Estimation of the snow water equivalent using Muon Scattering Radiography

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Key Points:

- We test the suitability of Muon Scattering Radiography to infer the Snow Water Equivalent.
- Numerical simulations show the technique can estimate the Snow Water Equivalent with a precision of around 1 cm.
- Laboratory measurements confirm the results obtained with simulation.

Abstract

Despite the important hydrological and ecological implications of the snowpack, its real time monitoring remains challenging. This is particularly relevant in relation to the *Snow Water Equivalent* (SWE), as the available technologies which measure it, exhibit a number of limitations that difficults their operational implementation. In this work, we explore the potential of a new technology, *Muon Scattering Radiography* (MSR), to infer the SWE. We coupled snowpack simulations generated by the SNOWPACK model, with a muon scattering simulation program based on GEANT4. The SWE is modelled as a function of the muon scattering distributions. Predictions of the SWE along the year are provided showing a *root-mean-square error* (RMSE) of 12 mm for 5 hour continuous measurements. We also performed laboratory measurements using ice samples, confirming the SWE estimation capabilities and the potential of the technique to operate as a SWE monitoring tool.

Plain Language Summary

The monitoring of the seasonal snowpack is important to understand and predict the dynamics of the hydrological and ecological processes, but its continuous monitoring is still a scientific challenge. Particularly in relation to the *Snow Water Equivalent* (SWE), which represents the depth of water that would result if the snow melted. The available technologies to monitor the SWE exhibit a number of limitations that prevent its use in many real world cases. Here we explore the potential of a new technology, *Muon Scattering Radiography* (MSR), to quantify the SWE. MSR is a technique based in the detection of the natural and innocuous radiation of muon particles. The technique consists in the measurement of muon deviations, which depend on the material they traverse. The larger or denser the material is, the bigger the deviations they undergo. This study begins with a detailed simulation. Firstly, we simulated the snowpack evolution itself, and secondly its measurement process. Thirdly, we determined the relation between muon deviations and SWE. And finally, we estimated the precision in the determination of SWE comparing the predictions to the ground truth in the simulations. The results yielded a precision of about 1 cm. We also performed laboratory measurements with ice samples, using a 4 layer muon detector based on multiwire proportional chambers and confirming the potential of the technique to operate as a SWE monitoring tool.

1 Introduction

The seasonal snowpack plays a key role in the hydrology of the areas where it is present and beyond (Barnett et al., 2005), but its real-time monitoring still represents a big challenge for the scientific community and water management agencies. Real-time monitoring systems strongly rely on remote sensing and numerical modelling. However, to date, there is still no effective approach to retrieving the snow water equivalent (SWE) from orbital sensors, especially over complex terrain (Luojus et al., 2021). In addition, even the most sophisticated physically based snowpack models suffer from the limitations of the quality of the forcing (Raleigh et al., 2016), its parametrizations (Günther et al., 2019), and the uncertainty caused by the wind and avalanche snow redistribution (Vionnet et al., 2021).

Direct observations of the snowpack are very appreciated for water management purposes, long-term climatological studies, as well as for model and remote sensing product validation or data assimilation. However, as a consequence of the difficulties of snowpack monitoring and increased costs, the available SWE time series are often scarce, incomplete, or just inexistent (Alonso-González et al., 2018). In addition, despite nowadays it is possible to retrieve the snow depth using relatively cost-effective techniques (Revuelto et al., 2021), the monitoring of the SWE remains elusive.

Traditional SWE monitoring techniques including snow pillows exhibit a number of limitations that prevents their usage for many applications and environmental conditions. Their installation requires very complex logistics and additionally, these devices often require manual re-calibrations (Moreno et al., 2010). Moreover, their accuracy is very limited in ephemeral or shallow snowpacks. In this context, the use of cosmic-ray neutron-based sensors is not uncommon, being the solution chosen by several water agencies for their operational networks. It is possible to deploy neutron-based monitoring networks, even in mountainous or remote regions (Jitnikovitch et al., 2021). However, its precision is still limited and requires a proper in-situ calibration. Despite the relative success of neutron-based techniques, there is still a need for scientific innovation in the field of SWE sensors.

