Nordic Hydrology, 23, 1992, 105-120

The Influence of Basin Aridity on the Efficiency of Runoff Predicting Models

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The connection between runoff predicting models efficiency and basin aridity is investigated by using data from five representative basins in the mountainous central and northern Greece. Two substantially different models were selected, a monthly water balance model and an empirically fitted rainfall runoff model of the Kalman filter type. Both models were calibrated and validated in each basin and their overall efficiency was evaluated for each basin. The five basins were classified by using a humidity index and were found to range from humid to semi-arid. The efficiency of each model was then tested in terms of decreasing aridity and the two models exhibited a clearly contrasting behaviour; a decreasing efficiency of the Kalman filter model was observed, whereas the water balance model efficiency showed to increase with decreasing aridity. This behaviour is explained by considering the autoregressive characteristics of the corresponding five runoff time series, which are imparted in them by the filtering action of the basin. This factor becomes more important the more arid the basin is. Conclusively, the model of the Kalman filter type, designed to take account of the runoff autoregression, is shown to perform better with increasing aridity while in contrast, the water balance type of model where runoff memory is not accounted for, performs better the more humid the basin is, hence the runoff autoregressive characteristics become less significant.

Introduction

The question often arises in engineering practice what kind of runoff predicting model is most appropriate for a certain application (Burges and Lettenmaier 1977; James and Burges 1982; Klemeš 1986; Sarma, Delleur and Rao 1973; WMO 1975).

Notwithstanding very important selection criteria such as the purpose of the application or the kind of data available, the authors wish to report in this paper how the relevant answer may be affected by basin aridity.

To this end, two completely different types of models have been selected from two distinguishing broad categories of models: the moisture accounting models which are based on a conceptualization of the physical processes in the basin and the systems approach type of models which are relating the input and output processes to each other without representing the physical character of the precipitation-runoff process.

The first is a monthly water-balance model and the second is an autoregressive, empirically fitted model of the Kalman filter type (Mimikou, Kouvopoulos, Cavadias and Vayiannos 1991; Mimikou 1983).

The two models were compared in five Greek basins of varying aridity. Both were calibrated and verified and their predicting efficiencies were calculated throughout the period of available data. Each model showed a certain degree of linear correlation between its efficiency and basin humidity. The two models revealed opposite trends and this gives an answer to the question posed earlier. Clearly, basin humidity (or aridity) affects the performance of the two models in a different manner, favouring the use of the autoregressive model in arid basins, although in a wide range of moderate basin aridity values, model efficiencies did not significantly differ from one another.

Study Area

The study area comprises two distinct mountainous regions. The first lies in central Greece between 39°13′ and 39°42′ N and comprises the Mesohora, Sykia and Pyli drainage basins. The second lies further north between 39°47′ and 40°50′ N and comprises the Venetikos and Koromilia drainage basins. All the above basins with their characteristics are presented in Table 1.

The study area with the drainage basins and the associated hydrometeorological stations is depicted in Fig. 1.

Table 1 – Basin characteristics.

Drainage Basin	River	Area (km^2)	Mean elevation a.m.s.l. (m)
Mesohora	Acheloos	633	1,390
Sykia	Acheloos	1,173	1,299
Pyli	Portaikos	134.5	800
Venetikos	Venetikos	817	1,031.4
Koromilia	Aliakmon	391	1,231.4

