Revision of

"Historical snowfall measurements in the Central and Southern Apennine Mountains: climatology, variability and trend"

RC (X) = Referee comment (number X)
AR (X) = Authors' reply (number X)

REVIEWER #1

AC: Dear Referee, we are grateful for the time dedicated to the revision of our manuscript and for the suggestions, which help us to improve our paper. Here we provide a point-by-point response to his/her comments. All required changes will be included in the new manuscript version.

RC (1): This paper presents a valuable collation of historical snow records for an understudied region. As such, the authors should fully document and deposit the data in a public repository, in compliance with the Copernicus Publications data policy: https://www.the-cryosphere.net/policies/data_policy.html
AC (1): Following this valuable suggestion, we have deposited the dataset that supports this study in the Zenodo open data repository (CERN). The dataset can be accessed through the following link: https://zenodo.org/records/12699507

RC (2): The cluster analysis is detailed, but I am not sure that the discussion reveals much more than could have been illustrated by plotting the snow metrics against elevation and examining the outliers. Although the wavelet analysis is rather preliminary and descriptive, it presents results and so should be moved to the Results section.
AC (2): Following your recommendation, in new manuscript we'll move the wavelet analysis in the Results section.

RC (3): 15
The difference between "snow cover duration" and "number of days with snow" is not clear, and is not made clear until line 183. State "number of days with snowfall" throughout.
AC (3): Ok, thank you for the suggestion.

RC (4): 31
Snowfall is certainly an essential climate variable, but it is not a GCOS Essential Climate Variable distinct from precipitation, so do not use that specific term.
AC (4): Ok, in the new manuscript version we'll remove this term.

RC (5): 257-300
The description of Climatol tests is barely comprehensible without reading the references.
AC (5): Following this suggestion, we have revised the description of Climatol test. Here we provide the new description. Note that the changes with respect to the original manuscript version are highlighted in yellow.

"The tolerance test has been performed using the Climatol method. The latter has been developed by Guijarro (2018) and is widely employed for the QC, homogenization and in filling of the missing data for a set of climatological time series. The Climatol data processing starts with a normalization of the original data. In this respect, Climatol offers different approaches for normalization, depending on the climatological variable. In this study, the type of normalization (std) has been set to 1 (which means that data normalization is based on deviations from mean) for SCD and NDS, whereas we selected std = 2 (which means normalize using ratio to normal climatological value) for HN. The approach used by Climatol to detect outliers is inspired by the principles of the spatial consistency check. In particular, for any candidate time series, this method use data from neighbouring stations to estimate a corresponding reference series as a weighted average, employing a geographic proximity criterion using Euclidean distances.

In the default settings of the Toolbox, the vertical and horizontal distances (expressed in meters and kilometres, respectively) between a suitable neighbouring station and the candidate one have the same weight. Following Buchmann et al. (2022), to take into consideration the influence of altitude on the snow, in this study we have adjusted the scale parameter of the vertical coordinate (wz) so that the elevation counts 100 time more; in other words, the approach used in our work means that an altitude difference of 500 m corresponds to a horizontal distance of 50 km. The estimated reference series are used to create time series of anomalies for their corresponding observed series by subtracting the estimated values from the observed ones. The values of the anomalies time series that exceed a determined threshold (dz.max) are labelled as outliers and so the correspondent data in the original series are discarded. More specifically, the dz.max value, set by default to ±5 standard deviations, was properly tuned to ensure that the flagged outlying values were not rejected because of their extremeness. After several sensitivity experiments, in which we manually inspected the data flagged as potential outliers, the dz.max parameter has been set as follows: dz.max = 15 for SCD and NDS and dz.max = 20 for HN. Using this criterion, the tolerance test flagged as outliers only two NDS monthly observations, related to Frigento and Roccasicura time series.

Climatol has been employed in this study also to check for homogeneity of the investigated time series. The use of this toolbox for the homogenisation of snowfall data has been explored, with encouraging results, in some recent works (Buchmann et al., 2022; Buchmann et al., 2023). As described in detail by Guijarro (2018) and by Kuya et al. (2022), the Climatol homogenization method is based on the Standard Normal Homogeneity Test (SNHT; Alexandersson, 1986) for the identification of the breaks and on a linear regression approach for the adjustments (Easterling and Peterson, 1995). The SNHT is applied to the anomalies time series previously introduced in the description of the tolerance test. In brief, the Climatol homogenization process is structured in two procedures: the application of the SNHT on stepped overlapping temporal windows and on the whole series.

In the first one, called "stepped overlapping windows", the toolbox computes the SNHT test for all series, retaining the maximum SNHT value for each series. The series having a maximum SNHT value greater than a specific threshold (snht1) are split into two subseries at the point of the maximum SNHT value. Subsequently, the sub-series are tested again and the procedure is iterated until the maximum SNHT value of the sub-series is below the snht1 threshold.

After this procedure, the test is applied to the whole series in order to detect further breaks, using a threshold value snht2. Once detected a break for a determinate candidate time series, the latter is corrected back in time starting from the most recent homogeneous time interval. The break magnitude corrections are computed as the variation of the mean before and after homogenisation procedure.