Muons are leptons, elementary particles similar to electrons but with a mass about 207 times greater. Cosmic rays, very high-energy particles and nuclei that constantly reach the earth from deep space, collide with the upper layers of the atmosphere producing a shower of several types of secondary particles. Some of them manage to reach the sea level, indeed, muons are the most numerous charged particles at this atmospheric depth (Workman et al. (Particle Data Group), 2022).

Thus, cosmic muon production is a very common natural phenomenon. Muons exhibit high penetrating capabilities, being interesting candidates for the development of SWE sensors. Although they have great potential, their option as a resource to measure the SWE is largely underexplored yet. Consequently, there is a lot of room for research and development in this field.

There are two different types of muography: *Muon Absorption Radiography* (MAR), a technique that uses muon counts to extract information, and Muon Scattering Radiography (MSR), which utilises muon deviations. Recently, Gugerli et al. (2021), applied MAR and proved the potential of muon counters to infer the SWE in the field, comparing the decreasing muon count rate with in situ SWE measurements.

The objectives of this study are: (1) to infer SWE by conducting a detailed study using snowpack and a detailed muon numerical simulation and (2) to test the capabilities of a real-world hardware designed by us to measure SWE contained in artificial snow samples.

2 Materials and Methods

2.1 Physical principle

Muons, being a charged particle, suffer many small-angle scatters when traversing matter. Most of this deflection is due to Coulomb scattering with nuclei of matter, as described by the Rutherford cross section. The multiple scattering phenomenon can be described through the theory of Molière. Although large scatters produce a non-Gaussian tail in the probability distribution of the total deviation of muons when traversing a certain material, it can be approximated by a Gaussian distribution with a RMS width (θ_0) of (Workman et al., 2022; see also Bethe, 1953; Highland, 1975; Lynch et al., 1991):

$$\theta_0 = \frac{13.6\ (MeV)}{\beta p}\ \sqrt{\frac{x}{X_0}}\left[1 + 0.038\ ln(\frac{x}{X_0\beta^2})\right] \quad (1)$$

Where p and βc are the momentum and velocity of the incident particle. x is the distance traversed by the particle inside the material and X_0 is the radiation length of the material. β represents the ratio between the particle velocity and the speed of light. The constant 13.6, is measured in millions of electronvolts (MeV) and θ_0 represents the RMS value of muon deviations projected in a plane.

2.2 Experimental setup

Muon data used in this work has been collected with our muon detection system (Figure 2, b). This muon monitoring system is currently in use for both scientific and industrial purposes (Martínez-Ruiz del Árbol et al., 2022). The particle detectors are composed of four Multi-Wire Proportional Chambers (MWPC) and each chamber has two layers with 224 detection wires, all of them separated by 4 mm. The two layers form a two-dimensional grid of wires which covers an area of 89.6 x 89.6 cm and detects the positions where muons cross it.

The synchronisation electronics identify a muon when signals are obtained in a space of time on the order of hundreds of microseconds in all the chambers, in both the upper and lower detector. This condition distinguishes signals produced by muons from signals produced by other charged particles which could activate detection wires, since this kind of simultaneous activations on the earth's surface are practically only produced by muons. However, various sources of noise should be considered, such as charged hadrons, electrons, and positrons (“fake muons”), and also muons with relatively low momentum (“soft muons”) (Bonechi et al., 2020).

When a muon event is identified, our system detects four points located in the horizontal two-dimensional grids, two points before the particle goes through the target and another two points after the particle traverses it. With this data, way-in and way-out trajectories can be reconstructed, and muon deviations calculated. Specifically, in the numerical analysis of this

work, we utilised the projection of muon deviations in two planes perpendicular to the detection wires, in agreement with the deviations represented by θ_0 in the Equation 1.

