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Climate Change Science Program

Uses and Limitations of Observations, Data, Forecasts, and Other Projections in Decision Support for Selected Sectors and Regions

Chapter 5. “Decision Support for Water Resources Management”

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1. Introduction

Water resource managers have long been incorporating information related to climate in their decisions. The tremendous, regionally ubiquitous, investments in infrastructure to reduce flooding (e.g., levees and reservoirs) or assure reliable water supplies (e.g., reservoirs, groundwater development, irrigation systems, water allocation, and transfer agreements) reflect societal goals to mitigate the impacts of climate variability at multiple time and space scales. As the financial, political, social, and environmental costs of infrastructure options have become less tractable, water management institutions have undergone comprehensive reform, shifting their focus to optimizing operations of existing projects and managing increasingly diverse, and often conflicting, demands on the services provided by water resources (Bureau of Reclamation [BOR], 1992; Beard, 1993; Congressional Budget Office, 1997; Stakhiv, 2003; National Research Council [NRC], 2004). Governments have also made substantial investments to improve climate information and understanding over the past decades through satellites, *in situ* measuring networks, supercomputers, and research programs. National and international programs have explicitly identified as an important objective ensuring that improved data products, conceptual models, and predictions are useful to the water resources management community (Endreny et al., 2003; Lawford et al., 2005). Although exact accounting is difficult, potential values associated with appropriate use of accurate hydrometeorologic predictions generally range from the millions to the billions of dollars (e.g., National

29 Hydrologic Warning Council, 2002). There are also non-monetary values associated with more efficient,
30 equitable, and environmentally sustainable decisions related to water resources.

31 Droughts, floods, and increasing demands on available water supplies continue to create concern,
32 and even crises, for water resources management. Many communities have faced multiple hydrologic
33 events that were earlier thought to have low probabilities of occurrence (e.g., NRC, 1995), and long-term
34 shifts in streamflows have been observed (Lettenmaier et al., 1994; Lins and Slack, 1999; Douglas et al.,
35 2000), leading to questions about the relative impacts of shifts in river hydraulics, land use, and climate
36 conditions.

37 Until the last two decades, climate was viewed largely as a collection of random processes, and
38 this paradigm informed much of the water resource management practices developed over the past 50 years
39 that persist today. However, climate is now recognized as a chaotic process, shifting among distinct
40 regimes with statistically significant differences in average conditions and variability (Hansen et al., 1997).
41 As instrumental records have grown longer and extremely long time-series of paleoclimatological
42 indicators have been developed (Ekwurzal, 2005), they increasingly belie one of the fundamental
43 assumptions behind most extant water resources management—stationarity. Stationary time series have
44 time-invariant statistical characteristics (e.g., mean or variance), meaning that different parts of the
45 historical record can be considered equally likely. Within the limits posed by sampling, statistics computed
46 from stationary time series can be used to define a probability distribution that will also then faithfully
47 represent expectations for the future (Salas, 1993).

48
49 Further, prospects for climate change due to global warming have moved from the realm of
50 speculation to general acceptance (Intergovernmental Panel on Climate Change [IPCC] 1990, 1995a,
51 2001a, 2007). The potential impacts of climate on water resources, and their implications for management,
52 have been central topics of concern in climate change assessments (e.g., EPA, 1989; IPCC, 1995b, 2001b;
53 National Assessment Synthesis Team, 2000; Gleick and Adams, 2000; Barnett *et al.*, 2004). These studies
54 are becoming increasingly confident in their conclusions that the future portends statistically significant
55 changes in hydroclimatic averages and variability.

56 There has been persistent and broad disappointment in the extent to which improvements in
57 hydroclimatic science from large-scale research programs have affected resource management practices in
58 general (Pielke, 1995, 2001; NRC, 1998a, 1999a) and water resource management in particular (NRC,
59 1998b, 1999b,c). For example, seasonal climate outlooks have been slow to be entered into the water
60 management decision processes, even though they have improved greatly over the past 20 years (Hartmann
61 et al., 2002a, 2003). Water managers have been even more resistant to incorporating notions of hydrologic
62 non-stationarity in general and climate change in particular in decision processes. Until recently, hydrologic
63 analysis techniques have been seen as generally sufficient (e.g., Matalas, 1997; Lins and Stakhiv, 1998),
64 especially in the context of slow policy and institutional evolution (Stakhiv, 2003). However, an
65 inescapable message for the water resource management community is the inappropriateness of the
66 stationarity assumption in the face of climate change.

67 Several ongoing efforts are leading the way forward to establish more effective ways of
68 incorporating climate understanding and earth observations into water resources management (Pulwarty,
69 2002; Office of Global Programs, 2004; NASA, 2005). While diverse in their details, these efforts seek to
70 link hydroclimatological variability, analytical and predictive technologies, and water management
71 decisions within an end-to-end context extending from observational data through large-scale analyses and
72 predictions, uncertainty evaluation, impacts assessment, applications, and evaluations of applications (e.g.,
73 Young, 1995; Miles et al., 2000). Some end-to-end efforts focus on cultivating information and
74 management networks; designing processes for recurrent interaction among research, operational product
75 generation, management, and constituent communities; and developing adaptive strategies for
76 accommodating climate variability, uncertainty, and change. Other end-to-end efforts focus on the
77 development of decision support tools (DST) that embody unique resource management circumstances to
78 enable formal and more objective linkages between meteorological, hydrologic, and institutional processes.
79 Typically, end-to-end DST applications are developed for organizations making decisions with high-impact
80 (e.g., state or national agencies) or high-economic value (e.g., hydropower production) and that possess the
81 technical and managerial abilities to efficiently exploit research advances (e.g., Georgakakos et al, 1998,
82 2004, 2005; Georgakakos, 2006). If linked to socioeconomic models incorporating detailed information

83 about the choices open to decision-makers and their tolerance for risk, these end-to-end tools could also
84 enable explicit assessment of the impacts of scientific and technological research advances.

