Association For Science

Georgian Scientists

ქართველი მეცნიერები

Vol. 8 Issue 1, 2026

https://doi.org/10.52340/gs.2026.08.01.06

Solar Activity and the Dow Jones Industrial Average

Darejan Japaridze[1,2], Tamar Paatashvili[3], Bidzina Chargeishvili[4], Tengiz Mdzinarishvili[5]

[1]Georgian E. Kharadze National Astrophysical Observatory, Senior researcher; [2]Ilia State University, Associate Professor, Centre for Computational Helio Studies; darejan.japaridze@iliauni.edu.ge; [3]Georgian E. Kharadze National Astrophysical Observatory, Data processing specialist; tpaatashvili@abao.ge; [4]Georgian E. Kharadze National Astrophysical Observatory, Senior researcher; bidzina@aidio.net; [5]Georgian E. Kharadze National Astrophysical Observatory, Senior researcher; tengiz.mdzinarishvili@iliauni.edu.ge

Abstract

We examined the relationship between solar activity and the Dow Jones Industrial Average from 1896 to 2021. We employed sliding-window correlation, cross-correlation, and wavelet coherence analyses. It was discovered that the correlation with 11-year periodicity is more than 0.5 during the 1906–1936 and 1964–2000 time periods, and is visible with a 95% confidence level during the 1910–1930 and 1990–1994 time periods. This correlation is proved by coherence, with a high 95% confidence level revealed between cosmic ray data and the Dow Jones Industrial Average in the same periods where the correlation between sunspot numbers and cosmic ray data is high (1964–2000), but with a distinct phase difference. Because financial indices reflect many simultaneous influences, revealing a correlation between studied events is difficult. nevertheless, it's significant to study the intercorrelations between financial indices and solar activity or cosmic rays for forecasting financial models and systemic risk assessments.

KeyWords: Dow Jones Industrial Average, Solar Activity, Sunspot Number, Cosmic Rays

1. Introduction

Solar variability modulates the near-Earth space environment through changes in electromagnetic emissions and energetic particle fluxes. Solar phenomena such as solar flares and solar coronal mass ejections can disrupt technological systems (Buzulukova et al., 2025) and influence human psychological state and health (Neale et al., 2023), which in turn may affect economic activity. There is a correlation between solar activity and various economic characteristics (Gorbanev, 2012; 2020; Walsh, 1993; Krivelyova and Robotti, 2003; Peng et al., 2019).

The Dow Jones Industrial Average (DJIA) is one of the oldest and most popular stock indexes. The DJIA, while composed of 30 U.S. firms, is widely used as a proxy for market sentiment and global financial linkages. It can be considered not only a leading indicator of the US economy (Stock and Watson, 1989) but also an indicator of global business performance, due to its strong influence on other stock markets (Zheng and Chen, 2013). A sharp drop in the DJIA could indicate the onset of a large-scale crisis. Therefore, its changes are closely monitored to assess future economic performance expectations (Hester and Gibson, 2003; Goidel et al., 2010).

This study we revisited the DJIA–solar relationship and cosmic rays using long historical records and modern correlation and cross-correlation methods and the wavelet coherence approach.

2. Data and methods

Monthly sunspot numbers were obtained from the SILSO World Data Center (website: http://www.sidc.be/silso/) for 1818-2021. Cosmic-ray neutron monitor data were taken from the Oulu station (Sodankylä Geophysical Observatory, Finland) for 1964–2021. Historical DJIA values for 1896–2021 were retrieved from public market archives (Free Historical Market Data – Stooq, https://stooq.com/^DJI - Dow Jones Industrial - U.S. - Stooq).

2.1 Detrending

To remove the long-term upward trend in the DJIA, we applied an 11-year moving average chosen to match the dominant solar periodicity. After subtracting the smoothed data from the original data and multiplying it by 100, we get seasonal fluctuations around the DJIA trend as a percentage (DJ). Fig. 1 depicts the results.

