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Technical Memorandum | Final

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Subject:	**CRWAS Phase 1 | Task 6.4 | Methods for Alternate Hydrology and Water Use**
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Introduction

This Technical Memorandum summarizes information developed as part of Task 6 of the Colorado River Water Availability Study (CRWAS or Study).

The objective of Task 6 is to extend historical hydrologic data using currently available tree-ring data and stochastic methods to develop alternate hydrologic traces in formats usable in the CDSS. Sub-task 6.4 involves development of methods for developing alternate hydrology and water use.

This memorandum documents the approach used to develop alternative historical hydrology implemented in CRWAS Task 6.4 and to be used in CRWAS Task 6.5. Subsequent sections of this technical memorandum discuss: 1) CRWAS Requirements, 2) Description of Selected Methodology, and 3) References.

CRWAS Requirements

The Study scope of work called for: A) selection and implementation of a method to use information from prehistoric tree-ring records to extend observed records of flows (i.e., to develop an “alternative historical hydrology”); B) the use of information from paleo records to be used to extend the data set that represents conditions during the observation period assuming development of climate change (the *climate-perturbed observed flows); and C)* the generation of an ensemble of flow traces containing at least one hundred (50- to 100-year) traces of alternative hydrology. Thus, methods of extending flow traces using information from tree-rings (as detailed herein) must be applicable to both natural flow records and the climate-perturbed record.

The water resources models to be used in the Study are the Bureau of Reclamation’s Colorado River Simulation System (CRSS) model and the State of Colorado’s StateMod model, part of the Colorado River Decision Support System (CRDSS). Both of these models (as used in the Study) require monthly inflows. The CRSS model requires monthly inflows at 29 inflow points throughout the basin. The CRDSS StateMod models to be used in the Study require monthly flows at hundreds of *baseflow* gage points throughout those portions of the Colorado River Basin within the State of Colorado. Thus, the method that is adopted to extend flow records must be capable of generating traces of monthly flows at two different levels of spatial detail throughout the Colorado River Basin.

Description of Selected Methodology

Candidate methodologies for extending historical hydrology were evaluated in a separate CRWAS Phase 1 Technical Memo covering Task 6.1 Literature Review and Method Evaluation, Task 6.2 Analyses of Tree-Ring Data and Task 6.3 Recommendation for Extending Historical Hydrology. Based on the advantages and disadvantages of the candidate methodologies set out in that Technical Memo, it was recommended, and the State accepted, that CRWAS extend historical hydrologic data by re-sequencing years from the observed record, based on an existing re-construction at Lees Ferry, and using a method adapted from Prairie et al. (2008). This method has the required level of accuracy, cost-effectiveness, documentation, and compatibility with CRWAS goals.

The proposed approach is based on theories of stochastic hydrology and paleohydrology covered in the reviewed and referenced literature. Two approaches are available to use Markov chain models to develop alternative hydrologic[1] sequences from historical observed and reconstructed time series for the CRWAS. These are re-sequencing of observed hydrology based on a homogeneous (static) transition probability derived from observed flow states and re-sequencing of observed hydrology based on non-homogeneous (varying) transition probability derived from observed flow states. The first approach is referred to as the *Homogeneous Markov Chain (HMC) Simulation with Resampling*, and the second approach is referred to as the *Non-homogeneous Markov Chain (NHMC) Simulation with Resampling*.

The HMC approach was not used by Prairie et al. (2008) and is not recommended for use in CRWAS. However, it is presented here to provide background that will facilitate a better understanding of the NHMC approach. The NHMC approach to re-sequencing flows was the approach used by Prairie et al., (2008) and is recommended for use in CRWAS.

i) Homogeneous Markov Chain Simulation with Resampling

Markov chain simulation using a single (hence the notion of homogeneity) transition probability matrix is described in Haan (1977), which also provides several examples of Markov chain models. In application to the Colorado River the reconstructed flows at the Lees Ferry gage are classified into two states – dry and wet, based on a flow threshold such as the mean flow at the gage. Years where the annual flow is below the threshold flow are classified as dry years and years where the annual flow is equal to or above the threshold flow are classified as wet years. Using the sequence of dry and wet years, four state transition probabilities are developed. These are, (i) dry-dry, (ii) dry-wet, (iii) wet-dry, and (iv) wet-wet. In this application, the transition probabilities are calculated based on the entire record of reconstructed and observed flows. The historical Lees Ferry naturalized

[1] Re-sequencing techniques can be applied to streamflows, water use, or meteorological data, hence the general term “hydrology” is used to demonstrate that point.

flow time series is also classified into two states, and the years are placed in two bins according to their state.

