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Calibration of a Distributed SWE Model Using MODIS Snow Cover Maps and In Situ Measurements

Nikola BESIC*†, Gabriel VASILE†, Frédéric GOTTARDI†,
Joël GAILHARD†, Alexandre GIRARD★ and Guy d'URSO★

†GIPSA-lab, Grenoble INP / CNRS, 11 Rue des mathématiques, Grenoble, France

‡EDF DTG, 21 Avenue de l'Europe, Grenoble, France

★EDF R&D, 6 Quai Wattier, Chatou, France

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In this letter, we propose the calibration procedure for a Snow Water Equivalent (SWE) forecasting model, using Moderate-Resolution Imaging Spectroradiometer (MODIS) multi-temporal snow cover maps and *in situ* measurements. The presented study refers to one of the largest artificial lakes in the Western Europe - the Serre-Ponçon reservoir, on the Durance river, in the region of the French Alps. The SWE model, an integral part of the MORDOR hydrological model (*MOdèle à Réservoirs de Détermination Objective du Ruissellement*), provides the SWE as a function of the local precipitation and temperature, as well as of the accumulation and melting correction coefficients. The principal motivation for the proposed calibration method comes from the significant model sensitivity with respect to these two coefficients, which, given that they account for the influences of topology and mountain winds, ought to vary spatially. Three different optimization procedures are compared using the set of *in situ* measurements acquired by the EDF cosmic-ray snow sensors for four out of thirty-six ground stations in the regions of interest. The appropriate optimization method is selected and the corresponding representative optimal coefficients are derived for these four stations. Further, by combining the selected optimization algorithm and the continuous activation function, we are proposing a new method for deriving the spatially varying coefficients characterizing the entire region, using multi-temporal MODIS snow cover binary maps. When analyzed with respect to the Mean Square Error (MSE) criterion, the SWE model, calibrated in this manner, appears to be significantly more accurate than the original version (using *a priori* estimated, spatially fixed coefficients). Furthermore, the calibration procedure based on MODIS data is comparable and, for some ground stations, it exhibits even better performances than the one based on the *in situ* measurements.

1. Introduction

Snow Water Equivalent (SWE), a function of snow density and depth, is defined as the depth of the layer of liquid water that would be produced if all the ice in the snow pack were melted [Rees (2006)]. The estimation of SWE in mountainous regions appears very important for the hydroelectric power supply, since it allows anticipating the water resources available during the snow melting season [Tourasse (1995)]. The main French hydro-power company EDF (*Électricité de France*) uses the internally developed hydrological model MORDOR (*MOdèle*

*Corresponding author's email: nikola.besic@gipsa-lab.grenoble-inp.fr

à Réservoirs de Détermination Objective du Ruissellement) [Garçon (1996)] and local *in situ* measurements, in order to properly estimate the contribution of the melted snow to their water accumulations. Using thirty-six meteorological stations distributed around the accumulation reservoir of the Serre-Ponçon dam, the MORDOR forecasting hydrological model currently provides, among other parameters, the SWE used to evaluate the potential intakes to this reservoir and to optimize the operation of the corresponding power plant. The sub-model, providing the SWE, uses the available precipitation and air temperature measurements as input parameters. Aside from those, each station is supposed to be characterized with the appropriate accumulation (c_p) and melting (k_f) correction coefficients.

In this letter, we present the calibration of the SWE sub-model of MORDOR using *in situ* measurements and we propose a novel calibration strategy based on a multi-temporal set of Moderate-Resolution Imaging Spectroradiometer (MODIS) snow cover binary maps [Vasile *et al.* (2013)]. In fact, we are deriving a mean to properly establish the spatially varying accumulation and melting correction coefficients, required by the MORDOR model. These parameters represent a mean to account for the strong influence of the topology and mountain winds on the hydrological model [Bloschl *et al.* (1991a,b)]. The MODIS data were already, despite the ever-present issue with the cloud coverage, successfully used in calibrating and validating hydrological models [Parajka and Bloschl (2008, 2012)]. In this article we propose a suitable calibration procedure, reduced to the estimation of the spatially varying correction coefficients and, by comparing it with the one performed using *in situ* measurements, we demonstrate the utility of the remote sensing data in the context of the calibration of distributed hydrological models.

