The study of atmospheric effects on cosmic ray muons in the Low Background Laboratory for Nuclear Physics at the Institute of Physics Belgrade

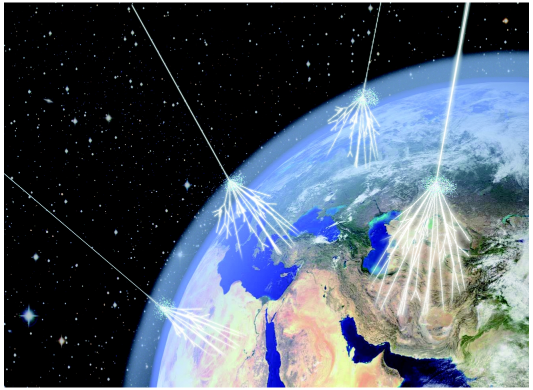
Mihailo Savić
Low background Laboratory for Nuclear Physics, Institute of Physics Belgrade

IV Meeting on Astrophysical Spectroscopy - A&M DATA – Atmosphere
01.06.2022 Fruška Gora, Serbia

Outline

- Primary and secondary cosmic rays
- Significance of atmospheric effects on secondary cosmic ray muons
- Modern day experiments and study of cosmic ray physics in Low Background Laboratory at IPB
- Theory of meteorological effects, its application and motivation for a new approach
- Meteorological data
- Two new empirical methods for modeling and correction of atmospheric effects
- Summary

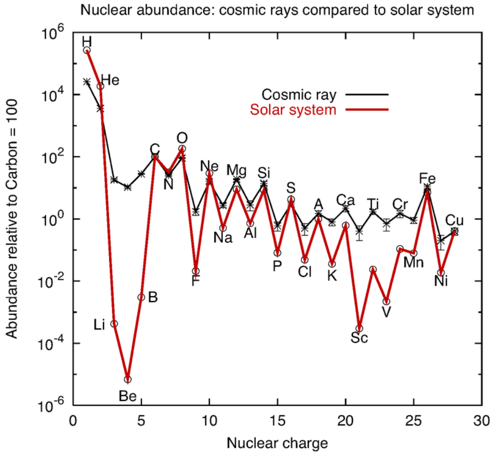
Primary cosmic rays

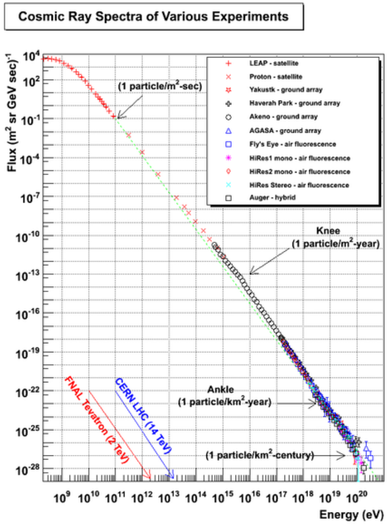


Primary cosmic rays are high-energy particles arriving at Earth from interstellar space, most likely sources of primary CR are extreme events such as supernova explosions. They are mainly of galactic by may also be of extra-galactic origin.

Primary CR composition:

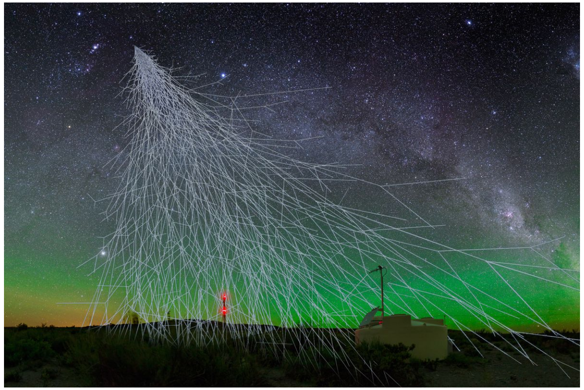
- Protons (≈ 90%)
- helium nuclei (≈ 9%)
- heavier nuclei, electrons, ... (≈ 1%)





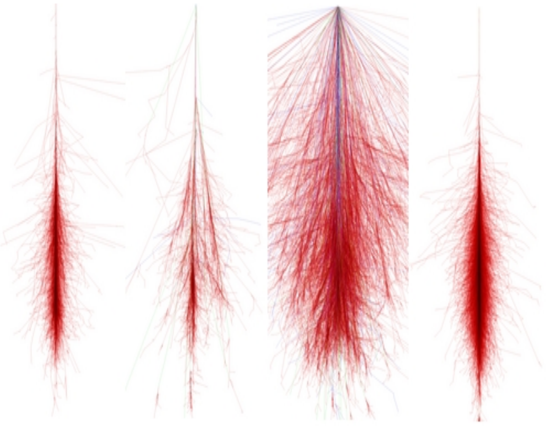
Energies vary from 10^8 to 10^{20} eV, greatly exceeding ones available in accelerator experiments. However, the frequency of extremely high-energy events is very low.

