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Unconstrained Nonlinear Optimization of a Distributed SWE Model Using Modis and In Situ Measurements Over the French Alps

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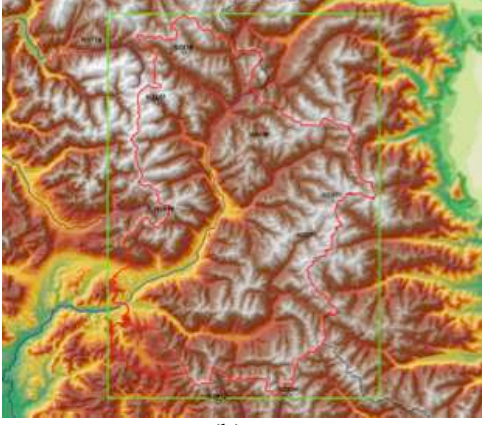
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(b)

Fig. 1: (a) the Serre-Ponçon dam, France,
(b) the area of interest.

Using 36 meteorological stations operated by EDF in the area of interest, the MORDOR forecasting model currently provides the snow water equivalent (SWE) used to evaluate the potential intakes to the reservoir and to optimize the operation of the Serre-Ponçon dam. Over one year, the snow water equivalent is analyzed in two phases: accumulation (SWE slowly increasing) and melting (SWE decreasing fast).

2. DISTRIBUTED SWE MODEL OPTIMIZATION

After kriging [2] the 36 in situ measures (temperature and precipitation), this physical model is anticipating the amount of water that is contained in the snow pack over one season [3]. The proposed optimization is carried out by comparing the MORDOR model with the SWE data measured on the terrain by remotely controlled cosmic-ray snow gauges (4 stations in the basin) [4], and also with binary snow maps derived from MODIS images [5]. We shall consider the problem of optimizing the snow model as an unconstrained nonlinear optimization problem. The MORDOR model will be described as a nonlinear function of two parameters that needs to be optimized: \mathbf{k}_f (the melting coefficient) and \mathbf{c}_p (the accumulation coefficient). Different optimization scenarios are studied:

1. according to the snow phase: accumulation or melting;
2. according to the parameter to be optimized: \mathbf{c}_p or \mathbf{k}_f ;
3. according to the MSE minimization method: Nelder-Mead, pattern search, genetic algorithms and simulated annealing.

To evaluate the difference between the data provided by the snow model and the data collected from the measurement stations, we use the standard Mean Squared Error (MSE) measure. Let $\mathbf{g}(\mathbf{c}_p, \mathbf{k}_f, \mathbf{t})$ be the SWE from MORDOR and let

$\mathbf{h}(\mathbf{t})$ be the measured SWE over one year. Then we can write the following equation:

$$[\mathbf{c}_p, \mathbf{k}_f] = f\left(MSE\{g(\mathbf{c}_p, \mathbf{k}_f, \mathbf{t}), \mathbf{h}(\mathbf{t})\}, [\mathbf{c}_{p_init}, \mathbf{k}_{f_init}]\right). \quad (1)$$

The proposed optimization \mathbf{f} starts at the point $\mathbf{x}_0 = [\mathbf{c}_{p_init}, \mathbf{k}_{f_init}]$ and finds the global minimum $\mathbf{x} = [\mathbf{c}_p, \mathbf{k}_f]$ for the MSE. Optimization strategies tested in this paper are:

- fmin search – Nelder-Mead simplex function minimization [6];
- pattern search – constructs a sequence of iterations that converge to an optimal solution [7];
- genetic algorithm – based on a natural selection process that mimics biological evolution [8];
- simulated annealing – probabilistic search algorithm that seeks to improve the current minimum by slowly reducing the extent of the search [9].

We can split the optimization problem in more phases (intervals):

1. first interval – phase of snow accumulation and melting (the whole year $[\mathbf{D}_s, \mathbf{D}_e]$),
2. second interval – the phase of snow accumulation $[\mathbf{D}_s, \mathbf{D}_m]$,
3. third interval – the phase of snow melting $[\mathbf{D}_m, \mathbf{D}_e]$.

To automatically detect \mathbf{D}_s (start day), \mathbf{D}_m (middle day) and \mathbf{D}_e (end day), we use gradient-oriented thresholding of the measured data.

3. MODIS MAP OPTIMIZATION OF THE SNOW MODEL

To compare the snow model SWE data with the data measured by MODIS (Fig. 2), the MORDOR output data must be firstly binarized. One way to do this is by choosing a specific threshold value T : all SWE values less than T are labeled to “0” and the values greater than T to “1”. Unfortunately this method does not allow conventional optimization since the function \mathbf{f} is not continuous. To obtain this, we propose to apply continuous binarization by using the tangent hyperbolic function:

$$bin = \frac{\tanh\left(\frac{h_s}{\sigma_b}\right) + 1}{2}, \quad (2)$$

where σ_b is a parameter depending of the incertitude of our maps and h_s is the height of the snow.