As a case study for the derivation and the demonstration of the proposed method, we use the formerly introduced Serre-Ponçon dam. Out of the existing thirty-six stations, local *in situ* measurements are available for four of them. These data sets are initially used for comparative optimization aiming both to derive representative coefficients (c_p, k_f) at these four locations and to select the most appropriate optimization method. Still being restricted to these four stations, we employ the formerly selected method in defining the parameters of the continuous activation function. Further, we derive the spatially varying coefficients characterizing the entire region, including the remaining stations, by rather relying on the MODIS multi-temporal set of snow cover maps. This is done through the optimization of the continuously thresholded (by means of the continuous activation function) SWE model, using the available remote sensing data acquired over the entire region. The final comparison with the *in situ* measurements indicates significantly increased accuracy with respect to the initial case, where the c_p and the k_f are considered as fixed for the entire region. Moreover, the proposed method based on the MODIS data, eventually appears to be superior with respect to the calibration using *in situ* measurements.

2. MORDOR hydrological model

The MORDOR model principally covers five hydrological processes [Paquet (2004)]: evapotranspiration, surface runoff, infiltration, dewatering and snow accumulation and melting. Basically, it assumes five different reservoirs and models their mutual exchange. They represent: snowpack, surface supply (absorption), stock of water which transforms to vapour, intermediary supply and deep supply (rivers).

Our particular interest is the sub-model dealing with the snow accumulation and

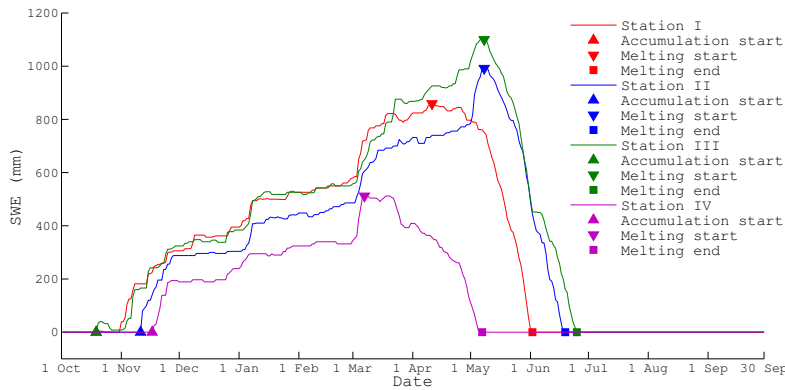


Figure 1. SWE measurements during the season 2001-2002.

melting. Namely, based on the precipitation and the air temperature measurements, this sub-model estimates the quantity of water contained in the snowpack (one of the assumed reservoirs). Aside from these meteorological parameters, the two coefficients characterizing the accumulation and the melting processes c_p and k_f , define the SWE as well.

The accumulation during one day is estimated rather commonly, using both precipitation and air temperature, where the later one defines the ice fraction in the former. However, the melting estimation, being more sophisticated, is performed by simultaneously assessing the superficial melting, melting due to the rain and the one caused by the geothermal flux. The first of them is modelled using a degree day model which relies on both the air temperature and the temperature of the snow. Only this summand is corrected by the coefficient k_f .

Unlike the precipitation and the air temperature, which can be measured [Gotardi and Gailhard (2009)] at the distributed meteorological ground stations and then interpolated [Goovaerts (2000)], the coefficients c_p and k_f have to be either assumed or determined based on some reliable measurements. The later is the topic of this article - proposing a method which exploits remote sensing measurements in order to derive the snow accumulation and melting correction coefficients.