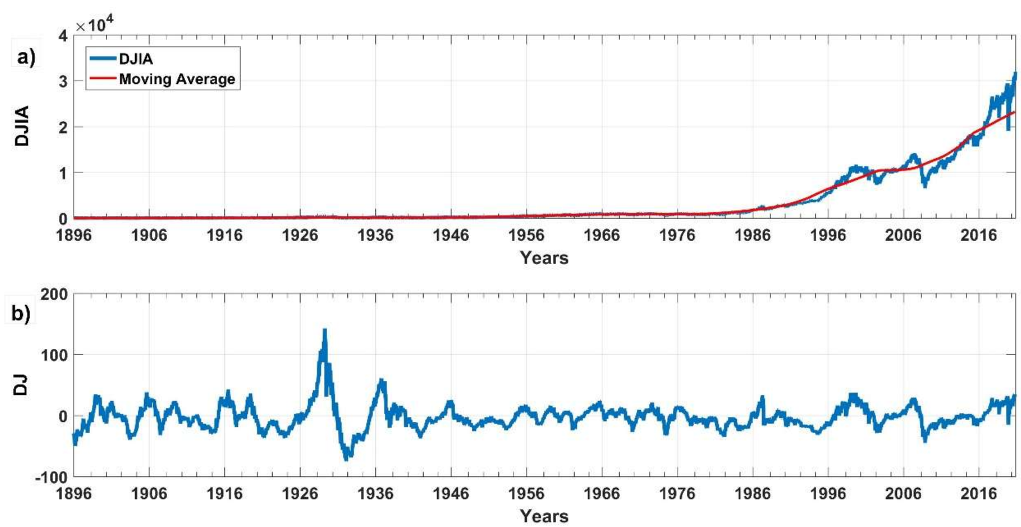

Fig. 1. DJIA data decomposition a) The DJIA (blue curve) and the moving average DJIA with an 11-year window (red curve); b) The detrended DJIA expressed as a percentage.

2.2 Correlation and cross-correlation

Over the full 1896–2021 interval, the monthly linear correlation between sunspot numbers and the detrended DJ is small but statistically significant, r = 0.1492 (0.0996-0.1980), but we can reject the null hypothesis ("no statistical relationship and significance") with high reliability because $P < 0.001$, indicating that the correlation is almost guaranteed. To see how this correlation changes over time, we compared smaller time intervals (several 11-year solar cycles). For this, we used a sliding window method. The linear correlation R between the data and the p-value for rejecting the null hypothesis was determined for each selected window. The window was then advanced by a relatively small-time step, and the same values were determined once more. The optimal time window length was chosen to be 22 years, with a time step size of one year. The results are shown in Fig. 2.

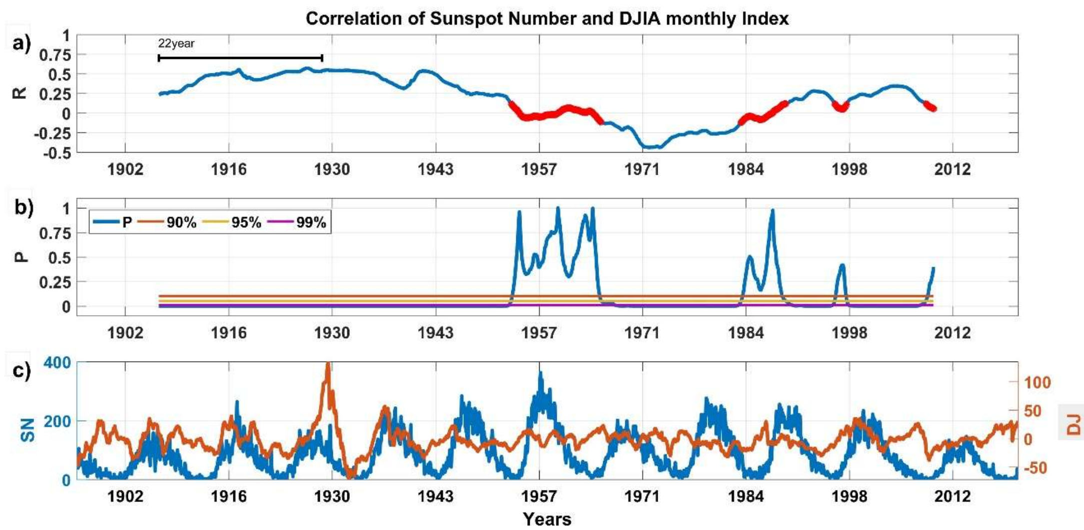

Fig. 2. Correlation charts between the SN and the DJIA detrended index (DJ) (the sliding window length is 22 years, and the step length is one year). a) Curve of correlation coefficients. The red dots indicate locations where we cannot reject the null hypothesis between events. b) The level of reliability of the hypothesis P; c) The blue curve represents the SN, while the red curve represents the DJ.

