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Method for Detection of Forbush Effects in Cosmic Ray Flux According to Neutron Monitors Data Using Wavelet Transform

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Abstract: The method developed by the authors for detection of Forbush effects in cosmic ray variations based on ground data of neutron monitors is presented. The method is based on the synthesis of the classical theory of risks with nonlinear approximating schemes in wavelet bases. The basis of the method are the rules composed by the authors. Numerical realization of the developed rules makes it possible to obtain a solution close to optimal without pre-training in near real-time mode. On the example of periods of extreme magnetic storms in 2024, method results confirming its efficiency are illustrated. General anomalous dynamics of the cosmic ray flux is distinguished. Anomalous changes, preceding the beginnings of the events under analysis, were discovered. The observed correlation with the changes of interplanetary environment parameters indicates the reliability of the obrained results.

Keywords: data analysis method, cosmic rays, neutron monitor data, Forbush effects, magnetic storms.

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Research Article

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1. Introduction

To this date, investigations of cosmic rays are of interest both for astrophysical researches and for applied fields associated with space weather problems [*Kuznetsov*, 2014; *Rycroft*, 2007]. Solar activity and its sporadic manifestations (flares, coronal mass ejections, shock waves) are the main sources of space weather, which determine power outage, radio communication noise, failures in satellite, aviation and navigation systems up to catastrophic faults [*Kuznetsov*, 2014; *Rycroft*, 2007]. As advanced technical systems develop, methods and tools capable of analyzing cosmic ray variations in real-time and with the required accuracy and preventing their negative consequences are becoming increasingly relevant and in demand [*Rycroft*, 2007].

At present time, cosmic ray variations are analyzed by the scientists of different countries in related disciplines. Mew methods are created and current methods are developed for obtaining the main characteristics of cosmic ray variations [*Getmanov et al.*, 2023; 2024; *Kovylyaeva et al.*, 2019; *Krymsky et al.*, 1966; *Lukovenkova et al.*, 2018]. The known Global Survey Method (GSM), which was suggested by the Russian scientists in 60-s of the last century for the first time [*Krymsky et al.*, 1966], has been successfully developed by the research group [*Belov et al.*, 2018] up to the present. The GSM is applied to estimate the anisotropy of galactic cosmic rays and, as a sequence, to predict geomagnetic disturbances. However, this method is efficient not for all kinds of anomalies in cosmic rays (for example, proton increase beginning), and it does not provide real-time results due to the complexity of estimations. The applied threshold algorithms [*Real-Time Database…*, 2024] are insensitive to small-amplitude anomalies that significantly decreases their efficiency. It was illustrated in a number of papers [*Kalashev et al.*, 2020; *Mandrikova et al.*, 2015] that application of current methods of artificial intelligence, based on neural networks, makes it possible to detect anomalies in cosmic rays in near real-time mode and with adequate accuracy. However, the efficiency of this approach depend on data training samplings and decreases significantly when natural process properties change that is inevitable. The investigations [*Borog et al.*, 2011; *Mallat*, 1999; *Mandrikova et al.*, 2024; *Mandrikova*, 2024; *Zhu et al.*, 2015] showed that the wavelet transform apparatus allows one to solve the problem of significant nonsationarity of data in a number of cases. For example, in the paper [*Zhu et al.*, 2015], successful application of wavelet analysis of cosmic ray flux for geomagnetic storm prediction was shown. The paper [*Borog et al.*, 2011] presents application of spectral-singular decomposition and wavelet transform for identification of galactic cosmic ray flux variations associated with interplanetary magnetic field disturbances.

This paper presents the automated method developed by the authors for detection of Forbush effects in cosmic ray variations. The method is based on the synthesis of the classical theory of risks with nonlinear approximating schemes in wavelet bases. Numerical realization of the method allows us to obtain a solution close to optimal one in near real-time mode. The advantage of the proposed method, in contrast to its analogues, is the absence of a training procedure. This allows the method to be used with limited data sets. In addition, the built-in adaptation mechanism, according to the developed rules, does not require periodic adjustment of the method parameters due to the continuous variability of natural data (changes associated with the level of solar activity, seasonal variations, etc.). Another important advantage of the method is its ability to suppress interference based on the construction of a tree of wavelet packets and the use of threshold functions. This advantage allows us not to use a preliminary data processing procedure, which reduces the methodological and computational complexity of the calculations performed. In order to be able to detect different types of structures in neutron monitor data, the paper proposes to use a superposition of discrete wavelet transform and nonlinear adaptive schemes in the dictionary of wavelet packets. It is known [*Mallat*, 1999] that wavelet packets have the best frequency-time resolution. On the example of extreme magnetic storms in 2024, the method results are presented. They confirm its efficiency.

