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Surface Water Hydrology: On-Line Estimation

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Calibration and Verification Procedures

The calibration process refers to the parameter identification phase of watershed modeling wherein a given CRR model is made specific to a given site. Some of the model parameters can often be estimated by study of the watershed characteristics but others, relating to the internal subprocesses of the watershed, which cannot be determined in this manner, must be indirectly estimated using observed hydrologic time series data. Two basic approaches, namely "manual" and "automatic" have been used for the latter. It is interesting to note that in manf of the reported studies involving the application of CRR models, aside from a brief mention of the calibration Procedure employed, there has rarely been any discussion of the merits of the calibration results. The main reason for this omission is probably the lack of agreement or understanding as to what exactly is to be achived in the calibration stage. The following is the question that must be addressed is the purpose of the calibration:

a. To obtain a conceptually realistic and unique parameter set which closely reflects our understanding of the physical system?
b. To obtain a (any) parameter set which gives the best possible fit between the model-simulated and observed hydrographs (i.e., for the calibration period)?

From a physical modeling point-of-view, it is clear that methods which emphasize both aspects would be desirable. Unfortunately, as Sorooshian and Dracup (1980) pointed out, most of the commonly employed calibration methods tend to emphasize aspect (b) (more so in the case of automatic techniques). The danger in such cases is as they discussed, that the resulting parameter set, though producing a close reproduction of the observed hydrograph during calibration, may result in poor performance when used for forecasting (this is a phenomena sometimes referred to as "model divergence"). They placed much of the blame for this on the inability to obtain unique and realistic parameter sets. From the work published during the review period, it seems that some researchers have started examining the adequacy of the calibration procedures (in particular the automatic techniques), with respect to their ability to satisfy both of the above aspects. Their work is reviewed in the context of the three requirements of automatic estimation procedures which are:

1. a suitable estimation criterion,
2. an efficient optimization algorithm,
3. appropriate calibration data.

The section concludes with some comments on manual calibration.

1. Estimation Criterion

In most reported cases where automatic techniques have been used, the selection of the estimation criterion has been rather subjective. However, as Sorooshian and Dracup (1980) pointed out, if the selected criterion lacks a proper description of both the stochastic elements of the data and the physical situation, it is likely that the estimated parameters will not assume values which closely approximate their conceptually or physically realistic values (i.e., they are biased). As they pointed out, the phenomena of model divergence during forecasting is most likely a consequence of the use of such parameter estimates.

Measurement errors in any of the data sequences involved in parameter estimation of CRR models (namely, precipitation, potential evapotranspiration and streamflow)will result in poor parameter estimates unless they are properly accounted for. For instance, the most commonly adopted criterion the simple least squares (SLS) provides efficient (minimum variance) and unbiased parameter estimates only if the following two assumptions are satisfied; a) the variance of the errors is constant and b) the errors are time independent. In the case that the errors come from a Gaussian distribution then these parameters will also be maximum likelihood estimated. It is well known that the errors in streamflow measurements are not homogeneous. Potter and Walker (1981), for instance, pointed out that for a discharge determined from a rating curve based on a directly measured stage, the standard deviation of the measurement error is usually some percent (around 10% or less) of the estimated discharge. Furthermore, above a given threshold (e.g. bank-full discharge) an indirect method is usually used to estimate flood discharges, for which the standard deviation of the error is probably several times larger. Note that this fact raises serious questions regarding the use of criteria for model calibration that emphasize eact reproduction of the hydrograph peak. As discussed by Sorooshian and Dracup (1980), suchcriteria will almost certainly result in severely biased parameter estimates. Note also that this emphasizes the fact that in many cases the quality of the measured data may be too poor for parameter estimates of better than a certain precision to be obtained.

Sorooshian and Dracup also remarked that there is enough physical evidence to support the suspicion that rainfall and runoff measurement errors are not only heteroscedastic (refers to inhomogeneous variances) but are also autocorrelated. Williams and Yeh (1982) suggested the use of the Generalized Least Squares (GLS) estimator to eliminate the effect of serially correlated errors associated with streamflow measurements. Kuczera (1982) showed that the theory of GLS could be used to handle estimation in the presence of one or more correlated output time series. Sorooshian anp Dracup (1980) suggested that Maximum Likelihood (ML) theory can provide a more general basis for the development of appropriate estimation criteria, if acceptable assumptions can be made about the probability distribution of the white noise component of the errors. Assuming a Gaussian distribution, they developed ML estimators for the separate cases of a) heteroscedastic-independent, and b) homoscedastic-first-lag-autocorrelated measurement errors, and demonstrated their superiority over the SLS and weighted least squares (WLS) in simulation studies. Sorooshian, Gupta and Fulton (1982b) used these estimators to calibrate the SMA-NWSRFS model to an U.S. watershed and found that the consideration of heteroscedasticity resulted in more realistic parameter values and substantially improved forecast performance. This was in spite of the fact that the SLS had obtained a superior fit to the calibration data. They noted that commonly used goodness-of-fit criteria (such as root mean square error) are therefore not reliable indicators of model fit. The study indicated that consideration of heteroscedasticity is substantially more important to the estimation procedure than the consideration of autocorrelation alone. An interesting problem for future research would be to investigate the nonlinear nature of the stage-discharge relationship to see if a more appropriate model of heteroscedasticity than the one used by Sorooshian and Dracup (1980) cae be found.

