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DISAGGREGATION MODELLING OF SPRING DISCHARGES

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Abstract

Disaggregation models are basically divided into three main groups: temporal, spatial and temporal-spatial. The focus of this paper is the application of temporal disaggregation models to disaggregate the seasonal flow in some large time intervals to sub-seasonal flows in some shorter time intervals.

Two basic models are applied: the original model of Mejia and Rousselle and the corrected extended Lin model one-stage disaggregation. The flow totals from some karstic springs are used. Data for five springs in different areas of Bulgaria for the aims of the study are executed. The synthetic data generation for the chosen spring stations for a new realisation of thirty years is obtained. The multi-variate lag-one auto regressive model (*AR*(1) model) is applied for generation of the annual flow sequences. The Lin model single-site is performed for thirty years generation period. The Lin model is an improvement compared to the original extended model. The new Lin approach succeeds in the preservation of the additivity as well as the moments. Applying the Lin model one-stage disaggregation results in consistent model parameter estimates. As a second step in the research multi-site disaggregation schemes are also applied.

Keywords: disaggregation models, karstic spring discharge.

Introduction

Disaggregation models are basically divided into three main groups: *temporal, spatial* and *temporal-spatial.* The summary of main temporal disaggregation models is presented in Table 1. *The main advantage* of any disaggregation model is the preservation of statistical properties at more than one time interval. *The second major advantage* of disaggregation is that it is a technique, which allows a more flexible approach for generation of synthetic data.

The focus of the paper is to apply temporal disaggregation models for the specific climatic and hydrological conditions in Bulgaria. The applicability of disaggregation models for karstic springs is studied. Two disaggregation models are executed. Furthermore, in the study both single- and multi-site disaggregation schemes are applied.

Disaggregation modelling is a process by which time series are generated from an already available time serie. If the set of independent series is available, the corresponding shorter-interval series can be obtained. Typically, the independent time serie has been previously generated and after these series are disaggregated into the sub-series, this may be done by any stochastic model desired. The independent input time series or so-

called “key” series can be different: annual, seasonal or monthly flows. The disaggregation can be done in one stage or in several stages. For example, annual to semi-annual, semi-annual to quarterly, and quarterly to monthly flows, a three-stage disaggregation approach.
Disaggregation models are designed to preserve the statistical properties at more than one level, i.e. monthly and annual. The statistical properties considered as important are the first two moments or in other words the mean and variance, the probability distribution of the series and some covariance’s.

Some remarks
All disaggregation models may be reduced to a form, which is termed the linear dependence model (Salas et al., 1985). A typical application of these models would be to generate a serie of monthly spring flows (*Y(t)*) from a given serie of annual spring flow totals (*X(t)*). In Table 2 the mathematical description of the used research models is presented. The two used models are original Mejia and Rousselle model (1976) (Case 1) and modified Mejia and Rousselle or so-call “extended” Lin model one-stage approach (1990) (Case 2).
Annual flow volumes, modelled by the *AR*(1) model, were generated and disaggregated to monthly values. To overcome the difficulty originating from the non-normality of the historical data series, the annual and monthly totals were transformed and standardised before modelling (Koutsoyiannis, 1999 and 2001). The sums of the monthly-generated streamflow totals were compared to the observed annual flow totals to check preservation of additivity. Plotting the original annual totals and the sum of disaggregated time series was carried out to check the additivity. The means and standard deviations were checked after back transformation using average percentage change (*APCh*) and root mean square (*RMS*):

$$APCh = mean\left(\frac{Generated - Original value}{Original value}\right) * 100\% \qquad (1)$$

$$RMS = \sqrt{\frac{\sum (Generated - Original value)^2}{Number of values}} \qquad (2)$$

The preservation of skewness was checked according to the type of transformation using the average percentage change (1) and the *RMS*. The preservation of the covariance matrices S_{xy}, S_{yy} and S_{yyl} was evaluated using the *APCh* for single-site disaggregation only (Bojilova, 2003 & 1997; Genev, 2002).

Disaggregation modelling
Five karst spring stations were selected for the application of disaggregation models. The chosen springs represent different climatic and hydrologic conditions and are included in the National Hydro-geological Network, see Table 3. The recharge of the karst springs is due to infiltration from snowmelt and/or rainfall in the catchment area.

Table 1 Summary table of temporal disaggregation models.