3. Calibration using *in situ* measurements

The *in situ* measurements are acquired at some ground meteorological stations by cosmic-ray snow gauges. Conventionally used in the characterization of the soil moisture [Zreda *et al.* (2012)], this technique proved to be an efficient method for the SWE estimation, as well [Paquet and Laval (2006)].

These, available *in situ* measurements, were used both to determine the representative optimal coefficients at the corresponding sites and to select the most appropriate optimization method. Firstly, we were identifying the characteristic periods (accumulation and melting) over one year. Later, we performed the comparative analyses by applying simultaneously three different optimization algorithms.

In order to identify the accumulation and the melting periods, we had to determine three dates: accumulation start date, melting start and melting end dates.

This was done using the smoothed gradient operator: positive gradient values correspond to snow accumulation, while negative indicate melting. Therefore, the radical change in gradient value points to the melting start. The other two dates are related to the first and the last non-zero values during the year of study (1 October 2000 to 30 September 2001).

We used the Mean Square Error (MSE) as optimization criterion. The goal was to find the values of the accumulation (c_p) and the melting (k_f) coefficients which lead to the smallest difference between the model output (given the local meteorological data) and the measurements. Actually, it is the minimum of the MSE function we were searching for:

$$[c_p, k_f] = f_{\text{opt}} (\text{MSE}\{g(c_p, k_f, t), m(t)\}, [c_p^0, k_f^0]). \quad (1)$$

with f_{opt} signifying the function of optimization, g being the model output as a function of time (t) and m representing the acquired *in situ* measurements. c_p^0 and k_f^0 are the fixed values of the coefficients used in the original model, derived statistically using several meteorological stations.

Three unconstrained non-linear optimization algorithms [Dennis and Schnabe (1983)] were compared using the available measurements:

- M1 - fmin search: the Nelder-Mead simplex function minimization. The algorithm creates a simplex around the initial guesses (c_p^0 and k_f^0) which is further modified in the iterative process. [Lagarias *et al.* (1998)]
- M2 - pattern search: the generalized pattern search (GPS). It relies on positive spanning directions by assuming the treated function (model output) is continuously differentiable [Charles and Dennis (2003)].
- M3 - genetic algorithm: natural selection process that mimics biological evolution. The only of the three used algorithms that doesn't require any initial guess, but rather creates random solutions, which are evolving toward the optimal ones [Michalewicz (1995)].

By relying on previously derived characteristic periods, the optimization procedure was performed using the values acquired during:

- the whole year (all),
- the accumulation (A) and melting (M) period (winter+spring),
- the accumulation period (winter),
- the melting period (spring).

At the end of this section, we had both the most suitable optimization method and the representative optimal coefficients, which were due to be considered as the reference in analysing the performances of the proposed method.

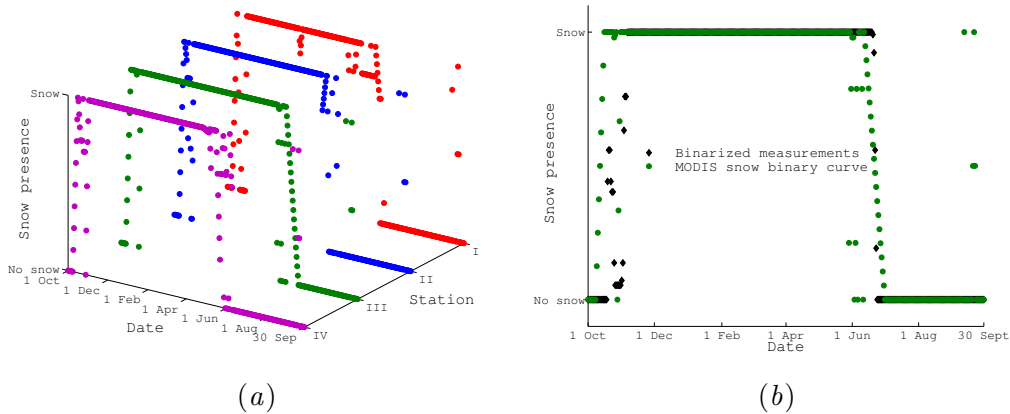


Figure 2. The MODIS binary snow maps: (a) interpolated SWE binary curves (four stations with *in situ* measurements); (b) comparison with the optimally binarized *in situ* measurements (station III).