It is interesting to note that the aforementioned work neglected the fact that the stage-discharge relationship usually displays differing behavior during the rising and falling phases of streamflow.

The ML estimation procedures reviewed above were developed under the assumption of a deterministic model and input. Goldstein and Larimore (1980), Larimore (1982) and most recently Restrepo-Posada and Bras (1982) have independently devoeloped ML parameter estimation procedures for their stochastic state-space version of the SMA-NWSRFS model, using concepts drawn from Kalman filiter theory and its extensions. They assumed that the erros in the model had a constant diagonal covariance matrix and that noises in the measurements were uncorrelated with constant coefficient of variation, and have reported good performance of the estimators. The use of filtering theory to improve the performance of CRR models certainly seems to be a step in the correct direction as it permits a more realistic manner in which all the various sources of uncertainty can be handled. It seems likely that development of more sophisticated techniques to represent the model and data uncertainties, based perhaps on the ideas of Sorooshian and Dracup (1980) can result in further improvements. Howerver, there also remain some unanswered questions regarding the use of filter the or in CRR modeling. The current approach has been to modify the structure of the model so as to meet the mathematical requirements of available estimalion methodologies which are based on extensions of linear systms theory. This approach may be acceptable in so far as it does not significantly modify the conceptualized behavior of the model. If it is found that such requirements cannot be met, it may be necessary to look for more sophisticated nonlinear approaches to handle the problem. Kitanidis and Bras (1978) remarked that simple suboptimal nonlinear filters could perhaps be devised based on the physics of the system and may be more appropriate in the presence of the highly nonlinear threshold elements of the highly nonlinear threshold elements of the model.

2. Optimization Algorithms

The algorithms most frequently used to calibrate CRR models have been the direct search procedures (e.g. pattern search method, Rosenbrock's method etc.). Gradient techniques which use numerical (fieite difference) approximation of the Hessian have been tested but have not been found to be more efficient than the dirert search procedures. A probable reason for this is that the response surface generated by the selected by the selected estimation criterion is often not smooth enough to permit a sufficiently accurate approximation of the Hessian. The estimation of CRR model parameters has been found to be far from simple due to the highly nonconvex nature of the response surface. Many researchers have demonstrated the existence of multiple optima, extended valleys (line optima), high parameter interaction and parameters with substantially varying degrees of sensitivity. They have also often reported the inability to obtain unique and realistic parameter values through the search process. Sorooshian and Gupta (1982) examined the main causes of the above response surface problems and identified the following three:

1. model structure representation and nonlinearity in the parameter space.
2. Imperfect representation of the physical process by the model.
3. Data and their associated measurement errors.

Examples of the types of response surface problems caused by one and two were discussed earlier. The role that the data measurement errors play in the deterioration of the response surface has only recently been studied. Sorooshian and Gupta (1982) demonstrated that the use of the ML estimation criterion, which realistically models the stochastic properties of the streamflow errors, resulted in a response surface with superior convergence properties and reduced incidence of data-caused multi-local optima. Another method that may be used to improve the convergence properties of the response surface is optimization in a transformed parameter space. For example Gupta and Sorooshian (1982) (discussed earlier) demonstrated that a simplified version of the Sacramento Model could be made identifiable by appropriate reparameterization of the model's structural equation. The problem of choosing an appropriate parameterization to improve the convergence properties of the response surface is a fundamental one that deserves much closer attention than it has received so far.

Since it has been demonstrated that the convergence properties can be markedly improved, a re-evaluation of the effectiveness of gradient algorithms is in order. Interest in this area appears to have been revitalized. Yeh (1982) and Williams and Yeh (1982) reported the use of a constrained quadratic programming algorithm in the calibration of a four-parameter Kinematic catchment model. Restrepo-Posada and Bras (1982) reported the development of a nonlinear constrained optimization procedure based on the Davidon-Fletcher-Powell method and on a gradient projection algorithm, and estimated the required partial dertivatives using functional approximations. Probably the most sophisticated application of gradient search algorithms was reported by Goldstein and Larimore (1980) who described the use of the Levenburg-Marquardt algorithm, constrained to remain in the subspace orthogonal to any nonidentifiable parameters. The aforementioned algorithms were applied to the calibration of state-space versions of the SMA-NWSRFS. A noteworthy aspect of the latter work is that the partial derivatives were calculated directly from the model through the filter equations.

Another aspect of the optimization problem that requires careful consideration is the choice of appropriate convergence criteria. The lack of an appropriate theoretical basis for selecting an estimation criterion and the reported poor convergence properties of the response surface have led researchers to employ arbitrarily chosen criteria, such as maximum number of function evaluations or some small percent change in the estimation criterion value. Sorooshian, Gupta and Fulton (1982b) showed that such a practice can result intermination of the search far from the ML values of the parameters whenever a high degree of parameter interaction is present. They, as well as Brazil and Hudlow (1980) employed a termination criterion based on the inability of successive reductions in the step size of the Patten Search Algorithm to improve the function value. Restrepo-Posada and Bras (1982) terminated their search when the optimization algorthm failed to improve the log-likelihood function by more than 0.01 units (the log-likelihood function evaluated at two standard deviation of the parameters is exactly two units smaller than the maximum) Goldstein and Larimore (1980) used a statistical convergence criterion whose objective is to make the error in the parameter estimates small relation to the expected error in the ML estimate due to sampling variability. This convergence criterion was based on a basic test of hypothesis using the chi-square statistic.

