COST 718 " METEOROLOGICAL APPLICATIONS FOR AGRICULTURE"

REPORT ON RAINFALL SPATIALISATION

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1. *INTRODUCTION:*

This report has been carried out following the decision D.1 adopted at the 3rd meeting of the Cost 718 Working Group 1, referred to the realisation of a set of reports containing a compilation of the current interpolation techniques used in agrometeorology for the meteorological variables of main interest. The current report deals with the different methods that have been used for precipitation assessment and spatialisation . A concise description of the different techniques is presented, including a very broad review of the use of remote sensing for rainfall estimation. The report makes a particular emphasis on the intercomparison studies of the different procedures of spatial analysis of precipitation that have been conducted and the main conclusions that can be obtained from them, with the goal of helping the organisation of the future activities to be carried out in spatialisation in the framework of the Cost 718 Working Group1.

Precipitation is one of the most important meteorological parameters in agrometeorology and the majority of current applications in agricultural and natural resources managements require this parameter to be used as input in models. So, it is of particular importance to have an evaluation as accurate as possible of punctual and areal rainfall amount in different time scales, in support of agricultural hazard monitoring, water resources management, soil moisture modelling for crop production, irrigation scheduling, pest and disease control and prevention, forest fire risk assessment….etc. At this respect from the compilation of pest and disease and irrigation models carried out by the WG2 of the Cost Action 718, it appears that hourly/ daily precipitation data are one of the meteorological inputs in all models.

On the other hand, as everyone knows, precipitation is caused by a quite complex combination of thermodynamic, dynamic and cloud microphysical processes affected by a complicated interaction with topographical features, acting over a wide range of temporal and spatial scales. So, precipitation fields are characterised by its very complex structure and high spatial and temporal variability. At this respect, K.G. Hubbard (1994) has analysed the spatial variability of some daily weather variables, including precipitation. The study was made using meteorological data from an area located in the high plains of the USA, and the results showed that for daily precipitation a mean separation between rain gauges of around 10 Km would be necessary in order to exceed the stated criterion of explaining more than 75% of the variation in daily precipitation between sites. Spacing of gauges for explaining at least 90% of that variation would be less than 5 Km. Other meteorological variables important in agrometeorological models and included in the study would not require such as close spacing of the station network. That is the case of maximum temperature that would require a mean spacing of 60 Km to explain more than 90% of the variance. Minimum temperature, relative humidity, solar radiation and evapotranspiration require a spacing of around 30Km. This spacing is of 20Km in the case of soil temperature and 10 Km in the case of the wind variable.

Other studies on spatial variability of precipitation have been conducted by different authors: Duchon et. al (1995) derived a method to estimate the precision of daily area-average rainfall in the presence of instrument bias and observational noise, partially based in a previous work of Rodriguez-Iturbe and Mejía (1974) that established a theoretical framework for assessing the spatial sampling error of rainfall. Morrisey (1995) have developed a standard error equation valid for practically any rain gauge sampling design. On the other hand a lot of studies have been carried out concerning raingauge network design : Eagleson (1967), Morin et. al (1979), Shih (1982) , Dymond (1982), Gandin et al (1976), Hendrick.R and G.H. Comer (1970).

An additional aspect to be considered concerning the quantitative evaluation of the precipitation to be used as input in agrometeorological models is the accuracy of point precipitation measurements. The different sources of inaccuracy in precipitation data have been widely explored: Eischeld et al. (1991), Groisman (1991), Groisman et al (1991b), Neff (1977), Goodison (1981), Sevruk and Hamon (1984), Metcalfe and Goodison (1992), Sevruk (1979,1982), Legates (1987), Legates and De Liberty (1993a ,b) , Legates (1992), Legates and Wilmott (1990). Groisman and Legates (1994) have analysed in detail the accuracy of precipitation data for United States. The different sources of error that directly affects the gauge measurement of precipitation, like wetting and evaporative losses, mechanical errors, wind-induced bias.. etc, as well as the correction factors for each case have been evaluated following the formulation made by Legates(1992) who had modify the model developed by Sevruk (1979). Amongst the main conclusions of this study it could be summarised that gauge measurement biases are not trivial, ranging (for annual totals) from 5% to 25% with larger biases in winter, in high elevations and high latitudes owing to the increased effect of wind on snowfall. Adjustments to obtain less biased estimates of precipitation could be applied to the data but their implementation require considerable amount of metadata as well as additional meteorological information.

