Optimum interpolation New Snow Depth Analysis in HIRLAM

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Abstract

A new optimum interpolation analysis for snow depth has been implemented in HIRLAM. It includes some modifications of the background field computation accounting for a very simplified snow metamorphism. Additionally second order autoregressive function structure function has been introduced to model background errors and a bias correction scheme has been developed and implemented. Apart from other diagnostics to asses the performance of the new snow depth analysis the validation of the analysed snow cover has been carried out using SSMI derived NESDIS snow cover product..

Introduction

Successive correction (S.C) algorithm seems to be not satisfactory when used to analyze snow depth in HIRLAM. The problems detected are inherent to the analysis method. The surface analysis routines have been modified to change the snow depth analysis method to optimum interpolation (O.I.). The superiority of optimum interpolation method is renforced with an additional quality control of the observations. The development of the new snow analysis in HIRLAM follows the Canadian global snow depth analysis [Brasnett,1999].

The previous studies [Cansado et al, 2003] have shown the superiority of optimum interpolation versus succesive correction analysis method. After that, a new computation of snow depth background field has been introduced to account for a very simplified snow metamorphism model.

Once the good behaviour of the optimum interpolation analysis and new first guess was tested, the structure function has been modified. A new second order autoregressive function has been properly tuned to fit the empirical autocorrelation data. Values for background and observation error standard deviation have been obtained. These error statistics together with the already mentioned developments for O.I. snow analysis have been tested through snow depth data assimilation experiments covering the whole winter season. The validation has included comparison of snow cover against satellite products (SSM/I derived snow cover).

The evaluation of these long period experiments revealed some deficiencies of the snow analysis when assimilating mountain stations data. Then, a bias correction scheme has been designed and implemented to be applied to innovations from complex terrain stations.

Finally, some experiments have been conducted using pseudoobservations of 0 cm snow depth from the available SSM/I snow cover product in snow free areas. The usage of satellite information is expected to contribute to a better representation of the snow cover edge in data sparse and transient snow areas.

O.I. Analysis Method and Snow Depth Background Field.

Optimum interpolation was preliminarily implemented using a gaussian function to model background errors. The horizontal length scale L_H was set to 85 km, which corresponds with an e-folding distance of about 120 km. The vertical length scale L_V was set to 565 km (e-folding vertical distance of 800 m). Histograms of innovations and residuals were generated showing a closer fit of both first guess and analysis to observations using O.I. instead of S.C.

In the former snow parameterization there was not a evolving snow density. In the accompanying snow analysis, a homogeneous, monthly varying, snow density was then used to convert the six hours forecast of snow water equivalent onto the snow depth background field. The new snow depth first guess, based on Brasnett (1999), introduces a snow density field and takes into account the changes that suffers the snow cover as time passes by. Essentially, snow aging (when temperatures are below 0º C) and snow melting (when temperatures raise above 0º C) effects are considered. Analyzed 2m temperature, six hours accumulated precipitation and the previous Snow Depth and Snow Density fields are used to create the snow depth background.

Fresh snow is considered to have a density of 100 kg m^{-3}. The snow density when temperatures are below 0º C evolves according the following equation

$$\rho = \rho_a + [\rho_{-6} - \rho_a] \exp\left(\frac{-6}{\tau}\right)$$

where ρ_a is an assimptotical value of the density which is 300 kg m^{-3} everywhere except in needleleaf forest where a value of 210 kg m^{-3} is set, τ is set to 100 hours and ρ_{-6} is the former density data.

Snow density can grow above when temperatures raises above 0º C and snow starts to melt. In this case, two effects are considered: First of all, density increases at a rate of 0.5 kg m^{-3} $hour^{-1}$, accounting for the effect of melt water infiltrating the snow pack and refreezing. By this way, density can reach 550 kg m^{-3}. Secondly, mass is removed from the snow pack at a rate of 0.15*(T – 273.16) mm $hour^{-1}$, where T is in ºK

Three experiments have been carried out to test the O.I. analysis and new first guess. All of them, were run using HIRLAM 6.2.0. at the DMR area and resolution covering February 1996:

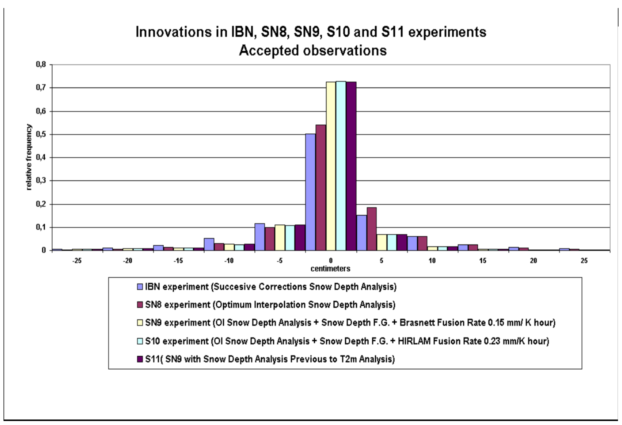

Fig.1. Histograms of innovations

IBN (dark blue) was the reference experiment using S.C. to analyze snow depth field.