4. Calibration using MODIS remote sensing data

Due to its accuracy and daily availability, MODIS remote sensing data represent a valuable tool in snow cover monitoring [Klein and Stroeve (2002)]. Despite the necessity to perform spatial and temporal filtering in order to decrease cloud obscuration, the overall accuracy of the derived snow cover maps stays above 90% [Parajka and Blöschl (2008)].

Therefore, MODIS snow cover maps happen to be particularly useful in calibrating and validating semi-distributed hydrological models [Parajka and Blöschl (1999)]. The standard procedure assumes comparing the SWE output of the hydrological model with the observed maps.

Obviously, the previously introduced calibration relying on the *in situ* measurements cannot be applied to the entire region of interest, unless the measurements are spatially interpolated. Even though both the air temperature and the precipitation are interpolated by means of kriging (Gaussian random regression), the same type of spatial continuity cannot be expected in case of correction coefficients. Therefore, in order to account for their strong spatial variability, we have developed a new strategy for exploiting the MODIS binary snow maps, instead. This method allows the calibration of the distributed hydrological model.

The proposed method consists in the following three steps:

4.1 MODIS data preprocessing

The set of multitemporal MODIS snow maps was derived out of georeferenced MODIS images, acquired in 2000/2001. The temporal binary curves derived for each pixel were then linearly interpolated in order to compensate for the eventual lack of the data during the year. Among them, four correspond to the meteorological stations characterized with *in situ* measurements (Fig. 2(a)).

4.2 Continuous thresholding of the SWE sub-model

The conventional "hard" thresholding with respect to the predefined threshold T (values less than T labelled by "0" and greater than T by "1"), did not appear to be appropriate, given that a non-continuous function does not suit any of the formerly introduced optimization methods. Therefore, we turned toward a continuous thresholding strategy, based on the continuous activation function:

$$x_b = \frac{\tanh\left(\frac{x-h}{\sigma}\right) + 1}{2}, \quad (2)$$

where σ reflects the uncertainty in the SWE sub-model, while h depends on the value order of SWE, here called x . The later value was selected *ad hoc*, while the derivation of the σ value assumed the optimization (algorithm M1) of the binarized *in situ* measurements ($m_b(\sigma, h, t)$) with respect to the corresponding MODIS temporal binary curve ($M(t)$) (Fig. 2 (b)):

$$[\sigma] = f_{\text{opt}}\left(\text{MSE}\{m_b(\sigma, h, t), M(t)\}, [\sigma^0]\right), \quad (3)$$

with σ^0 being the initial, assumed value of σ .

The completely defined linear binarization function was further to be applied on the SWE sub-model.

4.3 The derivation of the correction coefficients

Finally, we derive the correction coefficients (c_p and k_f) by minimizing the mean square error between: (1) the product of the binarized SWE sub-model output (g_b) with the model itself (g), and (2) the product of the smooth MODIS binary curves M with the SWE sub-model.

Empirically, we established that the optimization at the ground stations characterized by large SWE values, should be performed using the *a priori* assumed SWE sub-model (based on the initially assumed coefficients) paired with the MODIS measurements. Namely, in these cases, the SWE sub-model multiplying the smooth MODIS binary curves, is not the subject of the optimization:

$$[c_p, k_f] = f_{\text{opt}} \left(\text{MSE} \{ g_b(c_p, k_f, t)g(c_p, k_f, t), M(t)g(c_p^0, k_f^0, t) \}, [c_p^0, k_f^0] \right). \quad (4)$$

However, in other cases, where SWE values are not perceived as large (station IV), the optimization is to be performed by considering all the (c_p and k_f) coefficients as optimizable variables:

$$[c_p, k_f] = f_{\text{opt}} \left(\text{MSE} \{ g_b(c_p, k_f, t)g(c_p, k_f, t), M(t)g(c_p, k_f, t) \}, [c_p^0, k_f^0] \right). \quad (5)$$

5. Results

Firstly, we present the optimization results obtained using the *in situ* measurements. The comparison between three optimization algorithms indicates the best overall performances of the *M1* method. This method is therefore adopted as the standard optimization procedure in this article. Concerning the characteristic periods, it appears that the most suitable one is "accumulation+melting ($A+M$)" period (Fig. 3).