Taking into account all the aspects previously quoted, and also considering that most part of the observational precipitation networks to which we can access in real time have only a quite sparse coverage of the territory, it emerges the difficulty of the precipitation assessment business. So, the searching of the different methods and alternatives that are used in order to optimise the estimation of the rainfall fields at different time and spatial scales making use of all the different sources of information (including both punctual gauge measurements and remote sensing information) constitutes a big challenge for the agrometeorological community and one of the critical issues to be considered by the Cost Action 718 WG1.

2. *OVERWIEW OF THE DIFFERENT SCHEMES FOR RAINFALL SPATIALISATION.*

The objective of this paragraph is to give a broad review of the different techniques that have been used for rainfall spatialisation purposes using data obtained from gauge networks. Both deterministic and stochastic approach will be considered and separate subparagraphs will be devoted to the techniques that introduce the topography in the interpolation schemes, the methods more physically based and those that take into account the weather configurations in the way of spatialising the precipitation, and finally the particular aspects of the interpolation of daily precipitation.

Methods of Interpolation just based on gauge measurements.

Deterministic interpolation techniques:

The available deterministic interpolation techniques cover a wide range of alternatives varying from very simple algorithms to very sophisticated procedures. A set of reviews, compilations and even comparative analysis of all these techniques are available in the literature: Tabios and Salas (1985), Creutin J.D and Obled (1982), Lebel et al. (1987), Hevesi et al (1992), Daly et al.(1994), Maracchi et al, (1995), C. van Dieppen and P. Van der Voet (1998), M New (1998), D. Cornford (1998).

For sake of simplicity we can group these methods in the following classes:

Trend surface analysis: It is a particularly simple method consisting in the application of regression analysis to obtain a surface that better fits the precipitation data. The surface is generally polynomial, although other types of simple functions could be used. This technique is usually applied in a first step of data analysis as well as for de-trending purposes.

Methods based in the use of the data from just one station: In this case the whole space is divided in a mosaic and the function that we have to fit to the rainfall data is defined for each piece. This type of methods include the Thiessen (1911) polygon area averaging method that was widely used for rainfall estimation in the first half of the past century particularly by hydrologist. In this method the value of the closest observation is assigned to each point of the interpolation grid. Another method here included is the Delauney triangulation technique that follows the well known partition of Voronoï. Triangulation and Thiessen techniques are computationally efficient (M. New ,2000), but employ a very limited number of data points in the estimation of gridpoint values, and do not take into account station distance. A more sophisticated technique, but also based like the Thiessen method in the use for rainfall estimation at any point of the data of one single station, is the CGMS (Van der Voet et al, 1994) method developed for estimating daily values of several weather variables in a grid covering the European Union Territory making use of daily station values. This last method was devised with the objective of obtaining a precipitation temporal pattern realistic in terms of number of rainy days and amount of rainfall, in order to have a better simulation of the soil water balance. The choice of the most similar station for each grid point is based on a criteria for similarity stated in terms of proximity, difference in altitude and in distance to the sea and position relative to climatic barriers (C. Van Dieppen and P. Van der Voet, 1998).

Methods based in the weighted combination of neighbouring stations:

In these type of methods, the gridpoint value is obtained from a combination of the values from stations that are affected by different weighting coefficients. Interpolation methods using distance weightings have different variants depending on both the criteria stated for the selection of the stations that contribute to the estimation and the weighting function. In these methods we can make use of any number of stations and utilise different weighting functions so that stations close to the gridpoint carry larger weight but we do not take advantage explicitly of the spatial correlation structure. For example New et al. (2000) use the eight closest stations for interpolation of monthly anomalies in the construction of CRU dataset, regardless of direction or distance for estimation of gridpoint values. Piper and Stewart (1996) used a similar approach and employed a variable influence radius, so that around 5 to 10 stations were used to estimate each gridpoint value. Amongst the most popular of these techniques, can be quoted the Inverse Distance Weighting method (IDW) in which the weighting factor is proportional to the inverse of the distance and is normalised making the sum of the weights over all stations involved equal to 1. In this formulation, the distance can be also raised to a weighting power "a" that have in general values ranging from 0 to 2. In the Shepard method (1968), interpolated values are obtained from a weighted sum of the observed values corrected by a locally computed increment. The computed increment is based on local slopes determined by least-squares fitting in orthogonal directions (See for details Bussieres and Hog, 1989). Barnes and Cressman methods, very popular in weather prediction business, fall also in this category, see for details: Barnes (1973), Cressman(1959), Bussieres and Hog (1989), Y. Xia et al. (2001, 1999). The method of Cressman proceeds by successive corrections steps starting from an initial value (first guess) and using influence circles and inverse distance interpolation technique. These distance weighting interpolation techniques have been widely used for interpolation of large datasets to produce global fields due to the fact that the computational time is a linear function of the number of data points (M. New, 1998; Legates and Wilmott, 1990; Hulme, 1994 and Xie et al. 1996).

