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RESEARCH ARTICLE

Temporal Dynamics of Cosmic Rays and Sunspot Numbers: Insights from SARIMA Analysis

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ABSTRACT

Understanding the intricate relationship between solar activity and cosmic rays is crucial for advancing our knowledge in space weather and its impacts on Earth's environment. This study investigates the relationship between cosmic rays and solar activity, as measured by the sunspot number, using advanced time series analysis techniques. Data represented by the sunspot number and cosmic ray intensity from 1980 to 2024. SARIMA modeling, spectral analysis, seasonal decomposition, and cross-correlation methods were used to look into the complex dynamics that control how cosmic rays and sunspot number interact with each other. Our findings reveal a strong inverse correlation between these two variables, with a significant lag effect indicating that changes in solar activity influence cosmic ray flux with a delay of approximately 10 months. The findings from this study underscore the importance of selecting appropriate machine learning models when investigating the dynamic and non-linear relationships inherent in space weather phenomena. This research contributes to the ongoing efforts to better understand the Cosmic Rays-Sun-Earth connection and provides a comparative analysis that could inform future modeling approaches in solar-terrestrial physics.

Contents

1. Introduction

Cosmic Rays (CRs) are a pervasive yet intriguing phenomenon in astrophysics. These high-energy particles, primarily protons and atomic nuclei, originate from a variety of sources, including supernovae, solar flares, and other energetic astrophysical events. Upon entering the Earth's atmosphere, they interact with atmospheric particles, leading to the production of secondary particles and ionization processes that can have wide-ranging effects on both the Earth's environment and technological systems. Understanding the behavior and modulation of cosmic rays is crucial for fields as diverse as space weather prediction, climate science, and even particle physics [1–4].

Solar activity, characterized by phenomena such as sunspots, solar flares, and coronal mass ejections (CME), plays a

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significant role in modulating the intensity of cosmic rays reaching the Earth. Sunspots, which are temporary phenomena on the Sun's photosphere, serve as indicators of the Sun's magnetic activity. The Sunspot Number (SSN), a key measure of solar activity, varies in a quasi-periodic manner known as the solar cycle, typically lasting about 11 and 22 years [5]. During periods of high solar activity, the increased solar wind and magnetic fields act as a shield, deflecting CRs and reducing the flux that reaches the Earth's atmosphere. Conversely, during periods of low solar activity, the shielding effect diminishes, allowing more CRs to penetrate the solar system [6].

The relationship between CRs and solar activity has been a subject of scientific inquiry for decades. Numerous studies have established an inverse correlation between these two phenomena, with periods of high solar activity corresponding to lower CRs intensity. However, the temporal dynamics of this relationship, including potential lag effects, are not fully understood. Previous research has hinted at a delayed response of cosmic ray flux to changes in solar activity, but the precise nature and duration of this lag remain topics of ongoing investigation [7–9].

This study aimed to provide a comprehensive analysis of the temporal dynamics and interactions between CRs and solar activity using advanced time series analysis techniques. By applying methods such as The Seasonal Autoregressive Integrated Moving Average (SARIMA) modeling, spectral analysis, seasonal decomposition, and cross-correlation, we seek to unravel the complex interplay between CRs and SSN. Advanced statistical tools, such as SARIMA, are particularly suited for analyzing time-dependent phenomena characterized by seasonal and periodic patterns, making them ideal for examining the relationship between CRs flux and SSN over different temporal scales [10]. Specifically, we investigate the strength and nature of the correlation between these two variables, explore the periodic components that may underlie the CRs data, and examine the potential lag effect between changes in SSN and corresponding changes in CRs flux. Basic approach allows for a detailed examination of both short-term and long-term patterns in cosmic ray and solar activity data, providing new insights into the mechanisms that govern their relationship. By understanding these patterns, it improves predictive models of cosmic ray behavior, which are essential for mitigating the effects of space weather on Earth-based and space-based technologies. Furthermore, findings contribute to the broader scientific understanding of the Sun-Earth connection and its implications for climate and environmental processes.