More specifically, given a time series Y, the correction factor (CF) is calculated as:

$$CF = \frac{\sigma_Q \mathrm{Y}_b + \mathrm{Q}_m}{\sigma_Q \mathrm{Y}_a + \mathrm{Q}_m} \tag{1}$$

Where Y_b and Y_a are the mean values between the beginning of the measurements of Y and the break point (before) and from the break point to the end (after), respectively. Q is the non-standardised ratio

time series, defined as the ratio between the reference and candidate, and σ_Q and Q_m are the standard deviation and mean of Q, respectively.
Additional details about the calculation of the adjustment factor can be found in Guijarro (2018), in Kuya et al. (2022) and in Buchmann et al. (2023). The last step of Climatol processing consists in the filling of all missing values using the weighted ratios of neighbouring series and in the production of the final high quality, homogeneous and complete time series. It is important highlighting that Climatol offers the opportunity to carry out a first explanatory analysis of the data, which is very useful for the tuning of several parameters, including snht1 and snht2. The main settings adopted to run Climatol for tolerance test of QC and homogenization are listed in Table 1.
Using this set-up, Climatol flagged as inhomogeneous seven SCD and two NDS time series. Details about date in which the breaks occurred and the corresponding value of SNHT are supplied in the Supplementary Material. From a visual inspection of such time series, the results of the homogeneity test seemed very reasonable. The identified breaks were further examined against the metadata reported on the Hydrological Yearbooks. However, the latter contain only few useful information, that allowed to verify only if the stations were relocated (this is not the case for any of the stations identified as inhomogeneous).
We therefore do not have enough information to determine the cause of the inhomogeneities. We decided to adopt a precautionary approach and, therefore, the detected breaks were accepted."

RC (6): 360
Relationships of PCs to geographical features are stated but not made clear to the reader.
AC (6): Thank you for this comment. Here we provide a detailed description of the Principal Component Analysis (PCA) results for each of the three investigated variables: snow cover duration (SCD), number of days with snowfall (NDS) and height of new snow (HN). Such analysis will be included in the new version of the manuscript as Appendix B. It is important highlighting that the aim of our PCA analysis is to identify the dominant recurring spatial patterns over time of the investigated parameters. A natural evolution of this type of analysis is the research of the atmospheric circulation characteristics that are associated with the identified spatial structures of SCD, NDS and HN variables. This aspect is very interesting and fits well with our research interests. However, it falls out the scope of this paper, so it will be addressed in future work.

For SCD, we have selected the first four Principal Components (PCs), which account for the 75% of the total variance. Fig. 1 of this document shows the spatial pattern of the PC scores. Please consider Fig. 1 of the original manuscript for locations mentioned therein. The first PC (Fig. 1a), which represents the 61% of the total variance, reflects the altitude-related variability across the whole elevation range. Areas with positive scores coincide with some of the main mountain ridges of the considered region (Gran Sasso, Marsicani, Majella and Partenio). Negative scores mark low-elevation areas as well as the eastern and southern mountain slopes of the Central Apennine chain, where the local topographic features are not favourable to the persistence of snowfall on the ground. More compelling evidence about the relationship between PC1 and elevation is provided by Fig. 2, in which the PC1 scores are plotted against the altitude. A solid positive correlation was found (the linear correlation coefficient, ρ, is equal to 0.87).
The PC2 (Fig. 1b) separates the Central Apennine sector (Abruzzo and Molise regions) from the Southern area. In the first one, the scores are generally positive, whereas in the second one they are slightly negative. The high positive scores found in several sectors of Abruzzo and Molise (mainly in the Gran Sasso and Marsicani areas) indicate relevant positive SCD anomalies.
PC3 spatial pattern (Fig. 1c) is characterized by a clear west-east gradient. More specifically, positive scores have been found in the Majella area, in the eastern side of Marsicani mountains and in the eastern side of Molise and Southern Apennine. In the western sector of Abruzzo region, negative scores prevail, instead. This pattern might reflect specific large-scale atmospheric weather regimes,

associated with the incoming, over the study region, of cold continental air masses from the Balkan Peninsula. Such atmospheric scenario promotes conditions favourable to the occurrence and persistence of snowfall on the ground over eastern slopes of Apennine.
In the PC4 spatial pattern (Fig. 1d), the scores are generally around 0.0, except for the northern side of Abruzzo (Gran Sasso mountains). This pattern might reflect specific atmospheric conditions that enhance the snow duration on the ground only in high-elevation sites of the northern Abruzzo region.