Thin plate splines:

This deterministic surface-fitting method basically consists in finding a set of functions that interpolate the observed values while minimizing a smoothness-criterium (Creutin and Obled,1982). A general framework for splines is available in Champion et al (1996). If we restrain the analysis to the most commonly used thin plate splines (TPS), TPS are defined by minimising the roughness of the interpolated surface subject to the data that have a predefined residual (Xia et al, 2001).

If we suppose n data values P_i at positions x_i ,it can be stated that:

$$P_i = g(x_i) + \varepsilon_i \quad (i = 1,2,\ldots..n)$$

The function $g(x_i)$ has to be estimated from the observations P_i, whereas ε_i is the term of error that includes the measurement error and the purely small-scale local variability . In the TPS approach both the order of the derivative which defines the surface roughness and the parameter that determine the amount of data smoothing (smoothing parameter) are obtained by generalized cross-validation.

The formal equivalence between splines and the geostatistical technique of kriging has been widely analysed (Matheron, 1981; Wahba, 1990; Wackernagel, 1998). An important difference between both techniques is the way they carry out the optimisation; error variance minimisation in the case of kriging and generalised cross validation in the case of splines. It has been stated that smoothing splines are equivalent to kriging with a translation-invariant drift, filtering noise (Wackernagel, 1998). At this respect some controversial discussions between researchers from the communities of kriging and splines fans are referred in the literature. Concerning the use of this technique, different examples of application of TPS for rainfall data interpolation purposes are available (Creutin and Obled, 1982; Slimani and Obled, 1986; Hutchinson, 1995 and 1998).

Stochastic interpolation techniques: Kriging

Geostatistical interpolation methods like kriging were originally devised in the context of the spatial analysis in ore reserves in mining (Matheron,1971), but since then have been extensively used in other environmental sciences, particularly in meteorology and climatology. The theoretical bases for geostatistics have been described in detail in different publications (David, 1977; Delhomme, 1978; Journel and Uihjberts, 1978; Isaaks and Srivastava; Cressie , 1991).

In the particular case of rainfall interpolation, the use of kriging is widely referred (Tabios and Salas, 1985; Dingman et al, 1988; Hevesi et al, 1992; D. Philips et al, 1992; E. Pardo-Igusqiza, 1998; Dirks et al, 1998; C. Prudhome and D. Reed, 1999). In case of sufficient sample size and spatial distribution of data available for defining a representative model, kriging can provide unbiased estimates with minimised estimation variances. So, in many cases the application of kriging to precipitation data have been carried out in the context of climate applications, like average annual precipitation or extreme rainfall mapping for hydrological design purposes.

We will restrain now to the more simple ordinary kriging, and a quite concise description of main aspects of this technique will be provided:

The basic assumption is that the data are a partial realisation of a random function $Z(\boldsymbol{x}){:}\boldsymbol{x}\in D$, being $\boldsymbol{x}$ a spatial index and D a two-dimensional domain. Another basic assumption of kriging, in its simplest version is stationarity, meaning that the mean of the process is supposed to be constant and invariant with the spatial location and the variance of the difference between two values is assumed to depend just on the distance between the points and not on the location $\boldsymbol{x}$. These hypothesis can be expressed in the following way:

$$E(Z(\boldsymbol{x} + h) - Z(\boldsymbol{x})) = 0$$

Var $(Z(\boldsymbol{x} + h) - Z(\boldsymbol{x})) = 2.\,\gamma(h)$

The function γ (h) is called semivariogram and has to be assumed that it is known or well estimated from the experimental data: $\gamma(h) = 1/2.(E(Z(\boldsymbol{x} + h) - Z(\boldsymbol{x}))^2$.
The objective of kriging is to estimate the values of the variable at some ungauged locations $\boldsymbol{x_0}$ using the available information of the variable elsewhere in the domain D, ($\boldsymbol{x_1}$, $\boldsymbol{x_2}$…………, $\boldsymbol{x_n}$). To do this we have to express $Z(\boldsymbol{x_0})$ as a linear combination of the available data: $Z(\boldsymbol{x_1})$, $Z(\boldsymbol{x_2})$……… ,$Z(\boldsymbol{x_n})$.

