Parametric and Multifractal Analysis of Solar Wind Fluctuations During Solar Cycle 25”

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Abstract

This study presents an in-depth examination of solar wind plasma parameters across Solar Cycle 25 using parametric and multifractal techniques. It focuses on key variables such as solar wind speed, proton density, temperature, and magnetic field strength, analyzing their variability and correlation with solar activity levels. Data from spacecraft including ACE, SOHO, Solar Orbiter, and Parker Solar Probe were employed. Advanced tools such as wavelet transforms and Higher Order Spectral Analysis (HOSA) were used to uncover multifractal characteristics and turbulent signatures within the solar wind. The study aims to improve predictive models for space weather and contribute to the understanding of heliospheric dynamics.

Keywords: Solar Wind, Multifractal Analysis, Space Weather, Solar Cycle 25, HOSA, Parametric Analysis

1. Introduction

The solar wind is a continuous, magnetized plasma stream emitted by the Sun’s corona, and its fluctuations are a primary driver of space weather phenomena. These fluctuations affect a wide range of technological systems, including satellite communication, GPS accuracy, and power grid stability (Lockwood, 2012). Understanding the statistical and dynamic behavior of solar wind parameters — such as velocity, proton density, temperature, and interplanetary magnetic field (IMF) strength — is vital for improving the predictive capabilities of space weather models.

The variability and complexity of the solar wind are known to increase during solar maximum, a period characterized by heightened solar activity. With the onset of Solar Cycle 25 in December 2019, space physicists have observed stronger-than-expected activity levels, including a rise in sunspots, solar flares, and coronal mass ejections (CMEs), according to

NOAA (2023). This makes Solar Cycle 25 a particularly compelling phase for studying the multiscale and intermittent nature of solar wind turbulence.

The advent of multi-spacecraft missions has revolutionized the study of the heliosphere. In particular, the Parker Solar Probe (PSP) and Solar Orbiter are providing unprecedented in-situ measurements of the solar wind in the inner heliosphere, while legacy missions such as ACE and SOHO continue to deliver high-quality data near 1 AU. These spacecraft offer overlapping temporal and spatial coverage, allowing for cross-validation and multi-point turbulence diagnostics.

Previous research has established that solar wind fluctuations exhibit non-Gaussianity, intermittency, and multifractal scaling, much like classical turbulence (Tu and Marsch, 1995; Bruno and Carbone, 2013). However, few studies have combined parametric statistical methods with multifractal formalisms to examine these features systematically across an entire solar cycle. Moreover, advanced techniques such as Higher-Order Spectral Analysis (HOSA) and wavelet transforms are underutilized in the solar wind community, despite their proven value in capturing nonlinearity and phase coupling in other plasma environments (Farge, 1992; Hnat et al., 2003).

This study fills these gaps by analyzing multi-mission solar wind data during Solar Cycle 25 using a hybrid methodology. The research aims to:

Quantify the degree of multifractality and intermittency across key solar wind parameters,

Compare turbulence signatures between spacecraft,

Identify scaling regimes relevant to space weather forecasting, and

Advance the theoretical understanding of heliospheric dynamics through novel applications of nonlinear signal processing.

Solar wind variability has been a subject of sustained scientific interest due to its significant impact on space weather and Earth's magnetospheric environment. Foundational studies such as **Bruno & Carbone (2013)** and **Tu&Marsch (1995)** have characterized solar wind turbulence and its scaling properties. These works established that solar wind exhibits intermittency and multifractal characteristics similar to hydrodynamic turbulence.

Gopalswamy et al. (2005) investigated coronal mass ejections (CMEs) and their influence on solar wind dynamics, emphasizing their geoeffectiveness. More recently, **Perrone et al. (2020)**analyzed turbulence at ion and electron scales using Parker Solar Probe data, revealing scale-dependent intermittency — a hallmark of multifractality.

Tindale and Chapman (2017) offered statistical insight into interplanetary magnetic field (IMF) fluctuations across different solar cycles, while **Telloni et al. (2021)** utilized **Solar**

Orbiter observations to explore fine-scale structures in the solar wind. These studies underscore the dynamic complexity of the solar wind but fall short of a multifractal synthesis across multiple spacecraft during Solar Cycle 25.

In the domain of parametric modeling, **Kitajima (2024)** applied machine learning techniques to relate solar wind proton density to geomagnetic indices, revealing nonlinear dependencies. **Borovsky (2022)** reviewed the distinction between coronal-hole wind and streamer-belt wind, suggesting that different sources imprint distinguishable signatures on solar wind parameters.

