UCRL-JRNL-210008

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February 25, 2005

Model Parameter Extimation Experiment (MOPEX) Special Issue

Paper Submitted to MOPEX Special Issue

MODEL PARAMETER ESTIMATION EXPERIMENT (MOPEX): OVERVIEW AND SUMMARY OF THE SECOND AND THIRD WORKSHOP RESULTS

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Abstract: Model Parameter Estimation Experiment (MOPEX) is an international project aimed to develop enhanced techniques for the *a priori* estimation of parameters in hydrologic models and in land surface parameterization schemes of atmospheric models. MOPEX science strategy involves three major steps: data preparation, *a priori* parameter estimation methodology development, and demonstration of parameter transferability. A comprehensive MOPEX database has been developed that contains historical hydrometeorological data and land surface characteristics data for many hydrologic basins in the United States and in other countries. This database is continuing to be expanded to include more basins in all parts of the world. A number of international MOPEX workshops have been convened to bring together interested hydrologists and land surface modelers from all over world to exchange knowledge and experience in developing *a priori* parameter estimation techniques. This paper describes the results from the second and third MOPEX workshops. The specific objective of those workshops is to examine the state of *a priori* parameter estimation techniques and how they can be potentially improved with observations from well-monitored hydrologic basins. Participants of these MOPEX workshops were given data for 12 basins in the Southeastern United States and were asked to carry out a series of numerical experiments using *a priori* parameters as well as calibrated parameters developed for their respective hydrologic models. Eight different models have carried all out the required numerical experiments and the results from those models have been assembled for analysis in this paper. This paper presents an overview of the MOPEX experiment design. The experimental results are analyzed and the important lessons from the two workshops are discussed. Finally, a discussion of further work and future strategy is given.

1. Introduction

A critical step in applying a hydrologic model to a watershed or a land surface parameterization scheme (LSPS) of an atmospheric model to a specific grid element is to estimate the coefficients or constants in the model or LSPS known as parameters. These parameters are inherent in all models. While certain parameters may take on universally accepted values (e.g., gas constant, acceleration of gravity), the values of many parameters are not universally constant and may be highly uncertain. In general, they vary spatially so they are unique to each watershed or a grid point. Some may also vary seasonally. Moreover, some parameters may be space-time scale dependent (Koren et al., 1999, Finnerty et al, 1997). How to estimate model parameters has been receiving increasing attention from the hydrology and land surface modeling community (Franks and Beven, 1997, Bastidas et al., 1999, Gupta et al., 1999, Duan et al., 2001, Duan et al., 2003, Jackson, et al., 2003).

A common approach in hydrologic modeling community to parameter estimation is to calibrate hydrologic models to historical observations by tuning model parameters. A plethora of model calibration techniques have been reported in the literature. For a detailed review of model calibration techniques, readers are referred to Duan et al. (2003) and Duan (2003). To conduct model calibration, a sufficient amount of historical hydrologic data is required. Hydrologists have the advantage of working with watersheds, many of which are well monitored with raingauges and stream gauges. For ungauged basins and for LSPS applications, it is difficult to obtain adequate data needed for model calibration. A further complication is that LSPSs are typically applied to large spatial scales and involve many grid elements. To estimate model parameters in those cases, it is necessary to assign model parameters *a priori*.

A priori parameter estimation procedures are available for many hydrologic models and LSPSs. But these procedures have not been fully validated through rigorous testing using retrospective hydrometeorological data and corresponding land surface characteristics data. This is partly because the necessary database needed for such testing has not been available until recently. Moreover, there is a gap in our understanding of the links between model parameters and the land surface characteristics. Generally available information about soils (e.g., texture) and vegetation (e.g., type or vegetation index) only indirectly relates to model parameters such as hydraulic properties of soils and rooting depths of vegetation. Also it is not clear how heterogeneity associated with spatial land surface characteristics data affects those characteristics at the scale of a basin or a grid cell. Consequently, there is a considerable degree of uncertainty associated with the parameters given by existing *a priori* procedures.

The Project for Intercomparison of Land-surface Parameterization Schemes (PILPS) has revealed widely discrepant simulation results by different LSPSs (see Chen et al., 1997; Wood et al., 1998; Pitman et al., 1999; Schlosser et al., 2000; and Slater et al., 2001). Interestingly, the LSPSs participated in the PILPS experiments were driven by the same meteorological forcing data and they were required to prescribe the same values for commonly named parameters such as soil hydraulic properties and vegetation phenology parameters. The large scattering of model results can be partially explained by the uncertainty in the values of the parameters used in each scheme.