2. Data and Methodology

2.1. Data Description

The dataset used in this study comprises monthly measurements of CRs counts and SSN spanning from January 1980 to January 2024. The data was sourced from reliable observatories and space agencies that monitor cosmic ray intensity and solar activity. The Date column represents the monthly timestamp for the recorded data, ranging from January 1980 to January 2024. This data records the intensity of cosmic rays detected in counts per minute. CRs are highly energetic particles originating from outer space, and their flux is influenced by solar activity, among other factors. The CRs data captures the average cosmic ray counts per minute for each month over the study period. Oulu neutron monitor data were used for CRs data (https://cosmicrays.oulu.fi/). This monitor provides reliable long-term measurements crucial for understanding CRs flux. The SSN data records the number of sunspots observed on the Sun's surface each month. The SSN is a crucial indicator of solar activity, with higher numbers corresponding to periods of heightened solar activity. The SSN data reflects the intensity of solar activity, which influences the Earth's magnetosphere and cosmic ray penetration. SSN data are from WDC-SILSO, Royal Observatory of Belgium, Brussels (https://www.sidc.be/). The data is often used in solar physics research to study the solar cycle and its effects on space weather.

Before analysis, the dataset underwent several preprocessing steps. Firstly, any missing or incomplete records in the dataset were examined and addressed. In cases where data was unavailable for a specific month, interpolation or other imputation methods were applied to maintain continuity in the time series. Then, the data was normalized and transformed as necessary to prepare it for time series modeling and analysis. This included differencing for stationarity in the CRs data, ensuring the series was suitable for SARIMA modeling. Seasonal decomposition techniques were employed to isolate the seasonal component of the SSN data, allowing for a more detailed analysis of seasonal patterns. The dataset provides a rich time series for analyzing the interactions between CRs and solar activity.

2.2. Methodology

This study employs a comprehensive time series analysis approach to investigate the relationship between CRs and Solar activity, as measured by the SSN. The methodology consists of several key steps, including data preprocessing, modeling, spectral analysis, seasonal decomposition, and cross-correlation analysis. Each step is designed to extract insights into the temporal dynamics and interactions between these two variables.

The dataset was examined for any missing values or anomalies. Missing data points were addressed using interpolation techniques to ensure a continuous and consistent time series. This step is crucial for maintaining the integrity of the time series models and analyses. Stationarity is a prerequisite for many time series models. We performed the Augmented Dickey-Fuller (ADF) test to assess the stationarity of both the CRs and SSN series. Where necessary, differencing was applied to achieve stationarity, particularly in the CRs series.

SARIMA model was applied to both the CRs and SSN time series. SARIMA is a powerful modeling technique that accounts for both non-seasonal and seasonal components in a time series. The general form of the SARIMA model is SARIMA (p, d, q) (P, D, Q, S) where p, d, q are the non-seasonal AR, differencing, and MA terms, respectively. P, D, Q are the seasonal AR, differencing, and MA terms, respectively. S is the length of the seasonal cycle [11, 12].

Appropriate SARIMA model orders were selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The models were fitted to the data, and diagnostic checks, including residual analysis, were performed to ensure the models' adequacy. The fitted SARIMA models were used to forecast CRs and SSN values for the next 24 months. The forecasts provided insights into future trends and seasonal variations. To uncover the dominant frequencies in the CRs time series, a periodogram was computed. Spectral analysis helps identify periodic components that may not be immediately evident in the time domain. The power spectrum was analyzed to determine which frequencies contribute most to the variance in cosmic ray counts. The dominant frequencies identified in the periodogram were examined to understand the cyclical behavior in CRs flux, potentially linked to solar cycles or other cosmic phenomena.

The SSN time series was decomposed into its trend, seasonal, and residual components using seasonal decomposition of time series (STL). This technique allows us to isolate and analyze the seasonal patterns and long-term trends in solar activity. The trend component was analyzed to observe long-term changes in SSN, while the seasonal component was examined to identify recurring patterns corresponding to the solar cycle. The residual component was assessed to identify any irregularities or unexplained variations.