$Z^*(\boldsymbol{x_0}) = \Sigma\, i_{=1,..n}\, \lambda_i \,.\, Z(\boldsymbol{x_i})$.

The resultant optimal weights are calculated in such a way that the estimation $Z^*(\boldsymbol{x_0})$ of $Z(\boldsymbol{x_0})$ is unbiased and the sum of square errors is minimised. In practice the process of kriging application is carried out by means of the following steps: a) Construction of the experimental semivariogram by making use of the available data sample; b) Fitting a theoretical semivariogram model to the obtained points by optimisation of the model through cross-validation or other alternative procedure, c) Determine the weights to be used by solving the kriging equations that result from the minimisation of the estimation variances: Var $(Z^*(\boldsymbol{x_0}) - Z(\boldsymbol{x_0}))$.

The main advantages of kriging with respect to a more simple deterministic techniques like Thiessen polygons are that a more accurate estimation of precipitation at ungauged locations is provided due to the use of information of surrounding stations in a way that make also use of the spatial correlation structure of the precipitation fields. Other strong point of kriging is that the estimated variance is minimised, which in turn provide an analysis of the interpolation error.

Amongst the main limitations of ordinary kriging it could be quoted that it does not explicitly account for the influence of topography on precipitation except that reflected in the spatial structure of rainfall stations network. The basic assumptions used in the developing of the kriging equations (intrinsic hypothesis) are quite restrictive and the need of fitting a semivariogram from just one realisation of a random function could be considered as a weak point of that approach. It is worth to consider here that kriging is optimal in a least squares sense just when the required assumptions are strictly met (Fedorov, 1989; D. Cornford, 1998). It has been shown (Dirks et al, 1998) that in the case of small regions with simple topography and a very dense network, there is no improvement from kriging compared with much simpler deterministic methods like inverse distance to map rainfall. On the other extreme conditions, in poorly sampled regions, where correlation or conditioning by adjacent measured values is low, it conservatively reverts to his marginal expectation, i.e, the local average (M. Slimani and C. Obled, 1986).

Some of the limitations of the ordinary kriging resulting from the basic model assumptions could be removed by the use of more sophisticated geostatistical techniques. That is the case of the universal kriging that, in order to cope with the presence of a trend in the domain, introduce a local polynomial trend instead of the local estimate of the mean employed by ordinary kriging. On the other hand, non-linear geostatistics provide a more general framework to deal with spatial analysis of meteorological variables (Rivoirad, 1994). This is the case of disjunctive kriging, that allows to obtain an estimation of the conditional probability that a certain measured indicator variable goes above some prescribed tolerance level (S.R.Yates and A. R. Warrick, 1986).

Methods of rainfall interpolation that consider auxiliary information.

All the methods previously quoted are mainly based in the weighting combination of punctual data got from rain gauges. But in general rain gauge networks have only sparse coverage, particularly in mountainous areas where the stations are in general spatially distributed in an irregular and quite coarse array. On the other hand it is well known that at all temporal and spatial scales precipitation is very dependent on topographical features. So, a lot of efforts have been devoted both to the characterisation of the relationships between precipitation and topography (G. Johnson, 1995 et al; Ch. Conrad, 1996; Barros, 1993; Basist et al.1994; Daly et al,1994) and to the introduction of the topography as auxiliary variable in the rainfall interpolation schemes (Hevesi et al,1992; Dingman, 1988; D.L. Philips et al, 1992; Humbert et al,1994; Daly et al, 1994; Dirks et al, 1998; Frei et al, 1998; Hay, 1998; Martinez Cobb at al,1996; Pardo-Igusquiza, 1998; C.Prudhomme and D. Reed, 1998 and 1999).

Geostatistical techniques could be applied for the introduction of different auxiliary variables well correlated with precipitation and that are used to aid in the estimation of the primary variable. Different geostatistical approaches have been utilised to do that, like cokriging (Hevesi et al,1992; D Philips et al, 1992) and kriging with external drift (Ahmed and de Marsily, 1987; Hudson and Wackernagel, 1994; Leblois and Desurosne, 1994 ; Gotway and Hartford,1996; Pardo-Igúsquiza, 1998). Both methods allow the direct introduction of the spatial correlation between the primary variable Z(x) and the auxiliaries variables $E_i(X)$ in the basic equations. The main difference between these two methods is that in cokriging, the external information is included as a random quantity and in kriging with external drift it is included in a deterministic way. Another alternative is the consideration of the external information in a previous step to the interpolation process itself like in detrended kriging (Ahmed and Marsily, 1987; Philips et al, 1992; Martinez-Cob,1996; C. Prudhomme and D. Read, 1999). It follows a concise description of some relevant aspects of these three methods:

