SPATIAL INTERPOLATION OF SURFACE WEATHER OBSERVATIONS IN ALPINE METEOROLOGICAL SERVICES

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Spatial interpolation of surface weather observations in Alpine meteorological services

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1 Introduction

Spatial interpolation, or the estimation of a variable at an unsampled location using data from surrounding sampled locations, has great importance in all geophysical sciences. Geophysical disciplines all share the impossibility of sampling accurately enough, in space or in time, their object of study.

Names given to spatial interpolation can differ depending on the field of study. In meteorology and oceanography, the process of defining the best estimate of the state of the system at a given time (using both observations and the a-priori knowledge of physical processes) goes under the name of spatial analysis, or objective analysis to distinguish it from the earlier manual charting methods.

Atmospheric data analysis has developed strongly in the last decades, in conjunction with the development of numerical weather prediction models. For a review of the subject see for example Daley (1991) or Kalnay (2003). The best estimates of the state of the atmosphere are nowadays produced by data assimilation (DA) procedures, to which most of the computing resources available for Numerical Weather Prediction (NWP) are dedicated.

Data Assimilation is the process through which a numerical model, representing our knowledge of the dynamics of a system (e.g. an atmospheric and/or oceanic flow), and the observations, representing our knowledge of its actual state, are combined together to estimate as accurately as possible the system state at a particular time, or during a time interval (Talagrand, 1997). Though DA uses the fullness of the information available to the analyst, and produces the best results, the process is computationally intensive, needs highly qualified and experienced staff for implementation and maintenance, and is today applied only to assimilation of synoptic observational network in General Circulation Models (GCM).

Most of the surface observational networks in the Alpine Space (with which this report is primarily concerned) have a meso-β-scale spatial resolution (20 to 200 km), and the bulk of their observations are outside the Global Observation System, being over-dense with respect to the resolution of GCMs. The resolution of local observational networks is in fact comparable with the typical resolution of operational Local Area Models (LAMs), ranging from 5 to 10 km. Since the late eighties researchers have investigated the possibility of assimilating asynoptic observations in LAMs (Stauffer and Seaman, 1990; Stauffer et al., 1991) but, though most of the LAMs currently available can implement some kind of DA, it is still unclear which is the best way of doing it and what are the consequences on the analyzed fields (Guo et al., 2000; Macpherson et al., 1996). This is particularly true for surface observations.

Moreover, most institutions in the Alpine Space, even if responsible of observational network management, do not have the means to implement a full numerical model and to support the staff needed for its operation.

Lastly, it has been argued that for some applications, as for example NWP inter-comparison or verification studies, a model-independent analysis is preferable (Steinacker et al., 2000).

For one or for all of the above reasons, data assimilation at mesoscale resolution is generally not available in the Alpine Space weather services. Even so, analyzed fields of meteorological parameters, however obtained, are required in many applications. Some, as forecast verification
and observational network management, are internal to the institutions that own the data; others lie in very different fields, as air pollution modeling, agronomy, hydrology, energy planning, environmental consulting, etc.. In fact, many meteorological centers in the Alpine Space currently produce and in some cases disseminate analyzed meteorological fields (e.g. the VERA group at the University of Vienna, or the regional meteorological service of Piemonte), generally obtained through statistical interpolation.

This report aims at collecting information on which interpolation or assimilation methods are in use for meteorological observations in the institutions involved in FORALPS Project. Other institutions and meteorological centers of the Alpine Space have been added for reference purposes, if the information is available to project partners.

As spatial interpolation techniques have historically been developed in very different fields and for different purposes, very similar techniques are called in literature with different names, whereas the same algorithms can show different characteristics depending on the implementation choices. For this reason a first part of the report is dedicated to a cursory overview of the most common and used interpolation methods; this section wishes to be an annotated bibliography, mainly for reference purposes in the FORALPS project and in this report. The second part of the review collects the documentation and examples of spatial analysis methods in use, and is mainly targeted toward statistical interpolation methods, as no FORALPS Project Partner operationally runs a data assimilation procedure.

## 2 Interpolation and spatial analysis of surface observations from mesoscale meteorological networks

In this Chapter we will illustrate the main interpolation methods that are used operationally in mesoscale meteorological data analysis. Most of them can also be used in data assimilation, which is essentially a dynamic interpolation in space (from the irregularly spaced observations to a gridded field) and in time (throughout the assimilation window to the initial time of a NWP model run). Also, most real time analysis schemes can be considered as the first steps of data assimilation procedures.

As pointed out by Lorenc (1986b), many of these methods, such as splines, Kriging, and optimal interpolation, are actually formally equivalent to each other under the usual assumptions in which they are derived.

### 2.1 Function Fitting

#### 2.1.1 Polynomial Interpolation

The first method we are going to discuss is the polynomial fitting technique of Panofsky, Cressman and Gilchrist. It is based on Lagrange’s classic interpolation formula (for instance, see Abramowitz and Stegun, 1972). In Panofsky’s original scheme (Panofsky, 1949), observations were interpolated on a regular grid by polynomials, whose coefficients were determined with the least square method. The geostrophic relationship was included as a dynamical constraint. The
method was then improved by Gilchrist and Cressman (1954) who introduced the concept of a region of influence: only those observations which lie within the region of influence (i.e., in a neighborhood) of a point will contribute to the interpolated value in that point.

By way of illustration, consider a point of a 2D grid, which is taken as the origin of a local coordinate system (Daley, 1991). Suppose there are k observations within its region of influence, \( f_0(r_k) \), \( k=1,\ldots,K \), where \( r_k \equiv (x_k,y_k) \) are the coordinates of the k-th observation point.

We can represent the interpolated value \( f_a(r) \) by a polynomial expansion such as:

\[
f_a(r) = \sum_m \sum_n c_{mn} x^m y^n, \quad m + n \leq M, \quad m, n \geq 0.
\] (1)

We then form the quadratic cost function:

\[
J = \frac{1}{2} \sum_{k=1}^K [f_a(x_k) - f_0(x_k)]^2
\]

\[
= \frac{1}{2} \sum_{k=1}^K \left[ \sum_m \sum_n c_{mn} x_k^m y_k^n - f_0(x_k, y_k) \right]^2,
\] (2)

which is essentially the mean square error between the interpolation and the observations.

We want an estimator for \( f_a \) that minimizes this error, so we differentiate \( J \) with respect to the \( c_{mn} \) and set the result equal to 0. This obtains a linear system which can be solved (provided that the resulting coefficient matrix is not singular) with standard algebraic techniques. In particular the interpolated value is then given by \( c_{00} \).

\( J \) is the distance between the interpolation and the observations in the L_2 (Euclidean) norm. If the observations were normally distributed, then the maximum likelihood principle would naturally lead to this choice, and our estimator would also be the optimal one. However, we made no explicit provision for the statistics of the observations, so the choice of the L_2 norm is somewhat arbitrary, albeit simple and intuitive. Namely, it leads to linear estimators. But it may not always be ideal: for instance if the variables come from fat tailed distributions, the L_1 norm (absolute value) may be preferable.

If we know \( S_k \), i.e. the error variances of the observations, we can rewrite \( J \) as:

\[
J = \frac{1}{2} \sum_{k=1}^K \frac{[f_a(r_k) - f_0(r_k)]^2}{S_k^2},
\] (3)

that is, we weight each increment by the corresponding variance. The choice M=1 corresponds to the familiar least squares linear regression.

