What is MuDRain (Multivariate disaggregation of rainfall)?[#] [$] [K]

MuDRain is a methodology for spatial-temporal **disaggregation** of rainfall. It involves the combination of several univariate and multivariate rainfall **models** operating at different time scales in a disaggregation framework that can appropriately modify outputs of finer time scale models so as to become consistent with given coarser time scale series.

Potential hydrologic applications include **enhancement of historical data series** and **generation of simulated data series**. Specifically, the methodology can be applied to derive spatially consistent hourly rainfall series in raingages where only daily data are available. In addition, in a simulation framework, the methodology provides a way to take simulations of multivariate daily rainfall (incorporating spatial and temporal non-stationarity) and generate multivariate fields at fine temporal resolution.

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Why disaggregation? # $ K

A common problem in **hydrological studies** is the **limited availability** of data at appropriately fine temporal and/or spatial resolution. In addition, in hydrologic simulation studies a model may provide as output a synthetic series of a process (such as rainfall and runoff) at a coarse scale while another model may require as input a series of the same process at a finer scale. Disaggregation techniques therefore have considerable appeal due to their **ability to increase the time or space resolution** of hydrologic processes while simultaneously providing a multiple scale **preservation of the stochastic structure** of hydrologic processes.

Why_disaggregation

$ Why disaggregation?

K Disaggregation, usefulness

Why multivariate disaggregation? [#] [$] [K]

The multivariate approach to rainfall disaggregation is of significant practical interest even in problems that are traditionally regarded as univariate. Let us consider, for instance, the disaggregation of historical daily raingage data into hourly rainfall. This is a common situation since detailed hydrological models often require inputs at the hourly time scale. However, historical hourly records are not as widely available as daily records. An appropriate univariate disaggregation model would generate a synthetic hourly series, fully consistent with the known daily series and, simultaneously, **statistically consistent** with the actual hourly rainfall series. Obviously, however, a synthetic series obtained by such a disaggregation model could not coincide with the actual one, but would be a likely realization. Now, let us assume that there exist hourly rainfall data at a neighboring raingage. If this is the case and, in addition, the cross-correlation among the two raingages is significant (a case met very frequently in practice), then we could utilize the available hourly rainfall information at the neighboring station to generate **spatially and temporally consistent** hourly rainfall series at the raingage of interest. In other words, the spatial correlation is turned to advantage since, in combination with the available single-site hourly rainfall information, it enables more realistic generation of the synthesized hyetographs. Thus, for example, the location of a rainfall event within a day and the maximum intensity would not be arbitrary, as in the case of univariate disaggregation, but resemble their actual values.

[#] Why_multivariate_disaggregation
[$] Why multivariate disaggregation?
[K] Disaggregation;multivariate, usefulness

Problem formulation # $ K

CASE 1

We assume that we are given:

1. an hourly point rainfall series at point 1, as a result of either:
   - measurement by an autographic device (pluviograph) or digital sensor
   - simulation with a fine time scale point rainfall model such as a point process model,
   - simulation with a temporal point rainfall disaggregation model applied to a series of known daily rainfall (e.g. using Hyetos, a computer program for temporal rainfall disaggregation using adjusting procedures);
2. several daily point rainfall series at neighboring points 2, 3, 4, 5, … as a result of either:
   - measurement by conventional raingages (pluviometers with daily observations), or
   - simulation with a multivariate daily rainfall model.

We wish to produce series of hourly rainfall at points 2, 3, 4, 5, …, so that:

1. their daily totals equal the given daily values; and
2. their stochastic structure resembles that implied by the available historical data.

We emphasize that in this problem formulation we always have an hourly rainfall series at one location, which guides the generation of hourly rainfall series at other locations. If this hourly series is not available from measurements, it can be generated using appropriate univariate simulation **models**

The essential statistics that we wish to **preserve** in the generated hourly series are:

1. the means, variances and coefficients of skewness;
2. the temporal correlation structure (autocorrelations);
3. the spatial correlation structure (lag zero cross-correlations); and
4. the proportions of dry intervals.

If the hourly data set at location 1 is available from measurement, then all these statistics apart from the cross-correlation coefficients can be estimated at the hourly time scale using this hourly record. To transfer these parameters to other locations, spatial stationarity of the

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Problem_formulation

$ Problem formulation

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process can be assumed. The stationarity hypothesis may seem an oversimplification at first glance. However, it is not a problem in practice since possible spatial nonstationarities manifest themselves in the available daily series; thus the final hourly series, which are forced to respect the observed daily totals, will reflect these nonstationarities.

CASE 2

If hourly rainfall is available at several (more than one) locations, the same modeling strategy described below can be used without any difficulty with some generalizations of the computational algorithm. In fact, having more than one point with known hourly information would be advantageous for two reasons. First, it allows a more accurate estimation of the spatial correlation of hourly rainfall depths (see discussion below) or their transformations. Second, it might reduce the residual variance of the rainfall process at each site, thus allowing for generated hyetographs closer to the real ones.

If more than one rainfall series are available at the hourly level, at least one cross-correlation coefficient of hourly rainfall can be estimated directly from these series. Then, by making plausible assumptions about the spatial dependence of the rainfall field an expression of the relationship between cross-correlation could be established (see **Estimation of crosscorrelation coefficients**.)

Modeling approach [#] [$] [K]

Models involved

a. Models for the generation of multivariate fine-scale outputs. The first category includes two models that provide the required output (the hourly series).

The first model is a **the simplified multivariate rainfall model**of hourly rainfall that can preserve the statistics of the multivariate rainfall process and, simultaneously, incorporate the available hourly information at site 1, without any reference to the known daily totals at the other sites. **The statistics** considered here are the means, variances and coefficients of skewness, the lag-one autocorrelation coefficients and the lag-zero cross-correlation coefficients. All these represent statistical moments of the multivariate process. The **proportion of dry intervals**, although considered as one of the parameters to be preserved, is difficult to incorporate explicitly. However, it can be treated by an indirect manner .