2.3 Simulation setup

The snowpack was simulated using a one-dimensional snow model forced by surface meteorological data. We have used the SNOWPACK model (Bartelt & Lehning, 2002; Lehning et al., 2002a; Lehning et al., 2002b) to realistically simulate the behaviour of the snowpack along two seasons, 2015/2016 and 2016/2017 (Figure 1). SNOWPACK is a physically-based multilayer model that simulates the state and microstructure of the snowpack. It is based on the energy and mass balance of the snow, and it is widely used for both research and operational snow avalanche forecasts. For this study, SNOWPACK was forced by the ERA5-Land surface reanalysis (Muñoz-Sabater et al., 2021). The simulations were performed in the Pyrenees, using the ERA5-Land cell whose centroid falls closer to the Monte Perdido massif (42.7°N, -0.1°E), at an elevation of 2041m asl. The main objective of these simulations was to generate detailed snowpack state variables that realistically evolve along the time dimension, providing information on the different conditions in both accumulation and melting periods, as well as its internal structural characteristics. Once the SNOWPACK simulations were performed, we retrieved from them the ice, liquid water, and air content of each variable height snow layer which constitutes the whole sample, as well as the bulk density and the total snow depth.

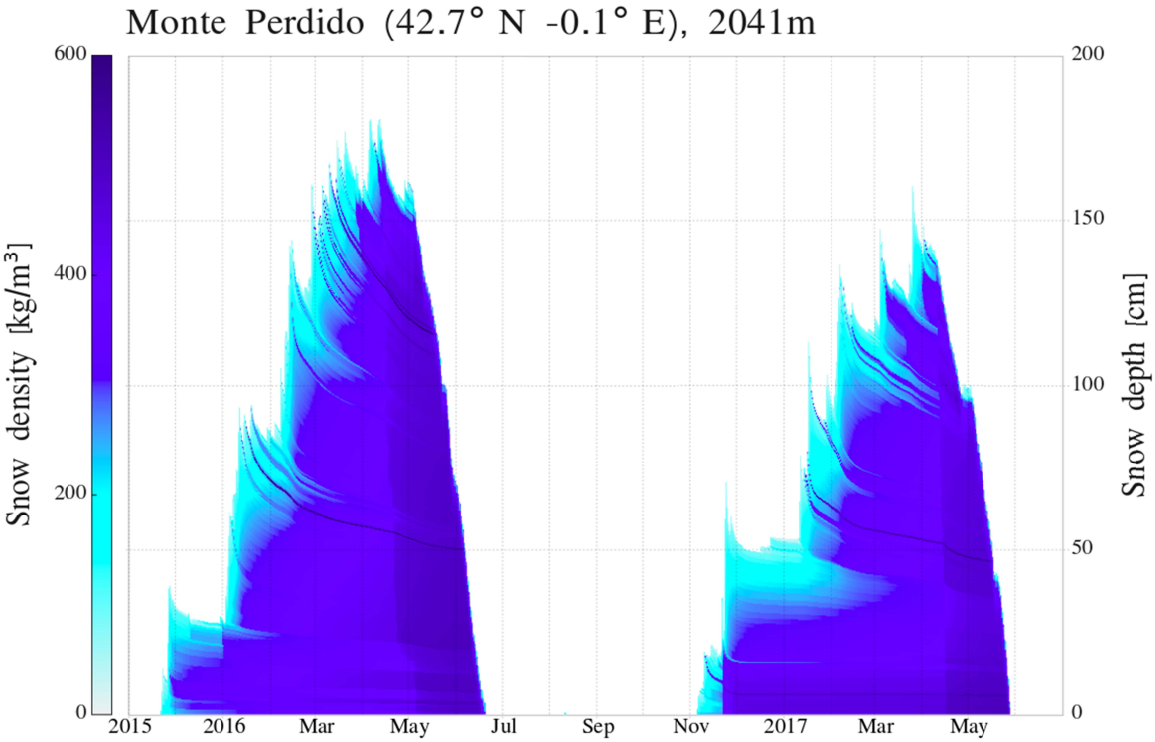

Figure 1. Snowpack density and depth time evolution during 2015/2016 and 2016/2017 hydrological years simulated withSNOWPACK model forced by ERA5-Land.

