Possible Interactions between Some Solar Activity Indicators for the Last two Cycles

Kilcik A. [1], *Sarp V.* [1]

[1] Akdeniz University, Faculty of Science, Space Science and Technologies Department, Antalya/Turkey
E-mail: alikilcik@akdeniz.edu.tr

Abstract

In this study we investigated the possible linear and nonlinear interaction between some solar activity indicators which are MCMESI, Fl, SSA, SSN, F10.7 and TSI for the time period of 1996-2018. Here, we used Convergent Cross Mapping (CCM) to examine the non- linear relationship and cross-correlation analysis to examine the linear relationship between the MCMESI and all other solar activity indicators. We found that FI, SSN, F10.7 and SSA show symmetrical relationship while the only TSI data show moderate asymmetric relationship with the MCMESI. The highest nonlinear relationship with the MCMESI is obtained for F10.7 data. This relationship is a symmetrical bidirectional coupling; when the library sample size gets smaller CCM score is increasing up to about 50 then it decreasing sharply. As a result, we can get information about the future of both data sets from each other`s manifold. From the cross correlation analysis we also found that the F10.7 has the strongest correlation with the MCMESI. Thus, we may argue that this relationship can be used for further dynamical modelling and prediction approaches.

Introduction

It is important to analyze the causal understanding of solar activity cycle indicators to interpret and to predict solar activity variations. Balogh A. et al. (2014) reviewed correlations and causal relations of a selection of solar activity indicators and concluded that important pieces in the puzzle of solar activity variation are still missing. The Maximum CME Speed index (MCMESI) was introduced by Kilcik A. et al. (2011) and found as a strong indicator of geoeffective solar disturbances. Later, Ozguc A. et al. (2012) analyzed its hysteresis effects with typical solar activity indices during Solar Cycle 23.

In this study we focused on the possible non-linear interactions of the MCMESI with Flare Index (FI), Sunspot Area (SSA), Sunspot Number (SSN) version 2.0 (Clette F. and Lefèvre L., 2016) 10.7 cm Solar Radio Flux (F10.7) and Total Solar Irradiance (TSI) during Solar Cycles 23 and 24. Causal relationship between two dynamical variables can be established if they belong to a common dynamical system, which can be reconstructed from time-delay embedding of each observed time series. For this purpose, we applied the method called Convergent Cross Mapping (Sugihara G. et al. 2012) to above mentioned time series so that we can reveal their interactions during the investigated time period.

Data

The CME data are taken from SOHO/LASCO CME catalog and the maximum CME speed index (MCMESI) are calculated as daily values and then the monthly values were produced as introduced by Kilcik A. et al. (2011). The ISSN data are taken from the WDC-SILSO, Royal Observatory of Belgium, Brussels, as a monthly mean values. Here we used the second version ISSN data. Hα flare index (FI) data are taken from Bogazici University Kandilli Observatory as daily values. Then, monthly average values were calculated. F10.7 data are downloaded from NASA OMNIWeb system as a daily values and the monthly values were calculated. SSA data are taken from Debrecen Photoheliographic Data (DPD) sunspot catalogue as a daily data, and then the monthly values were calculated. The TSI data are taken

