RIVERWARE'S INTEGRATED MODELING AND ANALYSIS TOOLS FOR LONG-TERM PLANNING UNDER UNCERTAINTY

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Abstract: Planning water allocation and reservoir operations under hydrologic uncertainty benefits from modeling capabilities that include 1) the generation of stochastic hydrologic ensembles that characterize the future hydrologic variability; 2) a multi-objective river and reservoir modeling tool that can represent various planning alternatives and easily run the stochastic ensembles, while exporting the output data of interest; and 3) a statistical analysis tool that can easily compare planning alternatives with respect to probabilistic values of decision variables as they evolve over time. Such an integrated set of tools is available as part of the RiverWare® suite of modeling and analysis tools developed at the University of Colorado's Center for Advanced Decision Support for Water and Environmental Systems (CU-CADSWES). Stochastic sequences are derived from historic and paleo flows. These sequences are developed through block resampling and other non-parametric approaches based on the K-nearest neighbor (K-NN) framework (Lall and Sharma, 1996). Hydrologic sequences are automatically loaded into RiverWare, a generalized, object-oriented, multi-objective river and reservoir modeling framework. The entire ensemble of flow sequences is run through a RiverWare model for several planning alternatives. RiverWare models represent planning alternatives simply by alternative rulesets- each ruleset expresses the operating policy via a prioritized set of logical statements constructed by the modeler in a syntax-directed editor. The rules execute and set values in the model, with higher priority rules such as minimum flows and flood control over-writing the effects of lower priority rules such as guide curves. The values of variables of interest, e.g., reservoir storages or pool elevations, shortages, hydropower generated, for each run are exported to a statistical analysis tool built in Excel, the Graphical Policy Analysis Tool (GPAT). GPAT computes probabilities for the variables of interest based on the range of outputs that correspond to the ensembles of flow sequences, and plots the probabilities over time for each alternative. This paper describes these tools and presents an example application on the Colorado River using the Bureau of Reclamation's RiverWare-based Colorado River Simulation System. A variety of RiverWare rulesets were analyzed, including one that reflects the pre-2007 "Law of the River" and those developed in coordination with stakeholder groups. The results are shown in GPAT plots and include risk-based predictions of the effects of the various policies and hydrologic inputs.

INTRODUCTION

For planning studies that consider risk and reliability, it is useful to make many runs and use the aggregated results from all the runs to get probabilistic output, like a Monte Carlo simulation. RiverWare includes a utility called Multiple Run Management (MRM) that sets up and executes multiple runs automatically and sends the results to output files that can be analyzed by post-processing programs. Using MRM, the user can make many runs over a planning horizon, using a variety of stochastically generated hydrologic inputs. MRM exports the results of the runs to one or more files in RiverWare Data Format (rdf). Then, a post-processing analysis program, the Graphical Policy Analysis Tool (GPAT) can import the rdf files and generate probabilistic information about the occurrence of certain events or the effectiveness of proposed operating policies. This paper describes methods for generating the stochastic traces, how RiverWare can be utilized to generate multiple simulations, and how GPAT can be used to analyze the results.

STOCHASTIC STREAMFLOW SIMULATION

Efficient management and planning of water resources planning requires a robust estimation of the variability of streamflows at several locations on the river network. This requires the ability of generating plausible streamflow scenarios at key nodes based on limited historical data. Stochastic methods have long been the staple for this purpose and are based on the premise stationarity – i.e., the statistical properties of the historical streamflow will continue in the future. Below we describe briefly stochastic simulation tools and recent methods that can incorporate nonstationarity by combing historical and paleo reconstructed streamflows.

<u>Traditional (Parametric) Approach:</u> Traditional stochastic streamflow models, also known as parametric approaches, were developed within the linear Auto Regressive Moving Average (ARMA) and Periodic Auto Regressive (PAR) frameworks (Bras and Iturbe, 1985; Salas, 1985; Stedinger and Taylor, 1982). In this, a linear function is fitted to relate the streamflow at a current time y_t with flows from previous time steps y_{t-1}, y_{t-2}, *etc.* The best order of lags is objectively determined. One of the widely used parametric models for streamflow generation is the lag-1 PAR (Salas, 1985), which linearly relates the streamflows in a season (or month) to the previous season, and has the form of:

$$y_{\vartheta,\tau} = \mu_\tau + \Phi_{1,\tau}\left(y_{\vartheta,\tau-1} - \mu_{\tau-1}\right) + \varepsilon_{\vartheta,\tau} \qquad (1)$$

Where, ϑ is the year, τ is the season (or month), μ_τ is the mean of the streamflow process in season τ, and $\Phi_{1,\tau}$ is the auto regressive parameter. The error $\varepsilon_{\vartheta,\tau}$ is assumed to be normally distributed with mean 0 and variance $\sigma^2(\varepsilon_\tau)$. The model parameters μ_τ, Φ_1, and $\sigma^2(\varepsilon)$ are estimated for each month from the data either by using Method of Moments or by approximating Least Squares or Yule-Walker equations (Salas, 1985; Bras and Iturbe, 1985). The model, by construction, preserves the mean, standard deviation, and lag(1) autocorrelation. By implication, y_t is also assumed to be normally distributed, and consequently, the joint $f(y_t, y_{t-1})$, and conditional $f(y_t|y_{t-1})$ probability density functions (PDF) are also normally distributed.

