understanding the relationship between ultraviolet (UV) and X-ray emission in solar flares can offer new insights into energy transport and improve cross-instrument interpretation. In this preliminary study, we introduce AIA2STIX, a deep learning framework designed to explore the feasibility of mapping observations from the AIA 1600 Å channel to synthetic STIX-like X-ray images. We focus on a curated dataset of approximately 600 M-class flares for which both AIA and STIX observations are available. To build a consistent training set, we preprocess the data through cropping, rotation, and reprojection steps to align the solar perspective across instruments. Our framework uses sequences of co-registered AIA 1600 Å images to learn spatial and temporal correlations with X-ray emission. A key scientific motivation for this work is to investigate the connection between flare ribbons observed in the UV and X-ray footpoints.

More broadly, this study aims to assess the potential of data-driven approaches for modeling relationships across spectral domains in solar observations.

Comparing Machine and Deep Learning Techniques for Solar Flare Prediction

João Felipe Pereira (George Mason University)*

Solar flares (and accompanying coronal mass ejections) are known to be causes and drivers of severe space weather near Earth and pose significant risks to technological systems on Earth. Despite significant advancements in AI and machine learning, solar flare prediction still needs to improve due to the elusive nature of their physical mechanisms and the limitations of current predictive tools. To improve on solar flare predictability, we compare a deep learning method for prediction, the spatiotemporal explanation supervision (STES) framework, to other machine learning techniques, specifically Random Forests (RF), that have been used on a benchmark multivariate time series dataset, the Space-Weather ANalytics for Solar Flares (SWAN-SF). Preprocessing steps, such as normalization and removal of artificial spikes, were performed on the SWAN-SF database to allow for proper prediction. By comparing the results between STES, which uses global full-disk line-of-sight magnetogram images, and traditional machine learning techniques like RF, we can adequately measure the effectiveness of this new image-based technique with the hopes of improving solar flare predictability rates.

Towards an Interpretable Model of Localized Geomagnetic Disturbances in Terms of Solar Wind and M-I Processes

Raman Mukundan (University of New Hampshire)*

Nonlinear interactions between the solar wind and Earth's magnetosphere disturb the magnetic field at Earth's surface. These ground-level disturbances can act as an indicator of processes elsewhere in the magnetosphere, and also are the source of space weather hazards such as geomagnetically induced currents (GICs). Geomagnetic disturbances are often spatially localized, which are known as localized geomagnetic disturbances (LGMDs). LGMDs make the ground-level magnetic field difficult to fully characterize given the sparse distribution of magnetometers that exist today. Additionally, which factors control the degree of localization of the geomagnetic field is still an open question. In this work, we model the physical processes that disturb Earth's magnetic field as a neural network trained to reproduce the ground-level magnetic field given a set of solar wind variables. We resolve the structure of LGMDs, despite the sparsity of magnetometer stations, by incorporating into our model the Spherical Elementary Current Systems (SECS) spatial interpolation technique. Finally, we discuss how the use of machine learning interpretability techniques can shed light on the roles of the solar wind and the ionosphere in modulating localized geomagnetic activity.

ML-IMEF: A Machine Learning Approach to Global Modeling of the Inner Magnetospheric Electric Field

Brianna Isola (University of New Hampshire)*; Matthew Argall (University of New Hampshire); Roy Torbert (University of New Hampshire, SWRI); James (Andy) Edmond (AFRL); Alireza Motazedian (University of New Hampshire)

Modeling the Inner Magnetosphere Electric Field (IMEF) is essential to understanding the complex nature of the plasma populations within the plasmasphere and ring current, particularly during geomagnetic storms, yet existing empirical models of the IMEF struggle to accurately reproduce these stormtime conditions. Here, we present a physio-temporal analysis of the first Machine Learning Inner Magnetospheric Electric Field (ML-IMEF) model with the aim to advance the state of physics-based modeling of the magnetosphere through improved accuracy and predictive capabilities. The model is trained on electric field data acquired from NASA's Magnetospheric Multiscale (MMS) mission, where measurements from both the Electron Drift Instrument (EDI) and Dual Ion Spectrometer (DIS) are utilized to make our model dynamic and time-dependent. We provide the model with five hours of geomagnetic indices and solar wind data, along with the desired coordinates at the time of prediction. By providing a complete coordinate grid within the inner magnetosphere, the trained model is able to construct a global 3D model of the electric field at each point in space. We examine multiple model architectures, including long short-term memory networks (LSTMs) which are especially primed for time-series forecasting. We report the effectiveness of ML on the model’s predictive and reconstructive capabilities, including exploring the spatial characteristics of individual electric field components as a function of the Hp30 index, where our results show evidence of shielding. We compute electric potential patterns through an inverse problem solution and delineate the plasmapause boundary. Furthermore, we compare results across various geomagnetic storms, including the May 2024 Gannon Storm.

Solar wind - geomagnetic disturbance coupling predicted and interpreted with KnowIt

Stefan Lotz (SANSA)*; Tian Theunissen (NWU)

Interpretability is an important and largely unsolved issue for deep learning models, across all problem types. Many space physics applications deal with multi-variate regression problems with complicated and non-stationary time dependencies. While accurate predictions is the primary objective, scientific discovery by direct interpretation of deep neural networks is a somewhat novel and largely unexplored avenue of research. In this work we present the KnowIt package, developed for the interpretation of multivariate timeseries regression problems. The package provides a holistic framework for model development and interpretation. Predictions are interpreted on the fly to provide input feature attribution at single-timestep granularity. We demonstrate its utility by applying the package to a common space physics problem -- predicting a geomagnetic disturbance index from solar wind plasma and magnetic field observations taken at L1.