We coupled the SNOWPACK simulations with a full MSR simulation setup that uses the Cosmic RaY generator (Hagmann et al., 2012) to reproduce the atmosphere muon flux and GEANT4 (Agostinelli et al., 2003) to simulate the muon scattering caused by the snowpack (Figure 2, a). GEANT4 is a state-of-the-art software designed and maintained at CERN to simulate the interactions of particles and matter in high-energy and nuclear physics. Our simulation framework contains a model of our experimental setup including the muon detectors and their response. This framework has been successfully applied to multiple industrial problems, for instance, to steel-made pipe wear (Martínez-Ruiz del Árbol et al., 2018). Similar simulation frameworks are typically used to research applications of muography (Mori et al., 2017).

Once the numerical SNOWPACK simulations were developed, we expanded the one-dimensional snowpack geometry to a 1m² snow column, assuming homogeneous snow layers in the longitude and latitude dimensions. Then, we propagated and measured muons penetrating the whole snow column, virtually reproducing the detection process using GEANT4 and collecting $\square_0$ for different accumulations of snow during the two simulated seasons.

2.4 Measurements and analysis strategy:

The detection angular resolution is a key parameter in MSR application. This resolution refers to the smallest muon angular deviation measurable by the detectors, and it is determined by the separation of the wires within detection layers, the separation of the chambers of each trajectory detector (in this case, upper detector, and lower detector) and the materials of the detectors themselves, which inevitably produce an intrinsic angular deviation of the muons. The resolution strongly impacts the final performance of the technique and it is of great importance for this work, where the target object is composed of a low density material such as snow.

To demonstrate the capability to infer the SWE and to explore the previously commented influence of detector resolution and of their material itself, we analysed MSR data produced in different scenarios. We built 4 simulation scenarios to study in detail the changes induced by the factors affecting the resolution. The first scenario considers muon detectors with a perfect spatial resolution and neglecting the effect of the detector materials. In the second scenario, the effect of the detector materials is simulated but still assuming a perfect spatial resolution. In the third scenario, detector materials are considered and the spatial resolution is degraded by setting the wire separation to 4 mm. All these scenarios assume a detector layer separation of 257 mm. The forth scenario is similar to the previous but assuming a detector layer separation of 130 mm, coincident with the experimental setup. In each of these scenarios we quantify the correlation between measured muon deviations and SWE. Finally, we made laboratory measurements on blocks of ice of different heights, to test the performance of our hardware and confirm the simulation results.

For each type of simulation (scenarios 1, 2, 3, 4), we analysed weekly measurements of 5 hours during the first snowing season, the hydrologic year 2015/2016 (Figure 1). These simulations were used to model the relation between θ_0 and SWE in different conditions. With this data we wanted to study the influence of the spatial resolution of the detection wires, of the chamber separation, and of the detector material itself. Finally, we produced additional data with the realistic resolution and all the other simulation settings of scenario 3, to use it for validation. We simulated the measurement of the whole hydrologic year 2016/2017, gathering continuous 5-hour measurements.

We used our laboratory setup to measure the SWE of artificial snow samples of known density and volume. The samples were composed of crushed slices of ice, emulating real snow (Figure 2, c). The first one consisted of an empty container, and it was used as a reference to measure the intrinsic θ_0 observed in our setup. In the second, we introduced 10.60 Kg of material with a bulk density of 448.70 Kg/m³, reaching a height of approximately 22.3 cm in the container and 99.8 mm of SWE. Finally, in the third sample, we used 21.20 Kg of material with a bulk density of 494.92 Kg/m³, reaching 40 cm and summing 197.97 mm of SWE. We performed a single 5-hour measurement, for each sample.

