
MACHINE-LEARNING METHOD FOR RECONSTRUCTING NEAR-EARTH LOW-ENERGY COSMIC RAY FLUXES FROM GROUND-BASED SOPO NEUTRON MONITOR DATA

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Abstract. Nowadays, there are a large number of ground-based neutron monitors. These detectors measure neutron fluxes produced by the interaction of primary cosmic rays (CR) with Earth's atmosphere. Since their invention in the 1950s, they have become very popular for studying variations of CR intensity on different time scales. These detection systems are stable and therefore can conduct continuous measurements for decades. However, they exhibit low sensitivity to cosmic ray fluxes with energies ≤ 1 GeV, whereas heliospheric variations of these fluxes are most pronounced at lower energies. The rapid growth of the space industry has made it possible to perform direct measurements of CR fluxes by a variety of scientific instruments installed on board spacecraft. Satellite-borne detectors measure cosmic ray fluxes across a wide energy range, from tens of keV up to tens of TeV. Nonetheless, experimental data collected by spacecraft is not always immediately accessible and is often published with a significant delay. Moreover, the radiation in outer space is gradually reducing the efficiency and stability of satellite systems, so their operating time in orbit is limited. Ground-based detectors are less susceptible to radiation damage, and their data is always available for scientific research. Therefore, developing methods to reconstruct

top-of-atmosphere CR fluxes from ground-based detector data is increasingly urgent. This paper presents the method for calibrating the high-latitude SOPO neutron monitor by machine-learning algorithms, using data on cosmic proton fluxes with energy >500 MeV from the P11 channel of the proton sensor installed aboard the GOES-16 satellite. The machine model obtained as the result of training was employed to reconstruct the low-energy cosmic ray flux from SOPO data. Then it was compared with actual data from the GOES-16 proton sensor.

Keywords: cosmic rays, Forbush decreases, geomagnetic storm, solar activity.

INTRODUCTION

Galactic cosmic rays (GCRs) are high-energy particles generated primarily by supernova explosions [Blasi, 2013; Gabici, 2022]. As these particles propagate through interstellar space, they undergo various acceleration and deceleration processes [Ptuskin, 2012; Bykov et al., 2018]. GCRs consist mainly of protons ($\sim 89\%$) and helium nuclei ($\sim 10\%$) [Dong et al., 2024]. GCR particles interact with the solar wind and the interplanetary magnetic field as they penetrate deep into the heliosphere, altering their trajectory and transport behavior. Such effects are observed in the energy range up to 30 GeV [Potgieter, 2013, 2014]. Monitoring the time evolution and variations of GCR fluxes is an important tool in studying solar activity on various time scales. The Sun is a source of low-energy solar CRs (SCRs)

[Miroshnichenko, 2018], which shows up most vividly during turbulent processes occurring in the solar corona, such as coronal mass ejections (CMEs) [Kilpua et al., 2017]. CMEs are often accompanied by solar energetic particle (SEP) events [Desai, Giacalone, 2016; Bruno et al., 2018] and solar flares [Curto, 2020]. Charged CR particles in near-Earth space interact with Earth's atmosphere, thereby giving rise to a large number of secondary particles whose fluxes are recorded by ground-based instruments [Riggi, 2023]. Note that low-energy CR fluxes are the main source of dangerous atmospheric radiation at aviation altitudes. This can negatively affect the stability of electronic systems particularly during geomagnetic storms [Rozelot et al., 2018] and cause software errors, which is a critical aspect of the safe operation of onboard electronic systems [Mertens, To-

biska, 2021; Tomsia et al., 2024]. The latter, in turn, is especially relevant in light of the recent precautionary fleet action for Airbus A320 aircraft because of the software vulnerability detected due to the destructive effects of solar radiation fluxes on aircraft avionics [https://www.airbus.com/en/newsroom/press-releases/2025-11-airbus-update-on-a320-family-precision-fleet-action]. That is why the long-term monitoring of low-energy CR fluxes is critical to understanding the physical aspects of space weather and their impact on human life and activities. Real-time data on abrupt changes in low-energy CR fluxes is also useful for issuing warnings and forecasting space weather conditions, which, in turn, is necessary for planning and safety of space missions.