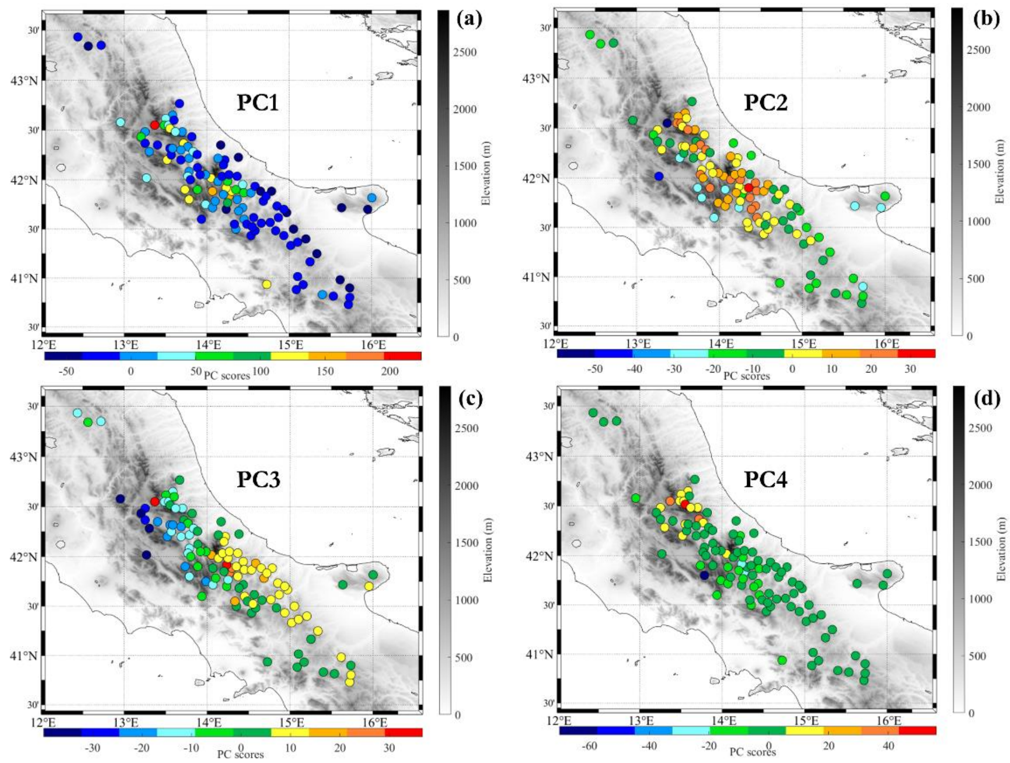

Fig. 1. Spatial patterns of the first four modes resulting from the Principal Component Analysis applied to monthly SCD data.

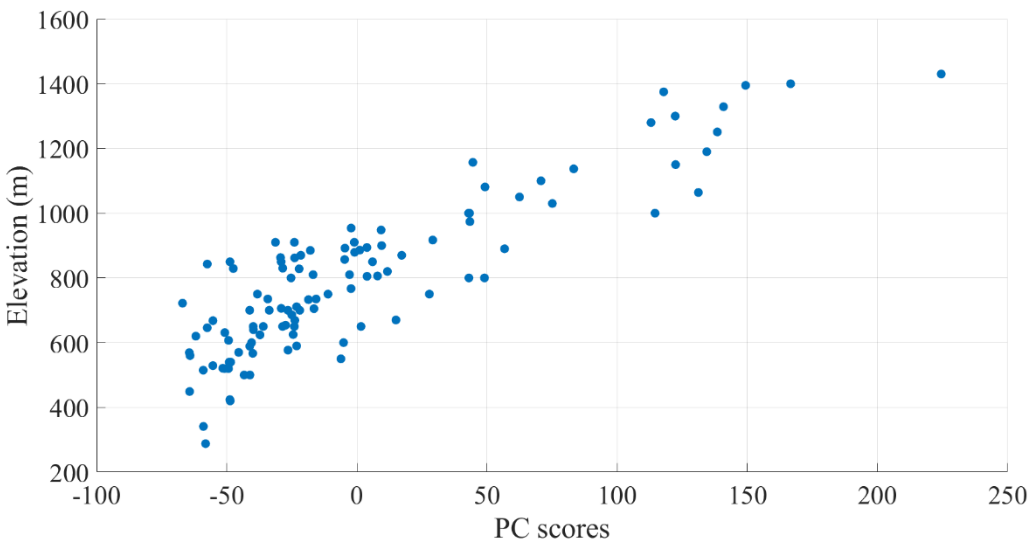

Fig. 2. First principal component (PC1) scores resulting from PCA applied to monthly SCD data as function of the elevation (in m). Each point represents one station.

For NDS variable, we have selected the first nine PCs, which capture the 70% of the total variance. According to Fig. 3a, the first PC represents a scenario in which the spatial distribution of the considered parameter is strictly related to the elevation. In this sense, additional evidence comes from Fig. 4, which clearly demonstrates the strong relationship between PC1 scores and elevation (ρ = 0.87).

In the PC2 spatial pattern (Fig. 3b), there is a relevant gradient in terms of PC scores in the Abruzzo region. More specifically, the scores gradually switch from negative to positive values moving eastward. Areas with positive scores match with Majella, Marsicani, Matese and with Southern Apennine reliefs (Partenio, Picentini and Lucania mountains). It may hypothesize that behind this NDS spatial pattern there is a synoptic scale atmospheric circulation scheme like that described for PC3 of SCD variable, i.e. a configuration associated with the incoming, over the Italian Peninsula, of cold air masses from Balkan region.

In the PC3 spatial pattern (Fig. 3c), the scores are negative over a large part of the study area. Positive values are restricted to the Campania Apennine (Partenio and Picentini mountains). Therefore, this spatial pattern might represent meteorological scenarios in which the snowfall events mainly affect the meridional sector of the considered area.

The PC4 (Fig. 3d) exhibits a spatial structure close to PC2. However, in this case the zonal gradient is not limited to the Abruzzo region, but it is extended to the whole area. As for PC2, scores gradually increase from west to east, so the largest values have been found on the eastern slopes of Apennines and over the Gargano area.