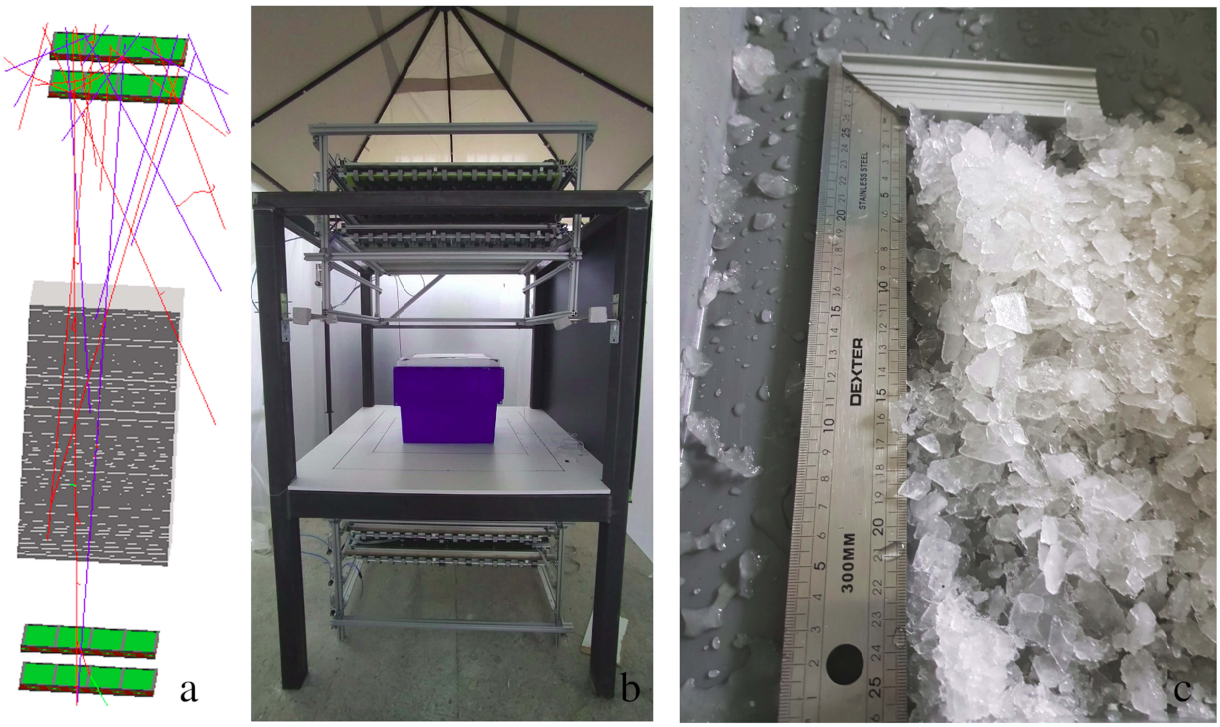

Figure 2. Experimental setups. (a) Simulation scenario with the virtual copy of the hardware, a snow sample and representation of particle propagation. (b) The hardware, with a snow sample placed between the detectors. (c) Detail of the crushed ice used to emulate the composition of the snow.

A simple mathematical model has been developed in order to connect the SWE with the standard deviation of the muon angular deviations. This model considers a constant term to account for the intrinsic resolution due to all the instrumental effects, and a term proportional to the square root of the SWE. The second term assumes that the SWE is proportional to the number of radiation lengths of the target, according to equation 2.

$$\theta_0 = p0 + p1\sqrt{SWE} \quad (2)$$

We fitted Equation 2 to all scenarios, expecting to obtain different fit parameters $p0$ and $p1$ for each of them, since different detector conditions are being considered.

