Temporal Dynamics of Solar X-ray Flux: A Robust Autocorrelation and PCA Analysis of GOES Data

Understanding the temporal structure of solar X-ray flux is critical for characterizing patterns of solar variability, particularly those related to flares and transient energetic events. High-frequency X-ray measurements from geostationary satellites like GOES provide a rich time series for studying the fine-scale dynamics of solar emissions. However, the extreme skewness, high noise levels, and non-stationary nature of the data pose challenges for conventional time series analysis, especially when evaluating autocorrelation properties over extended periods. Temporal dependence (how current observations relate to past values) can offer insights into the underlying processes governing solar activity. Short-term autocorrelation may reflect lingering flare activity or decaying turbulence, while longer memory structures could indicate persistent regimes or solar rotation effects. However, such dependencies are unlikely to remain constant over time, especially during years with fluctuating solar conditions.

In this study, we investigate how the autocorrelation structure of GOES X-ray flux varies over time using robust, nonparametric methods. We specifically examine whether dominant modes of temporal dependence differ between two years, 2017 and 2019, using block-wise Kendall tau autocorrelations and Principal Component Analysis (PCA) to identify and summarize patterns in the data.

For this analysis, we look into the temporal dependence structure of solar X-ray flux measurements obtained from the GOES satellite time series (containing 14 million observations). The time series consisted of high-frequency X-ray flux observations sampled every two seconds. The distribution of flux values is extremely skewed and exhibits non-stationarity making it difficult to interpret the autocorrelation function. Therefore, we will perform a block-wise autocorrelation analysis using robust rank-based measures. To do this, the time series was divided into blocks of approximately 4 hours, consisting of about 8000 observations. This block size provides sufficient resolution for capturing local autocorrelation structure while also maintaining a manageable level of non-stationarity within each block.

Within each block, we computed the Kendall tau autocorrelation at a sequence of time lags ranging from 1 to 190 time steps (about 2 - 380 seconds/ 0.03-6.3 minutes). For each lag, the autocorrelation between the original block and its lag-shifted version was estimated. This created a lag-by-block matrix of Kendall autocorrelations. The variation of Kendall tau autocorrelation was visualized by randomly subsetting 100 block-wise autocorrelation functions and graphing a spaghetti plot. We then computed and plotted the 25th, 50th, and 75th percentiles of the autocorrelation values across blocks for each time lag.

Additionally, Principal Component Analysis (PCA) was applied to the mean-centered autocorrelation matrix to reduce the dimensionality of variation in block-wise autocorrelation functions. The first two principal components were analyzed to characterize cominate modes of variation in the autocorrelation structure across blocks. We examined the first two PCs and visualized their effect on the mean autocorrelation curve by adding and subtracting one standard deviation of the corresponding PC scores. To further investigate temporal trends in the autocorrelation structure, we projected each block onto the first two PCs and plotted the resulting scores as a function of time. LOWESS smoothing (locally weighted scatterplot smoothing) was applied with a 10 percent bandwidth to capture slow-moving trends in each component score time series. This can determine if the principal component is trivial or non-trivial (statistical good).

To assess interannual differences in short-term temporal dependence structure, we repeated the above methods separately for data for both 2017 and 2019. Specifically, we can compare the smoothed PC score trajectories between years to evaluate changes in dominant autocorrelation patterns over time.

After estimating block-wise Kendall tau autocorrelations, Figure 1 shows a representative subset of the curves for 2017 and 2019. In 2017, many blocks maintain high tau values (less than 0.8) at short lags (0 to 0.5 minutes), indicating strong monotonic dependence over brief intervals. A rapid drop within the first 2 minutes suggests that the X-ray flux signal has limited short-term memory, likely reflecting quick fluctuations in solar activity. Beyond 3 minutes, autocorrelation patterns diverge, with tau values ranging from near zero to about 0.7, pointing to non-stationarity and variable temporal structure across blocks.