Sliding-window correlations vary between approximately –0.5 and +0.5. Positive correlations are prominent in the early 20th century, reverse in the 1970s–1980s, and reappear toward at the end of the twentieth century and the beginning of the twenty-first century.

Because the process is non-linear and non-stationary, with many intermediate links, it is difficult to explain what this change depends on. The correlation modulus reaches 0.5, a significant value, while the areas of unreliable correlation (bold areas on the curve in Figure 2a) are relatively short and mostly coincide with areas of correlation sign change.

Cross-correlograms computed within moving with a 22-year windows reveal a non-stationary structure: the maximum cross-correlation (from -0.65 to 0.65) and peak lags shift between roughly –1 and +3 years. A top view of the resulting 3D image (contour plot) is depicted in Fig. 3, and it clearly demonstrates that the connection between the studied data is non-stationery and changes over time.

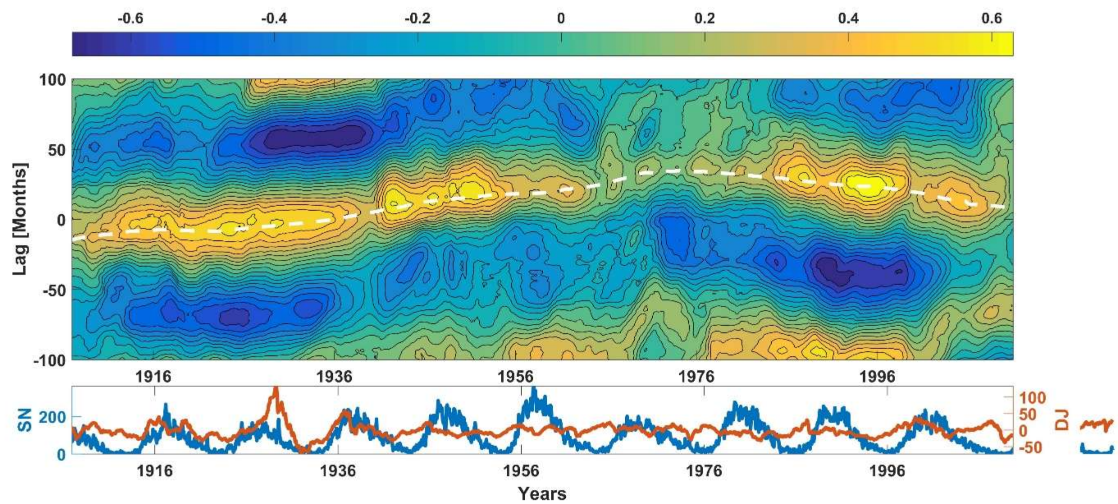

Fig. 3. The upper panel shows an SN-DJ cross-correlogram, with the horizontal axis representing date and the vertical axis representing phase lag; the white dashed curve shows lag variation corresponding to maximum cross-correlation; and the lower panel shows activity variations for SN and DJ, with the blue curve representing SN and the red curve representing DJ.

2.3 Wavelet coherence

Wavelet cross-correlation and wavelet coherence methods scale-dependent synchronizations have recently been widely used to identify potential relationships between two time series (Addison, 2017).

In general, the value of wavelet coherence ranges from 0 to 1 and, like the correlation coefficient, allows us to quantify the correlation between events.

We used software packages developed by Torrence and Compo and Grinsted to calculate the wavelet coherence between the monthly average SN and DJ data. The statistical significance level of wavelet coherence is estimated using Monte Carlo methods with red noise to calculate the 5% level of significance (300 calculations) (Torrence and Webster, 1999; Grinsted et al., 2004).

In addition to wavelet coherence, the wavelet coherence phase difference is calculated, which indicates how far apart the study events are for a given frequency and time. The areas of significant coherence (with a 95% level of confidence) are denoted by the black line contours. The arrows represent the relative phase of two-time series; a right-pointing arrow indicates in-phase coherence between the two signals, while a left-pointing arrow indicates anti-phase coherence. A phase arrow pointing down indicates that one time series is 90 degrees ahead of another, while one pointing up indicates that it is 90 degrees behind. When arrows are strongly horizontal (0 or 180 degrees), it indicates a linear relationship between the two phenomena being studied; non-horizontal arrows indicate an out of phase situation and a more complex non-linear relationship (Velasco Herrera et al., 2018).