Authors, year	Model name	Index	Advantage of the model	Disadvantage of the model
Valencia and Schaake, 1973	basic model	V-S	statistics at both annual and seasonal levels are preserved; basic clean form.	link with the past only at annual level; large number of parameters.
Mejia and Rousselle, 1976	original extended model	M-R	link with the past at seasonal level.	the model does not preserve the statistics, which was desired to preserve.
Lane, 1979	condensed		decreasing the number of parameters.	it fails to preserve the additivity.
Hoshi and Burges, 1979		H-B	seasonal correlations and statistical moments are preserved; successfully maintains correlations between the season that join successive water year; introduced scheme for 3-PLN Distribution.	distortion in the additivity property occurs.
Todini, 1980	modification of V-S and M-R		suggested scheme for preservation of the skewness.	
Stedinger and Vogel, 1984		S-V	reproduce the covariance between current upper and lower level flows as well as the covariance of the lower level with themselves; in addition, reproduce reasonable lag one covariance matrix of lower level flow vectors.	in particular case, the lag-1 covariance matrix was both practically and statistically different from the true population values.
Stedinger-Pei-Cohn, 1985	modification of condensed	SPC	preserve the additivity and correlation among the seasonal generated value.	it does not preserve exactly additivity.
Grygier and Stedinger, 1988	combination of spatial and temporal scheme	G-S	preserves the additivity and correlation among the seasonal generated flows.	it preserves the at-site lag-1 correlations in each month, and not the lag-1 cross-correlations.
Lin, 1990	modification of M-R	Lin	the corrected parameter estimate was proposed for two-stage disaggregation; the parameter estimation equations are mathematically consistent; the model can preserve the important moments and the additivity.	

*After Bojilova, 1997

Table 2. Mathematical descriptions of the models.

Model	Mathematical form of the models*
Mejia and Rousselle model (Case 1)	$Y(t) = AX(t) + BV(t) + CY(t-1)$
Lin model one-stage (Case 2)	$X(t) = GX(t-1) + HU(t)$ $Y(t) = AG[X(t-1) + HU(t)] + BV(t) + CY(t-1)$

Where: $Y(t)$ is a nm - dimensional zero-mean vector of normally distributed monthly spring flows;
m is a number of months in the year;
n is a number of sites, in the single-site scheme $n = 1$;
$X(t)$ is a n - dimensional zero-mean vector of normally distributed annual spring flows;
t is an index corresponding to the year;
A and B are $nmx\,N$, $nm\ x\,nm$ coefficient matrices, respectively;
$V(t)$ is a $nmx\,N$ - dimensional matrix of independent standard normal deviates;
$Y(t-1)$ is a nm - dimensional zero-mean vector of normally distributed monthly spring flows for the year $t-1$;
C is a additional parameter matrix $nm\ x\,nm$;
$X(t-1)$ is a n - dimensional zero-mean vector of normally distributed annual spring flows for the year $t-1$;
$U(t)$ is a n - dimensional vector of independent standard normal deviates;
G and H are $n\ x\ n$ parameter matrices.

Table 3. General information for chosen karst springs.

N°	Name	Village	Situation
	Mediterranean hydrological zone		
40	Gazero	Drugan	Radomir valley
86		Polska Skakavitza	Zemen mountain
39a	Beden	Beden	Rhodopes mountain
59	Jazo	Razlog	Rila mountain
	Danube hydrological zone		
30	Peshta	Iskrez	Balkan mountain, Western part
	Black sea zone		
48	Kotel	Kotel town	Balkan mountain, Eastern part
63	Dokuzaka	M Tarnovo city	Strandja mountain (Stoilova synclinal)

In Bulgaria the observations of karst springs start from 1959-1964. Time series of spring discharge data were subject of study in this research. The analyses were made for the period 1959-2000. The chosen karst springs are perennial. In the frame of the Danube basin (spring Peshta) they are related to an elevated massif of Triassic, Jurassic and Cretaceous limestones. Karstic and fissure-karst waters are widely spread in middle and upper Triassic limestones and dolomites that are fissured and karstified (Antonov & Danchev, 1980).