Nowadays, CR flux variations are examined using both ground-based detectors and satellite-mounted scientific instruments [Picozza et al., 2018; Battiston, 2020]. Satellite detectors provide high-precision direct measurements of top-of-atmosphere (TOA) CR fluxes in various time and energy ranges, but space experiments are much more expensive than ground-based ones. Radiation levels in space are about a hundred times higher. This results in accelerated degradation of electronic components, which, in turn, reduces the measurement efficiency and can lead to failure in space instruments, especially during SEP events. Such impacts can distort or destroy experimental data and disrupt scientific equipment [Calligaro, Gatti, 2018].

Neutron monitors (NM) are detectors that measure the integral intensity of secondary cosmic radiation near Earth's surface [Hatton, Carmichael, 1964; Strauss et al., 2020; Aspinall et al., 2024]. Such instruments are easy to maintain and upgrade; they are installed in different geographic regions and are capable of making continuous measurements for decades.

Ground-based detectors are not susceptible to radiation damage; however, they record the secondary CR component produced by the interaction between primary CRs and Earth's atmosphere. Therefore, they have much

lower sensitivity to the low-energy CR component (<1 GeV) compared to satellite detectors [Alanko et al., 2003]. The energy sensitivity of NM depends on geomagnetic cutoff rigidity (R_c , GV) [Chu et al., 2022] and atmospheric depth at the detector location [Mishev et al., 2020]. The geomagnetic cutoff rigidity is the minimum rigidity value (the ratio of a particle's momentum to its charge) corresponding to the threshold for recording a particle flux in Earth's magnetosphere due to the shielding effect of the geomagnetic field. By analogy, the term “atmospheric cutoff energy” is introduced — the energy that a CR particle loses when penetrating to a given depth of Earth's atmosphere. Obviously, high-latitude NMs are more sensitive to the low-energy CR component due to the lower geomagnetic cutoff rigidity. They are, therefore, more suitable for studying various effects associated with solar modulation. Figure 1 shows normalized daily count rates of several NMs. The amplitude of the 11-year solar cycle is seen to be much higher for NMs located in places with lower R_c . This opens up the possibility of developing methods for reconstructing near-Earth CR fluxes from data obtained on Earth's surface. The development of such methods will significantly expand the capabilities of the network of ground-based neutron monitors in terms of examining low-energy CR variations in the vicinity of Earth. Such methods can also be useful for verifying satellite data during orbital flight. In turn, this will make it possible to more rationally choose location for new NM stations [Siruk et al., 2025].

Currently, some steps are already being taken in this direction [Usoskin et al., 2005; Väisänen et al., 2023]. However, they are based on a very simplified description of CR propagation in the heliosphere, known as the force-field approximation [Gleeson, Axford, 1968]. The assumptions underlying this approach allow us to obtain an analytical solution of Parker's transport equation [Moraal, 2013] describing CR transport in the heliosphere. Within this approximation, for GCR proton and helion fluxes it can be written