Improper choice of model parameters results in poor model performance (Liston et al, 1994; Duan et al., 1995). It is necessary to develop enhanced *a priori* parameter estimation methodologies for hydrologic models and LSPSs. Toward this goal, a project known as the Model Parameter Estimation Experiment (MOPEX) was initiated in 1996. MOPEX project has been truly an international collaborative endeavor, with the involvement of international scientists and hydrologic data assembled from different countries. MOPEX has the endorsement of several international organizations and projects, including World Meteorological Organization (WMO) Commission on Hydrology and International Association of Hydrological Sciences (IAHS) Prediction for Ungauged Basins (PUB) Initiative (Sivapalan, 2003). The Office of Global Programs in the National Oceanic and Atmospheric Administration (NOAA) and the funding agencies in different countries have provided financial support for scientists to participate in MOPEX activities. A series of international workshops on MOPEX have been convened over the last few years. The first one was held in July 1999, as a part of International Union of Geodesy and Geophysics (IUGG) 21st General Assembly in Birmingham, England. The second MOPEX workshop, co-sponsored by National Weather Service Hydrology Laboratory (NWS/HL) and National Science Foundation Center for Sustainability of semi-Arid Hydrology and Riparian Areas (SAHRA) at the University of Arizona, was held in Tucson, Arizona, in April 2002. The third MOPEX workshop was held in Sapporo, Japan, in July 2003 as a part of the 22nd IUGG General Assembly. The fourth MOPEX was held in Paris, France in July 2004, co-sponsored by Cemagref of France and NWS/HL. The fifth MOPEX workshop is scheduled in Foz do Iguaçu, Brazil, in April 2005.

The MOPEX workshops were designed to bring together interested international hydrologists and land surface modellers to share experience in estimation of hydrologic model parameters. Each workshop has a special focus, either in terms of hydroclimatology (i.e., humid or semi-arid) or in terms of special applications (i.e., flood forecasting). The workshops are also designed to allow different levels of participation. The driving science questions of these workshops are:

(1) How are the parameters of the hydrologic models related to basin characteristics such as soils, vegetation and climate?

(2) How can model calibration enhance existing *a priori* parameter estimates?

(3) What data are needed to develop enhanced *a priori* estimates of model parameters of the hydrological models?

(4) Can we transfer the knowledge about the parameters of one hydrologic model to another model? Related to this question, can we transfer the knowledge about the parameters of a hydrologic model from the well-gauged basins to the ungauged basins?

(5) How should we handle the uncertainty about model parameters and hydrologic modelling in general?

This paper concerns with the second and third MOPEX workshops. For those two workshops, a set of numerical experiments was constructed. The MOPEX participants were given data for 12 basins located in the Southeastern quadrant of the United States. Numerical test results from different modeling groups were assembled for the workshops and the analysis of the results is presented in this paper. The paper is organized as follows. First the MOPEX rationale and science strategy are presented. Then a discussion is given to the objectives and numerical experiment design. The data sets assembled for the workshop are described afterwards. A comprehensive analysis of the results is conducted to understand the differences in the results from different models. Finally, further work and future strategy are discussed.

2. Model Parameter Estimation Experiment Strategy

MOPEX science strategy involves three major steps (Fig. 1). The first step is to develop the necessary data sets. The next step is then to use these data to develop *a priori* parameter estimation methodology. . Step three is to demonstrate that new *a priori* techniques produce better model results than existing *a priori* techniques for basins not used to develop the new *a priori* techniques.

Step two is accomplished using a three-path strategy illustrated in Fig. 1. The first path is to make reference runs with model parameters estimated by using existing *a priori* parameter estimation procedures. The second path is to make model runs using calibrated or tuned values of selected model parameters. Then, the calibrated parameters are analyzed to improve the relationships between model parameters and basin characteristics including climate, soils, vegetation and topographic features. The new relationships are then used to estimate the new *a priori* parameters. The third path is to make new model runs using the new *a priori* parameter estimates. The success of step two is measured by how much improvement in model performance is achieved when the model is operated using new *a priori* parameters as compared to the reference runs.