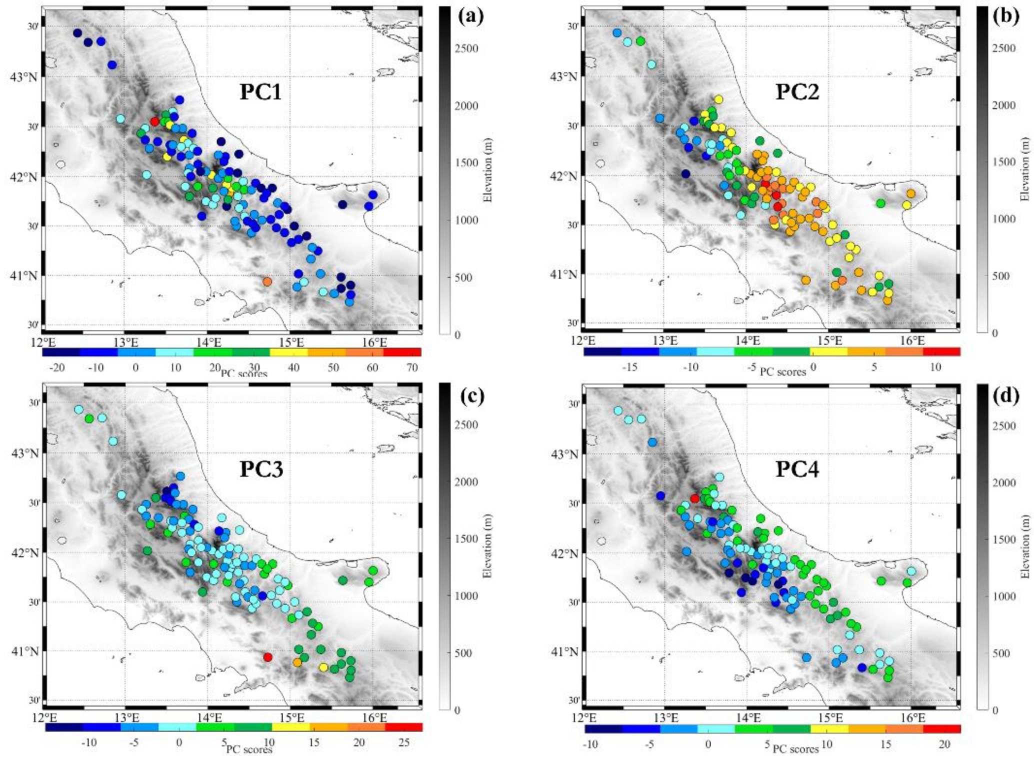

Fig. 3. Spatial patterns of the first four modes resulting from the Principal Component Analysis applied to monthly NDS data.

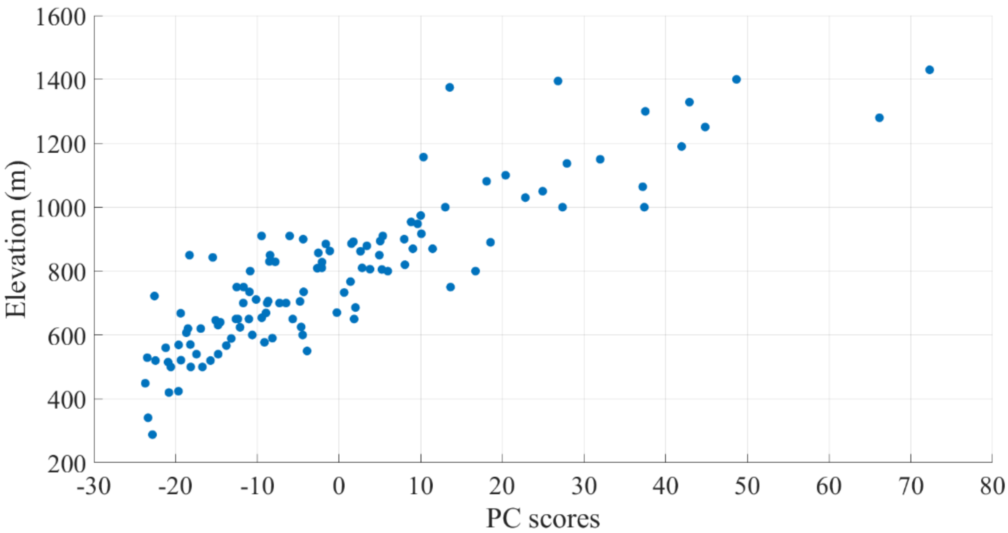

Fig. 4. First principal component (PC1) scores resulting from PCA applied to monthly NDS data as function of the elevation (in m). Each point represents one station.

The other five selected PCs are presented in Fig. 5. It is worth noting that such spatial patterns represent a very small fraction of variability (2% for PC5, PC6, PC7 and PC8, and 1% for PC9), so it is not straightforward identifying a "coherent" behaviour in the spatial distribution of the scores. More specifically, in the PC5 spatial pattern (Fig. 5a), the most relevant positive NDS anomalies occurred in the Gran Sasso area (northern of Abruzzo) and in the Campania Apennine (Partenio mountains). PC6 pattern (Fig. 5b) is close to PC5: however, in this case positive scores, and so positive NDS anomalies, are confined to the Marsicani mountains area. The PC7 spatial pattern (Fig. 5c) reflect meteorological scenarios that determine positive NDS anomalies over the central and northern sectors of Abruzzo region, Molise and Campania Apennine. In PC8 spatial pattern (Fig. 5d), positive scores are confined to specific sector of Abruzzo (Gran Sasso and Marsicani mountains) and to the southern sector of Molise. Finally, in PC9 the highest scores are located over the Gran Sasso area, Molise region and, locally, over the Campania Apennine (Fig. 5e).