These observations are reinforced by the quantile summary in Figure 2. All three quantiles (25th, 50th, 75th) decline sharply, highlighting that most blocks lose dependence quickly. However, the 75th percentile remains comparatively elevated, indicating that a subset of blocks retain longer memory or more structured dynamics. This heterogeneity suggests bursts of prolonged coherence within an otherwise rapidly changing signal.

In contrast, 2019 shows a more uniform decay across blocks, with tau values dropping faster and the upper quantile (75th percentile) declining more steeply reaching about 0.15 by 6 minutes. This suggests that fewer blocks sustain long-term dependence in 2019, and the signal is generally more short-lived in its monotonic structure. The reduced spread and faster decay collectively suggest that the 2019 data had more transient and less variable dynamics than 2017.

Principal Component Analysis (Figures 3 and 4) further characterizes this contrast. PC1 represents overall elevation or suppression of autocorrelation curves. The wider red-blue spread in 2017, especially at short lags, indicates broader variation in short-term dependence. By contrast, 2019 displays a narrower range, suggesting more consistency across blocks. This reduced heterogeneity supports the interpretation that the 2019 signal is less dynamic, with fewer block-level deviations. PC2 captures differences in curvature between short and longer lags. In 2017, the divergence between the red and blue curves around 1 to 2 minutes is more pronounced, implying a sharper transition from high to low correlation, which is consistent with episodic behavior. In 2019, PC2 has less curvature and subtler deviation from the mean, again supporting a more uniform and possibly lower-activity regime.

The temporal dynamics of these components are shown in Figures 5 and 6. In 2017, PC1 scores fluctuate throughout the year, with the smoothed red line indicating periodic structure. These trends suggest episodic shifts in autocorrelation magnitude, likely driven by recurring bursts or changes in solar conditions. In 2019, PC1 scores show concentrated activity early on, followed by a long period of low variation. The flat post-midyear trend implies a reduction in dynamical variability, consistent with fewer or less intense solar events later in the year. PC2 scores also differ between years. In 2017, the trend line shows broad, slow oscillations, reflecting gradual shifts in the balance between short- and long-lag dependence. In 2019, scores are noisier and less structured, suggesting weaker or more sporadic transitions in temporal structure. This supports the idea that 2019 data is more temporally stable, with fewer large-scale changes in dependence patterns over time.

This analysis reveals clear interannual differences in the temporal dependence structure of solar X-ray flux between 2017 and 2019. The 2017 data exhibited more heterogeneous and persistent autocorrelation patterns, with greater variation across blocks and stronger short-term memory, likely reflecting heightened or more complex solar activity. In contrast, the 2019 data showed faster decay in autocorrelation and more uniform dynamics, suggesting a quieter, more stable solar environment. These findings highlight the utility of robust, block-wise autocorrelation analysis and PCA in uncovering subtle shifts in solar behavior across time and provide a statistical basis for linking time series structure to solar activity regimes.

Thanks for a great semester, Julian! Good luck on your future endeavors :)