In practice most often, streamflows are not normally distributed, thereby violating the assumptions of the above model. Suitable transformations have been found to address this, but can be cumbersome and further, models fitted in transformed space are not guaranteed to preserve statistical properties when transformed back to the original space. Consequently, non-Gaussian features such as heavy skew or bimodality that may be present in the data will not be captured and reproduced effectively in the simulations. There are methods to address the non-Normality of the data, such as those based on Gamma distribution (Fernendez and Salas, 1986) – but such approaches introduce additional parameters and can be unwieldy for multisite situations. However, if the data is normally distributed or if it can be transformed to a normal distribution relatively easily, then the traditional linear methods can be easy and effective.

This approach has been extended to simulate streamflow at multi-sites jointly to preserve the spatial and temporal correlation structure. While multivariate PAR and ARMA models exists (see e.g., Bras and Iturbe, 1985) the most widely used approach and one that is unique to stochastic hydrology is the 'disaggregation' method. This takes advantage of the fact that on a river network the streamflow at a downstream 'aggregate' gauge is the sum of flows at upstream locations from this gauge. To this end, the linear model (equation 1) was extended to the disaggregation problem as

$$X = AZ + B\varepsilon \qquad (2)$$

Where X is a vector of disaggregated (e.g., monthly flows) flows at multiple locations and Z is the aggregate (e.g., annual) flows, subject to the condition that the disaggregated flows add up to the aggregate flows, which is the 'additive property'. Where A and B are matrices of the model parameters that are estimated to ensure the additivity property and ε is the error that is assumed to be normally distributed with mean 0 and variance 1. This linear stochastic framework for streamflow disaggregation was first developed by Valencia and Schaake (1973) and subsequently modified and improved by several others (Mejia and Rousselle, 1976; Lane, 1979; Stedinger and Vogel, 1984; Salas, 1985; Santos and Salas, 1992, Koutsoyiannis, 2001). The assumptions and problems that plague the linear model for a single site (equation 1) also afflict this multi-site model – more so, given the higher dimensionality of the problem. Given these shortcomings of the traditional approach it is limited in its ability to model a wide range of dependency structures (i.e., nonlinearities) and non-normal distributions.

Nonparametric Approach: With the increase in computational power nonparametric methods are gaining popularity. They are data driven and do not make any assumptions about the underlying form of the dependence (i.e. linear) or the PDFs present in the data. A good overview of nonparametric techniques and their wide-ranging hydrologic applications can be found in Lall (1995). For time series modeling and simulation three broad methods have been proposed – block resampling (or block bootstrap) of historical data, kernel density estimators and K-nearest neighbor (K-NN) resampling.

The simplest nonparametric approach is the Index Sequential Method (ISM, see, Ouarda et al., 1997; Kendall and Dracup, 1991), which involves sequential block resampling of historical data as a synthetic trace (i.e., simulation). This reproduces the historical sequence in its entirety and consequently, all of the statistical properties including the wet and dry spells, unlike the linear models. The main disadvantage is that only historic sequences can be generated, thus limiting the variety. ISM is simple and easy to implement; the Bureau of Reclamation (Reclamation) widely uses it in their planning and management efforts on the Colorado River.

Kernel based methods and, nonparametric methods in general, view the stochastic time series simulation as a simulation from conditional PDF. The kernel based methods employ a multivariate kernel density estimator to estimate the conditional PDF $f(y_t \mid y_{t-1})$ and consequently simulate from it (Sharma et al., 1997; Sharma and O'Neil, 2002). However, kernel methods tend to be inefficient and computationally expensive in higher dimension (Rajagopalan et al., 1997; Lall and Sharma, 1996; Lall, 1995) thus, making them unattractive to multivariate time series simulation.

Alleviating the disadvantages of the kernel based methods and the block resampling approach, Lall and Sharma (1996) developed a simple yet robust method called the K Nearest Neighbor (K-NN) resampling. In this method, K neighbors of y_{t-1} from the historic data are found, and then resampled via a weight function that assigns large weight to the nearest neighbors and less to those farther (Lall and Sharma, 1996). The main drawback is that point values not seen in the historic record cannot be simulated; however, unlike ISM, a rich variety in the sequences can be obtained. By fitting a local polynomial to the K-NN identified above (Prairie et al., 2005) and using the resulting regression fit to estimate the mean and the variance (i.e., a 'local' version of the linear model in equation 1) new values can be simulated.