As expected, the SWE sub-model, optimized this way, exhibits significantly increased accuracy with respect to the *in situ* ground measurements. This can be noticed in Table 1.

Further, we present the optimization results obtained using the MODIS binary snow maps (Fig. 4) for the four stations with the *in situ* measurements. Even though this optimization appears to be slightly more time consuming, the overall results (Table 1) indicate far better performances with respect to the original ones. Curiously, in case of two stations (I and IV) the obtained results are even better than the ones achieved using *in situ* measurements, which are considered as

Table 1. Calibration results using both the *in situ* measurements and the MODIS snow cover binary maps: $\text{MSE}_c/\text{MSE}_0$ - ratio between (1) the mean square error (MSE) of the calibrated model and the measurements, and (2) the MSE of the model before calibration and the measurements.

Calibration method	Station	$\text{MSE}_c/\text{MSE}_0$	Time (s)	c_p	k_f
Calibration using <i>in situ</i> measurements	Station I	0.6476	18.678	1.4077	2.5994
	Station II	0.2375	34.640	0.9581	6.0304
	Station III	0.2672	17.873	1.1898	2.3090
	Station IV	0.0094	26.655	1.4345	8.0675
	Average	0.2904	24.462		
Calibration using MODIS data	Station I	0.3578	52.116	1.3406	4.1960
	Station II	0.9946	65.782	1.5492	6.2212
	Station III	0.4071	48.683	1.3692	3.9532
	Station IV	0.0067	123.87	0.7738	10.4578
	Average	0.4415	72.613		

