Time	Mins	Speaker	Subject
10:00 - 10:30	**30**		**Coffee**
10:30 - 10:40	**10**	**Paul Wright** (University of Exeter)	**Welcome / Introduction**
Overview of Machine Learning for Space Weather			
10:40 - 11:00	20	**Andrés Asensio Ramos** (Instituto de Astrofísica de Canarias) [remote]	**Machine Learning in Heliophysics** [Invited]
11:00 - 11:15	15	Frank Soboczenski (University of York)	Empowering AI Research & Development: Demonstrating the Impact of ML Platforms like HuggingFace
11:15 - 11:25	**10**		**Break**

Session Topic: Data-Driven Approaches in Space Weather (Focus: Nowcasting, and interpretability in space weather predictions.)			
11:25 - 11:40	15	Edoardo Legnaro (University of Genova)	Deep Learning Techniques for Sunspot Classification
11:40 - 11:55	15	Hua-Liang Wei (University of Sheffield) [remote]	Knowledge Guided Transparent, Interpretable and Simulatable Machine Learning for Space Weather Forecasting
Session Topic: ML for Forecasting and Predictive Models (Focus: ML techniques for datasets, feature extraction, and event classification.)			
11:55 - 12:10	15	Ndifreke Nyah (University of Central Lancashire) [remote]	A Global and Spatiotemporal Time-Distributed Multivariate Deep Learning with Dynamic Data Sequencing for Solar Flare Forecasting
12:10 - 12:25	15	Dylan Weston (Northumbria University)	Using a Random Forest to understand and accurately predict flux levels in Earth's Van Allen Radiation Belts
12:25 - 12:35	**10**		**Break**

Lightning Talks			
12:35 - 12:55	3	Martin Sanner (University of Dundee) [remote]	An explainable model for solar active region detection towards evolution prediction
	3	Alexandra Ruth Fogg (DIAS)	Wavelet Scattering Network for detection of Sudden Commencements
	3	Besma Guesmi (Ubotica Technologies) [remote]	EoFTCNets: Efficient Solar Flare Nowcasting using 3D Temporal Convolutional Networks (3DTCN)
	3	Charles Bowers (DIAS)	Estimating Interplanetary Magnetic Field Conditions at Mercury's Orbit from MESSENGER Magnetosheath Observations using a Feedforward Neural Network
	3	Lightning Speaker 5	Lightning Talk 5
	3	Serhii Ivanov (DIAS)	Forecast horizon and the prediction of the geomagnetic Dst index
12:55 - 13:00	5	Shane Maloney (DIAS)	SolarMonitor Demo
13:00 - 14:00	**60**		**Lunch**

Session Topic: Operational Deployment and Monitoring (Focus: Institutional implementations and real-world forecasting systems.)			
14:00 - 14:20	20	**David Jackson** (UK Met Office)	**Machine Learning in operational space weather forecasting: challenges and opportunities** [Invited]
14:20 - 14:35	15	Andy Smith (Northumbria University)	Space Weather Forecasts of Ground Level Space Weather with Machine Learning: Performance, Limitations and Operational Challenges
14:35 - 14:50	15	Hannah Rüdisser (Austrian Space Weather Office) [remote]	Enhancing Space Weather Forecasting with Machine Learning at the Austrian Space Weather Office
14:50 - 15:10	20	**Greg Lucas** (LASP; SWx-TREC) [remote]	**LiveSWx: Challenges and Lessons Learned from ML Deployments for Space Weather Forecasting** [Invited]
15:10 - 15:25	15	Jinen Daghrir (Ubotica Technologies) [remote]	3CSD MLOps: Enhancing Edge MLOps with Computational Storage for Efficient Model Maintenance and Intelligent Triage Systems
15:25 - 15:28	3	Milo Buitrago Casas (UC Berkeley) [remote]	Early and Actionable Flare Alerts for Large Solar Flare Observation Campaigns
15:28 - 15:35	7		Closing Remarks
15:35 - 16:00			**Tea**