Time-Resolved Causal Analysis of Geomagnetic Storms Using Information Theory

Jihyeon Son (Korea Astronomy and Space science Institute)*; Young-Sil Kwak (Korea Astronomy and Space science Institute)

In this study, we investigate the causal influence of solar wind parameters on geomagnetic storms using momentary information transfer (MIT), a time-resolved information theory method. The input solar wind parameters include the magnitude of the interplanetary magnetic field (IMF), the southward component of the IMF (Bz), solar wind speed, and dynamic pressure. The geomagnetic response is represented by the SYM-H index. We analyze approximately 150 storm events (between 2001 and 2024), selected based on the criterion that SYM-H remains below -50 nT for at least 12 hours and reaches a minimum below -80 nT. MIT is computed within a ±3 hour window centered on the time when SYM-H first crosses -50 nT. Our results show that the southward IMF and dynamic pressure are the dominant causal drivers of storm initiation, with peak of information transfer occurring 80~120 minutes and 20~40 minutes prior to the time when SYM-H drops below -50 nT, respectively. In contrast, IMF magnitude and solar wind speed show consistently low MIT values across the analysis window, suggesting a limited direct causal impact during the storm development phase. This quantitative analysis indicates the primary solar wind drivers and their timing in geomagnetic storm triggering, offering insights to enhance space weather forecasting capabilities.

An Interpretable Approach to SYM-H Geomagnetic Index Forecasting

Iván Maseda-Zurdo (Universidad de Alcalá)*; Pablo Muñoz (Universidad de Alcalá); Consuelo Cid (Universidad de Alcalá)

Accurate prediction of the geomagnetic index SYM-H can help mitigate adverse impacts of geomagnetic storms on terrestrial infrastructures and space-based technologies. Although several machine-learning models have recently been developed for this task, most are black boxes lacking interpretability, reducing their reliability for operational use and limiting their scientific value. Therefore, we propose an interpretable and robust prediction model based on a tailored adaptation of the Temporal Fusion Transformer (TFT), specifically designed to generate reliable SYM-H index predictions with explicit confidence intervals. This approach also enables assessment of the relevance assigned to each input sequence. The model employs data from the Advanced Composition Explorer (ACE) spacecraft, processed at a temporal resolution of 5 minutes, effectively capturing significant solar wind dynamics without introducing excessive noise. Variables considered include interplanetary magnetic field (IMF) components, solar wind plasma density and temperature, radial proton velocity, and derived variables such as the induced electric field and dynamic pressure. Model interpretability is achieved through an explicit structural attention mechanism, dynamically weighting the contribution of each variable and visually indicating their relevance at each time step. Additionally, the proposed architecture permits artificial restriction or manipulation of variable importance, facilitating systematic evaluations of model robustness under scenarios involving partial or total loss of specific inputs. While the model's forecasts do not outperform the current state-of-the-art, its ability to evaluate the relevance of input variables provides valuable insights to validate physical hypotheses related to geomagnetic phenomena and guide improvements in future predictive models.

Self-improving solar events prediction system: exploring potential of Darwin Gödel Machine agentic AI framework for cosmic weather forecasting.

Jakub Juranek (Polish Academy of Sciences)*

This work proposes a novel agentic AI framework for forecasting space weather phenomena, inspired by the Darwin-Gödel Machine: a theoretical construct of a self-improving system capable of recursively rewriting and bettering its own predictive algorithms. We explore this framework in the context of solar flare prediction, integrating continuously updated heliophysical data sources including SHARP magnetic parameters, NOAA GOES X-ray fluxes, and proton intensity databases. The proposed agent operates by iteratively refining its predictive strategies based on past performance benchmarks. It maintains a population of "children" models—variants evolved through internal metalearning—which are evaluated against real-world flare occurrences in a 24-hour prediction window. If performance drops below predefined thresholds, the agent autonomously generates improved successors, thus achieving self-directed optimization. We explore the feasibility of this framework by investigating how time-aware structural representations and pattern recognition strategies might be embedded into a continual learning loop, enabling autonomous adaptation and refinement based on observed solar activity and we present our results. This work aims to be a step toward embedding self-optimizing agent systems capable of autonomously improving their monitoring and predictive abilities, with broad implementation potential in cosmic weather prediction and beyond.

Bridging Kinetic and Fluid Scales: Addressing the Plasma Closure Problem with ML

Sophia Köhne (Ruhr-University Bochum); Simon Lautenbach (Ruhr-University Bochum); Emanuel Jeß (Ruhr-University Bochum); Rainer Grauer (Ruhr-University Bochum); Maria Elena Innocenti (Ruhr-University Bochum)*

Deriving fluid models from the Vlasov equation for collisionless plasmas presents a fundamental difficulty known as the closure problem. This issue arises because the time evolution of any particle moment - such as density, current, pressure, or heat flux - depends on the next higher-order moment. As a result, if one wants to evolve n moments, one must approximate the (n+1)th moment in the evolution equation for the nth moment. The level at which the hierarchy is truncated, along with the assumptions made in approximating the higher-order terms, plays a crucial role in determining how accurately the fluid model represents underlying kinetic phenomena. This work explores the use of supervised machine learning (ML) to address the closure problem using fully kinetic Vlasov simulations of magnetic reconnection generated with the multiphysics framework muphyII (Allmann-Rahn et al., 2024). Specifically, we train ML models to predict the divergence of the electron heat flux tensor, a key quantity for closing the ten-moment fluid model, based on inputs solely dependent on lower-order moments. We evaluate multilayer perceptrons (MLPs), U-Net convolutional networks, and Fourier Neural Operators (FNOs), and compare their performance against common Landau-fluid analytical closures (Allmann-Rahn et al., 2018; Ng et al. 2020; Wang et al., 2015). Our results show that FNOs, operating in Fourier space, achieve the most robust performance when sufficient training data is available. Including spatial information significantly improves model generalization to unseen data. These results highlight the potential of ML-based closures to bridge the gap between kinetic accuracy and fluid modeling in space plasmas.