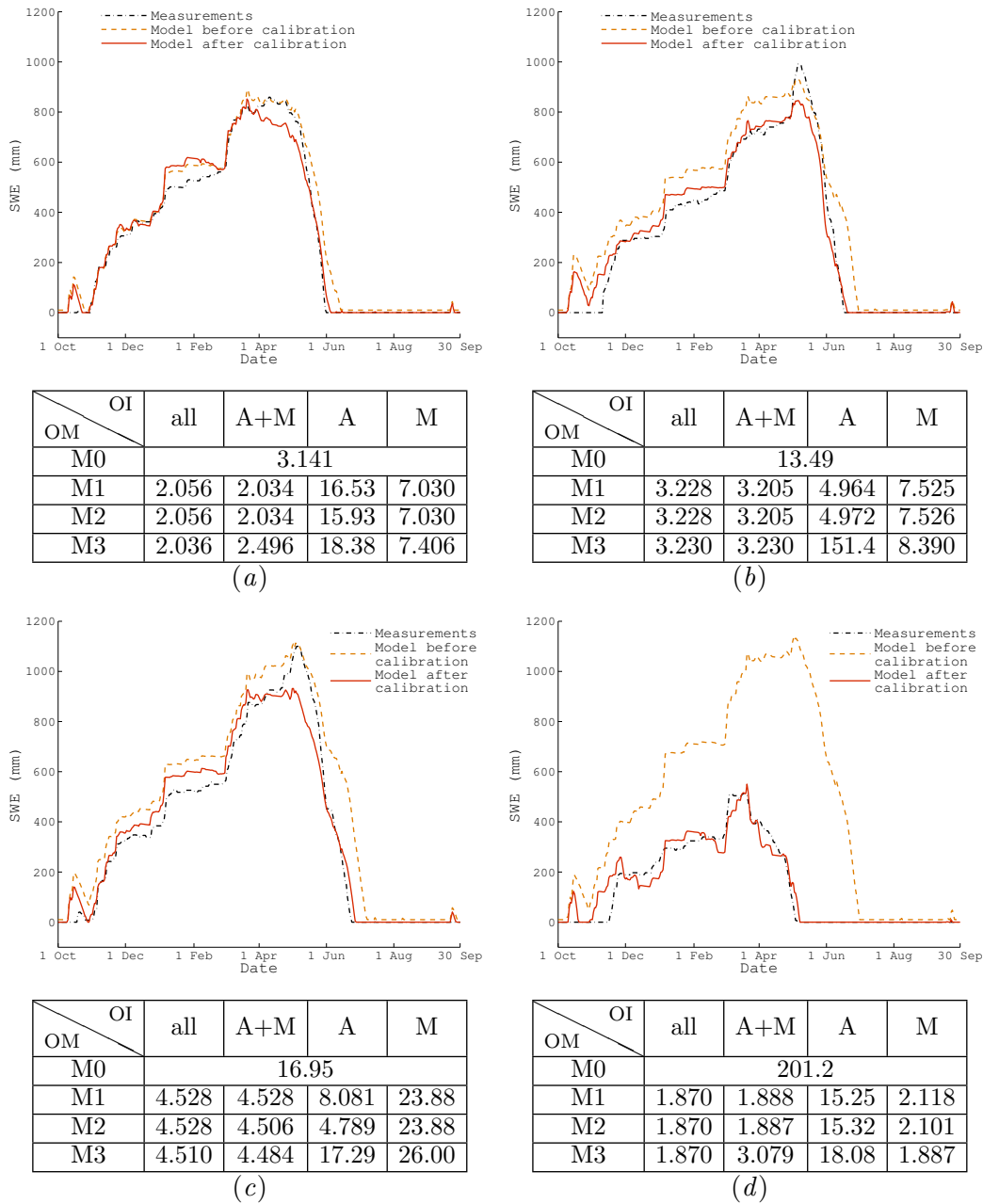


Figure 3. Qualitative and quantitative ($MSE \times 10^{-3}$) comparison of the calibrated SWE model (using *in situ* measurements) with the measurements from: (a) station I, (b) station II, (c) station III, (d) station IV. OM - optimization method, OI - optimization interval, M0 - non-calibrated model (based on the initial values of the correction coefficients), A - the accumulation period, M - the melting period, all - the whole year.

representative optimal solutions. This can be considered both as the validation of the proposed calibration procedure and the demonstration of the utility of remote sensing data in terms of calibration.

As anticipated, the proposed optimization in temporal domain results in spatially optimized maps. It can be seen in Figure 5 that the newly obtained SWE maps match far better the MODIS snow maps in terms of the presence/absence of snow. This is particularly true for the melting season, where the proposed optimization exhibits better performances, which can be analogously deduced from the comparison with the ground measurements (Fig. 4).