85 This chapter describes a river management DST, RiverWare, which facilitates coordinated efforts
86 among the research, operational product generation, and water management communities. RiverWare
87 emerged from an early and sustained effort by several federal agencies to develop generic tools to support
88 the assessment of water resources management options in river basins with multiple reservoirs and multiple
89 management objectives (Frevert et al., 2006). RiverWare was selected for use as a case study because it has
90 been used in a variety of settings, by multiple agencies, over a longer period than many other water
91 management DSTs. Furthermore, RiverWare can explicitly accommodate a broad range of resource
92 management concerns (e.g., flood control, recreation, navigation, water supply, water quality, and power
93 production). RiverWare can also consider perspectives ranging from day-to-day scheduling of operations to
94 long-range planning and can accommodate a variety of climate observations, forecasts, and even climate
95 change projections. RiverWare can incorporate hydrologic risk, whereby event consequences and their
96 magnitudes are mediated by their probability of occurrence, in strategic planning applications and design
97 studies, which can offer a way forward for decision makers reluctant to shift away from use of traditional,
98 stationarity-based, statistical analysis of historical data (Lee, 1999; Davis and Pangburn, 1999).

99

100 **2. Description of RiverWare**

101 RiverWare is a software framework used to develop detailed models of how water moves and is
102 managed throughout complex river basin systems. RiverWare applications include physical processes (e.g.,
103 streamflow, bank storage, and solute transport), infrastructure (e.g., reservoirs, hydropower generating
104 turbines, spillways, and diversion connections), and policies (e.g., minimum instream flow requirements
105 and trades between water users) (Zagona et al., 2001, 2005). At a minimum, RiverWare applications
106 require streamflow hydrographs as input for multiple locations throughout a river system. While
107 hydrographs can be generated within the DST, they can also be input from other sources, with the latter
108 approach being especially important in advanced end-to-end assessments. Detailed discussion of the role of
109 observations and considerations of global change using RiverWare are discussed in later sections.
110 RiverWare can be applied to address diverse water management concerns, including real-time operations,

111 strategic planning for seasonal to interannual variability in water supplies and demands, and examining
112 impacts of hydrologic non-stationarity. Because infrastructure, management rules, and policies can be
113 easily changed, RiverWare also allows examination of alternative options for achieving management
114 objectives over short-, medium-, and long-term planning horizons.

115 RiverWare was developed by the University of Colorado-Boulder's Center for Advanced Decision
116 Support for Water and Environmental Systems (CADSWES) in collaboration with the BOR, Tennessee
117 Valley Authority, and the Army Corps of Engineers (Frevert et al., 2006). CADSWES continues to develop
118 and maintain the RiverWare software, as well as offer training and support for RiverWare users (see
119 <http://cadswes.colorado.edu>). According to CADSWES, RiverWare is used by more than 75 federal and
120 state agencies, private sector consultants, universities and research institutes, and water districts, among
121 others.

122

123 *Example Applications*

124 Consistent with the intent of its original design, the use of RiverWare varies widely, depending on
125 the specific application. An early application was its use for scheduling reservoir operations by the
126 Tennessee Valley Authority (Eshenbach et al., 2001). In that application, RiverWare was used to define the
127 physical and economic characteristics of the multi-reservoir system, including power production
128 economics, to prioritize the policy goals that governed the reservoir operations and to specify parameters
129 for linear optimization of system objectives. In another application, RiverWare was used to balance the
130 competing priorities of minimum instream flows and consumptive water use in the operation of the
131 Flaming Gorge Reservoir in Colorado (Wheeler et al., 2002).

132 While day-to-day scheduling of reservoir operations is more a function of weather than climate,
133 the use of seasonal climate forecasts to optimize reservoir operations has long been a goal for water
134 resources management. RiverWare is being implemented for the Truckee-Carson River basin in Nevada to
135 investigate the impact of incorporating climate outlooks into an operational water management framework
136 that prioritizes irrigation water supplies, interbasin diversions, and fish habitat (Grantz et al., 2007).
137 Another example application to the Truckee-Carson River using a hypothetical operating policy indicated

138 that fish populations could benefit from purchases of water rights for reservoir releases to mitigate warm
139 summer stream temperatures resulting from low flows and high air temperatures (Neumann et al., 2006).