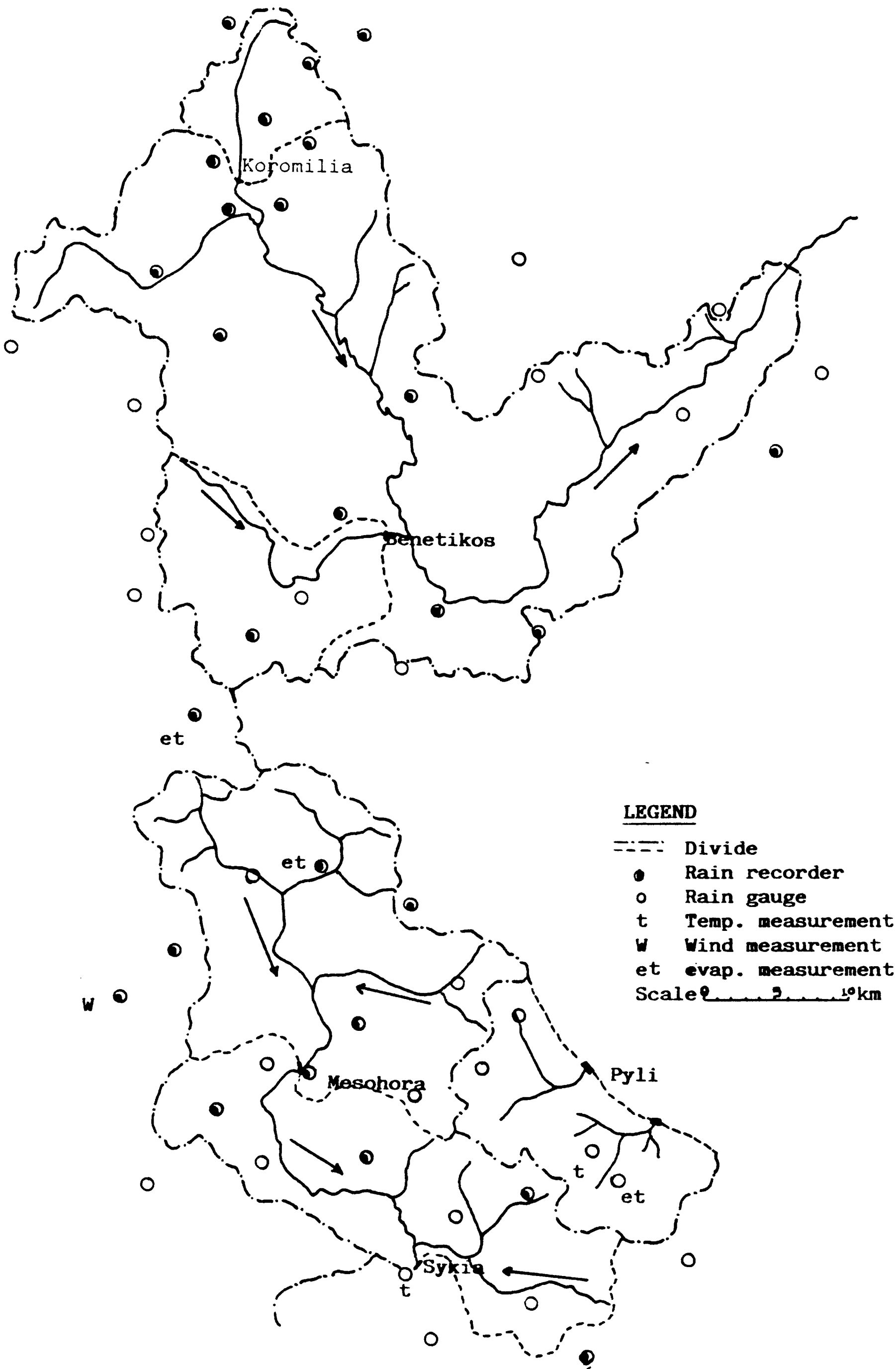

Fig. 1. General plan of the study area and of the hydrometeorological stations.

Data Used

The use of the water balance model requires a number of hydrometeorological data as input parameters. Namely, precipitation, runoff, temperature, sunshine duration, minimum relative humidity, and daytime wind speed were needed. Furthermore, some information about the soil cover of the basin was also needed.

The data were obtained from a quite satisfactory network of hydrometeorological stations, shown in Fig. 1. Soil information was obtained by consulting soil maps of the area.

For the Kalman filter model only areal precipitation and runoff time series were needed along with some information about the snow content of precipitation. All above information was available in a quite satisfactory form.

The operation periods of certain stations were short and this has affected the extent of the calibration and validation periods used. Under these circumstances, the above periods were determined as shown in Table 2. In this context it should be noted that the two numbers determining a period in Table 2 both correspond to the first calendar year of the respective hydrological year which commences in October.

Table 2 – Model calibration and validation periods.

Drainage Basin	Mesohora	Sykia	Pyli	Venetikos	Koromilia
Calibration	1971-79	1971-80	1971-80	1970-80	1978-84
Validation	1980-85	1981-86	1981-86	1981-87	1985-87

In order to be used as inputs to the models, the data series were properly processed and the following variables were obtained:

- Monthly areal precipitation P in mm, calculated by the Thiessen method.
- Mean monthly air temperature of the basin T in degrees centigrade, calculated after establishing a mean monthly temperature lapse rate for each basin. (Mimikou *et al.* 1991)
- Mean monthly minimum relative humidity RH
- Monthly relative sunshine duration SH
- Mean monthly values of daytime wind speed V in ms^{-1}.

The last three variables which are inputs to the water-balance model can be used in a qualitative form when more precise information is not available. The water balance model was properly designed to this end. Moreover, mean monthly values of the snow content in winter precipitation, that is percentage of precipitation that has fallen as snow, were estimated from snow meter data.

Runoff Predicting Models

General

A wide range of runoff predicting models are available, deterministic and stochastic, conceptual and blackbox (Thornthwaite and Mather 1955; Burnash, Ferral and Mc Guire 1973; James and Burges 1982; Linsley 1982; Box and Jenkins 1970; Clarke 1971; Hipel, Mc Leod and Lenox 1977). For the purpose of this study two models of completely different structures were selected among the most widely used model types. Namely, a water balance model (Mimikou *et al.* 1991) and an empirically fitted Kalman filter model (Mimikou 1983). The first is taken to represent the moisture accounting models which are based on a conceptualization of the physical processes in a basin and the second is taken to represent the blackbox type of models which are relating the input-output stochastic processes.