Secondary cosmic rays

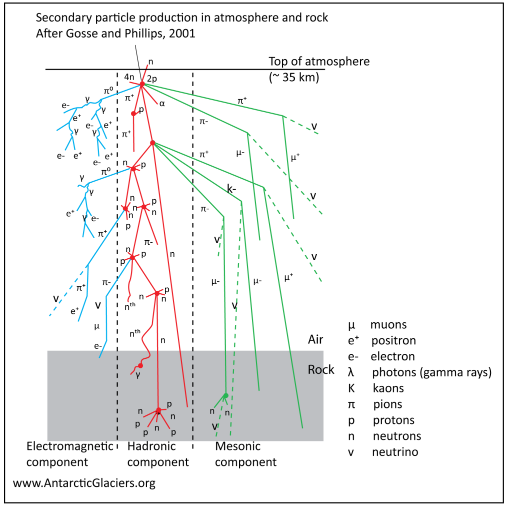


Upon arriving at Earth primary CR interact with air nuclei in the top layers of the atmosphere and produce particle cascades that propagate toward Earth's surface – air showers. These particles are called secondary cosmic rays.

Air shower profile (as well as type and number of particles arriving at Earth's surface) depends on the nature of primary particle.

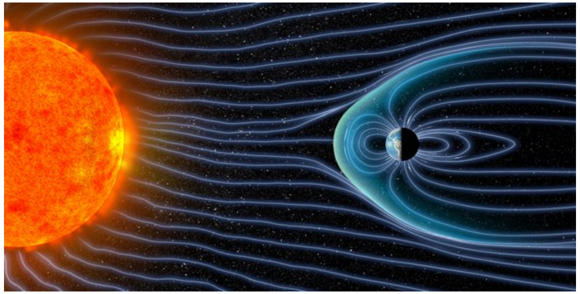


γ p Fe μ



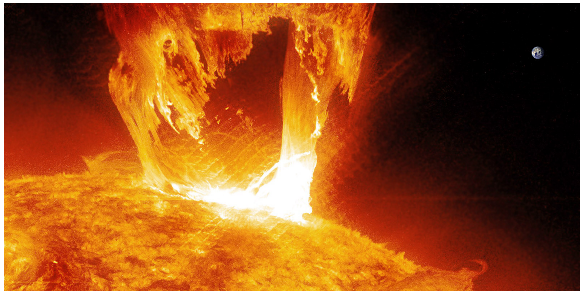
Most particles detectable by ground (and underground) based detectors belong to hadronic (primarily *p* and *n*) or meson components (almost exclusively muons).

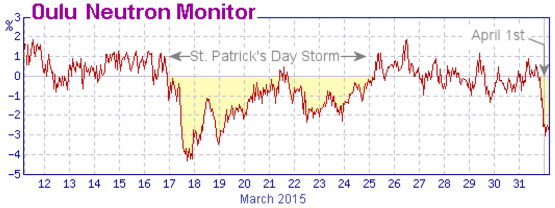
Solar modulation of cosmic rays



Prior to reaching Earth, primary cosmic ray flux is modulated in the heliosphere by Sun’s magnetic field embedded in the stream of particles that emanates from the Sun (solar wind), as well as by geomagnetic field in the magnetosphere.

Magnetic field in the heliosphere undergoes constant changes, which can be periodic (due to rotation and Sun’s magnetic cycles) or aperiodic (due to violent processes such as coronal mass ejections).



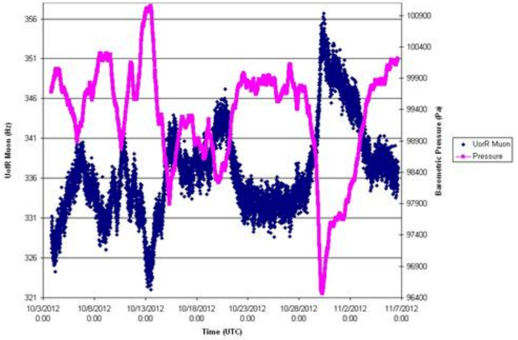


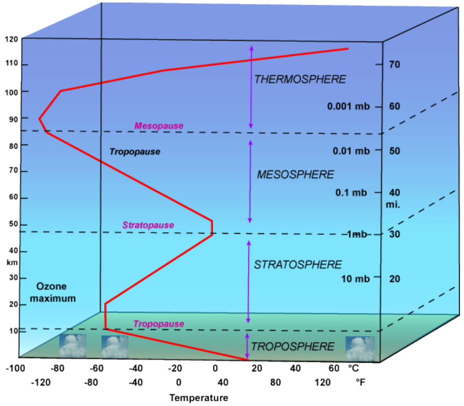
Consequently, such variations are reflected in the flux of primary and secondary cosmic rays, resulting in characteristic structures in CR time series (i.e. long-term 11-year variation due to Sun’s magnetic cycles or short-term Forbush decreases as a consequence of CME events).