140 RiverWare has also been used to evaluate politically charged management strategies, including
141 water transfers proposed in California's Quantification Settlement Agreement and the BOR's Inadvertant
142 Overrun Policy, maintaining instream flows sufficient to restore biodiversity in the Colorado River delta,
143 and conserving riparian habitat while accommodating future water and power development in the BOR
144 Multiple Species Conservation Program (Wheeler et al., 2002). RiverWare also played a key role in
145 negotiations by seven western states concerning how the Colorado River should be managed and the river
146 flow should be distributed among the states during times of drought. The BOR implemented a special
147 version of the RiverWare model of the Colorado River and its many reservoirs, diversions, and watersheds
148 (Jerla, 2005). The model was used to provide support to the Basin States Modeling Work Group Committee
149 over an 18-month period, as they assessed different operational strategies under different hydrologic
150 scenarios, including extreme drought (U.S. Department of Interior, 2007).

151

152 *Implementation*

153 RiverWare requirements are multi-dimensional. A specific river system and its infrastructure
154 operating policies are defined by data files supplied to RiverWare. This allows incorporation of new basin
155 features (e.g., reservoirs), operating policies, and hydroclimatic conditions without users having to write
156 software code. Utilities within RiverWare enable users to automatically execute many simulations,
157 including accessing external data or exporting results of model runs. Users can also write new modules that
158 CADSWES can integrate into RiverWare for use in other applications. For example, in an application for
159 the Pecos River in New Mexico, engineers developed new methods and software code for realistic
160 downstream routing of summer monsoon-related flood waves (Boroughs and Zagona, 2002). RiverWare is
161 implemented for use on Windows or Unix Solaris systems, as described in the requirements document
162 (<http://cadswes.colorado.edu/PDF/RiverWare/RecommendedMinimumSystemsRequirements.pdf>). An
163 extensive manual is also available (<http://cadswes.colorado.edu/PDF/ReleaseNotes/RiverWareHelp.pdf>).

164 RiverWare applications can be implemented by any group that can pay for access, both in terms of
165 finances and educational effort. Development of RiverWare applications requires a site license from

166 CADSWES. Significant investment is required to learn to use RiverWare as well. CADSWES offers two 3-
167 day RiverWare training courses, an initial class covering general simulation modeling, managing scenarios,
168 and incorporating policy options through rule-based simulation, and a second class covering rule-based
169 simulation in more detail, creating basin policies, and examining water policy options. Costs for the
170 original license, annual renewals, technical support, and training require several thousand dollars. The costs
171 of licensing and learning RiverWare mean that small communities and civic groups are unlikely to
172 implement their own applications for assessing water management options. Rather, large agencies with
173 technical staff or the financial means to fund university research or consultants are the most frequent users
174 of RiverWare. The agencies then mediate the access of stakeholders to assessments of water management
175 options through traditional public processes (e.g., U.S. Department of Interior, 2007). Conflicts may arise
176 in having academic research groups conduct analyses funded by stakeholder groups, with inherent tensions
177 between the open publication of research required by academia and the limited access to results required by
178 strategic negotiations among interest groups.

179

180 **3. Current and Future Use of Observations**

181 The specific combination of observations used by a RiverWare application depends on both the
182 decision context and the use of other models and DSTs to provide input to RiverWare that more
183 comprehensively or accurately describes the character, conditions, and response of the river basin system.
184 Figure 1 illustrates the information flow linking observations, RiverWare, other models and DSTs, and
185 water management decisions; it shows that RiverWare has tremendous flexibility in the kinds of
186 observations that could be useful in hydrologic modeling and river system assessment and management.
187 The types of observations that may ultimately feed into RiverWare applications also depend on the
188 timescale of the situation.

189 A detailed discussion of the role of satellite observations in RiverWare applications and selected
190 input models and DSTs (e.g., the BOR's ET Toolbox and Precipitation Runoff Modeling System [PRMS])
191 is given by the "Evaluation Report for AWARDS ET Toolbox and RiverWare Decision Support Tools"
192 (Hydrological Sciences Branch, 2007). Briefly, RiverWare can use a combination of observations from
193 multiple sources, including satellites, products derived from land-atmosphere or hydrologic models, and

194 combinations of both. Satellite observations can assist models in estimating evapotranspiration,
195 precipitation, snow water equivalent, soil moisture, groundwater storage and aquifer volumes, reservoir
196 storage, and water quality, among other variables. Measurements from sensors aboard a variety of satellites
197 are being considered for their usefulness within DST contexts and their impacts on reducing water
198 management uncertainty, including the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor
199 aboard the Earth Observing System (EOS) Terra and Aqua satellites, Landsat TM data, Advanced
200 Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Shuttle Radar Topography Mission
201 (SRTM), Advanced Microwave Scanning Radiometer–EOS (AMSR-E), Gravity Recovery and Climate
202 Experiment (GRACE), and Tropical Rainfall Mapping Mission (TRMM), among others. Future and
203 planned satellites with hydrologically relevant sensors and measurements include CloudSAT, the Global
204 Precipitation Mission (GPM), and the National Polar-Orbiting Operational Environmental Satellite
205 (NPOESS). Use of these observations can be enhanced by assimilating them into land surface models to
206 produce spatially-distributed estimates of snowpack, soil moisture, evapotranspiration, energy fluxes, and
207 runoff, which then provide inputs to RiverWare to base a more comprehensive assessment of river basin
208 conditions. The land surface models include the Community Land Model (CLM), Mosaic, Noah, and VIC,
209 among others, supported by NASA’s Land Data Assimilation System (LDAS) and Land Information
210 System (LIS) (NASA, 2006a).