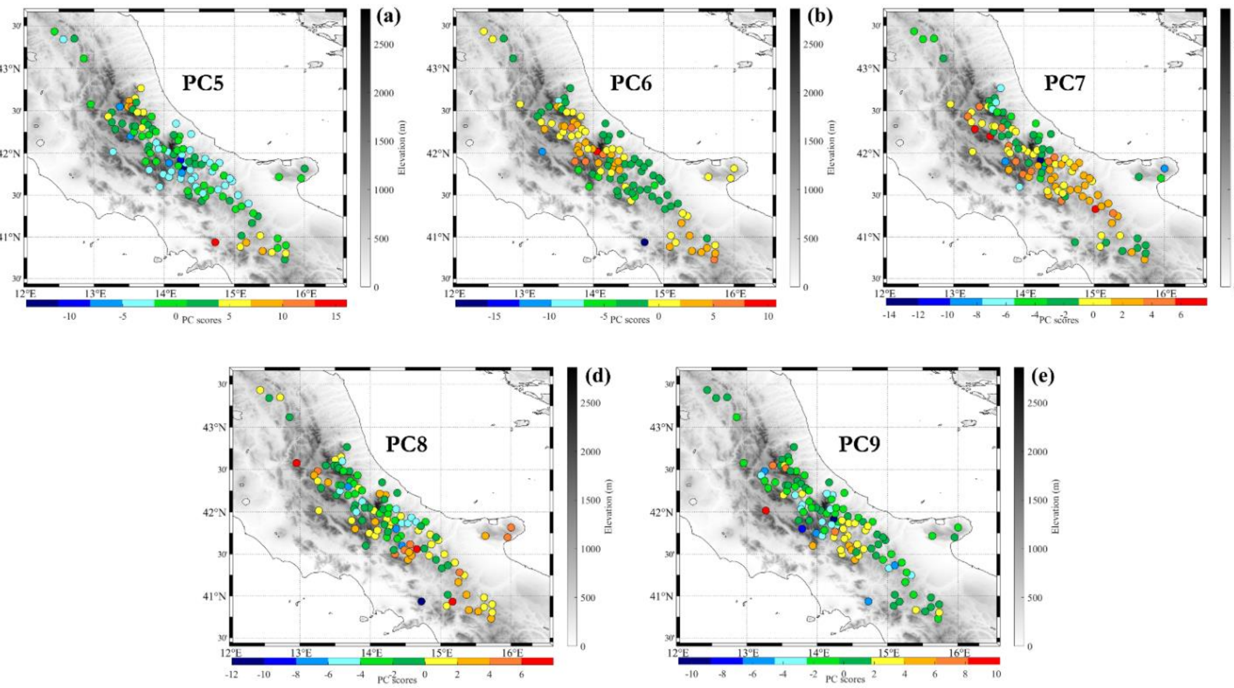

Fig. 5. Spatial patterns of the fifth, sixth, seventh, eighth and ninth modes resulting from the Principal Component Analysis applied to monthly NDS data.

The results for height of new snow variable (HN) are presented in Fig. 6. Similarly to SCD, the first four PCs have been selected. The first PC, accounting for the 52% of the total variance, shows a spatial pattern strongly modulated by the altitude (Fig. 6a). As for SCD and NDS, a strong positive correlation between scores and elevation has been detected (ρ = 0.83). However, in this case the scores associated to stations above 800 m ASL exhibit a great variability (see Fig. 7), due to the relevant incidence of orographic effects on snowfall amounts.

The analysis of PC2 spatial pattern (Fig. 6b) reveals a clear west-east gradient in the Central Apennine area. The large positive scores found over Majella area, Marsicani mountains, Matese and most of the Southern Apennine indicate that such areas receive snowfall amounts substantially higher than average, whereas the negative scores over western side of Apennines are synonymous of HN quantity near or below average. This spatial pattern can be interpreted as the result of large-scale configurations that promote the incoming of cold continental air masses in the Central Mediterranean area. In this scenario, the Central and Southern Italy are often affected by a cyclonic area driving a north-eastern flow, which enhances orographic precipitation events over the eastern slopes of Apennines.

In the PC3 spatial pattern (Fig. 6c), the positive scores are concentrated over the Southern Apennine, in some areas of Molise and in the Reatini mountains. In the Abruzzo region, the scores are generally negative, instead. Finally, the PC4 spatial pattern (Fig. 6d) is characterized by large positive scores over the western side of Marsicani area and the Reatini mountains. In both PC3 and PC4, areas marked with positive scores receive snowfall amounts higher than average. Such spatial patterns can be related to specific large-scale weather patterns that modulate the spatial distribution of snowfall precipitation in the considered region.