To include a physical constraint it is enough to require that the basis fitting functions satisfy the constraint, that the coefficients in the expansion are the same for each variable and that all the variables are fitted simultaneously. For example, consider the geostrophic relationship (Holton, 1992):

\[
u = -\frac{1}{f_0} \frac{\partial h}{\partial y}, \quad v = \frac{1}{f_0} \frac{\partial h}{\partial x}
\] (4)
where \( u \) and \( v \) are the horizontal wind components, \( h \) is the geopotential height and \( f_0 \) is the Coriolis parameter. Call \( e_{mn} \) (respectively \( f_{mn} \) and \( g_{mn} \)) the geopotential (respectively wind components) basis functions and expand \( f \) as in equation (1). If we have \( K \) observations of \( h \) in positions \( r_k \) and \( L \) observations of \( u \) and \( v \) in positions \( r_l \), \( J \) will be given by:

\[
J = \frac{1}{2} \sum_{k=1}^{K} \left[ \sum_{m,n} c_{mn} e_{mn}(r_k) - h(r_k) \right]^2 + \frac{1}{2} \sum_{l=1}^{L} \left\{ \left[ \sum_{m,n} c_{mn} f_{mn}(r_l) - u(r_l) \right]^2 + \left[ \sum_{m,n} c_{mn} g_{mn}(r_l) - v(r_l) \right]^2 \right\}.
\]

The method then proceeds as before.

A constraint such as equation (4) must be included when the interpolated fields are used in NWP models, to guarantee that they satisfy the balance conditions required by the models (in this case, the geostrophic balance). Otherwise some spin-up steps are necessary to let the fields achieve the same balance dynamically.

2.1.2 Splines

Spline interpolation is a special case of interpolation (Abramowitz and Stegun, 1972) where the interpolant is a piecewise polynomial, that is, a function \( S(x):[x_0,x_n] \to \mathbb{R} \) such that:

\[
S(x) := \begin{cases} 
S_0(x), & x \in [x_0,x_1], \\
S_1(x), & x \in [x_1,x_2], \\
\vdots & \vdots \\
S_{n-1}(x), & x \in [x_{n-1},x_n], 
\end{cases}
\]

(6)

where \( x_0 < x_1 < \ldots < x_{n-1} < x_n \) and the \( S_k(x) \), \( k = 1, \ldots, n-1 \), are polynomials of degree \( M \). The usual choice is \( M = 3 \), that is, cubic splines (Prince and MacPherson, 1973).

We must require that both \( S(x) \) and its first two derivatives be continuous on \([x_0,x_n] \), that is, \( S(x) \in C^2[x_0,x_n] \). In other words, that on each subinterval border \( x_k \), the following conditions must hold:

\[
\begin{align*}
S_{k-1}(x_k) &= S_k(x_k) \\
S'_{k-1}(x_k) &= S'_k(x_k) \\
S''_{k-1}(x_k) &= S''_k(x_k)
\end{align*}
\]

(7)

For \( k = 1, \ldots, n-1 \).

Spline interpolation is preferred to polynomial interpolation because the interpolation error can be made small even when low degree polynomials are used.

Usually, in meteorology the interpolation is done over a 2D or 3D grid, so that the interval \([x_0,x_n] \) in the definition of the spline is replaced by a rectangle or a cube and the continuity conditions are imposed on the gradients of the splines across the pluri-interval boundaries.
2.1.3 **Kriging**

Kriging is probably the most widely used technique in geostatistics to interpolate data. It was formalized in the sixties by the French engineer George Matheron (Matheron, 1963) after the empirical work of Danie G. Krige (Krige, 1951).

Kriging is a form of linear interpolation: The value of a field \( f \) in a position \( r_0 \) interpolated from the \( N \) neighboring values \( f(r_i), i = 1, \ldots, N \) in its region of influence is given by

\[
f_a(r_0) = \sum_{i=1}^{N} \lambda_i f(r_i),
\]

(8)

where the \( \lambda_i \) are a set of weights.

To determine these weights, we first use the variogram

\[
\gamma(h) = \frac{1}{2} \sum_r [f(r + h) - f(r)]^2
\]

(9)

to write the cost function (that is, the mean square error – equation 2) as:

\[
J = 2 \sum_i \lambda_i \gamma(r_i - r_0) - \sum_{i,j} \lambda_i \lambda_j \gamma(r_i - r_j).
\]

(10)

The weights used in Kriging are those that minimize \( J \) subject to the constraint \( \sum \lambda_i = 1 \). Introducing the Lagrange multiplier \( \mu \) to take care of the constraint it follows that the \( \lambda_i \) satisfy the system:

\[
\begin{cases}
\sum_j \gamma(r_i - r_j) \lambda_j + \mu = \gamma(r_i - r_0) & i = 1, \ldots, N, \\
\sum \lambda_i = 1.
\end{cases}
\]

(11)

which is a system of \( N+1 \) linear equations in as many unknown variables. If the \( r_i \) are all different then it can be shown that it always admits one and only one solution. Given that Kriging is essentially a least square estimator, it implicitly relies on the usual (but rather optimistic) assumption that all the variables \( f(r_i), i = 1, \ldots, N \) have the same normal distribution.

Of course, since \( f(r_0) \) is not known (its calculation is indeed the goal of the whole procedure), then \( \gamma(r_i - r_0) \) cannot be computed directly from the data. Thus, in order to use Kriging, one must first fit a model variogram to the empirical one (estimated from the data). Actually, the model variogram is usually expressed as a sum of elementary models (nested structure). All elementary models are semi-positive by definition and such that \( \gamma(h=0) \equiv 0 \). Moreover, it is worth to remember that the variogram is related to the spatial covariance \( C(h) \) by \( \gamma(h) \equiv C(0) - C(h) \).

The most widely used models in geostatistics are the power law model (and its particular case, the linear model), the spherical model, the exponential model and the Gaussian model.

**Power model:**

\[
\gamma(h) = a + b \|h\|^p,
\]

(12)

where \( p=1 \) is the linear model;
Spherical model:

\[
\gamma(h) = \begin{cases} 
  a + b||h|| - c||h||^3 & ||h|| \leq h_R \\
  C(0) & ||h|| > h_R 
\end{cases};
\]

Exponential model:

\[
\gamma(h) = a + b \exp(-c||h||); \tag{14}
\]

Gaussian model:

\[
\gamma(h) = a + b \exp(-c||h||^2); \tag{15}
\]

where \( ||h|| \) is the norm of the lag \( h \).

The first model is used if the variogram does not have a threshold value (or sill) but rather grows indefinitely. This means, by the way, that the variance of the corresponding random variable is infinite. The latter three models can all be used to fit a variogram which, for \( ||h|| \) sufficiently large, flattens out. The spherical model admits a range \( h_R \) such that, for \( ||h|| > h_R \), the variogram is constant (and of course equal to the sill), while for the exponential and Gaussian models the range is infinite, so that the sill is more properly an asymptote. The last two models however differ by the behavior near the origin: linear for the former, parabolic for the latter. Actually, another elementary model is also used, usually in conjunction with any of the above: the so-called nugget model, which is written as \( C(1-\delta(h)) \) and models the nugget effect. Indeed, when an experimental variogram is extrapolated back to the origin, it may approach a non-zero variance. The amount by which the variance differs from zero is known as the nugget variance, and the sill \( C \) of the nugget model is taken equal to this amount.

2.2 Successive Corrections Methods

2.2.1 Barnes Technique

In the early 1960s, Barnes introduced a new convergent weighted-averaging interpolation scheme based on the hypothesis that the spatial distribution of the atmospheric variables can be described by a Fourier integral representation (Barnes, 1964). Now, Barnes’s technique is usually discussed in the context of the Successive Corrections Method (SCM — see Daley, 1991).

In SCM, the analysis is updated iteratively by the analysis increment until the difference between two iterations is less than a set threshold. That is, if \( f_a^j(r_i) \) is the \( j \)-th analysis iterate at point \( r_i \), and \( f_o(r_k) \), \( k=1, \ldots, K \), are the \( K \) observations within the influence radius \( R \) as in the previous section, then the \((j+1)\)-th analysis will be given by:

\[
f_a^{j+1}(r_i) = f_a^j(r_i) + \sum_{k=0}^{K} w(r_k)(f_o(r_k) - f_a^j(r_k)). \tag{16}
\]

According to Bergthorsson and Doos (1955), the weights \( w(r_k) \) are specified a priori, thus making the computational requirements easier to satisfy.
In particular, for the Barnes algorithm we have:

\[ f_{0}^{a}(x_{i}) = \sum_{k=0}^{K} w(r_{ik}) f_{0}(x_{k}), \]  

(17)

where

\[ w(r_{ik}) = \exp \left( -\frac{r_{ik}^2}{2L^2} \right), \]  

(18)

and L is the average data spacing.