Atmospheric effects on secondary cosmic rays

Varying conditions in the atmosphere affect the propagation of secondary cosmic rays. Various atmospheric parameters may contribute to this, main ones being atmospheric pressure, atmospheric temperature, humidity etc. These effects are collectively called meteorological effects.

Atmospheric pressure is directly related to the effective thickness of the atmosphere. This affects propagation of both hadronic and mesonic components and well known anticorrelation of detected CR flux and atmospheric pressure called *the barometric effect*



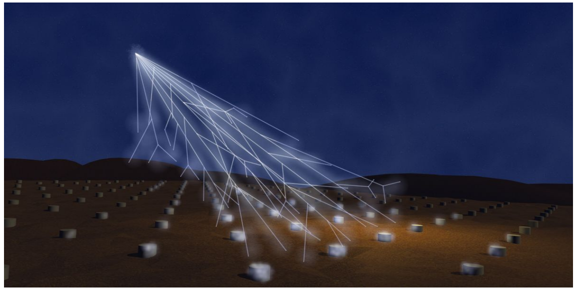


Atmospheric temperature also plays an important role in these processes, especially when muon component of secondary CR is concerned. The effect is two-fold: *positive temperature effect* affects the generation of CR muons while *negative temperature effect* affects their propagation and probability of them reaching observation level

Cosmic ray experiments

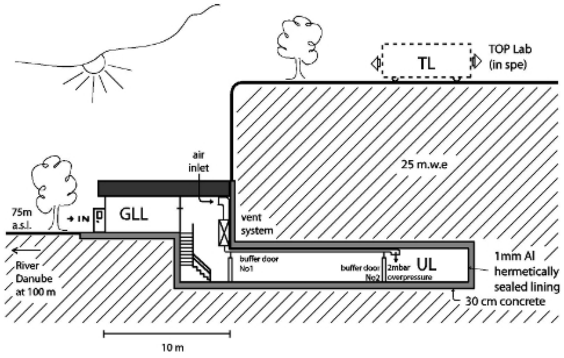
Direct measurements of primary cosmic rays have seen expansion especially in the last two decades. These experiments involve either satellite mounted detectors or balloons at the top of the atmosphere.

Earth-based detectors have a complementary role as they are typically sensitive to higher energies due to unrestricted volume. Main representatives of this type of detectors on a smaller scale are neutron and muon monitors. They are often designed as telescopes/hodoscopes making them sensitive to the direction of incident particles.



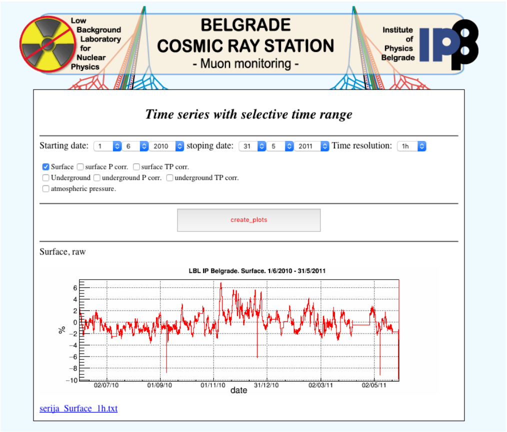
Most complex type of CR detectors are Earth-based detector arrays. These detectors usually cover large areas (up to thousands of square kilometers), their purpose being to detect extensive air showers induced by high and ultra-high energy primary cosmic rays, possibly of extra-galactic origin.

Low Background Laboratory for Nuclear Physics



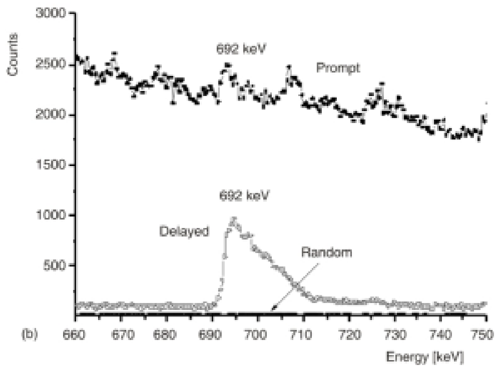
Low Background Laboratory for Nuclear Physics at the Institute of Physics Belgrade has been primarily designed for low-background gamma measurements. In addition, a lot of effort has been put into study of the main contributors to background in such measurements – cosmic rays and radon.