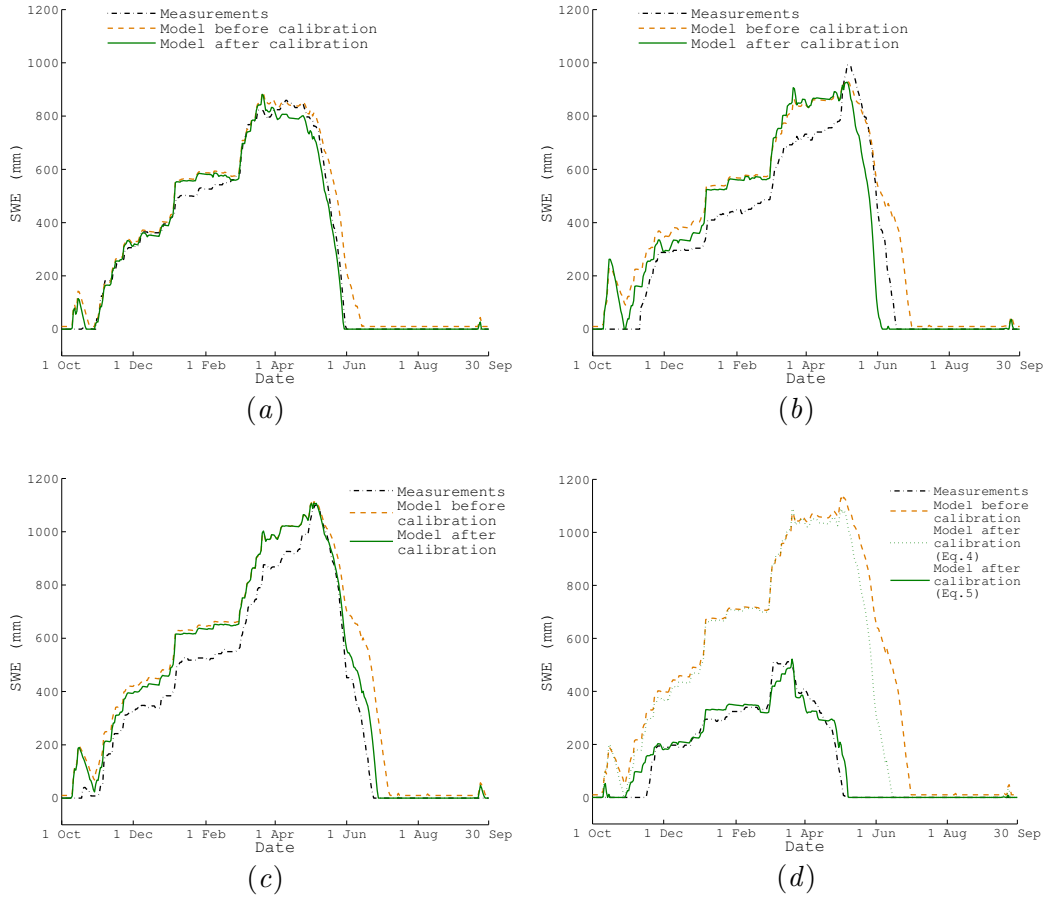


Figure 4. Qualitative comparison with *in situ* ground measurements of the SWE model calibration scheme based on MODIS data: (a) Station I, (b) Station II, (c) Station III, (d) Station IV.

6. Conclusion

Due to their role in introducing the influences of topology and mountain winds, the SWE sub-model of the MORDOR hydrological model appears to be quite sensitive with respect to the accumulation and melting correction coefficients. Due to the spatial discontinuity of these coefficients, interpolating locally estimated values, like it is the case with the air temperature or the precipitation, doesn't appear as a proper solution. Therefore, we proposed a new strategy for their derivation using multi-temporal MODIS binary snow cover maps and *in situ* ground measurements. Firstly, we compared several optimization methods in deducing the representative optimal coefficients for each of the four stations with *in situ* measurements. Further on, using the method which proved as the most appropriate, we presented the strategy for deriving the accumulation and melting coefficients using the MODIS binary snow maps. This method allows covering the entire region of interest, by characterizing each spatial cell (pixel of the MODIS image) with a pair of coefficients. In the same time, it assures better accuracy with respect to the original SWE sub-model, which assumes global values for these two coefficients. Using only MODIS data, the obtained optimized results are comparable to the representative optimal coefficients, derived by the *in situ* data based optimization.

Future work aims to investigate the potential role of spaceborne multi-temporal Synthetic Aperture Radar data in improving the accuracy of the SWE sub-model of the MORDOR.