The Water Balance Model

Water balance models were first developed in late 40's and 50's. Since then they have undergone a lot of improvements so as to help solving a variety of hydrological problems. Their capability to incorporate soil moisture characteristics, reliable snow-melting and evapotranspiration routines, the easily accessible field data they require regarding meteorology, soil characteristics and vegetation and the accurate monthly, seasonal or annual assessments of a variety of significant hydrologic variables they provide, have made them very popular and widely used for the assessment of surface runoff. The water-balance model used in this work has been developed by the authors and presented in detail in Mimikou *et al.* (1991).

In brief, it operates on a monthly basis with precipitation P (mm), temperature T (°C), relative sunshine duration SH, minimum relative humidity RH and daytime wind speed V (ms^{-1}) as input variables. Model parameters which have to be fixed by calibration are: Maximum soil moisture S_{max} (mm), the watershed lag coefficient $K1$, the ground water reservoir coefficient $K2$, the temperature parameters $T0$ and $T1$ (°C), the minimum rain content of precipitation a, the melt-rate factor DF (cm $°C^{-1}day^{-1}$) and the storm runoff coefficient SRC. The model produces estimates of surface runoff QE (mm), soil moisture storage S (mm) and actual evapotranspiration ET (mm) as output variables. An outline of the model operation can be found in the flow-chart of Fig. 2.

The Empirically Fitted Kalman Filter

The empirically fitted Kalman Filter implemented in this study was originally developed by the first of the authors (Mimikou 1983).

The basic equation is

$$\hat{q}_{p,t} = \bar{q}_t + a_i Q_{p,t-1} + b_i P_{p,t} \quad (\text{for } t = 1 \text{ , } Q_{p,t-1} = Q_{p-1,12}) \qquad (1)$$

where indices p and t stand for the year and the month respectively and $\hat{q}_{p,t}$ in m^3s^{-1}

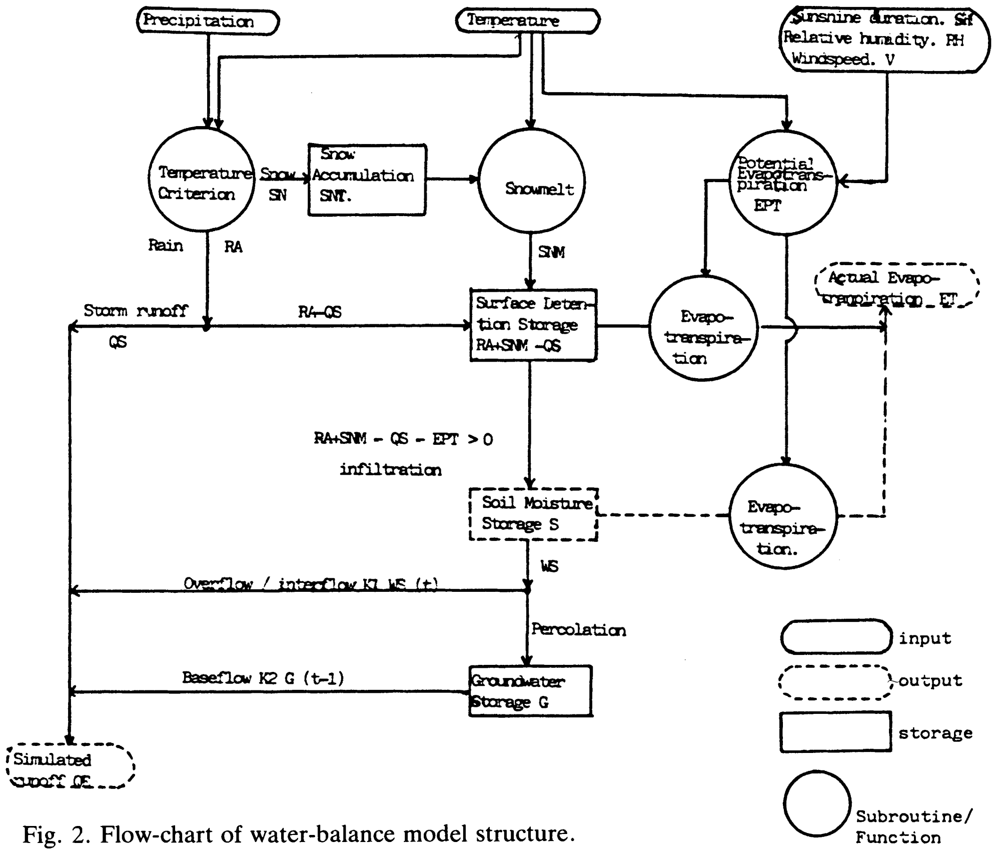

Fig. 2. Flow-chart of water-balance model structure.