The second model is a **transformation model** that modifies the series generated by the first model, so that the daily totals are equal to the given ones. This uses a (multivariate) transformation, which does not affect the stochastic properties of the series.

b. Models associated with inputs to a. above. The second category contains models which may optionally be used to provide the required input, should no observed series be available. These may include

- a multivariate daily rainfall model for providing daily rainfall depths, such as the general linear model (GLM) [*Chandler and Wheater*, 1998a, b];
- a single-site model for providing hourly depths at one location such as the Bartlett-Lewis rectangular pulses model [*Rodriguez-Iturbe et al.*, 1987, 1988; *Onof and Wheater*, 1993, 1994];
- a single-site disaggregation model to disaggregate daily depths of one location into hourly depths [e.g. *Koutsoyiannis and Onof*, 2000, 2001].

Such models may be appropriate to operate the proposed disaggregation approach for future climate scenarios.

[#] Modeling_approach
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Estimation of cross-correlation coefficients [#] [$] [K]

We assume that we are given:

1. several hourly point rainfall series at points 1,2,3 as a result of measurement by an autographic device (pluviograph) or digital sensor,
2. several daily point rainfall series at neighboring points 4, 5, 6, 7,8 … as a result of measurement by conventional raingages (pluviometers with daily observations)

We are able to estimate the cross-correlation coefficients between the raingages 1,2,3 at the hourly time scale and those between 1,2,…,8 at the daily time scale.

We need to estimate the cross-correlation coefficients between all raingages at the hourly time scale.

For this purpose we use the empirical relationship: $r_{ij}^{\mathrm{h}} = \left(r_{ij}^{\mathrm{d}}\right)^m$

where:

r_{ij}^{h} is the cross-correlation coefficient between raingages *i* and *j* at the hourly time scale

r_{ij}^{d} is the cross-correlation coefficient between raingages *i* and *j* at the daily time scale

m is an exponent that can be estimated by regression using the known cross-correlation coefficients at the hourly and daily time scale or, in case no hourly data is available, its value can be assumed approximately in the range 2 to 3.(*Fytilas P*. 2002)

[#] Estimation_of_crosscorrelation_coefficients
[$] Estimation of cross-correlation coefficients
[K] Estimation of cross-correlation coefficients

The simplified multivariate rainfall model [#] [$] [K]

For *n* locations, we may assume that **the simplified multivariate rainfall model** is an AR(1) process, expressed by

$$\mathbf{X}_s = \mathbf{a}\,\mathbf{X}_{s-1} + \mathbf{b}\,\mathbf{V}_s \qquad (1)$$

where $\mathbf{X}_s := \left[X_s^1, X_s^2, ..., X_s^n\right]^T$ represents the hourly rainfall at time (hour) *s* at *n* locations, **a** and **b** are ($n \times n$) matrices of parameters and $\mathbf{V}_s$ (*s* = …, 0, 1, 2, …) is an independent identically distributed (iid) sequence of size *n* vectors of innovation random variables (so that the innovations are both spatially and temporally independent). The time index *s* can take any integer value. $\mathbf{X}_s$ are not necessarily standardized to have zero mean and unit standard deviation, and obviously they are not normally distributed. On the contrary, their distributions are very skewed. The distributions of $\mathbf{V}_s$ are assumed three-parameter Gamma.

Equations to estimate the model parameters **a** and **b** and the moments of $\mathbf{V}_s$ directly from the statistics to be preserved are given for instance by *Koutsoyiannis* [1999] for the most general case. In the special case examined here, for convenience, the parameter matrix **a** is assumed diagonal, which suffices to preserve the essential statistics, and is given by:

$$a = diag\left(Cov\left[X_s^l, X_{s-1}^l\right] / Var\left[X_{s-1}^l\right]\right), \; l = 1,....,n \qquad (2)$$

The parameter matrix **b** is determined from

$$b \cdot b^T = Cov\left[X_s, X_s\right] - a_s \cdot Cov\left[X_{s-1}, X_{s-1}\right] a_s \qquad (3)$$

If **b** is assumed lower triangular, which facilitates handling of the known hourly rainfall at site 1, then it can be determined from $\mathbf{b}\,\mathbf{b}^T$ using Cholesky decomposition.

Another group of model parameters are the moments of the auxiliary variables $\mathbf{V}_s$. The first moments (means) are obtained by

$$E\left[V_s\right] = b^{-1}\left(I - a\right) \cdot E\left[X_s\right] \qquad (4)$$

where **I** is the identity matrix. The variances are by definition 1, i.e., Var[$\mathbf{V}_s$] = $[1, \ldots, 1]^T$ and the third moments are obtained in terms of $\mu_3[\mathbf{X}_s]$, the third moments of $\mathbf{X}_s$, by

$$\mu_3\left[V_s\right] = \left(b^{(3)}\right)^{-1}\left(I - a^{(3)}\right) \cdot \mu_3\left[X_s\right] \qquad (5)$$

where $\mathbf{a}^{(3)}$ and $\mathbf{b}^{(3)}$ denote the matrices whose elements are the cubes of **a** and **b**, respectively At the generation phase, V_s^1, the first component of $\mathbf{V}_s$, is calculated from the series of X_s^1 rather than generated. Given that **b** is lower triangular, its first row will have only one nonzero item, call it b^1, so that from (1)

[#] The_simplified_multivariate_rainfall_model

[$] The simplified multivariate rainfall model

[K] The simplified multivariate rainfall model

$$X_s^1 = a^1 X_{s-1}^1 + b^1 V_s^1 \quad (6)$$

which can be utilized to determine V_s^1 This can be directly expanded to the case where several gages of hourly information are available provided that **b** is lower triangular.