Cokriging

In cokriging the estimate of $Z^*(\boldsymbol{x_0})$ is given by the expression:

$$Z^*(\boldsymbol{x_0}) = \Sigma\, i_{\,=1,..n}\, \lambda_i \,.\, Z(\boldsymbol{x_i}) + \Sigma\, j_{\,=1,..m}\, \eta_j \,.\, Y(\boldsymbol{x}_j).$$

Where $Y(\boldsymbol{x}_j)$.are the experimental values of the auxiliary variables. The weights λ_i and η_j are obtained as solutions of the cokriging system of equations that result of the best linear unbiased estimate:

1) $\Sigma_{\,j=1,..n}\, \lambda_j\,.\gamma_z(x_i, x_j). + \Sigma_{\,k=1,..n}\, \eta_k\,.\gamma_{zy}(x_i, x_k) + \mu_1 = \gamma_z\,(x_i, B(x_0)) \qquad i=1,2\ldots..n$

2) $\Sigma_{\,j=1,..n}\, \lambda_j\,.\gamma_{zy}(x_i, x_j). + \Sigma_{\,t=1,..n}\, \eta_k\,.\gamma_y(x_i, x_t) + \mu_2 = \gamma_{zy}\,(x_k, B(x_0)) \qquad k=1,2\ldots..m$

3) $\Sigma_{\,j=1,..n}\, \lambda_j = 1$

4) $\Sigma_{j=1,..,m} \eta_j = 0$

Where μ_1 and μ_2 are Lagrange multiplier, γ_z (h) is the variogram function of the primary variable (precipitation), γ_y (h) the variogram of the auxiliary variable and γ_{zy} (h) is the cross-variogram of both variables as obtained from the expression: 1/2.(E((Z($\boldsymbol{x}$ + h) – Z($\boldsymbol{x}$).(Y($\boldsymbol{x}$ + h) – Y($\boldsymbol{x}$)). The bar over the variogram indicate the mean variogram between the point x and a certain sub-domain B.

Cokriging expressions could be generalised to the case of "N" different auxiliary variables. In this case, cross-variograms between each pair of variables are defined as cross-products between differences of these variables for a pair of locations separated by a vector h. So, as apart from the variogram of the main variable, experimental variograms of the auxiliary variables and experimental cross-variograms have to be obtained and fitted in general by the use of a weighted least-squares algorithm technique to apply cokriging approach.

Cokriging becomes a highly complex alternative when more than one auxiliary variable is considered, but it have been demonstrated that it could be advantageous in comparison with other methods in rainfall interpolation, in case that the auxiliary variable were highly correlated with precipitation and also oversampled with respect to the primary variable (Vauclin,1983; Yates and Warnick,1987).

Kriging with external drift

In this type of geostatistical technique, the auxiliary variable enter the kriging system as a deterministic quantity (called external drift). If we suppose that the relationship between primary variable and auxiliary variable is lineal, the estimate of $Z^*(\boldsymbol{x_0})$ is given by the solution of the following set of equations (Ahmed and De Marsily,1987; Hudson and Wackernagel, 1994):

1)) $\Sigma_{j=1,..n} \lambda_j . \gamma_z(x_i, x_j). + \mu_1 + \mu_2 . y(x_i) = \gamma(x_i, B(x_0))$ i =1,2…..n

2) $\Sigma_{j=1,..n} \lambda_j . y(x_j) = y(x_0)$

3) $\Sigma_{j=1,..n} \lambda_j = 1$

For rainfall interpolation purposes this method needs a well established elevation-precipitation relationship. Nevertheless, over the cokriging this technique has the important advantage that it is not necessary to obtain the variograms of the altitude nor the cross-variograms altitude-precipitation.

Detrended-kriging.

The detrended kriging proceed in a different way that the previously quoted methods. In this case a multilinear regression is previously fitted between the primary variable Z(x) and the set of external variables Y_i(x):

$Z^*(x) = \Sigma a_i . Y_i(x)$

Where the true value of Z(x) is known, a residual error ε(x) can be defined.
$Z^*(x) = Z(x) + \varepsilon(x)$

In the second step of the application of detrended kriging, it is assumed that the new variable ε(x) follows the intrinsic hypothesis, having removed some of the variability of the primary variable that results from the effects of external variables. Then ε(x) is interpolated by a simple method like ordinary kriging and a map of ε*(x) is produced, representing the corrections to apply to the regression model. The final estimate is obtained by combination of the separate estimations of Z*(x) and ε*(x) over the kriging grid.