3. Calibration Data

It is evident that the success of any cailbration procedure is ultimately dependent on the nature (quantity and penality)of the data used. It is often suggested that the calibration data should be as "representative" of the various phenomena experienced by the watershed as possible. Many researchers have attempted to satisfy this requirement by using as great a length of calibration data as was possible. This approach has not, however, provided demonstratably superior results. Goldstein and Larimore (1980) and Sorooshian, Gupta and Fulton (1982b) note that it is not the length of data used, but the information contained in it (hydrologic variability) and the efficiency with which it is extracted, that is important. As Klemes (1982) remarked, there is a real danger of "over-fitting, which amounts to regarding part of the noise in the data as information. This error is easy to commit because the demarcation line between information and noise is often blurred in the data." Sorooshian, Gupta and Fulton (1982b) showed that the ML procedure based on consideration of heteroscedastic streamflow measurement errors was much less sensitive to various characteristics of the calibration data, such as hydrologic variability and length. They found that this procedure obtained realistic parameter estimates and uniformly good forecasts with only one year of calibration data; this use of longer data sets only serve to marginally improve the parameter estimates. They recommended that no less than one water-year of data should be used for adequate representation of the complete, seasonal hydrologic cycle, and that wetter years are more likely to ensure adequate activation of all model parameters during calibration.

Recently some researchers have raised a more fundamental question about the adequacy of runoff measurements as the sole source of information for model identification. Fiering and Kuczera (1982) pointed to the fact that runoff accounts for only about one-third of the throughput in a catchment and stated that existing models which concentrate on the relationship between rainfall and runoff exclude two-thirds of the throughput from contributing to the fitting or validation procedures. They stressed the need for collection of measurements on three or more selected fluxes and/or state variables, based on which a more comprehensive watershed budget can be developed The resulting continuity and transfer equations can then be simultaneously solved to obtain the parameters. They proposed a framework for such a model and suggested that it may no longer be called a "rainfall-runoff" model "because the parameters are jointly turned to rainfall, runoff, and other system fluxes or state variables." Kuczera (1982) used an example to illustrate the relationship between estimator reliability and time series data used in calibration. A simple linear lumped watershed model was employed, and in addition to runoff data, groundwater elevation data was also used for calibration. This additional information was shown to improve the reliability of the parameter estimates. The Fiering-Kuczera modeling approach is a further attmpt to obtain as accurate a model of the process as possible within a framework that will allow us to exploit more fully some recent developments in systems theory. This approach displays a lot of potential and certainly deserves closer attention in the years to come.

Finally, in regard to the calibration data, Linsley (1982) stressed the need for making available sets of "carefully checked data with as few errors as it is humanly possible to achieve," which can be used to more objectively test model performance. Such data sets should be selected from as many disparate climatic and geographical locations as possible and should be accompanied by as much additional relevant information as is available.

Manual Calibration

During the period under review there have been few reports of singificant contributions in the area of manual calibration. The U.S. National Weather Service (Brazil and Hudlow 1981) uses a combined manual automatic approach in the calibration of the SMA-NWSRFS model. For most practical purposes, CRR models are calibrated manually simply because automatic techniques are viewed by many as not being sophisticated enough to be fully trusted. In all fairness however, since most (if not all) operational CRR models were developed without specific consideration of the special requirements of automatic techniques, it is asking too much that an automatic method perform significantly better than a manual approach. Recently there has been a move toward the use of interactive computer graphics for manual calibration. Smith and Brazil (1980) reported the development of an Interactive Forecast Program (IFP) for the SMA-NWSRFS model and discussed the possible benefits of interactive graphic features for forecasting.

Model Validation

Conventional statistical measures (e.g., coefficient of variation, root mean square, % BIAS etc.) have usually served as the main criteria for testing the accuracy of calibrated models. However, as Sorooshian and Dracup (1980) and Sorooshian, Gupta and Fulton (1982b) showed, the statistical goodness-of-fit criteria, which are based on measured values of the model output, (which are costaminated with measurement noise) are not necessarily accurate indicators of the best model fit. Furthermore, good performance with respect to quadatic criteria does not necessarliy guarantee equally satisfactory performance in forecasting the most important characteristics of the hydrograph, such as the beginning of rising limb and the magnitude and timing of the peak(Kitanidis and Bras 1980c). The latter mentioned authors suggested the use of the "coefficient of Persistence" which compares model performance to the "no-model" prediction (predicted flow at time $t+1$ equals observed flow at time t). This indicator favors models that perform well under the highly nonstationary conditions of flood forecasting. Other indicators which have been reported include the following: a linear combination of the mean ratio and its standard deviation (Cunday and Brooks 1981); the % RMS error by flow group (Restrepo-Posada and Bras 1982); and the % BIAS by flow group (Sorooshian, Gupta and Fulton 1982b). The last mentioned statistic was shown to be useful in exposing any tendency of the model to reproduce one aspect of the hydrograph at the expense of another.

Finally, there is one aspect model validation that is often ignored. As discussed by Klemes (1982), an important characteristic of a conceptual R-R model should be its credibility under varied and diversed hydrologic conditions. Models are frequently calibrated and verified using rather similar periods of hydrologic record. Amore rigorous model validation procedure that should be performed whenever possible is to test its forecasting ability during a period which is as remotely different from the calibration record, in its characteristics, as possible. Suchran approach would also serve as an objective means of comparing the accuracy and reliability of different models or types of models.