The extended Mejia and Rousselle model (Mejia & Rouselle, 1976) and the Lin model (Lin, 1990) were applied using ten realisations of each model. The historical spring discharge data for the selected stations were used. The length of the data series for disaggregation aims was thirty-one years (Hakem, 1991). Two flow sequences - annual and monthly – were organised first. For discussed models the annual flow totals $X(t)$ were disaggregated into monthly spring flows $Y(t)$ of twelve months. In addition to single-site,

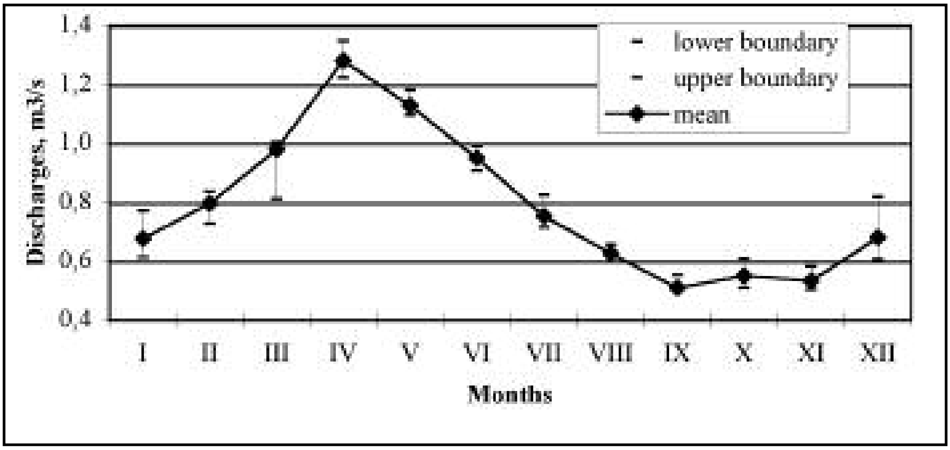

Fig. 1 - Preservation of mean, Case 2, Single-site, spring Beden, 1961-1990.

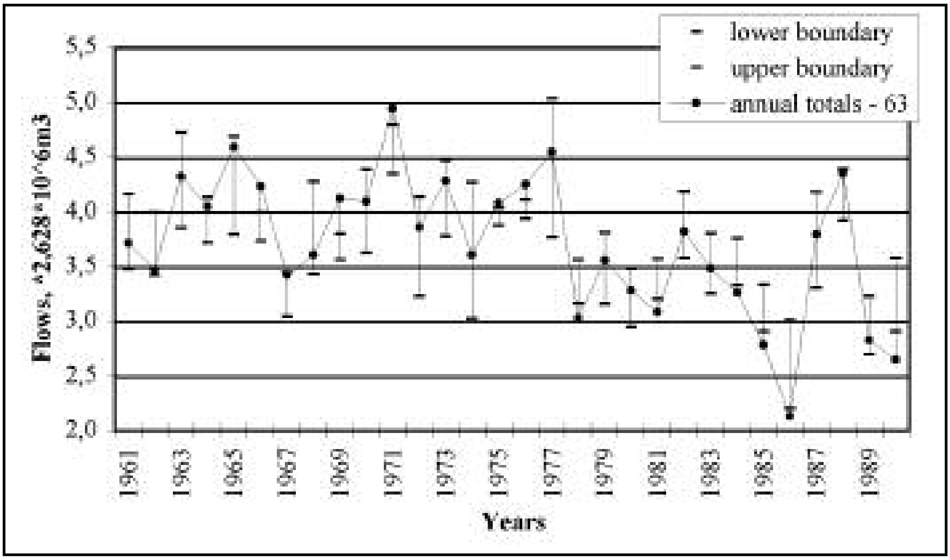

Fig. 2 - Additivity, Case 2, Single-site, spring 63, 1961-1990.

multi-site disaggregation was also executed. In the multi-site approach the models were applied for two-stations-at-a-time.

In Fig. 1 the preservation of the first order statistical moment for one of the selected springs is presented. Goodness-of-fit of the different disaggregation models to the water year totals - additivity was tested. In Fig. 2 the preservation of the additivity is shown. The obtained results are the averages from ten realisations. In Fig. 3 an example of the graphical comparison between the historical monthly values and generated monthly values for the chosen year is presented for spring Beden.

