COUPLING METEOROLOGICAL AND HYDROLOGICAL MODELS FOR RIVER DISCHARGE FORECASTING. PART II: A CASE STUDY ABOUT HYDROPOWER GENERATION MANAGEMENT

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Abstract: In a companion contribution (Bozzo et al., 2007), the development of a method for the downscaling of precipitation fields from general circulation models to the river catchment scale has been discussed. The analysis approach outlined there is now tested in a case study, where precipitation forecasts are used in an application related to hydroelectric power production.

Keywords: *Rainfall forecasting, Downscaling, Hydro-meteorological models, Hydropower production.*

1. INTRODUCTION

One of the economic activities where the knowledge of reliable meteo-hydrological information would be extremely beneficial is that of hydropower production. A water catchment in Trentino, North-Eastern Italy, is taken as a case study to assess how the availability of forecasts of precipitation and river discharge might improve the management of a power plant, by minimizing the loss of water resource and maximizing energy production.

The Vallarsa catchment (Figure 1) has an area of approx. 50 km^2 and corresponds to a mountain region with altitude ranging from 585 to 2230 m, with average annual precipitation of about 1100 mm. Runoff is captured by two distinct reservoirs (Speccheri, 800 m a.s.l., with a volume of approx 10^7 m^3, and La Busa, 585 m a.s.l. and $5 \cdot 10^5$ m^3), both serving the same hydropower plant located in Ala (148 m a.s.l.). Water from the Speccheri reservoir is channeled directly to the plant for production. The Busa basin is instead used as a compensation reservoir: the water collected there is lifted by pumps to the larger basin of Speccheri and hence conveyed to the power plant. The society managing the plant (AGSM Verona) sells power on the italian electricity market in hours of peak energy consumption during the day, and buys energy to supply water pumps at the Busa basin at a low cost in the nighttime. Because of its small volume, the Busa reservoir can fill up very quickly: in the most intense precipitation events a large amount of water is lost by dam spillover, as the discharge flowing into the basin is far larger than the maximum flow rate of pumps. Quantitative forecasts of rainfall and discharge in the tributaries of the two reservoirs would be beneficial in order to plan dam operations at least with a two-days advance, achieving a better management of the available water resources and a more profitable conduction of the plant. In fact, if heavy rainfall were forecast people in charge of the plant management would anticipate emptying the Busa reservoir, and accomplish a double advantage by (1) buying the power supply for the pumps in favourable hours, saving money in comparison with an unforeseen acquisition, and (2) capturing as much as possible of the surface runoff, thereby increasing production.

Using qualitative or coarse resolution quantitative rainfall forecasts does not allow a confident estimation of the occurrence and intensity of rainfall peaks. The downscaling approach outlined in Part I of this contribution is here specified in detail, and applied to provide an estimation of the expected rainfall. It is proved to drastically decrease the mean error in the precipitation estimate with respect to raw forecasts, and therefore to have a potential for improving the success of actions based on an evaluation of quantitative rainfall forecasts.

2. DOWNSCALING MODEL

In Part I of this contribution, a reliable downscaling chain composed of three elements has been proposed. These consist in: (1) a criterion to search for historical analogues to the day for which a rainfall forecast is needed, (2) a way to regionalize pointwise precipitation measurements, and (3) a statistical approach to isolate cross-scale joint variability modes which can be used progonstically. Here, a simple average of rainfall measurements from the rain gauges available in the Vallarsa basin is used as an alternative to spatialization by kriging to form the predictand data. Some more detail about the two other steps is provided below.

2.1 Teweles-Wobus analogue search (TWS)

This method is widely used in downscaling techniques based on an analogue search approach when gridded weather analyses are available. The TWS score between the target day (denoted by the subscript 0) and any other day (denoted by the subscript k) is given by:

$$TWS_k = \frac{\sum_{n=1}^{N} |g_k(x_n)| + \sum_{m=1}^{M} |g_k(x_m)|}{\sum_{n=1}^{N} |G_k(x_n)| + \sum_{m=1}^{M} |G_k(x_m)|} \tag{1}$$

$$g_k(x_i) = [P_0(x_{i-1}) - P_0(x_{i+1})] - [P_k(x_{i-1}) - P_k(x_{i+1})] \tag{2}$$

$$G_k(x_i) = \max\{[P_0(x_{i-1}) - P_0(x_{i+1})], [P_k(x_{i-1}) - P_k(x_{i+1})]\} \tag{3}$$

where N and M are respectively the number of gridpoints where a meriodional and zonal pressure gradient can be evaluated, and the index i in equations (2) and (3) denotes meridional or zonal differences accordingly. P can be either sea level pressure or geopotential height at a given isobaric surface. Low scores (close to 0) are verified for fields where gradients at every grid point have the same sign and are similar in absolute value, while high scores (close to 2) denote fields with opposite gradients.

