An innovative algorithm for unmanned validation of automatic snow depth measurements

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ABSTRACT: Ultrasonic snow sensors provide high temporal resolution snow depth and snowfall data used for hydrological applications and avalanche risk assessment. Nevertheless automatic snow depth measurements can be affected by errors and uncertainties due to the wind transport or interferences below the sensor. For this reason the data acquired by the automatic network of Arpa Piemonte - the regional environmental agency in Piemonte, Italy - have been usually validated by snow operators.

This work presents an innovative algorithm developed by Arpa Piemonte in collaboration with the Earth Sciences Department (University of Torino) for the automatic validation of ultrasonic-based snow depth measurements. This automatic procedure is able to find suspect data i.e. isolated peaks, outliers and errors due to the sensor malfunctioning. Several tests on the air temperature have been implemented and coupled with a snow-melting model to verify the measurement reliability. This technique has been validated comparing the output of the algorithm to the historical snow depth series manually checked. In the winter season 2012 this procedure has become operational and it is currently applied to half-hourly data. The automatically validated data are further daily checked by snow operators who approve or reject the algorithm corrections. This new process of automatic validation has improved the data quality removing anomalous spurious snow depth values and reducing the subjectivity of the manual validation.

KEYWORDS: Ultrasonic snow measurements, snow depth, automatic validation.

1 INTRODUCTION

The snow abundance in the Alps is closely related to the availability of water for agricultural and industrial activities in the downstream areas, to the hydroelectric power production, the winter tourism and the avalanche risk prevention. The snow monitoring is therefore of strategic interest for both socio-economic activities and for the proper management of environmental risks.

In recent decades the attention on the snow monitoring increased and many automatic snow gauges were installed in addiction to the traditional observations performed manually by operators. The use of automatic weather stations at high altitude presents significant advantages such as the possibility of having snowfall and snow depth measurements in remote places unsuitable for regular manned observations. On the other hand the full automation of procedures may result in sporadic measurement errors due to instrument anomalies, malfunctioning, instabilities or interferences affecting the sensors.

The availability of high-quality snow depth observations, checked and corrected from errors, is of fundamental importance for hydrological and engineering applications, in the natural risks prevention and in the assessment of climate change. In recent years the international scientific community has dedicated increasing efforts in defining the guidelines for the quality control of meteorological data (WMO 1982; Zahumensky, I., 2004; Aguilar et al., 2004). In Italy the Nivo-meteorological Services of the Regional Agencies for Environmental Protection (ARPAs) have achieved important results regarding the quality control of temperature and precipitation while no data quality control technique has been developed yet for snow (Salvati and Brambilla, 2008).

ARPA Piemonte in collaboration with the Earth Sciences Department of the University of Torino developed an algorithm for the identification of suspect data in the automatic snow gauge time series. In this work we present the technique used to find abrupt changes in the snow depth, outliers and improbable values given the seasonality of snowfall. The algorithm uses several threshold tests on the air temperature in order to check the plausibility of the snow accumulation/melting and invalidates erroneous data.

The accuracy of this technique has been assessed by comparing the automatically validated time series (algorithm output) with those validated manually by the ARPA snow operators ("truth").

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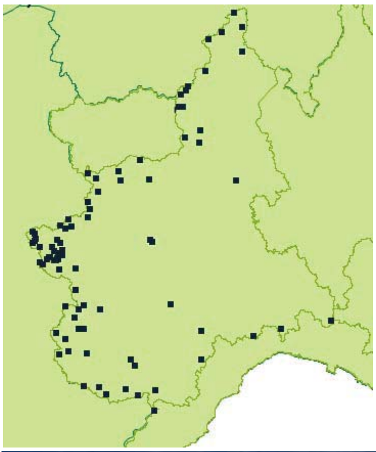
2 THE SNOW GAUGE NETWORK

In Piedmont the ARPA Nivo-meteorological Service monitors snow conditions through a network of 110 stations covering the whole Piedmontese Alps (Figure 1a). The network consists of 34 manned observation sites and 76 automatic stations equipped with ultrasonic snow gauges (Figure 1b): the former provide measurement of snow depth and snowfall on a daily basis, the latter perform measurements at 30 minutes temporal resolution and allow to have real-time data and monitor snow depth also in critical situations.

a)



b)

Figure 1. Spatial distribution of the ARPA Piemonte nivo-meteorological station network (a) and example of an automatic station with ultrasonic snow sensor (b).