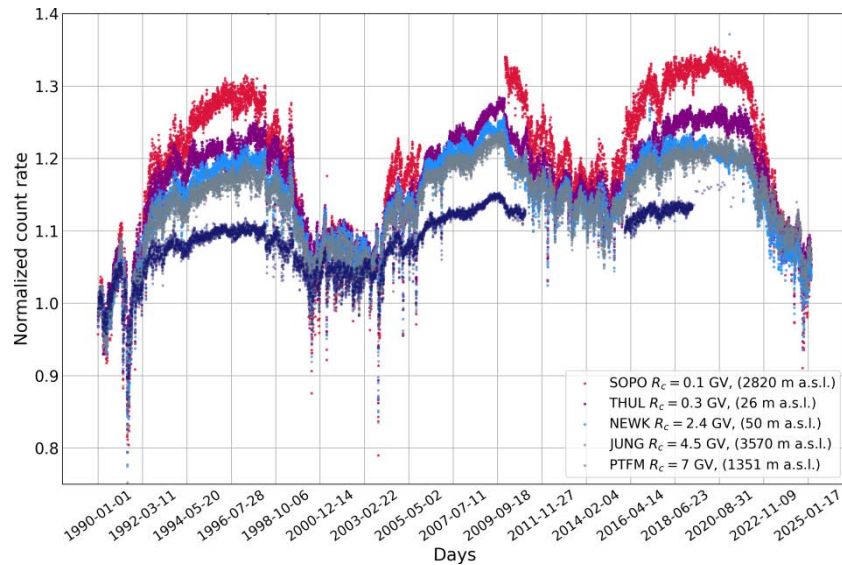


Figure 1. Normalized daily CR count rates measured on Earth's surface for several NM stations in 1990–2025. The normalization was carried out in January 1990. Dates are given in UTC

$$J(T) = J_{\text{LIS}}(T + \Phi) \frac{T(T + 2T_r)}{(T + \Phi)(T + \Phi + 2T_r)},$$

where T is the particle kinetic energy, GeV/nuc; $J(T)$ is the flux of particles with a given energy at a certain point in the heliosphere; $J_{\text{LIS}}(T)$ is the local interstellar spectrum; $Y = (eZ/A)\phi$ is the particle energy losses when moving deeper into the heliosphere; ϕ is the modulation potential; Z is the nucleus charge; A is the nucleus weight; e is the electron charge; T_r is the particle rest energy, GeV/nuc.

NM calibration algorithms based on this approximation can reconstruct the modulation potential ϕ from NM count rates. In addition to the limitations inherent in the force-field approximation itself [Caballero—Lopez and Moraal, 2004], this approach proves to be inapplicable for reconstructing CR fluxes with energies below 3 GeV [Koldobsky, Usoskin, 2024], whereas the effects associated with geomagnetic storms are most pronounced in this energy range of CRs [Lagoida et al., 2024]. This paper discusses an attempt to overcome the described limitations using machine learning algorithms.

The main task is to train the neural network (NN) to be capable of calculating near-Earth CR flux from ground-based NM data.

DATA AND METHOD

The training of NNs relies on a comprehensive dataset of CR fluxes recorded simultaneously in near-Earth space and on Earth's surface. The fluxes detected by the Solar and Galactic Proton Sensor (SGPS) on board GOES-16 were utilized as data on primary low-energy CR fluxes [Goodman et al., 2020; Kress et al., 2021]. This device has several measurement channels, each designed to record particles in a certain energy range. To tackle this task, the P11 channel is preferable because it measures the total proton flux with energies >500 MeV. The SGPS aperture is small since the detector itself is small in size. Hence, the P11 channel, as well as other integral channels in earlier versions of GOES satellites, does have an upper limit on the particle recording energy. The effective ener-

gy of detected CR particles for the integral channels is ~ 1 GeV [Bruno, 2017; Hu, Semones, 2022]. Figure 2 displays the time profile of the proton flux from the P11 channel during a solar flare in September 2017 [Kress et al., 2021]. Also shown is the diurnal flux of CR protons recorded by AMS-02 in the energy range 760–1100 MeV [Aguilar et al., 2021]. Comparing these data indicates that they are in good agreement.

Polar regions of Earth are characterized by low R_c ; therefore, the dominant factor affecting the sensitivity of polar NMs to the low-energy CR component is the atmospheric cutoff energy. According to today's calculations [Mishev, Poluianov, 2021; Poluianov, Batalla, 2022], its value does not exceed 450 MeV for polar stations located at sea level. That is why it is precisely the high-latitude NMs that should be sensitive to the energy range of the P11 channel of GOES-16.