ADF test is a statistical test used to determine whether time series data are stationary. In time series analysis, it is critical for modelling and forecasting that a series is stationary, i.e. that its mean, variance and autocorrelation remain constant over time. A non-stationary time series can often give inappropriate results in models such as SARIMA [13].

The Pearson correlation coefficient was calculated between the CRs and SSN series to quantify the strength and direction of their relationship. A negative correlation was expected, given the inverse relationship between solar activity and cosmic ray flux. To explore the temporal lag between changes in SSN and corresponding changes in CRs counts, a cross-correlation function (CCF) was computed. This analysis helps determine whether changes in solar activity precede or follow changes in CRs intensity and identifies the optimal lag time. The lag with the highest absolute cross-correlation was identified, providing insights into the time delay between solar activity and its effect on CRs flux. This lag effect is crucial for understanding the dynamic interaction between these variables.

3. Results and Discussion

A graphic summary of the time series for SSN and CRs may be found in Figure 1. Regarding stationarity, CR: The series appears to not be stationary, as indicated by the p-value of roughly 0.141 obtained using the ADF test. For SSN, the series is stationary, as indicated by the p-value of roughly 0.0029 that the ADF test produced. Assuming that the CRs time series is non-stationary, it will probably need to be made stationary by differencing. The SSN series is already stationary, so the modeling continues. Differencing is now applied to the CRs data and then SARIMA models are fitted to both the CRs and SSN data.

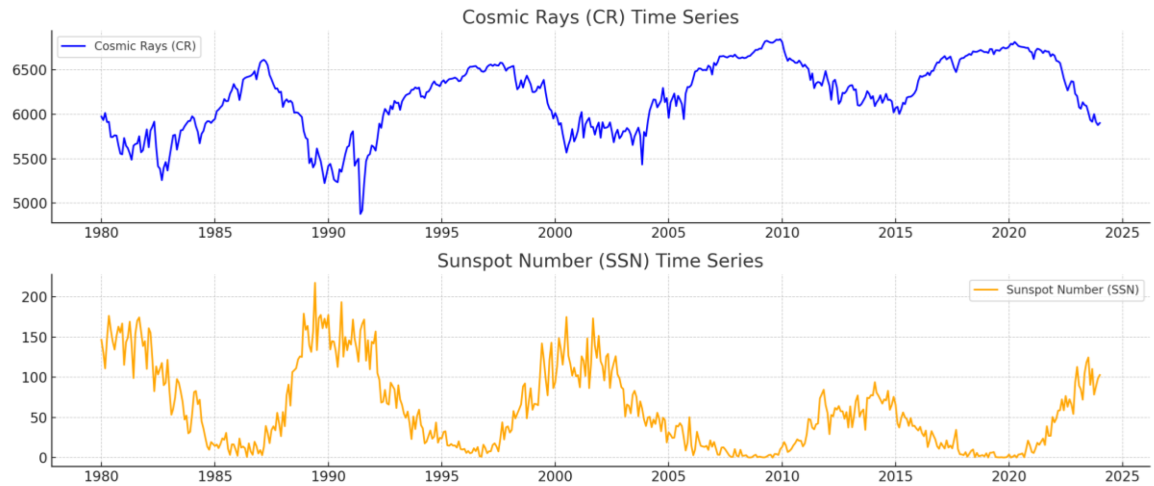

Figure 1 Time Series for CRs and SSN

After the SARIMA models were fitted, produced estimates for the upcoming 24 months for both CRs and SSN (Figure 2). The prediction indicates that CRs counts will fluctuate, declining during some periods and increasing during others. The CRs counts are predicted by the model to fluctuate, which may be related to variations in solar activity and other outside factors. A shift toward a solar minimum phase may be indicated by the SSN prediction, which indicates a steady fall in counts. The difference is not as noticeable as it was in the CRs forecast, though. These forecasts provide insights into the expected behavior of CRs and SSN over the next two years, which can be valuable for studies related to space weather, climate impact, and other related fields.