The K-NN resampling approach has been modified to develop a space-time multisite streamflow simulation technique by Prairie et al., 2007. This method has been shown to be simpler and more effective than the kernel based approach (Tarboton et al., 1998). Recently a much simpler approach for space-time (effective from annual to daily time scale) multisite flow simulation was developed by Nowak et al. (2010). The approach is largely the same as that described above, except, when a neighbor (i.e., a historical year) is selected the corresponding 'proportion' vector (i.e., the proportion of daily/monthly flow to the annual flow in that year) is selected and applied to the annual flow – thus, generating daily/monthly flows at all the locations simultaneously. This method has been shown to capture all the distributional and spell properties (Nowak et al., 2010).

Streamflow Simulation – Incorporating nonstationarity: As mentioned earlier, stochastic methods based on historical data are limited to reproducing statistical features observed in the data – i.e., assuming stationarity. Clearly, stationarity is a hard assumption to satisfy, especially in light of climate variability and change (Milly et al., 2007). Insights into nonstationarity can be obtained from long reconstructions of past climate from paleo-proxy data. On the Colorado River, tree ring-based streamflow reconstructions date back to 15th century A.D (Woodhouse, et al., 2006) and 9th century A.D (Meko et al., 2007). However, these reconstructions provide only a part of the variability with considerable uncertainty. As such, Prairie et al. (2007) propose that the paleo reconstructions can better capture the hydrologic 'state' (i.e., wet or dry) – thus, they modeled the state using a Markov Chain while the magnitude of streamflow was resampled from the observed flow data. This can be expressed as simulating from the conditional PDF $f(x_t \mid S_t, S_{t-1}, x_{t-1})$. Where S_t is hydrologic 'state' at the current time, '*t*', S_{t-1} is from the previous time '*t-1*' and, x_{t-1} is the flow from the previous time step. Prairie et al. (2007) applied this to the Colorado River Basin and showed that such a model can generate a very rich variety of streamflow sequences thus a rich variety of wet and dry spells – critical for water resources management. These flow simulations when used in the water management model of the Colorado River system provided robust risk estimates of various system components (EIS, 2007;

Prairie, 2007). They can also be combined with climate change projections to generate flow scenarios that can capture the nonstationarity in the flow variability – which is of immense use in water resources planning. This approach can be combined with the disaggregation methods described above to generate flow scenarios on the river network that will be required for river basin planning models.

POLICY ANALYSIS MODELING IN RIVERWARE

RiverWare is a general river and reservoir modeling tool widely used in the US due to its interpreted language for expression of multi-objective operating policies. RiverWare applications include operational scheduling and forecasting, planning, policy evaluation, and other operational analysis and decision processes (Zagona et al., 2001). The wide range of applications is made possible by a choice of computational time step ranging from 1 hour to 1 year. RiverWare has the capability to model: (I) Hydrology and hydrologic processes of reservoirs, river reaches, diversions, distribution canals, consumptive uses, groundwater interaction and conjunctive use (II) Hydropower production and energy uses and (III)Water rights, water ownership, and water accounting transactions.

RiverWare's object-oriented, data-centered approach enables the modeler to represent site-specific conditions by creating a network of simulation objects, linking them together to form the river/reservoir network, populating each with data, and selecting physical process algorithms on each object that are appropriate to the purposes of the object and its representation in the overall model. For example there are numerous methods for routing flow in river reaches, for evaporation calculations and for computing the hydropower generated. Figure 1 shows the RiverWare workspace and the palette of objects from which models are constructed.

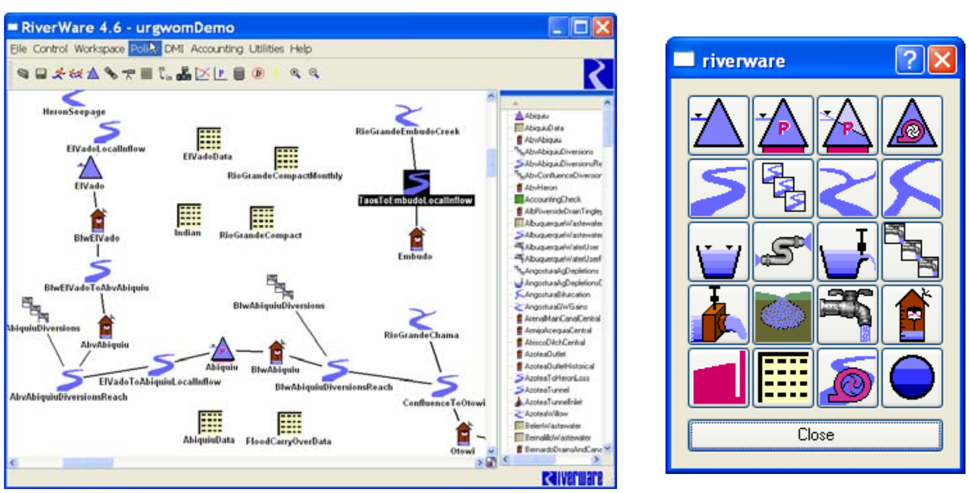

Figure 1. The RiverWare workspace and the object palette.