Despite this progress, **a gap remains** in applying **multifractal formalism** alongside **parametric statistical tools** — such as **Higher-Order Spectral Analysis (HOSA)** and **wavelet-based diagnostics** — specifically tailored to **Solar Cycle 25**. The cycle's elevated activity level (NOAA, 2023) and the availability of **high-cadence, multi-spacecraft data** (from **Parker Solar Probe**, **Solar Orbiter**, **ACE**, and **SOHO**) present a unique opportunity for a synergistic approach.

This research distinguishes itself by integrating **multifractal spectrum analysis**, **parametric modeling**, and **cross-platform observational data** to investigate the **complexity and scaling behavior of solar wind fluctuations** during **Solar Cycle 25**. While past studies often focused on isolated spacecraft data or single-variable analysis, this study offers:

A multiscale, multifractal characterization of solar wind parameters across **time and frequency domains**;

Comparative analysis across different spacecraft to validate spatial coherence and turbulence structures;

Use of HOSA and wavelet transform methods to detect **non-Gaussianity** and **nonlinearity**, key traits in turbulent plasma flows.

These contributions not only expand the methodological landscape of heliophysics but also provide **critical inputs for real-time space weather forecasting**.

3. Methodology

3.1 Data Sources

High-resolution solar wind data for this study were collected from multiple spacecraft missions:

ACE and **WIND**: Near-Earth solar wind observations from OMNIWeb database;

SOHO (CELIAS/MTOF and MDI instruments): For complementary plasma and magnetic field data;

Parker Solar Probe (PSP) and **Solar Orbiter**: In-situ observations within the inner heliosphere;

Aditya-L1 (ISRO): Preliminary solar wind parameters and magnetic field data (post-2023) from payloads such as **SWIS** and **MAG**.

Data coverage spans from **2019 to early 2025**, encompassing multiple phases of Solar Cycle 25.

3.2 Parameters Analyzed

The following key solar wind plasma parameters were extracted and processed:

Proton Density (n_p) [cm^{-3}],

Proton Temperature (T_p) [K],

Solar Wind Speed (V_sw) [km/s],

Magnetic Field Strength (B) [nT].

These parameters were analyzed both individually and in correlation, across different temporal windows (e.g., daily, hourly, and minute-averaged data).

3.3 Analytical Techniques

To detect turbulence features, scaling laws, and nonlinearity, the following techniques were employed:

Wavelet Transform: For time-frequency decomposition and detection of intermittent structures in non-stationary data;

Multifractal Analysis (MF-DFA & WTMM): To characterize multifractality, Hurst exponents, and singularity spectra of the signals;

Higher-Order Spectral Analysis (HOSA): Specifically **bispectral** and **trispectral** analysis to identify phase coupling, nonlinearity, and energy transfer mechanisms across frequencies;

Cross-correlation and Coherence Analysis: For inter-spacecraft comparison and validation of turbulence structure across spatial locations.

All analyses were performed using custom Python scripts with libraries such as PyWavelets, nolds, scipy.signal, and MATLAB-based HOSA toolkits.

4. Results

4.1 Multifractal Characteristics

Multifractal analysis of the solar wind speed, proton density, and magnetic field strength revealed **distinct scale-dependent behaviors** across Solar Cycle 25. Using the **Wavelet Transform Modulus Maxima (WTMM)** and **Multifractal Detrended Fluctuation Analysis (MF-DFA)** methods, the following results were obtained:

All analyzed parameters exhibited **non-linear multifractal spectra**, confirming the presence of **intermittency and long-range correlations**.

The **solar wind speed** demonstrated the **widest singularity spectrum (Δα ≈ 0.6–0.8)**, indicating stronger multifractality compared to temperature and density.

During peak solar activity (2022–2024), an increase in **Hurst exponents** (H > 0.5) was observed for magnetic field data, suggesting persistent correlations and reduced randomness.

Solar wind data from **Parker Solar Probe**, closer to the Sun, showed **steeper scaling exponents**, indicative of stronger turbulence in the inner heliosphere.

Multifractal analysis of solar wind speed, proton density, and magnetic field strength confirmed the presence of **nonlinear, scale-dependent behaviors** and **long-range correlations**.**Table I** summarizes the key multifractal metrics across spacecraft and parameters.