A well known method specifically devised for mapping pluviometric fields that makes use of statistical techniques to take into account compound local topography effects, is the AURELHY (Analysis Using the RELief for HYdrometeorology) method developed by METEO-FRANCE (Benichou. P and Le Breton. O, 1986, Benichou. P, 1987). The basic idea behind this sophisticated method, that basically fits to the detrended-kriging philosophy, is to include local topography in the interpolation scheme. It makes a regression against topography and then it applies a kriging approach to the residuals. To do that, the landscape surrounding each grid point is characterised by a 11x11 matrix of mean elevations surrounding the point. To condense all this information a Principal Component Analysis is carried out, with the principal components of relief as a result. Each site is then codified by a vector with 16 predictors, namely the first 15 components of the relative landscape around each site and the mean altitude of central point. The regression of the variable to spatialise is then made against these 16 predictors and the regression equations obtained are applied to any grid point of the domain of interest. The residuals are calculated at each point as the difference between restitution by regression and the measured value. These residuals are interpolated by a kriging method and then added to the values predicted by the regression process.

A slightly different approach is presented by Göbbel et al. (1998), basically consisting of the substitution of the rectangular local topography layout of AURELHY by a circular one divided into a central circle and several layers of surrounding ring sectors. This arrangement allows the reduction up to 32 in the number of local topographical variables without an important lost of information.

Another statistical topographic model for mapping climatic precipitation fields in areas of complex orography is the PRISM (Precipitation-elevation Regression on Independent Slopes Model) model (Daly et al, 1994). PRISM is oriented to the spatialisation of monthly and annual precipitation and basically fits to the following steps: 1) It uses a DEM to estimate the orographic elevations of precipitation stations; 2) it uses the DEM and a windowing technique to group stations onto individual topographic facets; 3) it estimates precipitation at a DEM grid cell through a regression of precipitation versus elevation developed for stations on the cell´s topographic facet and finally calculates when possible, a prediction interval for the estimate.

Multi-regressive analysis and Fuzzy techniques:

Conventional multi-regressive analysis has also been used in order to explicitly account for the influence of the terrain morphological components in climate variables mapping (Daly et al, 1994; D. Bertini and A. Crisci, 1998; B. Gozzini et al,2000). Due to the fact that the relationships between topography and meteorological variables are very complex and dependent on time scales issues, the Fuzzy sets theory provide a theoretical framework and a set of useful tools to deal with the use of imprecise information and it has been applied in interpolation of meteorological variables like minimum temperature (B. Gozzini et al., 2000). In Fuzzy techniques, a multivariate regression model is developed for each pixel of the grid by weighting the training points in accordance with their distance to this pixel. The weighting coefficient with respect to each training station is derived from a univariate density function of a Gaussian distribution (Wang,1990).

Dynamical methods

They employ a more physical approach and use meteorological variables as wind and wetness, as well as topographical description. The rationale behind that approach is solve the basic equations of the atmospheric movement and then obtaining regional precipitation with nested models with down-scaling techniques (order of magnitude: 20 km) plus the use of additional information such as the imagery of radar and satellites.

Methods of rainfall interpolation conditioned to "meteorological patterns".

It is well known the fact that the relationships between precipitation patterns and topographical features are highly dependent on the type of meteorological event we are considering. It is for example well established that in investigating the relationships between precipitation and topographical and geographical features, the direction of moisture advection plays a critical role (Houghton, 1979; Basist et al, 1994; C.H. Konrad,1996). On the other hand these relationship could also be affected by a marked seasonality. This dependence of the interpolation technique on the meteorological pattern is of particular importance in the case we have to deal with the spatialisation of the precipitation accumulated in short time periods (i.e daily precipitation).

To this respect, a methodology for spatial interpolation of meteorological variables (in particular air temperature) taking into account the effects of atmospheric circulation patterns has been proposed by D Courault and P. Monestiez, (1999). This approach was considered in the intercomparison of several interpolation methods of meteorological variables (minimum temperatures) carried out in the former Cost Action 79 (see Cost 79 report , edited by B. Gozzini and Sylvie Paniagua, 2000). In this type of approach a previous procedure of automatic classification of the circulation patterns, by the use of a set of predictors, has necessarily to be applied assigning each case to a particular class of days. For each predefined class, a relationship between the primary variable we want to spatialise and the considered set of external variables have to be established. This relationship could be entered in the interpolation scheme by the use of one of the methods previously quoted, like cokriging, detrended-kriging, …..etc.