As can be seen Barnes’s method is essentially a Gaussian weighted-averaging technique. This means that it is both a smoothing filter as well as an interpolator. The algorithm’s convergence is very fast: Koch et al. (1983) have shown that only two passes through the data are needed to achieve the desired scale resolution, provided that a numerical convergence parameter \( \gamma \in (0,1) \) is used to redefine L in equation (1) as \( L' = \gamma L \) in the second pass. The first pass produces a first-guess precipitation analysis which accounts for the longest waves. This is followed by a second pass with a narrower weight distribution that takes care of the shortest still resolvable waves and increases the amount of detail in the first guess.

Another appealing feature of the Barnes’s technique is that the response function determination is made a priori. This allows easy calculation of the weight parameter, given the average data spacing. Furthermore, to produce a smoother analysis it is possible to manually set the value of the average data spacing that can be greater or equal to the actual average data spacing, with the constraint that the ratio between grid size and the selected data spacing lies approximately between 0.3 and 0.5 (Barnes, 1964, 1973).

Finally, Barnes’s technique does not require a background guess (see section 2.3.1) as it is provided by the first pass (equation 17).

### 2.2.2 Inverse Distance Weighting

Inverse distance weighting is a very simple technique to obtain a gridded dataset from sparse observations, much used in all fields for exploratory data analysis. It is based on the very intuitive assumption that in any given location i the value of the field f is best approximated by a combination of the K closest measures weighted by a function of the inverse of the distance between the i-th point and k-th observation:

\[ f_{a}(x_{i}) = \sum_{k=0}^{K} w(r_{ik}) f_{a}(x_{k}), \]  

(19)

The a-priori weights are generally specified as:

\[ w(r_{ik}) = \left( -\frac{1}{r_{ik}^2} \right). \]  

(20)

This method can also be seen as a particular and simplified case of a SCM algorithm, with only one iteration (j=0).
The scheme is often used for its simplicity and low computational cost, but generally gives very poor results: it cannot take into account complex error in observations (though some uncertainty can be included) and it is heavily affected by anisotropy in data distribution. The algorithm easily gives unrealistic bull’s-eye patterns in the reconstructed fields.

2.3 Assimilation in NWP Models

2.3.1 Optimal Interpolation

Optimal Interpolation (Lorenc, 1986a) is a multivariate statistical interpolation scheme based on a Bayesian predictor-corrector scheme. It has been used in operational NWP until the mid-nineties, as the main data assimilation algorithm. However, as it requires that the observations to be assimilated are all taken at the same time (that is, synoptic observations), it is a three-dimensional scheme and has been replaced by more advanced, four-dimensional, schemes which allow the assimilation of non-synoptic observations.

To discuss Optimal Interpolation (henceforth OI), let us preface some notation. Following Ide et al. (1997) we will call \( x \) the state vector of the system (in the preceding sections only a scalar component of \( x \) was considered, called \( f(r) \)). It is a point in the \( n \)-dimensional phase space of the model, where \( n \) is its number of degrees of freedom. In particular \( x^a \) will be our interpolation, whilst \( x^b \) is the background state, that is, the first guess. In an analysis procedure, it would be given by a short range forecast, or it could be the product of a Barnes first pass (see section 2.2.1).

The interpolation is given by:

\[
x^a = x^b + W[y - Hx^b],
\]

where \( y \in \mathbb{R}^p \), for some \( p \) (usually smaller than \( n \)), are the data to be interpolated, \( H \) is an “observation” operator (if the data are actually observations, it maps the model phase space onto the observation space) and \( W \) is the optimal weight matrix, or gain.

If \( B \) and \( R \) are the background and the observations error covariance matrices, the analysis error is minimized when:

\[
W = BH^T[R + HBH^T]^{-1}.
\]

Equation (21) tells us that the analysis is made of a weighted linear combination of the background state and the innovation \( y - Hx^b \). Put differently, the background state (prediction) is updated with the difference between the observations and itself (correction). Note that the innovation vector is evaluated in the observations space, thus the background state first has to be mapped in that space via the application of the operator \( H \).

For conventional observations (e.g., radiosoundings), \( H \) turns out to be a simple interpolation operator (when the measures are taken in points in the physical space that do not correspond to the model’s gridpoints) or a transform from a spectral domain to a physical one. But more often, as in the case of remote sensing, it is not possible to directly observe the model’s variables. In this case \( H \) includes both the interpolation from gridpoints to observation points and the physical laws that allow the retrieval of the variable one is interested in from the, for example, measured reflectivity.
Finally, note that Optimal Interpolation is actually optimal only if B and R are correct. It is however impossible to know them precisely, and they must be estimated. How this is done, i.e., the correct modelization of error covariances, is perhaps the most important and delicate aspect of the interpolation scheme (see for example Cohn and Parrish, 1991). Moreover, H must be linear. Unfortunately, in many applications (and in particular for radiative transfer) this is not true. The usual way to solve this problem is simply to linearize H around the instantaneous trajectory, that is, H is linearized around the state occupied by the system at each time-step: H[x] ~ H_L x, where H_L is the linearization of H around x, and as such depends on x itself (and can change every time-step).

2.3.2 Kalman Filter

Kalman Filter (Kalman, 1960) is used in atmospheric data analysis as a sequential data assimilation algorithm. KF is optimal (in the maximum likelihood sense) only for linear systems with Gaussian noises. It is usually extended to nonlinear systems via linearization about the instantaneous trajectory (the so-called Extended Kalman Filter, or EKF) or with the inclusion of higher-order moments (see Miller et al., 1994), while the extension to non-Gaussian noises is not as straightforward (Sornette and Ide, 2001).

KF comprises two parts: a prediction step and a correction step. The core of the correction step is made of the following two equations (and is basically the same as Optimal Interpolation, if the forecast field is taken as OI background field, x^f = x^b – cfr. equation 21):

\[ x^a_k = x^f_k + K_k [y_k - H_k x^f_k], \]
\[ P^a_k = (I - K_k H_k) P^f_k, \]

where x^a_k and x^f_k are the analysis and the forecast while P^a_k and P^f_k are their respective error covariance matrices. The gain K_k is given by:

\[ K_k = P^f_k H_k^T [R + H_k P^f_k H_k^T]^{-1}, \]

and in equations (23) – (25) k is a time index.

The main difference between KF and OI (and the reason why KF is so computationally burdensome) is in the prediction step, where both the state vector and its covariance are updated. This entails that the gain must be recomputed every time step, whereas in OI it is constant (equation 22) or updated with suboptimal methods.

As can be seen from equations (23) – (25) KF includes the dynamics in a very indirect way, namely implicitly through the evolved quantities, but not explicitly. 4D variational methods provide a way to take into account the dynamics fitting the model solution to the whole set of available observations, rather than assimilating one observation at a time without feedback to anterior times.

2.3.3 4D-Var

In 4D-Var, the objective is to find the initial condition that minimize a cost function defined as the squared distance between the model’s solution and the observations in a given assimilation interval [t_0, t_N].
Typically the cost function can be written as:

\[ J[x_0] = \frac{1}{2} [x_0 - x_0^b]^T B_0^{-1} [x_0 - x_0^b] + \frac{1}{2} \sum_{i=0}^{N} [y_i - y_i^o]^T R_i^{-1} [y_i - y_i^o], \]

(26)

where \( x_0^b \) is the background state, \( B_0 \) its covariance matrix and \( y_i = H_i x_i \). We will say that the analysis \( x^a \) is such that \( J[x^a] = \min \{ J[x_0] \} \).

