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An End-To-End Framework for Seasonal Forecasting in Water Resources Management in the San Juan River Basin Using Stochastic Weather Generator Based Ensemble Streamflow Predictions

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An End-to-End Framework for Seasonal Forecasting

in Water Resources Management in the San Juan River Basin

Using Stochastic Weather Generator based Ensemble Streamflow Predictions

by

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An End-to-End Seasonal Forecasting Framework For Water Resources Management In The San Juan River Basin Using Stochastic Weather Generator Based Ensemble Streamflow Predictions

Thesis directed by Prof. Edith Zagona

Climate informed ensemble water supply forecasts are continually gaining popularity as enhanced methods improve skill and tools become available to incorporate these forecasts. This research builds on this idea, using an enhanced Ensemble Streamflow Prediction (ESP) method to create streamflow forecast ensembles. The drawback of ESP is that it uses historical weather sequences to generate ensembles. To address this, previous work adapted a stochastic weather generator that uses K-nearest neighbor resampling approach to incorporate probabilistic seasonal climate forecasts, more specifically winter precipitation forecasts in the San Juan River Basin. This enables generation of a rich variety of weather sequences that are consistent with large scale climate forecasts. We continue to use this flexible approach and incorporate spring temperature forecasts to attempt to better capture the timing of snowmelt runoff.

We then set up a framework to evaluate the streamflow forecasts using the US Bureau of Reclamation's probabilistic RiverWare based Mid-Term Operations Model (MTOM). The streamflow forecast ensembles become input to the San Juan River Basin (JSRB) portion of the MTOM, from which we analyze operational performance metrics to evaluate the enhanced streamflow forecasts methods. The management objectives in the basin include water supply for irrigation, tribal water rights, environmental flows, and flood control. The spring streamflow ensembles were issued at four different lead times on the first of each month from January -

April, and are incorporated into the MTOM for the period 2002-2010. Ensembles of operational metrics for the SJRB such as Navajo Reservoir releases, end of water year storage, environmental flows and water supply for irrigation were computed and their skills evaluated against variables obtained in a baseline simulation using historical streamflow.

Dedication

Thank you to my family for imparting a love of learning and encouraging me along the way.

And to my best friend, who decided, in the midst of this school journey, to stand next to me for the rest of our lives. To many more adventures, I love you.

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Chapter 1

Ensemble Seasonal Streamflow Forecasts using Stochastic Weather Generator Conditioned on Climate Forecasts

1.1. Introduction and Background

Ensemble water supply forecasts and the probabilistic information they provide have been described as 'more appropriate and articulate than deterministic forecasts' (Pagano and Garen, 2005). Deterministic forecasts omit much information about possible outcomes and uncertainty. Probabilistic information allows water managers to make risk based decisions within in their risk profile. The catch for the snowmelt-dominated western US is that these seasonal water supply forecasts have long relied on snowpack information, which limits the skill to April 1-lead and shorter lead time forecasts. Incorporating seasonal climate forecasts can help improve skill at longer lead times, before snowpack information is available, by reducing the uncertainty about future precipitation to the extent that the climate forecast does.

In the Colorado River Basin, ensemble streamflow forecasts are produced by the National Weather Service (NWS) Colorado Basin River Forecast Center (CBRFC). Of interest is the forecast for the snow melt season (April-July) at long lead times, typically, starting in January or early spring. Forecasts generated by CBRFC are from the physical model based Ensemble Streamflow Prediction (ESP, Day 1985). ESP uses current basin conditions with historical meteorological data within a conceptual hydrologic model to forecast future streamflow (Day 1985).

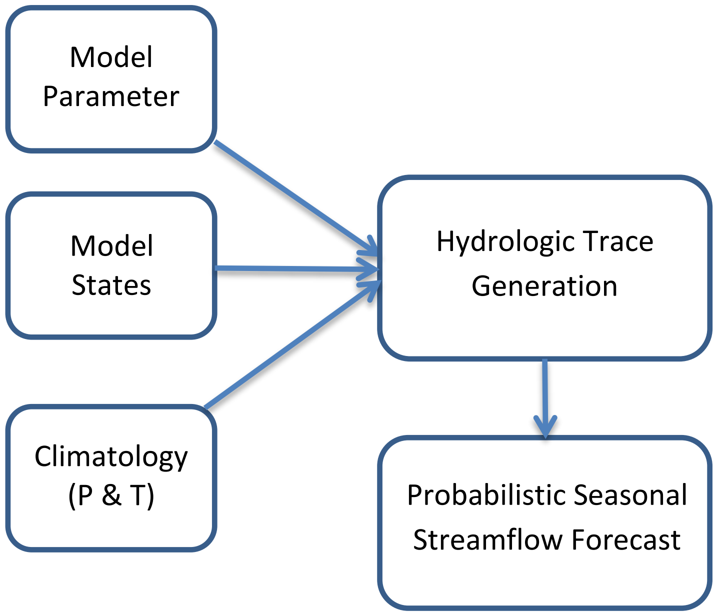


Figure 1.1 Ensemble Streamflow Prediction (ESP) Schematic

The schematic of the ESP is shown in Figure 1.1. The ESP uses the historic daily weather sequences to drive a physically based watershed model, the Sacramento Soil Moisture Accounting model (SAC-SMA) lumped with SNOW-17 temperature index model. In the SAC-SMA, Figure 1.2, flow is created by distributing moisture through a two zoned soil mantle (upper and lower), each with tension and free water components (Burnash et al, 1973; Burnash, 1995). Tension water is water tightly bound to soil molecules only evapotranspiration can remove it. Free water can move freely between the upper and lower zones. Direct runoff, surface runoff, interflow, and base flow in and between these zones are determined by about twenty parameters. The SNOW-17 simulates snow accumulation and ablation and outputs a rain plus melt time series that becomes input to the SAC-SMA model (Day 1985). Calibration includes historical rainfall, temperature, and streamflow and parameter changes so that the model output matches historical streamflow, for this research from 1981-2010 (Larson, 2002).

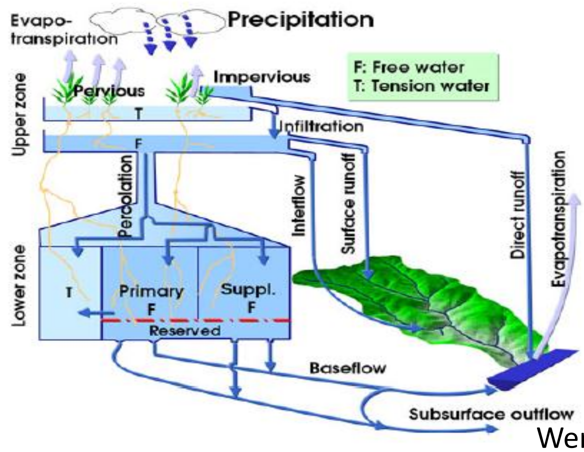


Figure 1.2 Sacramento Soil Moisture Accounting Model Schematic

The ESP approach is fairly robust and is widely used across the River Forecasting Centers (RFCs) and also in other parts of the world for hydrologic ensemble forecasting. However, one of its main drawbacks is that it relies on historical weather sequences to generate ensembles. For example, to produce ensemble streamflow for the period Nov 1 – Dec 31, the watershed model is initialized based on the conditions on Nov 1 and all the historical weather sequences for this period are input to the model to produce ensembles of streamflow for this period. Thus, the number of ensembles is restricted to the number of historical years. If climate information is to be incorporated, such as forecast of El Nino events, then the weather sequences are restricted to just the El Nino years in the historical record which further reduces the number of ensembles.

To address this, Caraway (2012) and Caraway et al. (2013) proposed and developed a significant enhancement to the ESP. In this, they adapted a stochastic weather generator that uses K-nearest neighbor resampling approach (Apipattanavis, et al., 2007; Rajagopalan and Lall, 1999; Yates et al., 2003) to incorporate probabilistic seasonal climate forecasts. This enables generation of a rich variety of weather sequences that are consistent with large scale climate forecasts, thus obtaining the probability density function of the streamflows in a robust manner. They applied this to long lead forecast of spring streamflows in the San Juan River Basin, which is a snowmelt dominated basin. Specifically, they incorporated only the winter (Nov-Mar) probabilistic seasonal forecast of precipitation (http://iri.columbia.edu/climate/forecast/net_asmt/link) to generate winter weather sequences from the stochastic weather generator and used climatology for the remaining months.

The hydrologic model forced by these simulated weather sequences produced more skillful streamflow forecasts at longer lead times than traditional ESP (Caraway 2012). Spring streamflow volumes forecasted using conditioned 'wet' winter precipitation climate forecasts displayed larger spring streamflow volumes and slightly smaller volumes for 'dry' winter forecasts. Thus if a climate forecast has skill, that skill would translate into the streamflow forecasts.

1.2. Motivation

The inclusion of skillful winter precipitation forecasts which drives the snow in the basin improves the skill in spring streamflow forecasts, as to be expected. However, the timing of spring streamflows is important for making decisions concerning flood control, seasonal water allocation, and reservoir storage (Hamlet and Lettenmaier 1999). The timing of spring streamflow is predominantly modulated by spring temperatures in snowmelt basins. All else being the same, warmer spring temperatures lead to early arrival of spring streamflow peak. A combination of winter precipitation and spring temperature could potentially influence the timing of spring streamflow.

We find these relationships in the San Juan River Basin, which motivates the proposed research. The basin and the flow locations are shown in Figure 1.3 and information on all the relevant hydrometeorological data is given in Table 1.1. The spring seasonal and monthly streamflow are shown in Figure 1.4.

The San Juan River is the third largest tributary of Colorado River, after the Green River and the Gunnison River, with 350 river miles before joining the Colorado River at Lake Powell. The San Juan River Basin has a drainage area of approximately 25,000 square miles in Colorado (23%), New Mexico (39%), Arizona (20%), and Utah (17%). Elevation ranges from 4,000 to 14,000 feet above mean sea level. Precipitation in this snowmelt basin varies from as much as 60 inches annually in the high peaks to less than 10 inches in most areas to less than 1/10 inch in others. The three largest tributaries to the San Juan River are the Animas, the Piedra, and the Los Pinos rivers.[1]

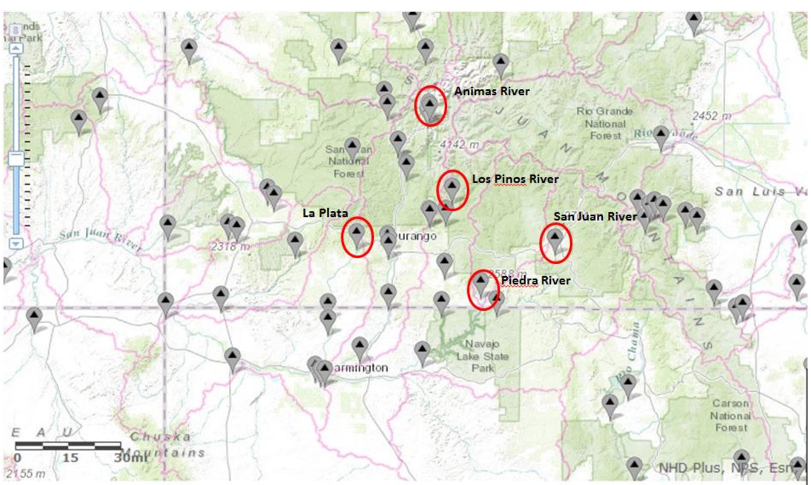


Figure 1.3 San Juan River Basin and location of the Headwater Gages

[1]http://www.usbr.gov/uc/wcao/rm/sjrip/

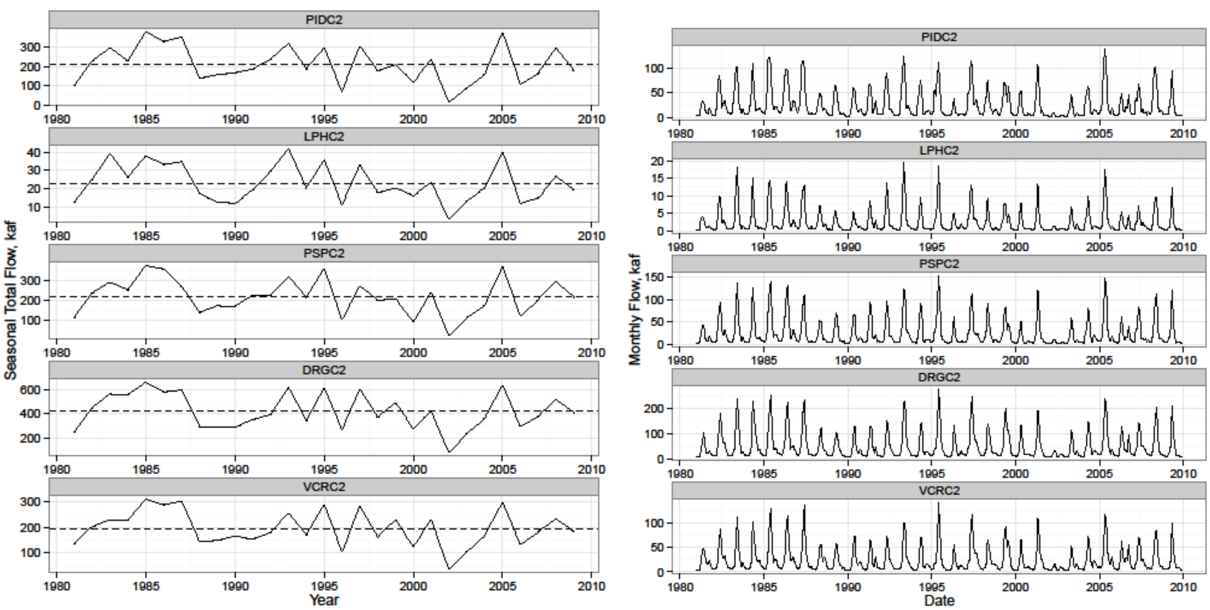
Table 1.1 San Juan River Basin Hydrometeorological Data Information

River	Location	USGS Number	CBRFC Gage	CBRFC Monthly Data	USGS Daily Data
La Plata	Hesperus, CO	9365500	LPHC2H	1980-2010	1980-2010
Piedra	Arboles, CO	9349800	PIDC2H	1980-2010	1980-2010
Los Pinos	Bayfield, CO	9352900	VCRC2H	1980-2010	1980-2010
Animas	Silverton, CO	9358550	DRGC2H	1980-2010	1995-2010
San Juan	Pagosa Springs, CO	9342500	PSPC2H	1980-2010	1980-2010

USGS Data: http://maps.waterdata.usgs.gov/mapper/index.html

CBRFC Data: http://www.cbrfc.noaa.gov/gmap/cmap2.php?con=wsup

Meteorological Data: Caraway 2012, pg 10



a) Seasonal (April to July) Volume b) Monthly Streamflow

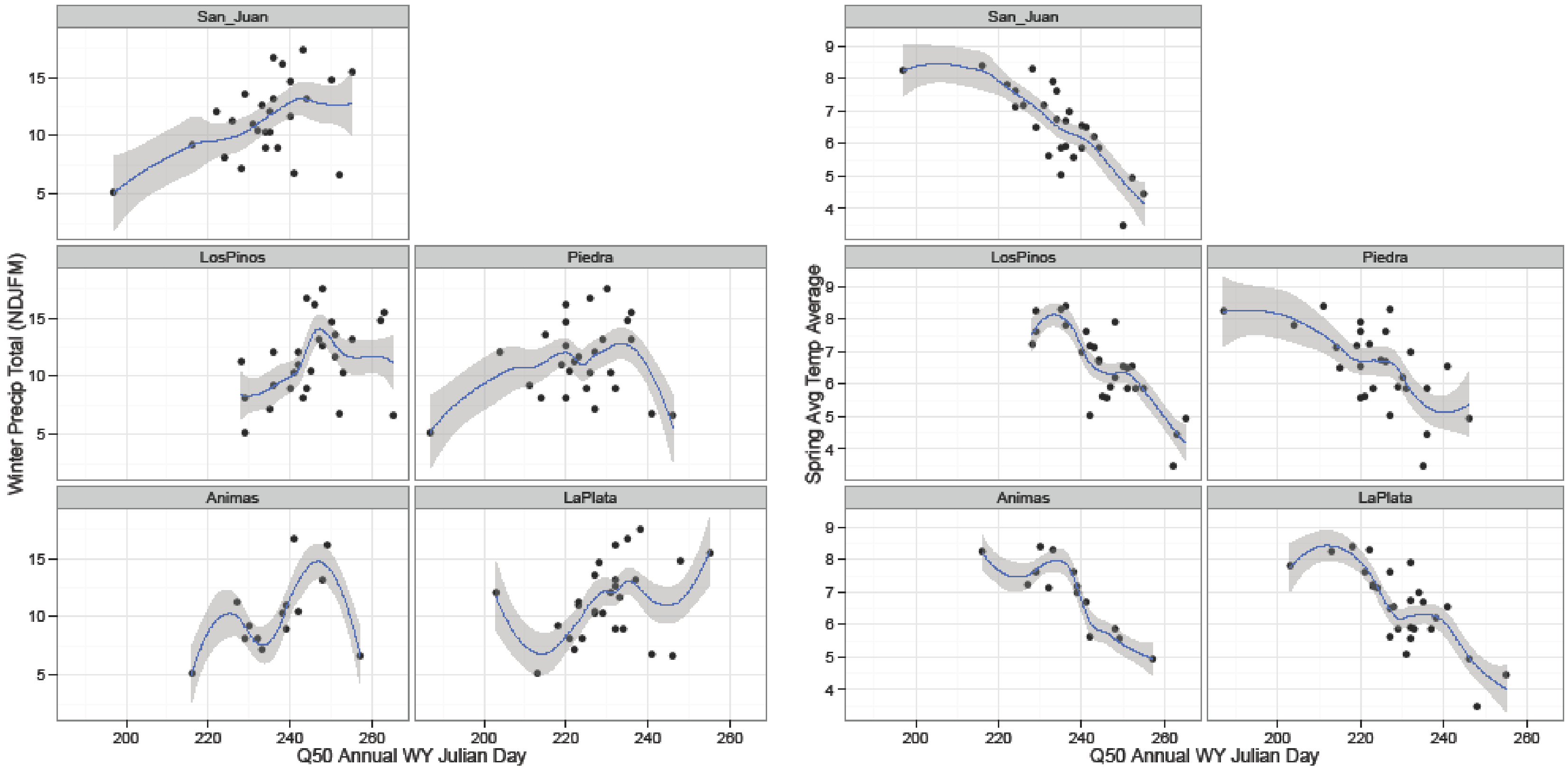
Figure 1.4 Gage Streamflow Climatology 1981-2010

The timing of spring streamflow peak can be highly variable and dependent on variables not included in this study such as sequencing of weather rather than monthly climate characteristics, thus we computed the Julian day on which 50 percent of the water-year or season flow is equaled or exceeded (denoted as Q50), as a more stable variable, later the translation of skill between the climate forecasts and the streamflow forecasts is shown, consistent with the observations of Regonda et al. (2005). The historical seasonal Q50 analyzes the runoff season from April to July and the historical annual Q50 is a check to see if historically the Q50 for the year is outside of the runoff season. Historical annual (Figure 1.5a-b) and seasonal (Figure 1.7a-b) Q50 are plotted against total winter precipitation (Nov-Mar) and average spring temperature (Apr-May). Also, surface plots of Q50 as a function of winter precipitation and average spring temperature are shown in Figure 1.6 and 1.8. As can be seen from these figures, increased winter precipitation and lower spring temperatures show the snow melting later in the year/season and vice versa. The surface plots reveal the same pattern on the boundaries, but non-linearity in the middle. For the Piedra and Los Pinos gages, the seasonal Q50 (Figure 1.6) reveals that between 5 and 6 degrees Celsius and 12 inches, an area exists that is earlier than the surrounding area and the opposite exists for the San Juan gage at similar location. Similar patterns appear for the annual and seasonal Q50 plots and also with Q70 (figures can be found in Appendix A).

Melting the snow earlier or later in the runoff season can also have an impact on spring runoff volume. A warmer spring which melts the snowpack earlier in the season could result in a decrease in runoff volume, making management and planning decisions, based on purely snowpack, inaccurate. A cool spring, which melts the snowpack later in the season, could result in increased volume with consequences of possible flooding. These management decisions can benefit from the knowledge that the spring temperature forecast could bring.

Spring temperatures introduce a nonlinear relationship that we wish to capture in streamflow forecasts. Motivated by the results presented above, we propose to incorporate the spring temperature forecast into the SWG and investigate the effects on the hydrologic skill, mostly in hydrograph attributes of seasonal timing and volume.