SN8 (purple) Snow Depth analysis using O.I. Method.

SN9 (cream) O.I. analysis and Snow Depth First Guess following Brasnett.

S10 and S11 were small modifications on SN9 (not considered here)

Histograms of innovations show the progressive improvement of snow analysis when introducing O.I. method and the new first first guess. This last development seems to produce the largest benefit, probably due to the usage of an spatially varying, time evolving snow density. The impact of the improvements shows to be higher in non-permantently covered areas, as in northern Europe (which in February are usually snow covered) showed very few or no impact.

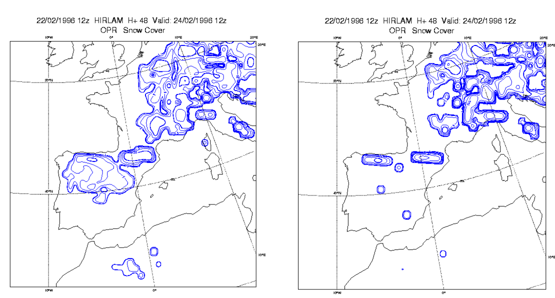

Fig. 2. 48 hours Snow Depth Forecasts

Nevertheless, individual forecasts of different experiments show very strong differences in some cases. The maps in figure 2 correspond to two H+48 forecasts of snow depth in Southwestern Europe using different analysis methods (S.C analysis left map, O.I. and new First Guess right map).

Significantly different snow cover regions appear over Spain. As a consequence two meter temperature forecasts differ up to several degrees over these areas (not shown), two meter temperature verifying analysis supporting O.I analysis method for snow depth.

It has been also observed that succesive corrections method produces noisier snow depth, snow cover spreads more, specially in southern regions, and the quality control of the observations is not satisfactory. Optimum Interpolation analysis solves “bull eye” phenomena due to acceptance of bad observations and produces a more realistic snow cover distribution, creating patchy snow covered areas where snow is non permanent instead of continuous non realistic distributions. Nevertheless, errors in model precipitation continue to produce spureous snow cover (specially over mountain ranges) and the model is not still able to follow the rapid thawings that sometimes happen.

Autorregressive Structure Functions and Winter Season Experiments

Hollingsworth and Lönnberg method [Hollingsworth et al, 1986] has been used to determine appropriate error statistics, as it has been done with 2 meters temperature and relative humidity. A time series of innovations for February 1996 has been used to fit the empirical autocorrelation data to a second order autoregressive (SOAR) function used to model the analysis structure function.

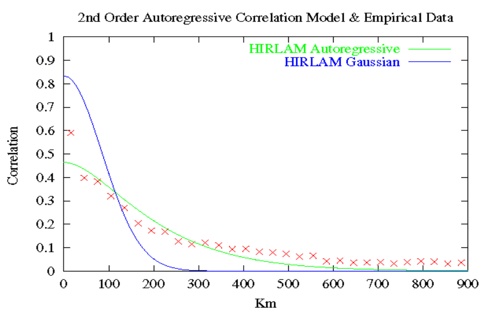

Fig. 3. Structure Functions of the analysis

The SOAR functions are non-linear functions defined as:

$$\alpha(r) = (1 + c\,r)\exp(-c\,r)$$

E04GYF routine included in NAG library has been used to get a value of c that fits the data. [Gill et al, 1978].

Red crosses in Fig. 3 show the empirical data of correlations. The blue solid line is the Gaussian we used in the O.I. analysis before and the green dashed line shows the best fit of the empirical data to a SOAR function.

The value of c obtained is 0.009 km^{-1}. Its inverse is the horizontal scale length, in this case about 110 km. Additionally, another remarkable result has been found. The total variance is almost equally due to observational and background errors. In fact, observations contributes with 53.6% to total variance and background errors contributes with 46.4%, in contrast with values used in S.C. method for which the ratio σ_O/σ_B was much smaller (1/5).