Abstracts

Talks

Andrés Asensio Ramos Instituto de Astrofísica de Canarias [Invited]	**Machine Learning in Heliophysics** The impact of data-driven machine learning (ML) methodologies over the past decade has strongly impacted solar physics and heliospheric research. By synergizing state-of-the-art neural architectures with the unprecedented availability of observational and simulation datasets, the performance and accuracy of ML models have seen remarkable advancements. These developments now enable rapid, high-precision solutions to complex classification and regression. In this contribution, I present a non-exhaustive overview of cutting-edge ML applications in heliophysics, trying to address key challenges hindering broader adoption.
Frank Soboczenski University of York	**Empowering AI Research & Development: Demonstrating the Impact of ML Platforms like HuggingFace** *Soboczenski, F. and Wright, P.* Contemporary machine learning platforms, exemplified by HuggingFace, stand as a cornerstone in advancing AI/ML development. Large Language Models (LLMs), such as the Mistral or the GTP series, have redefined natural language processing with their remarkable human-like text generation capabilities. Across various domains, LLMs or Transformers have demonstrated exceptional success. The infrastructure provided by such a platform for deploying Transformers and facilitating collaboration offers accessible tools, nurturing a dynamic ecosystem for developers and researchers. This paradigm's success hinges on democratizing AI/ML, empowering developers globally to leverage cutting-edge models without requiring extensive infrastructure or expertise. Through these platforms, developers and researchers gain access to pre-trained models, enabling fine-tuning for specific tasks and seamless deployment. This accelerates the development cycle, widens access to state-of-the-art AI/ML capabilities. Furthermore, such platforms foster knowledge exchange and collaboration, advocating a community-driven approach to model development. By utilizing models, datasets, and prototypes via these platforms, developers can swiftly prototype and deploy AI-powered solutions across diverse domains, spanning from language translation to object detection and beyond. Notably, recent additions to the platform include the NASA Solar Dynamics Observatory Vision Transformer and NASA GeneLab VisionTransformer on Microscopy Data. This presentation will showcase these additions and underscore how such a platform can facilitate seamless development, deployment, evaluation and robust community building when integrated into existing pipelines.

Edoardo Legnaro University of Genova	**Deep Learning Techniques for Sunspot Classification** *Legnaro, E., Guastavino, S., Piana, M., Massone, A. M., Wright, P., Maloney, S.* Solar active regions can significantly impact the Sun–Earth space environment, driving extreme space weather events such as solar flares and coronal mass ejections. Sunspots serve as key indicators of these regions, with certain sunspot types closely linked to such events. Consequently, the automatic classification of sunspot groups plays a crucial first step in enhancing the accuracy and timeliness of solar activity predictions. In this talk, we present our results on leveraging deep learning techniques to detect and classify active regions. We address both the task of classifying active regions from magnetogram cutouts and the detection and classification of active regions from full-disk magnetograms. This research is conducted as part of the Active Region Classification and Flare Forecasting (ARCAFF) project.
Hua-Liang Wei University of Sheffield	**Knowledge Guided Transparent, Interpretable and Simulatable Machine Learning for Space Weather Forecasting** *Wei, H.L.* The last decades have witnessed the quick development of a variety of data-driven modelling (DDM) techniques, among which we have seen the rapid advancement of machine learning (ML) and artificial intelligence (AI) tools and their successful applications in space weather forecasting.

	As part of DDM techniques, transparent, interpretable, sparse and simulatable (TISS) approaches have attracted considerable attention due to the high desire and demand for not only predicting happens but also breaking the black-box of interest to understand why it happens and how the potential drivers individually and collectively affect the behaviour of the system. The talk presents a TISS modelling tool adapted and extended from the well-known NARMAX methodology, which was originally developed from systems science and systems engineering perspectives, by introducing ensemble machine learning, sparse Bayesian learning, probabilistic forecasting, deep lagged input-output models, and so on. The design and development and their implementation are all centred around model selection, model training, interpretation, probabilistic forecasting, reproducibility, etc. The talk will provide several application examples of these methods in space weather forecasting including geomagnetic storm and radiation belt prediction.