2.2 Downscaling: Canonical Correlation Analysis (CCA)

Following Bretherton et al. (1992), CCA has been used to find a cross-scale prognostic relationship, after a preliminary approximation of the predictor and predictand datasets by an expansion on their principal components, as suggested by Barnett and Preisendorfer (1987). Let us denote the large scale predictor field and the local scale precipitation field as $\mathbf{S}(n,p)$ and $\mathbf{T}(n,q)$ respectively, where $\mathbf{S}$ and $\mathbf{T}$ contain data at n times from p gridpoints and q raingauges. The cross-covariance matrix between the two fields is defined as $\mathbf{C_{ST}}(p,q) = \mathbf{S^tT}$, while the covariance matrices of $\mathbf{S}$ and $\mathbf{T}$ are $\mathbf{C_{SS}}(p,p) = \mathbf{S^tS}$ and $\mathbf{C_{TT}}(q,q) = \mathbf{T^tT}$ respectively (the apex $\mathbf{t}$ denotes the matrix transpose operation).

The Singular Value Decomposition (SVD) of any matrix $\mathbf{A}(p,q)$ consists in finding $\mathbf{U}(p,m)$, $\mathbf{\Sigma}(m,m)$ and $\mathbf{V}(q,m)$ such that $\mathbf{A} = \mathbf{U\Sigma V^t}$ (the decomposition always exists if $\mathbf{A}$ is non-singular). Canonical Correlation Analysis is performed by forming $\mathbf{M} = \mathbf{C_{SS}^{-1/2}C_{ST}C_{TT}^{-1/2}}$ and carrying out its SVD, $\mathbf{M} = \mathbf{U\Sigma V^t}$. $\mathbf{\Sigma}$ is a square diagonal matrix containing the eigenvalues of the CCA decomposition in decreasing order. $\mathbf{U}$ and $\mathbf{V}$ are two bases in the phase spaces where $\mathbf{S}$ and $\mathbf{T}$ are cast, and contain the modes of joint variability between the two datasets sorted in order of decreasing cross-correlation coefficient. Canonical Correlation (spatial) Patterns (CCP) of the predictor and predictand can be defined respectively as $\mathbf{P}(p,m) = \mathbf{C_{SS}U}$ and $\mathbf{Q}(q,m) = \mathbf{C_{TT}V}$, while their Time Expansion Coefficients (TEC) are respectively $\mathbf{A}(n,p) = \mathbf{SU}$ and $\mathbf{B}(n,q) = \mathbf{TV}$. The original data can be recovered as $\mathbf{S} = \mathbf{AP^t}$ and $\mathbf{T} = \mathbf{BQ^t}$.

Suppose that CCA on coupled sets of historical data $\mathbf{S}$ and $\mathbf{T}$ lead to the identification of the CCPs ($\mathbf{P}$ and $\mathbf{Q}$) and TECs ($\mathbf{A}$ and $\mathbf{B}$). Then the TECs of the first mode, $\mathbf{a_{1}}_{(n,1)}$ and $\mathbf{b_{1}}_{(n,1)}$, can be related with a simple linear model: $\mathbf{b_1} = \alpha\mathbf{a_1} + \epsilon$. It can be proved that the least square estimate of α is the eigenvalue $\mathbf{\Sigma}_{11}$. If a forecast for the predictor variable is available, $\mathbf{s}$, then its TEC is obtained from its projection on the first CCP: $a = \mathbf{sp_1^t}$. By linear regression $b = \mathbf{\Sigma}_{11}a$; the predictand field may then be estimated as $\mathbf{t} = b\mathbf{q_1} = \mathbf{\Sigma}_{11}\mathbf{sp_1^tq_1}$. To generalize: if $m > 1$ couples of CCPs are considered, then a forecast for the predicted variable can be provided as:

$$\mathbf{t} = \mathbf{s\tilde{\Sigma}\tilde{P}\tilde{Q}^t} \tag{4}$$

where $\mathbf{\Sigma}$, $\mathbf{P}$ and $\mathbf{Q}$ are known from calibration, and the ~ symbol denotes matrices truncated to the leading variability modes, i.e. with $m < \min(p,q)$. In the Barnett and Preisendorfer (1987) method, the calibration is performed replacing the raw predictor data with a PCA approximation. Principal Component Analysis is a technique which allows to isolate the main modes of variability of a single dataset, by analizing the eigenvalue spectrum of its covariance matrix. It can be used to approximate a dataset by considering only the modes which provide the greatest contribution to its variance, thereby removing spurious variability.