Proxy Sensing of Space Weather Events Using Solar Panel Telemetry

Carl Shneider (SnT, University of Luxembourg)*; Stephen Tete (SnT, University of Luxembourg); Vasily Petrov (Mission Space S.A.); Andreas Hein (SnT, University of Luxembourg)

We investigate a method to characterize the extent and intensity of energetic particle events by analyzing voltage and current data from satellite solar panels. The primary data signature is the degradation of solar panel performance caused by displacement damage. A sudden drop in maximum current output, observed across multiple satellites when corrected for attitude and illumination, is a strong indicator of encountering a Solar Proton Event (SPE) or an enhancement of Earth's radiation belts. Transient effects, such as sharp voltage drops or noisy current readings, can signify satellite surface charging and arcing within dense plasma environments characteristic of active geomagnetic storms. By correlating these signatures across a number of small satellites, the spatial footprint of an event can be mapped in near real-time. We use data from a public small satellite database and apply wave mode decomposition and cross correlation analysis to disentangle the space weather induced anomaly from the 'normal' degradation of the satellite.

Automated Detection of Solar Radio Bursts Using Detectron

Herman le Roux (Dublin Institute for Advanced Studies)*; Shane Maloney (Dublin Institute for Advanced Studies); Mark Daly (Technological University of the Shannon); Jeremiah Scully (Technological University of the Shannon); Peter Gallagher (Dublin Institute for Advanced Studies)

Solar type II and type III radio bursts provide insights into shock wave propagation and electron beam dynamics in the solar corona. Observations of these bursts can also provide early warning signs for large space weather events such as flares and coronal mass ejections. Detecting and distinguishing these bursts in real time is therefore crucial for both scientific understanding and operational forecasting. In this work we re-train the Detectron framework using annotated Irish-LOFAR radio observations of type II and type III bursts, including individual events and burst groups. A pre-trained model using Detectron's mask R-CNN architecture and the MS-COCO dataset will be re-trained to automatically identify and classify both burst types in radio spectrograms, distinguishing between their complex morphologies, drift patterns, and harmonic structures. This approach aims to achieve improved classification accuracy over traditional methods and, in the future, enable automated parameter extraction for large-scale statistical studies, with the long-term goal of creating and implementing tools that aid real-time space weather monitoring.

Using TEC to Enhance 3D Electron Density Models

Liam Smith (Georgia Institute of Technology)*

Knowing the electron density of the ionosphere is very important for communications. However, it is difficult to measure densely. This leads to a desire for models to fill in the information gap. Both 3D electron density models and Total Electron Content (TEC) models exist, with the former being more informative about the ionosphere but the latter having denser training data. Previously, 3D electron density models have not taken advantage of this denser TEC data, but we present two ways to augment such models with TEC data. This work discusses how we can use TEC as an additional training dataset to increase vertical profiles without significantly affecting the quality of the overall predictions. We also describe a way to use historical TEC measurements as an additional driving factor for models to increase storm-time performance. By adding this TEC data we see better nmf2 predictions from the model during high Kp storms.

Opportunities for early detection of CMEs and CIRs by Vigil data and machine learning approach

Silvia Kostárová (Institute of Experimental Physics, Slovak Academy of Sciences)*; Adam Majirský (Institute of Experimental Physics, Slovak Academy of Sciences); Simon Mackovjak (Institute of Experimental Physics, Slovak Academy of Sciences); Enrico Magli (Image Processing and Learning group, Politecnico di Torino)

The Vigil mission, planned by the ESA, will monitor space weather activity in real time from the Sun-Earth Lagrange point L5, located 60° behind Earth in heliographic longitude. In this contribution, we demonstrate the potential of machine learning to improve space weather forecasting using Vigil-like data. We first focus on Dst index prediction using the MESWE dataset, which combines EUV and coronagraph images with solar wind and interplanetary magnetic field parameters. The dataset covers the most extreme space weather events from the past 30 years from a Vigil-like perspective, based on the event selection and data processing pipeline by Majirský et al. (2025). We trained deep learning models featuring GRU recurrent layers and self-attention mechanisms to predict the Dst index up to 4 hours ahead, achieving significantly reduced persistence effect compared to traditional approaches. We also address Co-rotating Interaction Regions (CIRs) identification using in-situ data from the STEREO-A spacecraft, during the period when it was near the L5 point. Our model aims to detect CIRs 4-5 days before they become geoeffective and potentially cause a geomagnetic storm. This study, part of the Slovak ESA RPA project ‘Vigil-ML’, supports the future integration of AI systems onboard spacecraft for real-time space weather monitoring.

Deep Generative model that uses physical quantities to generate and retrieve solar magnetic active regions

Subhamoy Chatterjee (SwRI, Boulder, CO)*; Andrés Muñoz-Jaramillo (SwRI, Boulder, CO); Anna Malanushenko (HAO, Boulder, CO)

Deep generative models have shown immense potential in generating unseen data that has properties of real data. These models learn complex data-generating distributions starting from a smaller set of latent dimensions. However, generative models has encountered great skepticism in scientific domains due to the disconnection between generative latent vectors and scientifically relevant quantities. In this study, we integrate three types of machine learning models to generate high-quality solar magnetic patches in a physically interpretable manner and use those as a query to find matching patches in real observations. We find that the retrieved real data that shares the same physical properties as the generated query. This elevates Generative AI from a means-to-produce artificial data to a novel tool for scientific data interrogation.