In light of these relationships and the motivation, we propose further enhancements to the stochastic weather generator approach of Caraway (2012), to include spring temperature forecasts in addition to the winter precipitation forecasts. These enhanced weather sequences will drive the hydrologic model to provide streamflow ensembles and their utility in capturing spring flow attributes is investigated. Seasonal climate forecasts are first described, and the methodology next. Results from the proposed approach and comparison to earlier methods are described next, concluding with summary and discussion.



a) Winter Precipitation (NDJFM)

b) Spring Average Temperature (AM)

Figure 1.5 Scatterplots for Annual Water Year Historical Q50 Julian Day

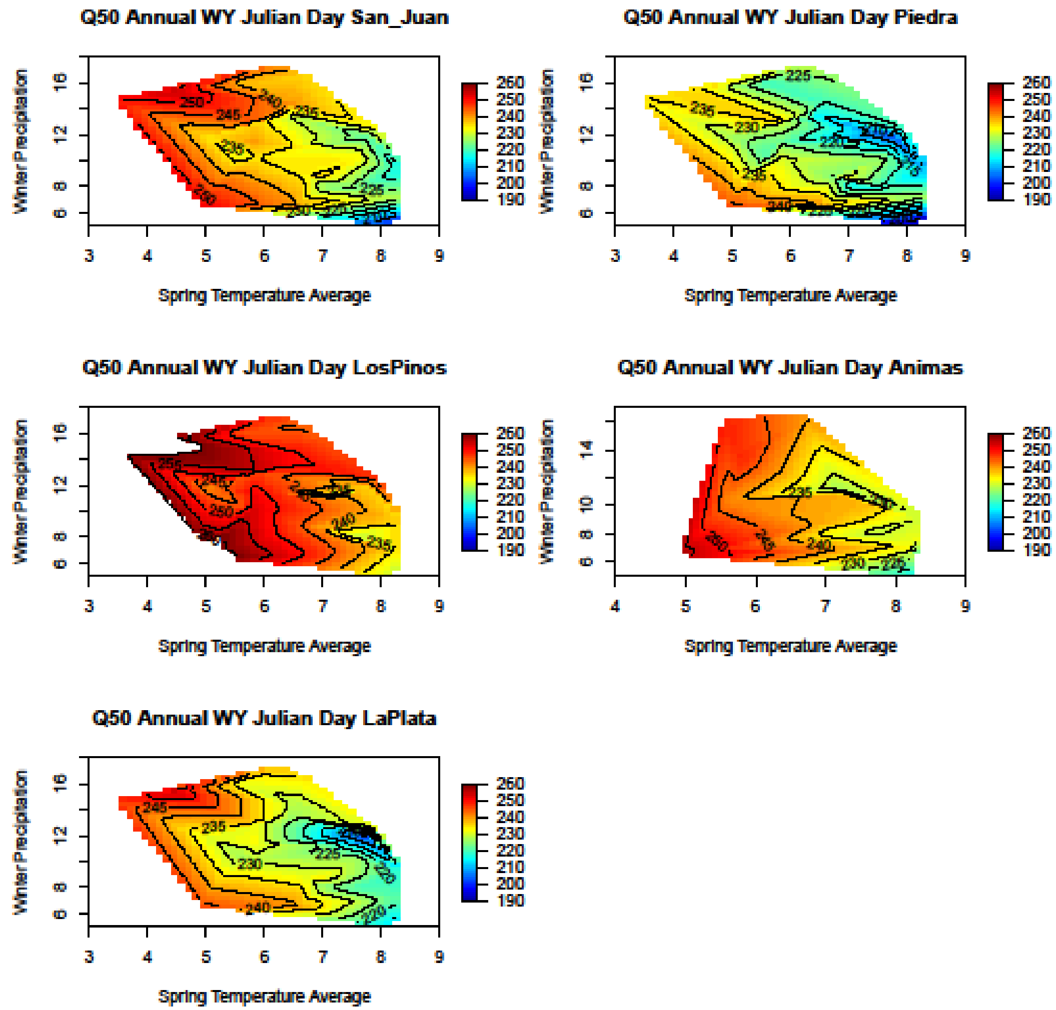
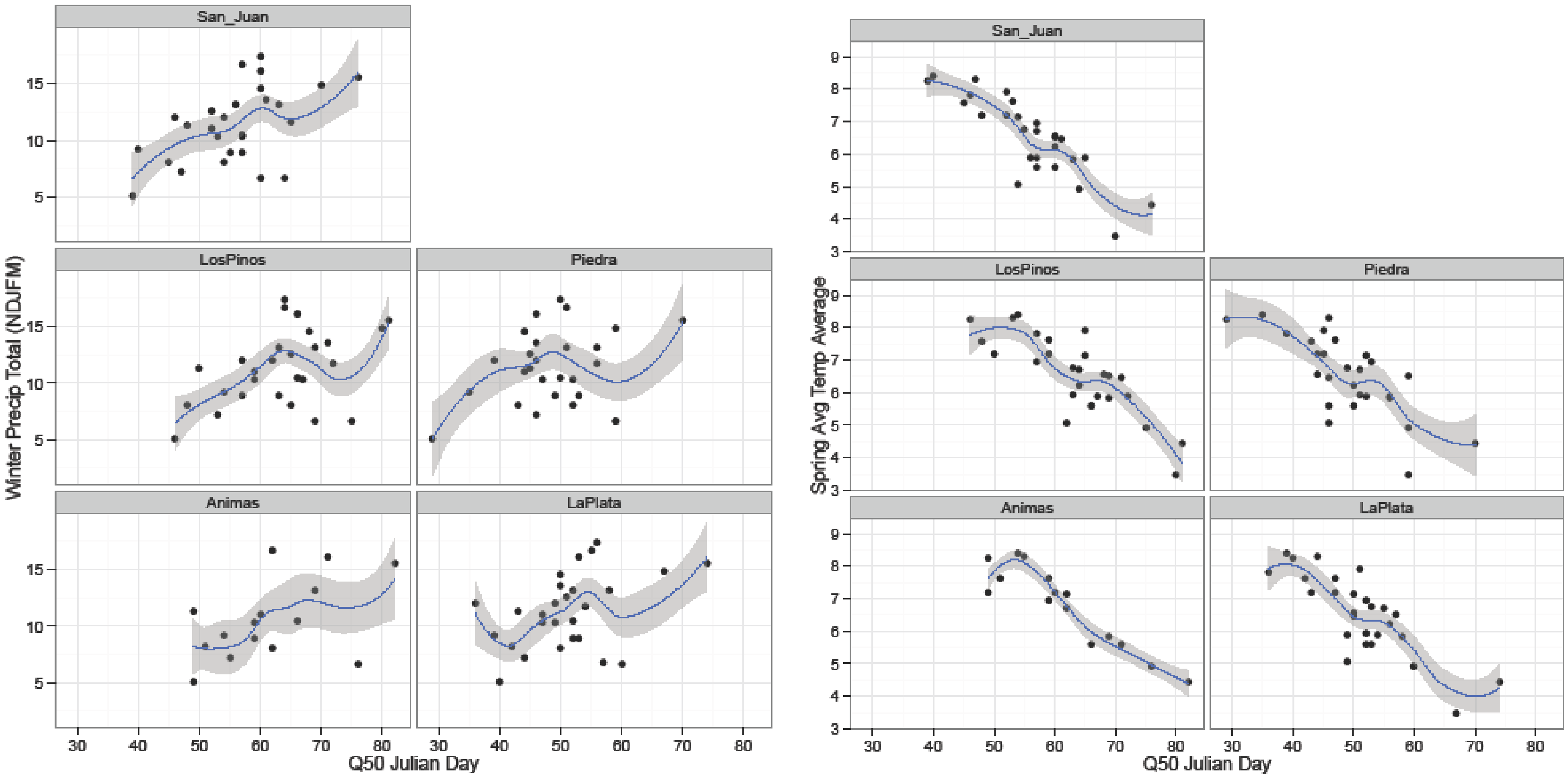


Figure 1.6 Winter Precipitation (NDJFM) and Spring Average Temperature (AM) Annual Water Year Historical Q50 Julian Day



a) Winter Precipitation (NDJFM) b) Spring Average Temperature (AM)

Figure 1.7 Scatterplots for Seasonal (AMJJ) Water Year Historical Q50 Julian Day

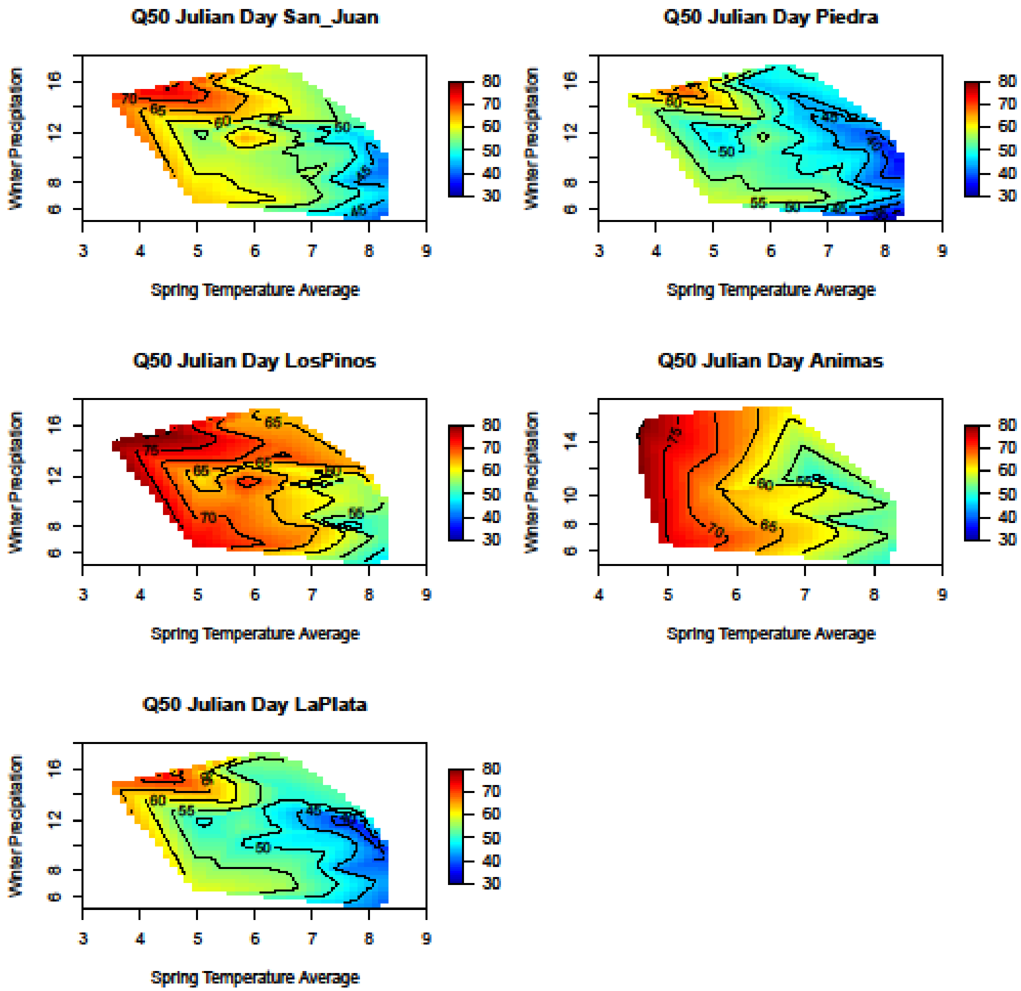
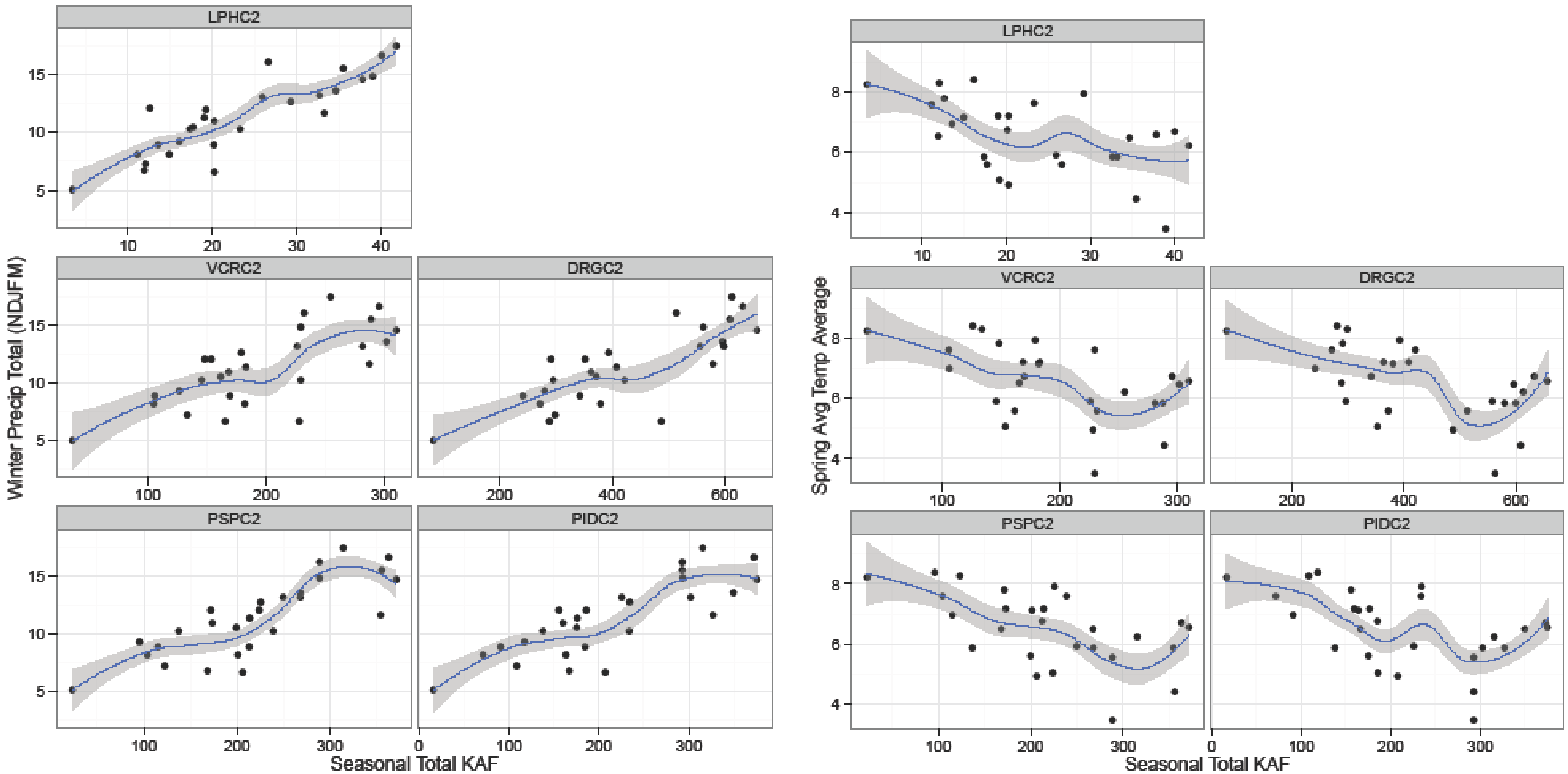


Figure 1.8 Winter Precipitation (NDJFM) and Spring Average Temperature (AM) Seasonal (AMJJ) Water Year Historical Q50 Julian Date



a) Winter Precipitation (NDJFM) b) Spring Average Temperature (AM)

Figure 1.9 Scatterplots for Seasonal Total Volume Flow (April-July)

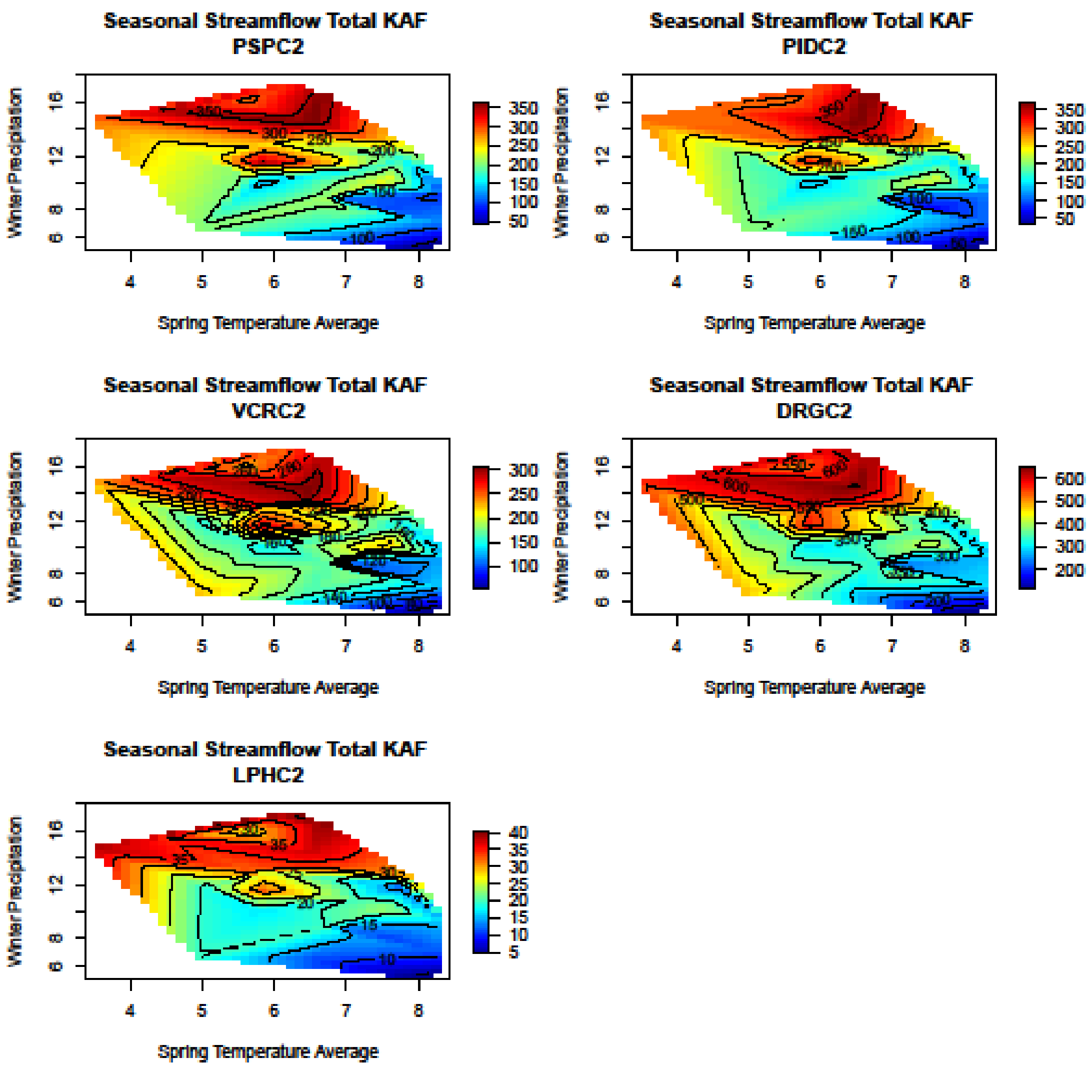


Figure 1.10 Winter Precipitation (NDJFM) and Spring Average Temperature (AM) Seasonal (AMJJ) Water Year Historical Q50 Julian Date

1.3. Data

1.3.1. Seasonal Climate Forecasts

We chose to condition the weather generator with the climate forecasts issued by the International Research Institute (IRI) for Climate and Society to provide continuity between Caraway's (2013) research and this research. IRI issues monthly seasonal precipitation and temperature forecasts on a global scale with a lead time of up to 6 months in 3-month moving windows. The precipitation and temperature forecasts are expressed as the percentage likelihood of A:N:B, where A denotes the percent chance of above-normal rainfall (wet) or average temperatures (warm), N denotes the percent chance of near-normal rainfall or average temperatures (climatology), and B denotes the percent change of below-normal rainfall. More specifically, a spring temperature forecast of [40:35:25] indicates that 40 of 100 years will be in the warm tercile, 35 of 100 years in the average tercile, and 25 of 100 years will be in the cooler tercile. General skill of both the precipitation and temperature forecasts perform better than climatology discussed in by Barnston et al. (2009). In the southern United States, skills peak during drier seasons.

Forecasts for the San Juan River Basin were visually obtained from the forecast maps around the US Four Corners location, for the period 2002-2010. For winter precipitation forecasts, we combined the forecasts issued in December and January for January-February-March (JFM) and February-March-April (FMA), respectively, into one forecast to use as input to the SWG, an example for winter of 2005 is shown in Figure 1.11a. For spring temperature forecasts, we use the temperature forecasts issued in February for March-April-May (MAM), an example of spring 2005 is shown in Figure 1.11b. Verification of the forecasts was done by visually inspecting the IRI verification maps. Table 1.2 shows the IRI forecasts for both winter precipitation and spring temperature for 2002-2010. We selected past climate forecasts based on observed hydrologic outcomes and climate forecasts verification. A dry (2002), normal (2004), and wet (2005) streamflow year, shown in Table 1.3, were chosen for analysis, years in blue in Table 1.2, all years had warm spring temperature forecasts (40:35:25) and accurate winter precipitation forecasts.

Table 1.2 IRI Precipitation and Temperature Forecasts for 2002-2010

a) Winter Precipitation Forecasts

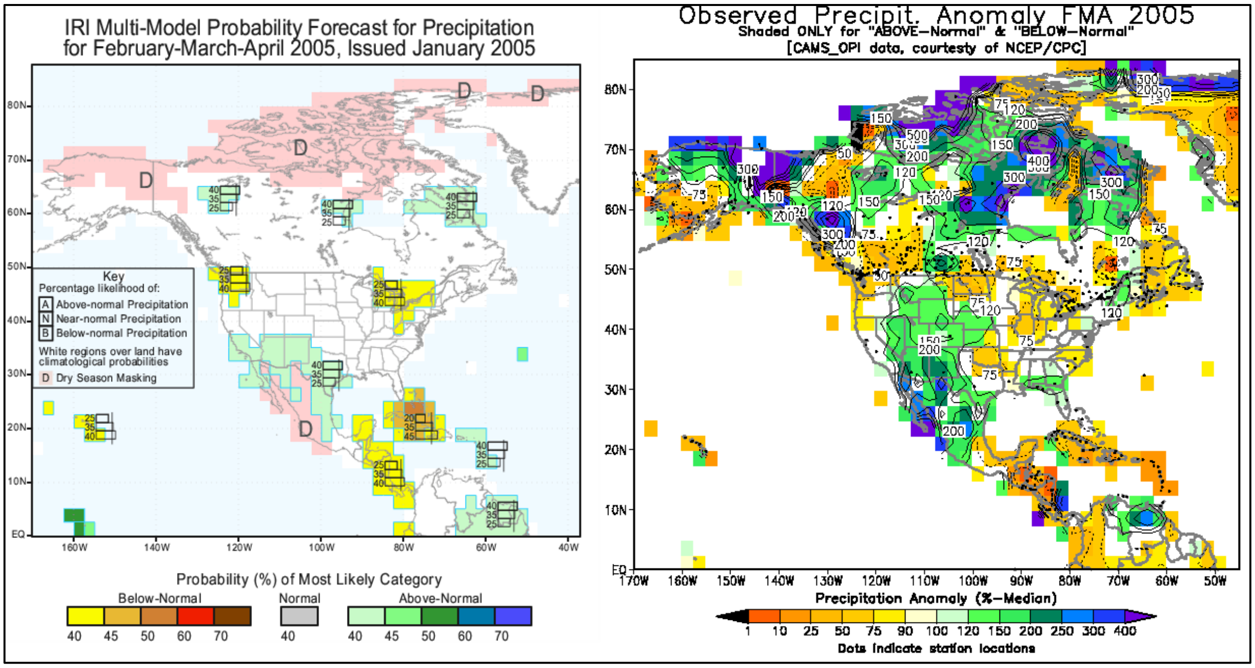
Winter Precipitation Forecasts					
Year	A	N	B	Forecast	Actual
2002	25	35	40	Dry	Dry
2003	40	35	25	Wet	Wet
2004	33	33	33	Normal	Normal
2005	40	35	25	Wet	Wet
2006	25	35	40	Dry	Normal
2007	40	35	25	Wet	Normal
2008	25	35	40	Dry	Dry
2009	25	35	40	Dry	Dry
2010	40	35	25	Wet	Wet

b) Spring Temperature Forecasts

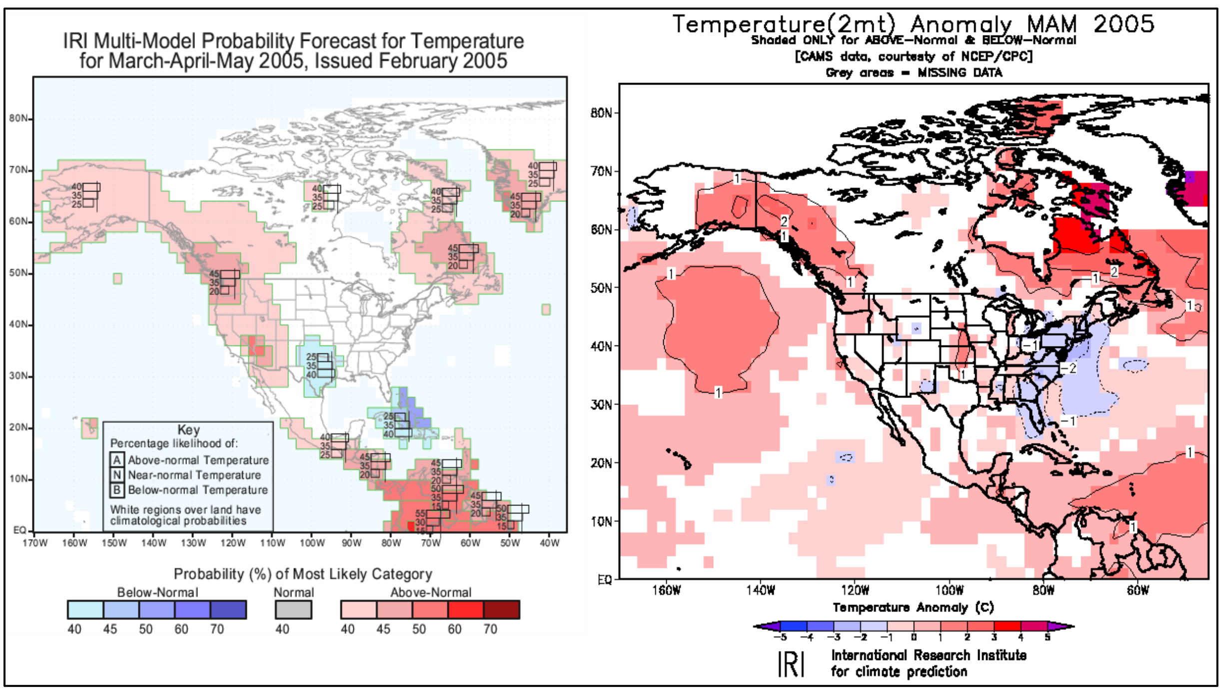
Spring Temperature Forecast					
Year	A	N	B	Forecast	Actual
2002	40	35	25	Warm	Warm
2003	40	35	25	Warm	Warm
2004	40	35	25	Warm	Warm
2005	40	35	25	Warm	Normal
2006	40/45	35/35	25/20	Warm	Warm
2007	40	35	25	Warm	Normal
2008	45/50	35/35	20/15	Warm	Cool
2009	40/45	35/35	25/20	Warm	Warm
2010	33	33	33	Normal	Normal

Table 1.3 Years and Forecasts Chosen for Simulation Runs

SWG CondII Runs			
		IRI Forecasts	
Year	**Observed Streamflow**	**Winter Precip.**	**Spring Temp**
2002	Dry	25:35:40	40:35:25
2004	Normal	33:33:34	40:35:25
2005	Wet	40:35:25	40:35:25



a) Winter Precipitation Forecasts Issued in January 2005 and Verification Map



b) Spring Temperature Forecast Issued in February 2005 and Verification Map

Figure 1.11 IRI Issued Climate Forecast Examples

1.4.Proposed Methodology

The proposed methodology which is enhancement to the stochastic weather generator framework of Caraway et al. (2013) is described below. The steps of the unconditional stochastic weather generator which is similar to that proposed in Apipattanavis et al. (2007) is first described for the sake of completeness. Then the modification to incorporate spring seasonal temperature forecasts is described. Lastly, the hydrologic model used to produce streamflow forecasts, using the weather generated sequences as input, is presented.