We chose data from the polar SOPO NM [Oh et al., 2012], located at an altitude of 2820 m above sea level with $R_c \sim 0.09$ GEV, as data on CR fluxes recorded on Earth's surface. The dataset used in this work comprises daily average fluxes from GOES-16 SGPS P11 and daily average NM count rates from the SOPO station. Figure 3 presents the normalized daily average proton flux recorded by the P11 channel versus the normalized SOPO NM count rate. The normalization was carried out to the average value calculated for two weeks from November 1, 2020.

A typical NN architecture comprises three main layers: input, hidden, and output. Together, these layers process data sequentially. Specifically, the input layer receives the data, hidden layers process information to identify patterns, and the output layer generates the final result. Neurons in adjacent layers are fully connected, meaning that a signal from every single neuron in the previous layer passes to every neuron in the next layer. The behavior of each neuron in the network depends on the activation function, which governs its response to the input signal [Lederer, 2021].

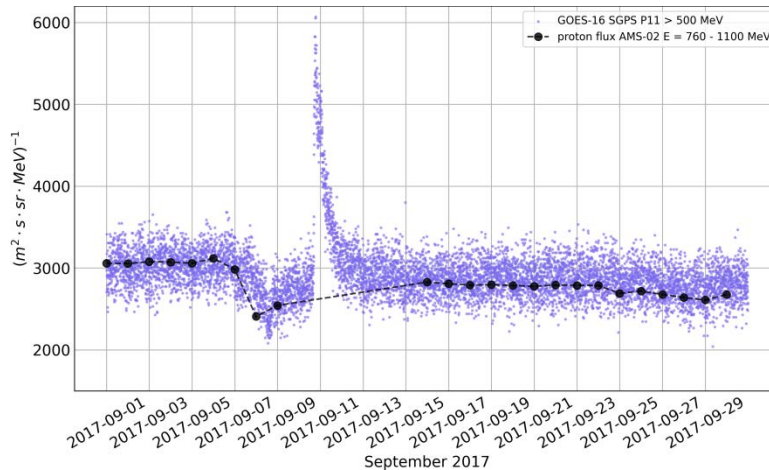


Figure 2. Five-minute proton flux values recorded by the GOES-16 satellite's P11 channel during a solar flare in September 2017, as well as daily proton flux values obtained by the spectrometer AMS-02 in the energy range 760–1100 MeV during this period. Dates are given in UTC

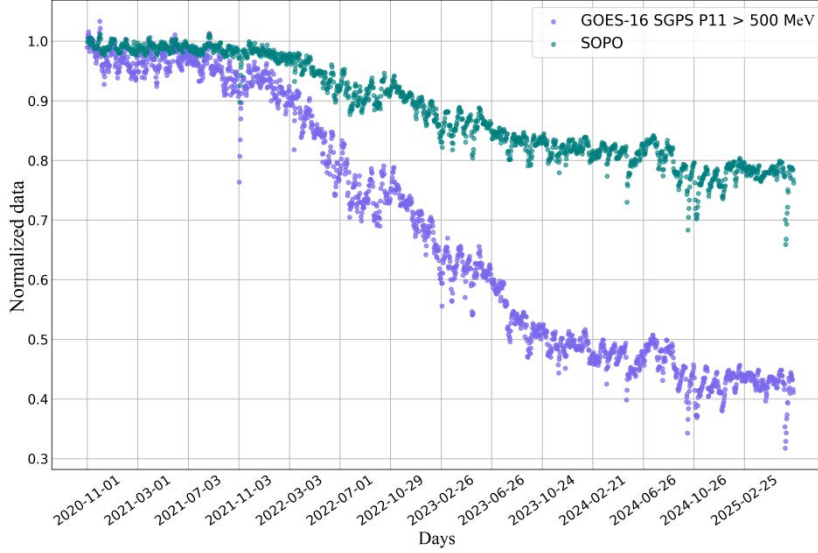


Figure 3. Daily average normalized cosmic proton flux, recorded by the P11 channel ($E > 500$ MeV) of SGPS installed on board GOES-16, versus normalized SOPO NM count rates for the period from November 1, 2020 to June 21, 2025. Dates are given in UTC