2. Method description

The recorded time series of data can be represented as

$$f(t) = \sum_{m,n} p_{m,n}\Psi_{m,n}(t) + R(t) + \epsilon(t) = A(t) + e(t), \quad (1)$$

where the component $A(t) = \sum_m \sum_n p_{m,n}\Psi_{m,n}(t)$ describes anomalous changes in data and is the informative component, the component $R(t)$ describes regular variations in data, the component $\epsilon(t)$ is noise; among the agreed notations, the component $e(t) = R(t)+\epsilon(t)$ is noise, the informative component $A(t)$ is determined by the basic functions: $\Psi = \left\{\Psi_{m,n}\right\}_{(m,n)\epsilon Z^2}$ is the wavelet basis, $\Psi_{m,n}(t) = 2^{\frac{m}{2}}\Psi\left(2^m t - n\right)$, $p_{m,n} = \left\langle f, \Psi_{m,n}\right\rangle$ are the coefficients, m is the scale parameter, n is the time parameter.

The problem of detection of anomalous changes, according to representation (1), is reduced to the problem of estimation of the component $\hat{A}(t)$ in the model. The recorded data are considered as the ones generated by time-changing random process. Due to the variety of anomalies, distribution of the component $A(t)$ probabilities is evidently typical. Then, as it was shown in the papers [*Mallat*, 1999; *Mandrikova*, 2024], to estimate $\hat{A}(t)$, nonlinear approximation is effective. Here the approximating vectors are determined adaptively to the structure of recorded input data. From the results of the papers [*Mandrikova et al.*, 2021; 2024], in this case, *nonlinear approximating schemes* in orthonormal wavelet basis are effective that agrees well with representation (1).

Considering wavelets as Ψ functions according to (1), we obtain a nonlinear approximating scheme of the following form from the results [*Mandrikova*, 2024] to estimate $\hat{A}(t)$

$$\hat{A}(t) = \sum_{(m,n)\in I_B} p_{m,n}\Psi_{m,n}, \quad (2)$$

where I_B is the set of indexes $p_{m,n}$, having the highest amplitudes $\left|\langle f, \Psi_{m,n}\rangle\right|$. The error of such an estimate is

$$\varepsilon\left[I_B\right] = \left\| f(t) - \tilde{f}_{I_B}(t)\right\|^2 = \sum_{(m,n)\notin I_B} \left|\langle f, \Psi_{m,n}\rangle\right|^2. \quad (3)$$

From the other side, as long as the nonlinear approximating scheme is expressed through the threshold function $\Pi_{T_{m,n}}(\cdot)$ [*Mandrikova et al.*, 2024], we have

$$\hat{A}(t) = \sum_m \sum_n \Pi_{T_{m,n}}\left(\langle f, \Psi_{m,n}\rangle\right)\Psi_{m,n}(t), \Pi_{T_{m,n}}\left(\langle f, \Psi_{m,n}\rangle\right) = \begin{cases} \langle f, \Psi_{m,n}\rangle, if \left|\langle f, \Psi_{m,n}\rangle\right| \geq T_{m,n} \\ 0, if \left|\langle f, \Psi_{m,n}\rangle\right| < T_{m,n} \end{cases}. \quad (4)$$

Based on the accepted ratio (4), we introduce the following *rule 1: we will consider that the data* $f(t)$ *contain anomalous changes on the scale* m *at the time moment* $t = n$, *if amplitudes of the coefficients* $p_{m,n} = \left|\langle f(t), \Psi_{m,n}(t)\rangle\right|$ *exceed the threshold* $T_{m,n}$ *on the scale* m *at the time moment* $t = n$.