Alternatively, the model can be expressed in terms of some nonlinear transformations X_s^* of the hourly depths $\mathbf{X}_s$ (see **Specific difficulties**), in which case (1) is replaced by

$$X_s^* = aX_{s-1}^* + bV_s \quad (7)$$

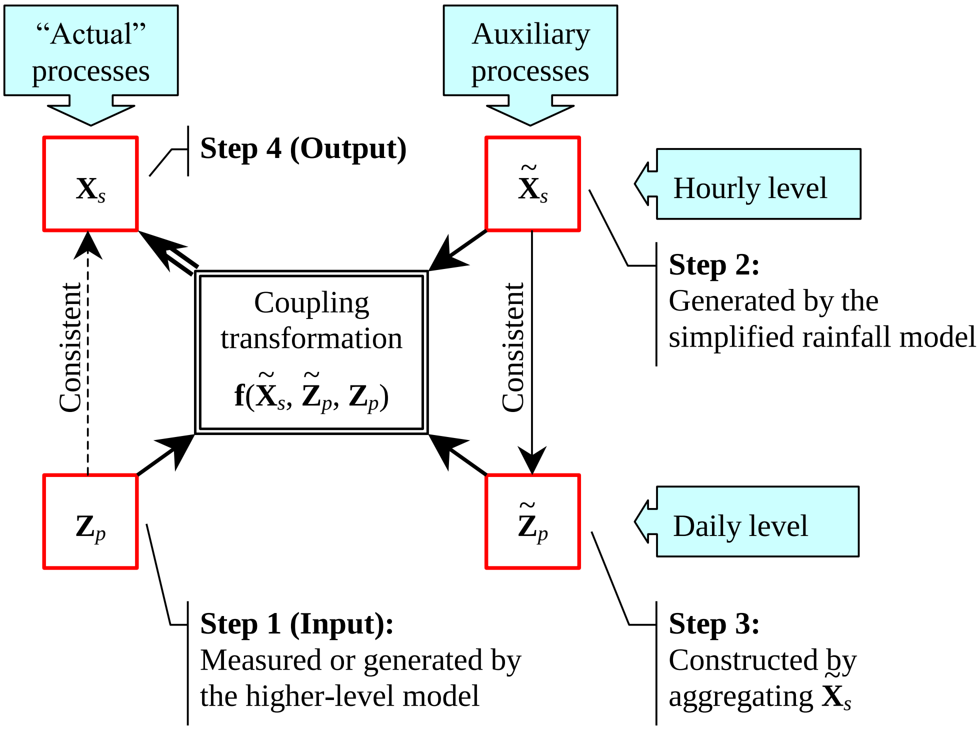
The transformation model # $ K

Transformations that can modify a series generated by any stochastic process to satisfy some additive property (i.e. the sum of the values of a number of consecutive variables be equal to a given amount), without affecting the first and second order properties of the process, have been studied previously by *Koutsoyiannis* [1994] and *Koutsoyiannis and Manetas* [1996]. These transformations, more commonly known as **adjusting procedures**, are appropriate for univariate problems, although they can be applied to multivariate problems as well, but in a repetition framework. More recently, *Koutsoyiannis* [2001] has studied a true multivariate transformation of this type and also proposed a generalized framework for coupling stochastic models at different time scales.

This framework, specialized for the problem examined here, is depicted in the following **schematic representation** where $\mathbf{X}_s$ and $\mathbf{Z}_p$ represent the "actual" hourly- and daily-level processes, related by

$$\sum_{s=(p-1)k}^{pk} X_s = Z_p \quad (8)$$

where k is the number of fine-scale time steps within each coarse-scale time step (24 for the current application), $\tilde{X}_s$ and $\tilde{Z}_p$ denote some auxiliary processes, represented by the simplified rainfall model in our case, which also satisfy a relationship identical to (8).



\# The_transformation_model

$ The transformation model

K Coupling transformation ;adjusting procedures

<u>The problem is</u>: Given a time series $\mathbf{z}_p$ of the actual process $\mathbf{Z}_p$, generate a series $\mathbf{x}_s$ of the actual process $\mathbf{X}_s$. To this aim, we first generate another (auxiliary) time series $\tilde{x}_s$ using the simplified rainfall process $\tilde{X}_s$. The latter time series is generated independently of $\mathbf{z}_p$ and, therefore, $\tilde{x}_s$ do not add up to the corresponding $\mathbf{z}_p$, as required by the additive property (8), but to some other quantities, denoted as $\tilde{z}_p$. Thus, in a subsequent step, we modify the series $\tilde{x}_s$ thus producing the series $\mathbf{x}_s$ consistent with $\mathbf{z}_p$ (in the sense that $\mathbf{x}_s$ and $\mathbf{z}_p$ obey $\sum_{s=(p-1)k}^{pk} X_s = Z_p$ (8)) without affecting the stochastic structure of $\tilde{x}_s$. For this modification we use a so-called coupling transformation, i.e., a linear transformation, $\mathbf{f(}\tilde{X}_s\mathbf{,}\ \tilde{Z}_p\mathbf{,}\ \mathbf{Z}_p)$ whose outcome is a process identical to $\mathbf{X}_s$ and consistent to $\mathbf{Z}_p$.

Let $X_p^* = \left[X_{(p-1)k+1}^T, ..., X_{pk}^T\right]^T$ be the vector containing the hourly values of the 24 hours of any day p for all examined locations (i.e., the 24 vectors $\mathbf{X}_s$ for s = (p – 1)k + 1 to s = pk; for 5 locations, X_p^* contains 24 × 5 = 120 variables). Let also $Z_p^* = \left[Z_p^T, Z_{p+1}^T, X_{(p-1)k}^T\right]^T$ be a vector containing

(a) the daily values $\mathbf{Z}_p$ for all examined locations,

(b) the daily values $\mathbf{Z}_{p+1}$ of the next day for all locations, and

(c) the hourly values $\mathbf{X}_{(p-1)k}$ of the last hour of the previous day p – 1 for all locations.