Fig. 4 depicts the wavelet coherence between SN and DJ data. The above-mentioned arrows indicate phase differences for coherence and correlation values greater than 0.5.

The 95% confidence level of wavelet coherence was estimated using the Monte Carlo method (300 calculations) and is indicated with a bold outline in Fig. 4. It shows that the similarities between these two events are greatest for about 11 years (approximately 128 months).

The strongest coherence appears near the 11-year band, with coherence values reaching high levels to 0.8 in the 1920s and 0.72 in the 1990s, and it exceeds 0.5 during 1906–1936 and 1964–2000. Significant 11-year synchronization is concentrated in subintervals such as 1910–1930 and 1990–1994.

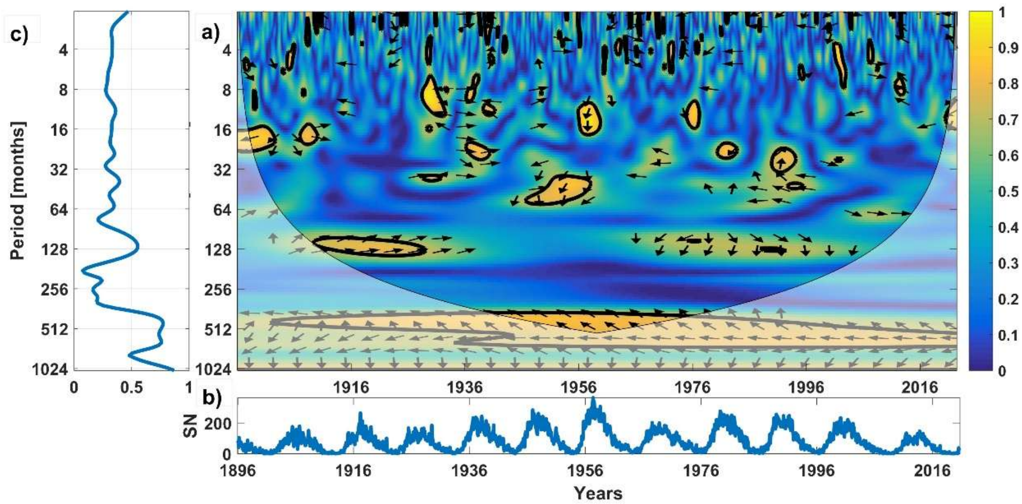

Fig. 4. a) Squared wavelet coherence between the SN and DJ time series. The color bar scale shows the wavelet coherence power. Arrows represent the relative phase relationship. The bold black contour denotes the 5% significance level calculated against a red noise background using Monte Carlo methods, and the normal contour denotes the cone of influence (COI). b) SN versus date c) The global spectrum of the wavelet coherence power.

Additional features (Fig. 4) include anticorrelated bands near 32 years and 50–60 years (with a value of 0.83); these may reflect to the long waves of Kondratieff, which are well-known in economics (Kondratieff, 1935; Korotayev, 2010, 2011; Galegatti, 2016; Modis, 2017). 50-60-year periodicity is also known for solar activity (Ogurtsov et al., 2002; Lomb, 1980, 2013) and the paleo-cosmic-ray record provided by cosmogenic radionuclides (McCracken et al., 2013).

These periodicities are also clearly visible in Figs. 4 and Fig. 5, though the data length of 120 years did not allow us to assess this periodicity convincingly because it is mainly found outside the cone of influence in Fig. 4. (COI). This period is presumably a modulation of the 11-year coherence between SN and DJ, but an explicit consideration is not possible due to the short observation time of DJ.

As we can see, wavelet coherence (i.e., in the frequency domain) allows us to investigate the relationship between two events at different scales and times more flexibly and straightforwardly than traditional linear correlation or even sliding linear analysis on different scales.

We investigated the wavelet coherence between CR and the DJ. For 1964–2021 the 11-year synchronization found between the SN and the DJ is also visible in the wavelet coherence between CR and the DJ (Fig. 5). As shown in Fig. 5, when the coherence between the SN and the DJ increases, around 1964-2000, there is a 95% confidence in coherence between CR and the DJ, but with a different phase shift. but with a consistent phase offset consistent with the known anticorrelation between solar activity and galactic cosmic-ray flux (Caballero-Lopez et al., 2019; Bhattachaya and Roy, 2014). In several epochs the cosmic-ray–DJ relationship appears stronger and more statistically convincing than the sunspot–DJ link.