We should note that the guarantee of the presence of anomalous changes in data, according to (4) is provided by the amplitude $\left|\langle f, \Psi_{m,n}\rangle\right|$ limitation by the lower boundary (the thresholds $T_{m,n}$). To optimize the estimates of $\hat{A}(t)$, following the paper [*Mandrikova et al.*, 2024], when determining the thresholds, we use the *likelihood ratio* [*Levin*, 1989] and introduce the following *rule 2: anomalous changes on the scale* m *at the time moment* $t = n$, *if*

$$\frac{\Pi\left(\left|p_{m,n}\right| |\Gamma_1\right)}{\Pi\left(\left|p_{m,n}\right| |\Gamma_0\right)} \geq T_{\alpha,m,n},$$

where $\Pi\left(\left|p_{m,n}\right| |\Gamma_0\right)$ *and* $\Pi\left(\left|p_{m,n}\right| |\Gamma_1\right)$ *are the probability densities* $\left|p_{m,n}\right|$, Γ_0 *is the zero hypothesis,* Γ_1 *is the alternative, the threshold* $T_{\alpha,m,n} = h_\alpha * \hat{\sigma}_{m,n}$ *is estimated in the vicinity of* (m,n) *with respect to Neumann-Pearson criterion from the condition* $\int_A W\left(\left|p_{m,n}\right| |\Gamma_0\right) d\left|p_{m,n}\right| = \alpha$, α *is the first-kind error.*

Using the *rule 2*, we detect anomalous changes in data according to the following *rule 3:*

Step 1. Basis $B_{l,m} = \{\Psi^l_{m,n}\}_{n\in N}$ *of wavelet packet space* B^l_m: $B_{l,m} = B^{2l}_{m+1} \oplus B^{2l+1}_{m+1}$ *is the basis*

$$B_{l,m} = \begin{cases} \Psi^l_{m,n}, if\, O\left(c^l_{m,n}\right) + O\left(c^{2l}_{m+1,n}\right) \geq O\left(c^{2l+1}_{m+1,n}\right), \\ \Psi^{2l}_{m+1,n} \cup \Psi^{2l+1}_{m+1,n}, if\, O\left(c^l_{m,n}\right) + O\left(c^{2l}_{m+1,n}\right) < O\left(c^{2l+1}_{m+1,n}\right), \end{cases}$$

where $O\left(c^{cl+k}_{m+k,n}\right) = \sum_{n\in I^{cl+1}} \left|c^{cl+1}_{m+k,n}\right|^2, c^l_{m,n} \in I^{cl} : \left|c^l_{m,n}\right| \geq T^l_{m,n}, T^l_{m,n} = k_\alpha * \sigma^l_{m,n}$.

Step 2. Error $B_{l,m}$ *is* $\varepsilon_{B_{l,m}} = \left\| f(t) - \tilde{f}_{I_B}(t)\right\|^2$ *(see (3)).*

Step 3. The best basis for $\hat{A}(t)$ *is* $R_{B_{best}} = \min_{B_{l,m}\in \mathrm{B}} \varepsilon_{B_{l,m}}$, B *is the set of wavelet bases.*

A fragment of the wavelet packet tree and *rule 3* elements are illustrated in Figure 1.

As an example, Figure 2 shows the numerical results of Step 1 and Step 2, performed according to the proposed rule 2. The wavelet packet tree was constructed for the data of the Inuvik st. neutron monitor. The numbers in the tree nodes show the estimated values of the function $B_{l,m}$. The nodes determined on the basis of rule 2 are marked in green.

As an example, Figure 3 shows the results of the proposed Forbush effect detection method performed for different threshold values (formula (4)). The calculations were performed using Oulu st. data for the period containing the geomagnetic storm (October 10, 2024). According to the proposed rule 1, the best threshold is determined, which

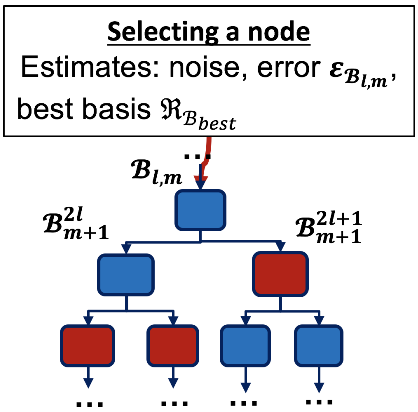

Figure 1. Fragment of the wavelet packet tree and the rule elements.

