Snow depth plays a critical role in the estimation of snow water equivalent (SWE). Snow depth data from measured ultrasonic instruments are an essential part of the validation and assimilation of these models. This paper showed that a Random Forest classifier can be used to train and perform classification of snow depth from weather stations to snow/bare ground. This will help to reduce noise in SWE model coming from the misclassification of the snow depth data. In general, this a well-written paper with clear objectives, results and discussion. I recommend this paper for publication with only a few minor comments.

We thank Reviewer 1 for their constructive comments. We are happy that the Reviewer appreciated the writing style. All requested revisions are feasible and we will work in this direction as soon as the interactive discussion will be finalized.

L31-L34. This sentence is long. Consider splitting into smaller sentences.

Thanks for the comment. Following the suggestion, we propose this new version :

Assessing the implication of snow-driven hydrological processes on streamflow and precipitation events helps with resource management. Indeed, a more in-depth understanding of snowmelt implications for the time and quantity of freshet supports forecasting for water management, dealing with water security and water related vulnerability. Most importantly, better understanding enables the development of a sustainable water resource carrying capacity, which is crucial to cope with the shift in water balance caused by climate change.

Section 2.2. Can you give more details on how this dataset is different or not from the training set? This is not evident if you are not familiar with this region of the world.

We apologize for the lack of details in describing a different dataset to an audience not familiar with the region we are working in. We will add a detailed description of the geographical and meteorological differences between Aosta Valley and the rest of Italy. Here the proposed text:

Italian climate presents a considerable variability from north to south. According to the Köppen-Geiger climate classification (Beck et al. 2018), in the Alps the climate is humid and continental. Central Italy, alongside the Apennines chain, is characterized by a warm, temperate, Mediterranean climate with dry, warm summers and cool, wet winters. In Southern Italy, where the climate is still a warm temperate, Mediterranean climate, winters are mild, with higher humidity and higher temperature during summer.

Concerning snow-cover distribution, accumulation across the Alps is generally higher and more persistent than across the Apennines, where it is spatially more limited and more variable from one season to the others. Rivers draining from the snow-dominated Alps and a handful of basins draining from central Apennines host the vast majority of snow water resources across the Italian territory. In particular, the Alpine water basins host nearly 87% of Italian snow. The central Apennines, accumulate about 5% of the national mean winter SWE, leaving the remaining 8% − 9% scattered across the remaining basins over the territory. Intraseasonal melt, expected in a Mediterranean region, is a common feature in sites where cold-alpine and maritime snow types coexist like the Apennines (Avanzi et al. 2023).*The validation dataset refers to the remaining of the the Italian Peninsula (Aosta valley excluded). Italy (*$\sim$*301* $\times$ *103 km*^{2}*) is a topographically and climatically complex region. Its mountain chains, the Alps and the Apennines, are among the highest peaks in Europe. Partially snow-dominated regions like the Po river basin or the central Apennines have high socio-economical relevance (Group 2021).*

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Section 2. Do all sensors were similar ultrasonic sensors? Any effect of the different sensor types?

To our knowledge, all snow-depth sensors operationally used in Italy are ultrasonic sensors, with an accuracy of a few centimeters (Avanzi et al. 2023). However, the implementation and everyday management of these sensors falls under the responsibility of Regional Environmental Agencies, thus only sparse information on sensor types was available for this study. Evaluating the performance of the algorithm as a function of sensor types is an interesting research question, which we will mention as a possible future development in the final section (pending availability of this information).

L116-L117. Consider adding a citation that relates snow depth to random forest. I can think of a couple.

We agree. We will cite the work of Meloche et al. (2022), which proved the ability of a Random Forest algorithm to predict snow depth distribution from topographic parameters with a root mean square error of 8 cm (23%) in western Nunavut, Canada.

L114. Some feature importance calculations can have a bias due to the correlation between features. This will split the importance between features (Strobl et al. 2007). Even if the feature seems uncorrelated in this case. Consider adding a sentence to acknowledge this. Reference : Strobl et al, 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. DOI : 10.1186/1471-2105-8-25

We thank the reviewer for pointing out an important aspect when dealing with Random Forest algorithms. We acknowledge the necessity of mentioning it and we plan to add the following text to section 4.2:

It is important to acknowledge that correlation among features and multicollinearity are problematic for feature importance and interpretation in a Random Forest. Features importance may spuriously decrease for features that are correlated with those selected as the most important (Strobl et al. 2007). On the other hand, Hastie et al. (2009) point out how that the predictive skill of the algorithm is relative robust to correlations thanks to de-correlation factors involved in bootstrapping. Indeed, even low-importance features may drive the decision process of the algorithm (Avanzi et al. 2019). In our case, we chose to use all the features after testing the lack of strong correlations across features (values below -0.5 or +0.5).

Figure 4. Typo in label of graph b). "Ground" should be ground.

We thank the reviewer for this remark. We will update the figure.

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