1.4.1. Unconditional Stochastic Weather Generator

This is abstracted from Caraway et al. (2013) and Apipattanavis et al. (2007).

1. A Markov chain model is fitted to the area-averaged daily precipitation state (wet/dry) and it is used to simulate the sequence of precipitation states, S_t
2. A 7-day window centered on the day of year (DOY), *t*, for which the weather vector is to be simulated, is considered for all the historical years. Thus, if weather vector is to be generated for Jan 10 the window would be Jan 7-13. Days within this window with matching, areal-averaged precipitation state transitions to day *t*, from previous day, *t-1* are extracted – i.e., all pairs of days with the same transition as the simulated, S_t, S_{t-1} pair.
3. Euclidean distances are calculated between area-averaged weather vectors of all candidate historical days from above with the previously simulated area-averaged weather vector on day *t-1*.
4. $K = \sqrt{N}$, number of nearest neighbors are selected from all the neighbors, where N is the total number of neighbors identified above (Lall and Sharma, 1996).

5. These K nearest neighbors are assigned a probability using a discrete decreasing kernel $$p(i) = \frac{1/j}{\sum_{j=1}^{k} 1/j}$$ (Lall and Sharma, 1996; Rajagopalan and Lall, 1999), where *p(i)* is the probability that the i^{th} neighbor will be selected, thus giving the nearest neighbor the most probability and the the K^{th} neighbor the least.
6. A neighbor (i.e., a historical day) is randomly resampled according to these weights.
7. The weather vector on its successive day in the historical record is the simulated weather for day *t*. The weather at all locations on the resampled day is selected to simulate weather vector at multi-sites – thus, capturing the spatial covariance. Variations to this have been proposed (Caraway et al., 2013). Also variations to the K-NN resampling approach for weather generation to enable newer values by adding perturbations have also been developed (Brandsma and Buishand, 1998; Rajagopalan and Lall, 1999; Buishand and Brandsma, 2001; Yates et al., 2003; Beersma and Buishand, 2003; Sharif and Burn, 2007).

1.4.2. Conditional Stochastic Weather Generator

Winter Precipitation Forecast

Caraway et al. (2013) made modifications to preferentially resample the K-nearest neighbors using winter seasonal precipitation forecasts. The steps are as follows.

1. Calculate seasonal precipitation totals (Nov-Mar) in each year and associate it with each day in the season. Thus, say, Nov 1990 – Mar 1991 seasonal total precipitation will get assigned to all the days within this season and so on.
2. Follow the K-NN algorithm through step 2: find all historical days in the 7-day moving window that match the simulated transitions, which we will call, **T**.

3. Then for a wet (dry) A:N:B probabilistic forecast, the $K = \sqrt{N}$ neighbors are identified as follows:
    a. Sort the matching days, **T**, based on decreasing (increasing) seasonal totals.
    b. The nearest (farthest) neighbors are A*K of head (tail) of **T**.
    c. The farthest (nearest) neighbors are B*K of tail (head) of **T**.
    d. What remains is filled by N*K/2 on either side of the median seasonal total of **T**.
4. Resume step 5 from the algorithm above.

Spring Temperature Forecast

A similar procedure is implemented to incorporate spring (April – May) temperature forecast, the steps are:

1. Calculate average spring temperature (April and May) in each year and associate it with each day in a given season.
2. Follow the K-NN algorithm through step 2: find all historical days in the 7-day moving window, which we will call, **T**.
3. Then for a wet (dry) A:N:B probabilistic forecast, the $K = \sqrt{N}$ neighbors are identified as follows:
    a. Sort the matching days, **T**, based on decreasing (increasing) average spring temperature.
    b. The nearest (farthest) neighbors are A*K of head (tail) of **T**.
    c. The farthest (nearest) neighbors are B*K of tail (head) of **T**.
    d. What remains is filled by N*K/2 on either side of the median average spring temperature of **T**.
4. Resume step 5 from the algorithm above.

1.4.3. Weather Generator based Extended Streamflow Predictions (ESP) Forecasts

The ESP forecasts of streamflow ensembles are implemented through a framework called Community Hydrologic Prediction System (CHPS) (Werner, 2011 and footnote 2). As mentioned earlier, the number of ensembles are restricted to the length of the historical data - for the San Juan River Basin, the ensemble is limited to 30 traces because the historical record spans 1981-2010.

With the stochastic weather generator, an unlimited number of weather sequences can be generated thus, produce a rich variety of streamflow ensembles and a robust estimation of the probability density function. We constructed input weather sequences using four different generator methods described above – (i) the original ESP – i.e., the historical sequence of 30 years, (ii) unconditional stochastic weather generator, SWG – 90 ensembles were generated to produce streamflow denoted as, 'WGESP', (iii) November through March weather sequences produced conditioned on the winter precipitation climate forecasts for FMA and unconditioned generation for all other months, the flow ensembles from this is denoted as 'CondI', and, (iv) weather sequences generated conditioned on winter precipitation and spring temperature climate forecasts for MAM, the flow ensembles from this is denoted as 'CondII.' For the CondI and CondII, 150 weather sequences were generated for each year at each lead time.

1.5. Results

The simulations from weather generators of the spring temperature attributes are first described followed by streamflow forecasts and its attributes. As previously described, dry (2002), normal (2004), and wet (2005) streamflow years were chosen for analysis, which all had warm spring temperature forecasts (40:35:25) and winter precipitation falling within the largest probability category of the forecasts (see Table 1.3).

[2] http://www.nws.noaa.gov/oh/hrl/chps/

1.5.1. Spring Temperatures

Boxplots showing the mean, standard deviation, interquartile range and skew of -precipitation, maximum, minimum and average temperatures, for April and May, issued on April 1, from simulations obtained from CondII are shown in Figure 1.12.

It can be seen from the figures that the mean of temperature variables for April and May are higher for the warm forecasts compared to cool and normal seasonal forecast. Also the mean and standard deviation of precipitation is reduced during a warm spring

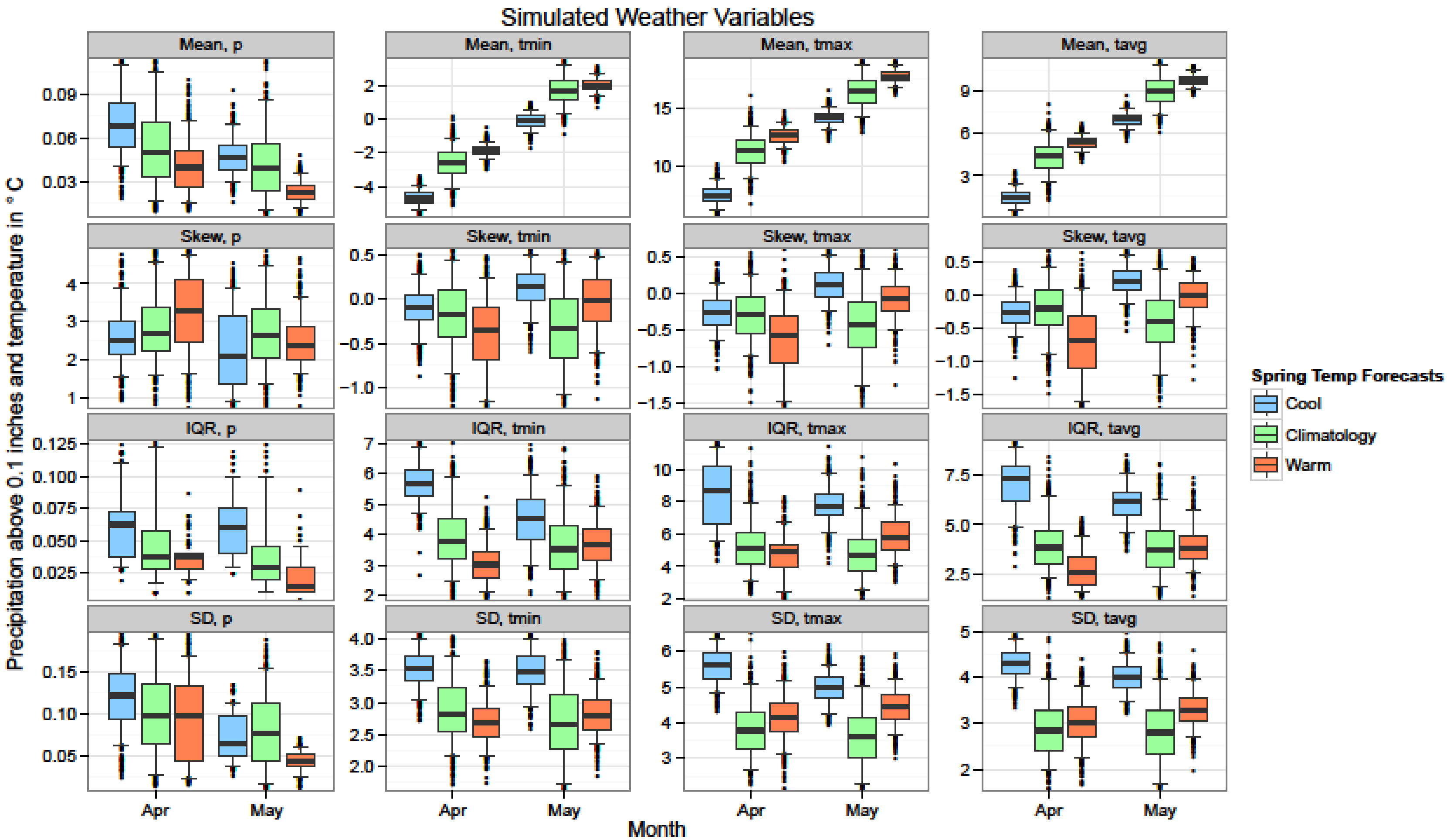


Figure 1.12 Boxplots of temperature statistics for April and May from CondII for Cool (ANB 25:35:40), Normal (ANB 33:33:33), and Warm (ANB 40:35:25) spring temperature forecasts corresponding to 2002, 2004 and 2005, respectively.

1.5.2. Ensemble Streamflow Forecasts

Ensemble streamflow forecasts for the period of interest Apr – Jul are generated on the 1st of each month starting Nov through April. Streamflow forecasts were made for each year, 2002, 2004, and 2005 using weather sequences generated from the four methods described above.
To analyze the timing of the streamflow, we computed the Julian day of Q50 from the ensembles at the five flow locations and at each lead time and plotted the probability distribution functions (PDFs) along with the corresponding values for 2002, 2004, and 2005 in Figures 1.13-1.15. For the dry year, 2002, on Apr 1st at all locations, except PIDC2, CondII simulations indicate have their forecast PDFs of Q50 Julian day closer to the observed. The other methods suggest a later occurrence of the spring flow peak. This is due to the fact that they do not incorporate the warm spring temperature forecast thus assuming normal conditions which are cooler than the seasonal forecast for that year, hence, indicating a much later arrival of the flow peak. This general feature is seen at other lead times but the CondII forecasts have lesser skill. For the normal year, 2004, Cond II forecasts are closer to the observed and in some cases simulating an earlier peak. Similarly, for the wet year, 2005, the CondII simulations are closer to the observed indicating good skill at long leads in predicting the spring flow timing. All of the years and gages show CondII being a much sharper forecast than the other methods.

Figures 1.16-1.18 show the forecasted PDFs and Figure 1.19 show the boxplots of seasonal volume forecasts (April to July) forecasts for each year. For all gages in the year 2002, CondII simulations shifts the PDFs to the left and closer to the observed values, but because the PDFs are so sharp and not shifted enough to the left, many times they miss capturing the observed value in the tail. During this dry year, antecedent conditions, which in this research are information produced from a hindcast, may have also played a role in reducing the flow volume that was not able to be captured by the dry winter precipitation and warm spring temperature forecasts. For the normal flow year, 2004, CondII simulations capture the observed flows better and tighter than the other methods. The wet year, 2005, shows CondII forecasting similar to the other three methods for the first three lead times (Nov, Dec, Jan), but by January, SWE begins to shift CondII to the right but not as much as other methods. The warm spring temperatures in CondII are trying to decrease the seasonal volume. By adding the spring temperature forecast, at least a warm forecast, the seasonal volume forecast becomes sharp and shifted to the left.