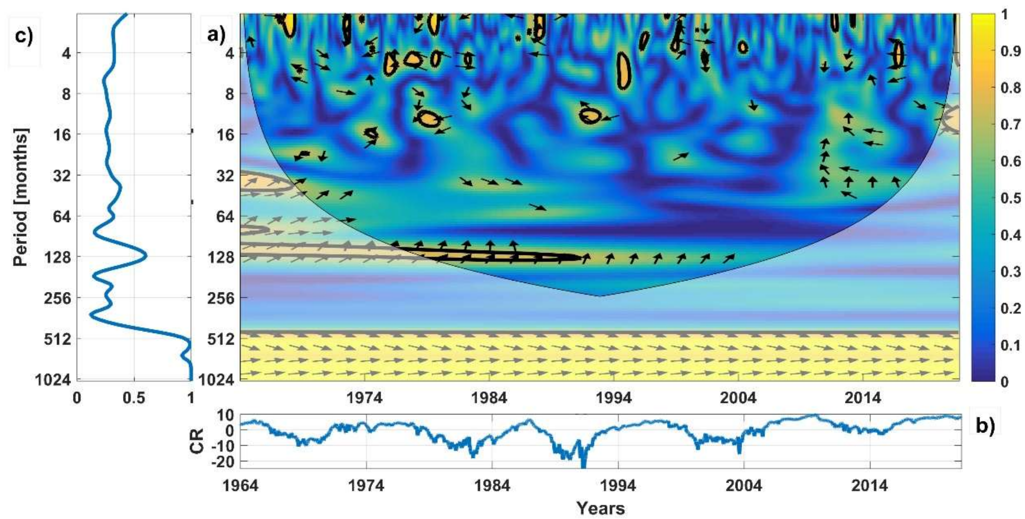

Fig. 5. a) Squared wavelet coherence between the CR and DJ time series. Arrows represent the relative phase relationship. The bold black contour denotes the 5% significance level calculated against a red noise background using Monte Carlo methods, and the normal contour denotes the cone of influence (COI). b) CR, c) The global spectrum of squared wavelet coherence.

3. Results

The relationship between solar activity and the DJIA from 1896 to 2021 is investigated. Using a novel approach called Wavelet coherence, it was revealed that the relationship between events is ambiguous and changes over time. There were detected synchronization time intervals with different periods, as well as changes in the coherence of these synchronizations over time.

Solar activity and the DJ have a non-stationary relationship, with quite high correlations occurring at different scales and time intervals. At the beginning of the twentieth century, high (0.7-0.8) coherence is observed in the region of 11-year periodicity.

The 11-year periodicity weakens and disappears in the middle of the twentieth century, a 3-4-year correlation emerges with a phase difference of about 1 year. However, by 1957, at the peak of solar activity, a one-year synchronization appears with a three-month phase difference. By the end of the twentieth century, an 11-year correlation appears with approximately 3-4 years of phase difference, as well as a 4-year periodicity antiphase and a 2-3-year periodicity with a six-month lead. At the beginning of the 20th century, there is a 6-year correlation with almost no phase difference. Also found a 32-year anticorrelation and a 50-60-year anticorrelation.

The search for correlations between solar activity, cosmic rays and DJIA is complicated by the simultaneous influence of numerous factors on financial indices. Economic dynamics emerge from intricate interactions among economic, political, social, environmental, and technological systems. Understanding the interconnections among these processes requires further investigation to uncover intermediate links and causal mechanisms. Such clarification is essential for improving DJIA forecasts and should be incorporated into the development of robust financial modeling approaches.

This research was funded by the Shota Rustaveli National Scientific Foundation of Georgia (SRNSF), grant number FR-24-14835.