3 Results

We modelled θ_0 for different scenarios of simulated and real snow samples as a function of the SWE using Equation 2. Figure 3 shows the results for all the scenarios including its fitted function. For this analysis, we rejected muons with projected deviations higher than 100 mrad, with the aim of reducing the previously mentioned sources of noise, namely, “fake muons” and “soft muons”. As expected, the observed data is compatible with a root square function. In all the scenarios the coefficient of determination between the two variables is around 0.98. Only a slight decrease is noticed in the case of scenario 2, the one with 4 mm wire separation and 13 cm chamber separation. All the models fit to the expected square root relation, but each one has different fit parameters $p0$, and $p1$. There is a bias at 0 mm of SWE ($p0$ variation), and also different intensity in the increment of the measured variable in relation to the SWE ($p1$ variation) depending on the scenario. These preliminary results clearly show the increase produced in θ_0 when detector material is considered, and when detector resolution is diminished. The θ_0 increase due to detector material significantly decreases in agreement with the SWE increment, while the θ_0 increase produced by the detector resolution is present in all the simulated SWE range.

In the results obtained with the two setups with perfect resolution (scenarios 1 and 2), an increase of θ_0 due to detector material can be observed, which is more noticeable at lower SWE measurements. The scenarios 2 and 3 show a θ_0 increase produced by the limited resolution of the detection wires. Furthermore, between the scenarios 3 and 4, a θ_0 increase produced by the change of detector separation appears. And finally, the laboratory measurements show higher θ_0 values. The main differences between our laboratory setup and the simulation scenario 4 are the precision of the alignment of the detectors, the presence of an additional steel-made structure, noise and effects not considered in simulation, and the snow samples themselves. Some of these factors are probably responsible of the higher θ_0 values obtained in our laboratory. It also has to

be mentioned that the laboratory measurements were performed inside a building which was not included in simulation.

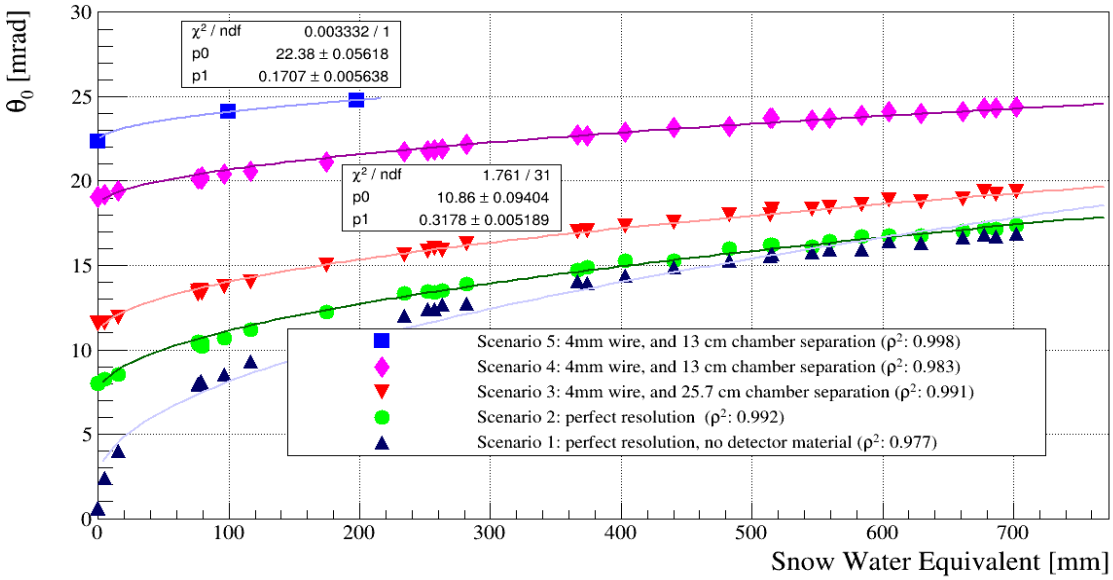

Figure 3. RMS of the muon scattering angles as a function of SWE for different scenarios. The laboratory setup or scenario 5, and the simulated cases: scenarios 4, 3, 2, and 1.