The MOPEX Project has assembled hydrometeorological data as well as land surface characteristics data that are needed to implement its parameter estimation strategy. Data from many basins in the United States and other parts of the world are being assembled. These basins cover a wide variety of climates. They are selected such that rain-gauge density of the basins must be above the minimum established by an empirical equation (Schaake et al., 2000). Also a minimum of 10 years of data is preferred for all MOPEX basins. The MOPEX basins are also free of streamflow regulation. A later section describes the data set used for the Tucson and Sapporo workshops.

A key in implementing the MOPEX strategy is to develop systematic procedures for calibration of selected model parameters and to apply these procedures to a large number of basins in different hydroclimatic regimes. Then, empirical relationships will be sought between the parameters and various characteristics of soils, vegetation and climate. Much progress has been made in the area of model calibration (Duan et al., 2003). Duan et al. (1992 & 1994) developed a robust optimization method known as Shuffled Complex Evolution (SCE-UA) method for optimal estimation of model parameters. Yapo et al. (1997) and Gupta et al. (1999) have extended Duan's approach in the context of multi-objective theory. Recently there is a surge of interest toward producing multiple sets of model parameters, as a means to account for uncertainty related to model structure, calibration data and model parameters. These methods use Monte Carlo sampling techniques to produce a set of solutions, all of which are regarded as "equifinal" (i.e., all of the solutions are equally valid). Examples of those are Generalized Likelihood Uncertainty Estimation (GLUE) by Beven and Binley (1992), Markov Chain Monte Carlo (MCMC) Metropolis scheme by Kuczera and Parent (1998) and the Shuffled Complex Evolution Method Metropolis (SCEM) scheme by Vrugt et al. (2003). For more on the state-of-the-art on model calibration methods, readers are referred to Duan et al. (2003).

Numerous studies have been directed at developing improved *a priori* parameter estimation procedures for hydrologic models and LSPSs. Earlier examples of *a priori* parameter estimation procedures are from the field of soil physics, in which soil hydraulic properties (as appeared in many hydrologic models and LSPSs) are related to soil texture classes in a tabular format (see e.g., Clapp and Hornberger, 1978, Cosby et al., 1984, Rawls et al., 1991, Carsel and Parrish, 1988). Many land surface modellers have directly adopted the *a priori* parameter estimation schemes developed by soil physicists to assign values to parameters in LSPSs (Dickinson et al., 1986, Sellers et al., 1986). Duan et al. (2001) pointed out that this practice is questionable because the tabular relationships between soil hydraulic properties and soil texture classes are based on analysis of soil samples tested at laboratories. These relationships may not hold up in the real world, especially over grid elements of several hundred to several thousand square kilometres. For typical hydrologic models and LSPSs, it is often the case that the relationships between many of the model parameters and land surface characteristics are not obvious. One approach to solve this dilemma is to develop *a priori* relationships between land surface characteristics and model parameters for basins where the model is appropriately calibrated (Abdulla et al., 1996, Duan et al., 1996). With the advent of Geographic Information System (GIS), many more *a priori* parameter estimation procedures have appeared. These schemes are model specific and are still being evolved. A number of those schemes are being tested in the second and third MOPEX workshops and are part of the analysis in this paper.

3. Design And Database Of The Second And Third MOPEX Workshops

3.1 Workshop Objectives:

The second and third MOPEX workshops focused on the second step of the MOPEX strategy: data preparation and development of parameter estimation procedures. The emphasis of the workshop was on validating existing *a priori* procedures and on evaluating potential improvement from model calibration. Because all hydrologic models are formulated differently, parameter estimation procedures are model-specific. A challenge facing hydrologic modelers is how the knowledge gained from one model can be transferred to another model. This is also the principal reason to convene these MOPEX workshops. A specific objective of these workshops is to examine the state of *a priori* parameter estimation techniques and how they can be potentially improved with observations from well-monitored hydrologic basins. Particularly we sought to answer the following questions:

(1) How do we define the relationships between model parameters and basin characteristics?

(2) How can model calibration be used to refine the *a priori* parameters?

(3) How do we evaluate the uncertainty due to model structure, calibration data and model parameters?

3.2 Design of MOPEX Numerical Experiment:

To answer these questions, a set of numerical experiments was set up. Data for 12 basins located in the southeastern quadrant of the United States were prepared. The data sets include hydrometeorological data as well as basin land surface characteristics data. More discussion on these data sets is given in the next section. The data were distributed to MOPEX participants via ftp and CD-ROMs. The MOPEX participants were asked to run two sets of runs. The first set of runs are to run their respective models on all 12 basins using existing *a priori* parameters developed for their models. The second set of runs involves model calibration for pre-selected common data periods. After model calibration, the participants are asked to run their models using calibrated parameters for the calibration and verification data periods. All results were collected for analysis by the MOPEX workshop organizers.