211 NASA has several pilot projects specifically focused on assessing the impact of satellite
212 observations in a variety of hydrologic models and DSTs as they feed into RiverWare applications (NASA,
213 2005, 2006b, 2007). For example, one project is comparing Terra and Aqua MODIS snow cover products
214 for the Yakima-Columbia River basins with land-based snow telemetry measurements, testing their use for
215 LIS simulations that also use the North American LDAS, connecting assimilated snow data with the
216 Modular Modeling System (MMS) Precipitation-Runoff Modeling System (PRMS), and then supplying the
217 simulated runoff as inputs to RiverWare. Another project on the Rio Grande River basin is assessing
218 MODIS and Landsat data to improve evapotranspiration estimates generated by the BOR DST, the
219 Agricultural Water Resources Decision Support (AWARDS) ET Toolbox, which then provides water
220 demand time series to RiverWare. While application of specific hydrologic models and observations

221 depend on the specific RiverWare application, significant processing of both model and observations are
222 required and can be resource intensive (e.g., calibration and aggregation/disaggregation).

223 Operational scheduling of reservoir releases depend on orders of water from downstream users
224 (e.g., irrigation districts) that are largely affected by day-to-day weather conditions as well as seasonally
225 varying demands. In these cases, the important observations are the near real-time estimates of conditions
226 within the river basin system (e.g., soil moisture or infiltration capacity), which affect the transformation of
227 precipitation into runoff into the river system, relative to constraints on system operation (e.g., reservoir
228 storage levels or water temperatures at specific river locations). Meteorological prospects are mediated by
229 those placing the water orders or through short-term weather forecasts that may affect operations when the
230 system is near some constraint (e.g., flood flows when reservoir levels are near peak storage capacity). In
231 these situations, the important observations are recent extreme precipitation events and their location,
232 which may be provided, separately or in some combination, by *in situ* monitoring networks, radar, or
233 satellites.

234 For mid-range applications, such as strategic planning for operations over the next season or year,
235 outlooks of total seasonal water supplies are routinely used in making commitments for water deliveries,
236 determining industrial and agricultural water allocation, and carrying out reservoir operations. In these
237 applications, it is also important for water managers to keep track of the current state of the watershed.
238 Such observations are often used as input to one of the many independent hydrologic models that can
239 provide input to a specific RiverWare application. In these situations, the important observations are those
240 that provide boundary or forcing conditions for the independent hydrologic models, including snowpack
241 moisture storage, soil moisture, precipitation (intensity, duration, and spatial distribution), air temperature,
242 humidity, winds, and other meteorological conditions.

243 For long-term planning and design applications, observations are less important because the
244 effects of recent conditions have less impact on long-term outcomes than future meteorological uncertainty,
245 or even institutions at multi-decadal time scales. In these applications, accurate representation of
246 anticipated natural hydroclimatological variability is important. In many western U.S. applications,
247 observed streamflows are adjusted to remove the effects of reservoir management, interbasin diversions,
248 and water withdrawals. The adjusted flows, termed “naturalized flows.” may be used as input to RiverWare

249 applications to assess the impact of different management options. Use of naturalized flows is fraught with
250 problems. A central issue is poor monitoring of actual human impacts, especially withdrawals, diversions,
251 and return flows (e.g., from irrigation). Alternative approaches include the use of proxy streamflows (e.g.,
252 from paleoclimatological indicators) or output from hydrologic modeling studies (Hartmann, 2005). For
253 example, Tarboton (1995) developed hydrologic scenarios for severe sustained drought in the Colorado
254 River basin based on streamflows reconstructed from centuries of tree-ring records; the scenarios were used
255 in an assessment of management options using a precursor to the current RiverWare application to the
256 Colorado River system.

257 The usefulness of the observations used within RiverWare depends on the specific
258 implementation, as well as the quality of the information itself. For example, one direct use of climate
259 information for long-term planning includes hydrologic and hydraulic routing of “design storms” of various
260 magnitudes and likelihoods, with the storms based on analyses of the available instrumental record
261 (Urbanas and Roesner, 1993). However, those instrumental records have often been too short to adequately
262 express climate variability and resulting impacts, regardless of the specific DSTs used to do the hydrologic
263 or hydraulic routing. In short- and mid-range forecasting applications, the use of observations is mediated
264 by the hydrologic model or DST that transforms weather and climate into streamflows, evaporative water
265 demands, and other hydrologic processes. In these situations, from an operational perspective, the stream of
266 observational inputs must be dependable, without downtime or large data gaps, and data processing, model
267 simulation, and creation of forecast products must be fast and efficient. The usefulness of observations may
268 be limited by other issues as well. The water resources management milieu is complex and diverse, and
269 climate influences are only one factor among many affecting water management policies and practices.
270 Factors limiting the use of observations or subsequent hydrologic model input to RiverWare for actual
271 water management include lack of familiarity with the available information, disconnects between the
272 specific information available (e.g., variables and spatiotemporal scales) and their relevance to decision
273 makers, skepticism about the quality and applicability of information, conservative decision preferences
274 due to accountability for poor consequences, and institutional impediments such as the inflexible nature of
275 many multi-jurisdictional water management agreements (Changnon, 1990; Kenney, 1995; Pulwarty and
276 Redmond, 1997; Pagano et al., 2001, 2002; Jacobs, 2002; Jacobs and Pulwarty, 2003; Rayner et al., 2005).