is the estimated monthly runoff; $\bar{q}_t$ in m^3s^{-1} is the yearly average monthly runoff (averaging over the calibration period); $Q_{p,t}$ in m^3s^{-1} is the stationarized monthly runoff: $Q_{p,t} = q_{p,t} - \bar{q}_{p,t}$; $P_{p,t}$ is the areal monthly precipitation expressed in units of discharge (m^3s^{-1}), and a_i and b_i are coefficients given by Schwartz and Shaw (1979)

$$a_i = a(1-b_i) \tag{2}$$

$$b_i \equiv \frac{A+a^2 b_{i-1}}{1+A+a^2 b_{i-1}} \tag{3}$$

In Eqs. (2) and (3), a is the first order autocorrelation coefficient of the output series according to

$$Q_{p,t} \equiv aQ_{p,t-1} + W_{p,t}, \quad |a| \leq 1 \tag{4}$$

where $W_{p,t}$ is a zero mean white noise part of the stationarized output series $Q_{p,t}$. The term A represents the ratio of the variance of the white noise part $W_{p,t}$ of the output series to the variance of the "observation noise" $n_{p,t}$ in the input-output relationship

$$P_{p,t} = Q_{p,t} + n_{p,t} \tag{5}$$

where $P_{p,t}$ is taken here with a zero mean.

Therefore

$$A = \frac{\sigma_w^2}{\sigma_n^2} = \frac{\sigma_q^2(1-a^2)}{\sigma_p^2-\sigma_q^2} \tag{6}$$

The dependence of both coefficients a_i and b_i on the runoff series autoregressive characteristics is thus evident.

However, in the empirically fitted filter (Mimikou 1983), coefficients a_i and b_i were modified so as to account also for additional factors such as the amount of rainfall, the trend of the rainfall (increasing or decreasing), the existence of significant snow during the current and/or previous month. These factors, as shown from experience, are related to the dynamic characteristics of the basin runoff response. Through these modifications, the above additional factors were incorporated into the filter response mechanisms improving thus its efficiency to represent the physical phenomenon and its dynamics (Mimikou 1983).

In its latest version that was used in this research, the model performance was reviewed and improved by some additional modifications. Particularly the relations for a_i and b_i were more efficiently re-established along the above lines. Guidelines on how these coefficients are defined and introduced under various circumstances are given in Table 3. In this respect it should be noted that the upper and lower critical rainfall values, P_s and P_o respectively, as well as the exponent k which appear in Table 3 are model parameters and have to be calibrated. Finally, in this modified version of the empirically fitted Kalman filter, a corrective algorithm was introduced for $\bar{q}_t$ in Eq. (1) for those special cases where $\bar{q}_t$ is high whereas rainfall is significantly low and runoff is then systematically overestimated.

In the application presented herein, the model operated as follows: The monthly areal precipitation $P_{p,t}$ was introduced to the model as an input series. $Q_{p,t-1}$ was an input too, but it was also the outcome of the previous iteration since the model operated in a recursive mode with a lag of two months with respect to the latest measured monthly runoff value. Coefficients a_i and b_i were obtained in each iteration by relationships and under conditions already specified in a concise form in Table 3.

Table 3 - Mechanism of variations of filter parameters.

Monthly rainfall $P_{p,t}$ (mm) at month t	Formulae for b_i at month t	Snowfall during previous consecutive months (t-1,...)	Discharge at month t-1	Formulae for a: at month t, with none or insignificant snowfall	Formulae for a: at month t, with significant snowfall
Increasing or constant		None or insignificant		$a_i=A(1-b_i)$	$a_i=a(1-b_i)$
$O \leq P_{p,t} < P_o$	$b_i=b_{i-1}$ or $b_i=b_{i-1}(1-L)$ *1*2				
$P_o \leq P_{p,t} < P_s$	$b_i=a^k(1\text{-L})$ or $b_i=a^{k+1}(1-L)$ *2				
$P_s \leq P_{p,t}$	$b_i=1-L$ or $b_i=a^k(1-L)$ *2				
Decreasing		Significant	$q_{p,t-1}<\bar{q}_{t-1}$	$a=a^{k+1}(1-b_i)$	$a_i=a(1-b_i)$
$P_s \leq P_{p+t}$	$b_i=b_{i-1}(1-a^2L^2)$ or $b_i=b_{i-1}(1-aL)$ *2				
$P_o \leq P_{p,t} < P_s$	$b_i=b_{i-1}(1-aL)$ or $b_i=b_{i-1}(1-L)$ *2		$q_{p,t-1}>\bar{q}_{t-1}$	$a=\frac{1}{a^{k-1}}(1-b_i)$ *3	
$O \leq P_{p,t} < P_o$	$b_i=b_{i-1}(1-L)$				

(*1) $L=1/(1+A+a_2b_{i-1})$
(*2) In the presence of significant snowfall in month t
(*3) If a exceeds 1, for $K \geq 2$, then it is set equal to 0.999...