The data recorded by the network have been so far controlled manually by an operator that every day verifies their correctness and confirms/invalidates them.

The study here presented aims to support the manual validation of snow data by introducing an algorithm that automatically identifies the suspect values.

3 ALGORITHM INPUT DATA

Among all the available automatic stations we selected 43 sites evenly distributed in the Piedmontese Alps and representative of elevations between 150 m and 2800 m a.s.l.. For each station we considered:

- the snow depth time series (HS_m) at 30 minutes temporal resolution. In particular we selected the data at 0700 UTC conventionally representative of the daily situation.
- the corresponding snow depth data validated manually by snow operators (HS_v) and considered as “truth”.
- the air temperature (T_a) at 30 minutes temporal resolution.

For the analysis we focused the attention on the most recent period, i.e. the last snow seasons from 01/10/2008 to 29/02/2012.

4 CRITICALITIES IN SNOW MEASUREMENTS

We considered the measured snow time series at a resolution of 30' to assess the daily evolution of the snow depth and to highlight the critical issues related to snow detection through automatic sensors.

The analysis has highlighted the variability of the snow depth measurements in a range of ± 3 cm due to the precision of the instrument. This effect can be mitigated by applying a moving average to the measured data. The moving average of 7 values usually allows to reduce the fluctuations.

A systematic analysis was performed in order to compare the measured snow depth at 0700 UTC (HS_m) and the corresponding data validated manually by operators (HS_v). This approach allows to find the wrong values and identify critical situations for the automatic snow detection.

Among the most important disturbances we found the wind that may accumulate or disperse the snow on the ground. In these cases the sensor performs measurements locally accurate but not representative of the real conditions of snow in that area. Such event can also lead to mistakes when estimating the amount of snowfall or melted snow from the difference of two consecutive daily HS_m values.

Another criticality occurs at the end of the snow season, after the complete snow melting, when vegetation grows under the sensor and therefore the snow gauge measures the height of the grass rather than the actual thickness of the snowpack.

Finally, another possible source of error is when obstacles temporarily cover the sensor and cause isolated peaks in the time series.

Basing on these issues we developed the criteria to filter erroneous data and we implemented them in an algorithm in R (R, 2010).

5 DESCRIPTION OF THE ALGORITHM

The presented algorithm aims to validate the snow depth measurements on a daily basis and uses the following data:

- HS_m at 0700 UTC. If the data is not available the previous/following one is considered.
- Corresponding HS_v (validated manually)
- Average, maximum and minimum temperatures (T, T_{max}, T_{min})

and it performs a series of tests to identify the erroneous data.

Initially the negative data are invalidated and replaced with zero. Then the abrupt variations of HS_m are identified and checked: if the difference $HS_m(t) - HS_v(t-1)$, where *t* is time expressed in days, exceeds a determined threshold, $HS_m(t)$ is classified as outliers. The thresholds are derived from the snow climatological analysis over the Piedmontese Alps during the period 1925-2010 (Terzago, 2012): the maximum daily snowfall has been set to 150 cm and the maximum daily melting has been fixed at 50 cm.

In the second phase the snow accumulation is checked through a control on the temperature data. In particular we invalidate an increase in snow depth if the minimum temperature in the 24 hours before the snow measurement has been $T_{min}(t)>2°C$. A special case occurs when $HS_v(t-1)=0$ and $T_{min}(t)>2°C$: in these cases for continuity we will set $HS_m(t)=0$. Otherwise $HS_m(t)$ is invalidated.