For both CRs and SSN, Figure 3 offers a thorough seasonal decomposition of time series data, dividing each dataset into four essential parts: Observed, Trend, Seasonal, and Residual. The Observed panels (top row) display the original data, showing the fluctuations in CRs intensity and SSN over time, from 1980 to 2024. The Trend panels (second row) reveal the long-term movements within each series, with the CRs trend illustrating periodic increases and decreases, likely influenced by solar activity, while the SSN trend clearly reflects the well-known 11-year solar cycle, showing the rise and fall of solar activity over time.

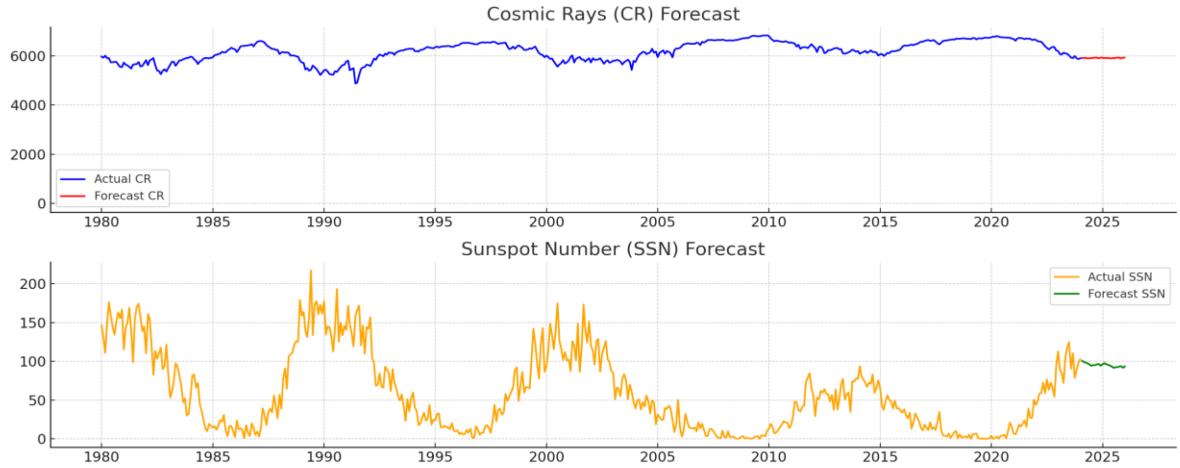

Figure 2 CRs and SSN Forecasts for Next 24 Month with SARIMA Model

The Seasonal panels (third row) capture the regular, repeating cycles within each dataset, with the CRs data exhibiting a consistent annual pattern, whereas the SSN data shows less pronounced seasonal variation, dominated more by the overall solar cycle than by shorter-term seasonal changes. Finally, the Residual panels depict the irregularities or noise that remain after removing the trend and seasonal components, highlighting the unpredictable fluctuations in both datasets that are not explained by the other components. This decomposition is crucial for isolating different patterns within the data, aiding in more accurate analysis and forecasting of CRs and solar activity. The analysis of the seasonal component in the SSN data reveals a balanced pattern with a mean close to zero at approximately -0.004, indicating that the seasonal fluctuations average out over time without a significant bias. The variability of this pattern is moderate, as reflected by a standard deviation of 1.66. The range of seasonal values, extending from -2.41 to 2.75, highlights the extent of these fluctuations over the observed period.