Ndifreke Nyah University of Central Lancashire	**A Global and Spatiotemporal Time-Distributed Multivariate Deep Learning with Dynamic Data Sequencing for Solar Flare Forecasting** *Ndifreke O. N., Walsh R. W., Gass D.* Given the dynamic nature and potential terrestrial impacts of X-class solar flares, it is important yet challenging to construct a flare forecast model. This is especially true when flare characterizations from NASA's Solar Dynamic Observatory's (SDO) extreme ultraviolet instrument (the Atmospheric Imaging Assembly (AIA)) have not been fully understood or investigated. Previous deep learning attempts do not fully consider the impact of different flare characterizations, instrumental capability and past observational data sequences. The proposed approach adopts a Convolution Neural Network and Bidirectional Gated Recurrent Network with dynamic data sequencing in order to learn the characteristics of global, spatial and temporal features from multiple observational channels (171, 193, 211, 335 Angstroms) of flaring and no-flaring active regions. The training images are constructed as a multivariate temporal sequence of flare or no-flare observations by considering dynamically the prior period up to the peak of each X-flare EUV emission across the four filters. We show that forecasting of future event observations can be improved and imbalance training data minimized using the proposed approach. Ten test observational samples with a cadence of 12 seconds per active region image are employed between February 2023 and August 2023, which are outside the time period of the training data. The result from an 8-minute future forecast corresponding to 40 observations shows a performance of 81% Precision, 79% ACC, 0.58 TSS, and 78% F1 Score, and decreases to 73% ACC (16 minutes) and 62% ACC (32 minutes). Further independent evaluation is undertaken on ten X-flare variant samples from February 2024 to July 2024 including the May 2024 event to demonstrate the robustness of the model, approach and predictor power.
Dylan Weston Northumbria University	**Using a Random Forest to understand and accurately predict flux levels in Earth's Van Allen Radiation Belts** *Weston D. J., Rae I. J.,Smith A. W., Watt C. E. J.* The Van Allen Radiation belts are highly dynamic in both intensity 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 simple machine learning model capable of forecasting the Outer Radiation Belt with considerable skill 3 days in advance, and even with some skill up to 6 days in advance, a longer forecast than current operational models provide. We use a Random Forest classification model to predict if the daily ~2MeV electron flux level across each L* Shell exceeds its respective 60th percentile. Each model shows a high level of accuracy at both nowcasting and forecasting up to 6 days in advance, a longer forecast than current operational models. By using feature importance, we determine the key inputs into each model in order to gain an insight into which drivers are important at which L* shell and the timescales over which they have an impact, something more complex machine learning methods cannot always provide. Interestingly we find solar wind inputs are not required for accurate forecasting for the vast majority of our Outer Belt models. Instead using only geomagnetic conditions from between 1- and 7- days prior, meaning that models such as these could be operationally viable for space weather stakeholders.

David Jackson UK Met Office [Invited]	**Machine Learning in operational space weather forecasting: challenges and opportunities** *Jackson D., Bingham S, Bocquet F., Englyst A., Gonzi S., Henley E., Mace R., and Marsh M.* The Met Office produces operational space weather forecasts for the UK. A major challenge is to develop a forecast system which can meet the requirements of a wide range of end users (eg

	power grid, aviation, satellites, GNSS position, navigation and timing) while at the same time having to address issues related to insufficient observational data, gaps in knowledge required for physics-based forecast models and constraints of computational power. Furthermore, any new forecast must be shown to work accurately and robustly for a wide range of space weather conditions, and this is an additional challenge in converting a promising research tool into an operational product. In this presentation we outline our requirements for accepting a new model for operational use, and in so doing outline some of the challenges that need to be considered when developing machine learning models, such as the use of near real time data and the representation of extremes. We also outline current machine learning-based activity at the Met Office, including applications to flare forecasting, CME characterization and forecasts of the surface magnetic field. We then discuss the Met Office ambition for developing its forecast systems and indicate where machine learning can fit into this vision. This includes attempting to improve forecasts of flares, CMEs and SEP events, but also applications in data assimilation and emulation of physics-based models. The associated range of potential ML applications covers a wide range of different physical domains, scales and complexity; coordination of efforts, and priorities, between the research and operational programmes is needed to deliver advances in space weather forecasting capability.
Andy Smith Northumbria University	**Space Weather Forecasts of Ground Level Space Weather with Machine Learning: Performance, Limitations and Operational Challenges** *Smith, A. W., Rae, I. J., Forsyth, C., Coxon, J. C., Walach, M.-T., Lao, C. J., Bloomfield, D. S., Reddy, S. A., Coughlan, M. K., Keesee, A., Bentley, S.* Space weather describes the dynamic conditions in near-Earth space, mostly driven by the variable interaction between the continuous flow of the solar wind and the Earth's magnetic field. Extreme space weather has the potential to disrupt or damage key infrastructure on which we rely, for example through the generation of large, anomalous Geomagnetically Induced Currents (GICs) in power networks and transformers. Accurately forecasting a risk of large GICs would enable key actions to be taken to mitigate their impact. Given the sparsity of direct GIC measurements, and their inherent specificity to the contemporaneous network properties and configuration, we turn to forecasting the driving factor: the changing ground magnetic field (R). In this talk we discuss a recent model developed to forecast whether the rate of change of the ground magnetic field (R) will exceed specific, high thresholds in the United Kingdom. The model uses a common space weather forecasting framework: an interval of data from the upstream solar wind is used to make a prediction as to future conditions at the Earth. We will use this model as an example to discuss forecasting performance, particularly with respect to different magnetospheric driving and processes. We demonstrate the use of techniques such as SHAP (Shapley Additive exPlanations) to investigate how and why the model is making the predictions that it does. What physical processes can this model set up capture? Where do we need to go in the future? Further, we discuss how this model was transferred to real-time operational use at the UK Met Office as a part of UKRI's SWIMMR (Space Weather Instrumentation, Measurement, Modelling and Risk) programme. We pay particular attention to the differences between running the model on near-real-time data and the original "scientific" version of the model.
Hannah Rüdisser Austrian Space Weather Office	**Enhancing Space Weather Forecasting with Machine Learning at the Austrian Space Weather Office** *Rüdisser, H.T., Nguyen, G., Le Louëdec, J., Bauer M., Amerstorfer, T., and Möstl, C.* Interplanetary Coronal Mass Ejections (ICMEs) are the primary drivers of space weather disturbances, making their accurate and timely detection crucial for mitigating potential impacts. However, traditional identification methods often rely on post-event analysis, limiting their applicability in real-time forecasting. Additionally, the quality of real-time data is often suboptimal, posing further challenges to operational space weather prediction. At the Austrian Space Weather Office, we employ various machine learning techniques to address these challenges and enhance space weather forecasting capabilities. Our operational tools include an automated detection system that identifies ICMEs in streaming real-time in situ data, already in use for space weather monitoring. Additionally, we are developing a method to automatically segment CMEs in heliospheric images, enabling more efficient and scalable analysis of their propagation. Furthermore, our Beacon2Science project leverages generative AI to enhance data quality in real time, improving the accuracy of space weather models. In this presentation, we provide an overview of these machine learning-based methods, discuss the key challenges and solutions in their development and implementation, and explore future directions for integrating AI-driven approaches into space weather forecasting at the Austrian Space Weather Office.