Low Background Laboratory has two integral parts – Ground Level Laboratory and Underground Laboratory (shallow underground – 25 m.w.e.). Both laboratories utilize almost identical setups for cosmic ray measurements designed to detect cosmic ray muons with high degree of accuracy.



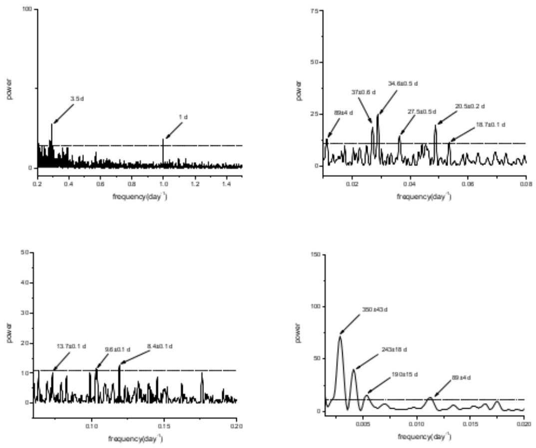
Continuous monitoring of cosmic ray muon flux has been going on since 2009. Online data access interface is available on the page of Belgrade Cosmic Ray Station, where users can access both raw data as well as data corrected for atmospheric effects.

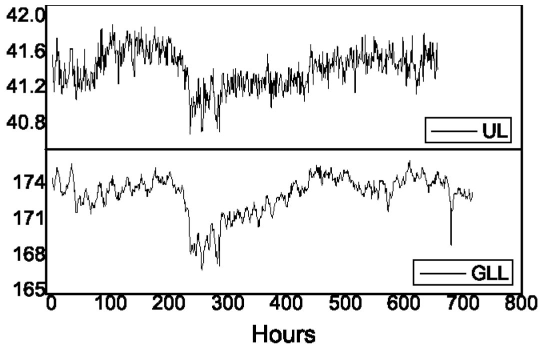
CR measurements in the LBL – Main results



Main CR related results include precise calculation of muon flux for both ground-level and underground laboratories, analysis of muons stopped in the detectors, as well as muon induced background in HPGe measurements caused by interactions of muons with the lead shielding.

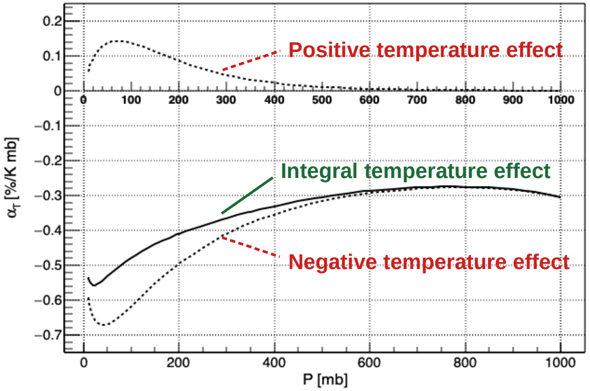
Long-term monitoring of CR flux allows for the study of different periodicities observable in muon time series. These also include many periodicities related to fluctuations of solar activity and solar cycles.





Also observable in CR muon time series are sporadic events such as Forbush decreases. FDs represent a reduction in detected CR flux as a consequence of disturbance of heliospheric magnetic field during a CME event. This provides additional way to study solar physics and space weather using Earth-based detectors.

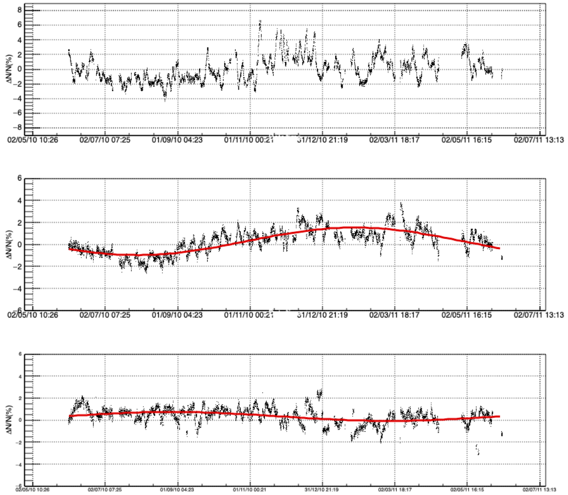
Meteorological effects – Theory and application (integral method)

