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Estimation of high resolution meteorological fields based on geostatistical approaches

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Abstract:

The meteorological data is a key input for any hydrological model because it mainly determines the volume of runoff in a ca

Climatological data are usually measured at point locations, while it is necessary to know these values everywhere; theref

The objective of this study is to develop interpolation methods for estimation of high resolution meteorological fields, whi

The first focus is to present two methods of interpolation, the **M**odified **U**niversal **K**riging (**MUK**) for interpolation of temperature, so called "**KLAM**" (**K**riging with **L**ocal **A**nisotropy **M**odel) method used for interpolation of precipitation, and the second is to show the results of cross-validation and sensibility-analysis of interpolation.

Keywords: *Distributed hydrological modelling, interpolation, variogram model fitting, uncertainty estimation of interpolation, global optimization.*

Kriging overview

The most promising stochastic tool may be the variogram analysis and Kriging (Cressie, 1985). Kriging is called the best linear unbiased estimator, because it provides linear regression estimate, which is unbiased and has minimum error variance. In general, the basic mathematical models are:

1. No trend in the data: Ordinary kriging (**OK**) is used for spatial prediction:

$$Z(\mathrm{s}) = \delta(\mathrm{s}) \tag{1}$$

1. <u>Trend in the data</u>: Universal kriging (**UK**) is used supposing that the trend is linear:

$$Z(\mathrm{s}) = \alpha_0 + \alpha_1 x(\mathrm{s}) + \alpha_2 y(\mathrm{s}) + \delta(\mathrm{s}) \tag{2}$$

where: **s** – is the location,

Z(**s**) – is a random variable at location **s**,

α_i– are coefficients of the linear trend (i= 0,1,2),

x(**s**), y(**s**) – are the coordinates of the location **s**,

δ(**s**) – is random process with existing semi-variogram γ(**h**),

and here **h** is a distance vector.

According to the kriging theory (Cressie, 1985), an estimated value Z*(**s**$_0$) can be expressed as a linear combination of the measured values on "n" locations:

$$Z^*(\mathrm{s}_0) = \sum_{i=1}^{n} \lambda_i Z(\mathrm{s}_i) \tag{3}$$

where the unknown λ_i (i=1,2,. . .,n) are constrained by: $\sum_{i=1}^{n} \lambda_i = 1$, which means that the expected value of the error of estimation $(E[Z^*(\mathrm{s}_0) - Z(\mathrm{s}_0)])$ is zero. Under second-order stationary, the estimation variance for spatial prediction using weighted average of the neighbouring precipitation data:

$$\sigma_E^2(\mathrm{s}_0) = E\left\{[Z^*(\mathrm{s}_0) - Z(\mathrm{s}_0)]^2\right\} = \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i\lambda_j\gamma(\mathrm{s}_i - \mathrm{s}_j) - 2\sum_{i=1}^{n} \lambda_i\gamma(\mathrm{s}_0 - \mathrm{s}_j) \tag{4}$$

Hence, determine the vector of weights λ in equation (**??**) leads to the following mathematical programming problem:

$\min\limits_{g(\lambda)=0} \sigma_E^2(\mathrm{x}_0)$, where $g(\lambda) := \sum_{i=1}^{n} \lambda_i - 1$ (5)

The solution of problem (5) can be find in Cressie (1985).

Draft description of interpolation method for mapping temperature data

In general, ordinary kriging is used for spatial prediction when there is no trend in the data. When there is a trend in the data, we use universal kriging (**UK**). Because the air temperature is rather correlated with the elevation than with the location of points, it was necessary to modify the basic equation of **UK** (**??**) as:

$$T\left(\mathrm{s}\right) = \beta A\left(\mathrm{s}\right) + \delta\left(\mathrm{s}\right) \tag{5}$$

where: **s** – is the location,

T(**s**) – is the estimated temperature,

A(**s**) – is the altitude at location **s**,

β – is the coefficient of A(**s**)

δ(**s**) – is a random process with existing variogram.

In order to use the experimental semi-variogram information in kriging it is necessary to model the experimental semi-variogram (see equation 4). Tree theoretical semi-variogram models were tested: exponential, Gaussian, and spherical. Following many several tests, the spherical semi-variogram model was chosen (supposing that no nugget effect, in other words, the measurement error/variability is negligible or equal to zero):

$$\begin{cases} \gamma(h) = c \cdot \left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] \; h \leq a \\ \gamma(h) = c \; h > a \end{cases} \tag{6}$$

where: a- is the spherical model range.

c- is the spatial variance (sill value when $h = a$);

This approach of interpolation can give more fine detailed texture of interpolated temperature than many other methods. In actual practice, uses of this method can be particularly significant in case of estimate accumulation and melting of snow.

The above mentioned interpolation technique was programmed on FORTRAN language with GINO graphics development tool, using OPENGL API, and also was developed a user-friendly graphical program-system for interpolating temperature data in automatic way on large-scale and long term.

Draft description of interpolation method for mapping precipitation data

Interpolation of precipitation is more complicated than for example interpolating temperature or other parameters, because the precipitation is strongly anisotropic process, although sometimes it isn't detectable in a "small" scale. However, real spatial phenomena often show complicated, non-linear spatial structures. Measurements along a particular non-linear spatial path may be highly correlated in dynamic process application, while the other direction shows a little or no correlation. Such processes are called anisotropic.

Themainpurposesofourworkweretodevelopaninterpolationtechniqueandsoftwarewhichcandescribethisabovement

The most full of promise tool for studying spatial variability may be the variogram since it can be used in the kriging process to estimate values of the precipitation at an unsampled location in the field. Several researchers have studied the spatial variability of precipitation, for instance M. Amani and T. Lebel (Amani, Lebel, 1997), E. Todini (Todini, 2001), etc. But these – and many other – studies are doesn't touch the topic of "nonlinear anisotropic" whereas it is very important.

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Summarily,ournewmodelisbasedoncombinationof"OrdinaryKriging"(seeequation1)takingsphericalexperimental

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The above outlined **KLAM** interpolation technique was programmed on FORTRAN language with GINO graphics development tool, using OPENGL API, and also was developed a user-friendly graphical program-system for interpolating precipitation data in automatic way on large-scale and long term.

Cross-validation and sensibility-analysis of interpolation

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Summary

- A new algorithm for interpolation high resolution precipitation fields has been developed. An approved geostatistic method also was applied in the case of temperature.
- The main advantage of using these methods is that they allow the estimation of uncertainty of interpolated fields.
- It has been proved statistically that applying these methods the uncertainty is consequently smaller comparing to other popular methods.
- Giving possibility to analyze influence of calculated uncertainty on river runoff.

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