Greg Lucas LASP; SWx-TREC [Invited]	**LiveSWx: Challenges and Lessons Learned from ML Deployments for Space Weather Forecasting** Deploying machine learning models for space weather forecasting introduces a unique set of challenges, particularly around unreliable or incomplete input data. In this talk, I will focus on our experience with LiveDst, a machine learning model designed for real-time space weather forecasting, and the hurdles we've faced during its operational deployment on a cloud-based model staging platform. I will highlight specific challenges related to data quality, missing or inconsistent data, and the complexity of ensuring model reliability in a constantly evolving space environment. Additionally, I will discuss the strategies we've employed to manage model drift, maintain robustness, and optimize the staging process for smooth transitions to production-ready status. Through our experience with LiveDst, this presentation aims to share key lessons learned and best practices, bridging the gap between academic research and operational deployment in space weather forecasting.
Jinen Daghrir Ubotica Technologies	**3CSD MLOps: Enhancing Edge MLOps with Computational Storage for Efficient Model Maintenance and Intelligent Triage Systems** *Daghrir, J., Guesmi, B., Moloney, D., Aranda, J. L. E., & Martin, E. H* The importance of AI (Artificial Intelligence) and ML (Machine Learning) in modern technological solutions cannot be disregarded. These technologies drive innovation across various sectors, enabling advanced data analysis, real-time decision-making, and automation of complex processes in applications such as computer vision, big data analytics, robotics, and speech recognition. In the context of space weather forecasting, AI and ML play a critical role in detecting and predicting significant solar events, such as Coronal Mass Ejections (CMEs), which are essential for understanding and mitigating their impact on Earth's space environment. However, the dynamic nature of solar activity introduces challenges like data and model drift, necessitating continuous retraining of ML models on new data to capture evolving CME and solar flare patterns. This need for frequent updates and retraining further complicates reliance on cloud-based processing, as the growing demand for deploying AI/ML solutions on edge devices has highlighted the limitations of cloud-based processing, including latency, bandwidth constraints, and data privacy concerns. Edge computing, which brings computation closer to the data source, addresses these challenges and offers a promising solution for deploying ML models in resource-constrained environments, such as space-based instruments monitoring solar activity. In this manner, we propose an innovative approach, titled 3CSD MLOps, to enhance Edge Machine Learning Operations (MLOps) by integrating Computational Storage Devices (CSDs) into the edge ecosystem. The integration of CSDs, which combine storage and processing capabilities within a single device, offers several key advantages for edge ML. These include reduced power consumption, minimized bandwidth requirements, and enhanced data privacy and security by processing data locally. Despite the potential benefits of CSDs, their application in edge ML remains under-explored. Training ML models are inherently resource-intensive, requiring significant time and memory to create efficient models. Moreover, deployed models must be continuously retrained to adapt to changing data, as the assumption that models will remain effective over time is often unrealistic. This necessitates a sustainable approach to data preprocessing and model training that minimizes memory usage and training time. By leveraging CSDs in edge environments, we can address these challenges while ensuring low power consumption, reduced bandwidth requirements, and robust privacy and security. The proposed 3CSD MLOps workflow introduces a novel pipeline for efficient and ongoing training of ML models at the edge. This pipeline leverages the benefits of edge CSDs to supervise, analyze, infer, and improve ML networks. The 3CSD MLOps framework comprises three main components: the NNS (Neural Network Supervisor), the Multistage LILLIAN-based ensemble, and the retraining strategy. These components work together to perform real-time triage, avoid redundant information, optimize data collection, and retrain models to improve neural network performance while minimizing resource consumption. By integrating intelligent triage subsystems, the framework prioritizes essential data, reducing the amount of data required for training and conserving computational resources. Additionally, the framework enhances privacy and security by processing data locally and minimizing the need for data transfer or reliance on cloud services. In summary, the proposed 3CSD MLOps workflow is designed to address the critical challenges in edge ML by filtering data at the edge, prioritizing essential information, and significantly reducing resource consumption while retraining. This is achieved through intelligent triage subsystems that efficiently manage data flow and determine which data should be processed by the MLOps pipeline. By ensuring that only the most relevant data is utilized for model updates, the framework conserves computational resources and improves training efficiency.