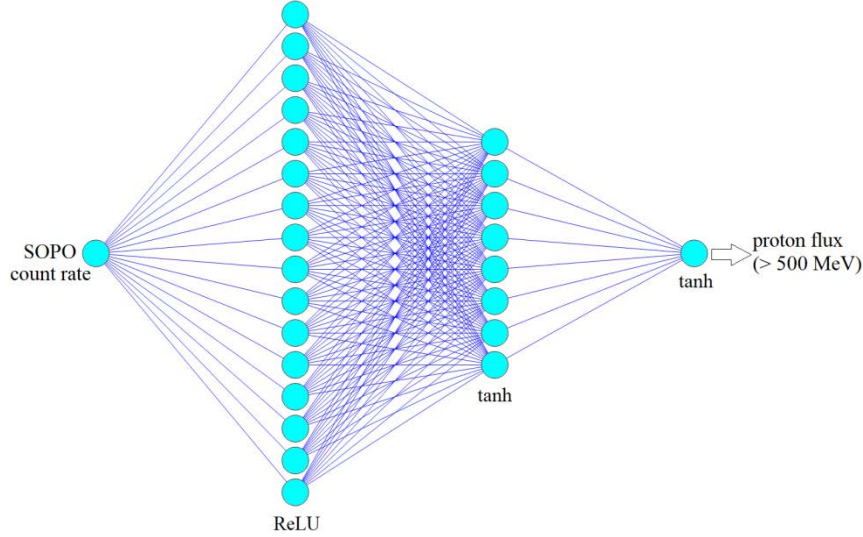


Figure 4. Architecture of the NN used for calibrating SOPO NM

This architecture allows the NN to effectively model complex nonlinear relationships. NN training involves solving the problem of minimizing the loss function. The loss function measures the deviation of NN predictions from the ground truth [Wang et al., 2022; Zhang et al., 2019]. This function is minimized by optimizing the parameters of the neurons — the network's elementary computing cells. The optimization process is carried out through an iterative training cycle, using the gradient descent algorithm or its modifications. This cycle continues until a specified target accuracy is achieved, or a predefined number of iterations is reached. Details of this process are thoroughly laid out in [Nielsen, 2015; Netrapalli, 2019]. Figure 4 shows the architecture of the NN in use. Normalized values of the daily SOPO NM count rate were fed to the network input. At the output, a normalized cosmic proton flux was expected which corresponds to the daily average flux recorded by GOES-16 SGPS P11. The ReLU activation function

was used for the first layer of neurons [Banerjee et al., 2019]; and the hyperbolic tangent activation function, for the second and third layers [Lau, Hann, 2018].

The resulting dataset corresponding to the time range of GOES-16 P11 measurements was divided into two parts: the first was employed for training; the second, for testing. The test dataset included data on every sixth day from November 1, 2020. Short-term variations in CR fluxes caused by various turbulent processes in interplanetary space were used to evaluate the generalization performance of the developed model. For this purpose, several Forbush decreases (FDs) were identified during the period of interest. The FD effect is the response of CR particles to CME propagation in outer space and involves a sharp drop in the recorded CR intensity [Cane, 2000]. Dates of the selected FD events, as well as some of their characteristics, are presented in Table. The FD amplitudes calculated from TOA CR fluxes are seen to be on average twice as high as those

measured from SOPO NM data. The FD amplitudes were calculated relative to the CR flux averaged five days before the beginning of the observed event.