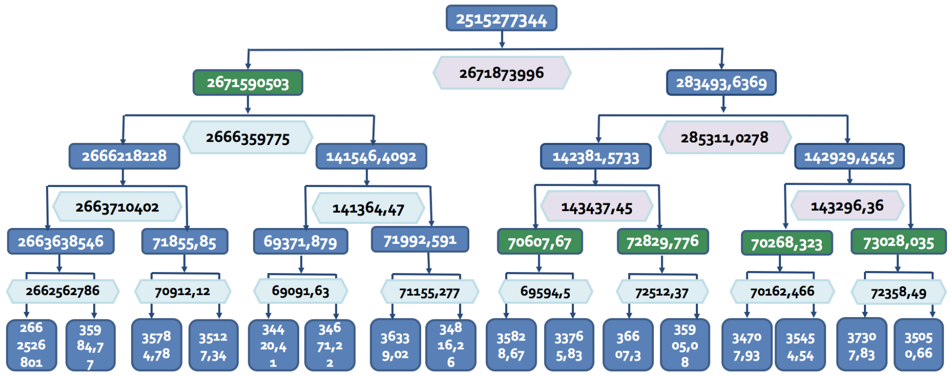

Figure 2. Wavelet packet tree.

minimizes the error in detecting Forbush effects shown in Figure 3d. The results with the best thresholds for the data from different stations are shown in Figure 5. Analysis of the results in Figure 3 shows that the best threshold allows suppressing the correlated noise associated with the daily variation of neutron monitor data. The results obtained confirm the importance of determining the best threshold in the process of implementing the method calculations and indicate the effectiveness of rule 1.

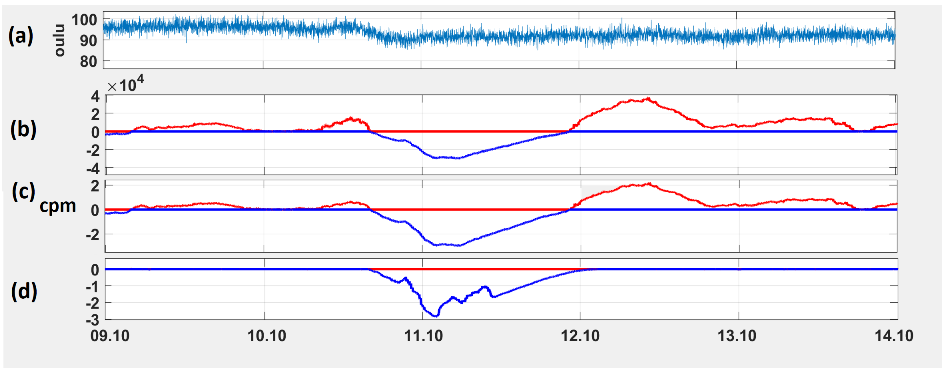

Figure 3. Neutron monitor data processing results.

3. Results and discussion

Neutron monitor data (www.nmdb.eu) and information on the parameters of the interplanetary environment and magnetosphere (ckp.gcras.ru, ipg.geospace.ru, spaceweather.izmiran.ru) was used in the investigation. Figure 4 shows the results of the developed method during the extreme magnetic storm on 10–11 May 2024. The near-Earth space state was calm before the magnetic storm on 8–9 May (ipg.geospace.ru). Based on the method results

(Figure 4 (c), (d)), cosmic ray (CR) intensity was within the background during the second half of the day on 9 May. Then, from the beginning of the day on 10 May, sudden anomalous increase of CR intensity occurred according to the data of all the stations under analysis. It lasted for about a day (indicated with red in Figure 4 (c), (d)). During the anomalous increase on 10 May, inhomogeneous accelerated fluxes from coronal mass ejection arrived at 16:00 UT and 22:00 UT, IMF fluctuations increased to Bz = −50 nT, solar wind velocity (SWV) grew to 790 km/s (ipg.geospace.ru). At the end of the day on 10 May, an extreme magnetic storm occurred. The time of the storm commencement is indicated by a vertical red line in Figure 4. The storm initial phase was accompanied by anomalous decrease in CR intensity. Deep Forbush decrease appeared (indicated with blue in Figure 3 (c), (d)). The next day, on 11 May, an inhomogeneous accelerated flux from a coronal whole and coronal mass ejection arrived at 10:00 UT, the SWV reached 1000 km/s (ipg.geospace.ru). CR variation intensity during that period decreased again. Based on the data of the stations under analysis, it took more than two days for the characteristic level of CR variations to recover (Figure 4 (d)). The distinguished general dynamics of CR confirms the reliability of the method results. Anomalous changes in CR flux variations agree with the results of other researchers [*Badruddin et al.*, 2019; *Belov et al.*, 2018; *Dorman*, 2005], confirm the importance of CR investigation and indicate the necessity of development of the methods for their analysis and extension of the observation network.