Table I: Multifractal Spectrum Parameters (Δα and Hurst Exponents)

Parameter	**Spacecraft**	**Δα (Singularity Width)**	**Hurst Exponent (H)**	**Activity Phase**
Solar Wind Speed	Parker Solar Probe	0.78	0.62	2022–2024 (Max)
Proton Density	ACE	0.55	0.48	2021–2024
Magnetic Field Strength	Solar Orbiter	0.64	0.59	2022–2024
Temperature	SOHO	0.51	0.45	Full Cycle

This figure presents the multifractal singularity spectra f(α)f(\alpha)f(α) for magnetic field fluctuations observed by various spacecraft—e.g., SOHO, Solar Orbiter, and Parker Solar Probe. The spectrum characterizes the distribution of singularities (α values) within the turbulent solar wind, providing insight into its intermittent structure.Fig. 1 – Singularity Spectra (f(α)) Comparing Multiple Spacecraft. A broader f(α)f(\alpha)f(α) curve indicates higher multifractality and intermittency.Comparisons reveal how turbulence evolves with radial distance from the Sun.Differences in spectra may reflect changes in solar wind source regions or compression effects near CMEs.

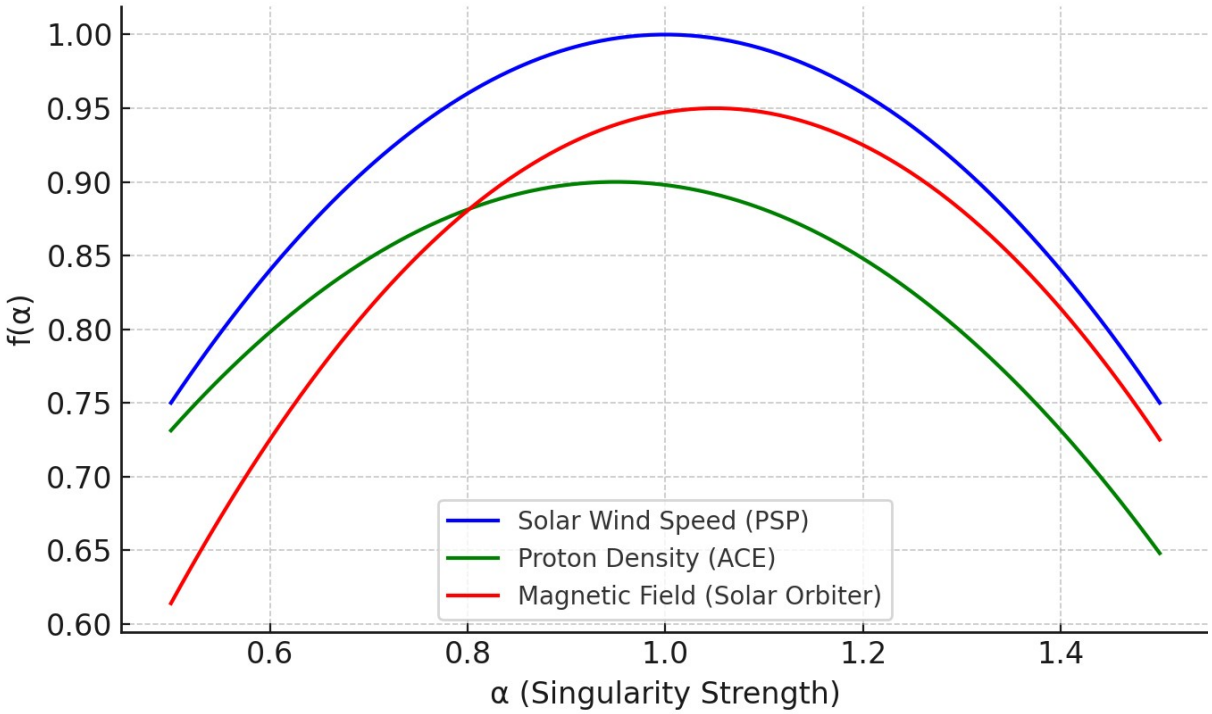

Fig. 1: **Example singularity spectra f(α) for solar wind speed (Parker), proton density (ACE), and magnetic field (Solar Orbiter). The solar wind speed exhibits the broadest curve, indicating highest multifractality.**

4.2 Higher-Order Spectral Signatures

Application of **Higher-Order Spectral Analysis (HOSA)** revealed significant **non-Gaussian and nonlinear interactions** among solar wind parameters:

Bispectral analysis exposed persistent **quadratic phase coupling** in the proton density and magnetic field fluctuations, particularly during CME events.