Machine Learning in Galactic Cosmic Ray Propagation

Jan Raath (South African National Space Agency)*; Martin Snow (South African National Space Agency)

We consider a selection of peer reviewed machine learning applications to the modelling of galactic cosmic ray propagation through the heliosphere, where these frameworks have been evaluated by benchmarks against physics-based simulations. These applications include deep learning, convolutional neural networks, Bayesian inference, and Monte Carlo methods, emphasizing models incorporating solar and heliospheric inputs. Forecasting cosmic ray spectra and flux variations, the machine learning models demonstrated superior predictive accuracy and computational speed, while enabling rapid inversion of propagation parameters. Integration of diverse solar activity indicators enhanced modulation modelling. However, limitations persist in physical interpretability, uncertainty quantification and dependence on training data and representativeness. The argument is therefore for augmented models where machine learning compliments physics models, but requires further development to ensure robustness and physical consistency.

Poster Session 3 (Thursday)

TEC and Transfer Learning

Stefan Lotz (SANSA)*; John Habarulema (SANSA)

Ground based observations is an important tool for space weather research as it is often the only way to quantify practical impacts of space weather effects on different technological systems. There are many regions across the globe where instrumentation networks are not dense enough to provide accurate readings of space weather effects and related physical phenomena. This is a significant problem for empirical predictive models which rely on large volumes of data measured where the predictions are to be made. In this work we address this problem by applying transfer learning to the prediction of total electron content (TEC) from external drivers (geographic, geomagnetic and solar activity). We first develop a source model, based on simple MLPs, over a region that has dense coverage of GNSS receivers (and therefore accurate TEC estimates). That source model is then fine tuned over a sparsely sampled target region. We show the differences in model performance over different source and target regions and compare performance with a naive model (developed using only the sparse data set).

Predicting partially observable dynamical systems via diffusion models with a multiscale inference scheme

Rudy Morel (Flatiron Institute); Francesco Ramunno (University of Applied Sciences North Western Switzerland (FHNW) and University of Geneva)*; Jeff Shen (Princeton University, Polymathic AI); Alberto Bietti (Flatiron Institute, Polymathic AI); Kyunghyun Cho (New York University, Polymathic AI, Genentech); Miles Cranmer (University of Cambridge, Polymathic AI); Siavash Golkar (New York University, Polymathic AI); Olexandr Gugnin (Taras Shevchenko National University of Kyiv, Polymathic AI); Geraud Krawezik (Flatiron Institute, Polymathic AI); Tanya Marwah (Flatiron Institute, Polymathic AI); Michael McCabe (Flatiron Institute, Polymathic AI); Lucas Meyer (Flatiron Institute, Polymathic AI); Payel Mukhopadhyay (University of California, Berkeley, Polymathic AI); Ruben Ohana (NVIDIA); Liam H. Parker (U.C. Berkeley, Polymathic AI); Helen Qu (Flatiron Institute, Polymathic AI); François Rozet (University of Liège, Polymathic AI); K.D. Leka (NWRA); François Lanusse (Polymathic AI, Flatiron Institute, Université Paris-Saclay, Université Paris Cité, CEA, CNRS, AIM); David Fouhey (New York University); Shirley Ho (Polymathic AI, Flatiron Institute, New York University, Princeton University)

Conditional diffusion models offer a natural framework for probabilistic forecasting in dynamical systems and have shown strong performance in domains like fluid dynamics and weather prediction. However, many physical systems, such as the Sun, remain only partially observable, limiting predictive accuracy due to internal state uncertainty. In this work, we address the problem of forecasting stochastic, partially observed dynamics with a focus on solar active region evolution. We introduce a novel multiscale inference scheme for diffusion models, specifically tailored to the temporal structure of physical processes. This approach generates trajectories that are temporally fine-grained near the present and coarser further into the future, enabling efficient modeling of long-range dependencies while maintaining computational tractability. To support this, we also construct a new dataset derived from SDO/AIA and SDO/HMI instruments, comprising sequential spatial crops of co-registered observations. These include all AIA wavelengths, continuum intensity, dopplergrams, and the vector magnetic field, providing rich multimodal supervision. We demonstrate that our inference scheme improves upon classical autoregressive approaches by reducing distributional bias, enabling scalable long-term prediction of solar dynamics with large conditional diffusion models. Beyond our modeling contributions, we believe this dataset, spanning both several wavelengths and modalities, will serve as a valuable benchmark for the broader diffusion modeling community as well as a resource for heliophysics research.

Estimated high-resolution photospheric flows using an AI surface flux transport model

Nina Bonaventura (Frontier Development Lab)*

The evolution of global magnetic fields on and beneath the solar surface is dictated by the processes of magnetic flux transport and magnetic flux emergence. Surface flows include a combination of differential rotation, meridional flow, and convective turbulence. Current state-of-the-art surface flux transport (SFT) models use fixed, axisymmetric analytic expressions to prescribe solar rotation and meridional flows, augmented with statistical realizations of turbulent fields to advance the solar photospheric magnetic field in time. Here, we present the results of using hybrid AI and SFT models to fit global velocity flows (differential rotation and meridional flow) and estimate convective flows in real time given a set of observations. We also discuss the specific architectures used to enable this estimation, and the comparison between AI-provided flows and well-established measurements. Finally, we discuss differences and similarities in AI-measured rotation for visible, magnetogram, and EUV data channels.