References

1. Addison, P. S., The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance (Boca Raton, FL: CRC Press), 2017.
2. Bhattachaya, R., Roy, M. Correlative Analysis ofCosmic Ray Intensity and Solar Activity Parameters, Journal of Engineering Science and Technology 6(2): 24-31, 2014.
3. Buzulukova, N., Kozyra, J., Fuller-Rowell, T., Dorodnitsyn, A., Extreme Space Weather Events, In book: Proc. of the United Nations/Germany Workshop on the International Space Weather Initiative, pp. 55-63, 2025.
4. Caballero-Lopez, R. A., Engelbrecht, N. E., Richardson, J. D., Correlation of Long-term Cosmic-Ray Modulation with Solar Activity Parameters, The Astrophysical Journal, 883:73 (13pp), 2019.
5. Gallegati, M., "Wavelet Estimation of Kondratieff Waves: An Application to Long Cycles in Prices and World GDP." Kondratieff Waves: Cycles, Crises, and Forecasts, 99-120, 2016.
6. Gorbanev, M., Sunspots, unemployment, and recessions, or Can the solar activity cycle shape the business cycle? MPRA Paper No. 40271, 2012.
7. Gorbanev, M., "Shifting Pattern of Extraordinary Economic and Social Events in Relation to the Solar Cycle." MPRA Paper No. 102163, 2020. University Library of Munich, Germany. [Online]. Available:
8. Goidel, K., Procopio, S., Terrell, D., Wu, H.D., Sources of Economic News and Economic Expectations. American Politics Research, 38, 759–777, 2010.
9. Grinsted, A., Moore, J. C., Jevrejeva, S., Application of the cross wavelet transform and wavelet coherence to geophysical time series, Nonlinear Process. Geophys. 11 (5–6), 561–566, 2004.
10. Hester JB, Gibson R. The Economy and Second-Level Agenda Setting: A Time-Series Analysis of Economic News and Public Opinion about the Economy. Journalism & Mass Communication Quarterly, 80, 73–90, 2003.
11. Kondratieff, N.D., The long wave in economic life. Rev. Econ. Stat. 17, 105–115, 1935.
12. Korotayev, A. V., Zinkina, J., Bogevolnov, J., Kondratieff waves in global invention activity (1900–2008). Technol. Forecast. Soc. Chang. 78 (7), 1280–1284, 2011.
13. Korotayev, A. V., Tsirel, S. V., A spectral analysis of World GDP dynamics: Kondratieff waves, Kuznets swings, Juglar and Kitchin cycles in global economic development, and the 2008–2009, Econ. Crisis Struct. Dyn. 4 (1), 3–57, 2010.
14. Krivelyova, A., Robotti, C., “Playing the field: Geomagnetic storms and international stock markets,” tech. rep., Working paper, Federal Reserve Bank of Atlanta, 2003.
15. Lomb, N., The sunspot cycle revisited. J. Phys.: Conf. Ser. 440 012042, 2013.
16. Lomb, N. R., Andersen, A. P., The analysis and forecasting of the Wolf sunspot numbers. Monthly Notices of the Royal Astronomical Society, 190(4), 723-732, 1980.

17. McCracken, K. G., Beer, J., Steinhilber, F., Abreu, J., A Phenomenological Study of the Cosmic Ray Variations over the Past 9400 Years, and Their Implications Regarding Solar Activity and the Solar Dynamo. *Sol Phys* 286, 609–627, 2013.
18. Modis, T., A hard-science approach to Kondratieff's economic cycle. Technol. Forecast. Soc. Chang. 122, 63–70, 2017.
19. Neale, R. E., Lucas, R. M., Byrne, S. N., Hollestein, L., Rhodes, L. E., Yazar, S., Young, A. R., Berwick, M., Ireland & C. R. A., Olsen, M., The effects of exposure to solar radiation on human health, Photokhemical&Photobiological Sciences, 22, 1011-1047, 2023.
20. Ogurtsov, M. G. Nagovitsyn, Yu. A., Kocharov, G. E., Jungner, H., Long-Period Cycles of the Sun's Activity Recorded in Direct Solar Data and Proxies, Solar Physics, v. 211, Issue 1, p. 371-394, 2002.
21. Peng, L., Li, N., Pan, J., Effect of Ap-Index of Geomagnetic Activity on S&P 500 Stock Market Return, Advances in Astronomy, vol. 2019, id.2748062, 2019.
22. Stock, J. H, Watson, M. W., New indexes of coincident and leading economic indicators. In: NBER Macroeconomics Annual 1989, Volume 4. MIT Press; 351–409, 1989.
23. Torrence, C., Webster, P., Interdecadal changes in the ESNO-Monsoon System, J.Clim., 12, 2679–2690, 1999.
24. Walsh, B., "Economic Cycles and Changes in the Earth's Geomagnetic Field", Cycles Magazine, Vol. 44, pp. 76-80, 1993. ISSN 0011-4294.
25. Velasco Herrera, V. M., Pérez-Peraza, J., Soon, W., Márquez-Adame, J. C., The quasi-biennial oscillation of 1.7 years in ground level enhancement events. New Astronomy, 60, 7–13, 2018.
26. Zheng X., Chen B. M., Analysis of Dow Jones Industrial Average. In: Stock Market Modeling and Forecasting. Lecture Notes in Control and Information Sciences, vol 442. Springer, London. pp. 43-51, 2013.
27. Wavelet software by C. Torrence and G. Compo - http://paos.colorado.edu/research/wavelets/
28. Crosswavelet and wavelet coherence software by A. Grinsted - http://noc.ac.uk/using-science/crosswavelet-wavelet-coherence
29. SILSO, Sunspot Index and Long-term Solar Observations - http://www.sidc.be/silso/datafiles Free Historical Market Data – Stooq;
30. https://stooq.com/^DJI - Dow Jones Industrial - U.S. - Stooq
31. Neutron monitors at the Sodankyla Geophysical Observatory in Oulu, Finland - https://cosmicrays.oulu.fi/