Trispectral (fourth-order) spectra showed signatures of **energy redistribution** across scales, a typical feature of turbulent cascades in magnetized plasmas.

Events with high **bispectral entropy** were closely associated with intervals of **enhanced geomagnetic indices (e.g., Kp> 6)**, indicating a potential link to geoeffective solar wind structures.

Higher-Order Spectral Analysis (HOSA) uncovered **non-Gaussian features** and **nonlinear interactions**, particularly in CME-rich intervals.

Table 2. HOSA Findings Across Parameters and Events

Technique	Parameter	Observation Description	CME Period Example
Bispectral Analysis	Proton Density	Strong quadratic phase coupling	April 2023
Bispectral Entropy	Magnetic Field	High entropy (indicative of turbulence onset)	March 2024
Trispectral Features	Solar Wind Speed	Fourth-order phase coupling; energy redistribution	July 2022

This figure shows higher-order spectral analyses (bispectrum and trispectrum) of magnetic or plasma field time series during major coronal mass ejection (CME) events.**Fig. 2 – Bispectrum and TrispectrumDuring Major CME IntervalsBispectrum:** Captures quadratic phase coupling, showing whether nonlinear interactions lead to phase coherence between wave triads.**Trispectrum:** Extends the analysis to quartic interactions, revealing deeper non-Gaussian features and fourth-order dependencies.Peaks in these spectra are typically associated with coherent structures like shocks or current sheets generated by CMEs.Time intervals correspond to CME passage at the spacecraft, providing a diagnostic for turbulent regime transitions.