This means that for 5 locations Z_p^* contains 3 × 5 = 15 variables in total. Items (b) and (c) of the vector Z_p^* were included to assure that the transformation will preserve not only the covariance properties among the hourly values of each day, but the covariances with the previous and next days as well. Note that at the stage of the generation at day p the hourly values of day p – 1 are known (therefore, in Z_p^* we enter hourly values of the previous day) but the hourly values of day p + 1 are not known (therefore, in Z_p^* we enter daily values of the next day, which are known). In an identical manner, we construct the vectors $\tilde{X}_p^*$ and $\tilde{Z}_p^*$ from variables $\tilde{X}_s$ and $\tilde{Z}_p$.

<u>*Koutsoyiannis* [2001]</u> showed that the coupling transformation sought is given by

$$X_p^* = \tilde{X}_p^* + h\left(Z_p^* - \tilde{Z}_p^*\right) \quad (9)$$

where

$$h = Cov\left[X_p^*, Z_p^*\right]\left\{Cov\left[Z_p^*, Z_p^*\right]\right\}^{-1} \quad (10)$$

The quantity $h\left(Z_p^* - \tilde{Z}_p^*\right)$ in (9) represents the correction applied to $\tilde{X}$ to obtain $\mathbf{X}$. Whatever the value of this correction is, the coupling transformation will ensure preservation of first and second order properties of variables (means and variance-covariance matrix) and linear relationships among them (in our case the additive property $\sum_{s=(p-1)k}^{pk} X_s = Z_p$). However, it is desirable to have this correction as small as possible in order for the transformation not to affect seriously other properties of the simulated processes (e.g., the skewness). It is possible to make the correction small enough, if we keep repeating the generation process for the variables of each period (rather than performing a single generation only) until a measure of the correction becomes lower that an accepted limit. This measure can be defined as

$$\Delta = \left\| h\left(Z_p^* - \tilde{Z}_p^*\right) \right\| / \left(m\sigma_x\right) \qquad (11)$$

where *m* is the common size of X_p^* and $\tilde{X}_p^*$, σ_x is standard deviation of hourly depth (common for all locations due to stationarity assumption) and **||.||** denotes the Euclidian norm..

Given the daily process $\mathbf{Z}_p$ and the matrix **h**, which determines completely the transformation, the steps followed to generate the hourly process $\mathbf{X}_s$ are the following:

1. Use the simplified rainfall model (1) or (8) to produce a series $\tilde{X}_s$ for all hours of the current day *p* and the next day *p* + 1, without reference to $\mathbf{Z}_p$.

2. At day *p* evaluate the vectors Z_p^* and $\tilde{Z}_p^*$ using the values of $\mathbf{Z}_p$ and $\tilde{X}_s$ of the current and next day, and $\mathbf{X}_s$ of the previous day.

3. Determine the quantity $h\left(Z_p^* - \tilde{Z}_p^*\right)$ and the measure of correction Δ. If Δ is greater than an accepted limit Δ_m, repeat steps 1-3 (provided that the number of repetitions up to the current repetition has not exceeded a maximum allowed number r_m, which is set to avoid unending loops).

4.Apply the coupling transformation to derive X_p^* of the current period.

5.Repeat steps 1 and 4 for all periods.

Specific difficulties [#] [$] [K]

Here we describe how to handle the peculiarities of the rainfall process at a fine time scale in the multivariate modeling scheme.

Negative values. The negative values, unavoidably generated by any linear stochastic model when the coefficient of variation is high (possibly in a high proportion but with low values), are not a major problem in our case. They are simply truncated to zero, thus having a beneficial effect in preserving the proportion of dry intervals (as also shown in next paragraph). A negative effect is the fact that truncation may be a potential source of bias to statistical properties that are to be preserved. Specifically, it is anticipated to result in overprediction of cross-correlations, as it is very probable that negative values are contemporary.

Dry intervals. As already mentioned, the proportion of dry intervals cannot be preserved by linear stochastic models in an explicit manner. However, after rounding off the generated values, a significant number of zero values emerges, which is added to the significant number of zero values resulting from the truncation of negative values. The total percentage of zero values resulting this way can be comparable to (usually somewhat smaller than) the historical probability dry. It was demonstrated that we can match exactly the historical probability dry by slightly modifying the rounding-off rule. For the multivariate case, the following technique was found effective: A proportion $\boldsymbol{\pi_0}$ of the very small positive values, chosen at random among the generated values that are smaller than a threshold $\boldsymbol{l_0}$ (e.g., 0.1-0.3 mm), are set to zero.

An alternative technique, based on a two-state (wet-dry) representation of hourly rainfall within a rainy day, can be also used. According to this technique, at periods when the known hourly time series indicates dry condition (zero depth) the unknown hourly time series are stimulated, with a specified probability $\boldsymbol{\varphi_0}$, to take zero depth as well.

Preservation of skewness. Although the coupling transformation preserves the first and second order statistics of the processes, it does not ensure the preservation of third order statistics. Thus, it is anticipated that it will result in underprediction of skewness. However, the repetition technique (see **transformation model**) can result in good approximation of skewness.

Homoscedasticity of innovations. By definition, the innovations $\mathbf{V}_s$ in the simplified multivariate rainfall model (see **the simplified multivariate rainfall model**) are homoscedastic, in the sense that their variances are constant, independent of the values of rainfall depths $\mathbf{X}_s$. Therefore, if, for instance, we estimate (or generate) the value at location 2, given that at location 1, we assume that the conditional variance is constant and independent of the value at location 1. This, however, does not comply with reality: by examining simultaneous hyetographs at two locations we can observe that the variance is larger during the periods of high rainfall (peaks) and smaller in periods of low rainfall (heteroscedasticity).

[#] Specific_difficulties

[$] Specific difficulties

[K] dry intervals; negative values; homoscedasticity; skewness

As a result of this inconsistency, synthesized hyetographs will tend to have unrealistically similar peaks. To mitigate this problem we can apply a nonlinear transformation to rainfall depths

The first candidate nonlinear transformation is the logarithmic one,

$$X_s^* = \ln(X_s + \zeta) \qquad (12)$$

with constants $\boldsymbol{\zeta} > \mathbf{0}$, where the logarithmic transformation should be read as an item to item one. The stationarity assumption allows considering all items of vector $\boldsymbol{\zeta}$ equal to a constant ζ. This transformation would be an appropriate selection if ζ was estimated so that the transformed series of known hourly depths have zero skewness, in which case the transformed variables could be assumed to be normally distributed. Then, preservation of first and second order properties of the untransformed variables is equivalent to preservation of first- and second-order statistics of the transformed variables [*Koutsoyiannis*, 2001]. However, evidence from the examined data sets shows that the skewness of the transformed variables increases with increasing ζ and it still remains positive even if very small ζ are chosen. This means that the lognormal assumption is not appropriate for hourly rainfall.

