Predictive Dynamics of Solar Cycles: An Analysis of Sunspot Patterns, Granger Causal Relationships, and Terrestrial and Space Weather Phenomena

Abstract

This paper attempts to understand the complex nature of solar cycles, primarily through the lens of sunspot data analysis, to predict future solar activity and explore its causality with Earth and Space phenomena such as global temperatures and CO2 Emissions. Using statistical time series analysis methods, including Seasonal AutoRegressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) networks, predictive models were developed based on historical sunspot records dating back to 1818 up to 2019. The aim was to create a forecast mechanism to indicate and predict future solar cycle patterns. Granger causality tests were used to investigate the influences of sunspot activity on other variables of interest, such as CO2 emissions and climate temperature variations. The findings of this analysis contribute to the growing research in astrophysics and environmental science to offer insights that could be beneficial for future research into solar phenomena and its effects on Earth.

1. Introduction

Sunspots, the darker and cooler areas on the Sun's surface, have been of interest to scientists for centuries. Sunspots are not mere surface phenomena but strongly correlate with the Sun's magnetic field activity leading to the solar cycle. Understanding this cycle is crucial as it is not just solar activity but a key driver in space weather phenomena. The study of sunspot cycles may hold paramount importance in understanding phenomena on Earth, such as variations in solar activity, as revealed by fluctuations in sunspot numbers, which may influence space weather and, thus, Earth's climate system. The primary objective of this research paper is to delve into the patterns of sunspot cycles and predict future solar activity. Another significant part of this endeavor is exploring the Granger causal relationships between sunspot numbers and other variables to provide a comprehensive understanding of how the solar cycle may influence both space and Earth. It is thought that a detailed analysis of sunspot data through predictive modeling will allow for the study of relationships between solar activity and Earth and space weather phenomena.

2. Literature Review

According to many past studies, the solar cycle is completed roughly once every eleven years. This means the number of sunspots has gone from a minimum to a maximum and back to the next minimum. However, there have been studies that point out that the solar cycle is extremely difficult to predict and can deviate from the expected roughly eleven-year cycle. As times of maximum sunspot activity are associated with a slight increase in the energy output from the Sun, there is debate over how much, if at all, this affects Earth's climate (National Weather Service). Previous research by NCAR used computational models of global climate to see that at solar maxima, there are often subtle impacts on tropical precipitation and weather systems around the world. Scientists have been aware that there may be a connection between long-term solar variations and certain weather patterns but have not established a physical connection between the solar cycle and global climate patterns (U.S. National Science Foundation). This research contributes to the predictive analysis of the solar cycle.

3. Methodology

This research focuses primarily on a dataset of historical records of sunspot numbers, a crucial indicator of solar activity, spanning over two centuries. This data was sourced from Kaggle. The other datasets provide accounts of Earth's changing climate and environmental conditions. The analysis began with the aggregation of sunspot data on a monthly and then annual basis, aligning it with the yearly records of the other discussed variables, such as CO2 Emissions and global temperatures. The first method used was predictive modeling. To test the performance of various models in predicting future sunspot numbers, the dataset was split into a training set comprising the first 80% of the time series and a test set comprising the remaining 20% of the time series. With SARIMA and LSTM networks trained on 80% of the data and tested on 20%, future sunspot cycles were proven to be able to be predicted. Granger causality tests were used to explore the potential influence of sunspot activity on Earth and space phenomena. Certain limitations were that the predictive models, which are contingent on historical patterns, do not capture future anomalies. Additionally, the Granger causality tests only infer statistical predictability and not true direct causation. This paper assumes the consistency and reliability of the datasets used and assumes that historical patterns in solar activity will continue to exhibit a similar trend in the future.

4. Results

This research began through the creation of a SARIMA model (Seasonal Auto-Regressive Integrated Moving Average) to predict future occurrences of the solar cycle. The SARIMA model includes several hyperparameters that must be tuned: AR (autoregressive) terms, differencing order, MA (moving average) terms, and seasonal terms. The process of hyperparameter tuning was done with grid search and Akaike Information Criterion (AIC) minimization. The best SARIMA parameters were found to be (2, 1, 2)x(0, 1, 1, 13) with an AIC of 1621.5. In the context of the SARIMA model created for this study, the parameters are crucial for understanding how the model predicts sunspot numbers. The notation (p, d, q)x(P, D, Q, s). The first number (p) tells that the model looks at the two most recent observations of sunspot numbers to predict the next one. The second number (d) takes the difference between the current and previous sunspot numbers before making predictions. This allows the model to understand how much change is happening over time. The third number, 2, means the model considers how much error there was in the last two predictions to improve forecasts. The next three numbers (0,1,1) are about the seasonal pattern of sunspots, which tends to repeat over a specific period. This model doesn't use past seasonal differences to predict the future. Still, it does take into account seasonal changes and looks at past errors in the seasonal pattern to refine predictions. The last number (13) represents the length of the cycle the model considered for the seasonal pattern. As the SARIMA model was tested, 11 years was found not to be the optimal seasonal timeframe, but 13. This shows the nuance and shifts in solar behavior that prove the ultimate length of the solar cycle changes and cannot be fully predicted. This SARIMA model is a good fit for the sunspot time series, as shown in Figure 1. Moreover, as shown in Figure 2, this SARIMA model was able to successfully predict future values of the solar cycle with relative accuracy in the period but not amplitude. This is most likely due to the variation of amplitude during the solar cycle and that this is a model focused on time-series analysis rather than specifically the number of sunspots.