Once we have computed the cost function for a forward run, 4D-Var proceed as follows: the gradient of \( J \) is calculated using the adjoint method (Errico, 1997; see also Sirkes and Tziperman (1997) for an important caveat on the adjoint of a finite difference model) and a new run with initial condition \( x_0^i \), \( \delta x_0 \) is launched; the procedure is iterated until the difference between two iterations is smaller than a set threshold.

The correction is given by:

\[ \delta x_0 = \alpha s \frac{\nabla J[x_0]}{\max \{ \nabla J[x_0] \}}; \]

(27)

where \( \alpha \) is a control parameter that allows us to determine the size of the correction and \( s \) is a dimensional parameter used to give the correction the proper dimensionality.

If there is only one observation in the assimilation window, the method is called 3D-Var and instead of the sum in the second member of the r.h.s. of equation (26) there would be the single term due to the difference between the forecast and that observation.

If the background state and covariance matrix are the same as in KF, and both the dynamics and the observation operator are linear, then it turns out that 4D-Var and KF give the same result at the final time of the assimilation window.

Note also that if the dynamics are nonlinear, there is no guarantee that the minimum found will be a global minimum.

## 2.4 Other Methods

### 2.4.1 Mass consistent diagnostic models

For the sake of completeness, it should be mentioned that there are several ready-to-use tools for interpolation of meteorological observations on a regular grid, much used in air quality modeling. These tools are diagnostic models, not taking into account the time dependency of the atmospheric equations; in other words, they do not integrate forward in time (Pielke, 1985).

These models are usually made of simple, robust, and low-computational cost interpolation procedures. Setting the parameters of an initialization file, the user can choose the interpolation scheme and tune it to the intended application. Typical interpolation schemes implemented for scalar variables are nearest neighbor and inverse distance weighting (section 2.2.2). For the wind field the algorithms usually minimize the divergence of the wind vector field, according to the law of conservation of mass, with the further constraint that the vector component normal to the surface is zero (Sherman, 1978; Barnard et al., 1987).
In general, these models can use all the observations available to the user (provided that they are not affected by gross measurement errors), without imposing any of the physical constraints that are needed for prognostic models. Nevertheless, the user must be aware that the interpolation method does not take into account the dynamics of the atmosphere to propagate information in data-sparse areas, so the output fields can be totally wrong far from available observations.

These ready-to-use tools are designed to interpolate surface observations of temperature, relative humidity, wind velocity and direction, global solar radiation, accumulated rain and atmospheric pressure. Furthermore, diagnostic models also output 3D fields of wind and temperature, even if starting from very isolated soundings and/or remote sensing data (sodar/rass).

For temperature and wind, these diagnostic models can also be set to use fields coming from numerical weather prediction models as a first guess; in fact they are often used for downscaling meteorological fields to a resolution appropriate for dispersion modeling, mainly to save on computational costs.

Examples of ready-to-use tools of the type described in this section are CALMET and MINERVE. The CALMET code is part of the CALPUFF modeling system, that is an advanced non-steady-state meteorological and air quality modeling system developed by ASG scientists (http://www.src.com/calpuff/calpuff1.htm). The MINERVE code (Geai, 1987) is a mass consistent wind diagnostic model developed by ARIA Technologies (http://www.aria.fr/english/aria/index.html).

2.4.2 Topographical methods

Though not used in meteorology, topographical methods are often employed in the interpolation of climatological data (as yearly and monthly precipitation observations, monthly minimum and maximum temperature), and so are worth mentioning in this review.

Topographical schemes exploit the average dependance of meteorological parameters on fixed topographical features, e.g. elevation, slope orientation, distance from the sea, etc.. These algorithms are usually used in areas of complex terrain, where a relevant part of the meteorological and climatological signal can correctly be attributed to orographic effects.

Long time series or climatological observations are used to construct multivariate regression functions dependent on the chosen features, which can differ in any particular implementation depending on the characteristics of the area, of the variable considered, of the season (e.g. temperature or precipitation, mountain or sea area, winter or summer…). The analytical functions obtained this way are then used to reconstruct the field from topographical information.

One example of such methods is the PRISM algorithm, Precipitation-elevation Regressions on Independent Slopes Models (Daly et al., 1994), used for example by Frei and Schar (1998) to obtain a precipitation climatology for the Alpine area.
3 Methods and algorithms for spatial interpolation in operational use in the Alpine Space

3.1 Zentralanstalt für Meteorologie und Geodynamik (ZAMG), Austria

The Central Institute for Meteorology and Geodynamics (Zentralanstalt für Meteorologie und Geodynamik - ZAMG) is Austria’s national weather service. Its main headquarters are located in Vienna (Wien). It is concerned with all meteorological and hydrological phenomena whose scales range from the national (synoptic and alfa-mesoscale) to the subregional (gamma-mesoscale). Its surface observation network covers an area of about 80000 km², that is, the whole area of Austria. All of its 150 weather stations are fully automatic. It runs the operational NWP model ALADIN–Austria (Aire Limitée Adaptation dynamique Développement InterNational – Austria). However, there is no assimilation of surface observations. ZAMG issues weather/water resource forecasts and provides input for a number of hydrological models in operational flood prediction and warning.

The interpolation scheme used by ZAMG is the INCA (Integrated Nowcasting through Comprehensive Analysis) system.

The INCA analysis and nowcasting system is being developed primarily as a tool for the forecaster and as a means of providing improved numerical forecast products in the nowcasting range (up to +2 h) and very short range (up to about +12 h). It should be stressed that the analyses generated by the system are not used as initial conditions for NWP model integrations. Thus the analysis methods are not constrained by specific NWP model dynamics or physics. This means that highly structured fields can be produced both in space and time without causing noise-related adverse effects in a subsequent forecast. Nevertheless, the basic approach to analysis and nowcasting used in INCA is strongly rooted in physical considerations. The computation of the three-dimensional temperature error field for example takes into account a surface-layer contribution to the temperature profile which depends on insolation.

The methods used for spatial interpolation are intentionally kept simple (distance-weighting in geometrical and physical space such as those shown in section). The idea behind this choice is, apart from its straightforward implementation, that the system should be as transparent as possible and should keep the number of “climatological” assumptions at a minimum. It also makes further developments and improvements easier and allows easier interpretation by the forecaster.

One of the main conceptual differences between INCA and VERA (section 3.12) is that INCA analyses use NWP model information for interpolation between observations, whereas VERA uses climatological information through a fingerprint method.

INCA is essentially a mass consistent inverse distance weighting scheme, with azimuthally dependent weights. In this system, a NWP (ALADIN’s) forecast is used as first guess. It is trilinearly interpolated to the 3-d INCA grid (δx=1 km, δz=200 m). Then the innovation is determined and interpolated. The first guess is then updated by the innovation. Other information that enter the analysis are digital elevation and surface type, radar data (for precipitation) and, last, satellite data for cloudiness. To a limited degree there exists a mutual dependence of the variables, e.g. humidity is constrained by not exceeding the local dewpoint, or the cooling by precipitation from convective cells observed by radar is taken into account in the temperature analysis.
The variables interpolated with INCA are precipitation, cloudiness (both every 15 minutes), temperature, wind speed, relative humidity and radiation (every hour). Some limited verification on the analysis quality of INCA has been done using cross-validation. It was found that the mean absolute error of the temperature analysis is between 1 and 1.5 K.

3.2 **ZAMG, Salzburg regional office, Austria**

The Salzburg ZAMG regional office is the area’s meteorological and hydrological service, and is concerned with the national/synoptic meso-α scale. Its surface observation network covers an area of 84000 km² and includes 300 stations, among which 140 are automatic. The ALADIN NWP model (without surface data assimilation), is used to issue weather forecasts. The INCA system (section 3.1) complements classical NWP forecasts by providing improved forecasts at short lead times using station observations, radar and satellite data.