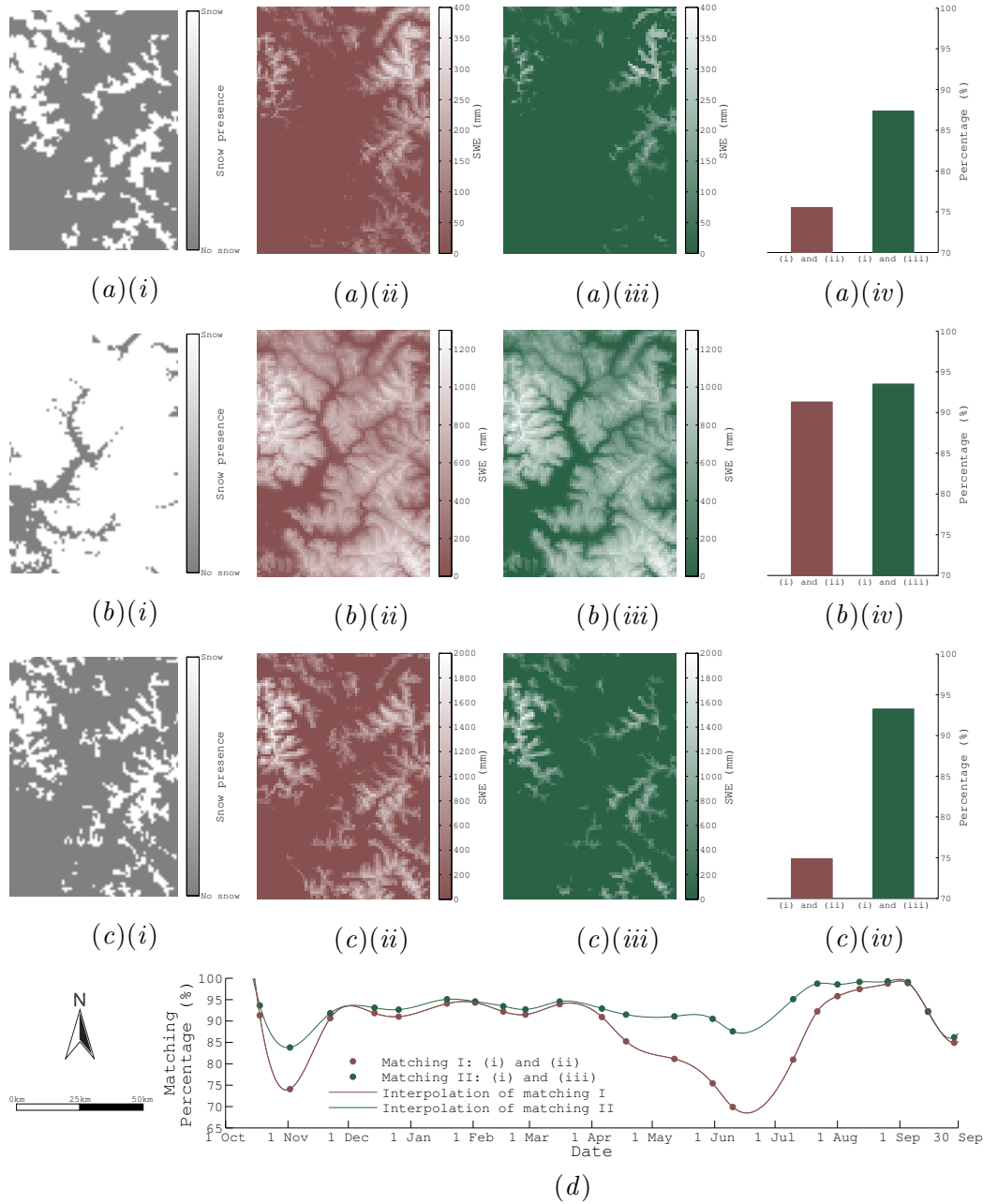


Figure 5. Matching of the obtained SWE maps for: (a) the 26 October 2000, (b) the 4 February 2001, (c) the 1 June 2001. Part (i) shows the MODIS map, part (ii) the SWE map before calibration, part (iii) the SWE map after calibration and part (iv) the matching percentages. (d) The (spline) interpolated matching curves covering the one year period (2000-2001). Geographical coordinates of the provided maps are $44^{\circ}16'N$, $06^{\circ}13'E$ (bottom-left corner).

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