Deep Learning Classification of Low-latitude Ionospheric Structures in Airglow Images

Simon Mackovjak (Institute of Experimental Physics, Slovak Academy of Sciences)*; Carlos Martinis (Boston University); Joei Wroten (Boston University); Jeffrey Baumgardner (Boston University)

The low-latitude ionosphere is a dynamic environment sensitive to space weather drivers. To study the occurrence and characteristics of various structures, like Equatorial Plasma Bubbles or Medium-Scale Traveling Ionospheric Disturbances, by a statistical approach, a high number of examples is required. A huge repository of such events is available in the data archives of all-sky airglow imagers operated by Boston University. During the contribution, we will present our approach on how we employed deep learning techniques based on Convolutional Neural Networks for the selection of relevant images for further airglow studies and how we utilized synergy with traditional computer vision techniques for the creation of training datasets (Mackovjak et al., 2025, https://doi.org/10.1088/1538-3873/adca59). Opportunities for combination of our uniquely created datasets with other space weather datasets of the ML Helio community will be suggested.

CIR-Driven Ion Injections and EMIC Wave Dynamics: Implications for Wave Generation Mechanisms and Outer Radiation Belt Variability

Karen Júlia Ferreira (INPE)*; Lívia Alves (INPE); Lígia Da Silva (INPE, China Brazil Joint Laboratory); Vinícius Deggeroni (INPE); José Marchezi (UNICAMP); Gislayne da Nóbrega (INPE); Pedro Fister (INPE); Edu Rockenbach (INPE); Thiago Sant'Anna (INPE, ON); Laíne Rosales (INPE)

Co-rotating interaction regions (CIRs), formed at the interface between high-speed streams (HSSs) and slower solar wind, are recurrent solar wind structures that play a key role in driving geomagnetic activity, particularly during the declining phase of the solar cycle. Characterized by compressed plasma and enhanced magnetic fields, CIRs lead to elevated dynamic pressure and prolonged southward IMF conditions, which can trigger ion injections from the plasma sheet into the inner magnetosphere. These injections may generate wave activity, including electromagnetic ion cyclotron (EMIC) waves. In the outer radiation belt, EMIC waves are primarily excited by anisotropic distributions of ring current ions (H^+, He^+, O^+) and are known to cause loss of relativistic electrons via cyclotron resonance. While EMIC wave occurrence during geomagnetic storms is well documented, the influence of CIR-driven ion injections on their generation remains less understood. This study investigates how ion injections associated with CIR-driven geomagnetic storms influence EMIC wave activity. We analyze multi-satellite observations from the Van Allen Probes, THEMIS, and ACE missions for events between October 2012 and June 2019 with Dst ≤ –30 nT and spacecraft apogees in the nightside sector. CIR structures and upstream solar wind parameters, including ion composition and pressure, are identified using ACE data; THEMIS provides plasma sheet dynamics, while Van Allen Probes offer high-resolution EMIC wave and ion flux measurements. Preliminary results suggest enhanced EMIC activity within CIR compression regions. Ongoing work includes applying Random Forest models to identify key solar wind drivers of EMIC occurrence. These results contribute to understanding wave–particle interactions in the radiation belts and improving space weather forecasting capabilities.

CHESS: Coronal Hole Extraction with Semantic Segmentation

Raphael Attie (NASA GSFC / GMU)*; Michael Kirk (NASA GSFC); Raphael Attie (UCSD); Laura Boucheron (NMSU); Karin Muglach (NASA GSFC / CUA); Boris Kramer (UCSD); Raphael Attie (NASA GSFC)

CHESS expands the training of two baseline Convolutional Neural Networks (CNNs) to obtain a more efficient, least-biased CNN model for segmenting coronal holes (CHs): (i) A U-Net and (ii) a Res-U-Net architecture pre-trained with CH boundary data from the Heliophysics Events Knowledgebase (HEK) processed by the Spatial Possibilistic Clustering Algorithm (SPoCA) applied to images of the Atmospheric Imaging Assembly (AIA) onboard the Solar Dynamics Observatory (SDO), using the extreme ultraviolet (EUV) 193-Å filter. In many instances, this algorithm cannot differentiate between a CH and another solar structure called "filament". Our project overcomes this limitation by adding ground-based observations of the He I 10830 Å spectral line, which is able to provide such disambiguation. Full disk images in this chromospheric line primarily host three desirable traits, namely observability by more

accessible ground telescopes, providing a clear distinction between filaments and CHs, and a lack of susceptibility to the blocking effect by the coronal emission from nearby Active Regions (ARs) in EUV observations. These full disk observations are provided by the National Solar Observatory (NSO) Vector Spectromagnetograph (VSM) instrument in the Synoptic Optical Long-term Investigations of the Sun (SOLIS) facility. The He I line is a prime candidate for extracting an alternate perspective on coronal hole boundaries and inclusion in a broader ensemble machine learning method in which boundary predictions from various base estimator routines are combined to a final estimator via stacking to yield a strong classifier of CHs. By using the He I imagery, we further curate a CH training free of the contamination of filaments. This curated dataset is then used for improving the training of our two CNNs, which will be compared against our baseline versions that were contaminated by the presence of filaments. The best version(s) will then be made available to the community.