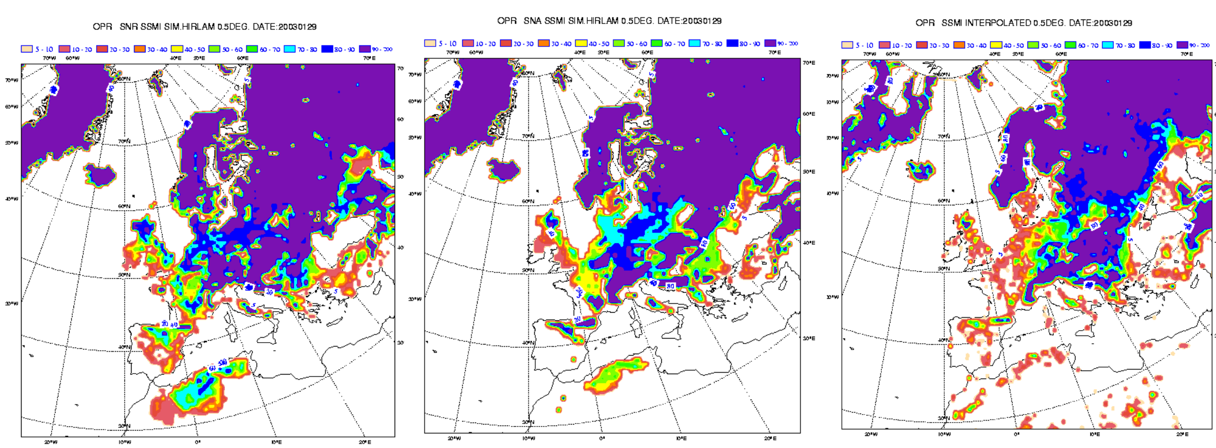

Fig. 4. Comparison between SNR (left), SNA (center) and SSMI derived data (right)

The following step was to run a whole winter season experiment including this SOAR structure function, O.I snow depth analysis and the new first guess. This experiment was called SNA. The reference experiment (S.C. analysis) was SNR. Both ran from October 2002 to May 2003 and include snow cover formation, evolution and thawing.

To validate the snow coverage from both experiments, SSMI snow cover data were used. The SSMI NESDIS snow cover product offers weekly and monthly, 1/3 degree resolution, information about the time percentage in which a pixel has been snow covered during the considered period. To compare the experiments (4 analysis / day) with SSMI product (once weekly) SSMI product was simulated at every 6 UTC analysis in the week. Fig.4 shows the comparison between SNR and SNA with SSMI. It can be seen that SNA analysis improve remarkably SNR analysis, eventhough differences can still be found between SNA and SSMI.

Bias Correction Scheme and Usage of Satellite Pseudoobservations

When obtaining some diagnostics of the assimilation performance, it was observed that a great number of mountain stations were rejected in the analysis, probably due to the new values of σ_o and σ_b. Very high values of bias were found in those data. The main sources of bias are probably the lack of representativity of snow depth measurements -in particular the difference between model orography and station altitude- and the spurious precipitation of the model. However, a careful inspection of the data showed that some information can be gathered from them if bias is removed previously.

A station by station bias correction scheme has been then implemented in the model. The scheme considers all the observations of the previous five days to calculate the bias in a given station, but only if there are five or more observations in the former five days the bias is calculated and corrected. In any other case, the bias correction is set to zero.

An experiment (SNC) running during February 2003 was performed to test the scheme. The results showed that a great number of mountain stations were accepted in the analysis after being corrected.

Additionally, in order to improve the snow cover in snow transient areas satellite pseudoobservations have been created. The aim is to test if the assimilation of satellite data in the analysis can help to improve its quality. The method employed consisted on using the pixels where the SSMI weekly product sees no snow create a zero cm snow pseudoobservation for every day of the week. No other information from SSM/I product was considered. This should help to remove the snow cover generated by the spureous precipitation of the model and to simulate the rapid thawing episodes that sometimes happen according to satellite data. Only 6 UTC analysis included pseudoobservations (when the amount of conventional information was big enough). Once the corresponding routines were developed and implemented, a new experiment was run in February 2003 that shown a significant improvement in snow cover in southern Europe and northern Africa.

Summary and conclusions

A new analysis for snow depth has been developed and implemented for HIRLAM. It is based on O.I. method with a tuned SOAR structure function and observation and first guess error standard deviations. A more sophisticated first guess has been introduced that considers a snow density time evolving field and a very simple model of snow metamorphism. A bias reduction scheme has been found to be needed and implemented in order to correctly assimilate snow depth observations from stations located in mountain regions.

The successive enhancements of this analysis have been separately tested showing the benefit of each of the new developments. Although the positive impact of this snow analysis is only slightly observed in the verification scores of two meter temperature and relative humidity, the diagnostics of the assimilation performance like histograms of innovations and residuals, as the number of observations accepted and rejected by the analysis have supported each of the new enhancement introduced progressively. The better performance of this new analysis has become evident when comparing the analysed snow cover against SSM/I snow cover products. This validation has also revealed some remaining problems of the model snow cover appearing in data sparse and transient snow areas. The possibility of assimilating pseudoobservations obtained from satellite snow cover has been shown with the weekly SSM/I snow cover product and indicates the potential of usage of daily satellite snow cover available at present from MODIS and from LAND SAF in the near future.

Acknowledgements

The authors wish to thank Ernesto Rodriguez for his helpful suggestions regarding the interpretation of the results.

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