Forecasting

The production of a streamflow forecast involves first the conversion of effective rainfall to channel inflow, using a soil moisture accounting model and second, the translation and attenuation of the flood wave as it travels down the stream to the measurement point, using a flood routing model. As previously mentioned, most operational flood forecasting models are operated in a deterministic manner. A serious deficiency of most reported studies is that the forecast is rarely accompanied by a statement of confidence in its value. Note, that since the model can never be calibrated to give an exact fit to the data, there is some inherent uncertainty in the forecast carried over from the calibration stage. Further, as discussed by Garen and Burges (1981), besides errors in the model structural form, there will be an inherent uncertainty in the model output due to uncertainty in the values the estimated parameters. With regard to the latter point, Garen and Burges using the Stanford watershed model, showed that approximates error bounds could be obtained using a first-order uncertainty analysis if the coefficents of variations on the sensitive parameters were less than 0.25. This allowed for a large reduction in computation over Monte Carlo methods.

A second aspect of the current "deterministic" approaches to the modeling of channel inflow and streamflow routing is their inability to utilize real-time information about the riverflow discharges for the continuous correction of the forecasts. Valuable contributions have recently been made in this area. The works of Goldstein, and Larimore (1980) and Kitanidis and Bras (1978, 1980 a,b,c) involved the stochastic state-space representations of the SMA-NWSRFS model (as discussed earlier) so as to permit the use of Kalman filter based methodologies for on-line updating of the model states. The ability of these models to provide superior forecasts have been demonstrated for certain catchments in the U.S. Kitanidis and Bras (1981 b & c)also discussed the stochastic nature of uncertainties that may be observed in the precipitation sequences, and provided an adaptive filtering methodology which explicitly accounts for abrupt errrors in the estimates of the effective rainfall. Goldstein and Larimore (1980) followed a different approach in modeling rainfall uncertainty; they assumed the true precipitation to be the output of a nonlinear model driven by white noise, and used both rainfall and runoff measurements to update the model states.

Goldstein and Larimore (1980) also demonstrated a method for obtaining reduced order state-space representations of the unithydrograph for routing of channel inflow, thereby reducing the computational complexity involved in the exeution of the filter estimation algorithms. Georgakakos and Bras (1982) presented a nonlinear stochastic model of the flood routing process. They proposed a linearization methodology suitable for their model and used Kalman filter-based theory for real-time estimation of the paramaters and states. They showed that showed that the new approach was capable of reproducing many of the characteristics of the observed hydrographs without the requirement of high quality input data and that the adaptive procedure was an improcedure was an improvement over the offline methodology.

It should be pointed out that an interesting consequence of the use of filter theory is its ability to provide explicit statements of confidence in the model predictions. It is the opinion of this reviewer that such statements contain invaluable information regarding the forecasting ability of a model, and should be provided along with the forecasts whenever possible.

An important aspect of the problem of realtime forecating is the "lead-time" for which reasonably reliably reliable forecasts can be generated. Kitanidis and Bras (1980c) reported that the conceptual SMA-NWSRFS model performed significantly better than an ARMAX linear stochastic medel, with adaptive on-line estimation of the parameters and the states, for lead times longer than six hours. Further, the linear stochastic model forecasts were reported to be unreliable in the case of changing hydrologic conditions, or errors in the measurements. Though the ARMAX model was found to forecast satisfactorily in the recession limb, the conceptual model was found to be more reliable in forecasting the most important features of the hydrograph, such as the beginning of the rising limb, the time and height of the peak and the total water volume.

The aforementioned work has demonstrated the feasibility of using filter theory for improving the quality of the forecasts of CRR models. Kitanidis and Bras stated, however, that the work done so far suggests that "the forecasting of river flows is considerably more difficult than has often been implied in the literature. In order to make the right corrections in the state of the system and thus enhance the accuracy of future forecasts, the correct structure of uncertainty, pretinent to the specific model and data must be hypothesized." Further, the reliability of these new forecasting techniques can be greatly enhanced if due attention is paid to the unresolved problems encountered in the model identification/parameter estimation stage. It is hoped that in the future this area will receive considerably more attention in the U.S. than it has so far.

This review would be sadly incomplete if there were no mention of the great strides in the practical utilization of CRR models for real-time forecasting. The U.S. National Weather Service operates a large number of river forecast centers throughout the country whose major purpose is to pervent or reduce the great losses of life and property caused by flooding. Burnash and Bartfeld (1980) and Burnash and Ferral (1982) have reported on the integration of an automated data collection and communication system that provides real time rainfall measurement with the SMA-NWSRFS model, so as to obtain a relatively inexpensive automated analysis capability for continuous evaluation of flood potential. They emphasize the following requirements: the flood warnings must have sufficient credibility so that they are not disregarded by the local residents; the lead time for a warning must be as long as possible, consistent with maintaining that credibility. With regard to the latter point it was stressed that an automated data collectioni system, with a capability of continuous and instantanous reporting, is absolutely essential. Finally, the use of effectively programmed on-site microcomputers, to allow the local communities to evaluate and respond to local threats with a higher level of timeliness and effectiveness was discussed. These computers can be linked to a larger central processing facility to provide important information on a regional basis.