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279 **4. Uncertainty**

280 The reliability of observations for driving hydrologic models that may provide input to RiverWare
281 applications is the subject of much ongoing research. The hydrologic models, because they incompletely
282 describe the physical relationships among important watershed components (e.g., vegetation processes that
283 link the atmosphere and different levels of soil and surface and groundwater interactions), are themselves
284 the subject of much research to determine their reliability. Streamflow and other hydrologic variables are
285 intimately responsive to atmospheric factors, especially precipitation, that drive a watershed's behavior;
286 however, errors in precipitation estimates are often amplified in the hydrologic response (Oudin et al.,
287 2006).

288 Obtaining quality precipitation estimates is a formidable challenge, especially in the western U.S.
289 where orographic effects produce large spatial variability and where there is a scarcity of real-time
290 precipitation gage data and radar beam blockage by mountains. In principal, outputs from atmospheric
291 models can serve as surrogates for observations, as well as providing forecasts of meteorological variables
292 that can be used to drive hydrologic models. One issue in integrating atmospheric model output into
293 hydrologic models for small watersheds (<1000 km²) is that the spatial resolution of atmospheric models is
294 lower than the resolution of hydrologic models. For example, quantitative precipitation forecasts (QPF)
295 produced by some atmospheric models may cover several thousand square kilometers, but the hydrologic
296 models used for predicting daily streamflows require precipitation to be downscaled to precipitation fields
297 for watersheds covering only tens or hundreds of square kilometers. One approach to produce output
298 consistent with the needs of hydrologic models is to use nested atmospheric models, whereby outputs from
299 large scale but coarse resolution models are used as boundary conditions for models operating over smaller
300 domains with higher resolution. However, the error characteristics of atmospheric model products (e.g.,
301 bias in precipitation and air temperature) also can have significant effects on subsequent streamflow
302 forecasts. Bias corrections require knowledge of the climatologies (i.e., long-term distributions) of both
303 modeled and observed variables.

304 Although meteorological uncertainty may be high for the periods addressed by streamflow
305 forecasts, accurate estimates of the state of watershed conditions prior to the forecast period are important
306 because they are used to initialize hydrologic model states, with significant consequences for forecast
307 results. However, watershed conditions can be difficult to measure, especially when streamflow forecasts
308 must be made quickly, as in the case of flash flood forecasts. One option is to continuously update
309 watershed states by running the hydrologic models continuously and by using inputs from recent
310 meteorological observations and/or atmospheric models. Regardless of the source of inputs, Westrick et al.
311 (2002) found it essential to obtain observational estimates of initial conditions to keep streamflow forecasts
312 realistic; storm-by-storm corrections of model biases determined over extended simulation periods were
313 insufficient. Recent experimental end-to-end forecasts of streamflow produced in a simulated operational
314 setting (Wood et al., 2001) highlighted the critical role of quality estimates of spring and summer soil
315 moisture used to initialize hydrologic model states for the eastern U.S.

316 Where streamflows may be largely comprised of snowmelt runoff, quality estimates of snow
317 conditions are important. The importance of reducing errors in the timing and magnitude of snowmelt
318 runoff are especially acute in regions where a large percentage of annual water supplies derive from
319 snowmelt runoff, snowmelt impacts are highly non-linear with increasing deviation from long-term average
320 supplies, and reservoir storage is smaller than interannual variation of water supplies. However, resources
321 for on-site monitoring of snow conditions have diminished rather than grown, relative to the increasing
322 costs of errors in hydrologic forecasts (Davis and Pangburn, 1999). Research activities of the NWS
323 National Office of Hydrology Remote Sensing Center (NOHRSC) have long been directed at improving
324 estimates of snowpack conditions through aerial and satellite remote sensing (Carroll, 1985). However, the
325 cost of aerial flights prohibits routine use (T. Carroll, NOHRSC, personal communication, 1999), while
326 satellite estimates have qualitative limitations (e.g., not considering fractional snow coverage over large
327 regions) and have not found broad use operationally.

328 Multiple techniques exist to more accurately represent the uncertainty inherent in understanding
329 and predicting potential hydroclimatic variability. Stochastic hydrology techniques use various forms of
330 autoregressive models to generate multiple synthetic streamflow time series with statistical characteristics
331 matching available observations. For example, in estimating the risk of low flows for the Sacramento River

332 Basin in California, the BOR (Frevert et al., 1989) generated 20 one-thousand-year streamflow time series
333 matching selected statistics of observed flows (adjusted to compensate for water management impacts on
334 natural flows); the non-exceedance probabilities of low flows were computed by counting the occurrences
335 of low flows within 1- through 10-year intervals for all 20 one-thousand-year sequences. The U.S. Army
336 Corps of Engineers (1992) used a similar approach to estimate flood magnitudes with return periods
337 exceeding 1,000 years, using Monte Carlo sampling from within the 95% confidence limits of a Log
338 Pearson III distribution developed by synthesizing multiple streamflow time series.