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Figures

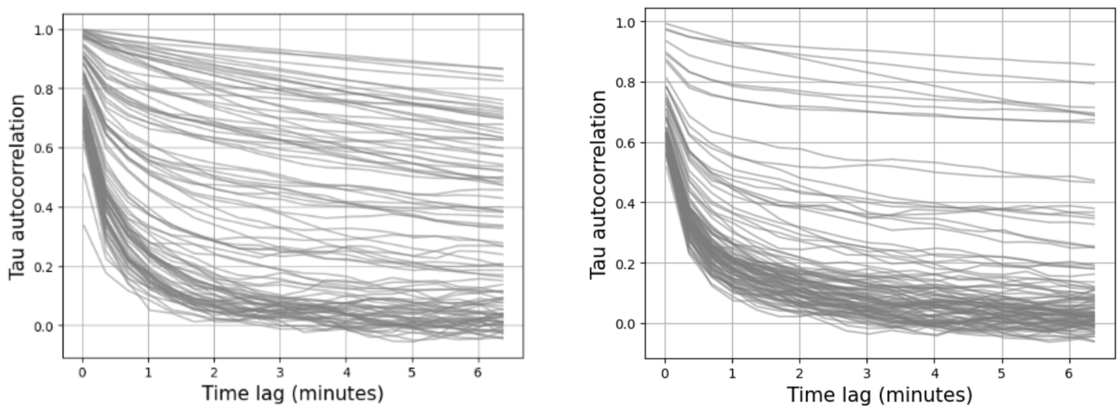

Figure 1: Tau autocorrelation vs. Time lag for 2017 (left) and 2019 (right).

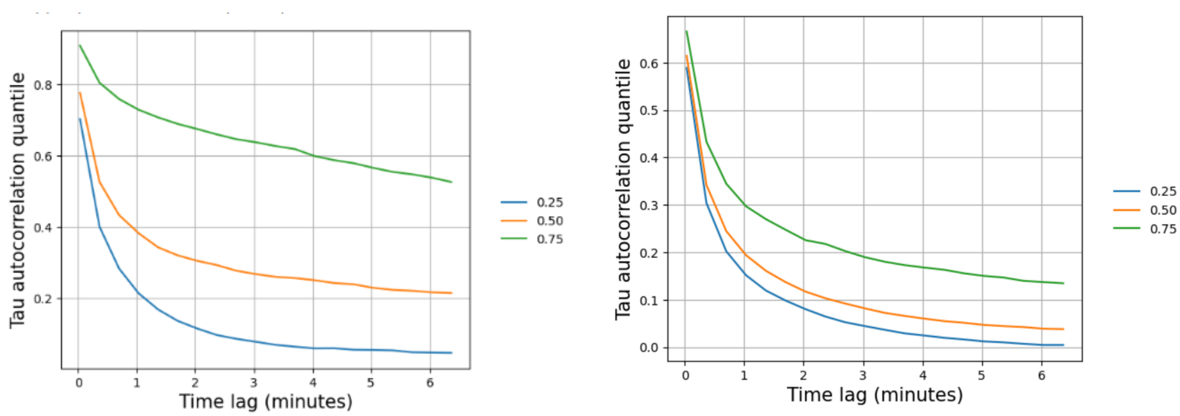

Figure 2: Plot of Tau correlation quantile vs. Time lag for 2017 (left) and 2019 (right).

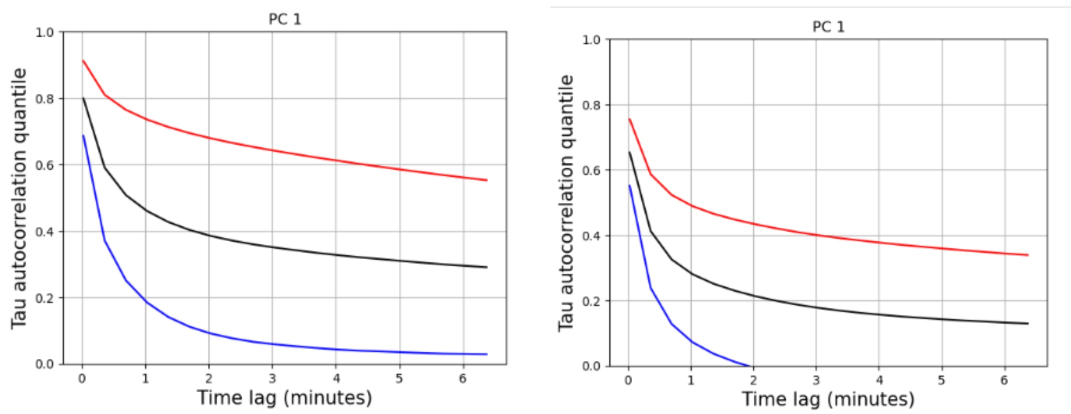

Figure 3: PC1 (mean autocorrelation +/- each PC for 2017 data (left) and 2019 data (right)