<u>Rulebased Simulation:</u> For multi-objective operational policy analysis and decision-making, RiverWare provides an interface for expression of operational policies as well as both descriptive and prescriptive solution algorithms driven by these policies. Rulebased simulation provides a means for simulation based on logical policy statements rather than explicitly specified input values for operations such as reservoir releases, storages, diversions, etc. In general, the operating policies, called *rules*, contain logic for operating the system based on hydrologic conditions, time of year, demands, and numerous other considerations. Operational policy is expressed in the RiverWare Policy Language (RPL), an interpreted language developed for, and exclusive to, RiverWare. RPL is a functional language in which assignments (to slots) are made only at the highest level of the rules. Rules are constructed in a syntax-directed editor that accesses a palette containing these elements. The rule set is a collection of prioritized rules that, as a whole, define the operating policy of the river system. The entire rule set is applied at each time step in the model. Figure 2 shows a ruleset and an example rule and the Ruleset Editor in which rules are prioritized and can be activated or deactivated.

Changing operating policies is of interest to water management agencies who must implement new objectives such as environmental flows or new agreements for sharing water in droughts. Also, the evaluation of future system reliability under climate change scenarios is of major concern in most river basins. Alternative operating strategies and water sharing arrangements can be modeled using RPL, then results of different policies can be simulated and compared as part of a decision-making process. The NEPA (National Environmental Policy Act) process for evaluating new operating policies mandates this type of comparison. RiverWare is often used for these types of studies, such as Reclamation's Environmental Impact Statement (EIS) for Colorado River Interim Guidelines for Lower Basin Shortages and the Coordinated Operations for Lake Powell and Lake Mead (EIS, 2007).

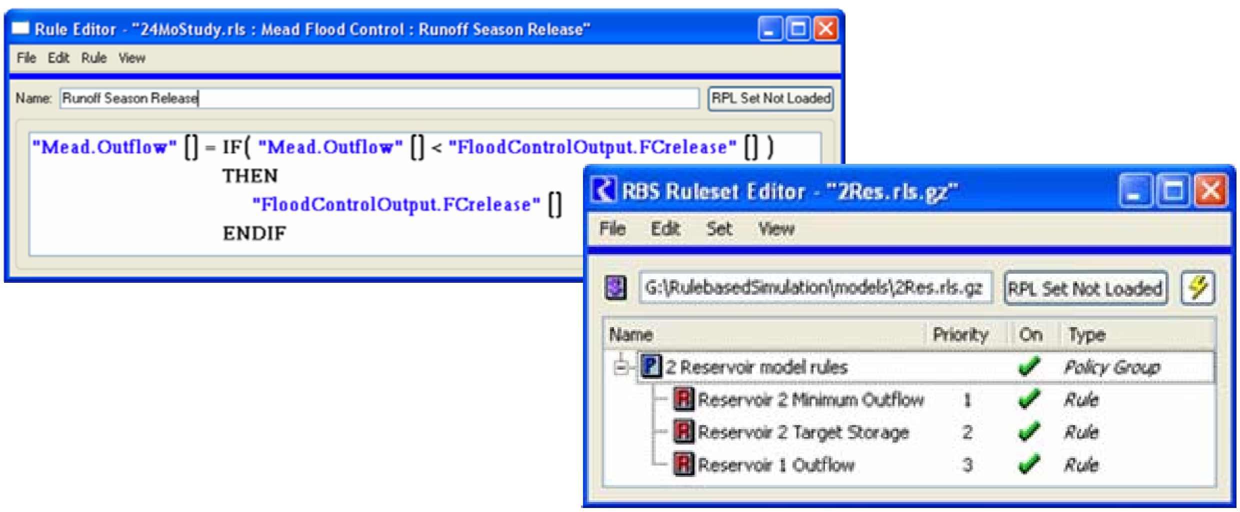

Figure 2. Example of an operating policy rule and the prioritized Ruleset Editor.

Multiple Run Management: For planning studies that consider risk and reliability, it is necessary to make many runs and use the aggregated results from all the runs to get probabilistic output, much like a Monte Carlo simulation. RiverWare includes a utility called Multiple Run Management (MRM) that sets up and executes multiple runs automatically and sends the results to output files that can be analyzed by post-processing programs. Using MRM, the user can make many runs over a planning horizon, using many traces of stochastically generated hydrologic inputs. MRM exports the results of the runs to one or more files in RiverWare Data Format (rdf). Then, post-processing analysis programs can import the rdf files and generate probabilistic information about the occurrence of certain events or the effectiveness of proposed operating policies. The hydrologic traces can be generated externally as described above.