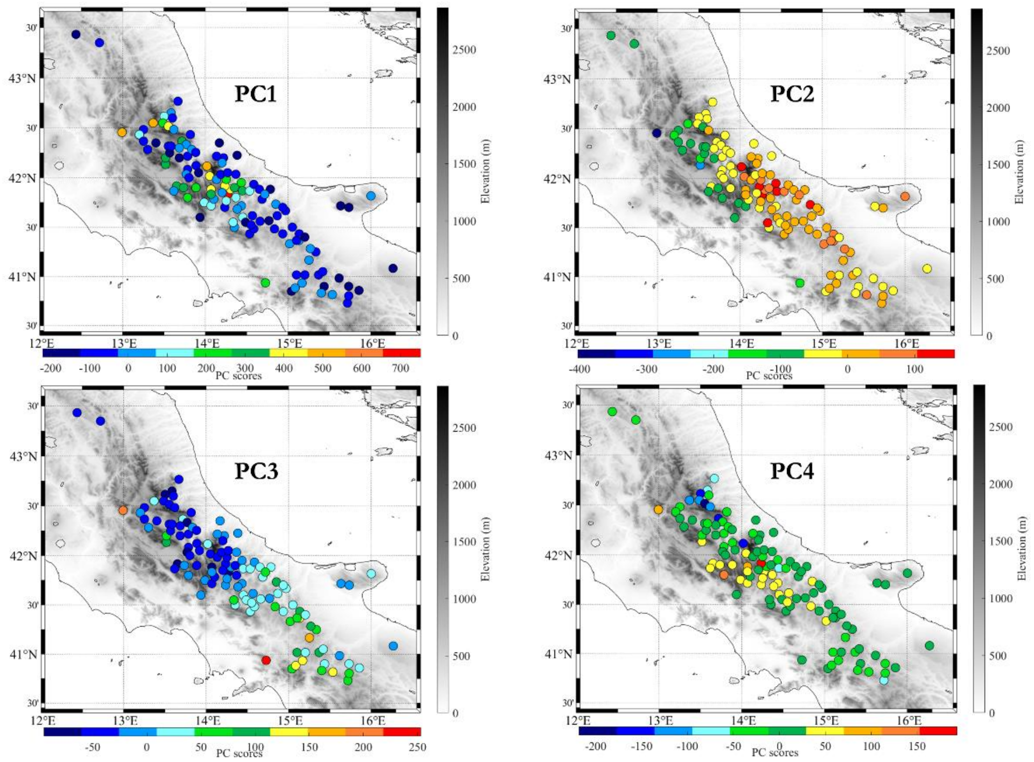

Fig. 6. Spatial patterns of the first four modes resulting from the Principal Component Analysis applied to monthly HN data.

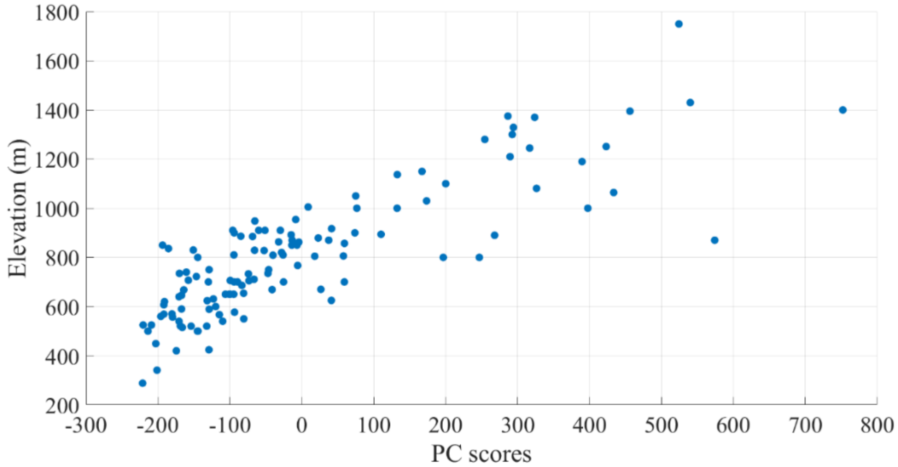

Fig. 7. First principal component (PC1) scores resulting from PCA applied to monthly HN data as function of the elevation (in m). Each point represents one station.

RC (7): 360

There is some appeal to having elevation on the y-axis, but it would conventional for it to be on the x-axis as the independent variable. This would also better show the overlap in elevation between clusters and the increasing gradient. Rather than the generic x = ay^b, it would be better to show the power fit equations as SCD = az^b.

AC (7): Following the valuable referee's suggestion, we have revised the Fig. 5, Fig. 6 and Fig. 7 of our manuscript. Here we present the new version of such figures. Note that the independent variable *z* in the power fit equations stands for elevation (in m).