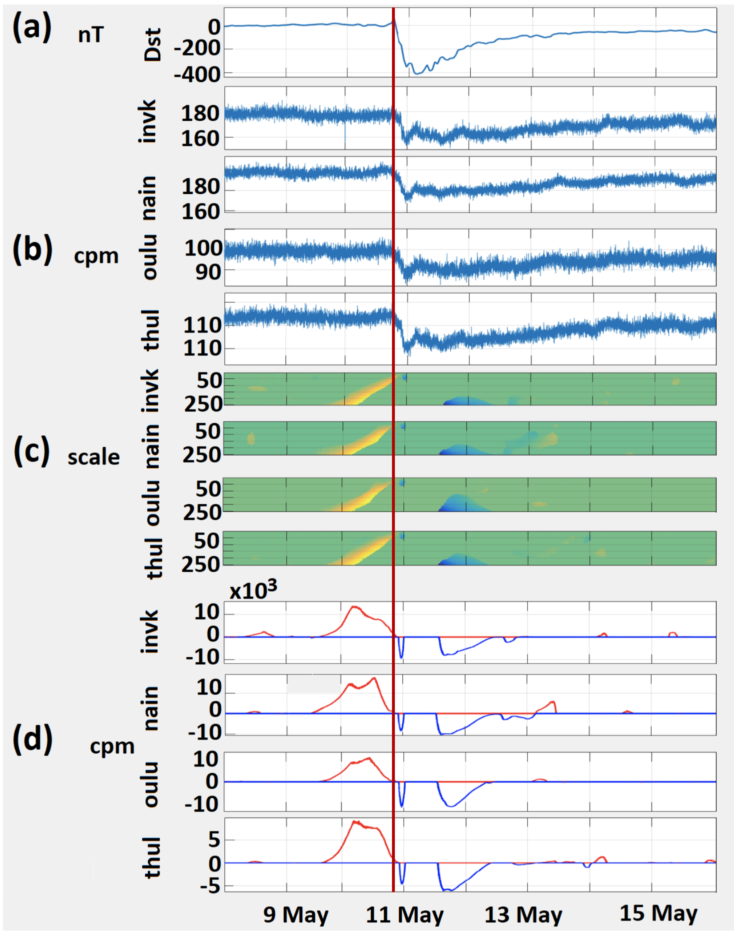

Figure 4. Neutron monitor data processing results.

Figure 5 illustrates the method results during the extreme magnetic storm on 10–11 October 2024. The magnetic field was unstable before the event. At the beginning of the day on 9 October, a moderate magnetic storm occurred (ipg.geospace.ru). The inhomogeneous accelerated flux from a coronal whole and coronal mass ejection (CME on 9 October) arrived at 14:00 UT on 10 October, IMF fluctuations were intensified to Bz = −46 nT, the SWV reached 760 km/s by 16:00 UT (ipg.geospace.ru). Based on the results of Sopo and Tule stations, a short-term weak increase of CR variation intensity occurred during the flux arrival (indicated with red in Figure 5 (l), (m)). During the initial phase of the storm, CR variation intensity decreased (Figure 5 (f)–(m)) and remained anomalously decreased during the main and the recovery phases. The Forbush decrease reached the maximum amplitude during the strongest geomagnetic disturbances (Figure 5 (j)–(m)). Then the SWV was within 760–650 km/s, IMF component fluctuated from Bz = −30 nT to Bz = +19 nT (ipg.geospace.ru). At the end of the day on 12 October, the SWV began to decrease and by the end of the period it reached 400 km/s. During this period, the CR variation level recovered (Figure 5 (f)–(m)).