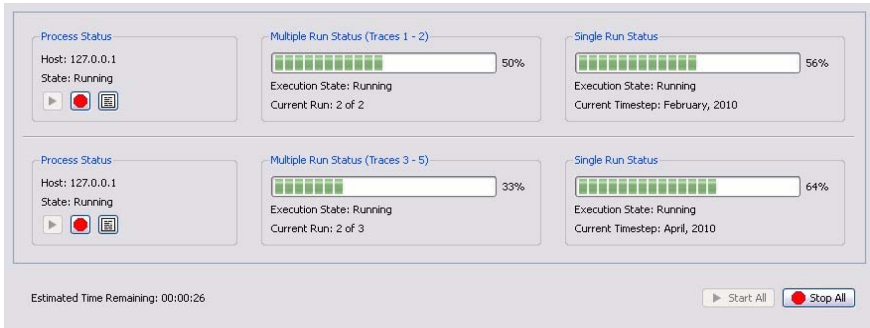

Figure 3. Run Status Panel for executing multiple stochastic traces on distributed grid.

As more data becomes available from sources such as tree ring data, the number and size of the hydrologic traces involved in the MRMs increases and greater computing power is required. RiverWare additionally has a utility to manage running simulations on multiple networked processors, then to bring the output files together for analysis. The utility, which can be started from within RiverWare, or as a stand-alone process, allows executing and tracking of simulation on the various machines from a single site. Figure 3 above shows the status panel for the runs.

Graphical Policy Analysis Tool (GPAT): GPAT, an Excel-based tool developed by CADSWES and Reclamation, compares the statistical results of multiple traces of two or more proposed operating policies in terms of their probabilistic effects on specified basin measurement criteria. In NEPA environmental impact studies, measurement criteria may include, for example, a stream flow or lake elevation that is expected to comply with biological recommendations.

To use GPAT for policy comparisons, the multi-trace runs are performed for each policy alternative, and the results imported into GPAT via the rdf output files generated by RiverWare's MRM utilities. GPAT can provide statistical information in various ways over four dimensions: model variables (e.g., a reservoir elevation, total power output, violation of fish flows, etc.), time, hydrologic trace, and policy (or other) alternatives. Various statistics can be selected such as minimums, maximums, means, variances, percentiles. Also, cumulative density functions, probability density functions, exceedence plots, duration curves, compound events, etc can be produced. GPAT stores the outputs of the selected model variables for all traces at all time steps and for each policy alternative. The tabular values of worksheets and the user-specified plots can then be created. GPAT has been used along with RiverWare for a number of policy and development studies.

APPLICATION ON THE COLORADO RIVER USING PALEO DATA

In May of 2005, the Secretary of the Department of the Interior tasked the Basin States (AZ, CA, CO, NV, NM, UT and WY) to develop a consensus plan to mitigate drought in the Colorado River Basin. A broad range of reasonable alternatives under various hydrologic scenarios were analyzed in the Final Environmental Impact Statement (Final EIS). These alternatives were developed in coordination with a diverse body of stakeholders, including the Basin States, a consortium of environmental non-governmental organizations (NGOs), Native American tribes, federal agencies, and the general public. A Record of Decision (ROD) was issued in December 2007 officially adopting the guidelines (Interim Guidelines) set forth in the Preferred Alternative. The ROD implements a robust solution to the unique challenges facing Reclamation in managing the Colorado River. The Interim Guidelines are limited in duration, extending through 2026 (EIS, 2007).

Instrumental in this landmark agreement among the Basin States was Reclamation's long-term planning tool, the Colorado River Simulation System (CRSS). This RiverWare model, coupled with GPAT allowed stakeholders to compare results and statistics for a variety of policy alternatives and hydrologic inputs. The following highlights the use RiverWare and GPAT throughout the NEPA process to compare policy alternatives and examine hydrologic variability.

Development and Comparison of Policy Alternatives: A total of six policy alternatives were considered and analyzed in the Final EIS. As stated earlier, these alternatives were developed in coordination with a diverse body of stakeholders, including the Basin States, a consortium of environmental NGOs, Native American tribes, federal agencies, and the general public. Alternatives generally contained provisions for conservation, delivery shortages, coordinated reservoir operations and delivery surpluses. Numerous system resources and components (reservoir elevations, hydropower production, shortage probability, etc) were examined in the comparison of policy alternatives.

For example, Rainbow Bridge National Monument, the world's largest known natural bridge is often accessed by boat ride across Lake Powell. This trip requires a minimum Lake Powell elevation of 3,650 feet, msl (mean sea level). Figure 4 shows the probability of being below this threshold for the various policy alternatives through time. It should be noted that after the interim period (post 2026), all policy alternatives revert to the No Action Alternative.