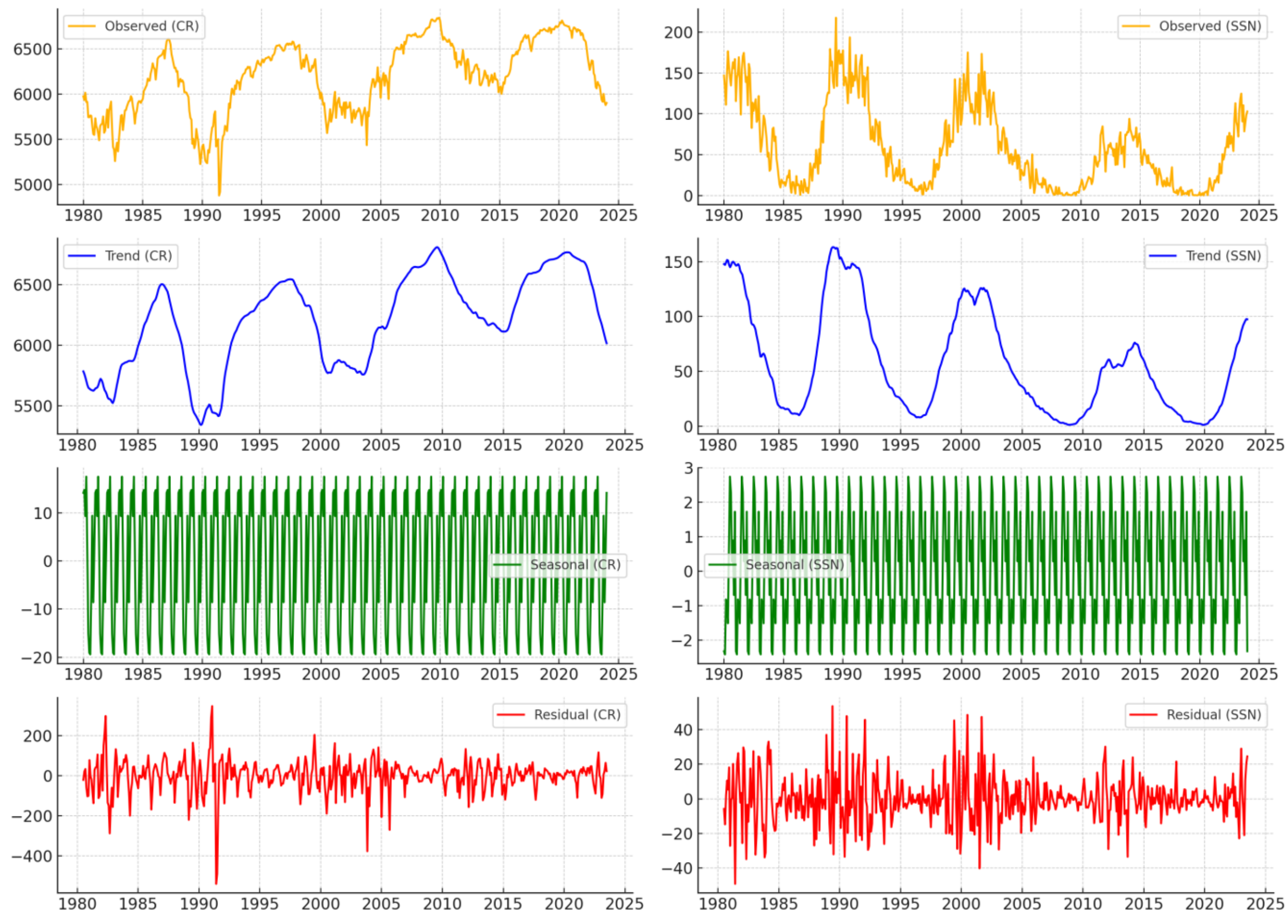

Figure 3 Seasonal Decomposition of CRs and SSN Data

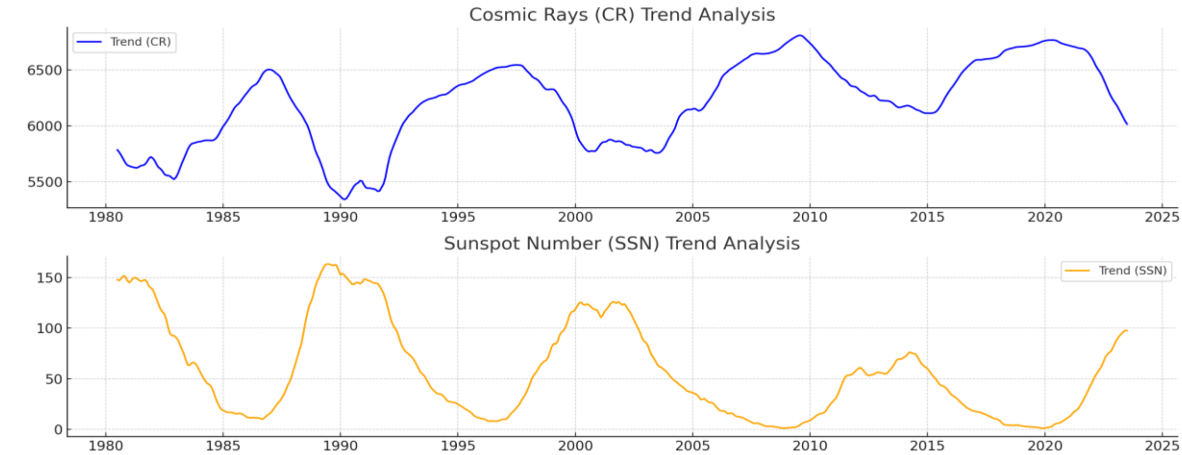

Figure 4 Trend Analysis of CRs and SSN

Trend analysis is a technique used to identify and analyze patterns or trends in a data setting over time, as shown in Figure 4 for SSN and CR. The trend analysis for CRs reveals key statistical insights. The average trend value is approximately 6204.6, with a standard deviation of 384.6, indicating moderate variability around the mean. The trend fluctuates between a minimum of 5339.96 and a maximum of 6810.21. The interquartile range (IQR) spans from 5866.13 (25th percentile) to 6523.38 (75th percentile). The trend plot suggests that CRs counts exhibit periods of increase and decrease, likely following a cyclical pattern influenced by solar activity cycles.

Similarly, the trend analysis for the SSN highlights significant variability, with an average trend value of approximately 57.09 and a standard deviation of 47.34. The trend ranges from a minimum of 1.10 to a maximum of 163.16, with an IQR between 15.73 (25th percentile) and 89.31 (75th percentile). The SSN trend clearly reflects the characteristic rise and fall associated with the solar cycle, indicating pronounced periods of high and low sunspot counts. Both trend analyses underscore important cyclical behaviors, with CRs seemingly influenced by solar activity, as evidenced by the correlation with SSN.