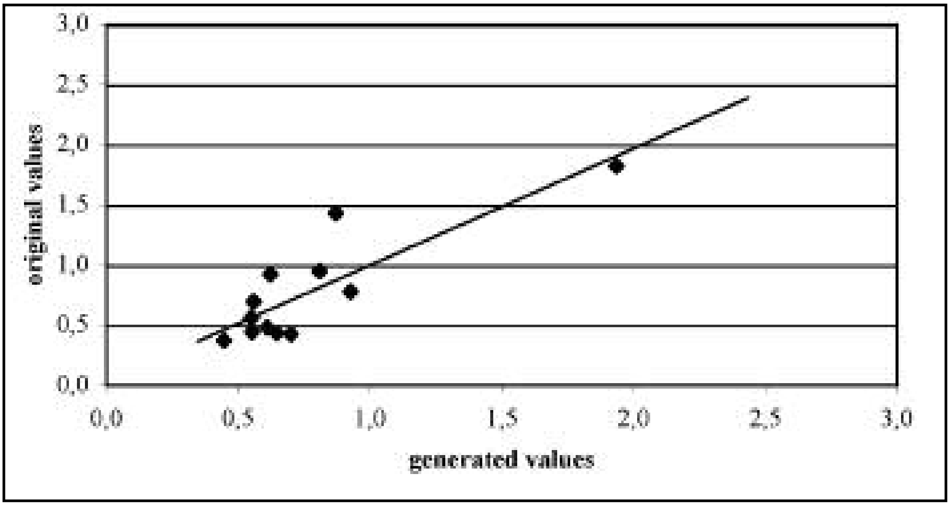

Fig. 3 - Montly flows, original vs. generated values, spring Beden, 1973.

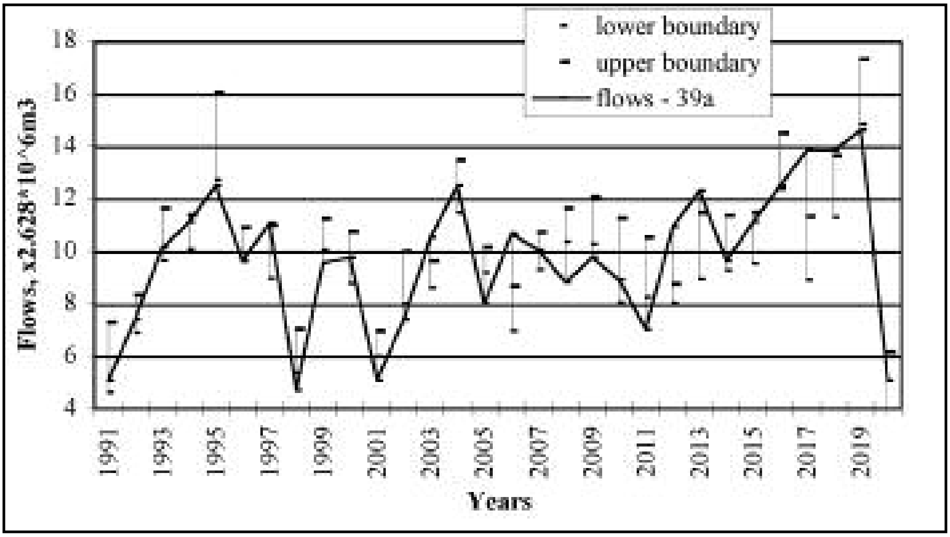

Fig. 4 - Additivity, Case 2, Single-site, Generation of Beden, 1991-2020.

Generation of karst spring data

For the chosen five stations the synthetic data generation for a new realisation of thirty years was carried out. The multi-variate lag-one auto-regressive model or *AR*(1) model was applied for generation of the annual spring flows - the “key” series for the disaggregation model. The existing period of observation (1959-2000) is used in the process of generation. The annual series or *X(t)* were generated using the *AR*(1) model. With the *AR*(1) model, sixty years of data for the chosen five stations were generated. The first

generated thirty years, or what is called the "warm-up" length, were neglected. The next thirty years were used to disaggregate the monthly spring flows. The annual generated series, transformed and normalised, were the input to the disaggregation models.
In the study the disaggregation process was performed using Lin model, single-site approach, Case 2, Fig. 4. The disaggregated series had zero mean and unit variance and were in normalised form, so that to obtain the generated monthly flows back transformations where needed. Using the results for *APCh* and the *RMS*, the preservation of mean, standard deviation and skewness are acceptable.

Conclusions and future study

The following conclusions can be drawn.

- The corrected parameter estimation in the Lin model succeeded in the preservation of the additivity and the covariance matrices as expected.
- The corrected Lin model is an improvement compared to the extended Mejia and Rousselle model (Mejia & Rousselle, 1976).
- The Lin model preserves the first two statistical moments and the covariance matrices rather well. As expected, the preservation of the second-order statistical moment (variance and covariance) is poorer than that of the first-order moment and the third-order is even worse.
- Both models are suitable for disaggregation of the karst spring flows with snowmelt conditions together with rainfall in the catchment areas.
- The models are applicable for disaggregation of spring flows for the specific climatic and hydrological conditions of Bulgaria. The best result was obtained from the corrected extended model, one-stage disaggregation for single-site approach.

Further studies should be carried out to test applicability of the models to more sites. In the research the models were used in the multi-site approach up to two-stations-at-a-time. Another interesting possibility for the future research is to apply the disaggregation models to the non-perennial springs.

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