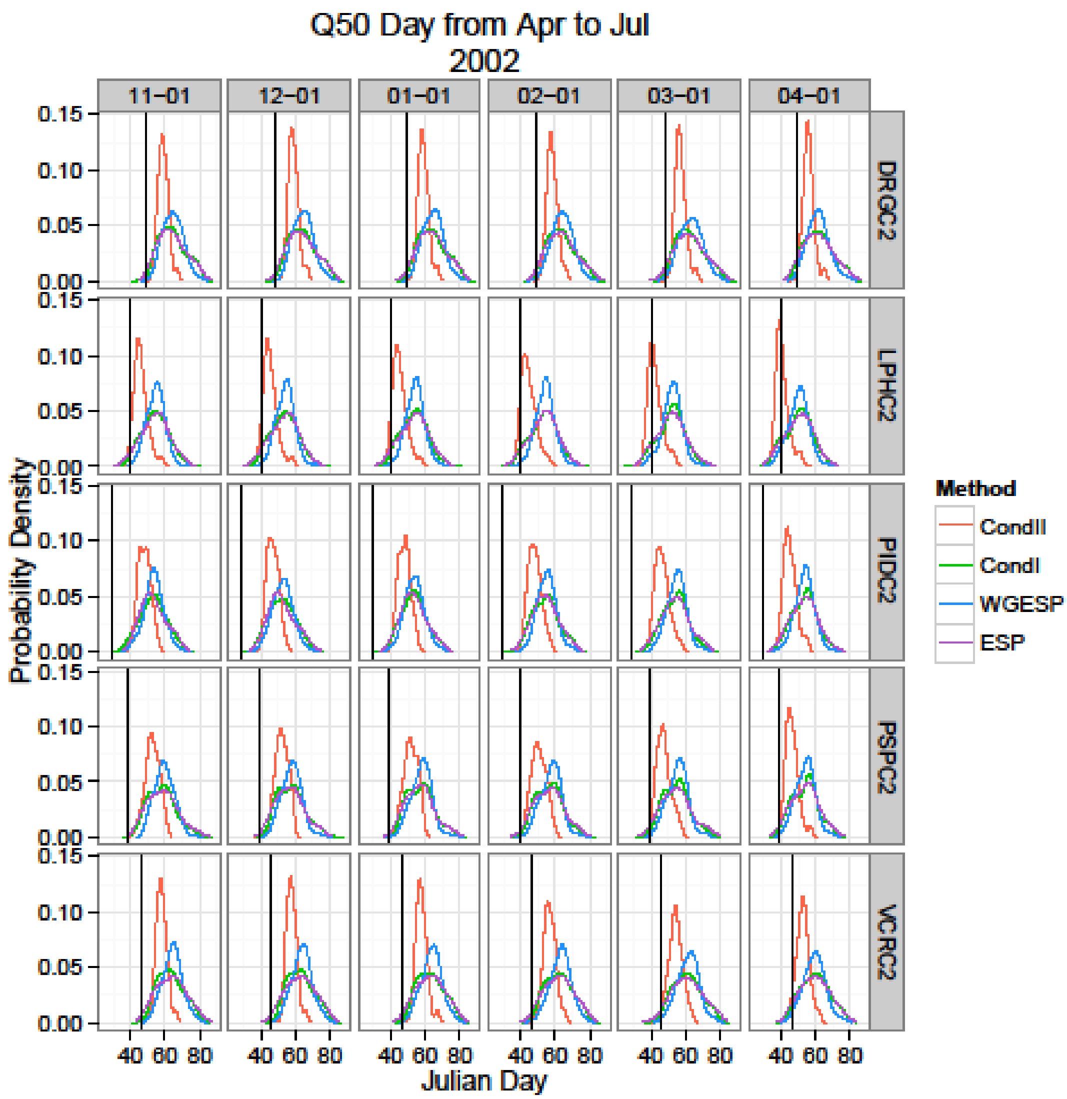


Figure 1.13 Q50 Julian Day between April and May for 2002

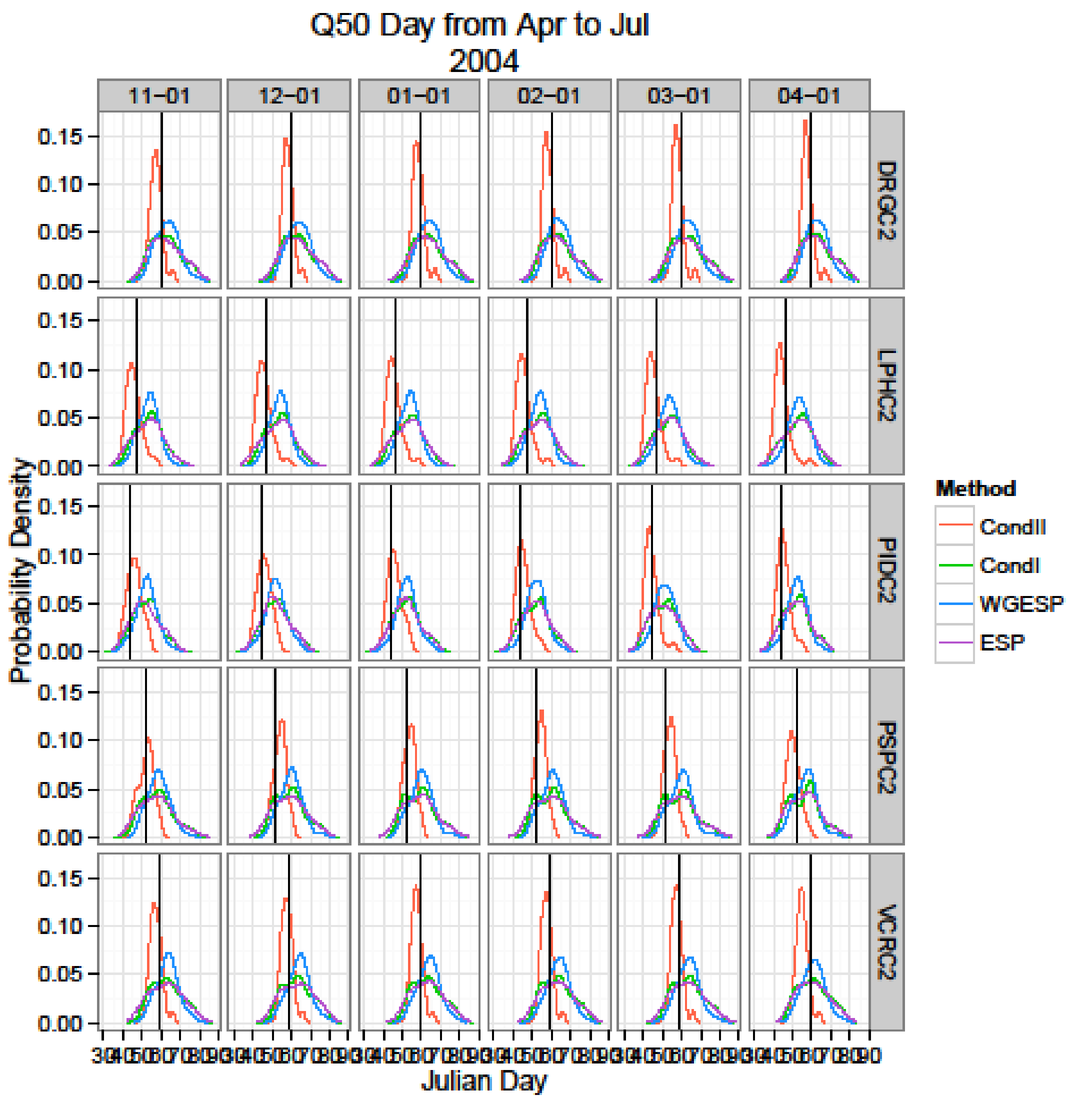


Figure 1.14 Q50 Julian Day between April and May for 2004

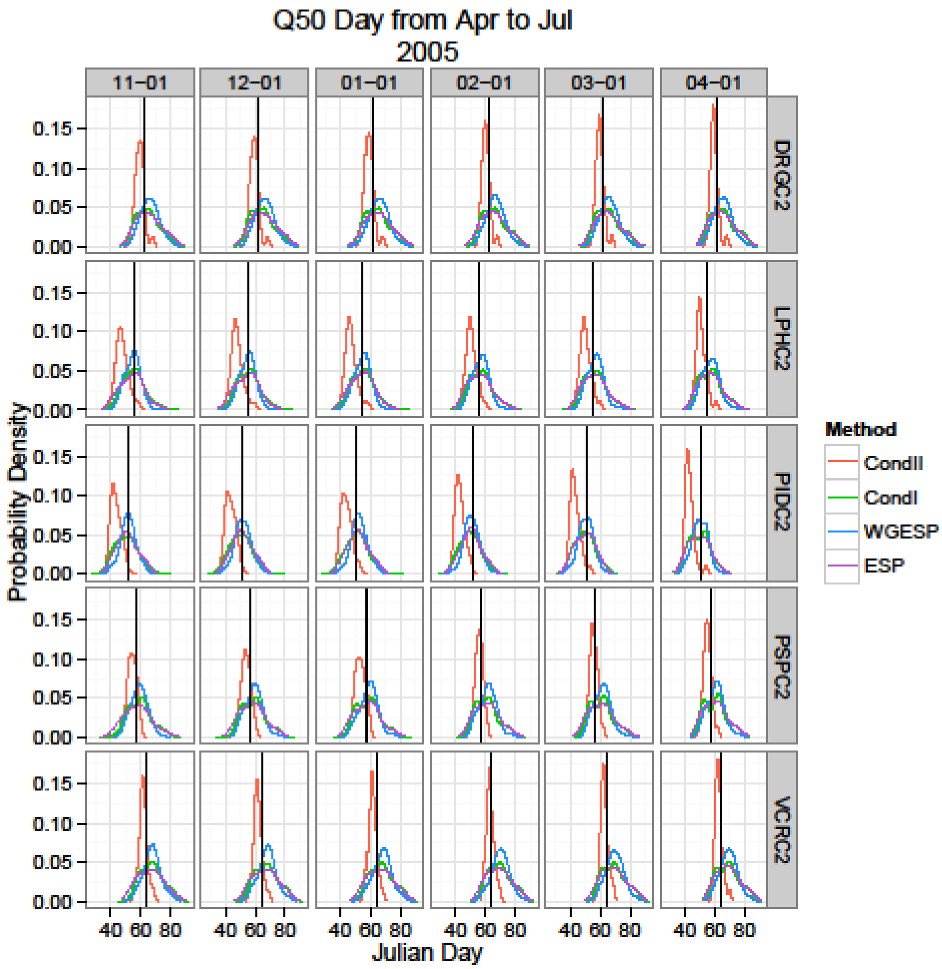


Figure 1.15 Q50 Julian Day between April and May for 2005

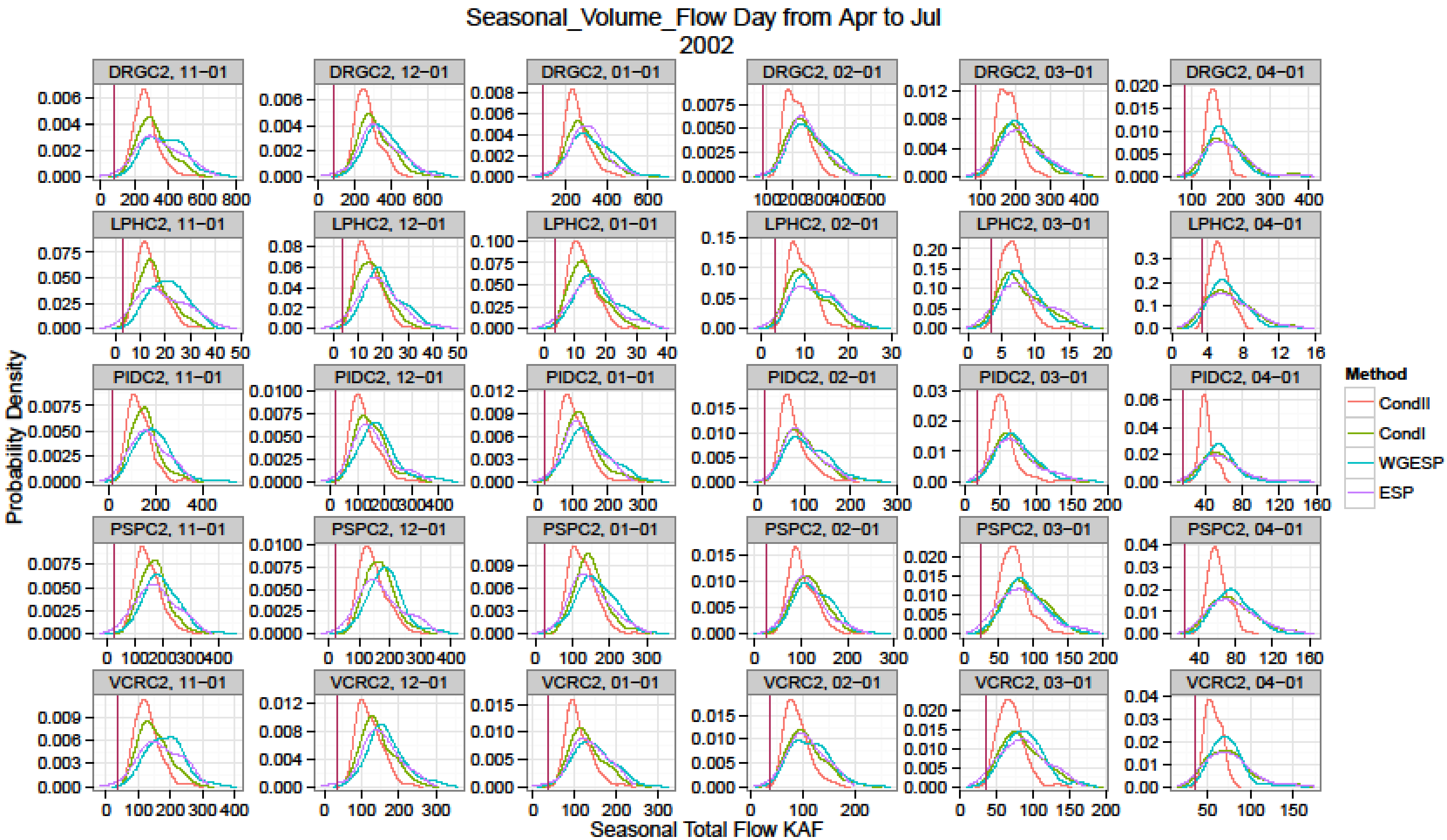


Figure 1.16 April through July Runoff Volumes in 2002, all gages, methods, and lead times.

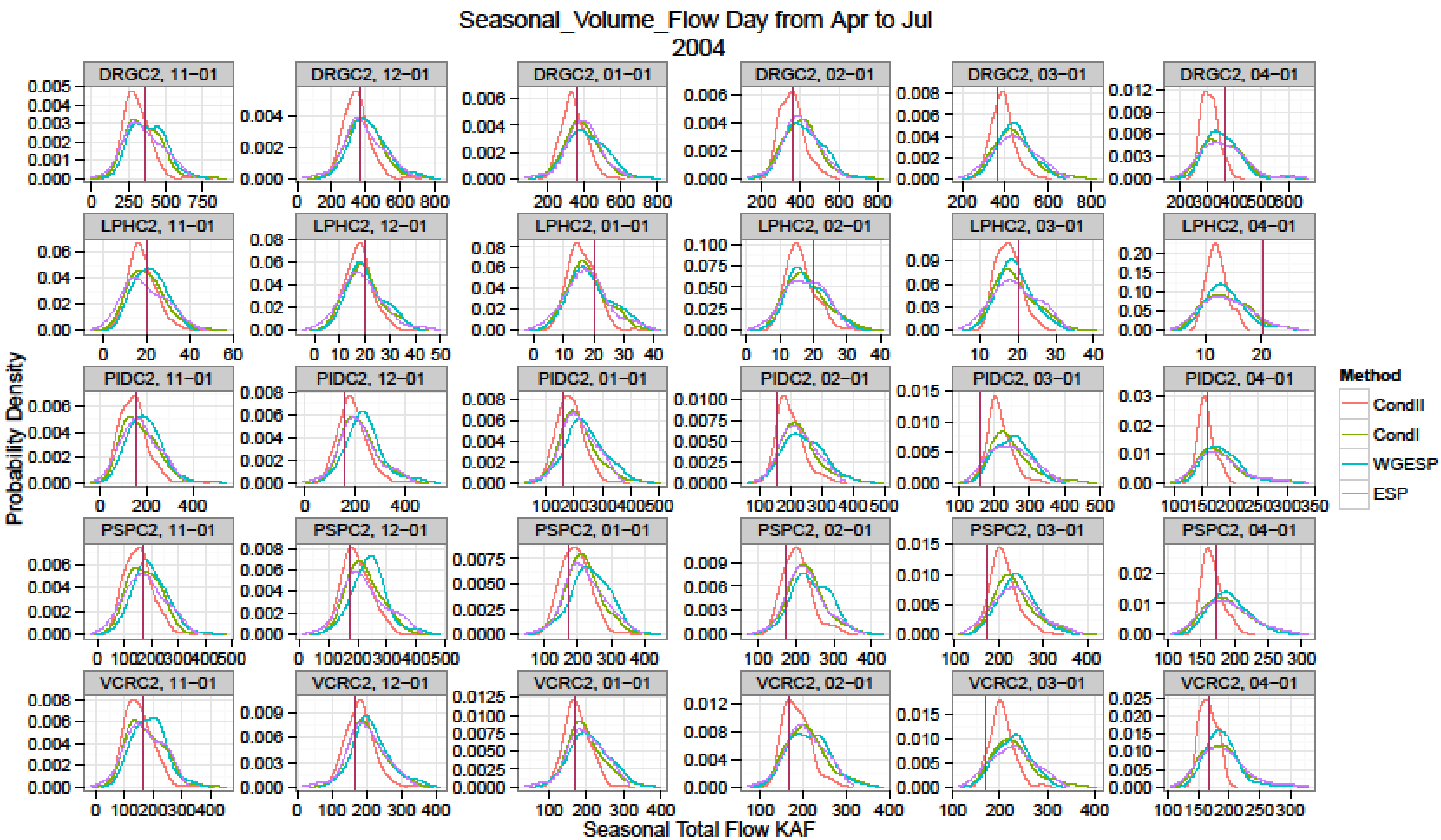


Figure 1.17 April through July Runoff Volumes in 2004, all gages, methods, and lead times.

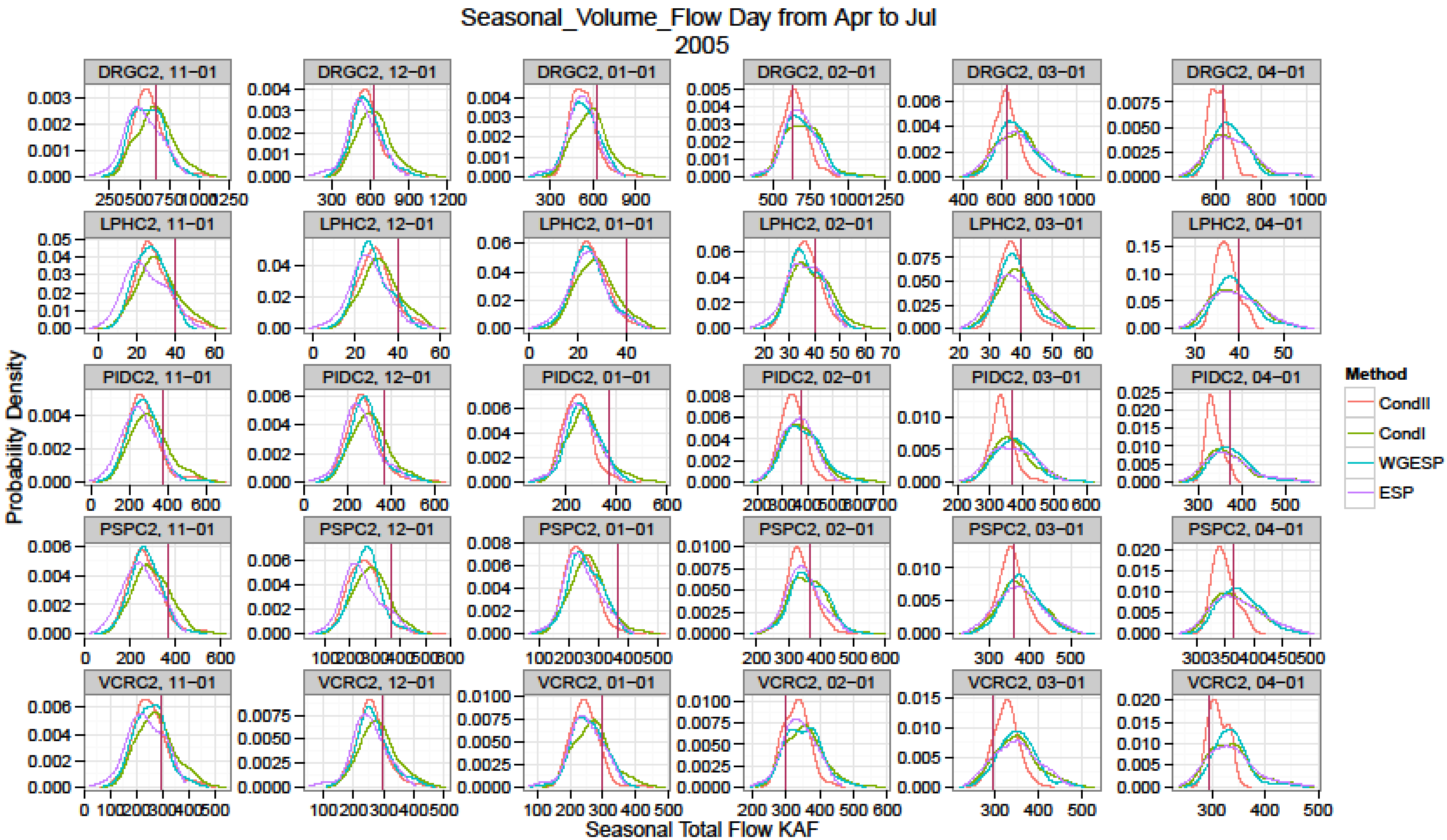
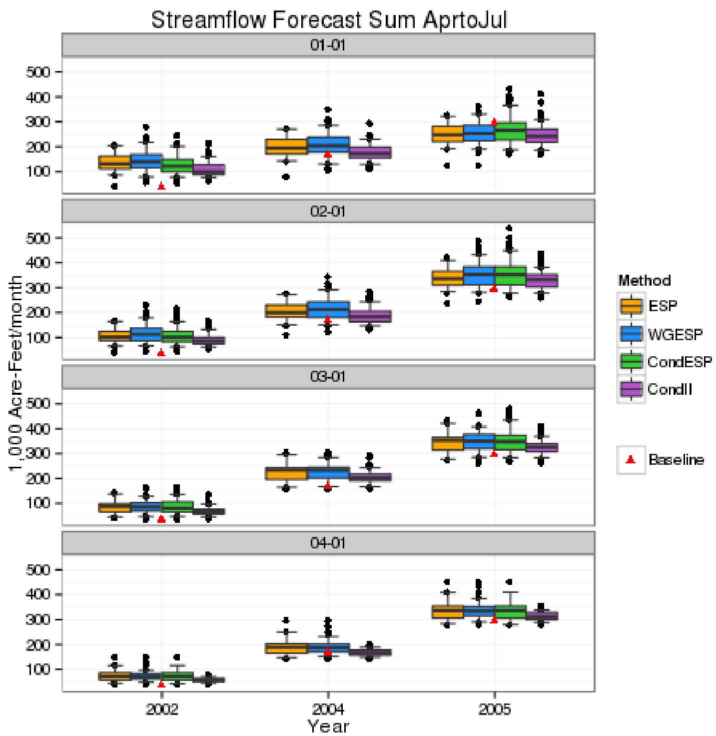
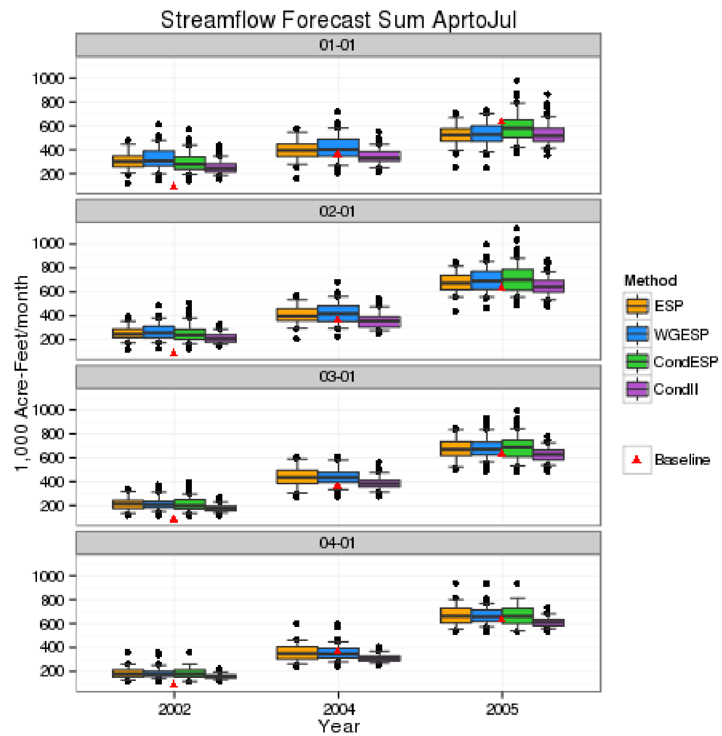


Figure 1.18 April through July Runoff Volumes in 2005, all gages, methods, and lead times.



a)Vallecito Gage



b) Animas Gage

Figure 1.19 CHPS Streamflow Forecasts for ESP, WGESP, and CondI for 2002, 2004, and 2005. CondII means the SWG was conditioned using the winter precipitation and spring temperature forecasts. The remaining gages can be found in Appendix A.

1.5.3. Synthetic Climate Forecasts

The stochastic weather generator, when conditioned with the winter precipitation and spring temperature forecasts, shows improvement in the skill of the hydrograph forecasts. However, these skills in the hydrologic variables are limited to the skills in the seasonal climate forecasts issued by IRI. Since these tend to be fairly conservative, rarely straying very far from climatology, the skills translated into the hydrologic forecasts are also modest. As a diagnostic test of the conditional weather generator method, we made the forecasts for 2002 and 2005 sharper to a warm forecast of 60:30:10 and a cool forecast of 10:30:60, respectively, to demonstrate the potential shifts in the hydrologic variables. The results from simulations using these synthetic forecasts are described below.

Figure 1.20 shows the precipitation and temperature variables from 500 simulations of CondII for April and March conditioned using the synthetic forecasts, 10:30:60 and 60:30:10. Notice that the temperature boxplots are smaller and tighter than those from more conservative forecasts in Figure 1.12 – suggesting that a sharper climate forecasts can result in a sharper forecast of daily weather attributes.

The Q50 Julian day PDF is slightly sharper using the synthetic forecasts (CondII-Synthetic, Figure 1.21) than with the conservative forecasts (CondII), but not shifted. So the warmer forecast for a dry year would not help forecast earlier timing days but, if the temperature forecast is accurate, may pinpoint the Q50 day with more certainty.

For the wet year, 2005, the Q50 PDFs were shifted to the right, meaning the Q50 days were forecasted to be later in the year, consistent with a cool forecast, compared to the conservative forecast (Figure 1.22). By accurately forecasting high winter precipitation and a cool spring temperatures, the timing of the snowmelt runoff shifts into later in the season.

The seasonal volume (April to July) forecasts are shown in Figure 1.23 for 2002 and Figure 1.24 for 2005. For 2002, the synthetic forecasts do not differ from the other methods, meaning a warmer forecast for a dry year does not decrease the seasonal volume. For 2005, the synthetic forecasts are similar to conservative forecasts for the lead times Nov-Jan. By February lead-time, the cooler synthetic temperature forecast is creating a larger, sharp seasonal volume forecast than the conservative forecast and closer to the observed value. A cooler spring temperature can increase snowmelt runoff volume.

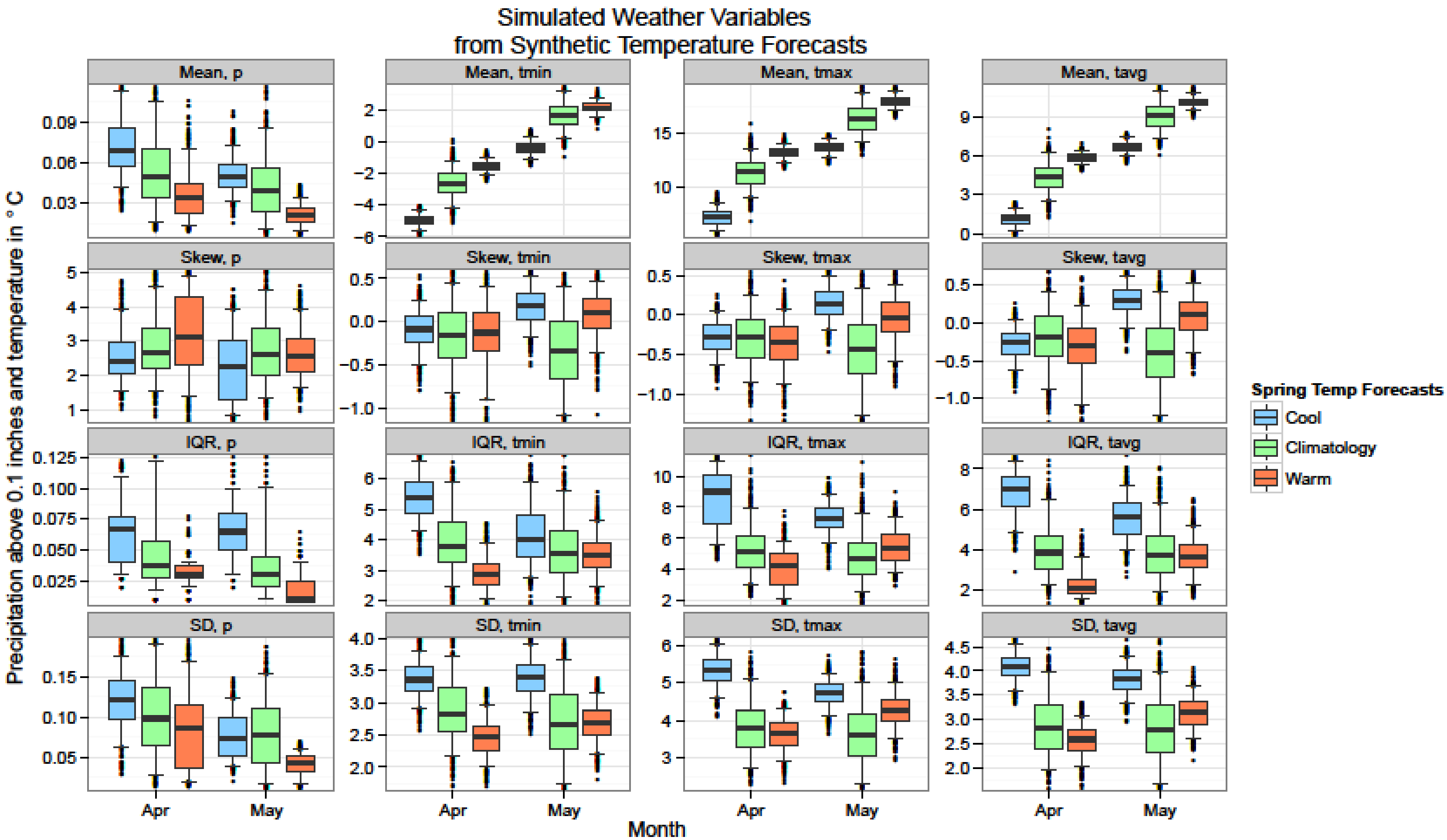


Figure 1.20 Weather Variables generated using the synthetic climate forecasts for April and May. Cool (ANB 10:30:60), Climatology (ANB 33:33:33), and Warm (ANB 60:30:10)

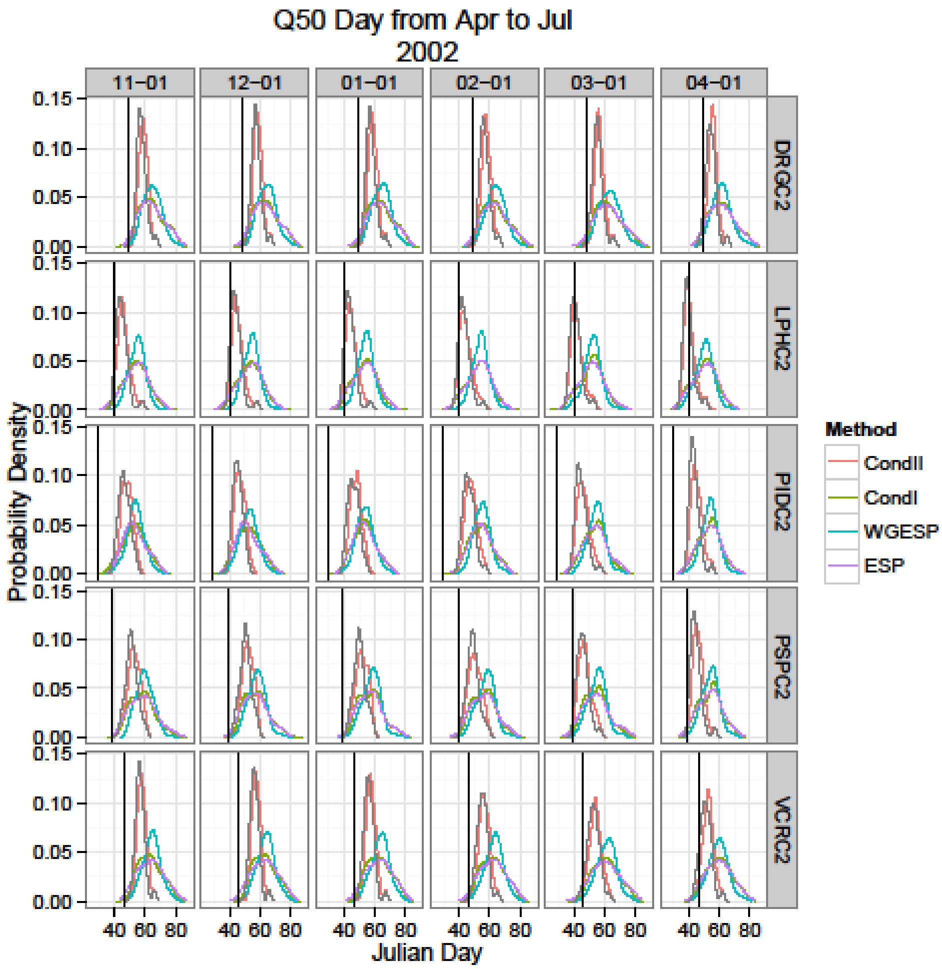


Figure 1.21 Q50 Julian Day between April and May for 2002 simulated using the synthetic climate forecasts.