Systems-Theoretic Models

During the 60's and the 70's, many significant advances were made field of linear systems identification and estimation theory. A number of these "systems-theoretic" modeling techiques have been adapted by the hydrologic community for the modeling of the R-R process, with varying degrees of success. In this review a system-theoretic model will be interpreted as one that is developed to establish a causal linkage between two or more observed phenomena without detailed consideration given to the internal description of the physical process under investigation. In constrast to the so-called "conceptual" models, the structure of a systems-theoretic model is often not specified apriori and must be established as a result of the "system's identification" process. In most cases the parameters of such models have limited physical significance and are chosen entirely on the basis of the optimization of some statistical criterion. Such models have been found to work extremely well in many real world applications. Their utility in surface hydrology, however, depends largely on the ability to satisfy the critical assumptions related to the underlying mathematical theory. Prior to this review period there was a proliferation of reports of the application of Box-Jenkins modeling and statespace/Kalman filtering theory in surface hydrology, culminating in the 1978 AGU Chapman Conference [Chiu 1978]. During the review period, however, most of the published papers seemed to concentrate on the resolution of the problems associated with the extension and adaption of these techniques to hydrologic modeling. The majority of the work reported are attempts to relate the input/output process within the framework linear models. The adequacy of the linear model structure has, however, been investigated by some researchers and there have been reports of extensions into the more general framework of nonlinear systems-theoretic modeling.

In this review we will examine the various contributions made by U.S. researchers in the past four years within the following two general areas: a) model identification and parameter estimation and b) forecasting.

Model Identification and Parameter Estimation

By far the most popular approaches in linear modeling of hydrologic time series have been the Box-Jenking ARMA, ARMAX, and transfer function-noise model approaches. The majority of the reports deal with the prediction of future a streamflow based on past flow data or with the causal relationship relating future streamflow to one or more hydrologic time series (e.g. past flow data and measurements of rainfall). In general the class of ARMA models has not been found effective in the modeling of short-term flows (e.g., daily and hourly) because of its inability to reproduce the highly time-variable characteristics of such time series. It appears they have their greatest utility in the modeling of weekly, monthly, seasonal and yearly flows. A very useful and comprehensive exposition on this topic is contained in the recent book by Salas et. al. (1980) entitled "Applied Modeling of Hydrologic Time Series." The ARMAX modeling approach, however, exploits the strong causal relationship between streamflow and other hydrologic time series, in particular precipitation, to obtain quite effective predicitions of short-term watershed response. There have been numerous reports in the literature of the application of such models. In many of these applications the common assumptions have been that the fllows may be related to effective rainfall by a timeinvariant model whose residuals are white noise. These assumptions have not always been found co be satisfactory. Yazicigil, Rao and Toebes (1981) modeled the daily flows in a number of river reaches by using multi-input linear transfer functions. They showed that by assuming the noise to be white the estimation procedure resulted in biased forecasts. The bias was reduced and the forecasting ability of the model substantially improved by the inclusion of a parallel noise processing model to accont for the correlation in the residuals. They also compared the ordinary least squares (OLS) method of parameter estimation to the constrained linear system (CLS) approach of Todini and wallis (parameters are restricted so as to preserve mass balance) and found that the latter reduced the bias in the forecasts and improved the overall accuracy of the models.

Recognizing that the assumption of linearity of the R-R process is inadequate to represent the highly variable characteristics of observed streamflow sehuences, many researchers have proposed the pre-processing of the precipitation to obtain a new "effective precipitation" time series which can then be transformed into streamflow through a linear operator. Datta and Lettenmaier (1982) used an approximate conceptual description of the interception storage, and infiltration processes to compute "net precipitation," which was subsequently related to the observed runoff using the constrained linear system (CLS) model. They demonstrated that certain problem related to calibration and prediction encountered in using the original CLS model were significantly reduced. Use of their model resulted in the incorporation of the nonlinear behavior of the system without the necessity for the multiple parameter vectors associated with the antecedent precipitation thresholds used in the original CLS. They also demonstrated that a square root transformation of the data resulted in a more consistent reproduction of both high and low flows. Although in this study the pre-processor was calibrated manually, the authors state that the application of automatic calibration would be reported subsequently.

It has ofton been suggested that one way to account for the time-varying nature of the process while retaining a linear model structure is to allow the parameters of the model to vary with time and to be estimated adaptively. There has been intensive work in this area outside of the U.S.. One of the few reported in the U.S. is that of Kitanidis and Bras (1980c). They fit an ARMAX model to the Cohocton River Basin using 6-hourly precipitation and runoff data and adaptively estimated all the parameters and error statistics on-line using a suboptimal filtering algorithm. The model was reported to have a one-step ahead (6-hours) forecast error sum of squares comparable to their version of the SMA-NWSRFS model, but its performance for longer lead times was considerably worse. In general, the ARMAX model was found to forecast satisfactorily in the recession limb of the hydrograph. However, the assumption of time-varying parameters resulted in on-line estimates representing only the most recent input/output behavior of the model, and thus in cases of changing hydrologic conditions or errors in the data the forecasts of the model were not reliable.