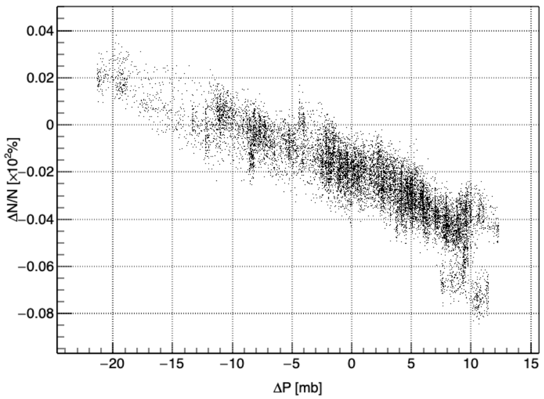


Adequate treatment and correction for atmospheric effects affects accuracy and precision of all mentioned results. Usually only temperature and barometric effect are corrected for. Generally considered to be the most reliable technique for correction of temperature effect is the integral method, based on the theory of meteorological effects.

Temperature coefficient density function is calculated theoretically for positive and negative temperature effects separately and then used to correct for them:

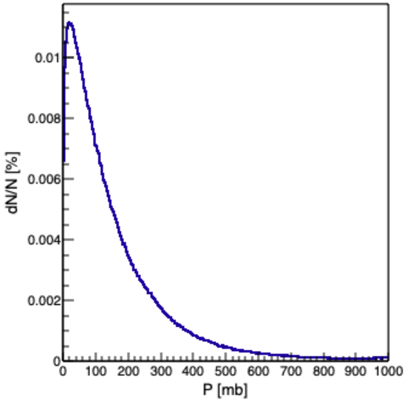
$$\delta I\big|_{temp} = \int_0^{h_0} W_T(h)\,\delta T(h)\,dh$$





Even though it is also possible to theoretically calculate correction for the barometric effect it is typically done empirically as the dependence is approximately linear. In addition to integral, there are several widely used methods (mostly for treatment of temperature effect) based on the approximation of the theoretical approach.

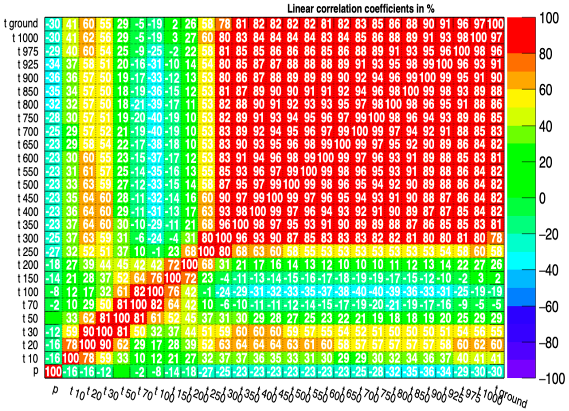
Motivation for a new approach

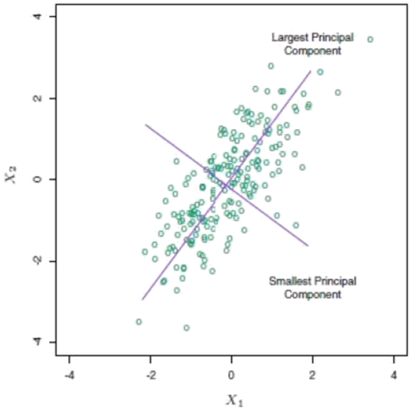


Integral (theoretical) method for the correction of temperature effect takes into account most relevant processes but is not so simple and straightforward to use. Alternatively, early empirical models were somewhat approximative in nature (i.e. not taking into account that muons are generated in all layers of the atmosphere), so some improvement is to be made there.

Fully empirical approach has the advantage that it does not assume anything upfront, is easier to implement and can easily be extended to include larger number of parameters. However, main problem in such analysis is high correlation of temperatures in different layers of atmosphere.