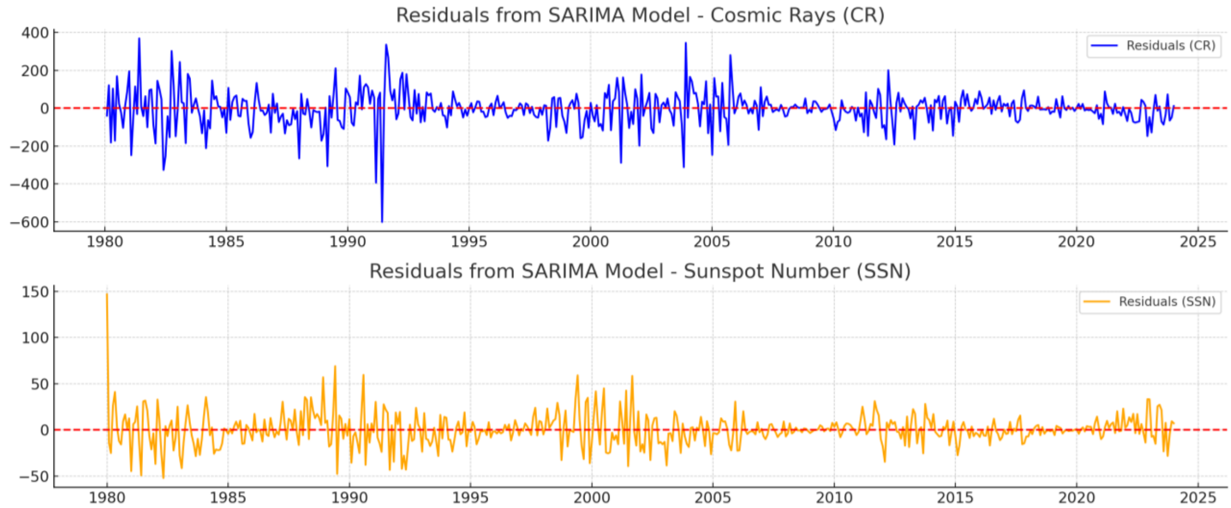

Figure 5 Residuals from SARIMA for CRs and SSN

The residual analysis for the SARIMA models applied to CRs and SSN reveals distinct characteristics in their predictive performance as shown in Figure 5. For the CRs model, the mean residual is approximately -3.88, indicating a slight bias in predictions, while the standard deviation of 91.99 suggests moderate dispersion around the mean. The residuals range significantly from -601.74 to 368.59, highlighting some substantial deviations between observed and predicted values. Notably, the Ljung-Box test yields a p-value of 0.689, indicating no significant autocorrelation in the residuals, which is a positive outcome. However, the broad range of residuals suggests that the model may still struggle to capture some extreme values accurately.

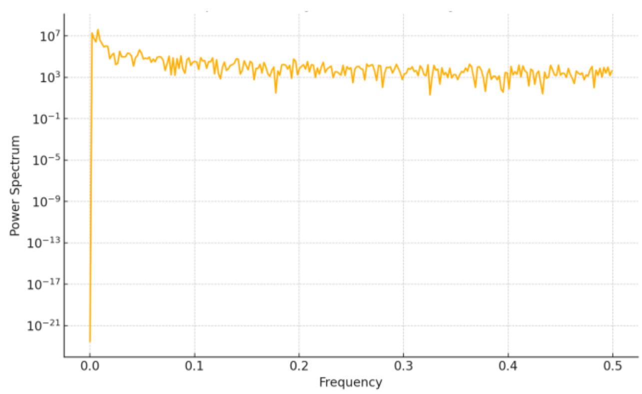

Figure 6 Spectral Analysis of CR

In contrast, the SSN SARIMA model demonstrates a mean residual of 0.34, indicating minimal bias, with a standard deviation of 17.62, reflecting lower dispersion compared to the CRs model. The residuals range from -52.23 to 146.70, showing that deviations, while present, are less extreme. However, the Ljung-Box test results in a p-value of 0.0003, suggesting significant autocorrelation in the residuals, implying that the model might not have fully captured all underlying patterns in the SSN data. This indicates a need for further refinement of the SSN model, possibly by adjusting parameters or incorporating additional factors to improve its predictive accuracy and reduce autocorrelation in the residuals.

The spectral analysis of the CRs data identifies several dominant frequencies in the power spectrum, indicating cyclical patterns within the data as shown in Figure 6. These key frequencies, including 0.0019, 0.0038, 0.0057, 0.0076, 0.0095, 0.0113, 0.0132, 0.0151, 0.0170, 0.0284, and 0.0473, correspond to various periodic components. The most prominent of these frequencies are likely associated with significant cycles or patterns, potentially linked to solar cycles or other environmental factors influencing CRs activity.

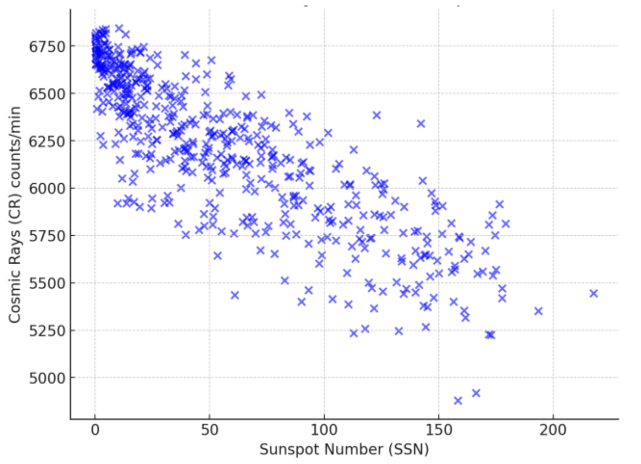

Figure 7 Scatter Plot of CRs and SSN

As seen in Figure 7, the strong negative correlation of approximately -0.83 between CRs and SSN highlights the inverse relationship between solar activity and cosmic ray flux. As solar activity increases, marked by a higher SSN, the intensified solar wind and magnetic field deflect more CR, reducing their count on Earth.