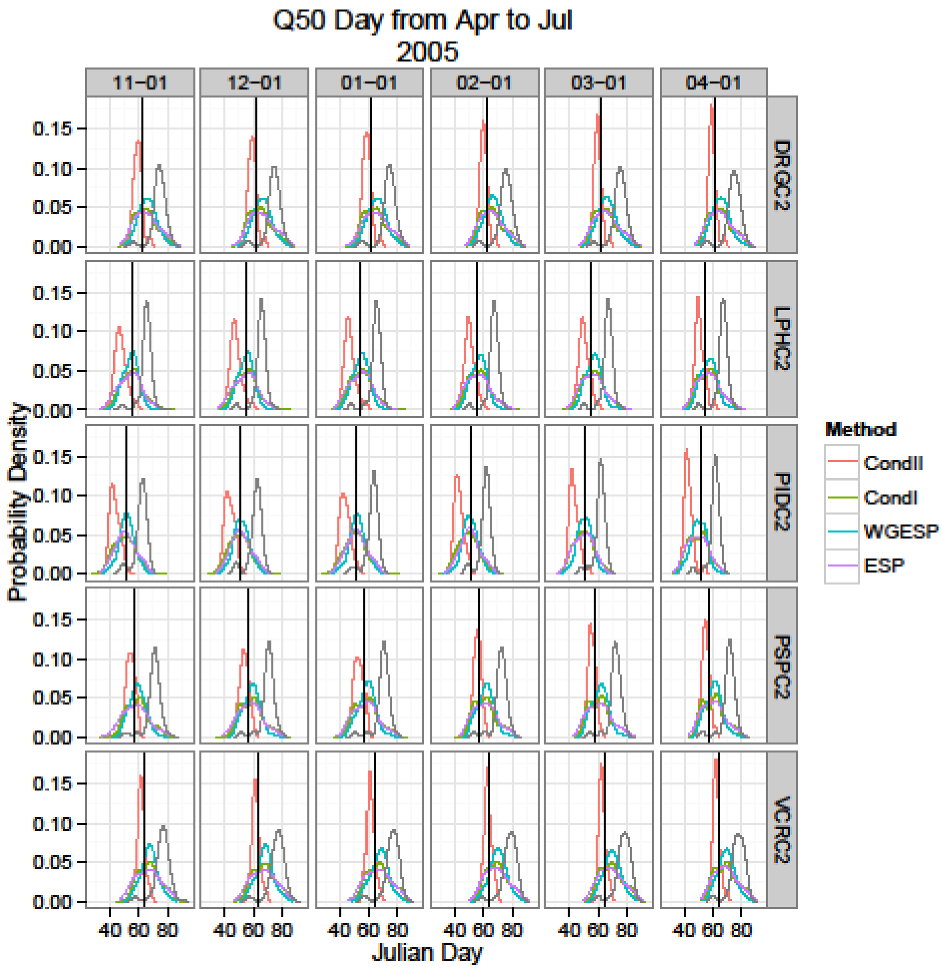


Figure 1.22 Q50 Julian Day between April and May for 2005 simulated using the synthetic climate forecasts.

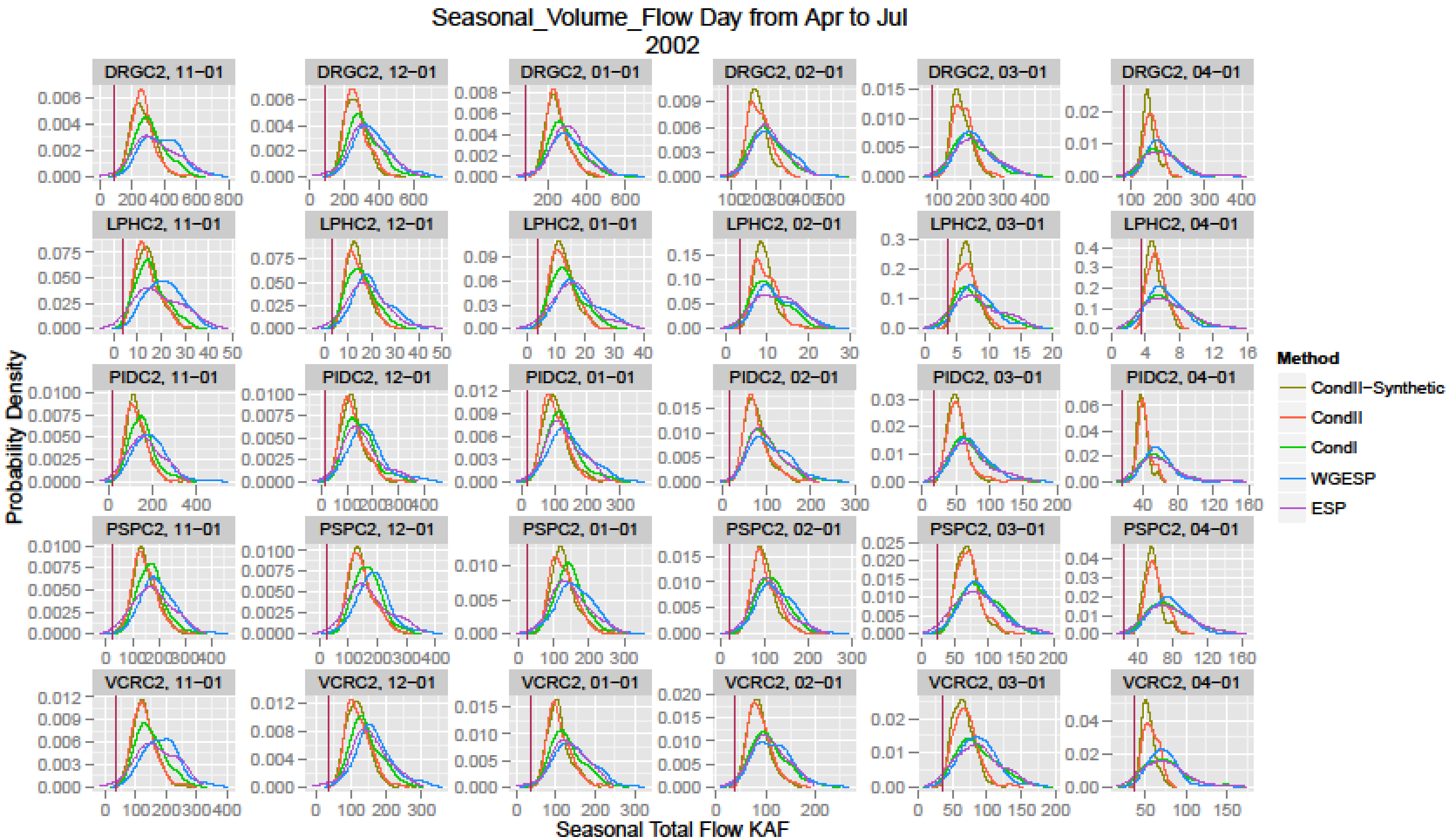


Figure 1.23 April through July Runoff Volumes in 2002, all gages, methods, and lead times using the synthetic climate forecasts.

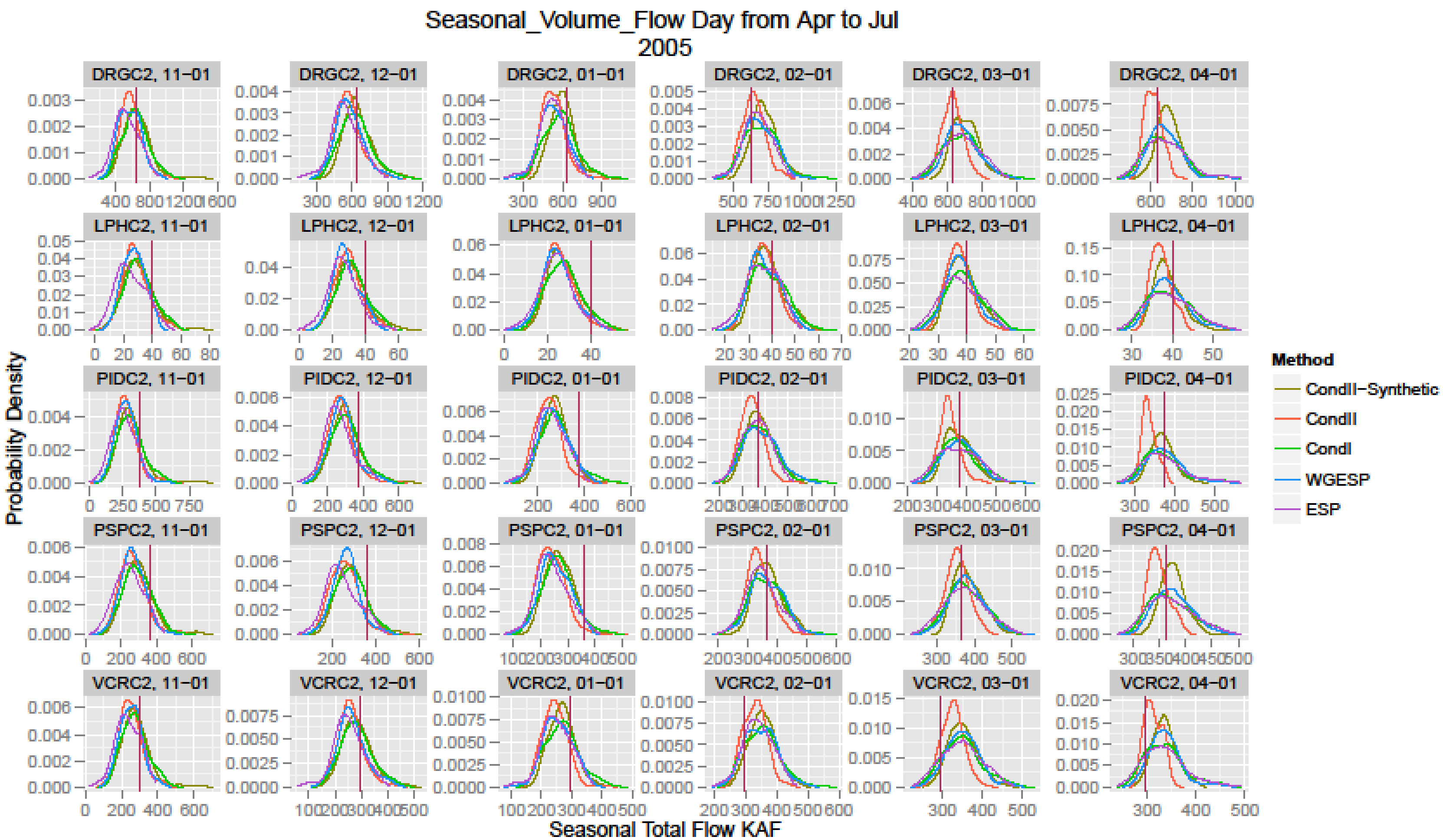


Figure 1.24 April through July Runoff Volumes in 2005, all gages, methods, and lead times using the synthetic climate forecasts.

1.5.4. Summary and Discussion

This research further demonstrates the flexibility of stochastic weather generators for use in streamflow forecasting. We explored the use of both the winter precipitation and the spring temperature climate forecasts for conditioning the stochastic weather generator. These simulated weather sequences were input to the hydrologic model to produce streamflow forecasts, and they exhibited improved skill in forecasting the timing of spring streamflow peak. The hydrologic model does seem to react to a warmer temperature forecasts by melting the snow earlier, especially for the dry and normal years.

The climate forecasts that the IRI issues tend to be conservative, rarely straying far from climatology. To show the utility of climate forecasts in streamflow forecasts, we created synthetic 'sharp' spring temperature forecasts to test the model. For the dry year, a 'warmer' forecast was able to shift the streamflow timing even earlier in the season than was seen using the conservative forecast. For the wet year, using a 'cooler' forecast, the timing shifted towards later in the season. This further indicated that the hydrologic models are sensitive to a sharper weather sequence.

The seasonal climate forecasts from IRI are based on large scale climate drivers and do not simulate features responsible for regional climate skillfully. A potential approach would be develop statistical forecasting methods for the specific basin of interest using large scale climate variables (e.g., Regonda et al., 2006; Grantz et al., 2005; Bracken et al., 2010). This will increase the skill of the seasonal precipitation and temperature forecasts, to consequently, improve the skills in hydrologic forecasting.

The next step to incorporating climate forecasts is to use both the spring precipitation and temperature forecasts to conditionally simulate weather sequences. By including the spring precipitation, rainfall or rain-on-snow events can be captured to better forecast increased seasonal volume, in addition to flow timing, which are of importance for water resources management.

Bibliography

Apipattanavis, S., F. Bert, G. Podesta, and B. Rajagopalan (2010). Linking weather generators and crop models for assessment of climate forecast outcomes. Agricultural and Forest Meteorology 150(2), 166-174.

Apipattanavis, S., G. Podesta, and B. Rajagopalan (2007). A semiparametric multivariate and multisite weather generator. Water Resources Research 43(11), W11401.

Barnston, Anthony G., Shuhua Li, Simon J. Mason, David G. DeWitt, Lisa Goddard, Xiaofeng Gong, 2010: Verification of the First 11 Years of IRI's Seasonal Climate Forecasts. *J. Appl. Meteor. Climatol.*, **49**, 493–520.

Beersma, J. J. and T. A. Buishand (2003). Multi-site simulation of daily precipitation and temperature conditional on the atmospheric circulation. Climate Research 25, 121-133.

Bracken, C. W. (2011). Seasonal to Inter-Annual Streamow Simulation and Forecasting on the Upper Colorado River Basin and Implications for Water Resources Management. Ph. D. thesis, University of Colorado at Boulder.

Brandon, D. G. *(*2005*)*, Using NWSRFS ESP for making early outlooks of seasonal runoff volumes into Lake Powell, paper presented at Hydrology of Arid and Semi-Arid Regions, Am. Meteorol. Soc. San Diego, Calif., *9 – 13 Jan.*

Brandsma, T. and A. T. Buishand (1998). Simulation of extreme precipitation in the rhine basin by nearest-neighbor resampling. Hydrology & Earth System Sciences 2(2-3), 195-209.

Buishand, T. A. and T. Brandsma (2001). Multisite simulation of daily precipitation and temperature in the rhine basin by nearest-neighbor resampling distribution. Water Resources Research 37(11), 2761-2776.

Burnash, R. J. C. (1995). The NWS River Forecast System - Catchment modeling. In V. P. Singh (Ed.), Computer Models of Watershed Hydrology, pp. 311-366. Water Resources Publications.

Burnash, R. J. C., R. L. Ferral, and R. A. McGuire (1973). A generalized streamflow simulation system - Conceptual modeling for digital computers. Technical report, Joint Federal and State River Forecast Center, U.S. National Weather Service and California Department of Water Resources.

Caraway, N.M., 2012. *Stochastic Weather Generator Based Ensemble Streamflow Forecasting*. University of Colorado at Boulder.

Caraway, Nina Marie… (2013) Multisite Stochastic Weather Generation Using Cluster Analysis and K-nearest neighbor Time Series Resampling. Journal of Hydrology.

Day, G.N., 1985. Extended Streamflow Forecasting Using NWSRFS. *Journal of Water Resources Planning and Management*, 111(2), pp.157–170.

Grantz, K., B. Rajagopalan, M. Clark, and E. Zagona (2005). A technique for incorporating large-scale climate information in basin-scale ensemble streamow forecasts. Water Resources Research 41, W10410.

Hamlet, A. F. and Lettenmaier, D. P. (1999), Effects Of Climate Change On Hydrology And Water Resources In The Columbia River Basin. JAWRA Journal of the American Water Resources Association, 35: 1597–1623.

Hartmann, H. C., R. Bales, and S. Sorooshian (2002). Weather, climate, and hydrologic forecasting for the US Southwest: a survey. Climate Research 21, 239-258.

Lall, U. and A. Sharma (1996). A nearest neighbor bootstrap for time series resampling. Water Resources Research 32(3), 679-693.

Larson, L. (2002). National Weather Service River Forecast System (NWSRFS). In V. P. Singh and D. K. Frevert (Eds.), Mathematical Models of Small Watershed Hydrology and Applications, pp. 657-706. Littleton, CO: Water Resources Publications, LLC.

Pagano, T. C. and D. C. Garen (2005). Integration of Climate Information and Forecasts into Western US Water Supply Forecasts. In J. D. Garbrecht and T. C. Piechota (Eds.), Climate Variations, Climate Change, and Water Resources Engineering. ASCE.

Rajagopalan, B. and U. Lall (1999). A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resources Research 35(10), 3089-3101.

Rajagopalan, B., U. Lall, D. G. Tarboton, and D. S. Bowles (1997). Multivariate nonparametric resampling scheme for generation of daily weather variables. Stochastic Hydrology and Hydraulics 11(1), 523-547.

Regonda, S.K. et al., 2005. Seasonal Cycle Shifts in Hydroclimatology over the Western United States. *Journal of Climate*, 18, pp.372–384.

Sharif, M. and D. H. Burn (2007). Improved k-nearest neighbor weather generating model. Journal of Hydrologic Engineering 12(1), 42-51.

Werner, K. (2011, August 12). Noaa's colorado basin river forecast center:”climate services on the colorado river: Capabilities, gaps, and chasms". In Climate Test Bed Joint Seminar Series, Camp Springs, Maryland. U.S. National Oceanic and Atmospheric Administration.

Yates, D., S. Gangopadhyay, B. Rajagopalan, and K. Strzepek (2003). A technique for generating regional climate scenarios using a nearest-neighbor algorithm. Water Resources Research 39(7), 1199.

Chapter 2

An End-to-End Framework for Seasonal Operations Ensemble Forecasting

2.1. Introduction

Climate informed ensemble streamflow forecasts are continually gaining popularity as enhanced methods improve skill and tools become available to incorporate these forecasts into operations forecasting and decision making (Pagano and Garen, 2005). From the global climate forecast to the regional water supply forecast to real-time operations forecast, this end-to-end ensemble framework helps to improve skill and lead time for seasonal forecasts and produces probabilistic information that allows for risk-based decision making within a water manager's risk profile. Pagano and Garen (2005) describe many more benefits of this framework and also the many 'gaps and hazards.' The hazards between the seasonal climate forecasts and the ensemble water supply forecasts includes ensuring correct identification of climate information for the region of interest and disseminating 3-month forecast period tercile probabilities of climates forecasts information for smaller timescales. The gaps between the ensemble water supply forecasting and the real-time operations forecasting include the lack of tools to implement the ensembles and where ensembles can be implemented then the lack of dynamic operations models. And if these forecast ensembles make it to the end of the framework to the water user, there is still inaccurate or misguided user perception of ensemble forecasts and the risk and uncertainty information the forecasts contain. This research attempts to capitalize on the benefits of this framework and address some of the 'gaps and hazards.'

Streamflow forecasts for the Colorado River Basin (CRB) are produced by the National Weather Service (NWS) Colorado Basin River Forecast Center (CBRFC). Forecasts for the peak runoff season (April-July) are made starting in January. CBRFC implements two techniques at a seasonal timescale: Statistical Water Supply (SWS), a regression-based method that relates observed data with future streamflow, and the model-based Extended Streamflow Prediction (ESP). ESP uses current basin conditions with historical meteorological data within a conceptual hydrologic model, the Sacramento Soil Moisture Accounting (SAC-SMA) model lumped with SNOW-17 model, to forecast future streamflow (Day, 1985). The final product of the coordination is an ensemble streamflow forecasts with as many traces as years of historical data. The ESP is produced through a model and database framework called Community Hydrologic Prediction System (CHPS).

The US Bureau of Reclamation (Reclamation) is the federal agency whose mission is 'to manage, develop, and protect water and related resources' in the West[3]. From the ensemble forecast, Reclamation uses the most probable (50th percentile) inflow trace as input to the 24-Month Study (24MS), a monthly timestep model built in the RiverWare modeling framework (Zagona, et al., 2001) for seasonal forecasting of operations (Grantz, 2011). With the 24MS, Reclamation develops an operations plan and reports the resulting forecast of releases, pool elevations and storages, hydropower production, and other operational data, for 12 projects in the CRB, to the public and stakeholders. In some cases, operational plans are developed and resulting data are reported also for the 10th percentile ("minimum probable") and 90th percentile ("maximum probable") forecasts.

One limitation of the 24MS model is that planned operations must be input manually by the various project managers and operators. The lack of operating rules in the model makes it impractical to develop

[3]http://www.usbr.gov/uc/aboutus/index.html
[4]http://www.usbr.gov/uc/water/crsp/studies/index.html

the operational plan for many inflow forecasts. Thus, the probability distribution for important operational variables is not available to stakeholders. Although the minimum and maximum probable inflows are reported for the water year, they are not realistic for making operational decisions, nor do they have sufficient probabilistic information to support risk-based decision making (Werner, 2011). To address this, in 2010, Reclamation began developing a RiverWare based probabilistic operations model for the CRB called the Mid-Term Operations Model (MTOM) (outlined in Grantz (2011) and described in detail in Bracken (2011)). This model includes rules to simulate reservoir operations under the entire range of possible hydrologic conditions, removing the need to explicitly input reservoir releases. The MTOM can simulate with an ensemble of inflow forecasts, producing an ensemble of operational forecasts with a quantified probability distribution. Reclamation is currently working towards transitioning from the 24MS to the MTOM for seasonal forecasting.

The ESP approach is fairly robust and is widely used across the River Forecasting Centers (RFCs) and also in other parts of the world for hydrologic ensemble forecasting. However, one of its main drawbacks is that it uses historical weather sequences to generate ensembles. Thus, the number of ensembles is restricted to the number of historical years and the variability in those years.

To address this, Caraway (2012) and Caraway et al. (2013) proposed and developed an enhancement to the ESP - a stochastic weather generator that uses K-nearest neighbor resampling approach (Apipattanavis, et al., 2007; Rajagopalan and Lall, 1999; Yates et al., 2003) to incorporate probabilistic seasonal climate forecasts. This enables generation of a rich variety of weather sequences that are consistent with large scale climate forecasts, thus obtaining the probability density function of the streamflows in a robust manner. They applied this to long lead forecast of spring streamflows in the San Juan River Basin (SJRB), which is a snowmelt dominated basin. Specifically, they incorporated the winter (Nov-Mar) probabilistic seasonal forecast of precipitation[5] to generate winter weather sequences

[5]http://iri.columbia.edu/climate/forecast/net_asmt/ link

from the stochastic weather generator and used climatology for the remaining months. The hydrologic model forced by these simulated weather sequences produced skillful streamflow forecasts at long lead times.