მზის აქტივობა და დოუ ჯონსის ინდუსტრიული საშუალო ინდექსი

დარეჯან ჯაფარიძე[1,2], თამარ პაატაშვილი[3], ბიძინა ჩარგეიშვილი[4], თენგიზ მძინარიშვილი[5]

[1] სსიპ - ევგენი ხარაძის ეროვნული ასტროფიზიკური ობსერვატორიის უფროსი მეცნიერ თანამშრომელი; [2] ილიას სახელმწიფო უნივერსიტეტის ასოცირებული პროფესორი, გამოთვლითი ჰელიოკვლევების ცენტრი; darejan.japaridze@iliauni.edu.ge; [3] სსიპ - ევგენი ხარაძის ეროვნული ასტროფიზიკური ობსერვატორიის მონაცემთა დამუშავების სპეციალისტი; tpaatashvili@abao.ge; [4] სსიპ - ევგენი ხარაძის ეროვნული ასტროფიზიკური ობსერვატორიის უფროსი მეცნიერ თანამშრომელი; bidzina@aidio.net; [5] სსიპ - ევგენი ხარაძის ეროვნული ასტროფიზიკური ობსერვატორიის უფროსი მეცნიერ თანამშრომელი; tengiz.mdzinarishvili@iliauni.edu.ge

ანოტაცია

შესწავლილი იქნა კავშირი მზის აქტივობასა და დოუ ჯონსის ინდუსტრიულ საშუალო ინდექსს შორის 1896 წლიდან 2021 წლამდე. გამოყენებული იქნა კორელაციისა და კროს-კორელაციის მეთოდები მცოცავი დროითი ფანჯრით და ვეივლეტ კოჰერენტულობის ანალიზი. აღმოჩენილია, რომ 11-წლიანი პერიოდულობით კორელაცია 0.5-ზე მეტია 1906–1936 და 1964–2000 წლებში და 95%-იანი სანდოობის დონით მოჩანს 1910–1930 და 1990–1994 წლებში. იმავე პერიოდებში მაღალი, 95%-იანი სანდოობით იქნა გამოვლენილი 11 წლიანი სინქრონიზაცია კოსმოსური სხივების მონაცემებსა და დოუ ჯონსის ინდუსტრიულ საშუალო ინდექსს შორის, ხოლო მზის ლაქების რაოდენობასა და კოსმოსური სხივების მონაცემებს შორის 1964–2000 წწ. კორელაცია მაღალია ფაზური სხვაობით. შესწავლილ მოვლენებს შორის კორელაციის გამოვლენა რთულია, ვინაიდან ფინანსურ ინდექსებზე ერთდროულად მრავალი ფაქტორი ახდენს გავლენას. მიუხედავად ამისა, მნიშვნელოვანია ფინანსურ ინდექსებსა და მზის აქტივობას ან კოსმოსურ სხივებს შორის კორელაციების შესწავლა ფინანსური საპროგნოზო მოდელებისა და სისტემური რისკების შესაფასებლად.

საკვანძო სიტყვები: დოუ ჯონსის ინდუსტრიული საშუალო ინდექსი, მზის აქტივობა, მზის ლაქები, კოსმოსური სხივები

კვლევა დაფინანსდა საქართველოს შოთა რუსთველის ეროვნული სამეცნიერო ფონდის (SRNSF) მიერ, გრანტის ნომერი FR-24-14835.