339 The ability to automatically execute many model runs within RiverWare, including accessing data
340 from external sources and exporting model results, facilitates using stochastic hydrology approaches for
341 representing uncertainty. For example, Carron et al. (2006) demonstrated RiverWare's capability to identify
342 and quantify significant sources of uncertainty in projecting river and reservoir conditions, using a first-
343 order, second-moment (FOSM) algorithm that is computationally more efficient than more traditional
344 Monte Carlo approaches. The FOSM processes uncertainties in inputs and models to provide estimates of
345 uncertainty in model results that can be used directly within a risk management decision framework. The
346 case study presented by Carron et al. (2006) evaluated the uncertainties associated with meeting goals for
347 reservoir water levels beneficial for recovering endangered fish species within the lower Colorado River.

348 With regard to RiverWare applications concerned with mid-range planning and use of hydrologic
349 forecasts, at the core of any forecasting system is the predictive model, whether a simple statistical
350 relationship or a complex dynamic numerical model. Advances in hydrologic modeling have been notable,
351 especially those associated with the proper identification of a model's parameters (e.g., Duan et al., 2002)
352 and the development of models that consider the spatially distributed characteristics of watersheds, rather
353 than treating entire basins as a single point (Grayson and Bloschl, 2000). Conceptual rainfall-runoff models
354 offer some advantages over statistical techniques in support of long-range planning for water resources
355 management. These models represent, with varying levels of complexity, the transformation of
356 precipitation and other meteorological forcing variables (e.g., air temperature and humidity) to watershed
357 runoff and streamflow, including accounting for hydrologic storage conditions (e.g., snowpack, soil
358 moisture, and groundwater). These models can be used to assess the impacts and implications of various
359 climate scenarios by using historic meteorological time series as input, generating hydrologic time series,

360 and then using those hydrologic scenarios as input to RiverWare. This approach enables consideration of
361 current landscape and river channel conditions, which may be quite different than recorded in early
362 instrumental records and which can dramatically alter a watershed's hydrologic behavior (Vorosmarty et
363 al., 2004). Furthermore, the use of multiple input time series, system parameterizations, or multiple models,
364 enables a probabilistic assessment of an ensemble of scenarios. The Hydrological Ensemble Prediction
365 Experiment (HEPEX) (Schaake et al., 2007) aims to address the unique challenges of expressing
366 uncertainty associated with ensemble forecasts for water resources management.

367 An additional concern for mid- and long-range planning is that, as instrumental records have
368 grown longer, they often show trends (e.g., Baldwin and Lall, 1999; Olsen et al., 1999; Andreadis and
369 Lettenmaier, 2006) or persistent regimes (i.e., periods characterized by distinctly different statistics) (e.g.,
370 Angel and Huff, 1995; Quinn, 1981, 2002), with consequences for estimation of hydrologic risk (Olsen et
371 al., 1998). Observed regimes and trends can have multiple causes, including climatic changes, watershed
372 and river transformations, and management impacts (e.g., irrigation return flows and trans-basin water
373 diversions). These issues enter into RiverWare applications directly through the use of naturalized flows,
374 which are notoriously unreliable. For example, in assessments of water management options on the San
375 Juan River in Colorado and New Mexico, the reliability of naturalized flows was considered to be affected
376 by the inconsistent accounting of consumptive uses between irrigation and non-irrigation data, use of
377 reservoir evaporation rates with no year-to-year variation, neglecting time lags in the accounting of return
378 flows from irrigation to the river, errors in river gage readings that underestimated flows in critical months,
379 and the lack of documentation of diversions that reduce river flows as well as subsequent adjustments to
380 data used to compute naturalized flows.

381

382 **5. Global Change Information and RiverWare**

383 *Climate Variability*

384 Decision makers increasingly recognize that climate is an important source of uncertainty and
385 potential vulnerability in long-term planning for the sustainability of water resources (Hartmann, 2005).
386 With the appropriate investment in site licenses, training of personnel, implementation for a specific river
387 system, and assessment efforts, RiverWare is capable of supporting climate-related water resources

388 management decisions by U.S. agencies. However, technology alone is insufficient to resolve conflicts
389 among competing water uses. Early in the development of RiverWare, Reitsma et al. (1996) investigated its
390 potential role as a DST within complex negotiations between hydroelectric, agricultural, and flood control
391 interests. Results indicated that while DSTs can help identify policies that can satisfy specific management
392 requirements and constraints, as well as expand the range of policy options considered, they are of limited
393 value in helping decision makers understand interactions within the river system. Furthermore, the burdens
394 of direct use by decision makers of a DST that embodies a complex system are significant; a more useful
395 approach is to have specialists support decision makers by making model runs and presenting the results in
396 an iterative manner. This is the approach used by the Bureau of Reclamation in the application of
397 RiverWare to support interstate negotiations concerning the sharing of Colorado River water supply
398 shortages during times of drought (Jerla, 2005; U.S. Department of Interior, 2007).

399 From the perspective of mid-range water management issues, the use of forecasts within
400 RiverWare applications constitutes an important pathway for supporting climate-related decision making.
401 Each time a prediction is made, science has an opportunity to address and communicate the strengths and
402 limitations of current understanding. Each time a decision is made, managers have an opportunity to
403 confront their understanding of scientific information and forecast products. Furthermore, each prediction
404 and decision provides opportunities for interaction between scientists and decision makers and for making
405 clear the importance of investments in scientific research. Perceptions of poor forecast quality are a
406 significant barrier to more effective use of hydroclimatic forecasts (Changnon, 1990; Pagano et al., 2001,
407 2002; Rayner et al., 2005); however, recent advances in modeling and predictive capabilities naturally lead
408 to speculation that hydroclimatic forecasts can be used to improve the operation of water resource systems.