Spring streamflow volumes forecasted using conditioned ‘wet’ winter precipitation climate forecasts displayed larger spring streamflow volumes and slightly smaller volumes for ‘dry’ winter forecasts.

In Chapter 1, the flexibility of the stochastic weather generator is further demonstrated by conditioning it with both the winter precipitation and the spring temperature forecasts. These simulated weather sequences were input to the hydrologic model to produce streamflow forecasts, and they exhibited improved skill over both baseline ESP and conditioning on the precipitation forecast alone in forecasting the timing of spring streamflow peak. The hydrologic model responds to warmer temperature forecasts by melting the snow earlier, especially for dry and normal years.

To test the utility of the enhanced ESP methods and the translation of the skill from streamflow to basin operations, we propose to apply these forecasting methods to the SJRB, a basin within the larger CRB, using the enhanced ESP methods to generate streamflow forecasts which then drive a the SJRB portion of the MTOM, limited to the SJRB. We provide a decision framework that begins with the generation of weather ensembles which force the hydrologic model to produce streamflows; the streamflow ensembles then are input to the MTOM, producing ensembles of operational output data, which are post-processed to provide probability distributions. With this framework we compare the effects of the ESP methods presented in Chapter 1 on operational forecasting.

Figure 2.1 showcases the current and proposed framework for seasonal forecasting. The blue is the current forecasting framework that uses the hydrologic model to produce the ESP hydrologic ensembles that become part of the joint water supply forecasts issued by the NWS, as described above. The ESP method was enhanced to produce skillful streamflow forecasts at long lead times (Caraway, 2012 and Chapter 1). Caraway added a stochastic weather generator (SWG) to produce synthetic weather sequences that became input to the hydrologic model to produce a rich variety of weather generator based extended streamflow predictions (WGESP), shown in red, labeled 'WG ESP.' The SWG can also be a downscaling mechanism when incorporating global climate forecasts that condition the resampling of the weather variables, shown in green, labeled 'CondI.' In Chapter 1, the use of different climate forecasts was explored to increase the skill of the streamflow forecasts by incorporating spring temperature forecasts, labeled 'CondII.'

This chapter first presents a description of the management practices in the SJRB, introduces the CRB MTOM, and discusses the SJRB MTOM used in this research. Next, we look at the analysis for the MTOM results, including data, model assumptions, and operational metrics. Finally the results and conclusions are presented.

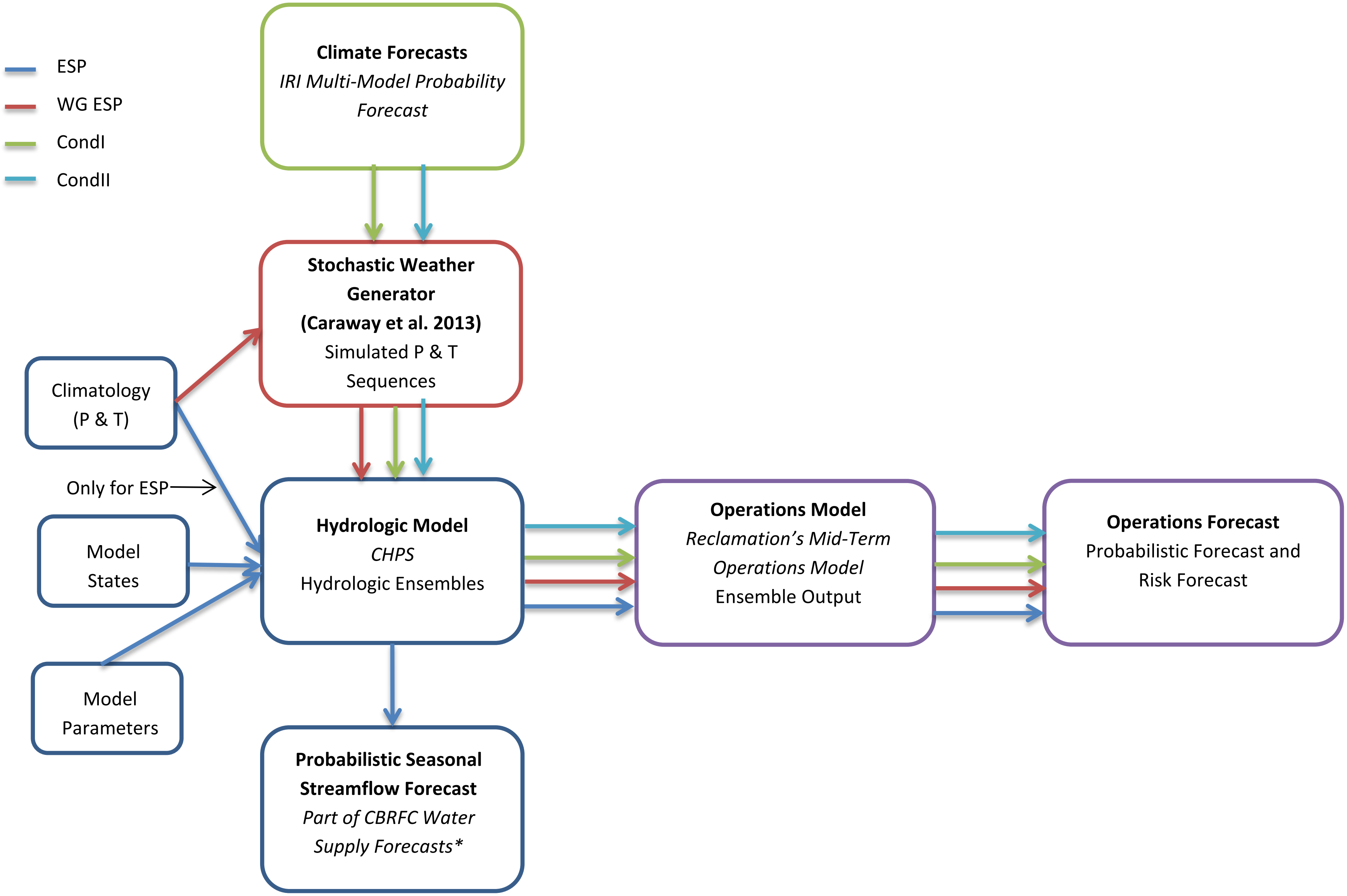


Figure 2.1 End-to-End Framework for Seasonal Forecasting

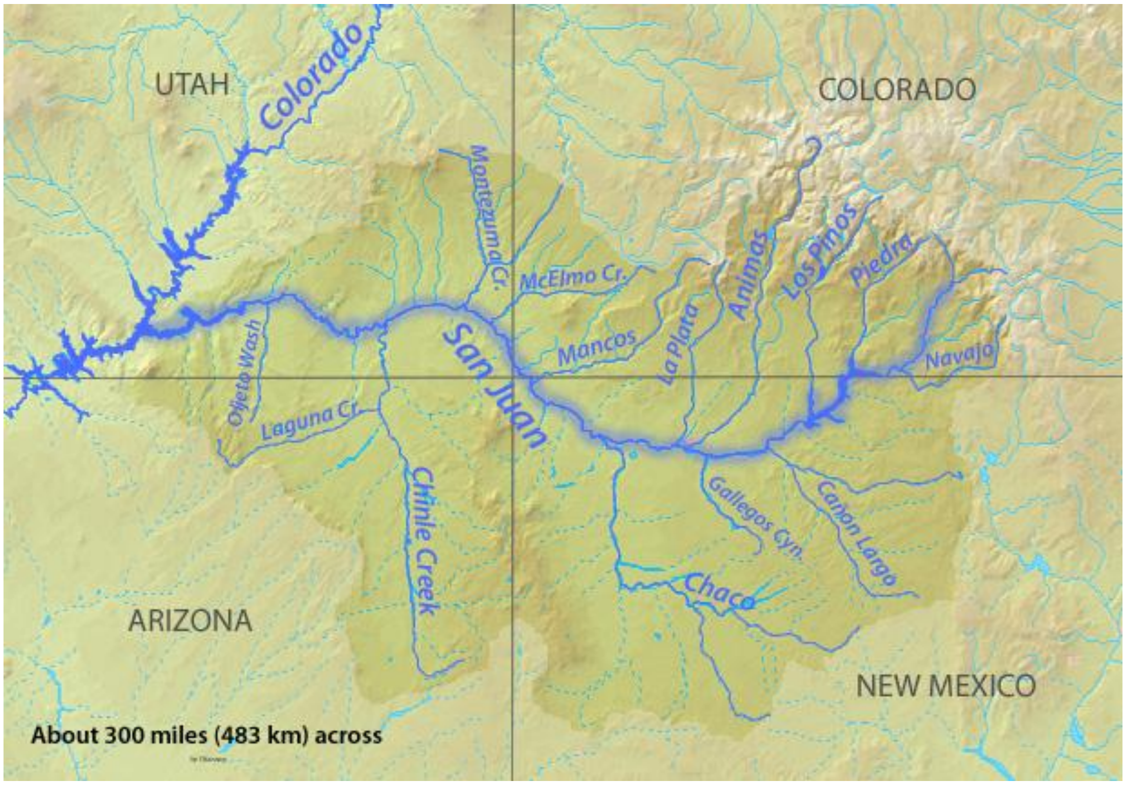


Figure 2.2 San Juan River Basin (Wikipedia)

2.2. Background of San Juan River Basin

The San Juan River, Figure 2.2, is the third largest tributary of Colorado River, after the Green River and the Gunnison River, with 350 river miles before joining the Colorado River at Lake Powell. The San Juan River Basin has a drainage area of approximately 25,000 square miles in Colorado (23%), New Mexico (39%), Arizona (20%), and Utah (17%). Elevation ranges from 4,000 to 14,000 feet above mean sea level. Precipitation in this snowmelt basin varies from as much as 60 inches annually in the high peaks to less than 10 inches in most areas to less than 1/10 inch in others. The three largest tributaries to the San Juan River are the Animas, the Piedra, and the Los Pinos rivers.[6]

The two main Reclamation projects in the San Juan River Basin are the Pine River Project and Navajo Unit, from which most of the management objectives revolve around. The Pine River Project is located on the Los Pinos River 18 miles northeast of Durango and provides water to the Southern Ute

[6]http://www.usbr.gov/uc/wcao/rm/sjrip/

Reservation. The project consists of Vallecito Dam and Reservoir, finished in 1941, has a total storage capacity of 129,700 acre-feet. Demands on the system, besides irrigation, include recreation, flood control and a 5.8 MW hydropower plant. [7]

The larger project, Navajo Unit, consists of Navajo Dam which was built under the Colorado River Storage Project Act (CRSPA) and finished in 1962[8]. Navajo Reservoir has a full capacity of 1.7 MAF at which the surface area is approximately 15,600 acres. During the irrigation season, the minimum operating level in Navajo is for the Navajo Indian Irrigation Project (NIIP) diversion intake at 5,990 feet (USBR, 2006). During the winter months, the reservoir may be drawn down to 5,985 feet, so long as the storage is recovered before the next irrigation season. The city of Farmington, New Mexico owns and operates, in coordination with Reclamation, the hydropower plant, which was constructed in 1985 and has a capacity of 30 megawatts (MW) (New Mexico Energy, Minerals, and Natural Resources Dept., 2004).[9]

The Navajo Unit also supports the San Juan - Chama Project, a trans-mountain diversion of water to the Rio Grande Basin. The longest diversion structure for this project is the 12.8 mile Azotea Tunnel, which is also the common name to which the project is referred. The project diverts about 110,000 acre-feet per year from the upper tributaries of the San Juan River.

Other water developments supported by the Navajo Unit include the Navajo-Gallup Water Supply Project (delivering water to the Navajo and Jicarilla Apache) and the Animas –La Plata Project (delivering water to the Colorado Ute Tribes)[10].

The operations at Navajo Reservoir are also in agreement with the Colorado River Storage Project Act (CRSPA), to provide long-term regulatory storage of water to the Lower Basin states[11]. A critical threshold for meeting downstream demands is in July, if Navajo storage is 1 million acre-feet

[7]http://www.usbr.gov/projects/Project.jsp?proj_Name=Pine%20River%20Project&pageType=ProjectPage
[8]http://www.usbr.gov/uc/rm/crsp/index.html
[9]http://www.usbr.gov/uc/rm/crsp/navajo/index.html
[10]http://www.usbr.gov/projects/Project.jsp?proj_Name=San%20Juan-Chama%20Project
[11]http://www.usbr.gov/uc/rm/crsp/

(MAF) or below, then shortage sharing for downstream users is generally put into effect. Other metrics, used in managing meeting downstream demands, look at April to July releases and the end of the water year storage.

Adaptive management for environmental flows was put in place by Reclamation's Record of Decision (ROD) (USBR, 2006). Research began in 1991 to assess the best way to protect the endangered fish species in the SJRB, the pikeminnow and the razorback sucker. The ROD details the specifics of releases from Navajo reservoir to mimic the natural hydrology of the river, to be able to do such things as protect and restore habitat and protect water quality. The releases mimic the natural hydrograph of the basin, with highly variable flows, low to zero lows and large highs due to frequent and large storms (5000-7500 cfs). Peak spring releases, mimicking snowmelt flows, are made based on the current available water and year-to-year variations (USBR, 2006). The available water is calculated based current reservoir conditions and if a threshold of 114,000 acre-feet is met then a peak spring release is made.

2.2.1. Mid-Term Operations Model

Bureau of Reclamation's mid-term probabilistic operations RiverWare (Zagona et al., 2001) model (MTOM) was developed for the entire Colorado River Basin (outlined in Grantz (2011) and described in detail in Bracken (2011)). The MTOM simulates all major basin reservoirs and flows throughout the basin, shown in Figure 2.3. The model requires unregulated reservoir inflows (forecasts), initial reservoir pool elevations and storages, and upper and lower basin demands. The CBRFC's 60-month ESP forecast ensemble drives the monthly timestep model. The model runs each of the forecast traces in the ensemble and analyzes the output of all runs collectively to provide the probability distributions of forecasted operational variables.

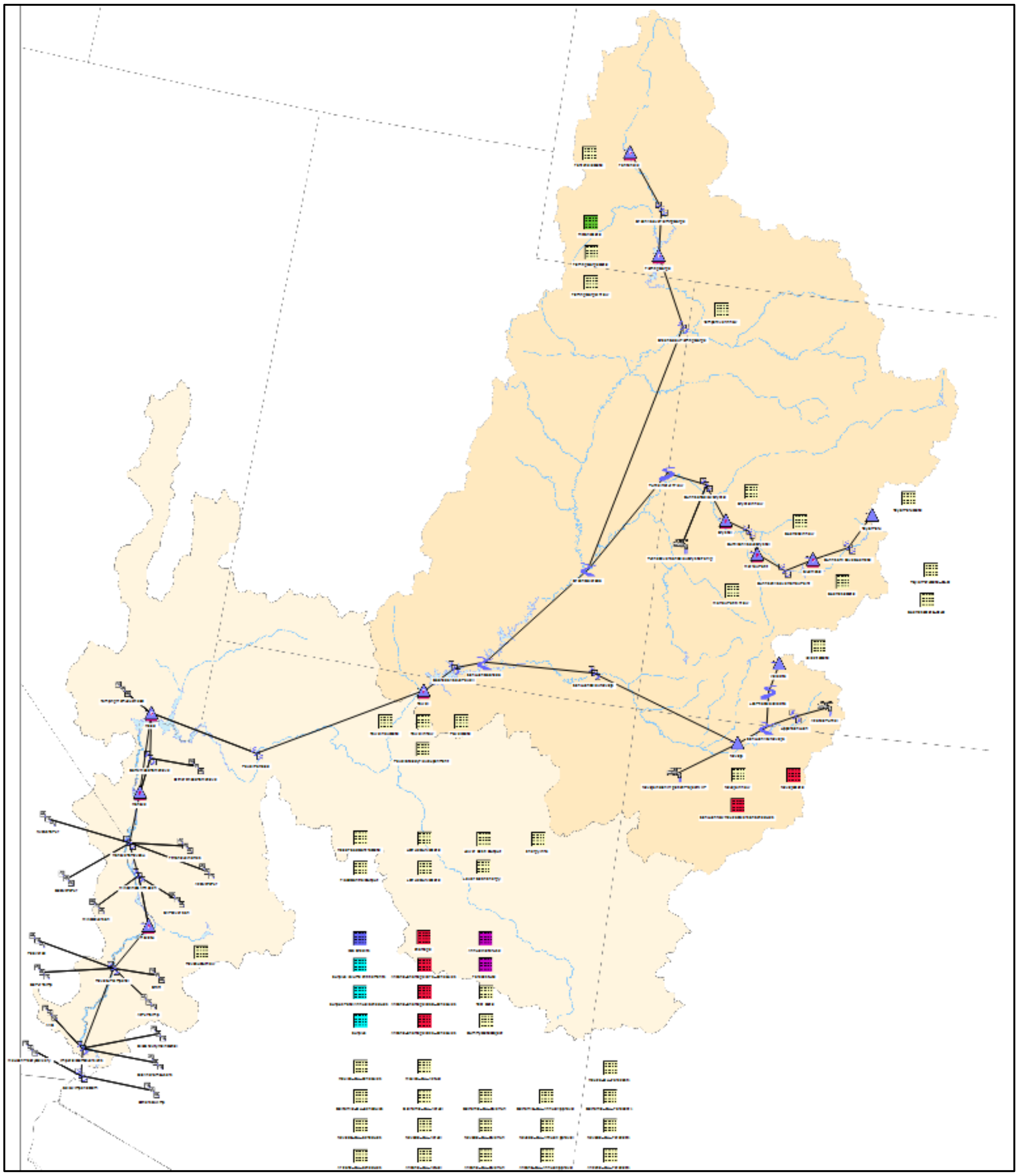


Figure 2.3 A screenshot of the MTOM of the Colorado River Basin in RiverWare.

2.2.2. San Juan River Basin Mid-Term Operations Model

The SJRB MTOM, shown in Figure 2.4, was developed specifically to meet the needs of this research by making modifications to Reclamation's Colorado River Basin MTOM. The original model was the official version of MTOM from November 2012. The model was modified to simulate only the

SJRB and for run periods of each year from 2002-2010 and each lead time of JFMA until December of that year, effectively producing 35 models.

The original MTOM simulates the entire Upper Colorado River Basin. To simulate only the SJRB, solving was disabled for objects (Reservoirs, River Reaches, Diversions, etc.), except those representing the SJRB and operational rules for those objects, were turned off. Three forecast input locations remained for the SJRB: Navajo Reservoir Modified Unregulated (NVRN5L), Vallecito Reservoir Inflow (VCRC2H), and Animas Local Inflow (DRGC2H). The following section describes the input data and the assumptions and modifications made to run the reforecasts.

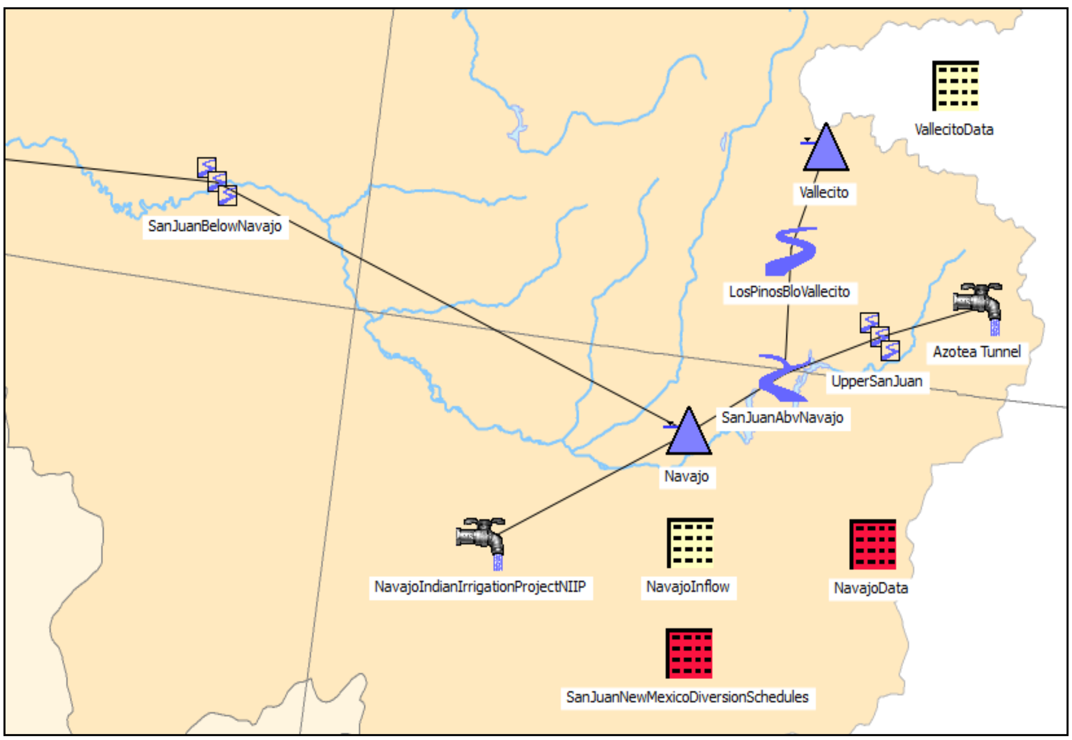


Figure 2.4 Screen shot of the San Juan River Basin MTOM used in this research. There are two reservoirs represented, Vallecito and Navajo and two water users, Azotea Tunnel and Navajo Indian Irrigation Project (NIIP).

2.3. Analysis

For this research, we use an operations forecasting model to evaluate and demonstrate the value of the enhanced streamflow forecasting methods. With the MTOM as our operations forecasting tool, we wish to implement the end-to-end framework (Figure 2.1) with two goals: 1) compare the values of key operational metrics under different streamflow forecasting methods with the 'observed' ('baseline', discussed below) and 2) determine if and/or to what extent streamflow forecasting skill translates to operational forecasting skill.

2.3.1. Climate Forecasts

The streamflow forecasting method CondI uses winter precipitation forecasts and the method CondII uses both winter precipitation forecasts and spring temperature forecasts. The skill of these climate forecasts must remain forefront when analyzing the results. In Table 2.1, the climate forecasts, forecast categories, and historical categories are shown for the years run for each method.

Table 2.1 Climate forecasts over the San Juan River Basin based on IRI seasonal climate forecasts. Winter precipitation forecasts are combined forecasts issued in December and January for JFM and FMA, respectively. Spring temperature forecasts were issued in March for AMJ. The actual category is based on basin average precipitation and temperature.

Winter Precipitation Forecasts					
Year	A	N	B	Forecast	Actual
2002	25	35	40	Dry	Dry
2003	40	35	25	Wet	Wet
2004	33	33	33	Normal	Normal
2005	40	35	25	Wet	Wet
2006	25	35	40	Dry	Normal
2007	40	35	25	Wet	Normal
2008	25	35	40	Dry	Dry
2009	25	35	40	Dry	Dry
2010	40	35	25	Wet	Wet

Spring Temperature Forecast					
Year	A	N	B	Forecast	Actual
2002	40	35	25	Warm	Warm
2004	40	35	25	Warm	Warm
2005	40	35	25	Warm	Normal

2.3.2. Ensemble Streamflow Generation

Table 2.2 MTOM Simulation Runs. Four ensembles – one for each lead time – were generated for each ‘x’ in the table

Method	Number of Traces for each year	MTOM Simulation Run Year								
		2002	2003	2004	2005	2006	2007	2008	2009	2010
ESP	30	x	x	x	x	x	x	x	x	x
WG ESP	90	x	x	x	x	x	x	x	x	x
CondI	150	x	x		x	x	x	x	x	x
CondII	150	x		x	x					

We extended the work of Caraway (2012) and generated streamflow forecasts for the CondI method from 2002-2010. The results and discussion can be found in Appendix B. The streamflow forecasts for all the other methods and all the other years were previously generated, either in Caraway (2012) or in Chapter 1. Each method was also used to generate an ensemble of streamflow forecasts at four different lead times for each year: January 1, February 1, March 1, and April 1. In total, there are 116 different ensembles with varying number of traces, as specified in Table 2.2, and a total of 2,730 traces.