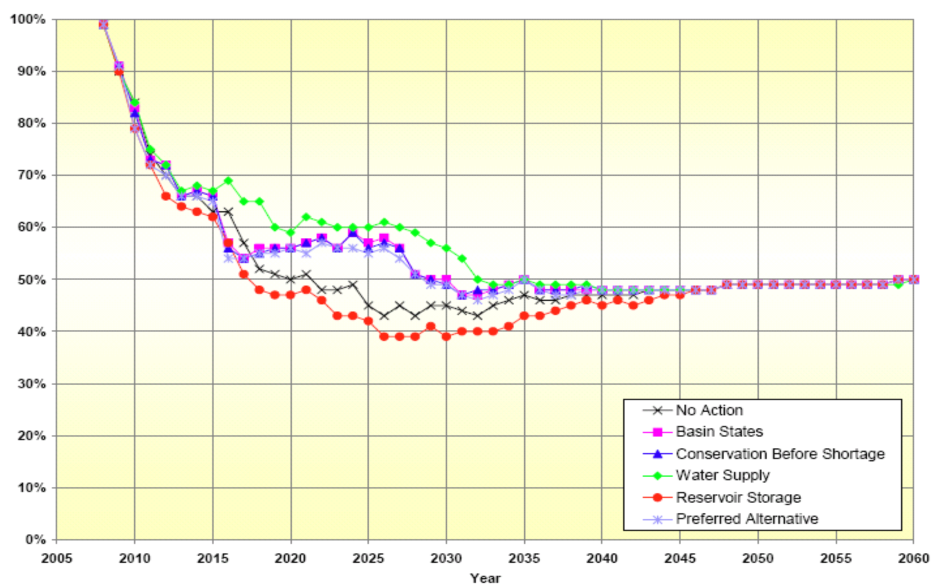

Figure 4. Display of GPAT output for end-of-September Lake Powell elevations; comparison of alternatives shown as percent of values less than or equal to 3,650 feet.

Hydropower is an important component throughout the Basin and policy alternatives were carefully compared to assess their impact on power production. Figure 5 shows how policy alternatives vary the annual average energy production at Hoover Dam.

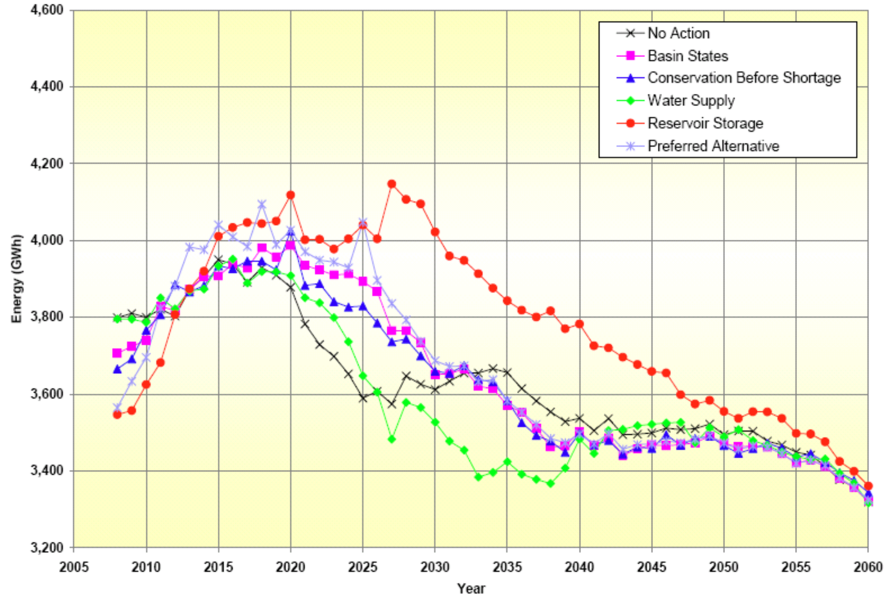

Figure 5. Display of GPAT output for average values of annual electrical energy production for various policy alternatives at Hoover Dam.

Sensitivity to Hydrologic Variability: For the purpose of policy alternative comparisons, streamflow inputs were generated using the ISM approach with the historic natural flow data (Direct Natural Flow Record). In addition to comparing the proposed policy alternatives to each other, the Final EIS also includes an analysis of hydrologic variability sensitivity (e.g. Figure 6).