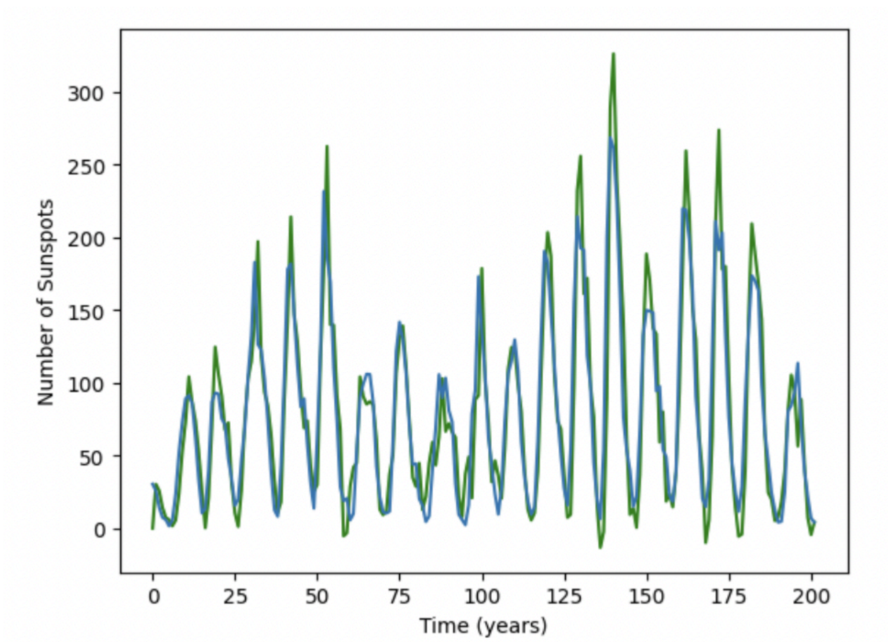

Figure 1: Fit of (2,1,1)x(0,1,1,13) SARIMA model to the full sunspot time series. The actual number of sunspots (blue) is shown along with the fitted time series (green). The horizontal axis represents the years since the start of the time series, which was in 1818.

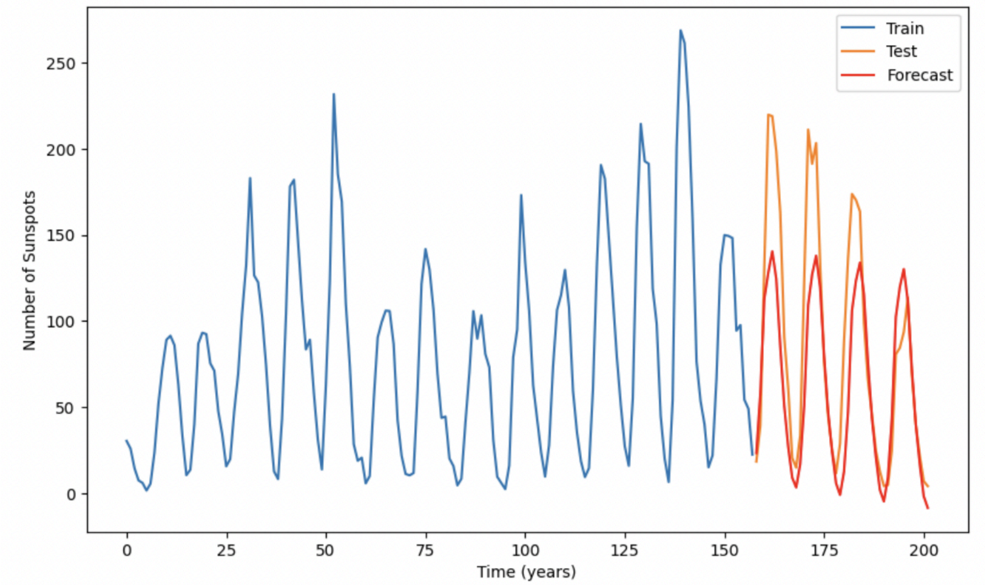

Figure 2: Testing the forecasting performance of the SARIMA model. The dataset in Figure 1 was split into a training set (80%) and a test set (20%). The trained SARIMA model was used to forecast the number of sunspots in the test set.