The interpolation scheme is kept intentionally simple with distance weighting in geometrical and physical space. The analysis grid size is 1 km. The variables used are summarized in Table.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interpolation method</th>
<th>Time scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Temperature</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Wind</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Wind speed</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Radiation</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
<tr>
<td>Insulation</td>
<td>Distance weighting</td>
<td>15 min</td>
</tr>
</tbody>
</table>

The ALADIN NWP provides 2D and 3D background information with 4 runs/day (1 hour and 9.6 km resolution). The used fields are: geopotential, temperature, relative humidity, u, v and w wind components (3D fields) and 2m temperature, relative humidity, u, v and w 10m wind components, precipitation, total cloudiness and low cloudiness (2D fields). The 3D fields are provided on pressure surfaces with a vertical resolution of 50hPa up to 600hPa.

Additional input data sources used are radar, satellite, elevation and derived topographic fields. The error covariance matrices/correlations are specified analytically at each analysis time.

3.3 **ZAMG, Tirol regional office, Austria**

The Innsbruck ZAMG regional office is a meteorological/hydrological service concerned with the regional/meso-scale. Its surface observation network, comprised of 46 weather stations of which 34 are automatic, cover an area of 15249 km². It does not run any NWP model but it does issue
weather/water resource forecasts. Interpolation of observation is done centrally at the national center of ZAMG in Vienna (see section 3.1). There, products are generated and visualized.

3.4 **Agency for Environmental Protection and Technical Services (APAT), Italy**

The Italian Agency for Environmental Protection and Technical Services (APAT), through its Department for Inner and Marine Waters, focuses its attention on the hydrological cycle, especially on issues concerning management, monitoring and forecasting water resources and risk connected to water cycle extremes, such as floods and drought. So, despite APAT acts on a national level, it is concerned with phenomena that result from a wide range of scales — which, in the Mediterranean area, are also deeply interconnected — from the synoptic (the Mediterranean basin) to the meso-beta (medium-small river catchment size).

APAT inherited on the national level the competence about monitoring of the former National Hydrographic and Marigraphic Service (SIMN), whose measuring network has been regionalized in the year 2002. The former Sistema Idro-Meteo-Mare (SIMM) network includes more than 4000 meteorological and hydrometric gauge stations over Italy (area: about 300,000 km), most of which are operational since the 1950s; whereas the longest historical records last since the 1920s. At present, the stations are maintained and managed by Regional authorities of the Italian “Sistema Agenziale” (mostly, the Regional Environmental Protection Agencies, ARPAs); APAT keeps the right to access data in non-realtime. The APAT hydro-meteorological modeling activity is issued through the SIMM system, which is operational since year 2000 and was designed in order to resolve simultaneously all the scales involved in the Mediterranean hydro-meteo-marine phenomenology.

SIMM (see Figure 1) is a chain of meteorological (QBOLAM), marine (WAM, POM and VL-FEM) and hydrological (TOPKAPI) models, which provides daily meteorological and sea-state
forecasts over the Mediterranean basin area, as well as sea height forecast over the Adriatic Sea and the Venice Lagoon. In particular, the QBOLAM model (which employs global ECMWF analysis and forecast as initial and boundary conditions respectively) produces daily 36-h meteorological forecast with a 10-km grid step in the domain shown with a solid line in Figure 1. Recently, the TOPKAPI hydrological model has been added to the model chain and coupled to QBOLAM forecasts, over the Reno river basin (Emilia-Romagna, Italy); an extension to the Adige river basin (north-western Italy) has been realized in the framework of FORALPS (see the FORALPS Report “Hydrological processes on the land surface: A survey of modelling approaches” by B. Lastoria). The SIMM products are operationally issued on the APAT web site (for BOLAM products, see http://www.apat.gov.it/pre_meteo/index.html; for WAM, POM, VL-FEM products, see http://www.apat.gov.it/pre_mare/).

Many of APAT's activities require some kind of spatialization of observed data, even if a data assimilation stage is not present in the SIMM. For instance, gridded analyses of observed data are required for model verification purposes. So, point-to-grid spatialization of rain gauge precipitation data is operationally (but not routinely) performed at APAT, both in a case-study approach and on longer time records, for statistical evaluation studies.

Since spatialization of observed data has been performed at APAT mostly in the context of

![Figure 2.](image)

**Figure 2.** Remapping procedure. Native grid boxes (referred as N-grid boxes) are indicated with solid line and numbered black triangle, whereas the post-processing boxes (referred as P-grid boxes) are indicated with dashed line and black circles. For the examined P-grid box, the 5×5 subgrid boxes (referred as P-subgrid boxes) are indicated with dotted line and small white circles.
quantitative verification of precipitation forecast, it is naturally addressed to “ground truth” reconstruction, and it is aimed to provide a basis for a “fair” model evaluation (i.e. model-independent). Thus, the discussion below is focused on some critical points: first, the difference between the “punctual” nature of the raingauge observation and the “areal” nature of model forecast (but also of radar and satellite observations); second, the severe inhomogeneity of ground observation density (considering both the land/sea distributions and the large variation of coverage in different countries and regions). Moreover, data assimilation is not yet a considered task, so that a pure observational analysis scheme (i.e., no background information) is preferred. Thus, a successive correction scheme is employed for rain-gauge precipitation spatialization: namely, a two-pass Barnes analysis scheme (cfr. section 2.2.1), which is appropriate when a high-resolution analysis is needed, like in APAT’s case (where numerical forecasts need to be verified at the model grid scale, and the average rain gauge spacing is comparable to the grid step in most of the target area). Due to inhomogeneities in the rain gauge density, some grid points are void after the analysis – which is but a minor inconvenient.

More in detail, the Barnes scheme is applied on the model verification grid, which is typically a 0.1° equally spaced longitude-latitude grid or a 0.1° rotated grid (these are the standard QBOLAM output grids; sometimes, coarser grids have been employed). In this case, the average data spacing in equation (18) is manually set to $L = 0.2°$, which is actually greater than the real average data spacing, thus resulting in a smoother analysis. Moreover, the method requires that the ratio between grid size and average data spacing lies approximately between 0.3 and 0.5. Grid points with no rain gauge within a 0.15° radius are marked as void. The second pass is meant to provide details to the first-guess produced by the first pass; the amount of detail is controlled by the parameter $\gamma$, which can be tuned manually. A value of 0.2 has been found optimal for this purpose (Accadia et al., 2003).

Beside point-to-grid transformations, spatialization techniques also include grid-to-grid transformations. Despite its simplicity, this issue should be not neglected as a trivial one, at least in the context of gridded forecast verification. Most of operational centers employ bilinear interpolation for horizontal grid transformations (e.g., post-processing). However, it has been found (Accadia et al., 2003) that model performances are significantly altered by such operation. Moreover, total precipitation amount is not conserved by bilinear interpolation. Thus, a less aggressive transformation algorithm, called remapping, has been implemented.

Remapping, which is a discretized version of an integration technique that uses an area-weighted average, is performed by subdividing the grid boxes centered on each postprocessing grid point in $n \times n$ sub-grid boxes (where $n$ is an odd number), and assigning to each sub-grid point the value of the nearest native grid point. Then, the remapped value of the postprocessing grid point is obtained by averaging these sub-grid point values (see Figure 2). The discretization procedure becomes more precise as the value $n$ is increased, although, after reaching a critical value $n_c$, the gain in accuracy obtained by remapping the field becomes infinitesimally small and it could be considered as negligible.

It is important to stress that, in contrast with the other interpolation techniques discussed in this report, remapping deals with area averages rather than point values. It is thus suited to spatialize NWP models forecasts or areal observations such as those provided by radar and satellites.
3.5 Regional Agency for Environmental Protection of Lombardia, Italy

3.5.1 Network characteristics and analysis grid parameters

In the context of FORALPS project, Lombardia’s Regional Weather Service (RWS) has acquired and optimized a statistical interpolation method earlier developed by F. Ubaldi (2006) for the neighboring Piemonte’s Regional Weather Service. The algorithm was originally developed only for temperature observations, but it has been extended to dew-point temperature measurements and will be applied, with the necessary modifications, also to wind speed and rain gauges observations. The RWS’s automatic observational network has high but non uniform horizontal and vertical density, with about 270 stations distributed over a ~260×260 km² analysis area on the southern slope of the Alps, characterized by complex topography. The sampling time varies from station to station, but all of them take at least one measurement every hour. The analysis grid size is 1.5 km, lower than the average inter-observation distance (ranging from 7 to 20 km), in order to better exploit the additional information available to the RWS, as the high resolution DEM (250 m). For the same reason, the analysis topography is not smoothed to but sampled on the DEM.