Lightning Talks

Martin Sanner University of Dundee	**An explainable model for solar active region detection towards evolution prediction** *Sanner, M., Meyer, K., McKenna, S.* Solar active regions are areas on the Sun's surface characterized by intense magnetic fields, and they are often associated with space weather events. These events can affect electronic systems on Earth and in its vicinity, making it essential to prepare for their occurrence. However, the definition of active regions is not uniform; different research teams focus on different parameters or apply distinct thresholds. We present a computer vision system for extracting candidate bipolar solar active regions, which can handle multiple definitions (thus allowing us to work with multiple databases), as well as tracking active regions through time. In this approach, active regions consist of two polarities combined according to an internal model assessing the viability of the total produced active region. By employing solar surface rotation models, we classify each candidate active region over time as either newly emerging or part of a previously tracked active region. These candidate active regions can then be compared to established active region databases, allowing us to explore the definitions of active regions and how they relate to the parameter preferences of the database creators. We evaluate our system's effectiveness through precision, recall, and average precision metrics, achieving an average precision of 79.9% on simulated synoptic magnetograms. Testing on historical synoptic (and eventually full-disk magnetograms) is ongoing, with our long-term goal being predicting the active region evolution over time through Physics-informed Machine Learning.
Alexandra Ruth Fogg Dublin Institute for Advanced Studies	**Wavelet Scattering Network for detection of Sudden Commencements** *Lo Presti, L., **Fogg, A. R.**, Dahyot, R., Domijan, K., Jackman, C. M.* Geomagnetic Sudden Commencements (SCs) are the Earth's electrodynamic response to rapid enhancements in solar wind dynamic pressure. The Earth's response to SCs is varied, but includes characteristic signatures in ground magnetometer data which are stratified in latitude and local time. While traditional detection methods for SCs rely on empirical criteria, in this study we present a machine learning approach to SC classification using both pure magnetometer signal, and that transformed using a wavelet scattering network (WSN). Better classification performance is demonstrated using WSN features, suggesting an intrinsic frequency component to the SC response. Additionally, without any information on the hours that follow the event, the models are able to distinguish whether or not SCs are followed by a geomagnetic storm.
Charles Bowers Dublin Institute for Advanced Studies	**Estimating Interplanetary Magnetic Field Conditions at Mercury's Orbit from MESSENGER Magnetosheath Observations using a Feedforward Neural Network** *Bowers, C.F., **Jackman, C.M.**, Azari, A.R., Smith, A.W., Wright, P.J., Rutala, M.J., Sun, W., Healy, A.* This work uses machine learning techniques to address the challenge of exploring planetary solar wind-magnetosphere interactions in the absence of an upstream monitor. Mercury's small magnetosphere is embedded in the dynamic and intense solar wind environment characteristic of the inner-heliosphere. Both the magnitude and orientation of the interplanetary magnetic field (IMF) traveling with the solar wind flow play a major role in the solar wind-magnetospheric interaction at Mercury, driving phenomena including the process of magnetic reconnection and the cycle of magnetic flux throughout the magnetosphere. The MErcury Surface, Space Environment, Geochemistry and Ranging (MESSENGER) spacecraft assessed Mercury's plasma environment by providing in-situ magnetic field measurements of the solar wind, the magnetosheath, and the magnetosphere along each orbit. However, the nature of single-spacecraft observations makes it difficult to directly measure the impact of the IMF on the Mercury's magnetosphere due to the temporal separation between sampling of these regimes, which often exceed 3 hours. Here, we present an feed-forward neural network (FNN) that estimates the strength and orientation of the IMF from the more than 250 days of magnetosheath observations obtained throughout the MESSENGER mission. The model was trained and tested on spacecraft position and magnetosheath magnetic field measurements to predict the magnitude and orientation of the IMF just upstream of the bowshock, thereby greatly increasing the temporal resolution of IMF measurements throughout the MESSENGER mission. The model achieves high accuracy predictions, increasing the temporal resolution of IMF estimates throughout the MESSENGER mission. Our results demonstrate how machine learning techniques can enhance our understanding of the relational complexity between the magnetosheath and magnetosphere.