3.3 Description of the Data Set:

3.3.1 MOPEX Data Requirements

The first step in MOPEX strategy is to assemble a large number of high quality data sets for a wide range of Intermediate Scale Area (ISA) river basins (500 – 10,000 km^2) throughout the world. There are strict requirements for MOPEX data sets in terms of data type, quantity and quality. Two basic data type are hydrometeorological data and land surface characteristics data. MOPEX basins should be unregulated basins and cover a variety of climate regimes. The basic hydrometeorological data required for MOPEX include daily precipitation, daily maximum and minimum temperature, daily streamflow data and climatic potential evaporation data. More desirable hydrometeorological data include hourly surface meteorological data include precipitation, incoming long-wave and short-wave radiation, air temperature, air humidity, atmospheric pressure, and wind speed, etc. The quality of precipitation data is critically important to parameter estimation. MOPEX has established a minimum density requirement for raingauges based on basin size (Schaake et al., 2000). To ensure various hydrologic events are represented in the hydrometeorological data, MOPEX requires that the data length exceed 10 years. Desirable data length is 20 years or more.

The basic land surface characteristics data include basin boundary, soil texture and vegetation type data. More desirable land surface data sets include high resolution (1 km or finer) Digital Elevation Model (DEM) data, seasonal land cover/land use data such as Normalized Deviation of Vegetation Index (NDVI), greenness fraction, snow cover and soil moisture climatology, etc.

3.3.2 MOPEX Data for the Second and Third MOPEX Workshops

For the second and third international MOPEX workshops, hydrometeorological data as well as basin land surface characteristics data for 12 basins in the Southeastern quadrant of the United States were assembled. Fig. 2 shows the location of the 12 basins. These basins represent a wide range of different climate, as indicated by the ratios of annual precipitation (P) and potential evapotranspiration (PE) in Fig. 3. A high value for P/PE indicates wet climate and a low value dry climate. The climatic seasonal precipitation and streamflow distributions are shown in Fig. 4.

The hydrometeorological data sets prepared for the workshops included hourly mean areal precipitation, daily streamflow, climatic daily potential evapotranspiration. The hourly precipitation data sets were developed by the NWS Hydrology Laboratory (HL) based on hourly and daily raingauge data from the National Climate Data Center (NCDC). The daily streamflow data were obtained from US Geological Survey (USGS).

The climatic potential evaporation data was derived from the NOAA Freewater Evaporation Atlas (Farnsworth et al., 1982). Also included are basin averaged hourly meteorolological forcing data, including precipitation, air temperature, wind speed, surface pressure, short-wave and long-wave radiation and specific humidity. All meteorological forcing data except precipitation were processed from the 1/8 degree meteorological forcing data for the conterminous US developed by the University of Washington (UW) (Maurer et al., 2001). The UW hourly meteorological data set is derived from NCDC daily precipitation, daily minimum and maximum temperature and analyzed wind speed data obtained from National Center for Environmental Predictions (NCEP). The historical data from different sources span over different data periods. For this study, a common period, 1960 to 1998, is chosen so data from all sources are available.

The land surface characteristics data sets assembled for this study include 1 km soil type data from the STATSGO data set (Miller and White, 1999), the 1 km vegetation type, and 5-min greenness fraction data (Loveland et al., 1999, Hansen et al., 1999, Gutman and Ignatov, 1998). Fig. 5 and 6 show the vegetation type and soil type distributions of the 12 basins. As shown in those figures, a number of different vegetation and soil type are represented. Other land surface data include basin boundary, elevation, monthly surface albedo and roughness length. Basin climatologic data such as monthly long-term average precipitation, streamflow and potential evapotranspiration have also been made available to MOPEX participants.