Another predictive method was employed – the Long Short-Term Memory Network (LSTM). LSTM is a recurrent neural network that is more accurate at predicting long-term dependencies on data. This LSTM network was designed to input historical data on yearly sunspot numbers and trained to predict values. An LTSM was used for sunspot number and solar cycle prediction because the solar cycle has long-range dependencies across the multiple years that span the solar cycle. As shown in Figure 3, the results show that the LTSM was also able to forecast the solar cycle accurately and with better accuracy for amplitude. However, it tends to consistently underpredict the amplitude of each period and lag behind the actual cycle.

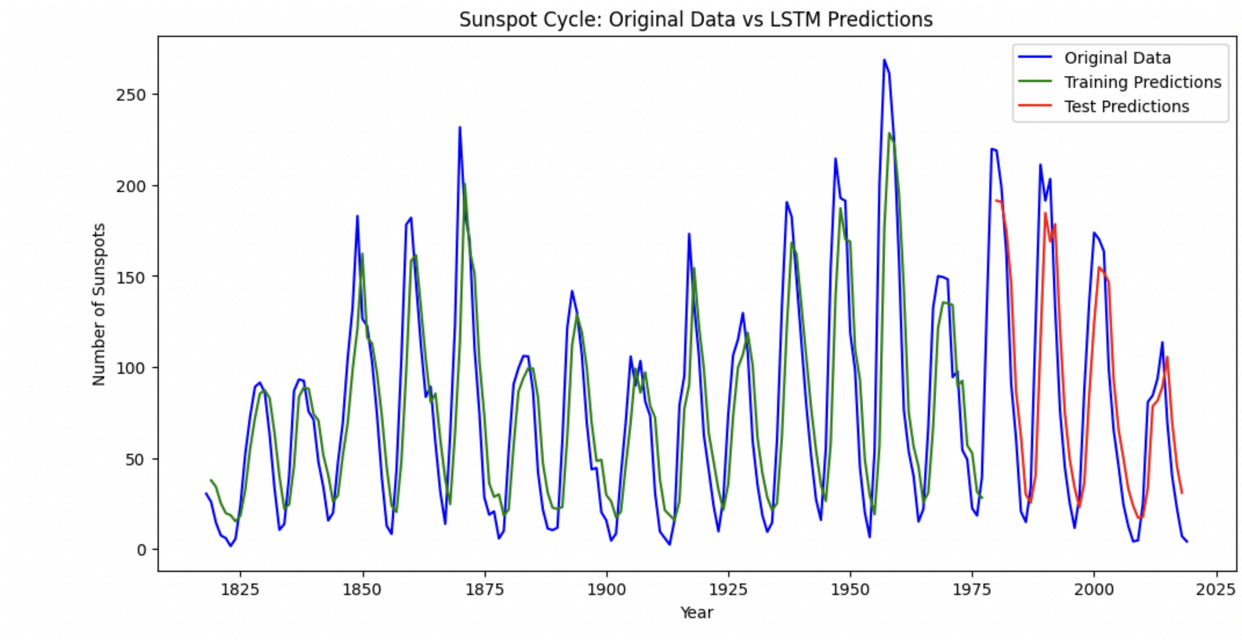

Figure 3: The LSTM model's forecasting performance was tested. The data set was split into training and test data, just as in the SARIMA model.

The next step in the research process was to explore the correlation between the solar cycle and Earth phenomena related to climate and weather patterns. The approach to this was to employ Granger causality tests. Granger causality is a statistical method to determine if the known values of one series can predict the future values of another. This research focused on the potential that the solar cycle time series Granger causes measurements related to Earth's climate and weather, such as global temperature and weather patterns, such as the time series shown in Figure 4. It is crucial to note that a limitation of Granger causality is that it suggests prediction and not absolute causation. As the solar cycle predictions dealt with yearly aggregated data, eleven lags were used for the Granger causality tests to capture an eleven-year cycle. The tests were unable to find Granger causality between atmospheric CO2 levels and the solar cycle or average global land and ocean temperature and the solar cycle. The p-values for the hypothesis that the coefficient on atmospheric CO2 levels or average global temperatures is nonzero are shown in Table 1. As shown in the table, the p-values are greater than 0.05, which indicates that the null hypothesis of no Granger causality cannot be rejected.