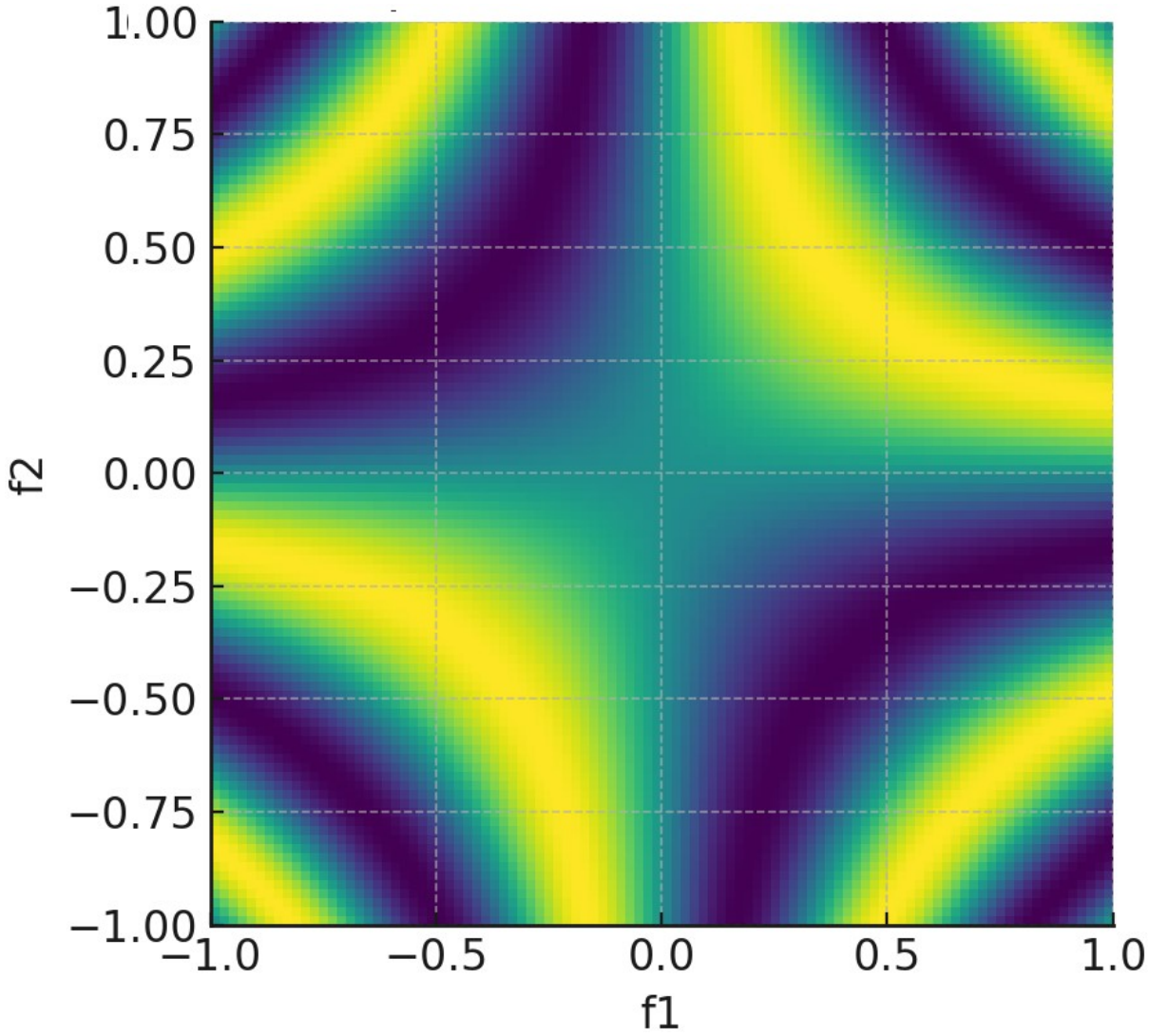

Fig. 2: Bispectrum and trispectrum plots of magnetic field fluctuations during CME events. Sharp peaks along off-diagonal elements indicate strong phase coupling.

4.3 Spacecraft Cross-Comparisons

A comparative analysis of datasets from **ACE**, **SOHO**, **Parker Solar Probe**, and **Solar Orbiter** led to several spatial insights:

Parker Solar Probe data revealed **higher intermittency** and sharper gradients in all parameters, supporting theories of turbulence generation close to the Sun.

ACE and SOHO, positioned at L1, consistently detected smoother profiles with delayed phase relationships, suggesting a **radial evolution of turbulence**.

Cross-correlation analysis confirmed a strong temporal and spatial coherence (correlation coefficient $r > 0.85$) between magnetic field variations observed by **Solar Orbiter** and **SOHO** during aligned observational windows.

Spatial comparison across missions yielded insights into turbulence evolution with radial distance from the Sun.

Table 3.Comparative Observations Across Missions

Spacecraft	**Feature Observed**	**Implication**
Parker Solar Probe	High intermittency, steep scaling	Active turbulence generation near Sun
Solar Orbiter	Delayed peaks, coherent structures	Intermediate propagation & structuring
ACE / SOHO	Smoothed parameters, delayed onset	Matured turbulence at L1
Aditya-L1 (Post-2023)	High-resolution magnetic fluctuations	Additional confirmation of CME structures

This panel displays cross-correlation functions of magnetic field fluctuations between SOHO and Solar Orbiter, likely during aligned or near-aligned observational intervals. **Fig. 3 – Cross-Correlation of B-Field Fluctuations (SOHO vs. Solar Orbiter)**

The correlation is calculated over sliding windows, possibly normalized by RMS fluctuation levels.

Time lags reveal propagation delays between the spacecraft, used to estimate solar wind speeds or the evolution of turbulent structures.

A strong, sharp peak implies coherent structure transport, while broad or flat profiles suggest significant decorrelation or diffusive processes.