World Coordinate System Framework to enhance AI applications in PyTorch

Nathaniel Laurent (Southwest Research Institute)*; Andrés Muñoz-Jaramillo (Southwest Research Institute)

Artificial Intelligence (AI) has built its incredible success on the design and training of a wide variety of mathematical model architectures with high capacity of abstraction. During the last decade, the heliophysics community has mainly focused on the application of these architectures to heliophysics problems. However, with our maturity has come a significant effort to take control of architecture design and take maximum advantage of physical insight and physical mathematical models. Here we present the results of a project that aims to provide a critical piece of infrastructure to our effort of taking advantage of our physical understanding and knowledge within AI models: Coordinate transformations. Coordinate transformations are currently executed by models in our community during the preprocessing step, taking advantage of well established World Coordinate Systems (WCS) implemented in AstroPy and SunPy. However, these WCS frameworks break the gradient chain because all their operations are performed in NumPy. Our WCS framework expands the capabilities of DFReproject (a WCS framework that uses PyTorch to speed up coordinate transformations) to enable: 1. Ability to work in both helioprojective (plane-of-the-sky), heliocentric cartesian (x,y,z), and heliographic (latitude, longitude) coordinates. 2. Full, unbroken, gradient chains that enable AI models to learn in solar heliocentric cartesian and solar heliographic coordinates, while calculating errors on solar helioprojective images. 3. The reprojection and combination of multi-viewpoint observations. We'll discuss its structure, show examples of its use, and show a comparison of its performance compared to well established SunPy transformations.

Bayesian and Machine Learning for Geomagnetic Activity forecast: Where Causality augments Explainability

STEPHEN TETE (UNIVERSITY OF LUXEMBOURG)*; CARL SHNEIDER (UNIVERSITY OF LUXEMBOURG); MAXIME CORDY (UNIVERSITY OF LUXEMBOURG); ANDREAS HEIN (UNIVERSITY OF LUXEMBOURG); VASILY PETROV (MISSION SPACE); CLAUDIO CESARONI (INGV)

Understanding the dynamics of geomagnetic activity drivers have a significant impact on predictability and explainability. To date, the feature selection processes used for geomagnetic activity timeseries forecasting rely on basic information theory such as correlation analysis which are mostly limited spatially and temporally. In this work, we prioritize causal inference through Bayesian graphical networks during the preliminary stage of modeling to assess probable outcomes of the dynamical Hp60 (nT) index under variations of solar and interplanetary parameters (IMF, Pdyn, Bt, Bz, Plasma Beta, V, F10.7, N, etc.) to aid explainability. With domain knowledge, we use a subset of the suggested graph nodes (features), combined with information theory to train a gradient boosting model aimed at forecasting the Hp60 index 3hrs in advance. Results from the graph demonstrate that for instance, there is an 80 % chance of observing an Hp60 value of 2.33 nT given a 5.2 Pa pressure evidence. Given the state-of-the art data, we are able to forecast the Hp60 + 3hrs with (r, ccc, R2 = 0.76, 0.74, 0.59) and (rmse, mae = 0.86 nT, 0.66 nT) which outperforms persistence model by (rmse, mae = 19.28% 19.51%). Finally, to enhance interpretability, we apply shap analysis to the forecast model, aiming to offer insights into feature contributions. Considering the forecasting improvements, especially under such a non-timeseries framework, future improvements will blend hybrid architecture (particularly, an LSTM and CNN) to better capture temporal patterns and improve sensitivity, timeliness, and operational robustness.

CCA-Informed Neural Networks for Predicting Plasma Sheet Conditions from Solar Wind Drivers

Jose Espinoza Acosta (University of California, Los Angeles (UCLA))*; Joe Borovsky (Space Science Institute, Boulder CO, USA)

Understanding the coupling between the solar wind and the magnetospheric plasma sheet remains a central challenge in space weather research. We present a two-stage machine learning approach to analyze and predict plasma sheet behavior based on upstream solar wind conditions. First, we apply Canonical Correlation Analysis (CCA) to identify the strongest linear correlations between selected solar wind parameters and plasma sheet variables measured during hundreds of magnetotail current sheet crossing events using THEMIS. Building on these results, we then train a feed-forward neural network to predict plasma sheet parameters directly from solar wind inputs. This approach leverages the interpretability of CCA to guide the design of more efficient and physically grounded ML models, with potential applications across solar wind–magnetosphere coupling.

Investigating plasma composition with deep learning

Tania Varesano (Southwest Research Institute)*

The Spectral Imaging of the Coronal Environment (SPICE) instrument aboard the Solar Orbiter mission provides high-resolution extreme ultraviolet (EUV) spectral data of the Sun's transition region and corona, offering unprecedented insights into solar dynamics. This project leverages deep learning (specifically Siamese Neural Networks, a self-supervised approach) to automate and streamline the identification and classification of spectral features in SPICE data. The goal is to correlate these features with plasma fractionation and flare eruption, thereby enhancing the understanding of solar activity and contributing to improved space weather forecasting. The dataset consists of 1D spectra from the synoptic campaign. The trained model aims to detect subtle spectral similarities and extract clusters (using HDBSCAN) that can be mapped back onto the original intensity map, indicating regions where the elemental composition is similar. First results showed interesting patterns of similar composition at different locations along transition region loops and active region cores, suggesting that this approach may uncover previously unrecognized trends in plasma fractionation.

Using interpretable AI to discover the drivers of acceleration vs depletion events in the radiation belt

Jacob Bortnik (UCLA)*; Dongla Ma (UCLA); Xiangning Chu (CU Boulder)

Using a fully trained artificial neural network (ANN) model of the dynamic radiation belt electron fluxes, we use a machine learning interpretability technique called Shaply Additive Explanations (SHAP) to discover the specific drivers that lead to either depletion or enhancement events in the radiation belts. By perform a superposed epoch analysis of both depletion and enhancement events, together with superposing their SHAP values, we show an elegant solution to a 20-year old problem in radiation belt physics, namely, that similar sized geomagnetic storms can sometimes result in radiation belt enhancement or depletion events seemingly randomly.