In the third phase we check the melting of the snowpack. The hypothesis is that we have melting when $HS_v(t-1)>0$ and the average temperature of the previous 24 hours is $T_m(t)>0$. In these cases the amount of melted snow $m_i(t)$ is estimated with three different models *i*, *i*=1,2,3 (Schmidlin et al., 1995):

$$m_1(t)=25.4*0.08*T_m(t) \text{ (Carr, 1998)} \quad (1)$$

$$m_2(t)=25.4*0.05*T_m(t) \text{ (Wiesner, 1970)} \quad (2)$$

$$m_3(t)=25.4*0.02*T_m(t) \text{ (Bruce\&Clark, 1966)} \quad (3)$$

From the estimated amount of melted snow the "theoretical" snow depth $HS_{p,i}$ is calculated for each of the three models as:

$$HS_{p,i}(t)= HS_v(t-1) - m_i(t) \quad (4)$$

If $HS_{p,i}<0$ then $HS_{p,i}=0$ is imposed. The three series of $HS_{p,i}$ - HS_m relating to the sample station of Elva were investigated and it was found that the model of Bruce and Clark provides a Mean Residual Error slightly lower than the other two. However, since there were no significant differences in the accuracy of the three models we decided to use the combination of the three rather than restrict the choice to just one.

We considered, at time t, the difference between the predicted $HS_{p,i}$ and HS_m measured:

$$\Delta HS_i= HS_{p,i} - HS_m \quad (5)$$

If for at least one of the three models the difference ΔHS is in absolute value less than or equal to a threshold value estimated empirically of 12 cm, the measured value is considered valid

$$|\Delta HS_i| \leq 12 \Rightarrow HS_m \text{ OK} \quad (6)$$

otherwise the temperature is checked in order to verify possible snowfalls. If:

$$\begin{cases} -\Delta HS_i > 12 \text{ cm (i.e. } HS_m>HS_p+12) \\ HS_m(t)-HS_v(t-1)>3\text{cm} \\ T_{min}<2\ °C \end{cases} \quad (7)$$

it is assumed that there has been snowfall and the measured snow depth is confirmed.

If the situation does not fall into one of these two cases it is assumed that the discrepancy is due to the action of the wind and the data is invalidated. All data that have not been invalidated by the tests described above are confirmed.

At the end of this process we obtain a filtered series HS_{mod}, derived from HS_m, in which all outliers have been invalidated and the false positives (i.e. when the sensor measures vegetation height instead of snow) and the negative data have been set to zero. Each HS_{mod} value is associated with a flag that indicates whether the validation confirms the data, or otherwise, for which test it has been invalidated.

6 ALGORITHM VALIDATION

The automatic validation procedure described above was applied to the time series of the 43 selected stations during the period 01/10/2008-29/02/2012: for each station we obtained a filtered series HS_{mod} and a series with the validation flags. The large datasets available allowed to evaluate the accuracy of the algorithm by testing it on more than 40,000 data.

Initially we calculated the frequency of occurrence of the flag validation (total frequency, relative to all cases of study): 55% of the invalidated data was identified by the temperature test which discards the cases in which there is an increase of snow depth with temperature above 2°C. The "logical" test that imposes the non-negativity of the snow depth discarded the 43% of the invalidated data. Less than 2% of the invalidated data was discarded because it indicated an excessive snow melting. It is small, but not negligible, the number of outliers.

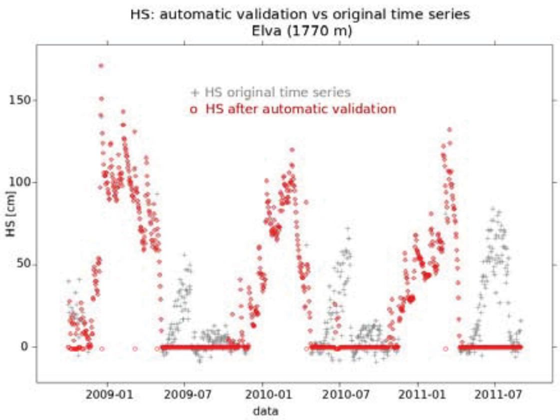


Figure 2. Snow depth at the station Elva (1770 m a.s.l.) before (gray) and after the automatic validation (red): the algorithm correctly identifies and corrects the false positives i.e. when the ground is snow free.