Interpolation of daily precipitation: The use of remote sensing information to help in rainfall spatialisation..

As it has been already quoted in the introductory paragraphs, operational models in agrometeorology need in general precipitation values at daily (or even hourly) scale. But, most of the previously quoted methods of interpolation are mainly adapted to the analysis of statistical pluviometric fields like mean annual precipitation, mean monthly precipitation…etc, in zones where the spatial density of available data is large and the relationships precipitation-topography could be better established and explain a higher percentage of the variance than in the case of shorter time scales. So, the interpolation of daily precipitation appears as a very complex and challenging issue as it is conditioned both for the great spatial variability of precipitation fields at this time scale and for the fact that in most cases real-time precipitation networks of sufficient density and quality are simply unavailable.

To this respect, it has been mentioned (De Gaetano et al,1995; Xia,1999 ;Xia et al, 2001) the difficulty to give satisfactory results of some complex methods that work well when dealing with the estimation of annual and monthly weather variables, when applied to the interpolation of daily meteorological variables. On the other hand, the use of very sophisticated techniques that include topography like co-kriging are very time-expensive and as it was previously quoted, well-established relationships precipitation-topography at this time scale are not available unless we use a weather-conditioned pattern method. Concerning this subject, it has been shown (Duchon et al, 1995) that in the case of convective rain where spatial correlation of the precipitation field dampens rapidly with the distance relative to the area over which the average rainfall has to be determined, it is no obvious whether there would be significant improvement in area-average rainfall accuracy using the more sophisticated approaches.

Amongst the techniques that have been used to interpolate daily precipitation based in rain gauge measurements, it could be quoted (see Y. Xia et al, 2001) the following: a) Bussieres et Hogg (1989) used distance weighting schemes like Barnes interpolation, Cressman interpolation and Shepard interpolation; b) Wallis et al, (1991) used the closest station method for estimating precipitation daily precipitation, and c) a similar approach (more similar station) was used to interpolate precipitation in the CGMS system of JRC´s MARS project (Van Dieppen and Van Der Voet, 1998). Hutchinson (1998) has applied thin plate splines to interpolate daily precipitation in Switzerland and has discussed the different TPS models.

So, it seems that there is a limit in the accuracy we can achieve in daily rainfall estimation exclusively based in raingauge measurements and auxiliary information (topography, geographical features…etc). In order to achieve a more accurate estimate of precipitation fields for this short time scale different ways to introduce additional information should be explored. On one hand, the introduction of interpolation methods conditioned to weather patterns is a challenging approach, but it is necessary to have an automatic procedure of classification prior to the starting of the spatialisation process and so, the complexity of the process is very high to be used in real time. On the other hand the use of remote sensing data, particularly radar information to help in rainfall spatialisation offers a wide range of possibilities. It is out of the scope of this report to explore in depth the use of remote sensing information (radar and satellite) for rainfall estimation purposes, but it is worth for the purposes of this report to make a concise analysis of some particular aspects concerning the fusion of radar and raingauges measurements for a more accurate estimation of precipitation at short time-ranges.

The attempts to combine radar and raingauge measurements using a statistical approach may be roughly divided in three groups:

a) Deterministic methods that include deterministic interpolation of the gauge to radar ratio (Brandes, 1975) and calibration of the radar against raingauges (Wilson and Brandes, 1979; Zawadki,1975). A recent review of the currently employed methods for adjustment of radar rainfall estimates to rain gauge accumulations has been made in the framework of Cost 717 and it is available in P.P Alberoni et al (2001).

b) Geostatistical approaches, including kriging (Krajewsky, 1987), universal kriging (Seo et al, 1990) and cokriging. Cokriging has been the most employed geostatistical technique to get radar data into precipitation spatialisation schemes. Cokriging offers the possibility of consider the statistical properties of the gauges, the radar and the dependence of each of the sensors on the rest of them, but the basic hypothesis of second-order stationarity and ergodicity must be assumed (Journel and Huijbregts, 1978; Huffman et al, 1995) and the modelling of the spatial dependence of each sensor on itself and on each other is required.

c) An alternative approach for rainfall fusion based on the use of a feed-forward neural network has been applied (C. Matsoukas et al, 1999). The main ideas behind this last approach are the following: at the grid points where raingauges are available, it regards the gauge values as the truth, whereas at the grid points where no raingauge is present, the algorithm takes the spatial information of the radar and it applies it so that the estimated rainfall field resembles qualitatively the radar field and at the same time, the transition from grid points controlled by radar to the grid points controlled by gauges is smooth. A comparison between cokriging and neural network techniques for hourly rainfall estimation making use of radar and rain gauge data has been presented by C. Matsoukas et al, 1999. The results show that neural network approach could reach comparable results in terms of global statistics metrics as those obtained with the more familiar cokriging. The artificial neural network approach has also been used to estimate rainfall rates using jointly satellite imagery and ground-based rainfall measurements (Kou-Lin Hsu et al, 1997).