409 Great strides have been made in monitoring, understanding, and predicting interannual climate
410 phenomena such as the El Nino-Southern Oscillation (ENSO). This improved understanding has resulted in
411 long-lead (up to about a year) climate forecast capabilities that can be exploited in streamflow forecasting.
412 Techniques have been developed to directly incorporate variable climate states into probabilistic
413 streamflow forecast models based on linear discriminant analysis (LDA) with various ENSO indicators,
414 (e.g., the Southern Oscillation Index [SOI]) (Peichota and Dracup, 1999; Piechota et al., 2001). Recent
415 improved understanding of decadal-scale climate variability also has contributed to improved interannual

416 hydroclimatic forecast capabilities. For example, the Pacific Decadal Oscillation (PDO) (Mantua et al.,
417 1997) has been shown to modulate ENSO-related climate signals in the West. Experimental streamflow
418 forecasting systems for the Pacific Northwest have been developed based on long-range forecasts of both
419 PDO and ENSO (Hamlet and Lettenmaier, 1999). In the U.S., the Pacific Northwest, California, and the
420 Southwest are strong candidates for the use of long-lead forecasts because ENSO and PDO signals are
421 particularly strong in these regions and each region's water supplies are closely tied to accumulation of
422 winter snowfall, amplifying the impacts of climatic variability.

423 While many current water management decision processes use single-value deterministic
424 approaches, probabilistic forecasts enable quantitative estimation of the inevitable uncertainties associated
425 with weather and climate systems. From a decision maker's perspective, probabilistic forecasts are more
426 informative because they explicitly communicate uncertainty and are more useful because they can be
427 directly incorporated into risk-based calculations. Probabilistic forecasts of water supplies can be created
428 by overlaying a single prediction with a normal distribution of estimation error determined at the time of
429 calibration of the forecast equations (Garen, 1992). However, to account for future meteorological
430 uncertainty, new developments have focused on ensembles, whereby multiple possible futures (each termed
431 an ensemble trace) are generated; statistical analysis of the ensemble distribution then provides the basis for
432 a probabilistic forecast.

433 Changnon (2000), Rayner et al. (2005), and Pagano et al. (2002) found that improved climate
434 prediction capabilities are initially incorporated into water management decisions informally, using
435 subjective, ad hoc procedures on the initiative of individual water managers. While improvised, those
436 decisions are not necessarily insignificant. For example, the Salt River Project, among the largest water
437 management agencies in the Colorado River Basin and primary supplier to the Phoenix metropolitan area,
438 decided in August 1997 to substitute groundwater withdrawals with reservoir releases, expecting increased
439 surface runoff during a wet winter related to El Nino. With that decision, they risked losses exceeding \$4
440 million in an attempt to realize benefits of \$1 million (Pagano et al., 2002). Because these informal
441 processes are based in part on confidence in the predictions, overconfidence in forecasts can be even more
442 problematic than lack of confidence, as a single incorrect forecast that provokes costly shifts in operations
443 can devastate user confidence in subsequent forecasts (e.g., Glantz, 1982).

444 The lack of verification of hydroclimatic forecasts is a significant barrier to their application in
445 water management, but it is not easy to resolve with traditional research efforts, because the level of
446 acceptable skill varies widely depending on the intended use (Hartmann et al., 2002a; Pagano et al., 2002).
447 Information on forecast performance has rarely been available to, and framed for, decision makers,
448 although hydrologic forecasts are reviewed annually by the issuing agencies in the U.S (Hartmann et al.,
449 2002b). Hydrologic forecast verification is an expanding area of research (Franz et al., 2003; Hartmann et
450 al., 2003; Bradley et al, 2004; Pagano et al., 2004; Kruger et al., 2007), but much work remains and could
451 benefit from approaches developed within the meteorological community (Welles et al., 2007). Because
452 uncertainty exists in all phases of the forecast process, forecast systems designed to support risk-based
453 decision making need to explicitly quantify and communicate uncertainties from the entire forecast system
454 and from each component source, including model parameterization and initialization, meteorological
455 forecast uncertainty at the multiple spatial and temporal scales at which they are issued, adjustment of
456 meteorological forecasts (e.g., through downscaling) to make them usable for hydrologic models,
457 implementation of ensemble techniques, and verification of hydrologic forecasts.

458

459 *Climate Change*

460 From the perspective of long-range water management issues, the potential impacts of climate
461 change on water resources, and their implications for management, are central topics of concern. Estimates
462 of prospective impacts of climate change on precipitation have been mixed, leading, in many cases, to
463 increasing uncertainty about the reliability of future water supplies. However, where snow provides a large
464 fraction of annual water supplies, prospective temperature increases dominate hydrologic impacts, leading
465 to stresses on water resources and increased hydrologic risk. Higher temperatures effectively shift the
466 timing of the release of water stored in the snowpack “reservoir” to earlier in the year, reducing supplies in
467 summer when demands are greatest, while also increasing the risk of floods due to rain-on-snow events.
468 While not using RiverWare, several river basin studies have assessed the risks of higher temperatures on
469 water supplies and management challenges. The near universal analytical approach has been one of
470 sensitivity analysis (Lettenmaier, 2003):

- 471 1) downscaling outputs from a dynamic general circulation model of the global land-atmosphere-
472 ocean system to generate regional- or local-scale meteorological time series over many decades,
473 2) using the meteorological time series as input to rainfall-runoff models to generate hydrologic time
474 series,
475 3) using the hydrologic scenarios as input to water management models, and
476 4) assessing differences among baseline and change scenarios using a variety of metrics.