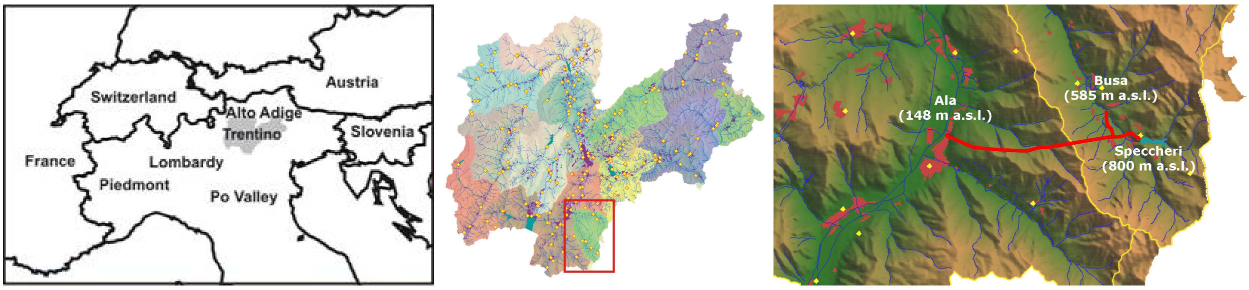

Figure 1: Left to right: location of Trentino in Northern Italy; location of the Vallarsa basin in Trentino; sketch of the Speccheri-Ala hydropower plant.

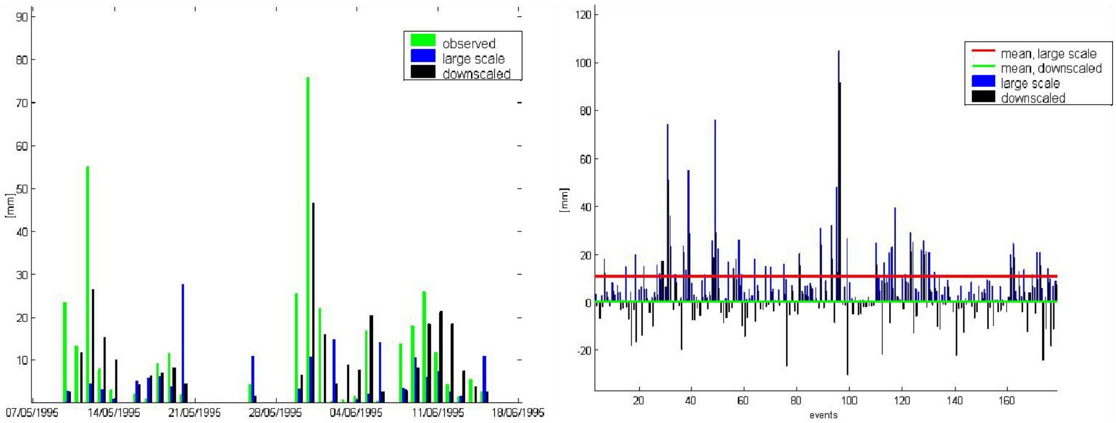

Figure 2: Left: rainfall observations (green bars) versus raw precipitation forecasts (blue bars) and downscaled precipitation forecasts (black bars). Right: mean error of raw (red line) and downscaled (green line) precipitation forecasts; differences (observation - forecast) are displayed.