The May 31, 2025 event was the most significant in amplitude at solar maximum during the period considered. It was also noted for the lowest value of the observed CR flux corresponding to the GOES-16 measurement period. In turn, the event recorded on November 3, 2021, proved to be the most significant during solar minimum over the same period. Including extreme values of the target physical quantities in the training set is essential for the model to successfully generalize across their entire range. The same is true for maximum amplitudes of the observed effects that can occur under various physical conditions, such as solar maxima and minima. These events have therefore been included in the training dataset for the NN. The information on CR fluxes during FDs that took place on March 13, 2022, March 24, August 10, and October 5, 2024 was excluded from the dataset selected for training the NN and

used to further assess the model's generalization ability. Figure 5 displays the time profile of CR fluxes corresponding to the highest amplitude FD event. Time profiles are also shown of the geomagnetic activity index Dst and the main characteristics of interplanetary space, such as the solar wind velocity SWV and the interplanetary magnetic field magnitude $|B|$ from the OMNI database [<https://omniweb.gsfc.nasa.gov/form/dx1.html>]. The CME-driven shock is seen to reach the vicinity of Earth around June 1. The maximum effect of the decrease was observed approximately on June 2, after which the FD recovery phase began. In the time profiles of the physical characteristics of interplanetary space, we can see significant fluctuations in values both before and after the observed phenomenon. The irregularity of the profiles is probably related to small CMEs that occurred on the Sun in the immediate vicinity of the main event on May 31, which is typical of solar maximum.

Characteristics of FD events selected for testing the model: date — the beginning of FD; CME — the CME event potentially responsible for the formation of the observed FD [Gopalswamy et al., 2009]; amplitude (P11) — the FD amplitude according to P11 data; amplitude (SOPO) — the FD amplitude from SOPO NM data

Date, UTC	CME, UTC	Amplitude (P11), %	Amplitude (SOPO), %
Nov. 03, 2021	Oct. 28, 2021, 15:48 Nov. 02, 2021, 02:48	~17 %	~9 %
Mar. 13, 2022	Mar. 10, 2022, 18:48	~9 %	~4 %
Mar. 24, 2024	Mar. 23, 2024, 01:25	~13 %	~6 %
Aug. 10, 2024	Aug. 09, 2024, 21:36	~10 %	~4 %
Oct. 05, 2024	Oct. 03, 2024, 12:48 Oct. 03, 2024, 20:36	~23 %	~13 %
May 31, 2025	May 31, 2025, 00:12	~27 %	~17 %