477 Early assessments of warming impacts on large river basins generally showed extant water
478 management systems to be effective for all but the most severe scenarios (Hamlet and Lettenmaier, 1999;
479 Lettenmaier et al., 1999), with a notable exception being the Great Lakes system where increased lake heat
480 storage was tied to loss of ice cover, increased winter lake evaporation, lower lake levels, and potential
481 failure to meet Lake Ontario regulation objectives under extant operating rules (Croley, 1990; Hartmann,
482 1990; Lee et al., 1994; Lee et al., 1997; Sousounis et al., 2000; Lofgren et al., 2002).

483 Extensive detailed studies of the ability of existing reservoir systems and operational regulation rules
484 to meet water management goals under changed climates are fairly recent (e.g., Saunders and Lewis, 2003;
485 Christensen, et. al, 2004; Payne et. al, 2004; VanRheenan et. al, 2004; Maurer, 2007). However, there is a
486 rapidly growing literature on broad considerations of climate change in water resources management
487 (Frederick et al., 1997; Gamble et al., 2003; Lettenmaier, 2003; Loomis et al., 2003; Snover et al., 2003;
488 Stakhiv, 2003; Ward et al., 2003; Vicuna et al., 2007). Some (Matalas, 1997) that contend that existing
489 approaches are sufficient for water resource management planning and risk assessment because they
490 contain safety factors; however, an inescapable message for the water resource management community is
491 the inappropriateness of the stationarity assumption in the face of climate change. While precipitation
492 changes may remain too uncertain for consideration in the near term, temperature increases are more
493 certain and can have strong hydrologic consequences.

494 Cognitively, climate change information is difficult to integrate into water resources management.
495 First, within the water resources engineering community, the stationarity assumption is a fundamental
496 element of professional training. Second, the century timescales of climate change exceed typical planning
497 and infrastructure design horizons and are remote from human experience. Third, even individuals trying to
498 stay up-to-date can face confusion in conceptually melding the burgeoning climate change impacts

499 literature. Assessments are often repeated as general circulation and hydrologic model formulations
500 advance or as new models become available throughout the research community. Furthermore, assessments
501 can employ a variety of techniques for downscaling. Transposition techniques (e.g., Croley et al., 1998) are
502 more intuitive than the often mathematically complex statistical and dynamical downscaling techniques
503 (e.g., Clark et al., 1999; Westrick and Mass, 2001; Wood et al., 2002; Benestad, 2004).

504 GCMs and their downscaled corollaries provide one unique perspective on long-term trends
505 related to global change. Another unique perspective is provided by tree-ring reconstructions of paleo-
506 streamflows, which, for example, indicate that in the U.S. Southwest droughts over the past several
507 hundred years have been more intense, regionally extensive, and persistent than those reflected in the
508 instrumental record (Woodhouse and Lukas, 2006). Decision makers have expressed interest in combining
509 the perspectives of paleoclimatological information and GCMs. While some studies have linked
510 instrumental records to paleoclimatological information (e.g., Prairie, 2006) and others with GCMs (e.g.,
511 Christensen and Lettenmaier, 2006), few link all three (an exception is Smith et al., 2007).

512 Conceptual integration of climate change impacts assessment results in a practical water
513 management context is complicated by the multiplicity of scenarios and vague attribution of their prospects
514 for occurrence, which depend so strongly on feedbacks among social, economic, political, technological,
515 and physical processes. For decision makers, a critical issue concerns the extent to which the various
516 scenarios reflect the actual uncertainty of the relevant risks versus the uncertainty due to methodological
517 approaches and biases in underlying models. The difficulties facing decision makers in reconciling
518 disparate climate change impact assessments are exemplified by the Upper Colorado River Basin, where
519 reductions in naturalized flow by the mid-21st century have been estimated to range from about 45% by
520 Hoerling and Eischeid (2007), 10 to 25% by Milly et al (2005), about 18% by Christensen et al. (2004), and
521 about 6% by Christensen and Lettenmaier (2006). Furthermore, using the difference between precipitation
522 and evapotranspiration as a proxy for runoff, Seager et al. (2007) suggest an “imminent transition to a more
523 arid climate in southwestern North America.”

524 However, in the face of circumstances nearing or exceeding the effectiveness of existing
525 management paradigms, individuals can become more cognizant of the need to consider climate change. In
526 the U.S. Southwest, over 1999–2004, Lake Powell levels declined faster than previously considered in

527 scenarios of extreme sustained drought (e.g., Harding et al., 1995; Tarboton, 1995), from full to only 38%
528 capacity in November 2004 (BOR, 2004). Resource managers, policymakers, and the general public are
529 now actively seeking scientific guidance in exploring how management practices can be more responsive to
530 the uncertainties associated with a changing climate.