Mao and Rao (1982) suggested that instead of using a time-varying system, the measured precipitation could be transformed into "modified rainfall" by accounting for factors which introduce nonstationarities into the R-R relationship such as evaporation and soil mositure storage. The parameters of this rainfall transformation model were specifically chosen to render as stationary as possible the relationship between the modified rainfall and runoff. They reported the cross correlation coefficients between the modified rainfall and runoff to be higher than those relating the original time series, thereby reducing the time variability of the model parameters to the extent that, updating did not necessarily lead to better forecasts. An interesting by product of this approach was that the residuals from the fitted models were found to be both white and free of periodicity, thus eliminating the need for a parallel noise processing model. The authors also reported the use of the instrumental variable-approximate maximum likelihood method (IV-AML) which is designed to eliminate biased estimation caused by the measurement noise, and encountered convergence problems for some data sets. The forecasting abilities of the IV-AML parameters were similiar but slightly worse than those obtained using OLR. It was concluded that although OLS parameter estimates were biased, they were accurate enough for the watersheds in question.

There have been surprisingly few reports published during the review period in which the adequacy of the assumptions commonly employed in the parameter estimation phase have been critically examined. It is normally assumed that the residuals of the models are Gaussian, homoscedastic white noise. In this case the popular OLS criterion provides efficient and unbiased ML parameter estimates. Miller et. al. (1681) provided a rather comprehensive case study in which they fit transfer function-noise models to a number of watersheds. They demonstrated that the skewness of the residuals was reduced and the forecasting ability of the model significantly improved by the use of log-transformations of the flows and the inclusion of second degree-polynomial precipitation terms. They found however, that the variance of the residuals tended to increase with the level of rainfall thereby contradicting the homogeneity assumption used in the OLS. They also reported that the residuals could not be adequately represented by a Gaussian distribution, or indeed any of the standard distributions such as those in the Pearson family and suggested that the Wakeby distribution might be a possible candidate. Their work indicated that far greater care is required in the selection of model criteria and the verification of modeling assumptions than is often taken.

Miller et. al. (1981) also examined the implications of assuming that the parameters of the model are unknown constants. They conjuctured that the daily river flows observed in different years might be generated from a single "super model" (transfer function plus parallel noise) whose parameters in any given year were themselves randomly generated. Using simulation studies they found evidence that the variation (from year-to-year) of the model parameters may have a greater impact on the flow characteristics than do variations in the rainfall. It was suggested that the parameter estimation techniques based on random coefficient models which have been discussed in recent statistical literature could prove to be more effective than the currently employed method.

To overcome the difficulties and the drawback of the ARMA and the ARMAX models in fitting daily data, Chang, Kavvas and Delleur (1982) formulated three new stochastic models; two for the simulation of daily precipitation sequences and one daily R-R transfer model to produce daily runoff series. First a qinary-discrete ARMA mixed with an exponential model (B-DARMA-E) was developed to model the wet-dry precipitation sequence. A multi-state discrete ARMA model (M-DARMA) was developed next to facilitate the classification of the precipitation quantities into several discrete states. Finally, a transfer ARMA model (T-DARMA) was used to produce daily runoff series from the above daily precipitation models. The models were successfully applied to five Indiana watersheds.

The approaches reported so far do not explicitly address the presence of noise in the measured data. Recent work on this problem has been reported by Troutman (1982a,b), Cooper and Wood (1980, 1982 a,b) and Wood and Cooper (1982). Troutman (1982a) discussed an important source of input error the spatial variability of precipitation. Usually measurements are available from only a single gage which is not centrally located in the basin thus introducing spatial sampling error. He analyzed the effect of these errors in the calibration of a regression model of runoff on precipitation using OLS and reported that the bias in the runoff forecasts takes the from of underprediction when the observed input is small and overprediction if the observed input is large.

Cooper and Wood (1982a) dealing with output measurement errors, demonstrated the manner in which a multivariate ARMAX model may be cast within the framework of a state-space model. The advantage of the state-space approach is that many different models can be cast within a single simple framework of two equations, a state equation (model equation) and a measurement equation in which the two major sources of errors, namely model inaccuracy and measurement processes can be treated separately. This framework enables more realistic modeling of the uncertainties involved and permits the use of linear filtering theory techniques (e.g. Kalman filtering) for the on-line adaptive estimation of states and/or parameters. The estimatiom methodology proposed by Cooper and Wood (1982a) can be used to relate multiple input and output vectors, using the notion of canonical correlation to determine the order of the composition of the state vector. In a later work Cooper and Wood (1982b) used the innovations from of the state vector model and presented the conditions under which the parameters of their model formulation can be estimated. They also discussed on-line and off-line ML estimation methodologies based on the method of scoring. The methodology was used to model a daily R-R process with three precipitation input, a four-site monthly-streamflow model, and input/output riverflow with tributary model.

An important aspect in the identification of lienar models is the selection of model order, for which methods such as the traditional autocorrelation function (AF), partial autocorrelation function (PAF), inverse autocorrelation function (IAF), inverse partial autocorrelation function (IPAF), and/or spectral analysis, are commonly employed. Salas and Obeysekera (1982) pointed out that these techniqueshave been found to be inadequate for the identification of models in which both autoregressive (AR) and moving average (MA) components are present. They showed that generalized PAF, and the Rand S functions reported in recent statistical literature, provide better tools for this purpose. Cline (1981) examined the utility of the "Akaike Information Criterion" (AIC) and the "Posterior Probability" (PP) criterion (developed by kashyap in complementing the classical hypothesis tests and the correlation methods mentioned above. The two methods were found useful for selection of parsimonious model order. Cline reported that in practice the difference between the AIC and PP results is small for the length of data sets that are usually available.