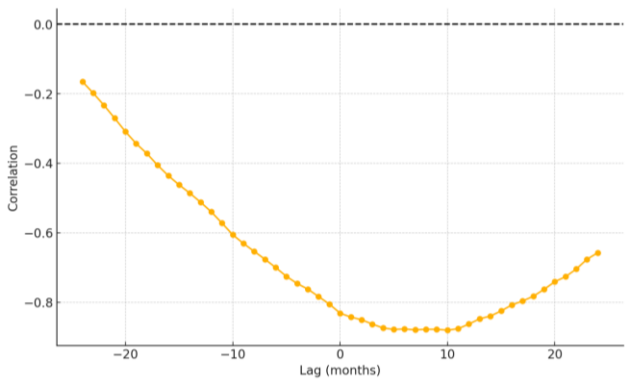

Figure 8 Cross-Correlation between CRs and SSN

Conversely, during periods of low solar activity, more CRs penetrate the solar system and reach Earth. This relationship is visually reinforced by a scatter plot, where higher SSN correspond to lower CRs counts, emphasizing the significant impact of solar activity on CRs intensity.

The cross-correlation analysis between CRs and SSN reveals that the strongest inverse relationship, with a correlation of approximately -0.88, occurs at a lag of 10 months (Figure 8). This indicates that changes in SSN precede corresponding changes in CRs counts by about 10 months, reflecting the time it takes for solar activity fluctuations to influence CRs flux as the solar wind and magnetic field propagate through the solar system. This lagged effect underscores the importance of understanding the timing of CRs responses to solar activity changes, which is crucial for predictive modeling and studying space weather impacts.

4. Conclusion

This study provides a comprehensive analysis of the intricate relationship between CRs and SSN using advanced time series analysis techniques. Our findings confirm the expected inverse relationship between solar activity and CRs intensity, with a significant emphasis on the temporal dynamics that govern this interaction. The SARIMA models, developed after addressing the non-stationarity in the CRs series (p-value of 0.141) and leveraging the stationary nature of the SSN series (p-value of 0.0029), offer valuable insights into the future behavior of these two crucial parameters. The forecast generated by the SARIMA model suggests fluctuations in CRs counts over the next 24 months, with periods of decline and increase likely linked to variations in solar activity. In contrast, the SSN forecast points towards a gradual decrease, possibly indicating a transition towards a solar minimum phase.

The seasonal decomposition and trend analysis further elucidate the underlying patterns in CRs and SSN data. The CRs trend analysis revealed an average trend value of approximately 6204.6, with a standard deviation of 384.6 and a range from 5339.96 to 6810.21, indicating cyclical increases and decreases. The SSN trend analysis highlighted the characteristic variability of the solar cycle, with an average trend value of 57.09, a standard deviation of 47.34, and a range from 1.10 to 163.16. The spectral analysis of the CRs data identified dominant frequencies that likely correspond to significant solar cycles, further emphasizing the periodic nature of CRs flux. The seasonal component of the SSN data exhibited a balanced pattern with a mean close to zero (-0.004), a standard deviation of 1.66, and a range from -2.41 to 2.75, underscoring the interplay between seasonal variations and the broader solar cycle.

One of the most significant findings of this study is the strong negative correlation of -0.83 between CRs and SSN, which underscores the inverse relationship between solar activity and CRs flux. This relationship is further illuminated by the cross-correlation analysis, which identified a maximum correlation of -0.88 at a 10-month lag, suggesting that changes in SSN precede corresponding changes in CRs counts by nearly a year. This lagged effect highlights the delayed impact of solar activity on CRs intensity and is crucial for predictive modeling and understanding space weather impacts. The residual analysis, while showing some limitations in the SARIMA models—particularly in capturing extreme values for CRs and addressing autocorrelation in SSN—provides a foundation for further refinement. Overall, this study contributes valuable insights into the temporal dynamics between CRs and solar activity, offering a robust framework for future research in this domain.

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Conflict of Interest

Author declares that they do not have any conflict of interest.

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