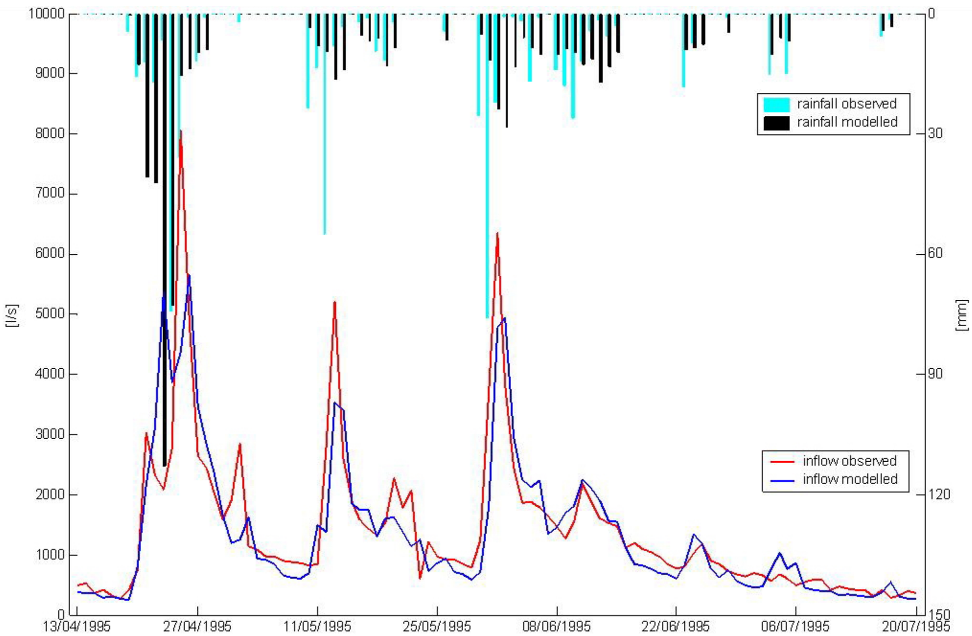

Figure 3: Precipitation in the Vallarsa region and total inflow in the Busa reservoir: observations (cyan bars and red line) versus downscaling simulations (black bars and blue line).

3. RESULTS

The method described above has been used to produce rainfall estimates for the 953 rainy days (i.e. days with measured measured rainfall $>$ 2 mm in any rain gauge in Vallarsa) occurred between 1995 and 2005. In a sort of cross-validation simulation, a forecast has been provided for each rainy day using the remaining 952 as the training set. For every day, the Teweles-Wobus approach was used to select a set of 350 analogues from the complete sample, by computing TWS scores from the geopotential height at the 850 hPa isobaric surface. CCA decomposition with PCA pre-filtering was then performed using ECMWF modelled precipitation as the predictor, and averaged precipitation measurements as the predictand. By trial and error, a number of 5 leading CCA modes has been deemed sufficient to describe the cross-correlation between the predictor and predictand.

A qualitative evaluation of downscaling results is reported in Figure 2. A sample of precipitation observations and forecasts for a representative continuous period of 40 days (left), and a sketch of the mean relationship between observations and raw or downscaled forecasts (right) are shown. While raw forecasts from the ECMWF model always underestimate precipitation in the catchment, downscaled forecasts have both a neglible bias and a smaller variance. The mean error in the daily precipitation estimate by raw forecasts is of -11.12 mm, but it decreases to -0.26 mm if downscaled forecasts are considered. This shows that the downscaling process has a potential for accurately reconstructing precipitation observations in the Vallarsa area.

Figure 3 shows a preliminary attempt at modelling both daily rainfall and daily discharge in the Busa basin. At present, discharge is modelled using an empirically based Artificial Neural Network (ANN) algorithm, where the non-linear relationship between rainfall and runoff is reconstructed as an interconnection of simple linear transfer functions. This approach is used as a temporary substitute for a physically based lumped rainfall-runoff model, to be developed in the near future. A simple two-layer feed-forward backpropagation network has been trained using historical data of rainfall and discharge measurements provided by AGSM Verona. The network estimates discharge at the day T using observations of rainfall and discharge in days $T-4$, ..., $T-1$, and rainfall forecast referred to day T and produced by the downscaling method. As shown in Figure 3, simulations and observations appear to be in fair agreement in this testing period, confirming that statistical postprocessing of coarse-resolution forecasts may be a valid alternative to fine-scale numerical modelling, at least as far as rainfall and discharge forecasts are concerned.

4. CONCLUSIONS

Preliminary results of a downscaling method for precipitation forecasting have been described. A thorough evaluation of the forecasting capabilities of the proposed downscaling approach is still being carried out. A verification of downscaled precipitation forecasts through the usual contingency table approach is planned, as well as a comparison between forecasts provided by the statistical downscaling model and a physically based LAM. Possible improvements of the modelling chain include the preparation of a kriging routine to process predictand data, the implementation of a nonlinear estimation of the predictand TECs in CCA by an ANN approach, and a replacement of the empirically tuned ANN used for discharge forecasting with a lumped hydrological model.

Acknowledgements: *The authors acknowledge AGSM Verona for providing access to its hydropower plants, as well as for sharing precipitation and discharge data.*

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