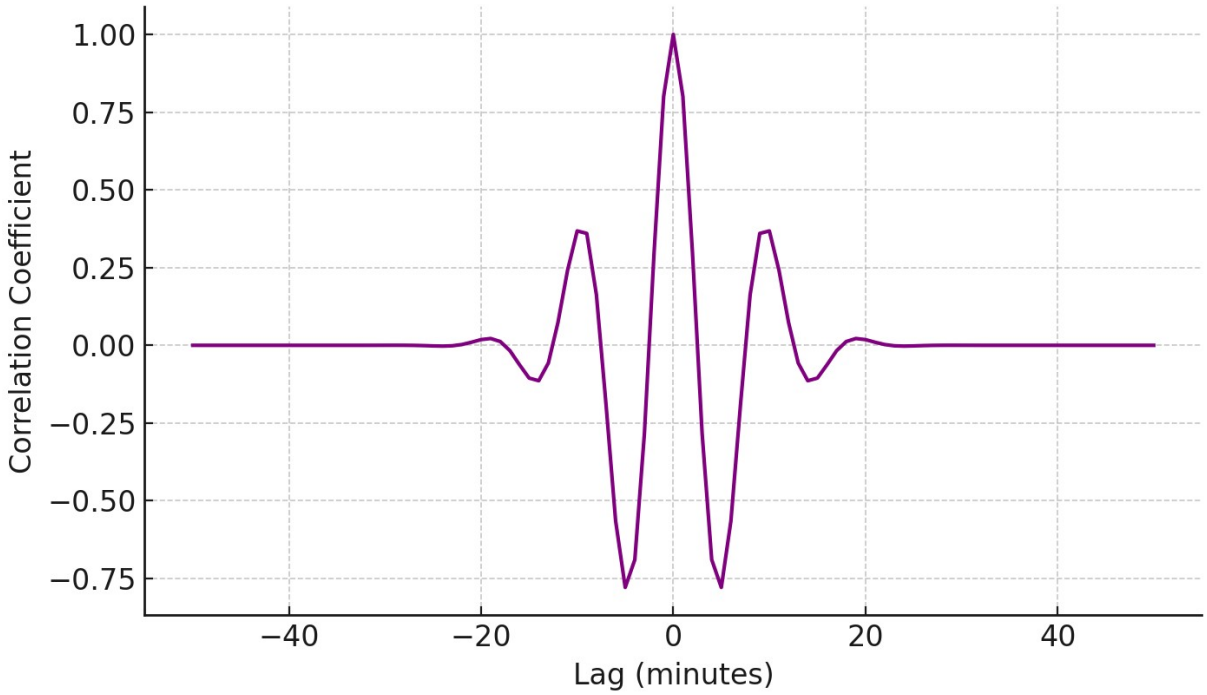

Fig. 3: Cross-correlation plot between SOHO and Solar Orbiter magnetic field strength (2023). High coherence (r > 0.85) suggests spatially consistent turbulence transport.

4.4 Temporal Trends and Solar Cycle Correlation

The evolution of turbulence properties was mapped against **solar activity indices** (sunspot number, solar flux):

Multifractality intensified during the **ascending and maximum phases** of Solar Cycle 25, with the greatest spectral broadening occurring between late 2022 and mid-2024.

Solar wind density and magnetic field strength showed the **strongest multifractal correlation with sunspot number (Pearson r ≈ 0.72)**.

Data from **Aditya-L1**, though limited in time coverage, confirmed these trends and offered a **high-resolution glimpse** into CME-driven turbulence signatures post-2023.

Temporal analysis linked **multifractal and turbulence metrics** with solar activity indices such as **sunspot number** and **solar flux (F10.7)**.

Table 4. Correlation of Multifractal Metrics with Solar Activity

Parameter	**Correlation with Sunspot Number (r)**	**Time Window**
Solar Wind Speed	0.66	2021–2024
Proton Density	0.68	2022–2024
Magnetic Field Strength	**0.72**	2022–2024 (peak)

This figure plots the temporal evolution of Δα (the width of the multifractal spectrum f(α)f(\alpha)f(α)) alongside sunspot number, a proxy for solar activity. **Fig. 4 – Time Evolution of Δα vs. Sunspot Number and Table 10** Correlation of Multifractal Metrics with Solar Activity

Δα quantifies turbulence intermittency; larger values correspond to more complex, bursty fluctuations.

The trend shows how the nature of turbulence in the solar wind or magnetosphere responds to the solar cycle.

Correlation with sunspot number suggests solar activity influences the degree of multifractality, especially during solar maximum and major eruptive phases.