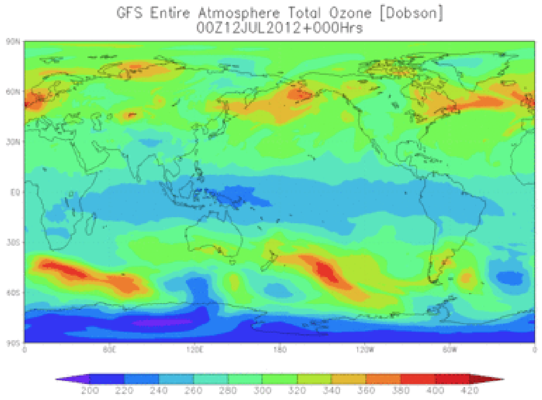
Correlation Matrix



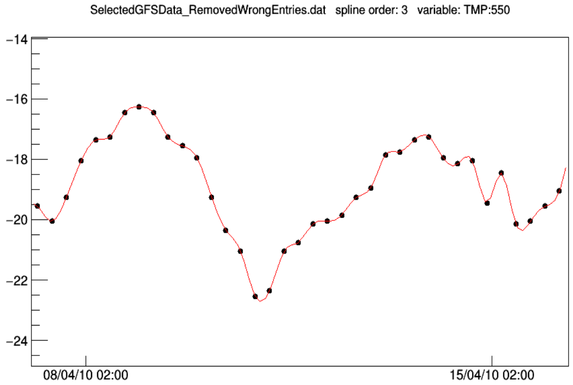


In order to overcome this limitation of empirical methods we have decided to employ well established techniques for decorrelation and dimension reduction: principal component analysis (PCA) and multivariate analysis with use of machine learning (MVA).

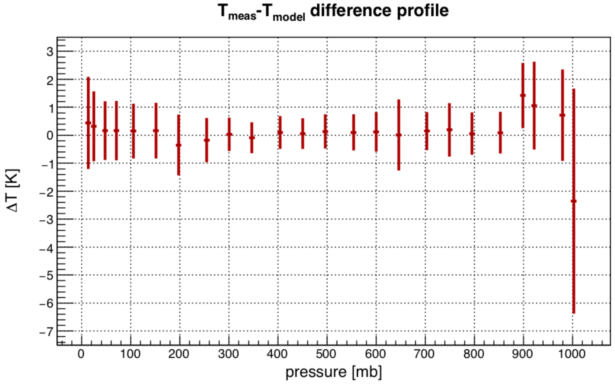
Meteorological parameters



That is why in similar types of analyses modeled data is used instead. We have tested several numerical atmospheric prognostic models and decided to use the Global Forecast Model as it is in the best agreement with meteorological balloon soundings for our location.

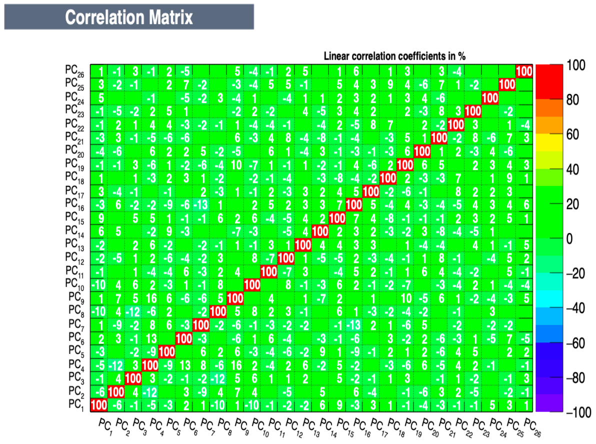


While atmospheric pressure data is readily available, in order to fully take temperature effect into account maximum information about the atmospheric temperature profile is needed. Such measurements are done by weather balloons but usually are not frequent enough nor available for every location.

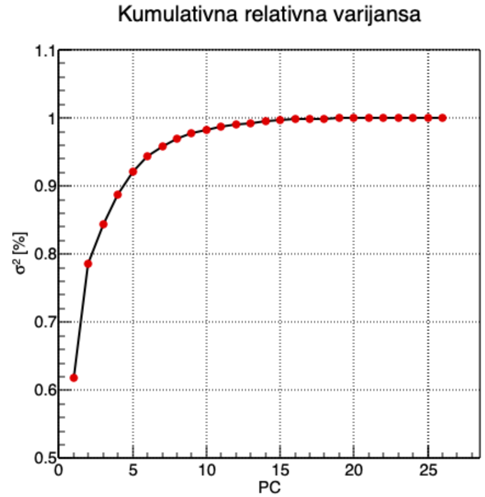


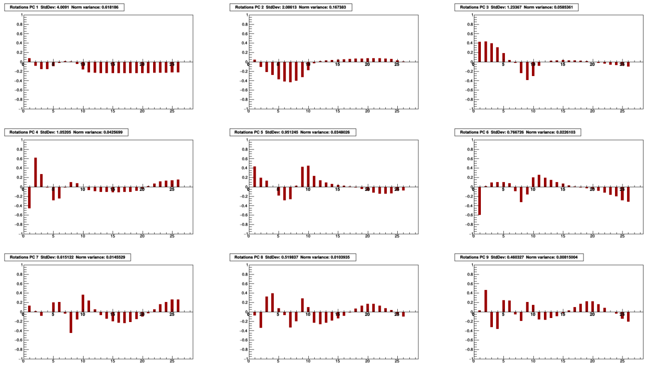
More precise time resolution needed for the analysis is achieved by interpolation. Ground temperature and atmospheric pressure data are obtained from local measurements and combined with modeled data to complete the set of input meteorological parameters.