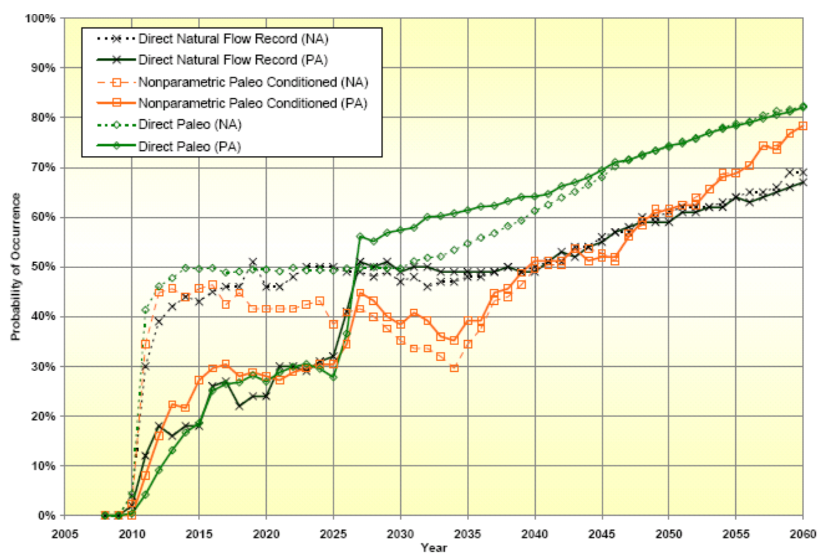

Figure 6. Display of GPAT output for probability of Lower Basin shortages for No Action (NA) and Preferred Alternatives (PA) with the three input hydrologic scenarios.

This portion examines the impact of alternative hydrologic inflow scenarios on system variables. Two additional simulation methods (beyond Direct Natural Flow Record) aimed at producing greater variability (wet/dry spell length) draw from the paleo reconstructed streamflow data of Meko et al. 2007. The first method is referred to as Direct Paleo and is simply an application of the ISM to the paleo reconstructed time series. The other is the technique of Prairie et al. 2008, whereby state (wet/dry) sequencing information from the paleo reconstruction is combined with flow magnitudes from the natural flow data, termed Nonparametric Paleo Conditioned (EIS, 2007). Figures 7 and 8 highlight the differences in outcomes between the three hydrologic input scenarios. It can be seen that the increased variability associated with the paleo methods increases the likelihood of shortage or being below a key reservoir level, compared to the Direct Natural Flow Record sequences.

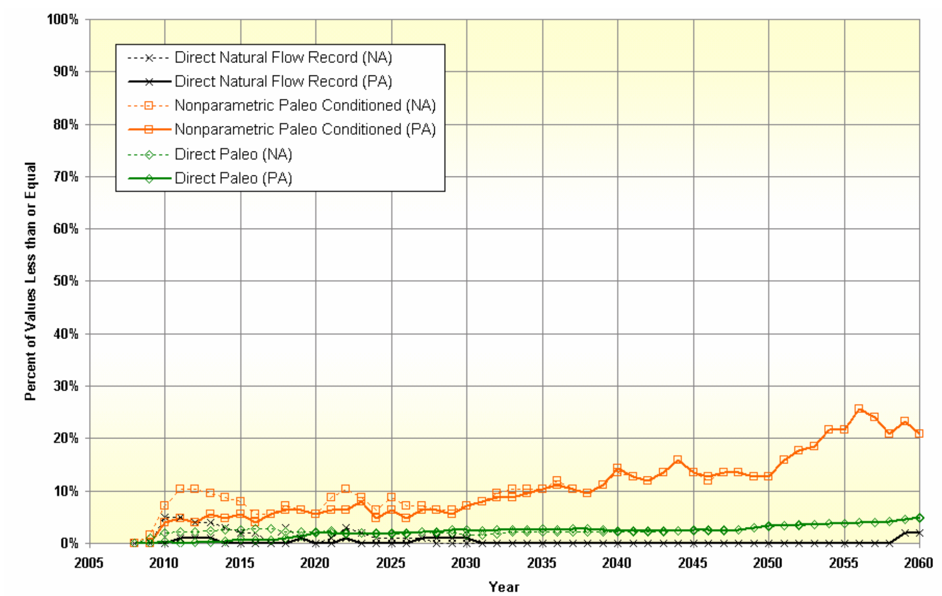

Figure 7. Display of GPAT output for Lake Powell end-of-July water elevations as percent of values less than or equal to 3,490 feet msl (power pool) for No Action (NA) and Preferred Alternatives (PA) with the three input hydrologic scenarios.

SUMMARY

In order to best manage water resources, flexible models with the ability to examine a range of policy alternatives for an ensemble of hydrologic traces are needed. Flow inputs need to be rich in variety and of appropriate spatial and temporal resolution to assess system robustness for a range of possible hydrologic conditions. An integrated tool for the visualization and analysis of results facilitates the discussion between agencies, stakeholders and the public to shape policy and management. The success of Reclamation's recent NEPA process demonstrates that when coupled with appropriate stochastic methods, RiverWare and GPAT fit this need quite effectively.

REFERENCES

Bras, R.L. and Iturbe, I. (1985), *Random functions and hydrology*, Addison-Wesley Publishing, Reading, Massachusetts.