3.5.2 Statistical Interpolation scheme

The interpolation scheme is an application of the Optimal Interpolation algorithm described in section 2.3.1. The observation operator is implicit, and specified by the assumption that the background error covariance matrices $G=BB^T$ and $S=HBH^T$ have the form:

$$G_{lm} = \sigma_b^2 \delta_{lm} = \sigma_b^2 e^{-\frac{(r_l-r_m)^2}{D^2}} e^{-\frac{(z_l-z_m)^2}{V^2}}, $$

(28)

$$S_{mn} = \sigma_b^2 \delta_{mn} = \sigma_b^2 e^{-\frac{(r_m-r_n)^2}{D^2}} e^{-\frac{(z_m-z_n)^2}{V^2}}, $$

(29)

where: i are gridpoints, m and n are station points, r is the horizontal distance and z is the vertical coordinate.

As errors in point measurements can be considered independent, it is a normal assumption that the observation error covariance matrix is diagonal. In this scheme it is further assumed that it is uniform for all observations: $R=\sigma_0^2 I$.

With these hypothesis, equation 21, for grid points and station points, takes the form:

$$x^a = x^b + \tilde{G}(\tilde{S} + \varepsilon^2 I)^{-1}[y^o - y^b], $$

(30)

$$y^a = y^b + \tilde{S}(\tilde{S} + \varepsilon^2 I)^{-1}[y^o - y^b]. $$

(31)

The parameters $\varepsilon^2 = \sigma_0^2/\sigma_b^2$, D and V have to be specified and strongly influence the output field, as they determine how much confidence is given to first guess over observations, and how the information is spread on the analysis points (though reasonably D and V cannot be chosen smaller than the typical distances between stations). As an independent background is not available (see next section), and more confidence is given to observations, $\varepsilon^2$ is chosen small (<1 for both temperature and relative humidity). For temperature, $D=15$km and $V=400$m; for relative humidity, as observations are further apart, $D=10$km and $V=400$m. Innovation vector statistics
can give some indication on how to choose error covariance models and parameters (Dee and Da Silva, 1999), and work is under way to tune the chosen parameters.

As a temperature observation is always available, relative humidity interpolation is performed on the dew-point temperature field and then converted back to relative humidity using the corresponding grid value of the temperature analysis. With this method some over saturation in the relative humidity field is possible; it is in any case filtered out above 103%.

3.5.3 Vertical and horizontal detrending

The background field does not come from a NWP model, but is estimated from the data themselves in such a way as to capture the main mesoscale trends present in temperature by a minimization of the function:

\[ J_{z_c} = \sum_{z > z_c} (T_c - \alpha_0 (x_k - x_0) + \beta_0 (y_k - y_0) + \gamma_0 (z_k - z_0) - T_k^0) + \]
\[ + \sum_{z < z_c} (T_c + \alpha_0 (x_k - x_0) + \beta_0 (y_k - y_0) + \gamma_0 (z_k - z_0) - T_k^0)^2 = MIN, \]

which allows for temperature inversions, frequent in the Po plain. \( T_c \) and \( z_c \) are the temperature and elevation at the inversion point respectively. Figure 3 shows a typical case. Blue dots in 3a show the surface temperature gradient as measured by the regional network. Black dots in 3b show the background field (at the stations). The last panel also shows the analysis on gridpoints (red).

The background function for relative humidity is obtained with the same method applied to dew-point temperature values obtained from RH observations using the correspondent observed temperature.

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**Figure 3.** Vertical distribution of temperature for a spring case with marked ground based thermal inversion. Left (a): hourly temperature observations. Centre (b): observations and background. Right (c): observations, background and analysis.
3.5.4 Method performance evaluation

OI has been implemented operationally, in testing mode, since Jan. 2006 for temperature and since March 2007 for relative humidity. It runs twice daily after a simple DQC producing analysis of the last 24 hours. The method is quite robust, producing good fields also in critical weather situations (orographic effects, strong gradients, thermal inversions). An example is shown in Figure 4 where persistent fog caused a marked temperature gradient in the plain. Panel 4b shows the MSG1-HRV image: the fog border pattern is in strikingly good accord with the gradient of the analyzed fields, giving good independent confirmation of both temperature (4a) and relative humidity (4b) patterns.

Figure 4. A winter case with persistent radiation fog in the Po plain.

Figure 5. Quantitative diagnostics on 2005 hourly temperature analysis (see text).
For a better quantitative understanding of the analysis characteristics, Figure 5a shows the yearly average (2005) of the increments of the analysis on the background field. Local patterns that are averaged out by the detrending procedure (as Alpine valley cold pools and Milano’s heat island) are systematically added back on the background by the analysis. The patterns are mostly representative of background error, but they also depend on the data distribution (as the strong minima and maxima in data void areas).

Figure 5b shows a plot of the distribution of the absolute difference between an observation $y_m^o$ and the analysis performed without the observation $y_m^a$, or cross-validation analysis (Cardinali et al., 2004), in °C. The boxes are plotted as a function of the station density influence (~0 for an isolated station, ~1 in data dense areas). The error median is always below 2°C, even in data sparse areas (where analysis ~ background). In data dense areas the median is about 1°C. Probability of large errors decreases with station density, but as expected $y_m^o - y_m^a$ doesn’t go to zero because the smallest scales are filtered out by the analysis.

### 3.6 Regional Agency for Environmental Protection of Veneto, Italy

The regional meteorological service of Veneto has two centers: the Teolo center issues generalistic forecasts for the whole region, while the Arabba center specializes in snow, avalanches and mountain weather forecasts.

**Figure 6.** Example of precipitation amount cumulated during the 12th of January 2008 interpolated using ordinary kriging.
The integrated meteorological monitoring network consists of two meteorological radars and a network of circa 200 automatic weather stations. The stations are distributed over all of Veneto’s regional territory and have different reporting times (15 min. for temperature observations and 10 minutes for rain amounts). The center in Arabba manages 17 more stations, which have additional sensors in order to measure snow-related parameters.

Teolo’s meteorological service produces interpolated fields from daily observations of temperature (minimum and maximum), precipitation (cumulated rain amount) and wind (integrated).

The interpolation scheme in use is ordinary Kriging (par. 2.1.3) and has been implemented using the commercial software Surfer (© Golden Software, Golden, Colorado). The semi-variogram is determined by the software for each interpolation time from the observations to be analyzed, using default settings. No external constraints are imposed on the correlations.

Studies are underway to optimize interpolation techniques and to optimize geographical display of temperature and precipitation data, but results are not yet available.

The interpolation scheme used can also be applied to observation periods longer than a day.

3.7 **Regional Agency for Environmental Protection of Friuli Venezia Giulia, Italy**

The Regional Meteorological Service of Friuli Venezia Giulia, OSMER (OSservatorio MEteorologico Regionale), manages a small but dense and efficient meteorological observation network, composed of nearly 100 automatic weather stations, a meteorological radar, hail pads and a volunteers observer project (also partially funded through FORALPS project).

OSMER issues short and medium range weather forecasts for the area, focusing on the meso-β-scale; the office does not run operationally a numerical weather prediction model, but acquires numerical output from the major Regional NWP centers and runs local area models in experimental mode for test cases, at present without mesoscale data assimilation.

Routine interpolation schemes are implemented on daily observations from the surface network (all variables) and on monthly temperatures. The daily analysis fields are obtained using GMT, an open source mapping tool (http://gmt.soest.hawaii.edu/), and choosing among the simple interpolation routines available there. Interpolated daily fields are meant for internal use only, and have the main purpose of facilitating daily data quality control procedures on the network’s observations.