PCA – Decomposition and selection of significant components



Even though principal components do not necessarily have physical interpretation we were able to identify components that are primarily composed of temperatures of certain atmospheric layers, while others have significant contribution of atmospheric pressure.

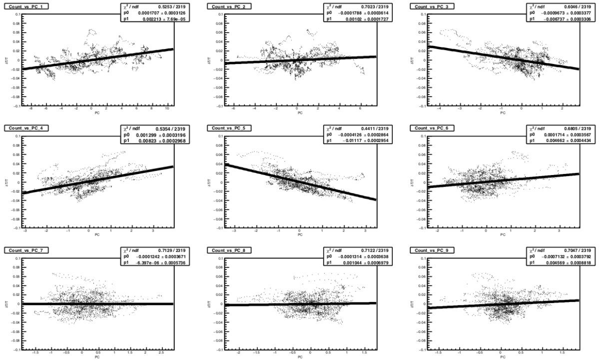




Input variables for the procedure are atmospheric pressure, ground level temperature and atmospheric temperature for 24 different atmospheric levels, from the top of the atmosphere to the near-ground layer. After decomposition we acquire a set of 26 nearly linearly independent principal components to be used for further analysis.

Additional feature of principal component analysis is that it allows to extract a smaller subset of components that are responsible for majority of the variance in the initial set of parameters and thus reduce the number of variables in the analysis. In our case we have been able to reduce this number from 26 to 6..

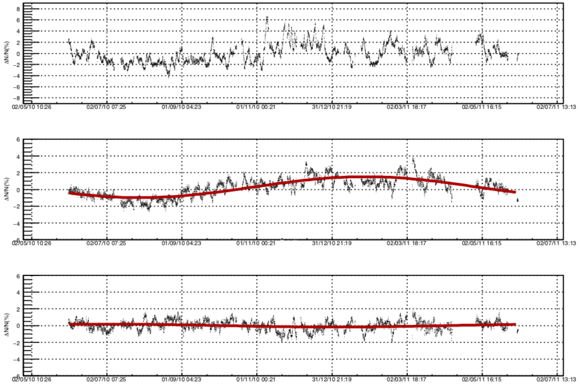
PCA – PT Correction



Through correlative analysis we were able to further reduce the subset of significant principal components as correlation between second PC and measured muon flux appears to be very weak. This is an interesting observation as it suggests that there is a large part of variation of meteorological parameters that does not affect the propagation of muons.

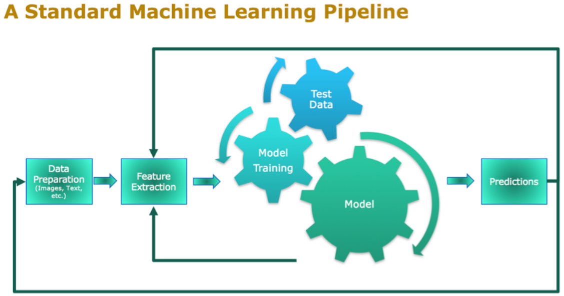
Correction coefficients are then determined through linear regression and used to calculate muon count rate corrected for barometric and temperature effects.

$$N_\mu^{(corr)} = N_\mu - \langle N_\mu \rangle \sum_i k_i PC_i ,$$
$$i = 1,3,4,5,6$$

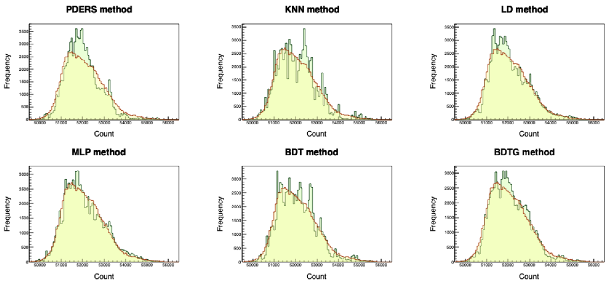


Such correction removes 64.5% of total variance in GLL and 38.1% of total variance in UL. Alternatively, relative to pressure corrected muon count rate time series the correction reduces the amplitude of annual variation by 86% for GLL and 54.9% for UL which is more efficient than the reference integral method.