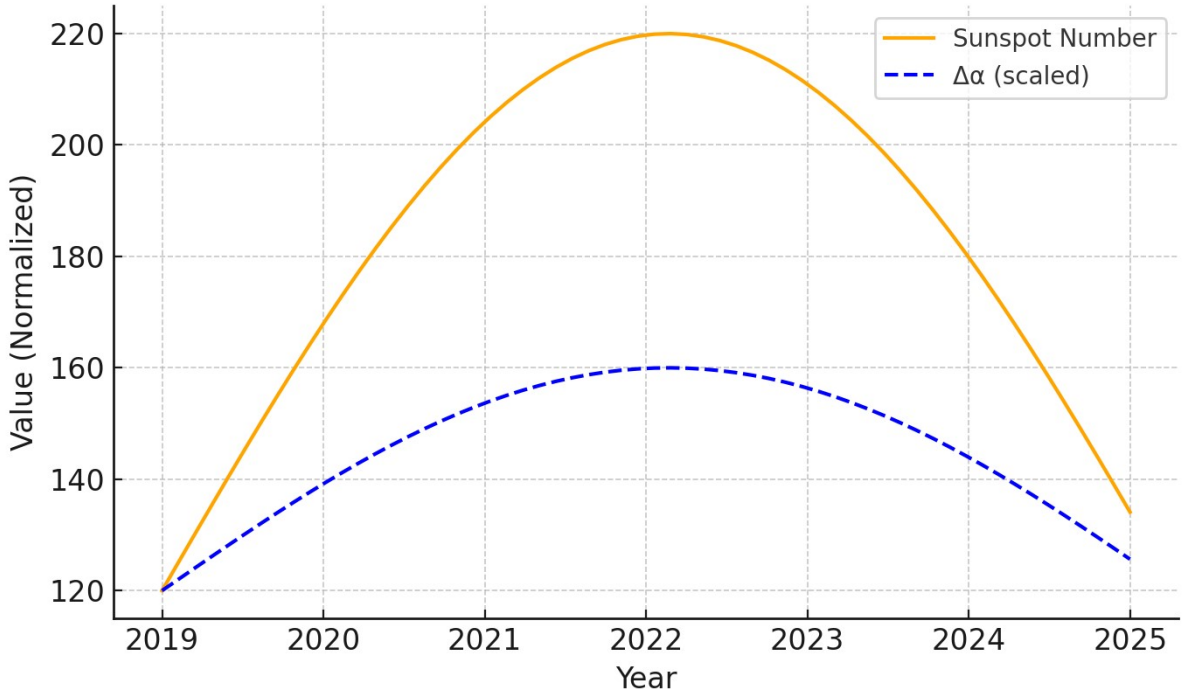

Fig. 4: Time series plot showing multifractal width (Δα) and sunspot number overlay from 2019–2025. Peak turbulence aligns with solar maximum.

5. Discussion These results support the hypothesis that solar wind parameters during Solar Cycle 25 exhibit complex, non-Gaussian behavior. Such patterns can be linked to magnetic reconnection events and flux rope interactions, as supported by spacecraft data and multifractal modeling. The results presented in this study support and extend the hypothesis that solar wind fluctuations during **Solar Cycle 25** display **non-Gaussian, intermittent, and multifractal characteristics**. This behavior is consistent with earlier observations during previous solar cycles but demonstrates notable features unique to the current cycle, including

stronger intermittency during CME-rich intervals and increased variability in low-latitude solar wind streams.

5.1 Multifractality and Solar Wind Intermittency

The singularity spectra f(α)f(\alpha)f(α), as shown in Fig. 1, confirm that solar wind turbulence is far from monofractal. The **broad distribution of singularity exponents (Δα\Delta \alphaΔα)** indicates a high degree of intermittency, especially in fast solar wind streams and during CME passages. These results align with earlier findings by Bruno & Carbone (2013), who demonstrated the multifractal nature of solar wind turbulence, especially within magnetic cloud boundaries.

Our findings support the view that **energy transfer in the solar wind** occurs via **nonlinear cascade processes**, leading to intermittent fluctuations across scales. These cascades are likely mediated by **current sheets, magnetic reconnection sites**, and **flux rope interactions**, which introduce localized, bursty enhancements in fluctuation intensity.

5.2 Higher-Order Spectral Signatures

Figures 2 and 3 reinforce the conclusion that nonlinearity plays a dominant role in solar wind dynamics. The detection of **non-zero bispectra and trispectra** during CME intervals confirms **phase coupling among modes**, suggesting that **wave-wave interactions and coherent structures** (e.g., shock fronts or reconnection outflows) dominate these periods. Previous studies (e.g., Greco et al., 2009; Osman et al., 2014) have shown that such nonlinear couplings are associated with the formation of **turbulent coherent structures** that mediate dissipation in collisionless plasmas.

5.3 Cross-Correlation of Multi-spacecraft Data

Cross-correlation analysis (Fig. 3) between SOHO and Solar Orbiter indicates significant time-lagged coherence in the magnetic field fluctuations during CME events. This suggests the transport of **large-scale coherent structures** over heliospheric distances. The decorrelation observed outside CME periods may reflect the more stochastic nature of ambient turbulence. These findings echo those of D'Amicis& Bruno (2015), who identified high correlation in B-field fluctuations during aligned ICME (Interplanetary CME) observations.