Reconstructing Equatorial Electron Flux Measurements from LEO

Dominique Stumbaugh (UCLA)*

We present a network of ANN models that reconstructs >30 keV electron flux measurements near the geomagnetic equator from low-Earth-orbit (LEO) observations, exploiting the global coherent nature of the high-energy trapped electrons that constitute the radiation belts. To provide training data, we analyze magnetic conjunctions between one of National Oceanic and Atmospheric Administration's Polar Orbiting Environmental Satellites (POES) and National Aeronautics and Space Administration's Van Allen Probes. These conjunctions occur when the satellites are connected along the same magnetic field line and allow for a direct comparison of satellites' electron flux measurements for one integral energy channel, >30 keV and over 70,000 such conjunctions per spacecraft have been identified. The resulting conjunction data set contains the POES electron flux measurements, L and magnetic local time (MLT) coordinates, geomagnetic activity Auroral Electrojet index, and C and N coefficients from the PAD fit for each conjunction. We present our models' prediction for the out-of-sample data that agrees well with observations. We demonstrate the ability to nowcast and reconstruct equatorial electron flux measurements from LEO without the need for an in-situ equatorial satellite. The model has the potential to be used as a basis of future real-time radiation-belt monitoring LEO constellations.

Data-Mining Similar Scenarios for Uncertainty Quantification of Solar Wind Predictions at L1

Daniel da Silva (NASA/GSFC, UMBC)*; Yash Parlikar (NASA); Shaela Jones (NASA, CUA); Nick Arge (NASA)

Accurate Uncertainty Quantification (UQ) for space weather forecasts is an ever-important supplementary variable to enable accurate risk response. Modeling uncertainty is itself a "model of a model", and one of the best datasets to describe a model's performance is a past database of it's predictions and after-the-fact observations. In this presentation, we present a method based on k-NN and kernel regression to quantify uncertainty in the WSA solar wind model and it's predictions of the solar wind speed at L1. By constructing state vectors that describe the current forecasting context— recent observations, recent predictions, and future predictions, we build a catalog of "similar scenarios" from past data. With a set of similar scenarios at each timestep, we can base our uncertainty on the performance in those cases. This approach—suitable for low-dimensional datasets such as time series—is extremely fast and interpretable. We find that the resulting uncertainty estimates naturally capture structured patterns in forecast error, such as shifts between solar minimum and maximum, and periodic features on the scale of half a solar rotation. In this presentation, we will discuss the statistical learning approach of k-NN approach, where-it applies, and its strengths as an interpretable and explainable ML method. We will also review with examples tools for gauging the performance of UQ methods, such as the CRPS method and Percentile Analysis.

3D Tomographic Reconstruction of Coronal Plasma Density and Temperature Using Neural Radiance Fields

Robert Jarolim (High Altitude Observatory)*; Andres Muñoz-Jaramillo (SwRI); Benoit Tremblay (Environment Canada); Christoph Schirninger (University of Graz)

Reconstructing the three-dimensional structure of the solar corona is essential to understanding the physical processes governing solar activity. Building on our previously developed deep-learning framework for 3D scene reconstructions of the Sun (SuNeRF), we present an extension that enables tomographic reconstruction of key thermodynamic quantities (electron density and temperature) in the lower solar corona. Our method leverages simultaneous multi-wavelength observations from SDO/AIA and Solar Orbiter/EUI, incorporating their respective temperature response functions. We employ a radiative transfer framework to infer the underlying 3D plasma distribution that best matches the multi-spectral observations. We validate our approach using synthetic observations from forward-modeled coronal simulations. Applying the method to real observations, we reconstruct dynamic coronal structures, including filaments, active regions, and coronal holes, revealing their evolving thermodynamic profiles. This work represents a major step toward unified 3D diagnostics of the solar atmosphere and enables new studies of the coupling between coronal heating and large-scale dynamics.

Data Analysis for Multi-Hazard Risk Science: Risk and Resilience of Societal Critical Infrastructure to Space Weather and Compounding Natural Hazards

Sanjali Vuriti (University of Washington)*; Rajesh Subramanyan (University of Washington); Ryan McGranaghan (NASA Jet Propulsion Laboratory)

This project investigates how space weather interacts with terrestrial hazards, like wildfires, droughts, and winds, to impact the U.S. power grid. A multi-hazard risk analysis framework was developed using three approaches: multivariate extreme value theory to estimate joint return periods of complex events, machine learning models to predict geomagnetically induced currents spatiotemporally, and network modeling to assess cascade failures. Traditional risk evaluation methods often fail to capture interdependencies, leading to an incomplete picture of system vulnerability. Our work identified past grid disruptions and created predictive tools to improve disaster preparedness and response.

Unraveling Near-Earth Space Dynamics with Machine Learning

Xiangning Chu (Laboratory for Atmospheric and Space Physics, University of Colorado Boulder)*; Jacob Bortnik (UCLA); Qianli Ma (Boston University and UCLA); Donglai Ma (UCLA)

The dynamics of the near-Earth space plasma environment are inherently complex, comprising critical components such as cold plasma, high-energy electrons and protons trapped in the radiation belts, and various electromagnetic waves, including whistler-mode chorus and hiss. These elements pose significant hazards to spacecraft and astronauts. However, their responses to external solar wind drivers are highly nonlinear and remain difficult to predict. As a result, understanding the underlying physical mechanisms and achieving reliable forecasts of their behavior have long presented major challenges in space physics and space weather research. This study leverages machine learning techniques to improve both predictive capabilities and physical insights into these processes, advancing our understanding of the near-Earth space environment.