4. Results and Analysis

Eight hydrologic models and LSPSs have completed all of the required numerical experiments as described in Section 3.2. A few additional groups submitted partial numerical experiment results for other models and those are not included in this analysis due to the incompleteness of those results. Table 1 lists the eight participating models. Of the eights models, the first four models (SWB, SAC, GR4J and PRMS) are watershed rainfall-runoff models, while the last three (ISBA, SWAP, and Noah models) are LSPSs. VIC model has been used both as a watershed model and a land surface scheme in atmospheric model. The analysis presented below is based on the comparison of the simulated streamflow from the 8 models and the corresponding observations at daily or monthly time step. We must emphasize that the purpose of the intercomparison study is not intended as a "beauty" contest. Instead, we seek to understand the differences between approaches and use this understanding to develop new *a priori* parameter estimation procedures. For this reason, the model names are not spelled out in the figures.

4.1 The simulation results using existing a priori parameters

The purpose of simulations using existing *a priori* parameters is to establish benchmarks for the current *a priori* parameter estimation procedures used by the participating models. Any new *a priori* parameter procedures developed in the future for those models should at least outperform the benchmarks. It should be noted that among the eight models under study, some models already have established *a priori* parameter estimation procedures, while others have no such systematic procedures. This discrepancy is reflected in the results shown below. Fig. 7 displays the comparison of the simulated annual streamflow totals from the *a priori* runs and the corresponding observed values. The spread of simulated streamflow annual totals is quite large between the models. None of the models were able to generate simulated streamflow values that match the observed values for all basins. The maximum over-bias exceeds 400 mm/year and the maximum under-bias is about 340mm/year.

Nash-Sutcliffe (NS) efficiency is a commonly used goodness of fit measure between the simulated time series and observed time series. It is expressed as:

$$NS = 1 - \frac{\sum_{i=1}^{n}(Q_i - Q^*{}_i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})^2}$$

where Q^*_i and Q_i are the simulated and observed values at time i.$\overline{Q}$ is the average of observed values. A value of 1 indicates perfect fit between Q^*_i and Q_i, while a value of < 0 implies that simulated value is worse than the long term average of the observations. Fig. 8 shows the NS efficiency of the daily streamflow simulations by the eight models. The NS values have been sorted from the lowest to the highest for each model. Fig. 9 a&b show, respectively, the means and the standard deviations of the NS values. These figures reveal some interesting findings. Even though some models have some of the higher ranked NS values for most basins, they do not rank high for all basins. On the other hand, some models (e.g., Model E) are shown to be consistent in all basins. This consistency is reflected in the low standard deviations for those models. In general, the models with the low average NS values also have the high standard deviations. It should also be noted that some models perform worse than long-term average for some basins, indicating a definitive need to improve *a priori* parameter estimates under those circumstances.

Fig. 10 and 11 show the same information for all models as in Fig. 8 and 9, but evaluated at monthly time step. The NS statistics for all models at monthly time step have improved over those at daily time step. Still for a couple of models, the model simulations produce worse statistics than the long-term average of observations for one basin. The fact that a model does well for most basins, but poorly for only a few, tells us that the modeler should probably focus attention on the basins with poor results when looking for enhanced *a priori* parameter estimates.

4.2 The Simulation Results Using Calibrated Parameters

There are several objectives in this exercise. First, we hope to quantify the potential improvement in model performance when the models are calibrated using observations, as compared to those using *a priori* parameters. Second, we want to make sure that there is consistency in streamflow simulations between calibration and validation data periods when the calibrated parameters are used. The ultimate objective of this exercise is to use the calibrated parameters to establish new *a priori* parameter estimates.

All model groups were asked to calibrate and validate their models for all 12 basins using historical hydrologic data. Originally, it was a split sample approach was to be used. Years 1980-1990 were to be used for calibration, while the first 19 years (1960-1979) were to be used for validation. Because different groups used different 19-year periods for calibration, it is not possible to make a direct comparison of all 8 models using the split-sample approach. But the differences in calibrated model performance between the different 19-year periods were much smaller than the differences in model performance between the *a priori* and calibrated runs, it seemed the best way to achieve the study objectives was to use the entire 1960-1998 period to evaluate model results for both the *a priori* and calibrated runs.

Fig. 12 shows the simulated annual streamflow totals using calibrated parameters versus the observed annual streamflow totals. Compared to Fig. 7, the scatter around the diagonal line is much smaller, indicating the agreement between the simulations using calibrated parameters and the observations is better than that using *a priori* parameters. Fig. 13 displays the sorted NS values for all models for the calibration period 1980-1998, while Fig. 14 shows the average NS values and standard deviations at daily time step. All of those figures confirm that the NS values are improved for almost all models compared to the *a priori* results. Except for one model in one basin, all NS values are positive when calibrated parameters are used.