In order to calculate the SWE of additional and independent snowpack samples, we extracted a SWE estimation function for the scenario 3 from its fitted model (Figure 3):

$$SWE_{\mu} = \left(\frac{\theta_0 - (10.86 \pm 0.09)}{(0.318 \pm 0.005)}\right)^2 \quad (3)$$

Where SWE_{μ} is the SWE estimation made by means of MSR for an individual measurement, and θ_0 is the RMS value of the measured muon deviations during the same measurement. To validate the defined function, we applied the SWE estimation formula to independent measurements of snow samples. For that purpose, we used the second season data (hydrologic year 2016/2017), obtaining results that show a RMSE of 11.5 mm, tending to underestimate (overestimate) the SWE during the minimum (maximum) accumulation periods (Figure 4). We obtained an average underestimation of 9.4% (14.3 mm SWE) for the month of december, while average overestimation during april was 3.3% (15.7 mm SWE).

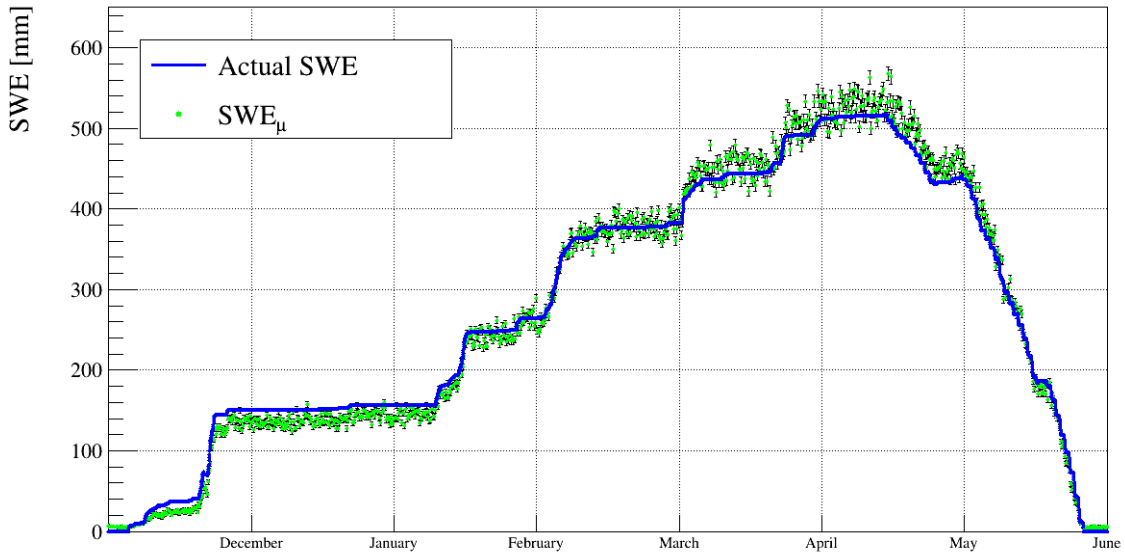

Figure 4. Validation of the SWE estimation function with data of the season 2016/2017 (scenario 3). The green dots are the results of the SWE estimation function (SWE_μ), while the blue line indicates the actual SWE. The black bars represent the uncertainty of the model, based on the propagation of the fitted parameter variance. In the horizontal axis, the beginning of each month is signalled.

4 Discussion and Conclusions

In this work we demonstrated that MSR can be used to determine the SWE, and therefore, it could be a viable technology to help solve the existing challenges in the real time monitoring of the snowpack.