Calibration and Validation

The models were calibrated and verified in each one of the five basins separately. The calibration and verification periods were the same for both water balance and Kalman filter models and are shown in Table 2.

The criterion used for calibration and verification was derived from Nash and Sutcliffe (1970)

$$E = 1 - \frac{\sum_{1}^{12} (\hat{Q}_i - Q_i)^2}{\sum_{1}^{12} (Q_i - \bar{Q})^2} \tag{7}$$

where

Q_i – the observed runoff in month i
$\hat{Q}_i$ – the estimated runoff in month i
$\bar{Q}$ – the mean annual runoff

More specifically, model predicting efficiency was computed for each hydrological year separately. The average of the values obtained through the period concerned (either calibration or verification) was assumed to represent the overall model efficiency throughout the period and is tabulated in Table 4 for the five basins. By regarding the results of the calibration-verification it is seen that the efficiency values obtained are quite satisfactory, given the limited extent of the data, especially of the verification period. In general, the average efficiency displayed in the verification runs complies well with the average efficiency obtained during calibration. To illustrate the performance of the two models, graphs of simulated and observed runoff time series for each basin are supplied in Figs. 3a and 3b for a common period of three years.

There are two exceptions however regarding the performance of the models, in the Koromilia basin for the water balance model and in the Pyli basin for the Kalman filter. In these cases the average efficiencies of the verification runs are

Table 4 – Models predicting efficiencies for the calibration and verification periods.

Drainage Basin	Water-balance model		Kalman-filter model	
	Calibration	Verification	Calibration	Verification
Mesohora	0.864	0.872	0.818	0.711
Sykia	0.877	0.854	0.848	0.848
Pyli	0.921	0.900	0.813	0.586
Venetikos	0.834	0.808	0.746	0.737
Koromilia	0.814	0.590	0.754	0.848
Mean values	0.862	0.805	0.796	0.746