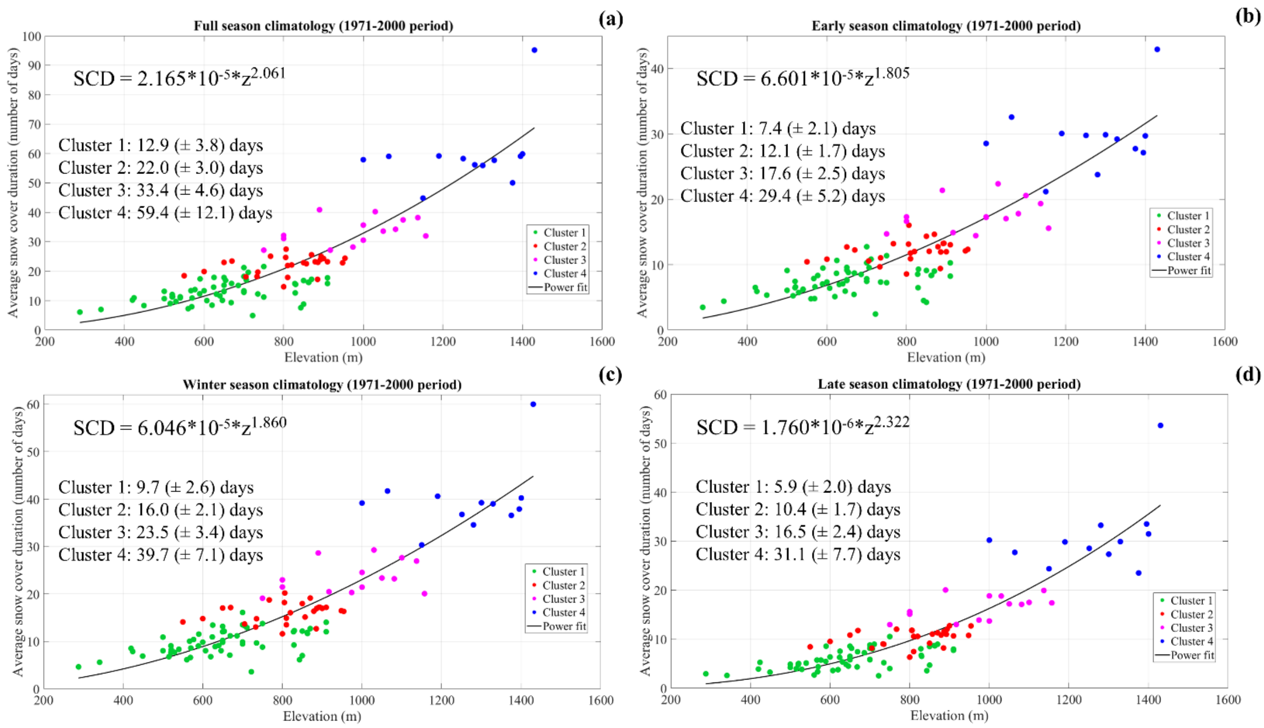

Figure 5: Climatology of snow cover duration (SCD) for (a) full, (b) early, (c) winter and (d) late season. Average values are for the period 1971-2000. Each point represents a station that is color-coded according to the membership cluster. The black solid line represents the power fit. The text boxes show the power fit equation and the average and standard deviation values for each cluster.

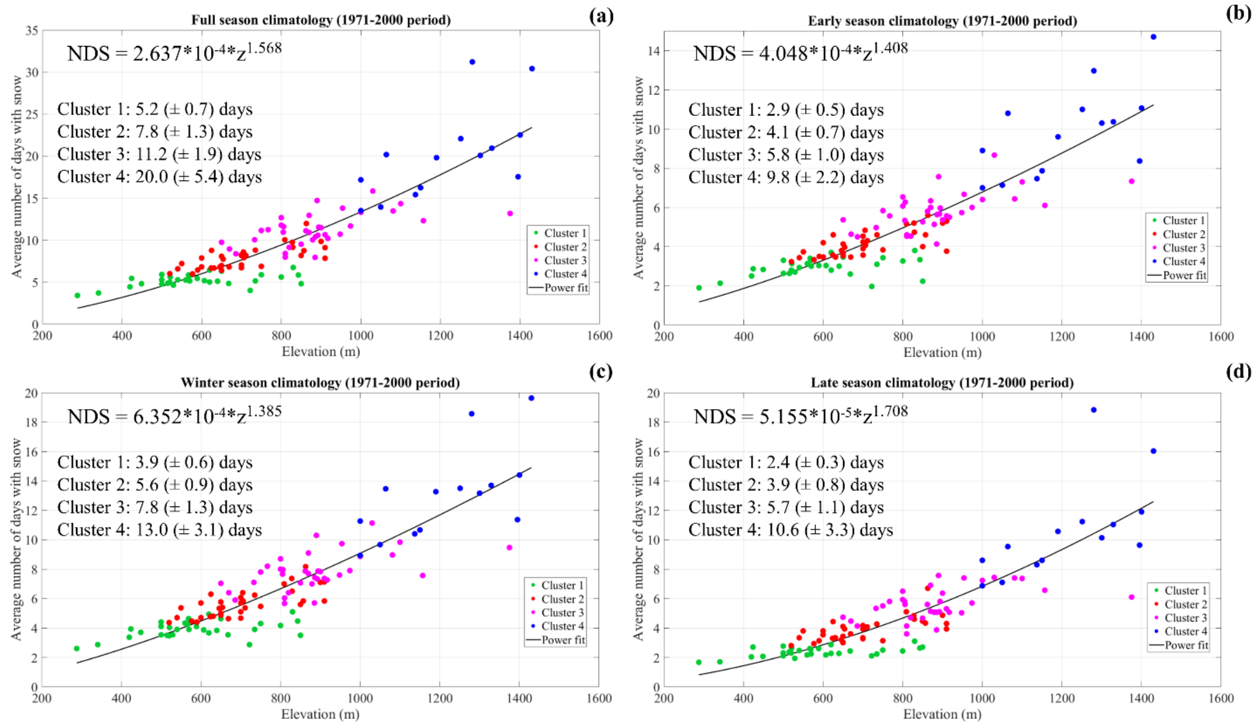

Figure 6: Climatology of number of days with snow (NDS) for (a) full, (b) early, (c) winter and (d) late season. Average values are for the period 1971-2000. Each point represents a station that is color-coded according to the membership cluster. The black solid 1095 line represents the power fit. The text boxes show the power fit equation and the average and standard deviation values for each cluster.