We have developed snowpack simulations and built and validated a simulation numerical model which identifies the relation between muon deviations and SWE. The theoretical reference represented by the Equation 1, and also previous studies analysing similar relations (Zeng et al., 2020) agree with our results. In addition, the simulation model is compatible with the three snowpack measurements performed in the laboratory, proving the agreement of our simulations with reality. The higher θ_0 obtained in the laboratory measurements, can be explained by the presence of the steel-made detection structure (Figure 2, b), and by millimetre scale misalignments of the detector chambers, noise and other effects of the detection process that could be minimised in specific designs. The mentioned factors are not included in the simulations, and they make the muons undergo higher deviations. The uncertainty created by the probable differences between simulation and laboratory muon flux and momentum spectrum, should be also considered. The laboratory measurements were performed inside a building, and this fact could produce significant changes on muon flux and momentum compared to the

simulations, which do not include the building effect. The different characteristics of the artificial snow sample and the simulated snow, such as the analysed surface and their material, are a source of uncertainty as well. But in spite of the mentioned subtle disagreements and uncertainties, the achieved compatibility is a very promising point regarding the possibility of using simulation data for SWE detection modelling, calibration and testing.

Although the agreement of data extracted from different scenarios matched our expectations, we performed additional studies about the influence of different factors that affect our SWE modelling procedure, such as detector resolution and their own material. The resolution modifies how we detect muon deviations, and as in these experiments the majority of muons undergo deviations on the order of tens of milliradians, when the resolution gets worse, the measured deviations increase significantly. On the other hand, the detector material increases the actual scattering that muons undergo. And both, detector resolution and material, influence the relation between the measured deviations and the SWE. Therefore, a specific modelling is required depending on the detection setup. But above all, it is remarkable that in all the measurement scenarios the coefficient of determination between the two variables is 0.98 or higher. In relation to the measurements performed in the laboratory with our hardware, it is desirable to continue exploring the potential of MSR and to test the technique in the field.

We also validated the simulation numerical model evaluating its estimates for additional and independent continuous measurements during the hydrologic year (2016/2017). The evaluation yielded successful SWE estimations, with an average RMSE of 11.5 mm for the whole year. This last validation demonstrates the ability of the technique to continuously monitor the SWE using a model built with weekly measurements made during a unique season.

Gugerli et al. (2021) already demonstrated the SWE monitoring capability of MAR, measuring in the field the muon attenuation and linking it to the SWE variation. Their muon measurements agree with neutronic detector measurements and also with manual observations. We exploited the simulation potential and the control of laboratory samples to identify the actual SWE, and quantify its correlation with muon deviations. The fact of measuring deviation (MSR) instead of absorption (MAR), gave us additional information of the physical phenomenons that muons undergo, adding information about the multiple scattering they suffer when traversing snow samples.

The application and testing of our technique in the field, together with further research and innovation of muon detection systems and reconstruction algorithms can lead to the implementation of an industrialised MSR method for SWE determination. Characteristics of muon radiation such as the penetrating power and innocuousness make MSR an appropriate technology for the real time SWE monitoring. This technique also provides information about the density and composition of the target, allowing to identify material properties (Åström et al.,

2016), as well as internal density distributions (Vanini et al., 2019). These potentialities could eventually lead to retrieval of the internal layered structure of the snowpack. Locating and estimating the characteristics of the produced muon deviations through their trajectories and applicating advanced muography algorithms (Schultz et al., 2007) (Sehgal et al., 2020) the snowpack density distribution could be estimated and voids or weak layers identified. The results of our proof of concept will be useful for the development of new sensors and detection algorithms, providing the necessary background for the future operational design of muon scattering based SWE monitoring networks.

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Open Research

The simulation and laboratory measurement snowpack and muon deviation data which is analysed in this paper is available in (Orio-Alonso et al., 2023) [Creative Commons Attribution International 4.0].

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