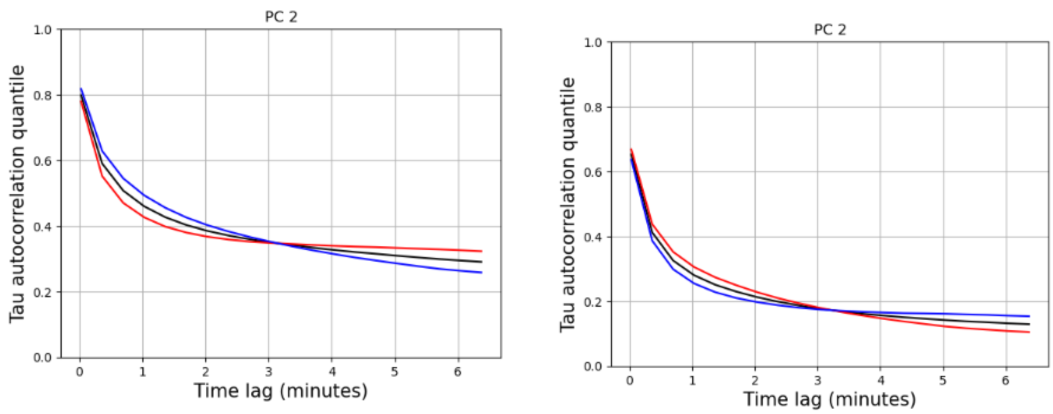

Figure 4: PC2 (mean autocorrelation +/- each PC for 2017 data (left) and 2019 data (right)

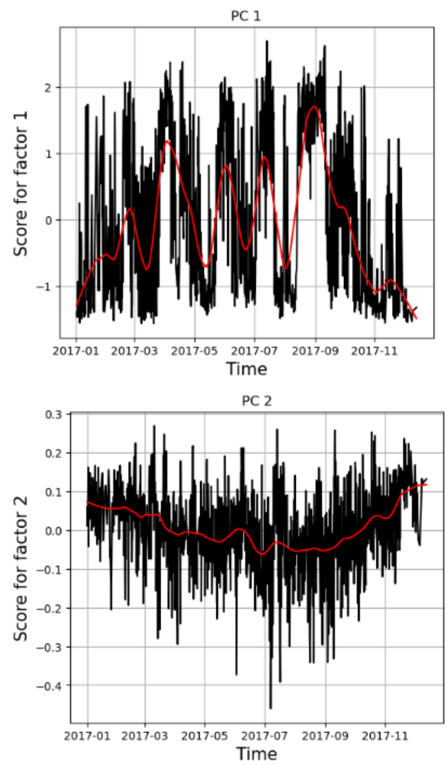

Figure 5: PC scores for each factor in 2017.

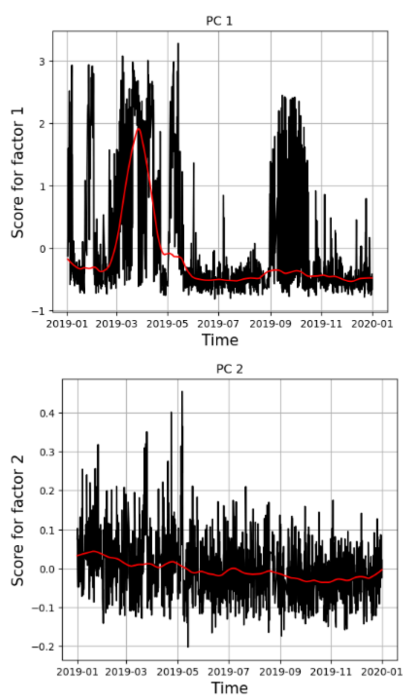

Figure 6: PC scores for each factor is 2017