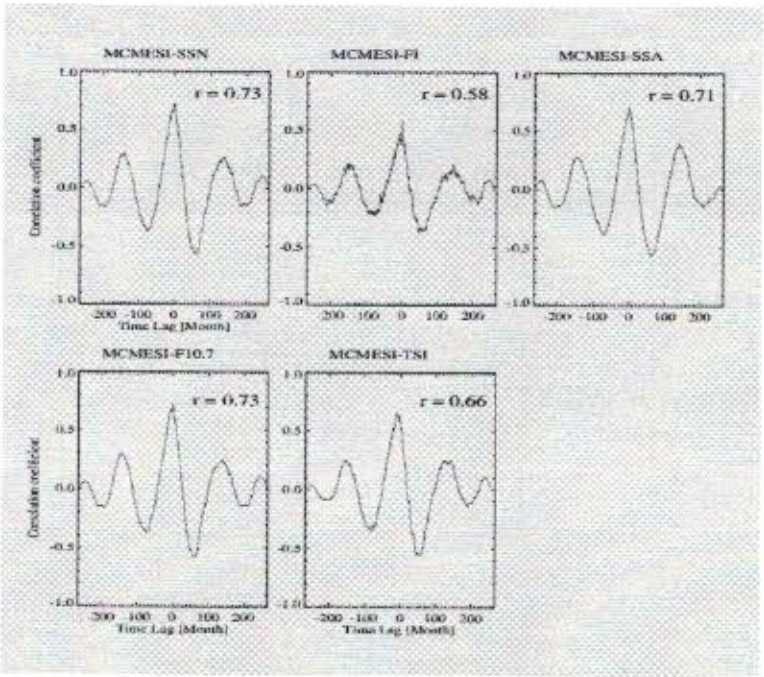


Figure 1 - Cross correlation analysis results between the MCMESI and all other solar indices.

from ftp://ftp.pmodwrc.ch/pub/data/irradiance/composite as a daily values and the monthly values were calculated.

Results

In order to investigate the linear relations between the MCMESI and other data sets used in this study, cross correlation analysis were applied. Results of cross-correlation analysis are given in Figure 1.

Optimal value for the embedding dimension and corresponding prediction performances are determined to use in CCM analysis. Simplex projection results for the MCMESI are given in Figure 2. It is also calculated for all other solar indices used in this study by the same method. The determined values are used to cross-map the indices to each other in order to analyze their non-linear interactions. These CCM results are given in Figure 3.

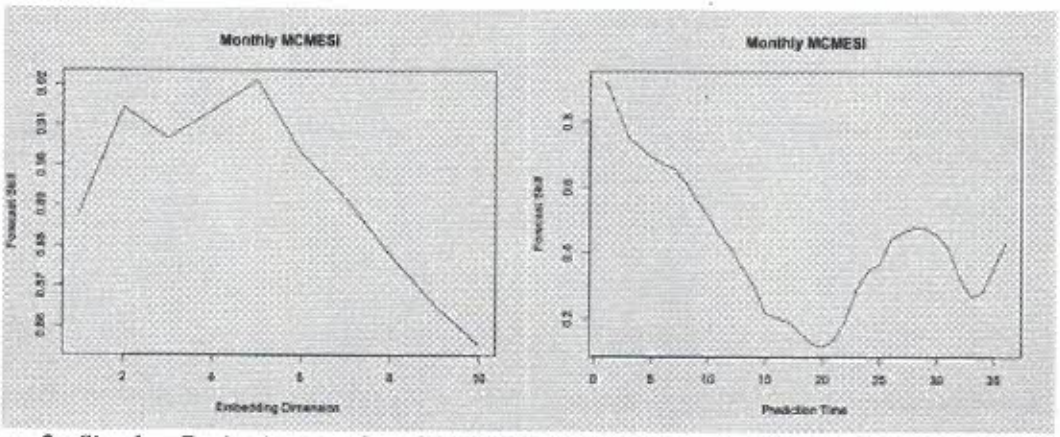


Figure 2- Simplex Projection results of MCMESI to calculate optimal embedding dimension and prediction decay