2.3.3. MTOM Simulations

All the assumptions and data are outlined in Table 2.3 and discussed in this section.

Streamflow forecast ensembles were generated for the three input locations in the MTOM: inflow to Vallecito (VCRC2H), inflow to Navajo (NVRN5L), and local inflow to Animas (DRGC2H). The MTOM was run with each of the 116 different ensembles as input to produce resulting values of operational variables for each trace. For one year, the MTOM output resulting from the 4 different streamflow forecasts can be compared. The observed values are not consistent with the model output due to subjective operations in real-time and the static assumptions made for the SJRB MTOM runs. Therefore, all the methods are also compared to the ‘baseline’ or benchmark run where MTOM is run with historical inflows. Initial conditions for each run period are historical basin conditions; therefore, each lead time for each year has its own baseline run, because the initial conditions change with each monthly advancement in run period. For example, forecasted values in January are not used as initial conditions for the other lead times (e.g., February), because the model will be re-run each month with current conditions of the reservoirs.

Reclamation makes historical data available for the Upper Colorado Region Reservoir Operations[12], including pool elevation, storages, inflow, and outflow. These historical values were used to initialization the model for every run period. Initial conditions do not need to reflect the previous month's operational forecasts because actual operations are more subjective than the model and each time the model is run, the start timestep is updated to reflect the current month.

Initial diversion and depletion requests for the two water users modeled in the basin, Navajo Indian Irrigation Project (NIIP) and Azotea Tunnel, were taken from the October 24MS models and reports from 2002-2010, provided by Reclamation. These values represent the forecasted diversion requests for the water users, whereas observed diversions are subjectively based on the weather forecasts, current basin conditions, and other short term conditions.

Peak spring releases from Navajo Reservoir are critical to meeting the environmental flows for endangered species. These peak releases are calculated based on the available water in the system (Computed Available Water) for the current year and the previous years' releases (Release Level). In the model, these values are calculated annually and stored in RiverWare, then used in subsequent years. For the reforecasts, a continuous hindcast from 1996-2010 was run to obtain the Computed Available Water and Release Level for each year using all the observed inflows. The next section describes the operational metrics used to compare the results of the SJRB MTOM runs.

[12]http://www.usbr.gov/uc/crsp/GetSiteInfo

Table 2.3 SJRB MTOM Assumptions and Data

Object	Slot	Start Timestep	End Timestep	Timestep	Notes
NavajoIndiainIrrigation Project NIIP	Diversion Requested	Start Timestep	End Timestep	monthly	Oct 24 Month Study Models
	Depletion Requested	Start Timestep	End Timestep	monthly	Oct 24 Month Study Models
Azotea Tunnel	Diversion Requested	Start Timestep	End Timestep	monthly	Oct 24 Month Study Models
	Depletion Requested	Start Timestep	End Timestep	monthly	Oct 24 Month Study Models
Vallecito	Inflow (Historical)	Start Timestep -1	-	monthly	Reclamation Online Database
	Inflow (Forecasts)	Start Timestep	End Timestep	monthly	CHPS forecast
	Pool Elevation	Start Timestep -1	-	monthly	Reclamation Online Database
	Outflow	Start Timestep -1	-	monthly	Reclamation Online Database
Navajo	Pool Elevation	Start Timestep -1	-	monthly	Reclamation Online Database
	Outflow	Start Timestep -1	-	monthly	Reclamation Online Database
NavajoInflow	ModUnregulated	Start Timestep	End Timestep	monthly	CHPS forecast
NavajoData	NIIPAnnualRequest	-	-	yearly	Sum of yearly Diversion Requested
	SpringPeakFlowDate	All years	-	yearly	June 4
	MinimumLevelOneFlowChartLevel	-	-	yearly	Values from NOV12 MTOM
	DaysOfSpringReleaseLevel0	-	-	yearly	Values from NOV12 MTOM
	DaysOfSpringReleaseLevel1	-	-	yearly	Values from NOV12 MTOM
	DaysOfSpringReleaseLevel2	-	-	yearly	Values from NOV12 MTOM
	DaysOfSpringReleaseLevel3	-	-	yearly	Values from NOV12 MTOM
	Puturbation (Perturbation)	-	-	yearly	Values from NOV12 MTOM
	ReleaseLevel	Start Timestep Year - 3	Start Timestep year -3	yearly	Values from hindcast run from 1996-2010 with observed input values from online database.
	ComputedAvailableWater	Start Timestep Year - 3	Start Timestep year -3	yearly	Values from hindcast run from 1996-2010 with observed input values from online database.
SanJuanBelowNavajo: AnimasRiver	LocalInflow (Forecast)	Start Timestep	End Timestep	monthly	CHPS forecast

(green)	Brought in by Excel DMI	**Online database**
(blue)	Calculated by Rule	http://www.usbr.gov/uc/crsp/GetSiteInfo
-	Not Applicable	

2.3.4. Operational Metrics

Operational metrics, shown in Table 2.4, are output variables from MTOM of interest to managers or stakeholder and that reflect the management objectives of the basin, as discussed in Section 2.2.

Table 2.4 Operational Metrics

Management Objectives	Operational Metric	Threshold	Implications
Environmental Flow	Computed Available Water	114,000 AF	Ability to mimic natural variability
Tribal Assets	NIIP Critical Pool Elevation Minimum	5990 ft	Water User Shortage
Downstream Water Users	July Pool Elevation Minimum	1 MAF/ 6029.1463 ft	Shortage Sharing
	April to July Total Flow		
	End of Water Year Storage		During the winter months, storage may go below NIIP PE if necessary.

Meeting environmental flow requirements can be evaluated by looking at the Computed Available Water value. Water available for environmental releases is calculated every March to determine the available storage for a given year using the storage above the carry over storage plus the forecasted inflow values for the year less the base release to determine the amount of available water there is for a peak release in the spring. If the threshold of 114,000 AF is computed, then there is water for a spring release.

Environmental flow, although included in this study's analysis, is not considered to be a good operational metric for the SJRB MTOM because the model simulates for less than a year. Environmental flow requirements are not specific to a single year, but consider flows over at least a ten year period. This metric will become more valuable for real-time forecasting as more data is collected and compared over time.

The minimum operating level of 5,990 feet for NIIP in Navajo Reservoir is an indicator of whether or not the NIIP demands can be satisfied during the irrigation months (April-July). This pool elevation must be met to pump water during the irrigation season. Our results indicate that the minimum pool elevation is violated most often in July; therefore our analysis focuses on this month.

Evaluation of meeting downstream demands of the Lower Colorado River looks at the storage in Navajo Reservoir at the end of the water year (end of July, beginning of October). Shortage sharing should be considered as a water management decision for the rest of the irrigation season if the July storage is 1MAF or below. This metric has been converted into a pool elevation of 6029.15 feet for analysis purposes.

Two other operational metrics that were evaluated are the end-of-water-year (October) storage, used to determine carry-over storage and make water resource management decisions for the winter season, and total outflow volume during the irrigation season (April to July).

2.4. Results

For demonstration purposes, the results are organized into two sections. The first section reports the values of the operational metrics from 2002-2010 using the CondI streamflow forecasts conditioned on the winter precipitation forecast. The second section presents the operational metrics for 2002, 2004, and 2005 using the CondII streamflow forecasts conditioned on the winter precipitation and spring temperature forecast. Both sections present results using the ESP and the WGESP methods, as well as the baseline results, for comparison.

Figure 2.5 shows the historical seasonal runoff volumes for April through July for the representative gages. From this figure and for the analysis of our research, we see that the 2002 and 2003 were very dry streamflow years and that 2005 is a wet year, with the remaining years as somewhere in between relative to 2002 and 2005.

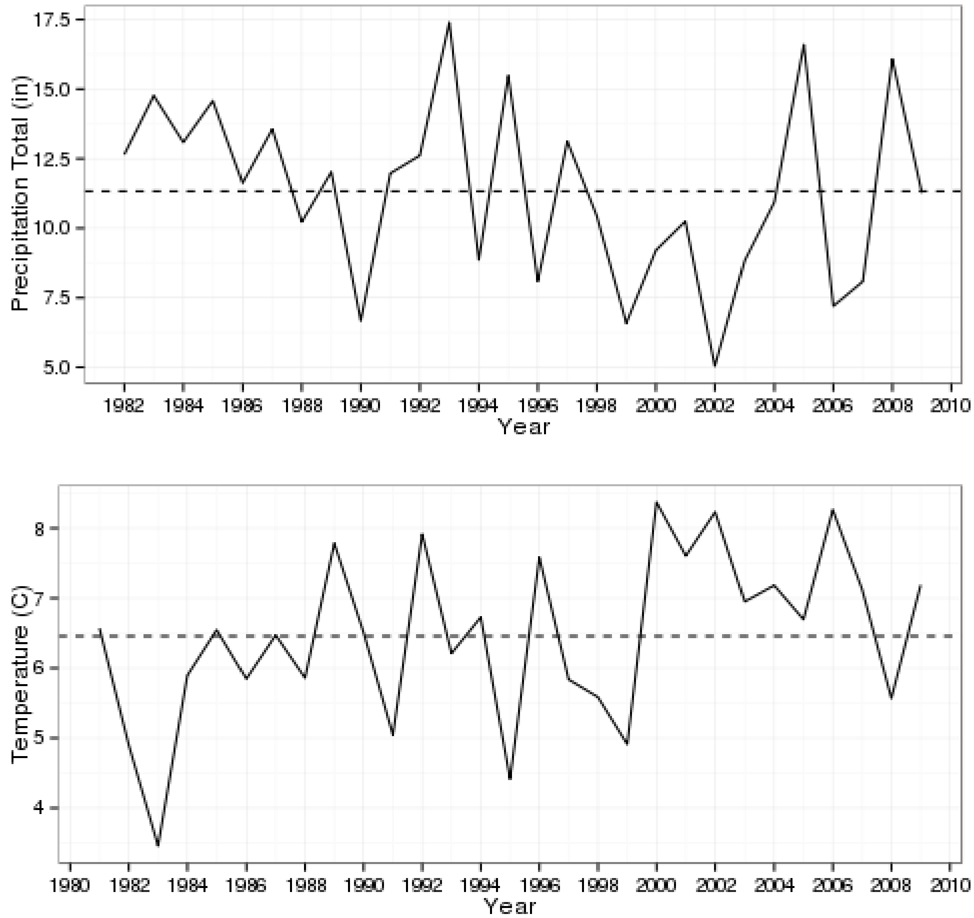


Figure 2.5 San Juan River Basin areal averaged historical weather variables from the CBRFCs weather stations in the basin. Top plot is the winter precipitation total from November to March. Bottom plot is the average spring temperature of April and May.

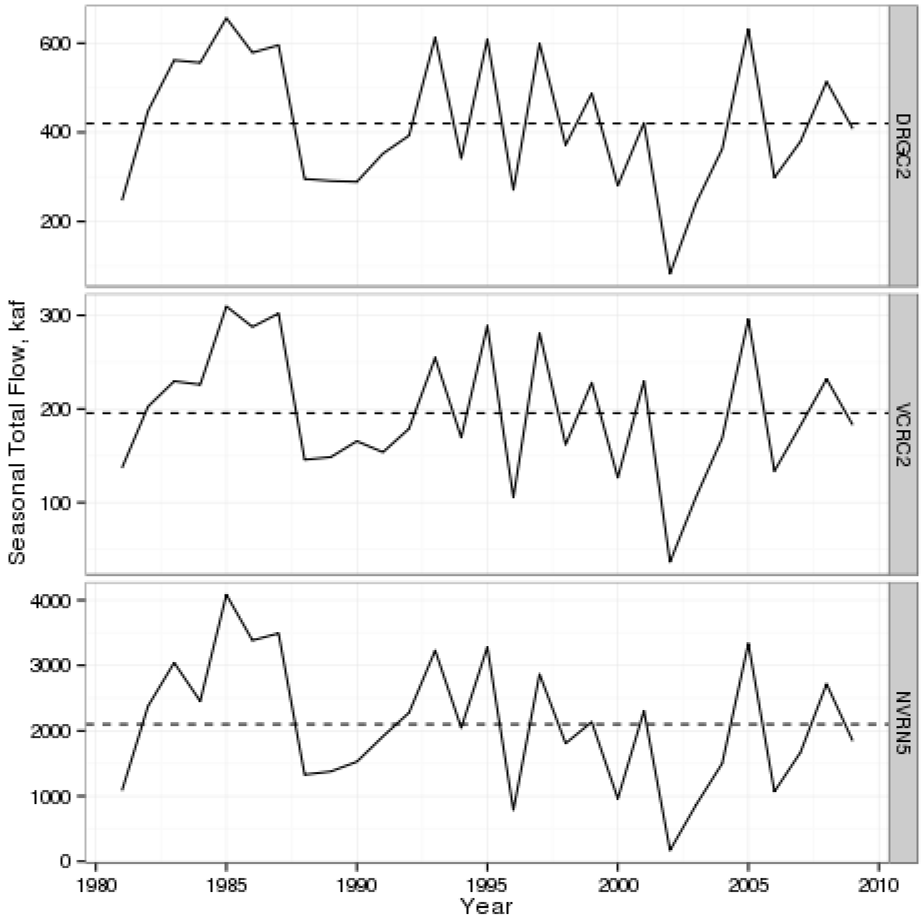


Figure 2.6 Historical April-July runoff volumes for 3 SJRB gauges with averages, shown as dotted lines from 1981-2010. Values calculated from CBRFC historical monthly streamflow data in KAF.

Table 2.5 Historical SJRB April-July runoff volumes for representative locations from 1981-2010. Values calculated from CBRFC historical monthly streamflow data in KAF.

Year	DRGC2	VCRC2	NVRN5
1981	247.21	136.90	1084.02
1982	448.57	202.56	2379.53
1983	561.80	229.58	3042.31
1984	556.08	225.88	2454.23
1985	656.18	309.60	4084.06
1986	578.63	287.68	3384.52
1987	595.43	302.01	3492.27
1988	295.54	145.63	1328.89
1989	291.16	148.44	1377.03
1990	289.05	165.49	1526.69
1991	352.42	153.68	1914.32
1992	392.72	178.85	2277.45
1993	612.55	254.72	3230.72
1994	341.59	169.49	2045.49
1995	608.83	288.73	3283.14
1996	271.06	105.44	787.16
1997	599.20	281.23	2867.69
1998	371.77	161.90	1807.18
1999	487.26	228.04	2135.89
2000	280.58	126.51	961.59
2001	421.17	229.72	2305.21
2002	83.32	36.37	170.86
2003	242.16	106.06	866.95
2004	362.74	168.71	1500.91
2005	631.27	295.85	3336.87
2006	298.73	133.54	1069.72
2007	379.58	182.23	1671.13
2008	513.51	231.91	2716.71
2009	408.02	182.79	1844.38

2.4.1. Operational Metrics Conditioned on Winter Precipitation Forecasts

The following results do not include 2004 CondI combination because the winter precipitation forecast for that year was climatology. Therefore the methodology for 2004 CondI and 2004 WGESP is the same and only 2004 WGESP is shown.

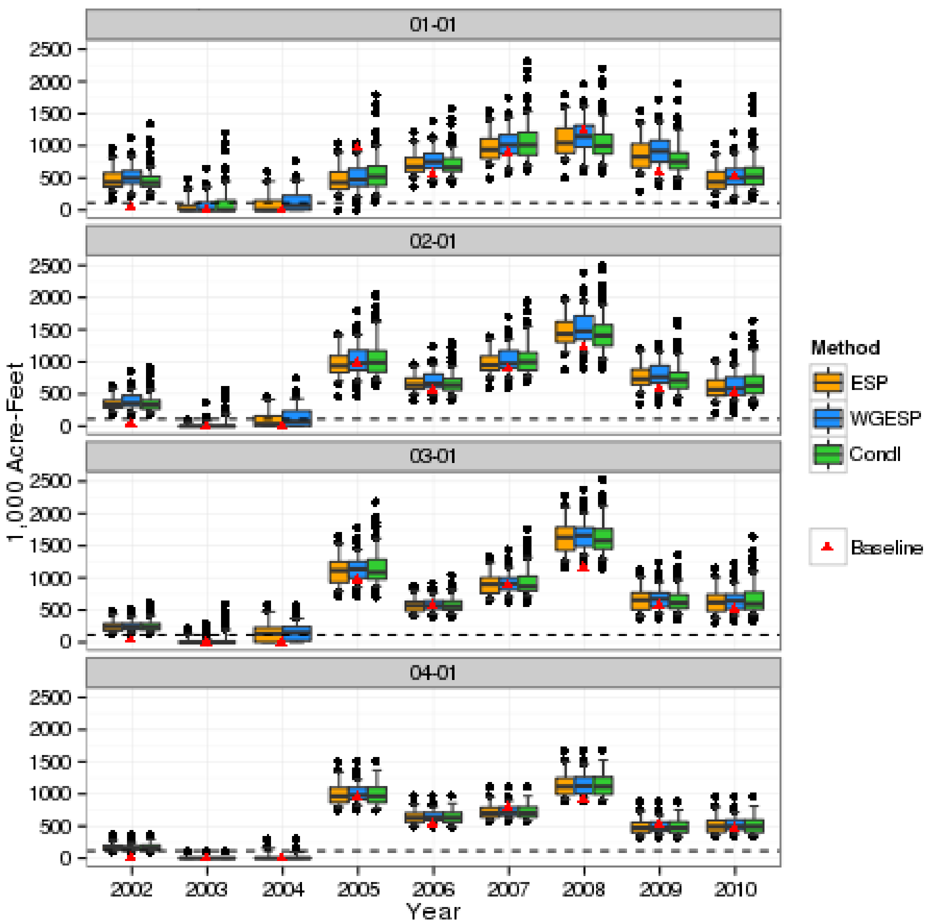
The computed available water in Figure 2.7a shows that it is an operational metric that is more sensitive to wet years (such as 2005) or years with more water in the system (such as 2006) when small changes in the hydrology can affect operations, shown as larger spread in the boxplots. Years 2005-2010 exhibit this sensitivity for the computed available water metric. We see an improvement in the forecast of CondI for long lead times in 2005 due to the wet winter precipitation forecast and wet observed winter, seen as the tight lower tail and the extended upper tail of the boxplot towards wetter conditions. The probability distribution functions (PDFs) in Figure 2.9 reflect the boxplots. The same pattern is seen in 2007 for CondI, except that the observed winter was actually dry, therefore not improving the CondI forecast over the other methods.

Figure 2.7b shows the July pool elevation in Navajo Reservoir boxplots with two minimum thresholds, the minimum operating level for NIIP at 5,990 feet and the shortage sharing threshold at 6,029.15 feet (1 MAF). The July pool elevation operational metric is more sensitive to dry (2002) or years with less water in the system, such as 2003 which was preceded by a very dry year of 2002. The operations are more sensitive to differences in hydrology in the dry years as displayed by the large spread of the boxplots. In 2003, the forecast ensembles for all methods are able to forecast that the pool elevation will be below the 1 MAF threshold at an early lead time of January. By using ensemble forecasts, risk-based decision making water managers may be aware at long lead times that shortage sharing may go into effect in July. Figure 2.10 shows the PDFs for the July pool elevation and 2006 shows that CondI forecasts at long lead time are an improvement over the other methods because CondI forecasts the baseline value with a higher probability than the other methods. And as lead time is closer to April, CondI consistently forecasts the baseline value with a higher probability than the other methods.

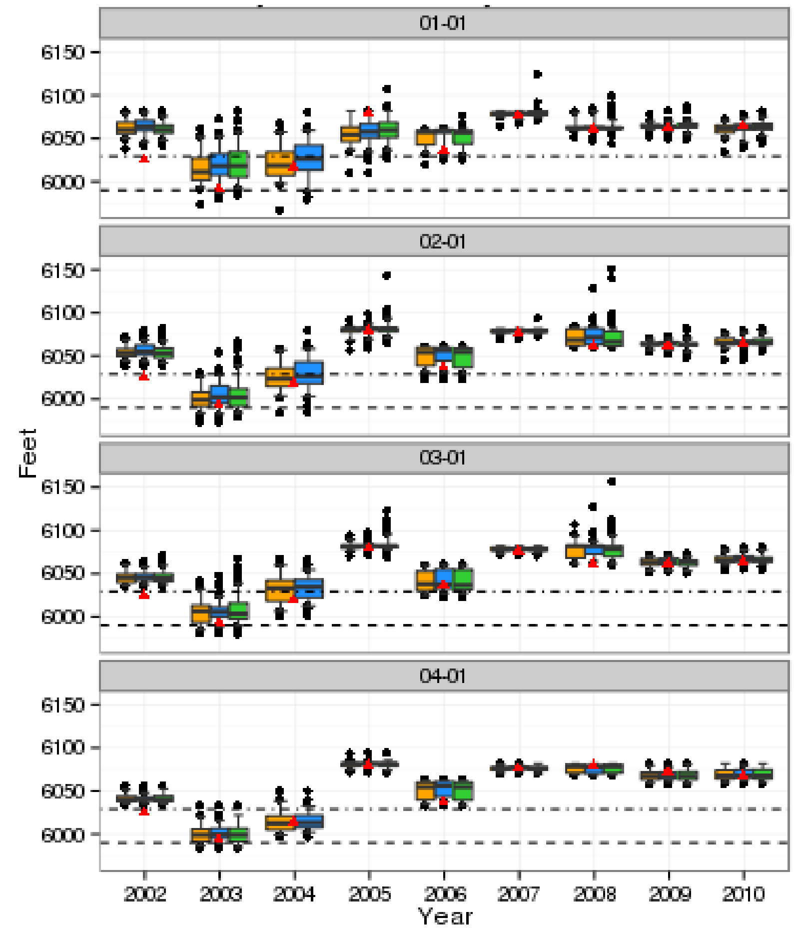
The WGESP operations forecast uses the unconditional weather generator based streamflow forecasts, meaning the weather generator resamples sequences from historical which produce a normal distribution of weather variables. This causes a sharp, normal PDF of WGESP operations forecast. The CondI operation forecast uses the conditional weather generator based streamflow forecasts; the weather generator conditionally resamples from history, choosing from years similar to the climate forecast, thus producing weather traces, and thus streamflow traces, similar to one another. These similar streamflow traces many times generally produce one of two different results, causing bimodality in the operations forecast.

The end of year water storage operational metric displays the same dry year sensitive characteristics as the July pool elevation, so for dry years this metric is also beneficial for risk based decision making. In Figure 2.8a, the boxplots display similar performance between the different methods, with the CondI generally showing more variability towards the wetter conditions, regardless of climate forecast. The PDFs, in Figure 2.11 reveal a variety of shapes, but for each year the methods are similar, with the CondI being slightly sharper than the other two methods due to the conditioning of the weather generator towards a more specific type of winter, whether wet or dry. The rules for operating the reservoir at the end of the water year manage to override any differences in streamflow forecast methods. This is because fall releases are made in September based on the October pool elevation forecast and since there is no skill in the October forecast at these lead times, the results vary widely.