A second candidate is the power transformation

$$X_s^* = X_s^{(m)} \qquad (13)$$

where the symbol (*m*) means that all items of the vector $\mathbf{X}_s$ are raised to the power *m* (item to item) where $0 < m < 1$. The stationarity assumption complies with the assumption that *m* is the same for all items. The preservation of the statistics of the untransformed variables does not necessarily lead to the preservation of the corresponding statistics of the transformed variables. However, the discrepancies are expected to be low if *m* is not too low (e.g., for $m \geq 0.5$).

References[#$K]

***Chandler, R. and H. Wheater**,* Climate change detection using Generalized Linear Models for rainfall, A case study from the West of Ireland, I, Preliminary analysis and modelling of rainfall occurrence, Technical report, no. 194, Department of Statistical Science, University College London, 1998a (http://www.ucl.ac.uk/Stats/research/abstracts.html)

Chandler, R. and H. Wheater, Climate change detection using Generalized Linear Models for rainfall, A case study from the West of Ireland, II, Modelling of rainfall amounts on wet days, Technical report, no. 195, Department of Statistical Science, University College London, 1998b (http://www.ucl.ac.uk/Stats/research/abstracts.html)

***Fytilas P*.**, Multivariate rainfall disaggregation at a fine time scale 2002,diploma thesis submitted at the *University of Rome "La Sapienza"*)

***Koutsoyiannis, D*.**, A nonlinear disaggregation method with a reduced parameter set for simulation of hydrologic series, *Water Resources Research*, 28(12), 3175-3191, 1992.

***Koutsoyiannis, D*.**, A stochastic disaggregation method for design storm and flood synthesis, *J. of Hydrol.*, 156, 193-225, 1994.

***Koutsoyiannis, D*.**, Optimal decomposition of covariance matrices for multivariate stochastic models in hydrology, *Water Resour. Res.*, 35(4), 1219-1229, 1999.

***Koutsoyiannis, D*.**, Coupling stochastic models of different time scales, *Water Resour. Res.*, 37(2), 379-392, 2001.

***Koutsoyiannis, D*., and E. *Foufoula-Georgiou*,** A scaling model of storm hyetograph, *Water Resour. Res.*,, 29(7), 2345-2361, 1993.

Koutsoyiannis, D., and A. Manetas, Simple disaggregation by accurate adjusting procedures, *Water Resour. Res.*, 32(7) 2105-2117, 1996.

***Koutsoyiannis, D., and C. Onof**,* A computer program for temporal rainfall disaggregation using adjusting procedures, XXV General Assembly of European Geophysical Society, Nice, *Geophys. Res. Abstracts*, 2, 2000. (Presentation also available on line at http://www.itia.ntua.gr/e/docinfo/59/)

***Koutsoyiannis, D., and C. Onof**,* Rainfall disaggregation using adjusting procedures on a Poisson cluster model, *J. of Hydrol.*, 246, 109-122, 2001.

***Koutsoyiannis, D., and D. Pachakis*,** Deterministic chaos versus stochasticity in analysis and modeling of point rainfall series, *Journal of Geophysical Research-Atmospheres,* 101(D21), 26444-26451, 1996.

Koutsoyiannis, D., and Th. Xanthopoulos, A dynamic model for short-scale rainfall disaggregation, *Hydrol. Sci. J.*, 35(3), 303-322, 1990.

***Onof, C. and H. S. Wheater*,** Modelling of British rainfall using a Random Parameter Bartlett-Lewis Rectangular Pulse Model, *J. Hydrol.*, 149, 67-95, 1993.

Onof, C. and H. S. Wheater, Improvements to the modeling of British rainfall using a Modified Random Parameter Bartlett-Lewis Rectangular Pulses Model, *J. Hydrol.*, 157, 177-195, 1994.

Rodriguez-Iturbe, D. R. Cox, and V. Isham, Some models for rainfall based on stochastic point processes, *Proc. R. Soc. Lond.*, A 410, 269-298, 1987.

Rodriguez-Iturbe, D. R. Cox, and V. Isham, A point process model for rainfall: Further developments, *Proc. R. Soc. Lond.*, A 417, 283-298, 1988.