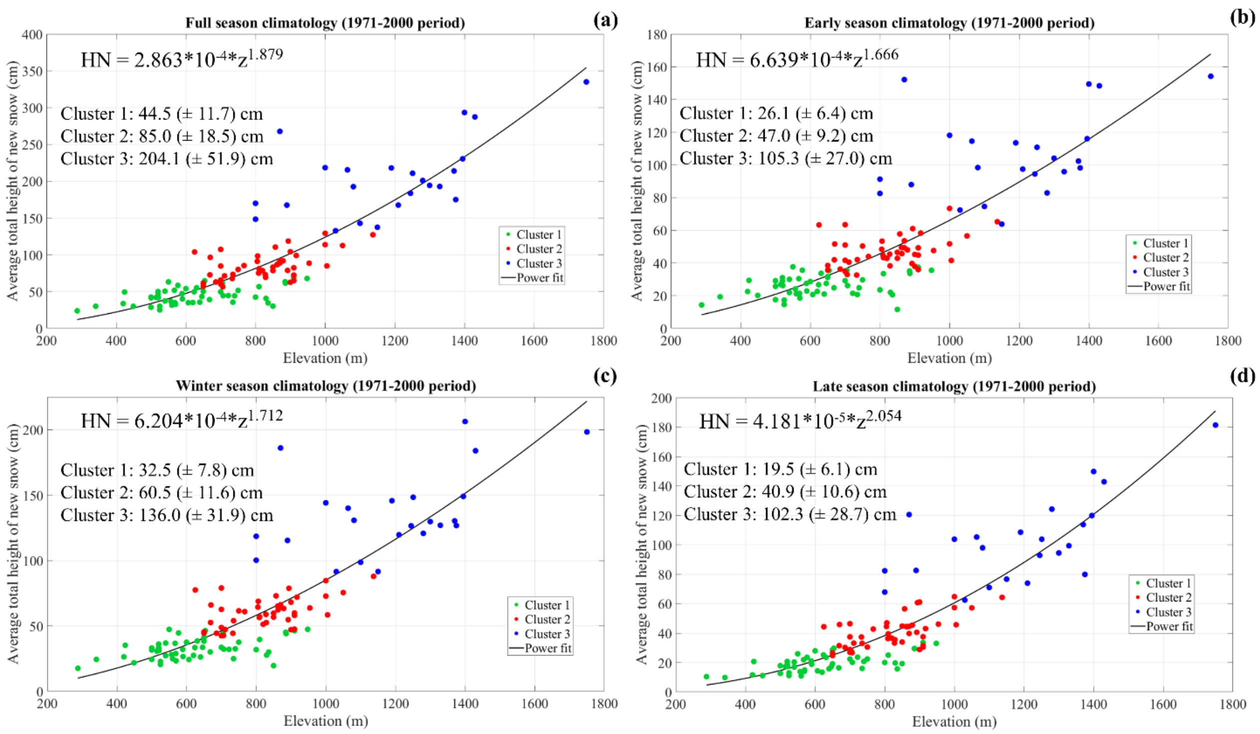

Figure 7: Climatology of height of new snow (HN) for (a) full, (b) early, (c) winter and (d) late season. Average values are for the period 1971-2000. Each point represents a station that is color-coded according to the membership cluster. The black solid line represents the power fit. The text boxes show the power fit equation and the average and standard deviation values for each cluster.

RC (8): 464
“subset” would be a more widely comprehensible term than “aliquot”.
AC (8): Ok, thank you.

RC (9): Figure 11
Does this contradict recovery of NDS in the Southern Apennines cited in the introduction?
AC (9): According to Capozzi et al. (2022) and Annella et al. (2023), a recovery in NDS has been observed, in the Southern Apennine area, in the last 20 years (i.e. in the 2000-2020 period). Note that this evidence emerged from the analysis of Montevergine time series, which is one of the few historical series that extends up to recent years. In our study, for the reason explained in Section 2.2, we focused on the 1951-2001 period. Therefore, the results sketched in Figure 11 are not in contradiction with the NDS recovery mentioned in the Introduction (i.e. the recovery occurred after 2000).

RC (10): 593
XX century?
AC (10): Yes, XX century, sorry for the mistake.

RC (11): Figures 12 and 13
The captions should state that arrows pointing to the right indicate that signals are in phase.
AC (11): Ok, we’ll follow this suggestion. Thank you.

RC (12): 675
When claiming 90% confidence, it would make more sense to quote the 90% confidence interval.
AC (12): Ok, thank you for this suggestion.