Monthly minimum and maximum temperature fields are disseminated by the on-line publication of the monthly outlook on the region, meteo.fvg mensile, available at http://www.meteo.fvg.it/. The scheme for monthly temperature is a topographical model (section 2.4.2) considering elevation, distance from the sea and valley effects as regression variables.
3.8 Regione Autonoma Valle d’Aosta, Italy

Valle d’Aosta is a sub-national administrative division, consisting of a single province on the western Alpine ridge, which covers an area of about 3263 km$^2$. The Regional Meteorological and Hydrological Service of Valle d’Aosta (RAVA) issues short and medium range weather forecasts for the area. RAVA also manages its own monitoring network, which consists of about 20 automatic stations measuring the main meteorological parameters. Real-time hourly and daily data are regularly published on web-site (Figure 8), validated, and stored in a central data base.
Two other regional surface networks are managed by ARPA Valle d’Aosta, the regional environmental protection agency, and by the Regional Civil Protection Agency. Observations from all three networks are available in real time to the Meteorological Service, for a total amount of about 90 observation sites.

Precipitation and temperature surface observations are interpolated on a 1km / 500m analysis grid using an Inverse Distance Weighting algorithm (section 2.2.2) and a topographical interpolation procedure respectively (section 2.4.2). The interpolation is performed on a routine basis (each hour, day, year) on hourly, daily, monthly and yearly observations.

3.9  Provincia Autonoma di Trento, Italy

The autonomous Province of Trento covers about 6200 km$^2$ of mountainous territory on the southern side of the Alpine Ridge; the Province has an independent office for civil protection and meteorology, Meteotrentino (http://www.meteotrentino.it/).

Meteotrentino does not operationally run a numerical weather prediction model, but issues daily short- and medium-range weather forecasts on the local scale (meso-β-scale) and manages the Provincial observational network, which consists of 98 automatic stations and 10 manned stations.
Almost all of the network’s stations measure temperature and precipitation, and about 38 stations measure some of the other meteorological parameters (pressure, wind speed and direction, relative humidity, etc.). The network is being redesigned at present.

Hourly analyses of temperature and precipitations are obtained twice daily (or manually at any time they are needed) using two different algorithms, while no spatial analysis is performed on the other parameters observed by the meteorological network.

3.9.1 Interpolation of precipitation observations

A spatial representation of the hourly precipitation amount cumulated in the network’s rain gauges is obtained by a Kriging algorithm (section 2.1.3).

The algorithm is implemented using a fixed length scale in the semi-varioigram specified through exponential functions. The optimal length scale for the Adige valley has been obtained by a statistical study performed to optimize the response of the basin’s hydrological model. Negative interpolated values of precipitation, which may occasionally result from the kriging procedure, are masked out a posteriori by setting all negative values to zero. The scheme is automated on hourly and daily precipitation observations, but can also be used interactively for events of any duration.

![Figure 9](image-url)

Station elevation on the y-axis. Temperature recorded on Jan 6th 2005 on the x-axis. The red diamonds are the observations, the green pluses the background estimates and the blue squares the analysis estimates on station points.
3.9.2 *Interpolation of temperature observations*

Temperature observations from the Provincial network are analyzed using an Optimal Interpolation scheme (section 2.3.1) originally developed by F. Uboldi for Piemonte’s Regional Meteorological Service. The scheme is analogous to that implemented by the Regional Agency for Environmental Protection of Lombardia (section 3.5) and it is extensively described in Uboldi et al. (2008).

As a background field is not available, a first guess is obtained using a de-trending procedure on the data themselves. The first guess field is the best fit of a linear function with the temperature values observed at each hour (the dependent variables are longitude and elevation, allowing for a vertical change of the thermal gradient). The average trend in the data can represent the larger scale meteorological signal, and, as long as the analysis domain remains sufficiently small, can be considered a reasonable choice for a first guess field.

The innovations are then used to correct the background field through analytical gaussian correlation functions (as in equations 28-29). The scale parameters, D and V, are set to the

![Figure 10.](image.png)

*Figure 10.* Temperature analysis map, same case as Figure 9. The indication of three orographic elevation isolines (blue: 500 m; red: 1000 m; black: 1500 m) highlights the warm band corresponding to the thermal inversion, warmer (white / green) with respect both to higher elevations (Adamello, Presanella, Cevadale: darker blue areas on the North-West) and to the bottom of the main valleys (light blue).
minimum scales resolved by the observing network.
The analysis grid size is 200 m, and the error on analyzed temperature values is characterized by statistical considerations using the algorithm’s properties of error minimization. The calculation of analysis residuals has also been used to check the scheme. No cross validation has yet been calculated.

As the analysis area is mainly mountainous, work is under way to improve the scheme by de-correlating slopes with different orientations.

3.10 Provincia Autonoma di Bolzano, Italy

The meteorological/hydrological service operating within the Autonomous Province of Bolzano (PAB) is concerned with the regional and sub-regional scales (i.e., meso-β and meso-γ scales). Its surface observation network covers an area of about 7500 km², with 114 weather stations, among which 82 are fully automatic and the rest are manned. Despite the fact that it does not operationally run a NWP model, PAB does issue weather/water resource forecasts. Weather forecasts are issued twice a day for 365 days per year, whereas flood forecast are only issued if needed. It is expected that seasonal water resource availability forecast will be possible at the end of 2008.

Figure 11. June 2007 - monthly precipitation (calculated in esri arcview spline neighbors 12 tension 0.5).
Figure 12. 20/21 June 2007; post event analysis (calculated in ESRI Arcview with splines, neighbors 12, tension 0.5).

Figure 13. 30 August 2007 - pluviobrowser 30 minutes precipitation at 00 UTC or 1:00 MEZ (calculated in grass regularized spline with tension 160).
The main interpolation methods used by PAB are splines (section 2.1.2), and Thiessen polygons for real time applications. The PRISM method is going to be applied in the interpolation of precipitation for water balance studies, to take into account orographic effects (Daly et al., 1994). The two spatially interpolated variables are the precipitation and the equipotential temperature at 850 hPa for snowfall limit forecasts. The temporal aggregation scales of the observations are 1 hour for real time simulation and forecast applications, and 1 month for water balance applications. The analysis is performed on a 500 m grid once or twice a day, or on demand for real time and water balance applications. A pluviometric browser for internal use will be set up in 2008 (for an example, see Figure 13); hence, interpolations will be performed every 30 minutes. The interpolation parameters are obtained from a qualitative analysis of historical data.

3.11 Environmental Agency of the Republic of Slovenia

The Environmental Agency of the Republic of Slovenia (EARS) is a meteorological/hydrological service concerned with the national (synoptic) and regional (meso-α) scales. Its surface observation network covers an area of about 20000 km², with 260 weather stations, among which 32 are fully automatic and the rest are manned. EARS runs an operational NWP model, ALADIN, and regularly issues weather/water resource forecasts.

The main interpolation methods used by EARS are least squares regression (see section 2.1.1) to account for the bulk of the variance, followed by Kriging (see section 2.1.3), Optimal Interpolation (section 2.2.1) or Mass Consistent Models (section 2.4.1) for the residuals. Table 2 summarizes which method is used to interpolate each variable and the temporal aggregation scale.