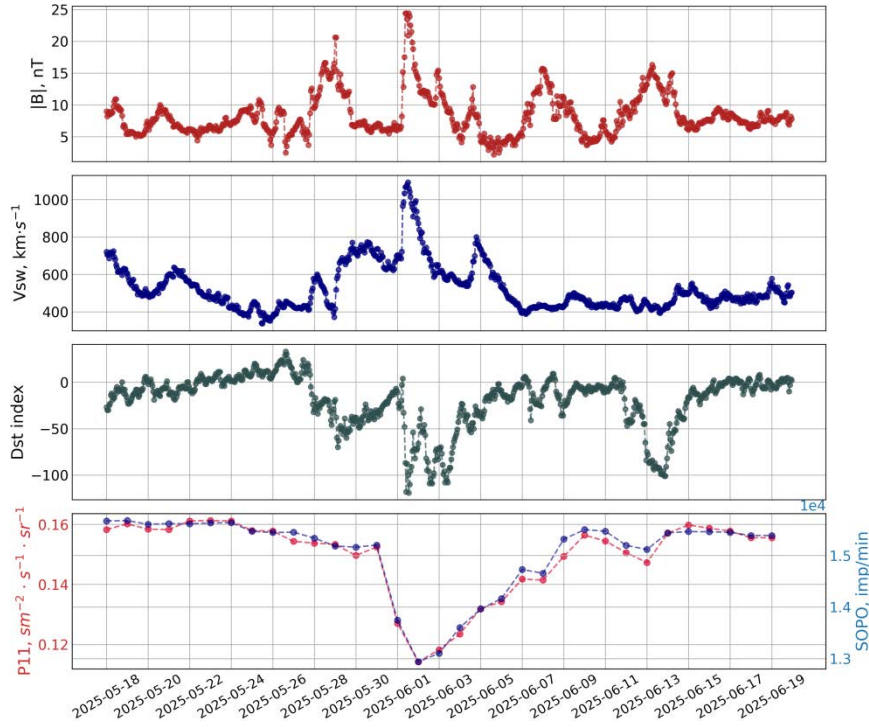


Figure 5. FD recorded in May 2025 in the cosmic proton flux (MeV), detected by GOES-16, and in the SOPO NM count rate. Also shown are the time profiles of hourly values of the interplanetary magnetic field magnitude $|B|$, the solar wind velocity SWV, and the geomagnetic activity index Dst . Dates are given in UTC

The NN was trained using an optimized stochastic gradient descent algorithm [Kingma, Ba, 2014] was employed to train the NN. The coefficient of determination R^2 and the mean absolute percentage error $MAPE$ were employed to compute the accuracy of the training and testing stages:

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{J}_i - J_i)^2}{\sum_{i=1}^n (J_i - \bar{J})^2}, \quad MAPE = \frac{1}{n} \sum_{i=1}^n \frac{J_i - \hat{J}_i}{J_i},$$

where J_i is the real proton flux recorded by GOES-16 P11; $\hat{J}_i$ is the proton flux reconstructed from SOPO NM data; $\bar{J}$ is the average value of the real TOA proton flux during the period under study; n is the total

number of days.

The Keras library for the Python programming language [<https://github.com/fchollet/keras>] was used to build the NN model. The training and testing results are presented in Figure 6. The convergence calculated from the metrics of the coefficient of determination for the test and training datasets $R^2 \approx 99.5\%$, and the mean absolute percentage error $MAPE \sim 1.7\text{--}1.8\%$ for both datasets. There is a good convergence between real TOA CR fluxes and those reconstructed from SOPO NM data for time segments not involved in NN training.

The results of the reconstruction of the time profiles of TOA CR fluxes observed during the March 13, 2022, March 24, August 10, and October 5, 2024 FDs, which were excluded from the training, are shown in Figure 7.

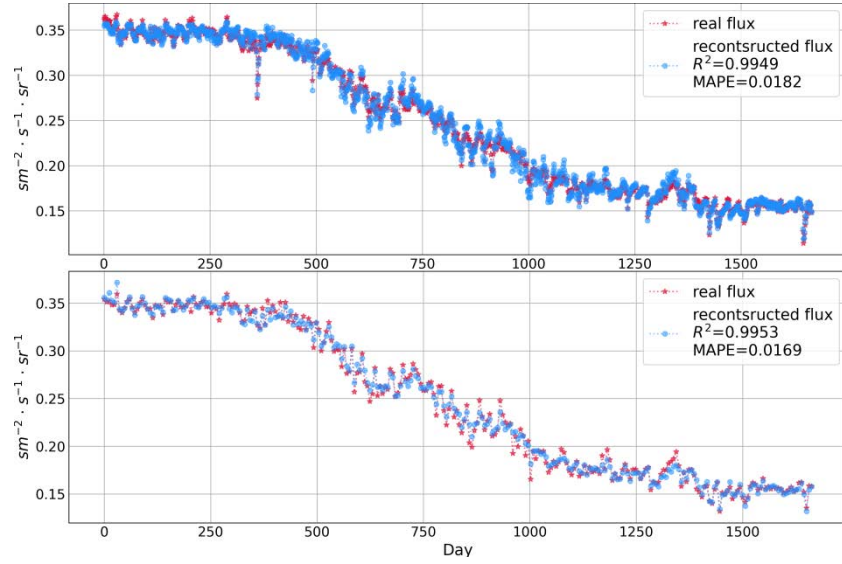


Figure 6. Cosmic proton fluxes recorded by GOES-16 P11 between November 1, 2020 and June 21, 2025 versus their values reconstructed from SOPO NM data. At the top are the reconstructed proton fluxes for the neural network (NN) training dataset. At the bottom are reconstructed proton fluxes for the test dataset (sampled every sixth day from November 1, 2020)