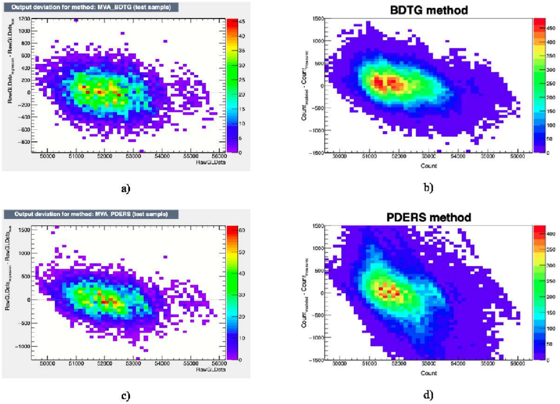
MVA – Training and Algorithm Tests



Algorithms are trained, tested and optimized on a subset of muon data to determine the mapping function. Obtained weights for trained algorithms are then used to predict the target value for the full data set.



We have applied several multivariate regression algorithms that employ machine learning to our problem. Standard set of meteorological variables is used as an input and measured muon count rates as target output. The idea is that the output produced by trained algorithms will ideally contain only variations due to atmospheric parameters, while the residual count rates will be unaffected by meteorological effects.



Performance of different algorithms was analyzed in terms of efficiency, consistency and the ability to reproduce realistic physical features. After a series of tests two algorithms separated themselves as the most reliable: LD (Linear Discriminant method) and BDTG (Gradient Boosted Decision Tree method).

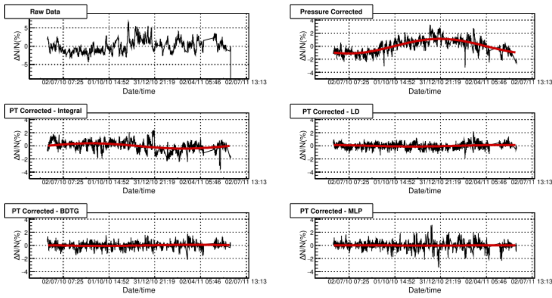
MVA – PT Correction

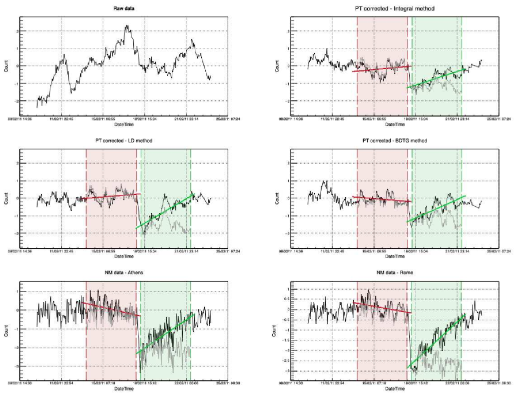
$$N_{\mu}^{(corr)} = \Delta N_{\mu} + \langle N_{\mu} \rangle$$

$$\Delta N_{\mu} = N_{\mu}^{(mod)} - N_{\mu}$$

Difference between modeled and measured count rate is assumed to hold all residual variations of non-atmospheric origin and is used to calculate the corrected muon count rate. Two major results of the correction are the effects it has on long term variations (primarily annual) as well as on short term variations (especially Forbush decrease events).

The correction using two best performing algorithms (LD and BDTG) shows reduction of annual amplitude of around 90%, which is more efficient than the reference integral method. When comparing this result to neutron monitor data there appears to be a slight overcorrection, but it could be due to the residual temperature effect in NM measurements.





Both methods prove to be equally effective when effect on short term aperiodic variations (more specifically FD events) is analyzed. They are able to significantly increase the sensitivity of our muon detector and even make it comparable to the sensitivity of neutron monitors. However, due to overall better consistency it is the LD method that is the recommended one, for this approach.

Summary

- Cosmic ray physics is as active as ever, making significant progress regarding most fundamental questions in the field and gradually moving toward larger and more complex experiments
- In the meantime smaller Earth-based detectors still play an important and complementary role to that of larger array-type experiments and satellite-mounted instruments
- In addition to fundamental significance, adequate modeling and correction of atmospheric effects also greatly increases the usability of muon detectors
- There are a number of advantages to empirical treatment of temperature effect if mayor obstacle of high correlation between temperatures of different atmospheric layers is overcame
- To do this we have employed two techniques widely used for decorrelation and dimensionality reduction: principal component analysis and multivariate analysis via machine learning
- Our methods proved to be as (if not more) effective than most widely used ones
- Analysis and evaluation of new methods is still ongoing, with possible further improvement in the future as well as possibility to include more atmospheric variables