There have been very few reports on the development of truly nonlinear systems theoretic approaches to watershed modeling, This is due, in part to the difficulties associated with choosing the nature of the nonlinearities, and in part due to the numerical difficulties associated with the solution of the state/parameter estimation problem. Helweg, Amorocho and Finch (1982) revived the work on the Amorocho-Branstatter Model which is based on a second-order Meixner expansion. They presented a quasioptimization approach to overcome the difficulties associated with the estimation of its three main parameters, memory, order, and truncation. This model is proposed as an alternative in those cases when the unit hydrograph approach is found to be unsatisfactory.

More tractable nonlinear approaches have been suggested by Ozaki (1980) and Singh and Buapeng (1981) who selected the forms of their model nonlinearities based on physical arguments Ozaki (1980) presented a nonlinear R-R model based on an approximation to Sugawara's tank model. The model was presented in state-space from and a nonlinear feedback system was proposed as an updating procedure. The AIC was used to select the appropriate model order and the degree of nonlinearity. Good performance of the model on the Kanna River and Bird Creek were reported.

Singh and Buapeng (1981) also discussed a general nonlinear runoff model in state-space from based on cascade of nonlinear storages, and the use of Phillips infiltration equation. Several linear as well as nonlinear models can be derived from the proposed model by restricting its parameters and input distribution. The model was calibrated for 38 different watersheds using a modified Rosenbrock-Palmer algorithm to minimize the OLS criterion. Good performance of the model was reported, however, attempts to establish correlation between the model parameters and the watershed characteristics were unsuccessful.

In the work presented so far, the emphasis has been on the developments of systems theoretic models which only establish the causal relationship between precipitation and runoff. As pointed out earlier there are other important fluxes influencing the behavior of the watershed [Fiering and Kuczera (1982)] which might be used to improve the performance of R-R models. Rao, Tao & Rukuichai (1980), for example, showed that the degree of saturation of a watershed is a highly correlated seasonal variable which strongly effects the statistical characteristics of daily runoff. Its inclusion into the model resulted in the ability to forecast a few days ahead with an improved accuracy. Padmanabhan and Rao (1982a,b) also examined the feasibility of using additional climatological and other time series and the work in this area is continuing.

Finally there has been one reported work examining the suitability of a nonparametric class of time series models for daily river flow forecasting. Yakowitz (1979) reviewed a number of reasons for dissatisfaction with the ARMA class of models for this purpose and presented as an alternative a nonparametric Markov modeling approach. Though the degree of conceptual difficulty and computational complexity were not negligible, the claim was made that it was not more so than required by the ARMA modeling procedure. Yakowitz pointed out that the ARMA parameter estimation involves a fairly difficult nonlinear programming problem. Moreover, the length of record required to estimate the parameters of even a low-order model such as ARMA (2,2), each with a relative error of less than 0.3, is at least a thousand observations, and the inaccuracies of the estimates increase dramatically as the order of the model increases. It is interesting to note that models reported in the literature are often identified using lengths of data that are not long enough to ensure high confidence in the parameter estimates.

Forecasting

Most systems-theoretic models of the ARMA, ARMAX and transfer function-noise model type utilize only information about the input data in order to generate streamflow forecasts. It seems inevitable however, in the light of modeling inadequacies and, consequently, errors in the forecasts, that some from of filtering theory must be employed to update the forecasts based on past model performance. This necessitates formulation of a state-space version of the model so that Kalman based filtering theory can be employed for on-line estimation. Examples of this have been reported by Kitanidis and Bras (1980c) Ozaki (1980), Singh and Buapeng (1981), Cooper and Wood (1982b) and Wood and Cooper (1982).

There has, however, been only one report dealing with the very real problem of forecasting in large catchments with numerous forecast points. Wood (1981) discussed the problem of using a state-space model/Kalman filter approach to handle this problem. Observing that the very large state vector dimension makes the application of a standard Kalman filter approach computationally unmanageable, wood suggested an approach based on the partitioning of the system into separate subcatchments so that a computational problem of reduced size can be solved. The interaction between the subsystems is accounted for through the supplementing of the process noise terms. The method was demonstrated to perfrom as well as a filter based on the entire unpartitioned state vector. Because many watersheds and reservoir systems require forecast information at a large number of points in the watershed, this approach provides a computationally attractive alternative that may result in superior forecasting ability than the currently employed methods.

Concluding Remarks and Recommendations

Recently, Kartevelishvili suggested that the development of an adequate causual theory of hydrologic processes may be much more demanding than was the development of the theory of relativity or the quantum theory (Klemes 1982). Considering that the existence of such a theory is essential in the development of an "ideal" watershed model (that is, one based on a sound understanding of the physics of the R-R process), it is unlikely that any single model (be it conceptual or systems-theoretic), that can perform satisfactorily in each and every situation, will be developed in the near future. Each of these modeling approaches has, and will continue to have, its own advantages and disadvantages, and hence its own particular areas of maximum utility. The field hydrologist or engineer, cannot await the arrival of an "ideal" model, and will therefore continue to excercise his/her engineering judgement in the selection of an appropriate flow forecasting technique (as crude and imprecise as it might be). In the light of the many disagreements that exists in the hydrologic community regarding the direction that future research should take, it is anticipated that the gap between theoretical developments and the degree of their practical application will continue to widen. There are two courses of action that might help to close this gap. First, it is essential that model user be adequately exposed to the mathematical foundations of the various new modeling concepts, so that he/she can relate the compatability of the underlying modeling assumptions with his/her own perception of the physical phenomena. It is alarming to note that many recent graduates from hydrology and water resource programs, who end up dealing with R-R models in one way or another, have not received any formal training in many of the newer concepts. Those who have, often become so preoccupied with the mathematical formalisms involved, that they lose sight of the basic motivation underlying their research. It is hoped that more schools will respond to this need and revise their curicula to establish better balanced hydrology/water resource management programs.