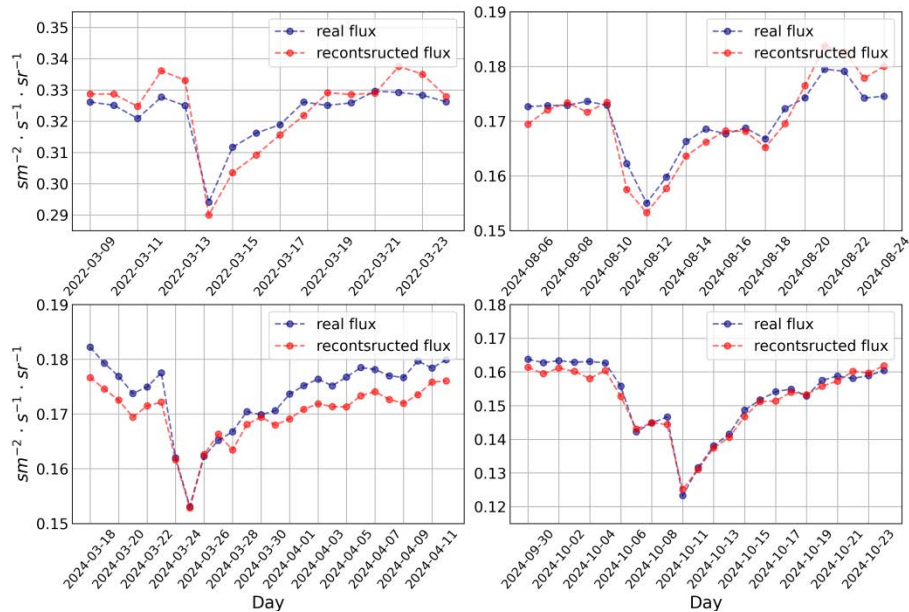


Figure 7. FD profiles reconstructed from SOPO NM data versus the actual measured CR fluxes. Dates are given in UTC

DISCUSSIONS AND CONCLUSIONS

We have described a method for calibrating NMs from satellite data on CR fluxes. As an example, the high-latitude SOPO NM was calibrated using the results of measurements of TOA CR fluxes between November 1, 2020 and June 21, 2025, made by the P11 channel of the proton sensor on board GOES-16. The NN, which receives normalized data on the daily SOPO NM count rate and calculates the corresponding low-energy proton fluxes for the P11 channel, has been trained. The CR fluxes reconstructed by this method from SOPO NM data are seen (Figures 6, 7) to check well with the real values obtained through direct measurements in the vicinity of Earth. Even for the test data, the mean deviation of the reconstructed fluxes does not exceed 2% relative to the values measured by GOES-16. Furthermore, the reconstructed FD time profiles closely match the observations during turbulent heliospheric processes, such as CME propagation.

Currently, no direct method exists to reconstruct low-energy CR fluxes from ground-based NM data. The results received in this work clearly demonstrate the prospects of applying the described approach in developing methods of reconstructing near-Earth low-energy CR fluxes in short and long periods, using data from ground-based detectors. This approach may be the only alternative to direct methods of reconstructing CR fluxes, since such results cannot be achieved with classical modeling due to the complexity and large scale of the physical processes occurring when primary CRs interact with Earth's atmosphere. The developed approach can be employed to reconstruct TOA low-energy CR fluxes, using data from one polar NM.

In future, the developed method is planned to be elaborated to explore the possibilities and to try to reconstruct the profiles of SEP (Solar Energy Particles) events, which are observed on much shorter time scales and have a dominant-negative impact on satellite and aviation electronic equipment.

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