These transition probabilities are used in the Markov chain algorithm (e.g., Haan, 1977) to simulate dry/wet sequences and generate ensembles of time series of dry/wet states (state traces). Each state trace is constructed as follows: An initial state is selected randomly. The next trace is generated based on the probability of transition from the first state. For example, if the first state is dry, the relevant transition probabilities would be dry-dry and dry-wet. This process is repeated until a trace of the desired length is obtained. Additional traces are constructed until an ensemble of traces of the desired size is obtained. Flow traces are generated based on each state trace to create an ensemble of flow traces. Each state trace is traversed from start to end, and for each state in the sequence an historical year is sampled with replacement from the dry or wet bin, depending on the state in the trace. So, each of the flow traces will be a trace consisting of a set of observed years in a sequence determined by the Markov chain model as captured in the corresponding state trace. Flow data corresponding to the resequenced years can be used to force water allocation or other impact models or for statistical analysis of droughts or other time series statistics.

The reader is referred to Haan (1977) for a complete description and several examples of the HMC approach.

ii) Non-homogeneous Markov Chain Simulation with Resampling

Application of the non-homogeneous Markov Chain simulation with resampling with an application to the Lees Ferry gage ensemble streamflow simulation is described in the paper by Prairie et al. (2008). The NHMC algorithm with resampling was successfully applied in the recent USBR EIS study (see Reclamation, 2007, Appendix N), and provides an elegant approach to combine observed hydrology and paleohydrologic state information in a consistent stochastic hydrology simulation framework. The following description is intended to provide an overview of the method for technical review and for technically-oriented natural resource decision makers. The details necessary to implement the NHMC algorithm are given in section 3.3 of the Prairie et al. (2008) paper, and the reader desiring a complete understanding of the method or who wishes to implement it is directed there.

Conceptually, the NHMC approach provides a method to combine transient state information (wet/dry) from paleohydrologic reconstructions of hydrologic markers (e.g., streamflow, Palmer Drought Severity Index – PDSI) with observed streamflow records to generate streamflow ensembles.

The basic concept of the NHMC approach as developed by Prairie, et al. (2008) is very similar to the conventional homogeneous Markov Chain algorithm (e.g., Haan, 1977) for simulating hydrologic states except that transition probabilities are calculated using a moving window framework and selection of years is constrained on the transition type (e.g. wet-dry, dry-dry) conditioned on flow magnitude. The NHMC approach in Prairie et al. (2008) is a two-step methodology. The first step is modeling hydrologic state and the second step is modeling flow magnitudes. A brief description of these steps is given below.

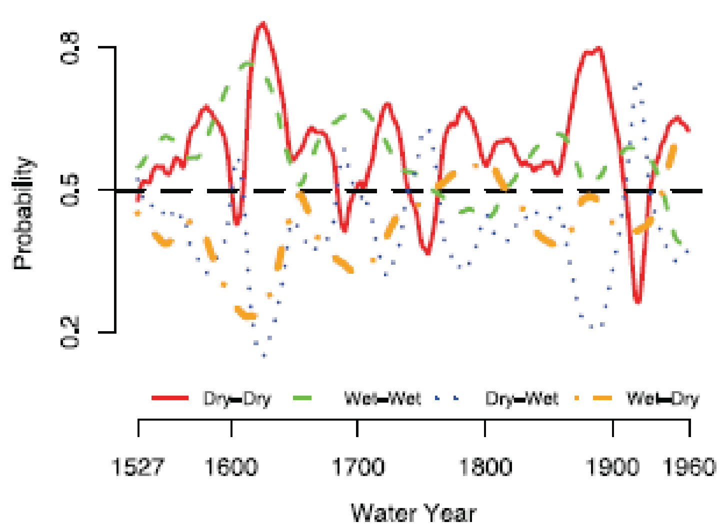
Modeling Hydrologic State

Similar to the homogeneous Markov chain approach, reconstructed streamflow at the Lees Ferry gage (e.g. those by Meko et al. [2007] or Woodhouse et al. [2006]) are used to derive a set of two-state non-homogeneous transition probabilities following the Prairie et al. (2008) algorithm. The first step in the process is to assign a dry or wet state to each of the years of the reconstruction period (e.g. 1490 through 1905 for the Woodhouse reconstruction). Based on a flow threshold, for example, the mean or median of observed flow (1906-2005) for the Lees Ferry gage, one would categorize each year as dry or wet based on the annual flow for that year in the paleoreconstructed flows. If the reconstructed flow in any year is below the threshold flow, then that year will be assigned state dry, else the year will be assigned to state wet. Thus the paleoreconstructed flow time series will be transformed into a binary time series (dry = 0; wet = 1).