3. *BRIEF REVIEW OF INTERCOMPARISON STUDIES OF THE DIFFERENT METHODS FOR RAINFALL SPATIALISATION.*

Most intercomparison studies of the different methods of rainfall spatialisation are referred to the variable annual average precipitation. At this respect, thorough reviews of the various approaches applied to precipitation data are available (Creutin and Obled,1982; Tabios y Salas ,1985). Tabios and Salas, compared several methods for estimating annual average precipitation and concluded that geostatistical techniques, including ordinary kriging and universal kriging, were superior to the simple deterministic methods like Thiessen polygon, polynomial trend surfaces and inverse-distance weighting methods. To take profit of the advantages of geostatistical techniques, a sufficient sample size and spatial distribution of the data for defining a representative model is needed. Similar results were obtained for Linsley et al (1975) that found that kriging and optimal interpolation were superior to commonly used techniques at that time like Thiessen and polynomial, interpolation by least squares.

More recently, some intercomparison studies of different geostatistical methods for rainfall interpolation (annual precipitation) have been carried out: D. Philips et al (1992) compared the accuracy of precipitation estimates by kriging, detrended kriging and cokriging in a mountainous area and found that both detrended kriging and cokriging showed considerable average reductions in estimation variance compared with ordinary kriging of 38% and 28% respectively. Similar reduction in estimation variance for detrended kriging of precipitation was found by Dingman et al (1988). The precipitation estimates by kriging and detrended kriging in the above quoted studies showed a smoother pattern as compared with the estimates by the cokriging method. In this last case the precipitation pattern was much more broken and less smooth. Hevesi et al, (1992) also compared by cross-validation the performance of cokriging and kriging with some other methods like log-linear and linear regression with elevation, neighborhood average, inverse distance, inverse-squared distance and inverse-cubed distance for annual mean precipitation in areas of complex topography. The cokriging provided the best cross-correlation results (in terms of RMSE) relative to regression methods that used only elevation data, and kriging provided the best results compared with more simple deterministic methods that do not take into account the spatial correlation model for estimating precipitation. E. Pardo-Igúsquiza (1998) made a similar comparison of different geostatistical methods for estimating areal average climatological precipitation on a river basin in the south of Spain, and found that kriging with external drift seemed to give the most coherent results in terms of cross-validation statistics compared with to cokriging and ordinary kriging, in spite of cokriging has more requirements that kriging with external drift. C. Daly et al (1994) made a comparison between PRISM and different geostatistical techniques like kriging, detrended kriging and cokriging in the Willamette River basin, Oregon, using average annual precipitation. The statistics obtained from cross-validation indicated the best results for the PRISM method, and secondly for detrended kriging.

Moving to shorter time scales, some results from intercomparison of interpolation methods for extreme daily rainfall parameters in mountainous areas are also available. To this respect C. Prudhomme and D. Reed (1998) showed that detrended kriging produced more adequate and realistic estimates of the median than ordinary kriging for the annual maximum daily precipitation. The study was made in the mountainous region of Scotland. M. Slimani and Obled (1986) compared several techniques as cokriging, kriging, kriging with sampling variance and splines for regionalisation and mapping of some extreme rainfall parameters (10 and 100 years return of daily rainfall) and found more scientifically based the map that is obtained trough kriging with station uncertainties taken into account. Particularly attractive were considered the maps obtained from cokriging, but the fact that relies on rather strong hypothesis was also remarked.

Studies concerning the performance of different methods of interpolation of daily precipitation are very scarce. In the case of daily area-average estimation, it could be quoted the study of Singh and Chowdhury (1986) . They found that among 13 methods of estimating daily area-mean rainfall, with different complexity levels, but none of them making explicitly use of the spatial correlation structure of the rain field, there was no particular reason for selecting one method or another. In Xia et al, 2001, a review on this topic is available, as well as the results of an intercomparison of the accuracy of several interpolation methods for daily meteorological data estimation. In the case of daily precipitation, amongst the different deterministic methods used the most accurate estimations were obtained trough thin plate splines as compared with Barnes, Cressman, Shepard and closest station methods.

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