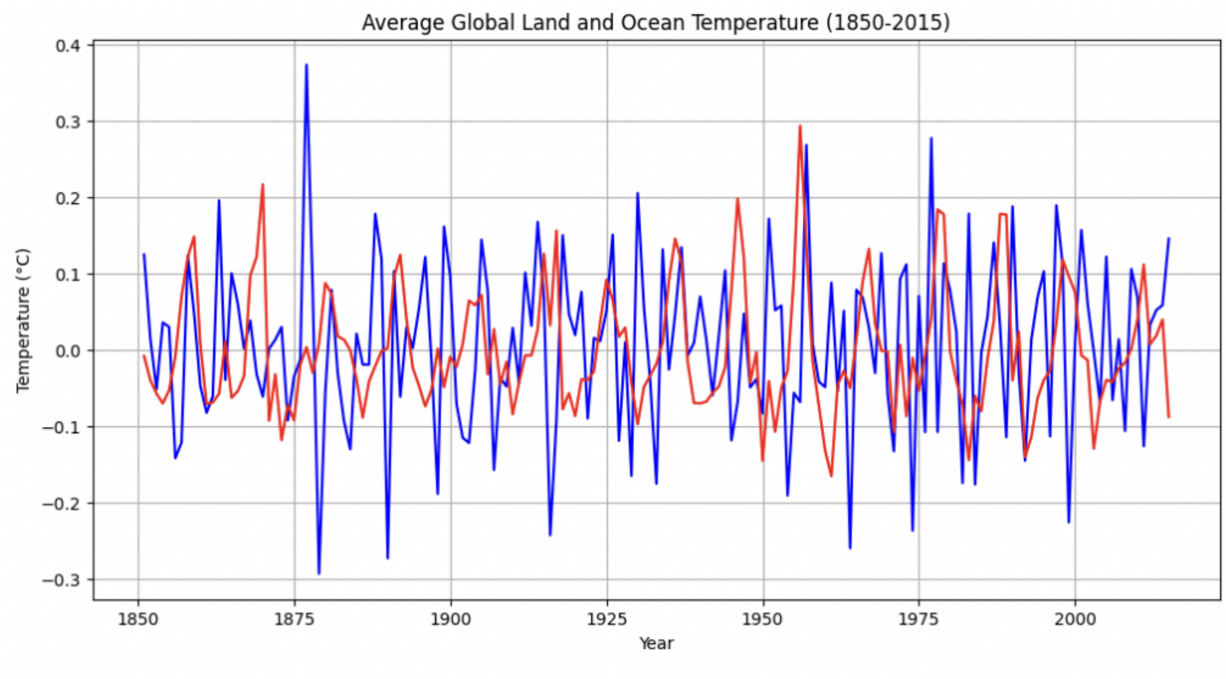

Figure 4: The first differences in average global land and ocean temperatures (in blue) and the number of sunspots (in red). No obvious correlations can be visually identified between the first differences in these time series.

Table 1: Tests for Granger causality.

Predictive variable	Dependent variable	p-value
Sunspot numbers	Average CO2 levels	0.1698
Sunspot numbers	Average global land and ocean temperatures	0.8252

5. Discussion

With the analysis of solar cycles, the SARIMA model demonstrated the ability to predict the timing of solar cycles, although it struggled with variations in amplitude. In contrast, the LTSM model, known for its ability to capture long-term dependencies, offered improved predictions for the amplitude of solar cycles with a tendency to underpredict the peak values. This underprediction underscores the complexity of solar dynamics and the challenge of capturing nuances with current modeling techniques. The absence of Granger causality between sunspot numbers and both CO2 levels and global temperatures in this study suggests that the direct impact of solar cycles on Earth's climate variables may be less pronounced or more intricate than these models can assume. This finding aligns with the broader scientific consensus that, while solar activity does have an influence on Earth's climate, the relationship is not straightforward and is impacted by many climatic factors. While solar activity can sometimes correlate with certain climatic phenomena, establishing a direct or causative link remains elusive based on the results of this study.

6. Conclusion

This study examined sunspot patterns in detail to predict solar activity and assess its potential effect on Earth's climate and space weather phenomena. The application of SARIMA and LTSM predictive models achieved an understanding of solar cycle dynamics, acknowledging that the relationship between the solar cycle and Earthly phenomena remains nuanced and not fully determined. The exploration of Granger causality relationships between sunspot activity and Earth's climate variables highlighted the complex interplay between solar and terrestrial systems.

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