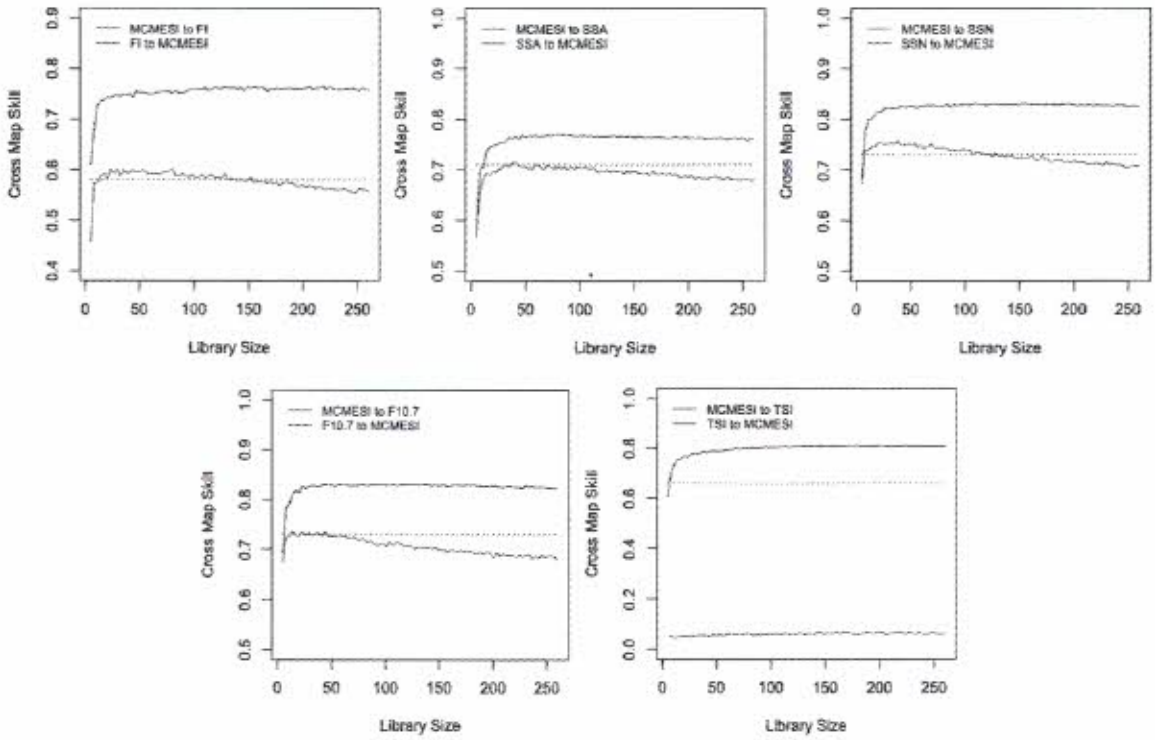


Figure 3 - CCM results for MCMESI cross mapped with other solar indices used in this study

Conclusions

1. The most complicated data are the MCMESI which has the highest embedding dimension (E = 5)
2. Forecast skills decrease with increasing time in a short duration. This indicates that all data sets used in this study can be approximated by deterministic chaos rather than stochastic process.
3. CCM results indicate that there are no bidirectional coupling in the long term (more than one cycle). Because one of the CCM curve always under the level of correlation coefficient.
4. In contrast, for the short term there are synchronized relations between two variables.
5. TSI behave differently than other data sets used; it has the weakest coupling with the MCMESI

Acknowledgment

This study was supported by the Scientific Research Projects Coordination Unit of Akdeniz University (Turkey) by the Project of FBG-2019-4914.

References

Balogh A., Hudson H.S., Petrovay K. and von Steiger R. (2014) Introduction to the Solar Activity Cycle: Overview of Causes and Consequences. Space Sci Rev. 186:1–15

Clette F., and Lefèvre L. (2016) The New Sunspot Number: Assembling All Corrections. Sol Phys. 291, pp. 2629-2651

Kilcik A., Yurchyshyn, V. B., Abramenko, V., Goode, P. R., Gopalswamy, N., Ozguc, A., Rozelot, J. P., (2011) Maximum Coronal Mass Ejection Speed as an Indicator of Solar and Geomagnetic Activities. ApJ. 727-1

Ozguc A., Kilcik A., Rozelot J.P., (2012) Effects of Hysteresis Between Maximum CME Speed Index and Typical Solar Activity Indicators During Cycle 23. Sol Phys. 281-2 pp. 839-846

Sugihara G., May R., Ye H., Hsieh C.H., Deyle E., Fogarty M., Munch S. (2012) Detecting causality in complex ecosystems. Science 338, p.496–500

Sugihara G., and May R.M., (1990) Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. Nature. 344, p.734-741