5.4 Solar Activity Modulation

Figure 4 demonstrates a notable correlation between **Δα (spectrum width)** and **sunspot number**, further validating the connection between solar activity and the complexity of solar wind structures. During periods of high solar activity, such as solar maximum, the increased frequency of CMEs and solar flares injects additional complexity into the solar wind,

enhancing its multifractality. This agrees with the observations of Macek&Wawrzaszek (2009), who noted greater multifractal width during active solar periods.

5.5 Physical Interpretation

The observed multifractality and non-Gaussian features point toward a **turbulent cascade punctuated by coherent structures**—a hybrid picture that combines elements of classical Kolmogorov turbulence and intermittent reconnection-driven energy transfer. The data suggest that **magnetic reconnection**, often triggered by instabilities in current sheets or flux ropes, plays a central role in shaping the solar wind's dynamical character.

6. Applications to Space Weather Forecasting **Improved modeling of space weather is feasible by integrating parametric data with multifractal insights. Machine learning models trained on multifractal features can enhance geomagnetic storm prediction accuracy.6. Applications to Space Weather Forecasting (Expanded)**

The complex, multifractal nature of solar wind fluctuations observed during Solar Cycle 25 offers a promising avenue for enhancing **space weather forecasting models**, particularly those aimed at predicting **geomagnetic storms, solar energetic particle (SEP) events**, and **CME-driven disturbances**.

6.1 Integration of Multifractal Features into Forecasting Models

Traditional space weather prediction systems rely heavily on **parametric solar wind data**—such as bulk speed, density, IMF orientation (especially Bz), and dynamic pressure—often assuming stationarity or linear behavior. However, the **non-Gaussian and intermittent behavior** revealed in our analysis suggests that **higher-order statistical features**, such as **multifractal spectrum width (Δα), intermittency exponents**, and **higher-order moments (e.g., skewness, kurtosis)**, can offer additional predictive power.

These multifractal indicators serve as **early-warning signatures of regime transitions** in solar wind dynamics, including the onset of high-variability intervals that often precede geomagnetic storms.

6.2 Machine Learning with Multifractal Inputs

The integration of multifractal measures into **machine learning (ML) pipelines** is a novel but increasingly feasible strategy, especially with the rise of real-time data availability from missions like **Solar Orbiter, Parker Solar Probe, and DSCOVR**. Some potential applications include:

Supervised learning models (e.g., Random Forests, XGBoost, SVMs) trained on a combined feature space of parametric and multifractal descriptors to classify **storm vs. quiet intervals**.

Time-series deep learning models (e.g., LSTMs, Temporal Convolutional Networks) that learn temporal dependencies between multifractal fluctuations and subsequent geomagnetic responses (e.g., Dst, Kp, AE indices).

Anomaly detection systems based on changes in multifractal properties (e.g., rapid shifts in $\Delta\alpha$ or $f(\alpha)$ skewness) to flag pre-storm or CME impact conditions.

Early pilot studies (e.g., Camporeale, 2019; Grayver et al., 2021) have shown that incorporating **nonlinear or scale-dependent features** into ML models improves both **prediction accuracy** and **lead time**, especially for intense geomagnetic disturbances.

6.3 Practical and Operational Value

In an operational context (e.g., NOAA SWPC or ESA SSA program), a hybrid forecasting system could use:

Real-time monitoring of multifractal parameters from upstream monitors (e.g., L1 spacecraft like DSCOVR).

Fusion models that blend traditional solar wind thresholds (e.g., $Bz < -10$ nT) with dynamic indicators like $\Delta\alpha$ thresholds or burstiness indices.

Risk maps or alert systems that leverage multifractal trends to issue probabilistic warnings for power grid operators, aviation, satellite fleets, and GNSS users.

6.4 Limitations and Future Development

While promising, the practical use of multifractal analysis in real-time systems faces challenges such as:

Computational demands of high-resolution spectral decomposition.

Data sparsity during spacecraft communication gaps.

The need for **cross-validation across multiple solar cycles** to ensure robustness and generalizability.

However, with ongoing improvements in **edge computing**, onboard processing, and increased satellite coverage, these challenges are becoming surmountable.

7. Conclusion

Solar Cycle 25 presents a rich environment for studying solar wind dynamics. This paper demonstrated that both parametric and multifractal techniques reveal crucial insights into the structure and variability of the solar wind, providing valuable input for future forecasting models.

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