Table 2. Summary of EARS spatial interpolation procedures.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interpolation method</th>
<th>Time scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>Kriging, regression, OI</td>
<td>day, month, year</td>
</tr>
<tr>
<td>Temperature</td>
<td>Kriging, regression</td>
<td>day, month, year</td>
</tr>
<tr>
<td>Wind speed</td>
<td>Kriging, regression, mass consistent model</td>
<td>month, year</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>Kriging, regression</td>
<td>month, year</td>
</tr>
<tr>
<td>Radiation</td>
<td>Kriging, regression, 1D radiation balance</td>
<td>month, year</td>
</tr>
</tbody>
</table>

The analysis is performed on a 1 km grid and it also accounts for altitude and other derived geographical variables such as distance to the NE slopes, relative altitude to the nearest NE slopes, curvature and, last, cold air pools potentials. However, as it is not a routine operation, it is not performed at precise time intervals. Semi-variograms and covariance matrices are obtained only from the data, at each analysis time. In most cases spherical and exponential variogram models are used to fit the empirical variograms (section 2.1.3). The choice is usually made subjectively, when visually examining empirical variograms. In some cases also Gaussian and Linear variogram models are used. If negative values appear (for small distances) the nugget is fixed to 0 and then the model variogram is fitted to the empirical one. If negative values appear for residual Kriging, usually the deterministic part of the model is examined again.
Figure 14.  Sunshine duration in winter (period 1971-2000).

Figure 15.  Analysis of an intense precipitation event (August 2005).

Although the analysis is multivariate, the parameters that are correlated and the dynamical/statistical constraints depend on the variables and the situation and they are determined for every specific analysis. Examples of spatial analyses are provided in Figures 14 and 15.
3.12 University of Vienna, Austria (a non-FORALPS institution)

VERA (Vienna Enhanced Resolution Analysis) is a high resolution real-time analysis tool with embedded quality control, which is particularly intended for use over complex topography. The basic philosophy of VERA is to use physical a priori knowledge (the so-called fingerprints) of typical meteorological patterns in meteorological fields that occur over complex terrain. VERA enables the user to efficiently downscale information to data-sparse regions without making use of any model input, i.e. it is data self-consistent.

The VERA analysis is related to the thin-plate spline method, but calculation is done by using finite differences. For an arbitrary meteorological parameter $\Phi(x)$ at location $x$, a cost functional $J[\Phi]$, defined as the weighted sum of squared spatial derivatives:

$$J[\phi] = \int \sum_i \lambda_i \left( \frac{\partial^2 \phi(x)}{\partial x^2} \right)^2 dx$$

(33)

is minimized. Here $\lambda_i$ denotes a weighting factor for the i-th spatial derivative. The assignment of spatial derivatives (particularly of first and second derivatives) is the method-of-choice in VERA and appears to be appropriate, since the atmospheric system tends to level out sharp gradients and to maintain rather smooth fields.

3.12.1 Data quality control in VERA

A huge amount of observational data from all over the Alpine region is included to the analysis. Despite the application of the latest observational techniques and data processing tools, it is inevitable that a certain amount of data is incorrectly measured, transferred or interpreted. In order to exclude erroneous data from the analysis process, a comprehensive data quality control module is used upstream the VERA analysis. This module is able to detect and filter out unrealistic single measurements and gross errors as well as systematic errors. Hence, erroneous patterns in the analysis which are due to data errors can be eliminated in the run-up of the analysis.

3.12.2 Fingerprint technique

Under undisturbed radiative conditions (e.g. on days with strong incoming solar radiation, weak synoptic pressure gradients and resulting weak winds, low cloudiness and low humidity) valleys exhibit a stronger daytime warming and nighttime cooling than the adjacent plains. This is due to the comparatively smaller volume of air to be warmed over the mountains as compared to the surrounding areas. This effect often referred to as differential warming can be described physically quite well. Consequently, it can be simulated by a simple model if topographic data are available. The mentioned effect of differential warming is by far not the only process over complex topography affecting meteorological fields. In case of a large-scale flow directed against an obstacle of the size of the Alps, Stau-effects are inevitably encountered. They may influence pressure, wind and precipitation fields near the obstacle. Likewise, in coastal areas or in the vicinity of large cities, topographic inhomogeneities might result in more or less significant alteration of meteorological parameters. If the mentioned patterns (fingerprints) are a priori

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1 This contribution was kindly provided by Benedikt Bica, University of Vienna.
known, their signals can be detected in data-rich regions and they can subsequently be impressed to the field in data-sparse regions, i.e. data is transferred from data-rich to data-sparse regions. VERA is run operationally at the Institut für Meteorologie und Geophysik der Universität Wien. It produces real time analyzes of sea level pressure, pressure tendency, potential and equivalent potential temperature, wind, precipitation and derived quantities, such as moisture flux divergence. The spatial representation of these fields gives a good overview of the current meteorological conditions in the analysis domain and can be used both for nowcasting purposes and for real time verification of different model forecasts.

4 Conclusions

The aim of the present report was to photograph the state-of-the-art in interpolation or assimilation methods used for meteorological observations by the institutions concerned with the Alpine arc region. To this end, we have discussed some widely used interpolation methods, and collected information about the project partners’ (and even non-project partner who were kind enough to answer our questionnaire) operational routines. Contributors to this survey are listed in Table 3.

From the quick overview of Chapter 3 it can be seen that there is a strong inhomogeneity regarding interpolation practices in the institutions involved in FORALPS Project. Austrian Project Partners all use the INCA interpolation scheme (mass consistent IDW on a model first guess), developed by the ZAMG Wien in its role of National Meteorological Service (NMS). The Slovenian partner, also a NMS, uses a variety of methods depending on the variable, aggregation time and purpose of the analysis (OI, Kriging, Splines). The differences become more marked on the southern side of the Alpine ridge between Italian partners, probably as a consequence of the lack of coordination between Regional and National Meteorological Services.

It is notable that, despite the advancement of data assimilation methods, interpolation practice seems, at least for mesoscale meteorology, to be well behind what has been obtained by the research community. There seems in fact to be little development done on the subject of interpolation of mesoscale observations, and the operational community suffers consequently.

To date, there seems to be no real consensus on what is the interpolation method best suited for different parameters and for different aggregation times of the observations. It is also apparent that, with some exceptions, interpolation errors and characteristics are little explored and seldom compared. Moreover communication between the institutions involved seems to be lacking, despite the involvement in specific international projects as FORALPS.

This means that there can be room for research that would concentrate on the practical implementation issues (an especially sensitive issue at the mesoscale) and eventually for development. However, each single institution alone has probably not enough manpower to improve, thus making a necessity larger investments on research and collaboration between institutions and also between services and research centers.
Table 3. Responsible of organization/department.

<table>
<thead>
<tr>
<th>Organization</th>
<th>Responsible of organization or department</th>
<th>Colleague/s working on interpolation</th>
</tr>
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<tbody>
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</tr>
</tbody>
</table>

5 References


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Foralps Partnership

UniTN (Lead partner) University of Trento
Department of Civil and Environmental Engineering www.ing.unitn.it

APAT Italian Agency for Environmental Protection and Technical Services www.apat.gov.it

ARPA Lombardia Regional Agency for Environmental Protection Lombardia
Meteorological Service-Hydrographic Office www.arpalombardia.it

ARPA Veneto Regional Agency for Environmental Protection Veneto www.arpa.veneto.it

EARS Environmental Agency of the Republic of Slovenia www.arso.gov.si

OSMER Regional Agency for Environmental Protection Friuli-Venezia Giulia
Regional Meteorological Observatory www.osmer.fvg.it

PAB Autonomous Province of Bolzano Hydrographic Office www.provincia.bz.it

PAT Autonomous Province of Trento Office for Forecasts and Organization www.meteotrentino.it

RAVA Valle d’Aosta Autonomous Region Meteorological Office www.regione.vda.it

ZAMG-I Central Institute for Meteorology and Geodynamics: Regional Office for Tirol and Vorarlberg

ZAMG-K Central Institute for Meteorology and Geodynamics: Regional Office for Carinthia

ZAMG-S Central Institute for Meteorology and Geodynamics: Regional Office for Salzburg and Oberösterreich

ZAMG-W Central Institute for Meteorology and Geodynamics: Regional Office for Wien, Niederösterreich and Burgenland www.zamg.ac.at
The project FORALPS pursued improvements in the knowledge of weather and climate processes in the Alps, required for a more sustainable management of their water resources. The FORALPS Technical Reports series presents the original achievements of the project, and provides an accessible introduction to selected topics in hydro-meteorological monitoring and analysis.