This binary time series will be used to develop the transient transition probability matrix corresponding to four transitions, (i) dry-dry; (ii) dry-wet, (iii) wet-dry, and (iv) wet-wet. In the NHMC, the transition probability matrix is not static but changes with time over the length of the reconstructed record. A moving window of selected width centered on each of the years (e.g. 1490 through 1905 for the Woodhouse reconstruction, and accounting for end effects) is used to develop the four transition probabilities: dry to dry, dry to wet, wet to dry, and wet to wet. The objective least squares cross-validation (LSCV) criterion is used in the technique adopted in Prairie et al. (2008) to determine the optimal window widths to calculate the transition probabilities; the LSCV criterion is given in equation (4) of the Prairie et al. (2008) paper. The derivation of the transition probabilities is completed using the non-parametric kernel smoothing algorithm; the relevant equations in the Prairie et al. (2008) paper are equations (1) through (3). It should also be noted that in estimating the transition probabilities, a quadratic smoothing function is also applied.

The non-homogeneous transition probabilities provide an opportunity to capture the fact that certain extended periods have a higher (lower) probability of transitioning from dry (wet) to wet (dry) states. This is shown in Figure 1.

Figure 1.
Plots of Transition Probabilities.
Source: Prairie et al. (2008), Figure 6



Note that during the late 19th Century the probability of a dry-dry transition was well above 50%, while the probability of a dry-wet transition (the complementary transition) was well below 50%. The relative magnitude of these transition probabilities reversed in the early part of the 20th Century. Similar changes are apparent throughout the period shown.

Modeling Flow Magnitudes

This model of annual flow magnitudes is given in equation (5) and explained in paragraphs 16 though 18 of the Prairie et al. (2008) paper as a conditional probability density function (PDF). Flow magnitudes are simulated based on a set of neighbors. The neighbors are a set of years which are constrained in three respects with the simulated year – (i) flow magnitude, (ii) hydrologic state, and (iii) hydrologic state transition.

The streamflow magnitudes are modeled based on the observed data and conditioned upon the hydrologic state that has been simulated using the paleodata, as described in the previous section. Streamflow magnitudes are modeled as a function of the feature vector $[S_t, S_{t-1}, x_{t-1}]$ where S_t is the current system state, S_{t-1} is the previous system state and x_{t-1} is the previous flow magnitude. The observed data are first paired by transition type e.g. *wet-wet, wet-dry, dry-dry, dry-wet* and then the pairs are categorized into four bins according to transition type. Based on the current state, S_t, and the previous state, S_{t-1}, a given transition category is selected, a flow pair $[y_{t-1}, y_t]$ is sampled from that bin conditioned on the similarity of x_{t-1} with y_{t-1} and the streamflow x_t is set equal to y_t. These steps are repeated by stepping through the trace of states until a trace of streamflows of the desired length has been generated. In this application, the method has been modified to select a one-year period of monthly streamflows at all sites necessary for a particular water resources model.[2]

The NHMC algorithm randomly selects an epoch of given length (56 years in this case[3]), randomly selects the initial state (dry or wet), and marches through the transitions to get the simulated 56-year state time series. In addition to how the flow sampling is conditioned, the principal difference from the HMC is that the transition probability matrix for NHMC changes as the algorithm moves from year to year in the selected epoch.

In this application, CRSS natural flow data are available for the period 1906-2005 and complete CRDSS flow data are available for the period 1908-2007. Gridded observed climate data are available from 1949 through 2005. The existing Lees Ferry reconstructions are based on water years, so flow magnitudes must be reconstructed on this basis. Thus, the intersection of these two datasets covers the period October 1949-September 2005, so only flows from this period will be used to model streamflow magnitudes. Therefore, each of the generated traces will consist of a 56-year re-sequence of the years 1950-2005. Flow data corresponding to the re-sequenced years (from either the CRDSS or CRSS datasets) will be used to populate the water allocation model.

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[2] For the purpose of calculating statistics only a single site is sampled, e.g. Lees Ferry, but for modeling all model input sites for a given year are sampled together.

[3] For the intra-state analyses, the models were initially set up to generate 100-year sequences, but a sub-set consisting of the initial 56 years in each realization was used in the water resources models. Before the big-river analyses were completed the models were modified to generate 56-year periods.

Details of Data and Implementation

Meko et al. (2007) developed a time series of reconstructed Lees Ferry flow for the period covering A.D. 762-2005. This time series of reconstructed Lees Ferry flow was used to estimate the time-varying transition probabilities using R[4] codes developed for the Prairie et al. (2008) publication (Jim Prairie, *personal communication*). Once the transition probabilities were estimated the resampling algorithm described in Prairie et al. (2008) was used to develop the year sequences. R codes to carry out the resampling were also provided by Jim Prairie (*personal communication*). All analysis was done on a water year basis based on the natural flow at the Lees Ferry gage. For each realization, a period of length 56 years is randomly selected from the paleohydrologic period to obtain the state transition probabilities, the R codes march through the string of transitional probabilities to generate a sequence of the same length. This process is repeated to develop the paleohydrologic ensemble of 100 realizations each of length 56 years.

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[4] R is a software environment for statistical computing and graphics. The R Project for Statistical Computing, 2009.

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