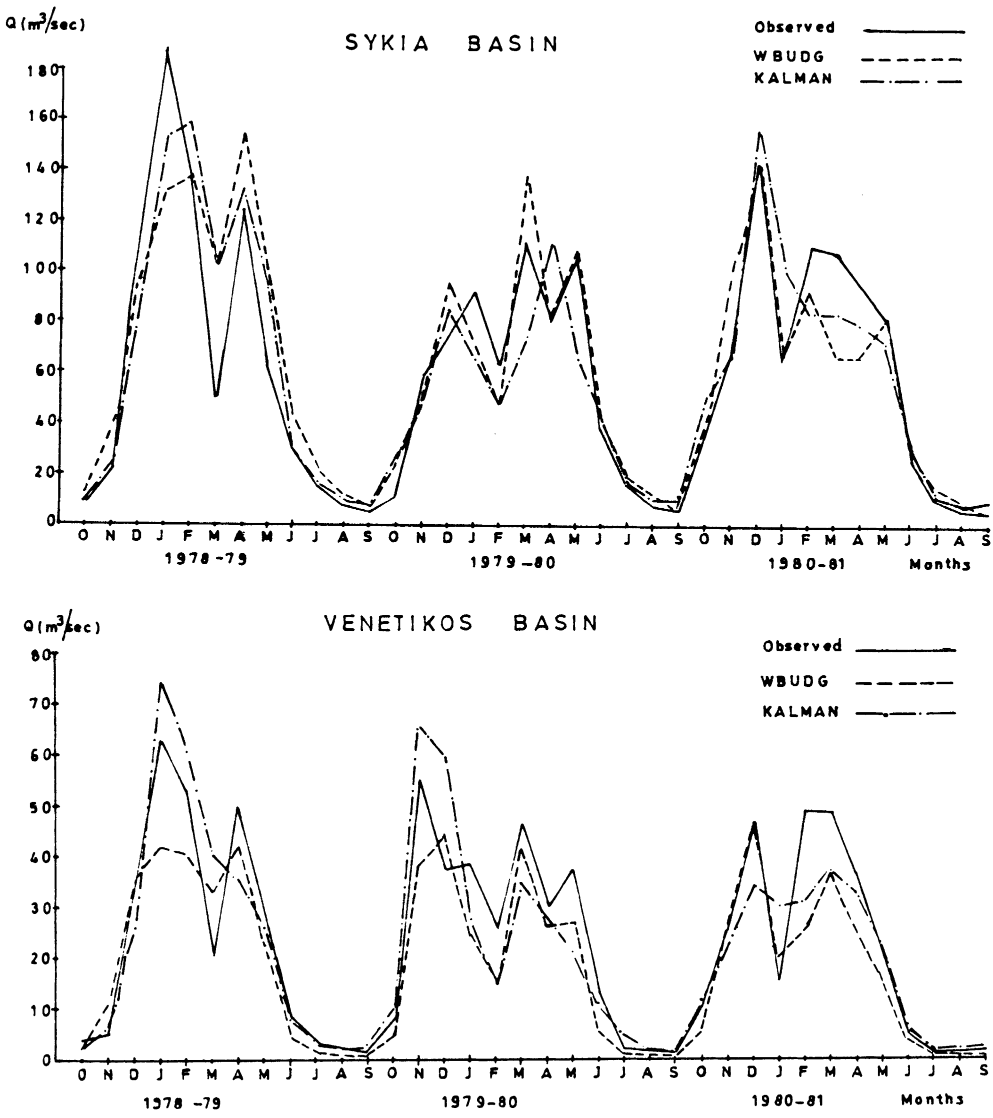

Fig. 3a. Simulated and observed runoff time series (corresponding efficiencies, Sykia basin: $\bar{E}_{WB} = 0.838$, $\bar{E}_{\mathrm{Kalman}} = 0.783$; Venetikos basin: $\bar{E}_{WB} = 0.803$, $\bar{E}_{\mathrm{Kalman}} = 0.766$)

significantly lower. On the other hand, the Pyli basin and the Koromilia basin are characterized by maximum efficiencies in the verification runs of the water balance and Kalman filter models respectively. This alternatively fair performance of the two models should be viewed in light of the relative position the two basins possess on the scale of the aridity index (at the extreme ends of the range examined). Relevant explanations of this behaviour are given in the following.

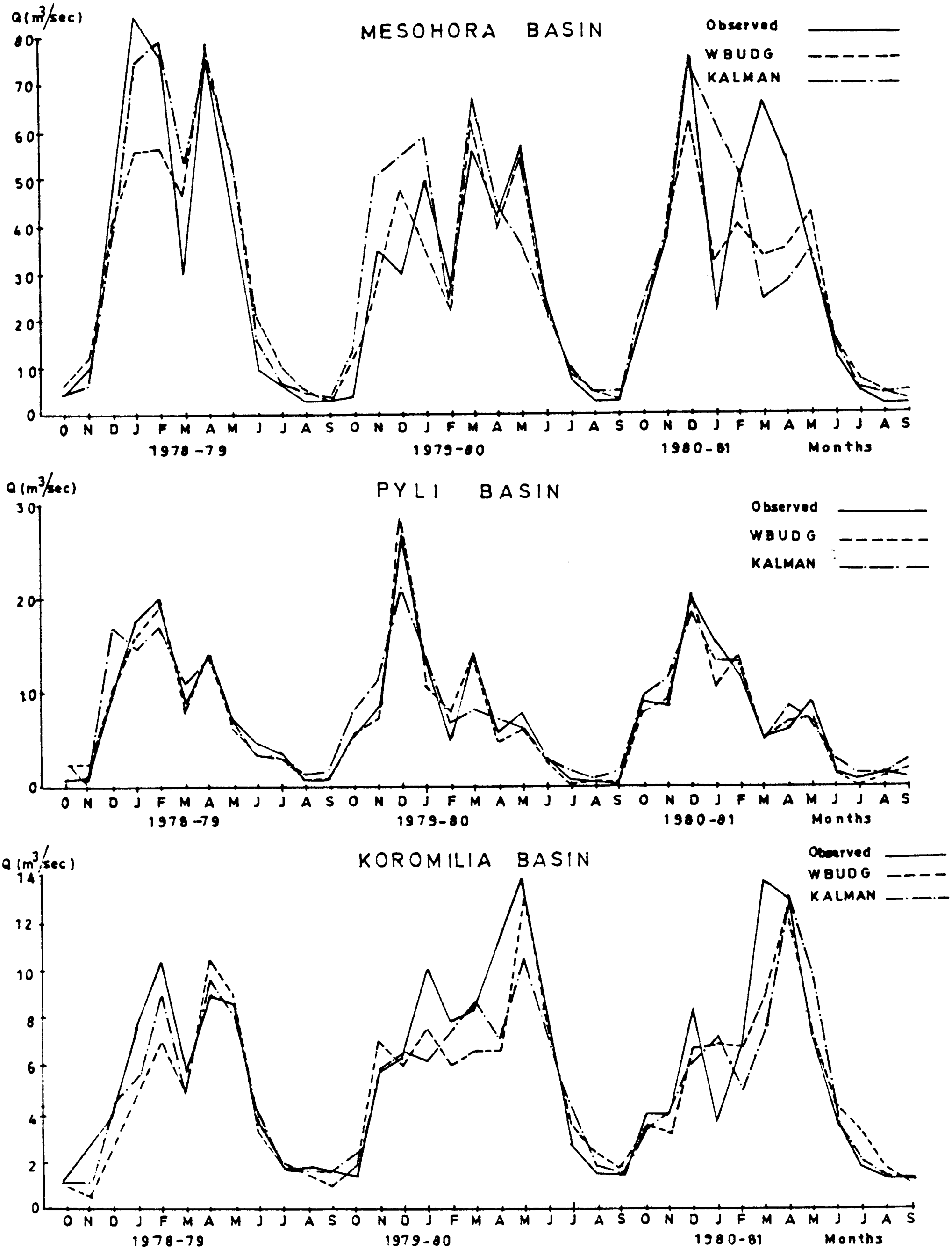

Fig. 3b. Simulated and observed runoff time series (corresponding efficiencies, Mesohora basin: $\bar{E}_{WB} = 0.792$, $\bar{E}_{\text{Kalman}} = 0.651$; Pyli basin: $\bar{E}_{WB} = 0.954$, $\bar{E}_{\text{Kalman}} = 0.874$; Koromilia basin: $\bar{E}_{WB} = 0.788$, $\bar{E}_{\text{Kalman}} = 0.780$).