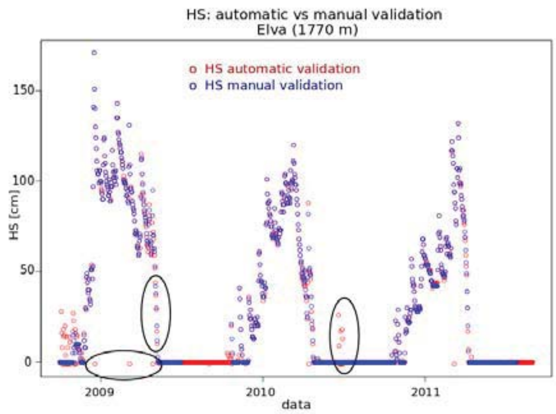


Figure 3. Comparison between the snow depth time series in Elva station: automatic (red) vs manual validation (blue). the correspondence between the series is good, the discrepancies are highlighted.

We compared the filtered series HS_{mod} to both the original data HS_m and the series validated manually by operators HS_v ("truth"). Figures 2 and 3 show the case relating to the station Elva. The comparison of HS_{mod} to the original data shows that the applied method is effective in detecting and correcting the false positives (i.e. when the sensor identifies snow but the ground is snow free).

If we compare the automatically filtered series with the manually validated one ("truth") we see a good agreement throughout the observation period, except for some incorrectly invalidated data (false alarms) in winter 2008-09 and others mistakenly accepted in the 2010 summer season.

The analysis described here has been repeated for all stations. In particular, for each station, each value HS_{mod} has been validated by comparison with the corresponding "true" value HS_v. At the end of the procedure we filled a contingency table (Figure 4) which counts the number of values correctly invalidated, correctly confirmed, erroneously invalidated (false alarms) and erroneously confirmed (misses).

		Observation (Manual Validation)	
		OK	INVALID
Automatic Validation	OK	Correct Neg. (CN)	Misses (M)
	INVALID	False Alarm (FA)	Hits (H)

$$ACC = \frac{H + CN}{H + M + FA + CN}$$

$$POD = \frac{H}{H + FA}$$

$$CSI = \frac{H}{H + M + FA}$$

$$FAR = \frac{FA}{H + FA}$$

$$BIAS = \frac{H + FA}{H + M}$$

ACC	0.98
POD	0.96
CSI	0.96
FAR	0.007
BIAS	0.97

Figure 4. Contingency table used for the validation of the algorithm performances and relative stistical indices.

From the sum of the partial results of the individual stations we calculated a total contingency table and the related statistical indices that describe the average properties of the algorithm over all the cases studied. The accuracy of the proposed method, i.e. the probability that the algorithm correctly classifies the snow data, is 98%, thus very high. The probability of a false alarm, that is, the probability of invalidating a correct value, is

0.7%. The algorithm proves to be reliable in identifying outliers and tends to be conservative, so the most common mistake is to confirm an erroneous value rather than invalidate a correct one.

6 CONCLUSIONS

In this study we propose a method to automatically identify suspect data in snow depth time series from automatic weather stations. The technique is based on a series of threshold tests that identify erroneous data, outliers and values that imply snowfall/melting not compatible with the registered temperature. The algorithm, tested on more than 40,000 data, shows an average accuracy of 98% while the probability of invalidating a correct data is 0.7%. Due to its high reliability the algorithm is an effective tool for validating automatic stations snow data and to support the work done by the operators.

In the winter season 2012 this procedure has become operational at ARPA Piemonte and it is currently applied to half-hourly data. The automatically validated data are further daily checked by the snow operators who approve or reject the algorithm corrections. This new process of automatic validation has improved the data quality removing anomalous spurious snow depth values and reducing the subjectivity of the manual validation.

Finally, the simple logic structure of the proposed algoritm makes it easily generalizable as it can be applied to every situation where both snow depth and air temperature measurements are available.

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