The second course of action is to encourage much closer cooperation between field work and modeling efforts. Such cooperation can lead to the formulation of better and more relevant field experiments. As Dunne (1982) has suggested, sophisticated field experiments can assist the hydrologist to "discover unexpected hydrologic phenomena, to develop new concepts about familiar processes, and to guide the development of mathematical models based on sound physical insights". It would also discourage much of "the aimless collection of data" (Dunne 1982), and motivate the collection of data of adequate quality and sufficient quantity for the purposes of model identification, calibration and validation.

This review has identified the following areas, related to the on-line estimation of river flows, that require closer attention.

1—Conceptual Rainfall-Runoff Modeling

a—the identifiability of CRR models should be studied with a view to establish appropriate parameterization for which unique and consistent (robust) estimates can be obtained using available data and calibration techniques. For this purpose parameter transformations that improve the convergence properties of the response surface could be explored.

b—The sensitivity of the forecasting ability of the models to the assumptions of spatially lumped and time-invariant parameters should be assessed.

c—The relative accuracy, from a physical point-of-view, of various subprocess equations employed in the model should be assessed with the view of identifying the nature and structure of the modeling uncertainties. This would facilitate the implementation of more appropriate parameter estimation and forecasting methodologies, and indicate those parts of the model that need to be improved. One of the model components that has been identified as requiring immediate attention is the representation process.

d—The estimation difficulties induced by the extreme nonlinearities associated with the presence of "threshold" parmeters must be further investigated.

e—The structure and distribution of the errors associated with measurements (and processing) of hydrologic data seruences must be established, so as to facilitate the development of objective stochastic estimation methodologies. In particular, the heteroscedasticity introduced by the nonlinear and time-varying nature of the stage-discharge relationship should be investigated.

f—Nonlinear filtering algorithms that are based on the special structure go the model and its associated uncertainties and will more fully exploit the information present in available hydrologic data sequences should be explored.

g—Guidelines should be established for the selection of data sequences of the type (in terms of variability and quality) and amount (in terms of length) most suitable for model calibration and verfication. It is noted that the critical factor to be examined is the "information content" of the data.

h—The possibility of using additional hydrologic time series data [as suggsted by Fiering and Kuczera 1982], such as groundwater levels, in our models of watershed response should be further explored.

i—Approximate methods for identifying the imprecision in the model forecasts caused by parameter and structural uncertainties in the model should be explored.

2—Systems-Theoretic Modeling

a—Methods by which the time varying and nonlinear behavior of the R-R process can be incorporated within the framework of systems-theoretic modeling should be further explored.

b—Transformations of the hydrologic time series that maximize the linear correlation between the independent and dependent variables should be examined.

c—Guidelines are required to establish the maxium time-step for which timevarying parameter linear models can be employed to adequately forecast the rapidly changing conditions associated with the rising limb of the hydrograph.

d—Estimation techniques should be developed that are less sensitive to, or account for, the usually incorrect assumption that the errors in hydrologic time-series are Gaussian. In particular, it is highly likely that, due to the nature of the stage discharge relationship the errors in the stremflow measurements are significantly skewed.

e—The utility of the state-space/Kalman Filtering approach which enables amore realiatic representation of uncertainties should be further explored. In particular, the use of techniques in nonlinear and distributed modeling of R-R process should be pursued.

f—A promising area that deserves special attention is the use of additional fluxes such as potential evapotranspiration, soil moisture, temperature and other climatological variables, so as to more fully exploit the various causal relationships that influence watershed response.

g—As suggested by Kelman (1980), systems theoretic models of the R-R process should be developed, that explicitly recognize the fact that the rising and the falling limbs of the hydrograph are the results of totally different physical processes. Such an approach might help resolve the often reported problems associated with forecasting of the rising limb and the peak of the flood hydrograph.

3—General

a—A concerted effort should be made to establish a data bank containing hydrologic information of high quality from a number of carefully chosen locations [with disparate climatic and geographical characteristics]. This is an essential step towards establishing an objective procedure for the testing and the validation of R-R models.

b—The various quadratic criteria that are commonly used for model validation should be replaced by measures which more accurately represent the various aspects of model fit under examination,

c—The use of precipitation prediction models, and techniques such as radar telemetry, to increase the lead-time for which adequate flow forecasts can be made be investigated.

d—It is highly recommended that greater consideration and attention be given to the examination of the many assumptions employed in the modeling process. Reported work should contain a clear listing of these assumption and the results of tests to establish their validity.

e—A concerted effort should be made to incorporate within the hydrology/water resources curiclua, a better balance between the teaching of both the physics of the hydrologic process and the mathematical techniques that can be used to model it.

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