Comparison of the Two Models

The two models were applied on the five basins of the study area and their performance was tested as a function of basin aridity. Basin aridity has been shown to be associated with the sensitivity of the response mechanisms of a basin (Dooge 1989; Mimikou and Kouvopoulos 1991). Therefore, by correlating this property with the performance of models of different structures, it was anticipated that some useful comparative conclusions can be derived about their suitability to better represent the runoff generation mechanism. In this paper, the inverse property was used, basin humidity, simply for reasons of convenience. It is expressed by the index P/AET, where P is the yearly precipitation and AET is the yearly actual evapotranspiration. The latter is computed from the long-term water balance equation

$$P = AET + Q \tag{8}$$

where Q is the yearly basin runoff. It is evident that

$$\frac{P}{AET} \geq 1$$

where the equality holds for completely arid conditions.

Model performance is represented by the coefficient of efficiency E, previously presented in Eq. (7). The two sets of values for E were obtained by having the two models run with their calibrated parameters throughout the complete period of existing data. Although it would be more proper for this purpose to use the verification period only, it was decided the other way due to the limited extent of the data available.

The values of the humidity index along with the achieved efficiencies of the two models in the five basins are shown in Table 5. These results are also plotted in Fig. 4, where a least squares line has also been fitted for each model. Relevant statistics for the significance of the regression lines are presented in Table 6. Regarding the Kalman filter regression, although weak it is not neglected, since it permits some conclusions of, at least, qualitative nature.

The differing behaviour of the two models is evident from first glance. While

Table 5 – Humidity index, model predicting efficiencies and 1st order autocorrelation coefficient for the five basins.

Basin	$\frac{P}{P-Q} = \frac{P}{AET}$	Efficiency		First order autoregression
		WBUDG	Kalman filter	
Koromilia	1.75	0.758	0.775	0.492
Sykia	2.52	0.868	0.848	0.426
Mesohora	2.57	0.867	0.775	0.400
Venetikos	2.86	0.824	0.742	0.290
Pyli	3.98	0.914	0.728	0.114

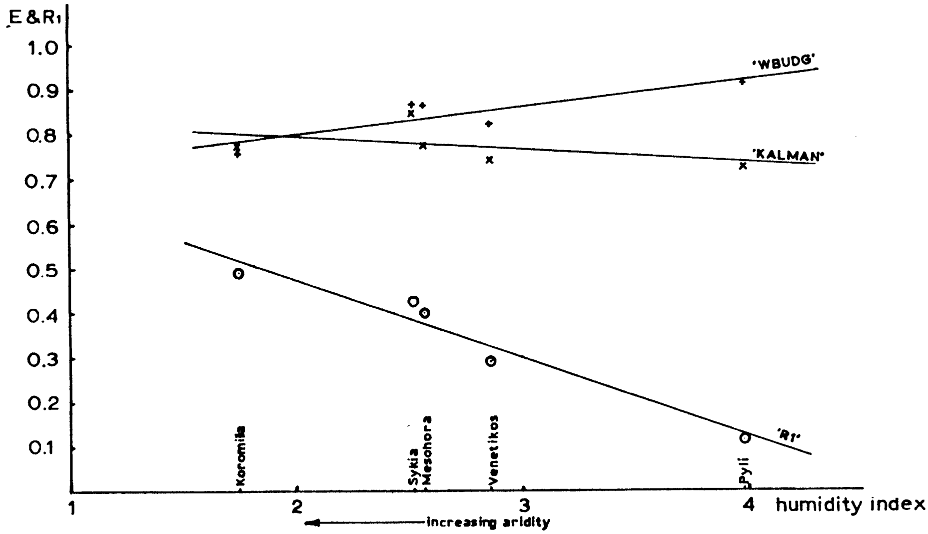

Fig. 4. Model's efficiency (E) and basin autoregression coef. (R_1) as a function of humidity index.

model efficiency is an increasing function of basin humidity (and inversely so for basin aridity) for the water balance model, it is a decreasing function of this variable for the Kalman filter model.