Fig. 15 and 16 show the same information as in Fig. 12 and 13 for all models, but the NS values are computed using monthly aggregated values. Note again that the two models with low average NS values also have high standard deviations.

4.3 Calibration versus a priori results

Figures 17a&b show the scatter plots of daily and monthly NS values of the entire data period where *a priori* and calibrated parameters are used. Both figures show that almost all of the points are on the left side the diagonal line, indicating improvement resulting from the calibration exercise. The improvement is more apparent when examining monthly NS statistics. There are certain cases when the NS values from the calibration runs do not improve those from the *a priori* runs. This is due to the fact that different modeling groups performed model calibration using different approaches. Particularly, one group did not tune its model parameter to fit observed streamflow data during calibration.

4.4 Joint correlation between simulated streamflow from multiple models and observations

It is recognized that each of the models participating in this study is an imperfect representation of the hydrologic process that occur in the real world. It seemed interesting to ask how much total information about each basin is contained in the set of all models. Accordingly, the simulated streamflow time series from all 8 models are used together as independent variables to construct a multiple regression model to predict the observed streamflow. The joint correlation coefficient from this regression aanlysis is a measure of the total information content of all of the models, jointly. By comparing the joint correlation coefficient from the regression analysis with the simple correlation coefficients for each model we can get an idea not only of the total information content but also which models contribute most of the information. Fig. 18 shows the scatter plot of the joint correlation coefficients and individual correlation coefficients at daily time step. All of the points lie on the left of the diagonal line, which delineates the limiting value of the regression coefficient for any individual model. The relative position of points along the abcissa indicates the contribution of individual models to the joint correlation. In Fig. 18a, it is clear that Model B contributes most to the joint correlation because most of the points associated with this model are closest to the diagonal line. In Fig. 18b, a number of models make significant contribution to the joint correlation.

These figures point to the potential that multi-model approach is a plausible approach to obtain improved prediction.

5. Lessons, Conclusions and Future Directions

We have presented a summary and analysis of the numerical experiment results of eight different models submitted to the second and third workshops. A number of lessons can be drawn from these results. First, the results confirm our earlier statements that the existing *a priori* parameter estimation procedures are problematic and must be improved.

Second, calibration results clearly demonstrate the huge potential for improvement in *a priori* parameter estimation. Third, different models seem to represent hydrologic processes differently and all of them are imperfect. This suggests it may be possible to improve some of the models. It also suggests that improved prediction may be possible through an ensemble of different models or, possibly, an ensemble of a given model using different parameter sets.

Much research needs to be done to understand how model parameters are related to basin land surface characteristics. Further, how to use the calibrated results for improve *a priori* parameters is still not clear and this issue needs to be looked at. Different modeling groups can learn from each other because many model parameters have similar physical interpretations and should have similarity in space-time patterns.

One issue that has not been examined in the workshops is the parameter transferability issue. This issue is very important for Predictions for Ungaged Basins (PUBs) and for application in land surface parameterization schemes. To study transferability issue, data from a wide range of climatic conditions should be used. The

MOPEX project has assembled data from many different countries. These data should be used to test enhanced *a priori* parameters.

One of the driving forces behind the progress in parameter estimation research is the increasing array of data sources, including satellite and other advanced observational technologies. With the new sources of data, it is important to investigate the ways to maximize the use of high resolution spatio-temperal information. Meanwhile the issue of uncertainty attributed to data errors should be addressed.

Any improvement in parameter estimation procedures must be tied to how we represent the physical processes. As our knowledge of the physical processes advance, more complicated distributed hydrologic models emerge. This will bring more challenge to us in terms of parameter estimation and model calibration. Much of the work cited above have already or are being carried out and reported by MOPEX project participants. With a true collaborative spirit by international scientists, enhanced *a priori* parameter estimation should be available to us. This in turn should result in improved skill in hydrologic predictions.

This work was performed under the auspices of the U.S. Department of Energy by University of California, Lawrence Livermore National Laboratory under contract W-7405-Eng-48.

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Table 1. Participating models and modeling agencies

Model Names	Model Agencies
Simple Water Balance (SWB)	NWS
Sacramento (SAC)	NWS
GR4J	Cemagref, France
PRMS	USGS, USA
VIC-3L	U.
ISBA	Meteor-France
SWAP	Russian Academy of Sciences
Noah LSM	NWS, USA