[#] References

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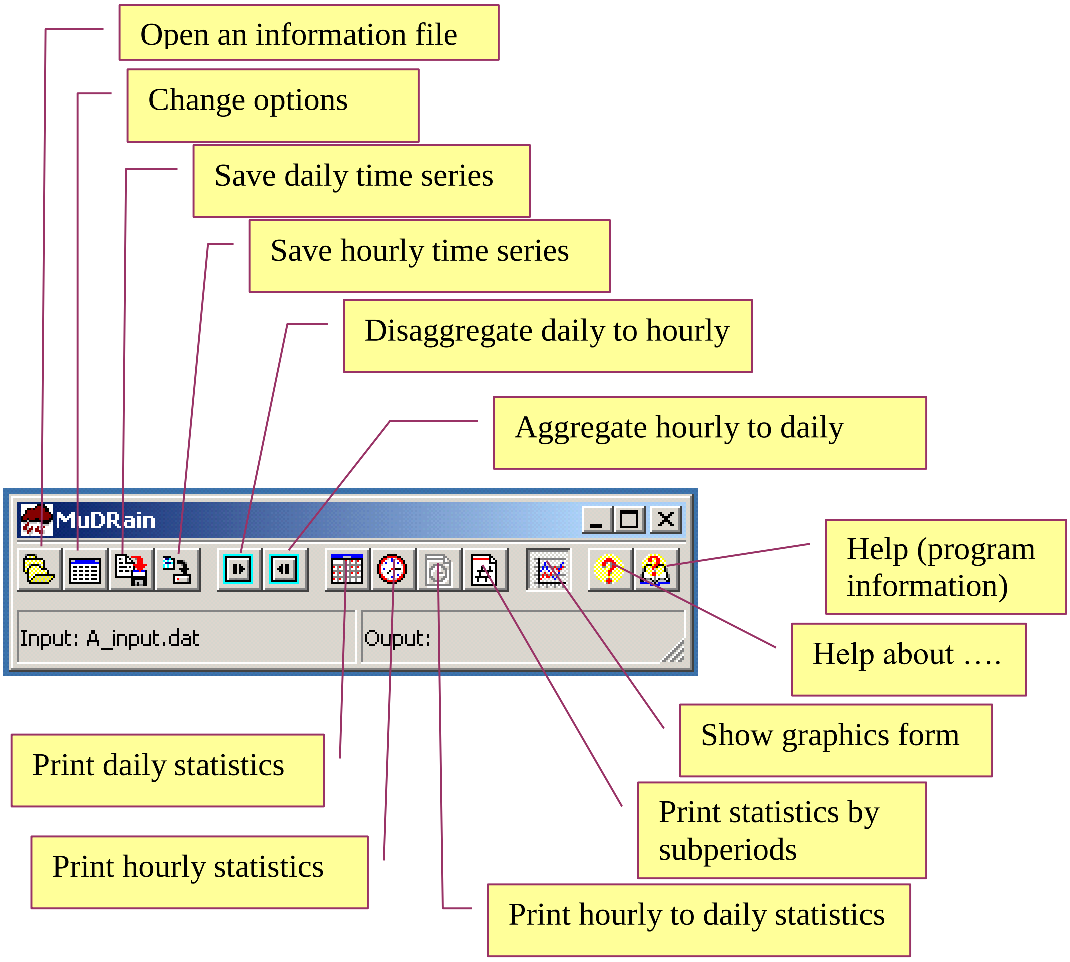
[K] References

Main Form # $ K

This is the main form of **MuDRain**. Use the on-screen hints of toolbar buttons displayed by placing and pausing the mouse pointer on them.
Here is a summary of toolbar buttons description:

The other forms of the software application **Options form**, the **Graphs form** and the Help About form appear by clicking the appropriate buttons of this form, whereas the **Visual output form** appears after opening an information file; see **Input files format**



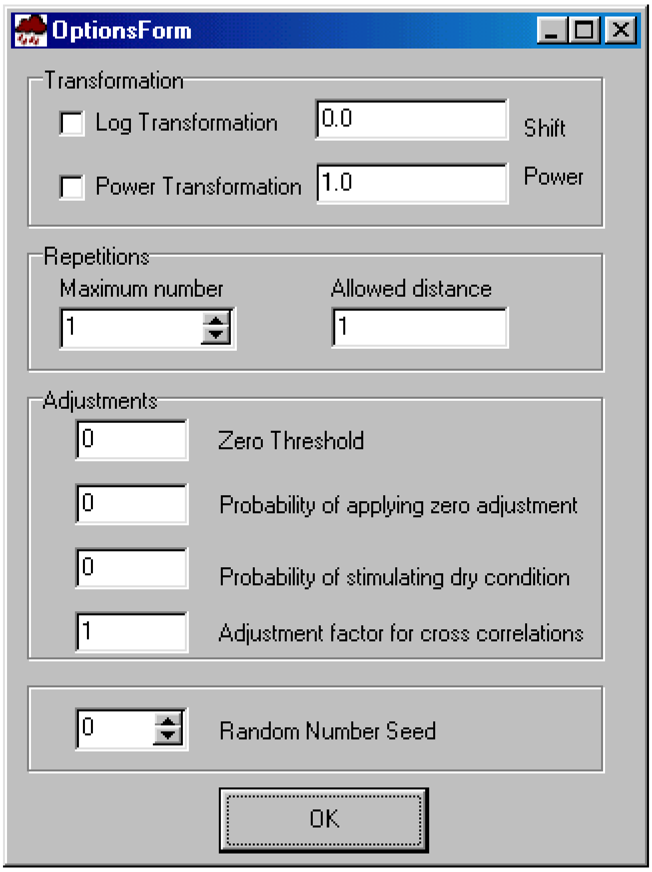
Main_Form
$ Main Form
K file, open, save; statistics, print

Options form[#] [$] [K]

Activate this form by pressing the appropriate button in the **Main form**.
The program offers three categories of options that must be specified by the user (for justification of these options see **specific difficulties**:
(a) the use or not of **repetition** in the generation phase,
(b) the use or not of one of the **transformations** and
(c) the use or not of the **two-state representation of hourly rainfall**.

In case of the adoption of each of these options, the user must specify some additional parameters for the generation, which are:
for (a), **the maximum allowed distance** Δ_m and **the maximum allowed number of repetitions** r_m (see **transformation model**);
for (b) the transformation constant ζ or m (as defined in equation (12) or (13), respectively see **specific difficulties**); and
for (c) the probability φ_0, to stimulate dry state in each of the locations. Two additional parameters are used, which are related to the rounding off rule of generated hourly depths, i.e. the proportion π_0 and the threshold l_0.

In the current program configuration, the options and the additional parameters must be specified by the user in a trial-and-error manner, i.e., starting with different trial values until the resulting statistics in the synthetic series match the actual ones. This can be seen as a fine-tuning of the model, which is manual. An automatic fine-tuning procedure, based on stochastic optimization, seems to be possible but has not been studied so far.