For a possible explanation of this behaviour one might look upon the first order autoregression coefficient of the runoff-time series. For one reason, this coefficient is a determining, structural component of the Kalman filter model as can be seen in Eqs. (1) through (6). The most important reason is, however, that it indicates the autoregressive, or memory characteristics of a runoff series. These are imparted in the runoff series by the filtering action of the basin. In turn, the filtering action of a basin is associated with flow detention which facilitates the increase of evapotranspiration. The latter is a determining factor of basin aridity. This linkage between runoff series autoregression $R1$ and basin aridity can be seen in Fig. 4 where the first order autoregression coefficient is also plotted *vs* basin humidity and, as can be seen, it is a decreasing function (or increasing with the aridity). Statistics of this regression are included in Table 6.

Table 6 – Statistical significance of the regression lines.

	Correlation coefficient r	Significance level (r=0) a (%)	Slope b	90 % Confidence interval for b
WBUDG	0.846	7.2	0.061	±0.053
Kalman	−0.522	37.2	−0.030	±0.067
R1	0.924	0.6	−0.178	±0.061

By examining now the structure of the two models, one can see that the Kalman filter model, being based on the preservation of the runoff autoregression, seems to perform better as basin aridity increases or, in other words, as the autoregressive characteristics of the runoff series become more significant. On the other hand, the water-balance model is essentially based on a representation of the basin processes intervening between rainfall and runoff. Although it is tried in the model to reconstruct this relation in a representative manner by incorporating algorithms (for watershed lag and groundwater lag) that account for runoff memory, these algorithms are also adding model uncertainties. Therefore when a closer association amongst rainfall and runoff exists, that is the more humid a basin is, the simulation becomes more simple and straightforward and the predictive efficiency is thus magnified.

A second remark that was made is that linear regression revealed a much stronger correlation between the coefficient of predicting efficiency and basin humidity in the case of the water-balance model. The weak correlation observed in the case of the Kalman filter model is attributed to modelling spatial discrepancies, more pronounced in the empirically fitted Kalman filter which does not possess the same flexibility as the water-balance model.

Finally, notwithstanding the differences presented above, the two models seem to operate almost equally well in the range of moderate aridity. It is the extremes of humidity and aridity that make the difference. However, although it was possible to detect in Greece a very humid basin, a correspondingly arid basin with available data could not be found. So the above assertion is not supported by field data regarding its extreme aridity part; it is only deduced by extrapolation.

Discussion of Results

For a discussion of the results it would be very useful to refer to the WMO work on the intercomparison of hydrological models (WMO 1975). Notwithstanding the integrity of the latter, the work presented here bears certain particularities anticipated to enrich the discussion on the general issue of model behaviour.

First, in the WMO intercomparison the system types of models examined were of quite different nature from the one employed here which is recursive and strongly dependent on series autocorrelation. Second, the Pyli basin has a high humidity index not mainly for climatic reasons (that is, in a sense of climatic humidity, as meant in the WMO report), but because of its specific physiographic characteristics (Mimikou *et al.* 1991) which favour a fast direct runoff. Although the basin receives almost the same amount of annual precipitation as the semi-arid Mesohora basin, a much lesser portion of it is left in the form of soil-moisture supply, rendering it semi-arid in this regard, but humid according to the definition employed here. Therefore, the general WMO conclusions should be cautiously applied here, respecting the basin peculiarities.

In general, the analysis and results presented above are strictly limited for the two models and within the range of the basin humidity index examined, that is between the extreme cases of the Koromilia and Pyli basins. It is apparent that this search should be extended to more basins. Specifically, considering a basin significantly more arid than the Koromilia basin and with a longer gauging period would be very useful and this is in the authors' intentions for the near future.

Conclusions

A comparative study of two runoff predicting models in five basins of varying aridity has revealed a tendency of the latter to affect the models predicting efficiency. The manner this influence is experienced is different in the two models and seems to depend on the nature of each model. A recursive model of the Kalman filter type based on the autocorrelation characteristics of the runoff series seems to become more efficient the more arid a basin is. Conversely, a water-balance model becomes more efficient the more humid a basin is. Possible explanations for this behaviour are given by paying attention to the first order autocorrelation coefficient of the runoff series and to its connection with the aridity of a basin.

The filtering characteristics that impart memory in the runoff series of a basin are also responsible for increased evapotranspiration losses and, hence, for increased aridity. So the Kalman filter model which by construction preserves the runoff series memory is more efficient with increasing aridity due to a stronger autocorrelation in the runoff series. On the other hand, the water balance model which is based on a, however complicated, rainfall-runoff relationship, becomes more efficient the more simple this relation becomes, that is in more humid basins.

Although model performance seems markedly different for the extreme values of basin humidity and aridity (extrapolated values), in the range of moderate aridity the two models do not exhibit significant differences in their predicting efficiencies.

Acknowledgements

The authors wish to thank the Public Power Corporation of Greece for providing the data necessary for the accomplishment of this work.

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First version received: 9 July, 1991
Revised version received: 12 February, 1992
Accepted: 18 February, 1992

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