EIS (2007), Final Environmental Impact Statement Colorado River Interim Guidelines for Lower Basin Shortages and Coordinated Operations for Lakes Powell and Mead, Bureau of Reclamation, Boulder City, NV.

Fernandez, B. and Salas, J.D. (1986), Periodic gamma-autoregressive process for operational hydrology, *Water Resour. Res*., 22(10), 1385-1396.

Kendall, D.B. and Dracup, J.A. (1991), A comparison of index-sequential and AR(1) generated hydrologic sequences, *J. of Hydrology*, 122, 335-352.

Koutsoyiannis, D. (2001), Coupling stochastic models of different timescales, *Water Resources Research*, 37(2), 379-391.

Lall, U. (1995), Recent advances in nonparametric function estimation: hydraulic applications, *U.S. Natl. Rep. Int. Union Geod. Geophys. 1991-1994, Rev. Geophys*., 33, 1093-1102.

Lall, U. and Sharma, A. (1996), A nearest neighbor bootstrap for resampling hydrologic time series." *Water Resour. Res.*, 32(3), 679-693.

Lane, W. L., (1979), Applied stochastic technigues, users manual, Eng. And Res. Cent., Bur. Of Reclam., Denver, Colo.

Mejia, J. M. and J. Rousselle (1976), Disaggregation models in hydrology revisited, *Water Resources Research*, 12(2), 185-186.

Meko DM, et al. (2007), Medieval drought in the upper Colorado River basin, Geophys. Res. Lett., 10.1029/2007GL029988.

Milly, P.C.D. et al. (2008), Stationarity is dead: whither water management?, *Science,* 319, 573-574.

Nowak, K., B. Rajagopalan, J. Prairie and U. Lall, (2010), A Non-parametric Stochastic Approach for Multisite Disaggregation of Annual to Daily Streamflow, (in review), *Water Resour. Res.,*

Ouarda, T., Labadie, J.W., and Fontane, D.G. (1997), Index sequential hydrologic modeling for hydropower capacity estimation, *J. of the American Water Resources Association*, 33(6), 1337-1349.

Prairie, J., B. Rajagopalan, T. Fulp, and E. Zagona (2006), Modified K-NN model for stochastic streamflow simulation, *Journal of Hydrologic Engineering*, 11(4), 371-378.

Prairie, J., et al. (2007), A stochastic nonparametric technique for space-time disaggregation of streamflows, *Water Resources Research*, *43*, -.

Prairie, J., K. Nowak, B. Rajagopalan, U. Lall, and T. Fulp (2008), A stochastic non-parametric approach for streamflow generation combining observational and paleo reconstructed data, *Water Resour. Res*. 43, W03432, doi:10.1029/2005WR004721.

Rajagopalan, B., Lall, U., Tarboton, D.G., and Bowles, D.S. (1997), Multivariate nonparametric resampling scheme for simulation of daily weather variables, *J. of Stochastic Hydrology and Hydraulics*, 11(1), 65-93.

Salas, J.D. (1985), Analysis and modeling of hydrologic time series, *Handbook of Hydrology*, D.R. Maidment, eds., McGraw-Hill, New York, 19.1-19.72.

Santos, E.G. and J.D. Salas, Stepwise disaggregation scheme for synthetic hydrology, *Journal of Hydraulic Engineering, ASCE*, 118 (5), 765–784, 1992.

Sharma, A., Tarboton, D.G., and Lall, U. (1997), Streamflow simulation: a nonparametric approach, *Water Resour. Res.*, 33(2), 291-308.

Sharma, A. and O'Neill, R. (2002), A nonparametric approach for representing interannual dependence in monthly streamflow sequences, *Water Resour. Res.*, 38(7), 5.1-5.10.

Stedinger, J.R., and Taylor, M.R. (1982), Synthetic streamflow generation, Model verification and validation, *Water Resour. Res.*, 18(4), 909-918.

Stedinger, J.R., and R.M. Vogel (1984), Disaggregation procedures for generating serially correlated flow vectors, *Water Resources Research*, 20(1), 47-56.

Tarboton, D.G., Sharma, A., and Lall, U. (1998), Disaggregation procedures for stochastic hydrology based on nonparametric density estimation, *Water Resour. Res.*, 34(1), 107-119.

Valencia, D. R., and J. C. Schaake (1973), Disaggregation processes in stochastic hydrology, *Water Resources Research*, 9(3), 580-585.

Woodhouse, C. A., S. T. Gray, and D. M. Meko (2006), Updated streamflow reconstructions for the Upper Colorado River Basin, *Water Resour. Res., 42*, W05415, doi:10.1029/2005WR004455

Zagona, E.A., Fulp, T.J., Shane, R., Magee, T.M. and Goranflo, H.M. (2001). "RiverWare: A Generalized Tool for Complex Reservoir System Modeling." Journal of the American Water Resources Association, 37(4), 913-929.