Options_Form
$ Options Form
K Options Form; options, repetitions; allowed distance; two state representation

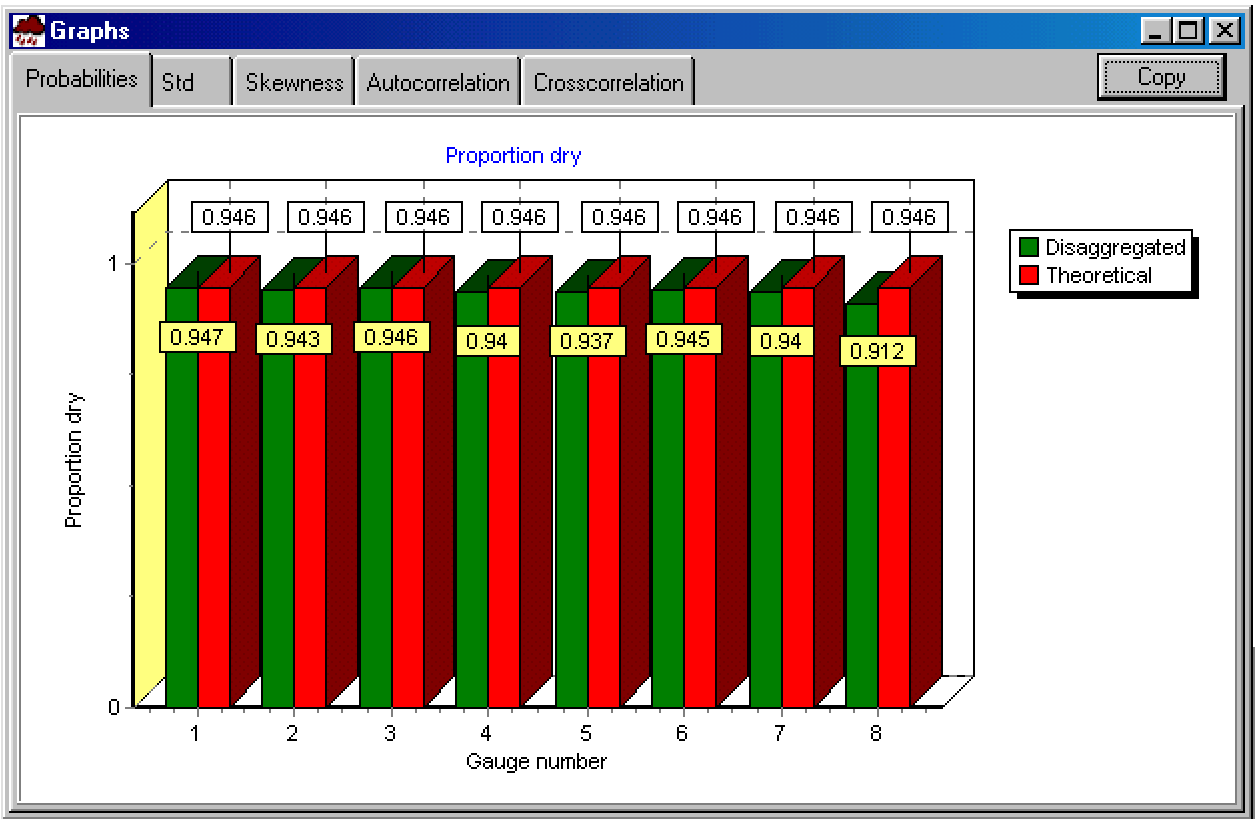
Graphs form#$K

Activate this form by pressing the appropriate button in the **Main form**.

Use this form, after performing the disaggregation, to visualize the graphical comparisons of historical and simulated statistics of hourly rainfall

To zoom in any of the graphs, drag on the region of interest downwards. To zoom out, drag on any region within the graph upwards. To move along the graph drag to the desired direction with the right mouse button pressed.

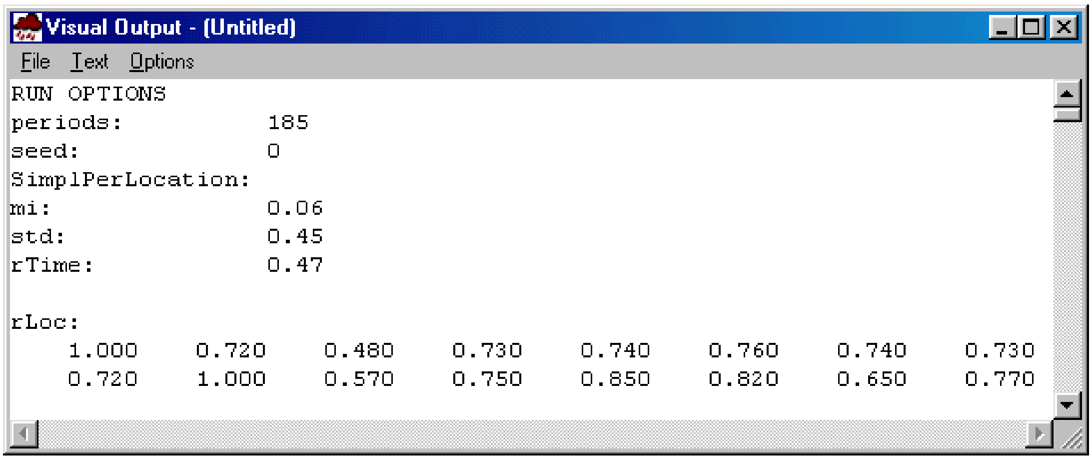
Using the Copy button, a graph is copied into the clipboard and can then be pasted to anywhere else (e.g. word processing programs etc.).



Graphs_form
$ Graphs form
K Graphs form; Form, graphs

Visual output form[#][$][K]

This form appears automatically when opening an information file (see **Input files format**). The content of the form, **results of the disaggregation, statistics etc.**, which are printed during the program execution, can be saved in a text file (use the file menu) or copied to the clipboard (press Ctrl-C).