To find the best binary fit of the MORDOR data, we must find the best value for σ_b by optimizing the snow model with the data from the MODIS maps and also with data from the in situ measurements:

$$[\sigma_b] = f\left(MSE\left(bin[g(\mathbf{c}_p, \mathbf{k}_f, \mathbf{t}), \sigma_b] \cdot g(\mathbf{c}_p, \mathbf{k}_f, \mathbf{t}), m(\mathbf{t}) \cdot \mathbf{h}(\mathbf{t})\right), \sigma_{init}\right) \quad (3)$$



(a)



(b)

Fig. 2: MODIS map for (a) 03/07/2000 and (b) 03/16/2000.

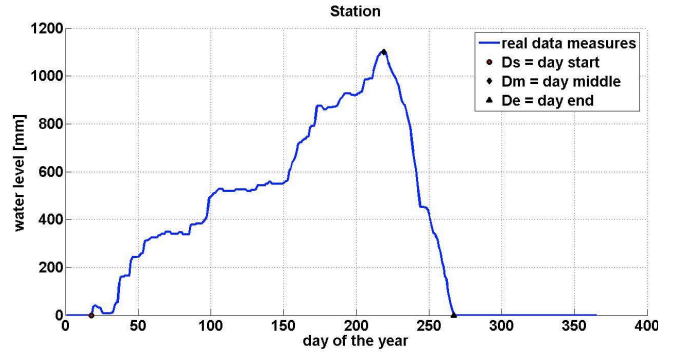
where \mathbf{m} is data from MODIS map. Using this new value for the binarization function we can optimize the snow model as in the previous section:

$$[c_p, k_f] = f \left(\text{MSE} \left(\text{bin} \left[g(c_p, k_f, t), \sigma_b \right] \cdot g(c_p, k_f, t), m(t) \cdot h(t) \right), c_{p_init}, k_{f_init} \right) \quad (4)$$

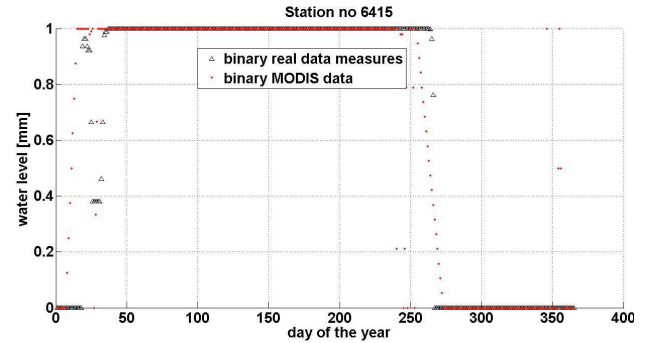
4. EXPERIMENTAL RESULTS

In this section, we present some results derived for only one station (6415). In the proposed experiment, the results from four stations were considered: station number 6415, 6460, 6470 and 6510. The obtained experimental results, illustrated in Fig. 3, indicate a good matching with respect to in situ SWE measures on each ground station.

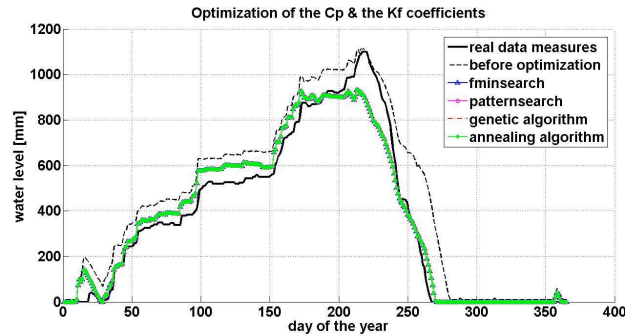
Finally, qualitative performance assessment is proposed in table 1.



(a)



(b)



(c)

Fig. 3: (a) D_s , D_m and D_e computed for one station, (b) binary data from real measures compared to binary data from MODIS maps, (c) Optimization of the c_p and the k_f coefficients of the MORDOR model for the snow accumulation phase.

TABLE I. OPTIMIZATION FOR THE FIRST INTERVAL 1-365 DAY

1-365 day				
Optimization Algorithm	cpoptim	kfoptim	time	MSE
<i>optimize Cp</i>				
before optimization	1.300	3.000	0.2	7.03E+03
fmin search	1.280	3.000	6.4	6.88220E+03
pattern search	1.280	3.000	19.0	6.88220E+03
genetic algorithm	1.281	3.000	263.0	6.88340E+03
anneal. algorithm	1.280	3.000	2795.4	6.88220E+03
<i>optimize Kf</i>				
fmin search	1.300	2.749	7.0	6.25610E+03
pattern search	1.300	2.749	15.8	6.25610E+03
genetic algorithm	1.300	2.745	260.8	6.25630E+03
annealing algorithm	1.300	1.940	647.5	1.78110E+04
<i>optimize Cp & Kf</i>				
fmin search	1.190	2.326	16.0	4.09820E+03
pattern search	1.190	2.326	48.4	4.09820E+03
genetic algorithm	1.197	2.331	260.5	4.11160E+03
annealing algorithm	1.190	2.326	3895.6	4.09820E+03

5. CONCLUSIONS

The optimization of the snow sub-model of MORDOR using MODIS and in situ measurements was performed for the case study of the Serre-Ponçon reservoir (one of the largest artificial lakes in Western Europe) on the Durance River in the French Alps. The problem of optimizing the snow model was treated as an unconstrained nonlinear optimization problem. Several optimization strategies were investigated.

6. ACKNOWLEDGEMENT

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