Serhii Ivanov Dublin Institute for Advanced Studies	**Forecast horizon and the prediction of the geomagnetic Dst index** *Ivanov, S.* One of the most promising approaches to predicting the Dst index is to consider this index as a nonlinear dynamic system with input parameters from the solar wind and the output being the Dst index itself. This system theory allows for high-quality predictions up to a certain limit, known as the forecast horizon. To estimate the forecast horizon, it's necessary to calculate the largest Lyapunov exponent from a time series. The local largest Lyapunov exponent is also often used in practice. Earlier, it was reported that this exponent for the DST index is positive, which indicates a property of systems with chaotic behaviour. The forecast horizon is determined by the inverse of the largest Lyapunov exponent, which is estimated to be around 11-12 hours ahead. As the input in the model it is used the solar wind velocity multiplied by Bs. “B” is the hourly average of the field magnitude with three components “Bx”, “By", and “Bz”. “Bs” is the southward component of the IMF (interplanetary magnetic field). The southward component “Bs” = −”Bz” for “Bz” < 0; otherwise “Bs” = 0. Solar wind parameters were measured in the GSM coordinate system. “V” is the solar wind velocity (plasma (flow) speed) in km/sec. In 2001, the NARMAX approach was first applied to predict Dst index by Boaghe et al. It's proposed to use a polynomial function in the NARMAX model to create a high-quality model. The one-hour-ahead model obtained using the training set from the first 1000 hours of 2020 is of the NARX type, which is a part of the NARMAX model without noise, and it was tested during geomagnetic storms in May and October 2024.
Milo Buitrago Casas UC Berkeley	**Early and Actionable Flare Alerts for Large Solar Flare Observation Campaigns** *Buitrago-Casas, J. C., Vievering, J., Peterson, M., Cooper, K., Glesener, L., Savage, S., Emslie, G., Massa, P., Herde, V., Hudson, H., Narukage, N., Sato, Y., Athiray, P. S., Chamberlin, P., Reeves, K., and Winebarger, A.* Solar flares rank among the most energetic events in our Solar System, emitting bursts of radiation across the electromagnetic spectrum that can disrupt space weather—triggering phenomena like radio blackouts and increased satellite drag. Traditionally, operational flare products have focused on long-term probabilistic forecasts (estimating the likelihood of a flare of a specific magnitude occurring within a given period) and reactive flare alerts (signaling when flare intensity has already escalated), leaving a critical gap in short-term prediction capabilities. For both scientific research and practical space weather management, there is a clear need for predictions that are more actionable than probabilistic forecasts and that offer earlier warning than current alerts. Early detection of significant flares not only benefits space weather mitigation but also enables prompt, targeted observations of intriguing solar events. In response to this need, we are developing a real-time early solar flare alert system designed to use early flare onset signatures to forecast the magnitude and duration of subsequent eruptive events. In this contribution, we outline the concept behind this system and detail its first implementation, which successfully supported an unprecedented solar-flare-triggered sounding rocket mission in April 17, 2024 that captured observations of a large flare using advanced solar instrumentation. We also highlight the observational advancements required to further enhance the capabilities of this alert system in the future.