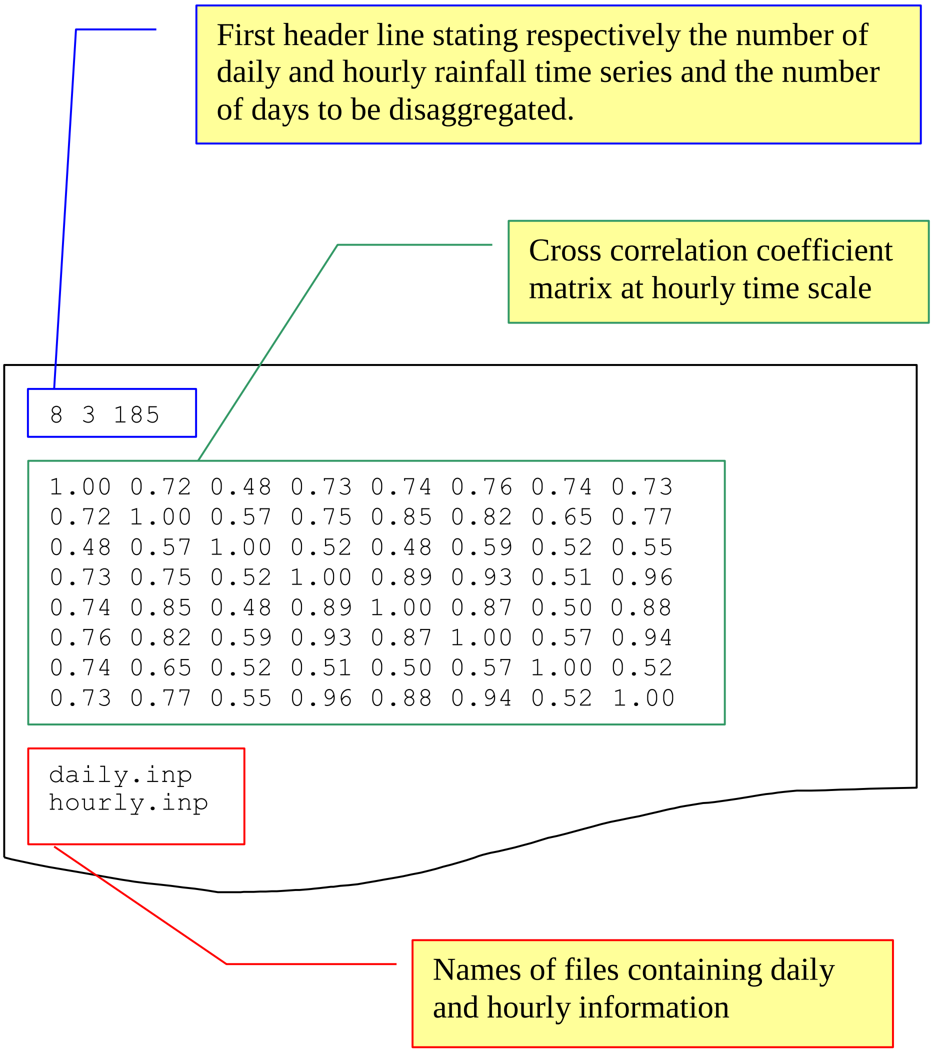


[#] Visual_output_form
[$] Visual output form
[K] Visual output form; Form, Visual output

Input files format[#$K]

File **input.dat :**

This is a text file that must be defined using the program **Main form** in order for the program to perform the disaggregation. The contents of the file are described below:



For the estimation of the unknown hourly crosscorrelation coefficients see related topic: (**Estimation of crosscorrelation coefficients** .)

File **daily.inp**: This is a text file containing the historical daily rainfall depths. In the current example we are considering 8 gages; historical hourly rainfall depths are available at gages 1,2,3 and historical daily rainfall depths are available for all gages.(The available hourly rainfall depths must be consistent with the daily rainfall depths of the same period).

[#] Input_files_format
[$] Input files format
[K] input; rainfall depths; crosscorrelation coefficients matrix

Historical daily rainfall depths for raingages n, m…,

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0.2	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0.2	0	0	0	0	0	0
0	0.2	0	0	0.2	0	0	0
0	0.2	0	0	0.4	0	0	0
0	0	0	0	0	0	0	0
0	0.2	0	0	0.2	0	0	0.2
0	0.2	0	0.2	0.2	0	0	0
0	0	0	0	0	0	0	0

Historical daily rainfall depths for raingages i , j, k, (in which historical hourly rainfall depths are also available from measurements)

File **hourly.inp**: **:** This is a text file containing the historical hourly rainfall depths available (3 in this example)

0	0	0
0	0	0
0	0	0
0	0	0
7.4	5.8	0
4.2	1.8	0
3.8	2.4	0
2	1.4	0
0.4	0.8	0
0.2	0	0
0	0	0

Caution: The daily and hourly input files must be compatible, e.g. the first entry of first column of daily file must equal the sum of the first 24 entries of the first column of hourly file, etc. Otherwise, the results of the program will be meaningless.

Output file format[#$K]

Press the appropriate button on the toolbar of the **Main form** to save the hourly (in case of disaggregation of daily to hourly) or daily time series (in case of aggregation of hourly to daily).

The output file is a text file that contains the produced hourly rainfall depths in several columns each one representing one raingage.

0	0	0	0	0.1	0	0	0.1
0	0	0	0	0.1	0	0	0.1
0	0	0	0	0	0	0	0.1
0	0	0	1.4	0.8	0.8	3.3	1.1
0	0	0	0.7	0.4	0.4	1.5	0.6
0	0	0	0.4	0.2	0	0.7	0.3
0	0	0	0.3	0	0.1	0.3	0.2
0	0	0	0	0	0	0.1	0.1
0	0	0	0.2	0	0	0.6	0.1
7.4	5.8	0	7.1	6.9	5.6	4.9	5.1
4.2	1.8	0	2.5	2.4	2.3	2.7	2.3
3.8	2.4	0	2.6	2.7	2.4	2.5	2.5
2	1.4	0	1.5	1.6	1.3	1.3	1.4
0.4	0.8	0	0.6	0.7	0.5	0.3	0.6
0.2	0	0	0	0	0	0	0.1

[#] Output_file_format
[$] Output file format
[K] Output file format