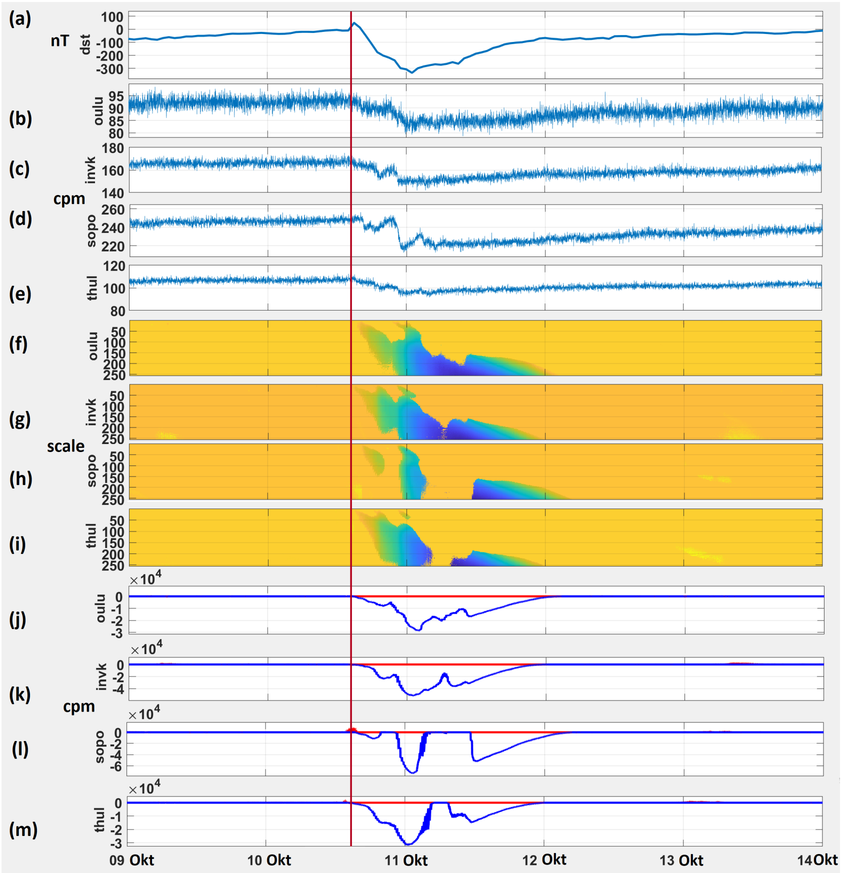

Figure 5. Neutron monitor data processing results.

The results of the method evaluation, performed using real data from neutron monitors (www.nmdb.eu), are presented in Table 1.

Table 1. Results of the effectiveness of the method.

Period	Number of Forbush effects	Results of algorithms (probability of detecting Forbush effects)
2013–2015 (high Solar activity)	285	Detected: 0.86 Not detected: 0.14 (probability of missing target) False alarm: 0.13
2019–2020 (low Solar activity)	174	Detected: 0.88 Not detected: 0.12 (probability of missing target) False alarm: 0.11
2023–2025 (high Solar activity)	127	Detected: 0.89 Not detected: 0.11 (probability of missing target) False alarm: 0.14

4. Conclusions

The results of the work confirmed the efficiency of the proposed method for the task of detecting Forbush effects based on neutron monitor data. Estimates based on real data showed:

- the probability of detecting Forbush effects for periods of high solar activity is ~0.87, with a target miss probability of ~0.12;
- the probability of detecting Forbush effects for periods of low solar activity is ~0.88, with a target miss probability of ~0.12.

Due to the absence of a training procedure, the method can be applied to limited data sets. The built-in adaptation mechanism, according to the developed rules, also does not require the procedure for periodic adjustment of the method parameters due to the continuous variability of natural data (changes associated with the level of solar activity, seasonal variations, etc.). In addition, the use of adaptive thresholds, when constructing a nonlinear approximating scheme, makes it possible to suppress interference and avoid the procedure of preliminary data processing.

The presented results show the necessity of taking into account the cosmic ray data when predicting space weather. On the example of the event on 10–11 October 2024, we have confirmed the impotence of development of real-time methods for data analysis, providing timely alarm notification on the beginning of a magnetic storm, and extension of observation network. The detected general dynamics in CR flux and the correlation with the parameter changes in interplanetary environment and magnetosphere as well as correspondence of the results to the data of other investigations [*Badruddin et al.*, 2019; *Belov et al.*, 2018; *Dorman*, 2005] indicate the reliability of the obtained results and confirm the suggested method efficiency.

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