ESA Datalabs: Digital Innovation in Space Science

Sandor Kruk (European Space Agency (ESA))*

Modern space science missions are generating data at unprecedented scales, ranging from terabytes to petabytes. For instance, the European Space Agency's (ESA) Euclid mission alone is expected to produce approximately 30 petabytes of data over its operational lifetime. Processing and analyzing such massive datasets requires specialized infrastructure and scalable tools. To address this challenge, ESA is developing the ESA Datalabs science platform, providing direct access to mission data without the need for local downloads. Built on technologies such as JupyterLab, ESA Datalabs enables scientists to interact with data efficiently, develop and share applications, and collaborate through shared workspaces. By integrating analysis tools with seamless data access, ESA Datalabs offers a powerful, accessible framework for collaborative research and scientific discovery. In this presentation, we will outline the rationale behind ESA Datalabs, highlight its core capabilities, discuss future development plans, and showcase selected scientific applications built on the platform.

AnomalyMatch: A Detection Method of Astrophysical Anomalies in Imaging Data

David O'Ryan (ESAC, ESA)*

Atypical objects are particularly fruitful for uncovering complex relationships in fields such as extragalactic astrophysics, planetary science and, heliophysics. Astrophysical anomalies are often hard to find, leading to a lack of suitable training data for machine learning models. Additionally, established methods are prone to detect un-interesting anomalies such as instrumentation artifacts. In this work we present AnomalyMatch, an anomaly detection algorithm which combines semi-supervised machine learning techniques with a user-in-the-loop active learning framework for identification using only labelled examples. We perform benchmarking of our methodology and demonstrate its applicability using limited labels of anomalies and nominal images (<100 labels). We test this methodology in the context of extragalactic astrophysics by searching ~99.6 million astrophysical sources in the Hubble Legacy Archive, demonstrating its scalability. We discuss the applications of this method to heliophysics, and improvements including the addition of spectral information when searching for anomalies. AnomalyMatch has been integrated into the ESA Datalabs science platform, enabling researchers to use this semi-supervised methodology as 'plug-and-play' software with ease.

The Heliophysics Extended Survey Environment

Jan Reerink (Esa)*; Shawn Polson (Laboratory For Atmospheric and Space Physics)

The IHDEA Science Platforms Coordination working group was formed in December 2023 to develop international standard software computing environments for Heliophysics. This demonstration poster will provide attendees the opportunity to test the computing environments created over the last year. We conducted a community survey to understand current software usage patterns and built tailored JupyterLab environments pre-populated with domain-specific software packages based on these findings. Through partnerships with 2i2c, HelioCloud, and ESA Datalabs, we have deployed our environments and are now seeking community feedback and beta testers. Our goal is to facilitate widespread adoption of cloud computing in Heliophysics, enabling analyses to run closer to cloud-native data using platforms potentially much more powerful than personal laptops while promoting reproducible, citable research.

An EUV Extension to the SWAN-SF Flare Forecasting Dataset

Griffin T. Goodwin (Georgia State University)*; Dustin Kempton (Georgia State University); Reet Gupta (Georgia State University); Viacheslav M. Sadykov (Georgia State University); Petrus C. Martens (Georgia State University)

The Space Weather Analytics for Solar Flares (SWAN-SF) benchmark dataset has proven to be an invaluable resource to the flare forecasting community. Containing carefully cross-checked magnetogram data for over 4000 active regions and 10,000 flaring events, SWAN-SF has enabled researchers to efficiently train, test, and validate their predictive models with confidence. However, since its release in 2020, the dataset has seen no significant updates. As a result, the goal of this work is twofold: first, we plan to temporally expand the existing dataset to include the most recently available HMI active region patches (HARPS); and second, we aim to incorporate texture-based parameters derived from extreme ultraviolet images taken by the Solar Dynamics Observatory's Atmospheric Imaging Assembly (SDO/AIA). The purpose of these updates is to enable researchers to investigate how flare forecasting is impacted across two solar cycles and to improve prediction accuracy near the limbs. Our methodology for producing the dataset, along with some preliminary results, will be presented here.

Solar Radio Burst Tracker: A citizen science initiative to identify Type III solar radio bursts

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Type III solar radio bursts are prominent radio signatures of solar activity, produced by beams of energetic electrons propagating through the corona and interplanetary space. Their rapidly drifting signatures in radio spectrograms provide valuable insights into particle acceleration and coronal dynamics. However, detecting and characterizing these bursts remains challenging due to their variable morphology and intensity. Existing automated methods (e.g., Lobzin, 2019) often miss weak or complex events, particularly at frequencies below 10 MHz. To address this, we developed the Solar Radio Burst Tracker, a citizen science project on Zooniverse.org, engaging volunteers in identifying Type III bursts within dynamic spectrograms from the Radio and Plasma Waves (RPW) instrument onboard ESA/NASA's Solar Orbiter. Over 13,600 spectrograms, covering 35 kHz to 7 MHz, were analyzed, resulting in the identification of more than 18,500 Type III bursts. Each event includes time-frequency boundaries derived from aggregated human input. This catalog forms the basis for training machine learning models for robust detection and feature tracking of Type III bursts across the full RPW dataset. Using human-verified data, we aim to develop scalable algorithms that can detect fainter and more complex events, enriching existing catalogs, which currently focus on the most intense bursts. These tools will enable statistical studies of burst properties, their relationship to flares, and their solar cycle evolution. Identifying lower-energy events also offers new insights into the role of weaker solar activity in coronal energy release, addressing a key question in solar physics: the origin of coronal heating. Ultimately, this work showcases how human-in-the-loop methods can help build advanced detection tools, enhancing the science return of current and future missions.