Navajo releases depend on many different variables such as inflow forecasts, demand forecasts and previous year conditions, so there is not a direct relationship between Navajo releases and inflow forecasts. The April to July release volume forecast boxplots shown in Figure 2.8b suggest this nonlinear relationship by showing that it is not sensitive to dry years, but no clear pattern for wet years as we have seen for previous operational metrics. The PDFs, Figure 2.12, show a slightly sharper forecast for the CondI because the conditioning due to the conditioning of the weather generator towards a more specific type of winter, whether wet or dry, which then for Navajo releases, produces a higher probability of a result.

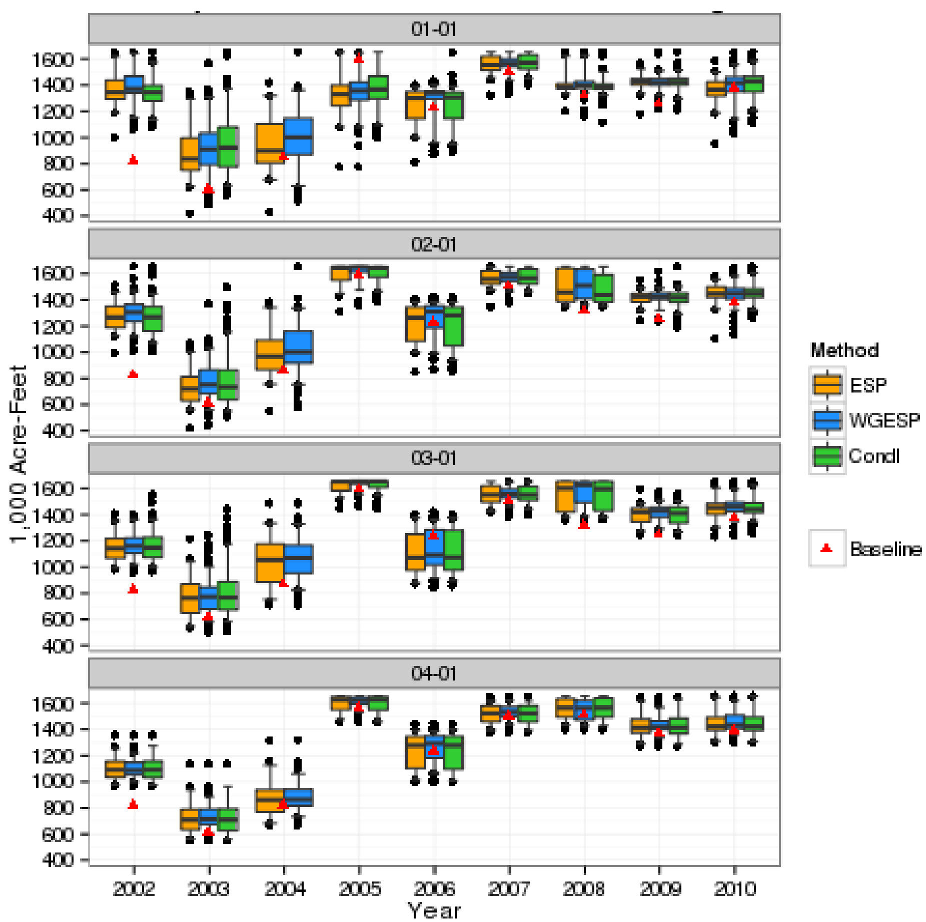


a) Computed Available Water: The dashed line is the 114,000 acre-feet threshold that if exceeded will allow for spring release from Navajo.

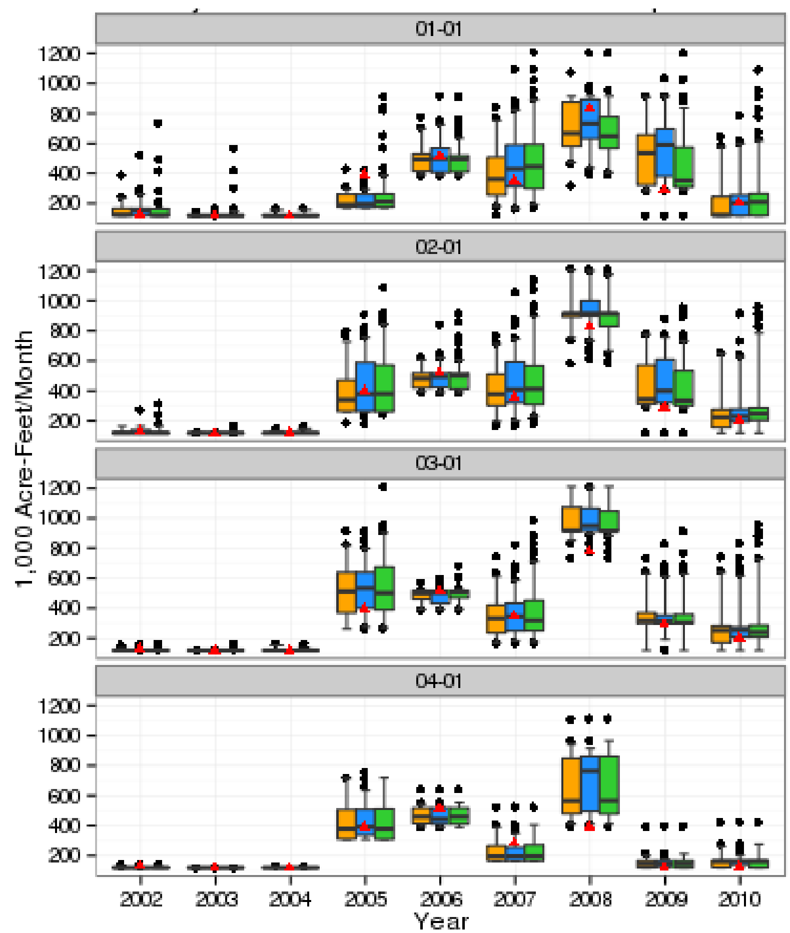


b) July Pool Elevation: The dot-dashed line minimum threshold of 1 MAF (6049.15 ft) and the dashed line is the minimum operating pool elevation for NIIP (5,990 ft).

Figure 2.7 Operational metrics showing each year from 2002 to 2010 and the values obtained using the three different streamflow forecasting methods.



a) End of Water Year Storage



b) Seasonal Release Volume (April to July)

Figure 2.8 Operational metrics showing each year from 2002 to 2010 and the values obtained using the three different streamflow forecasting methods.

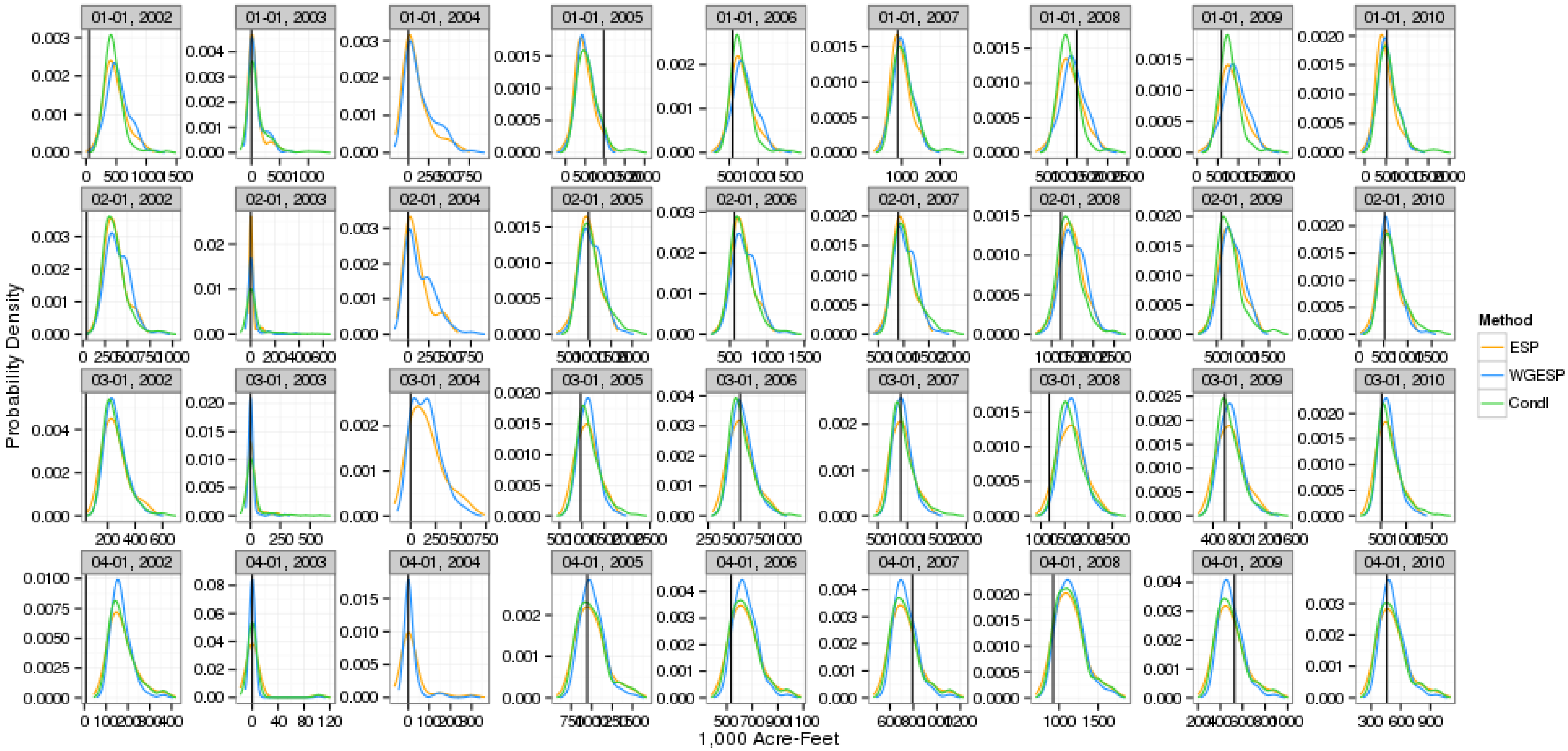


Figure 2.9 Computed Available Water PDFs. The black vertical line is the baseline value calculated at each lead time for each year.

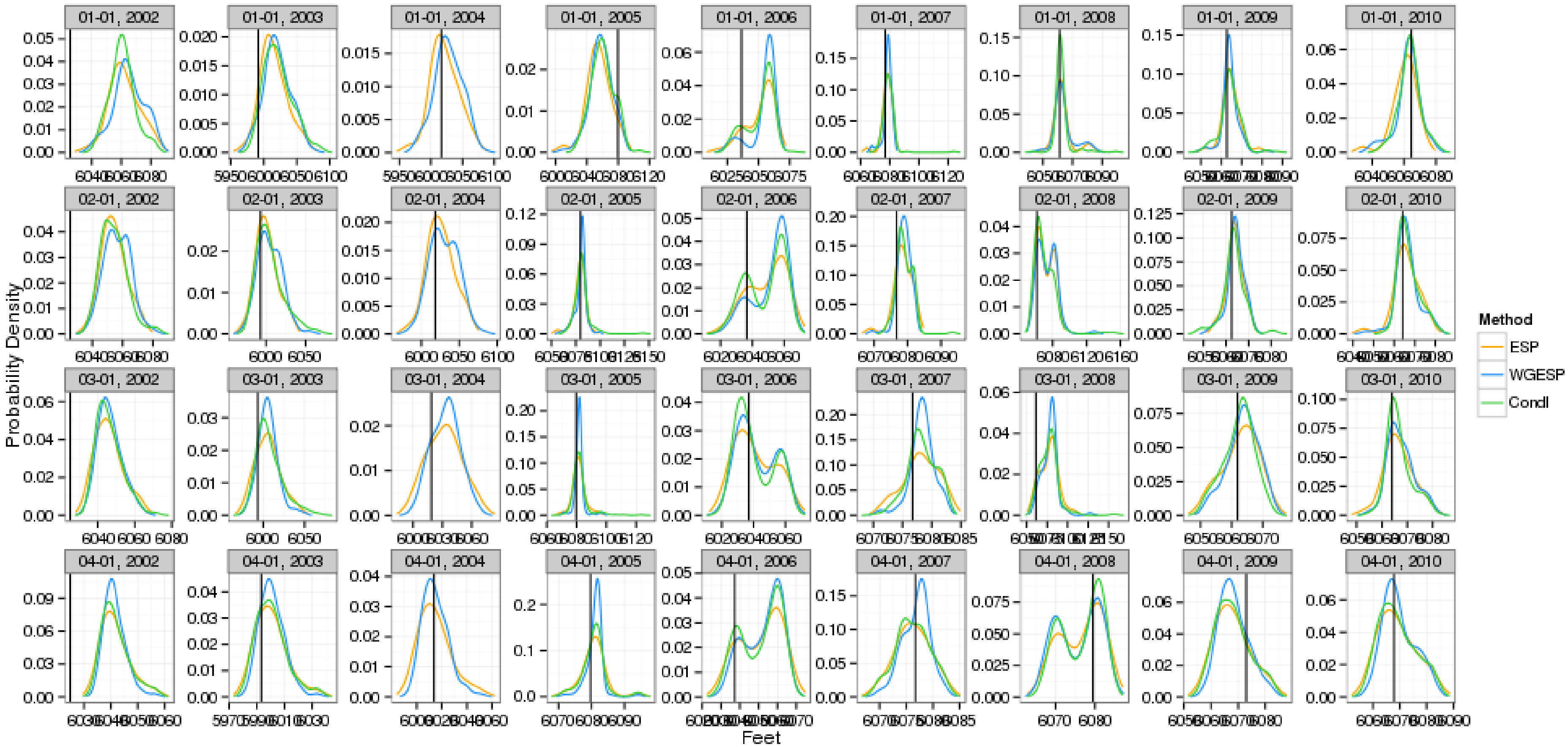


Figure 2.10 July Pool Elevation PDFs. The black vertical line is the baseline value calculated at each lead time for each year.

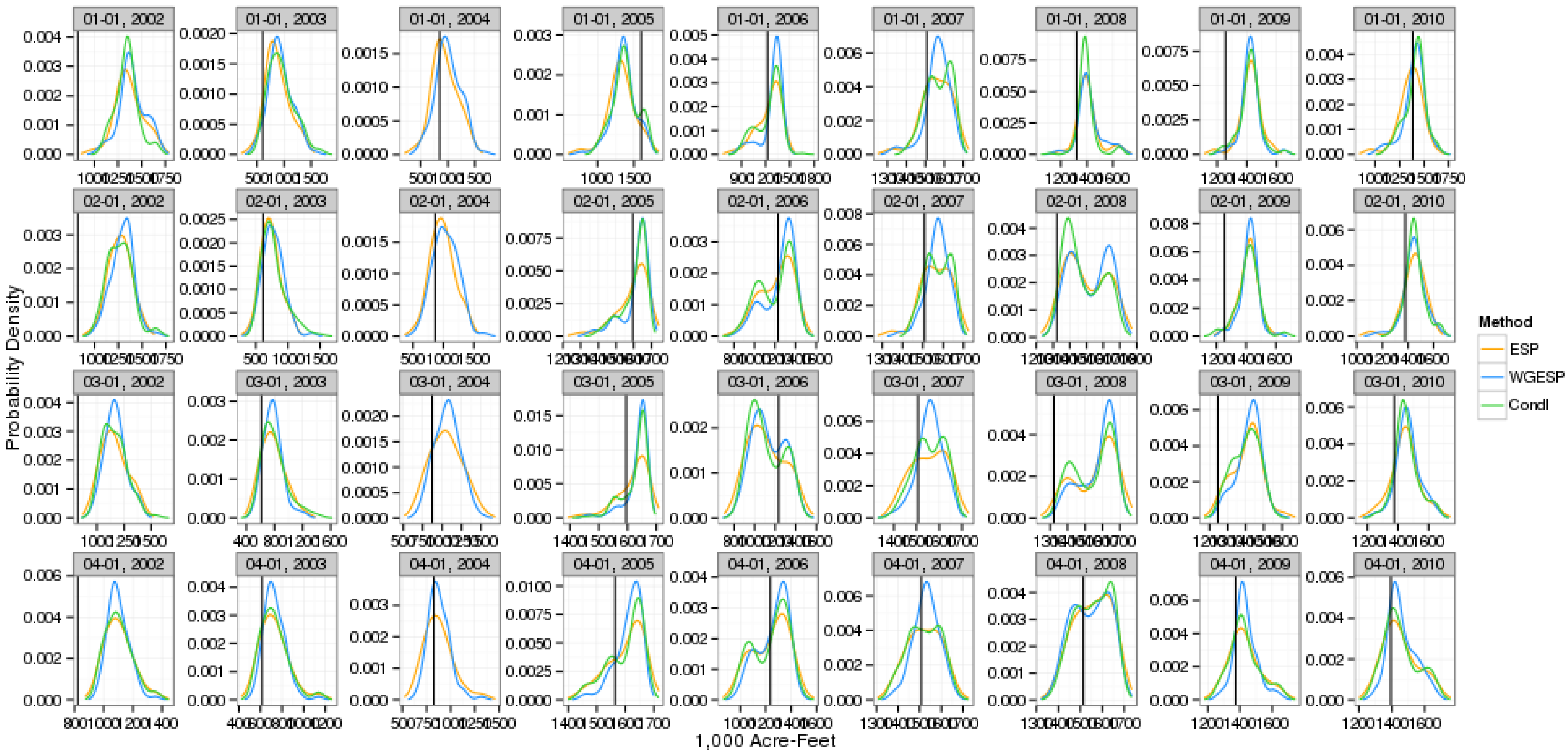


Figure 2.11 End of Water Year Storage PDFs. The black vertical line is the baseline value calculated at each lead time for each year.

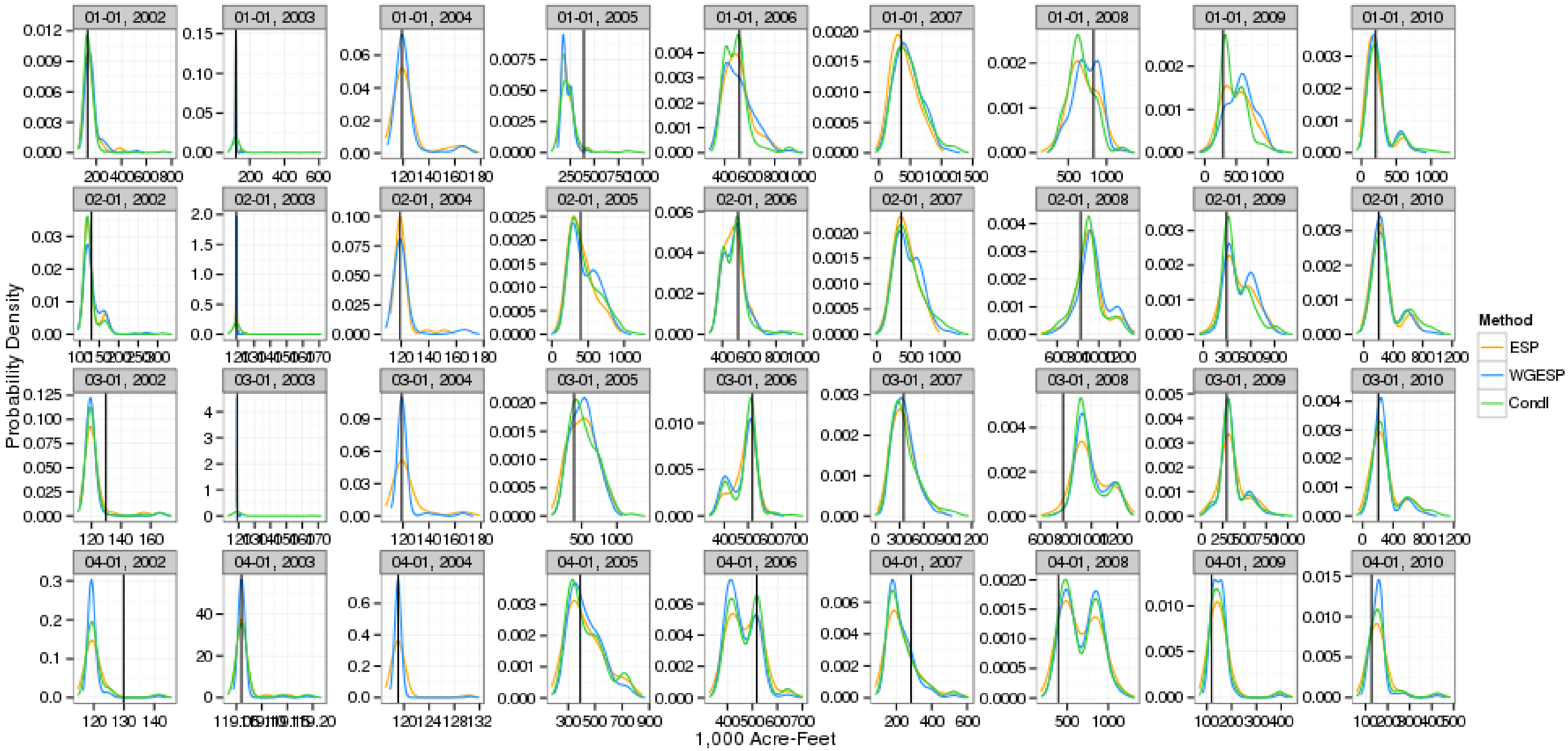


Figure 2.12 Seasonal Release Volume (April to July) PDFs. The black vertical line is the baseline value calculated at each lead time for each year.

RPSS

Rank probability skill score (RPSS) evaluates the model skill of the forecast in capturing categorical probabilities relative to the observed or truth; in this research, we use values from baseline runs as the observed data. Forecasts are divided into multiple categories (k); here we chose terciles (k=3) (33^{rd} and 66^{th} percentile boundaries). The forecast values from one of the modeling approaches, say ESP, are divided into k=3 categories for which the proportion of ensembles falling into each category constitutes the forecasts probability in a given year, (p_1, p_2, p_3). The baseline value in any given year is in one of the three probability forecast categories denoted as (d_1, d_2, d_3), i.e. of the form for category 1- [1,0,0], category 2- [0,1,0], or category 3 – [0,0,1]. These values are then used to calculate the rank probability score (RPS) for the model forecasts. The 'null' or climatological forecast probabilities for the three k categories are also (p_1, p_2, p_3), which in this case is [0.33, 0.33, 0.34] for calculating the RPS of climatology. The RPS is as follows, where k=3.

$$RPS = \sum_{i=1}^{k} \left[\left(\sum_{j=1}^{i} p_j - \sum_{j=1}^{i} d_j \right)^2 \right]$$

The RPSS quantifies the skill of the forecasts from the model relative to the 'null' or climatological forecast. The RPSS ranges from negative infinity to one with a value of zero indicating model skill to be same as climatology. Negative values indicate forecasts are worse than climatology, positive indicate better than climatology and value of one being a perfect categorical forecast (Wilks 1995).

$$RPSS = 1 - \frac{RPS(forecast)}{RPS(climatology)}$$

In Table 2.6, the RPSS values for each operational performance metric for each lead time and method reveal how well the skill from the streamflow forecasts has been translated into skill in the operations forecast. It is noted that all methods perform better than climatology The CondI shows improvement over ESP and WGESP for each metric at each lead time using all the years simulated, 2002-2010. From Figure 2.13, we see that WGESP generally outperforms ESP, while CondI always does better for all lead times and metrics.

Table 2.6 The RPSS value was calculated for each metric at each lead time for each method, using the baseline simulation as climatology.

Lead	Method	End of Water Year Storage	July Pool Elevation/ Storage	Runoff Outflow (AprtoJul)	Computed Available Water
01-01	ESP	0.1082	0.1163	0.0937	0.1174
	WG ESP	0.1573	0.1624	0.0532	0.1033
	CondESP	0.1952	0.2216	0.1286	0.1802
02-01	ESP	0.174	0.211	0.2586	0.3133
	WG ESP	0.1769	0.2143	0.2606	0.2887
	CondESP	0.2055	0.2947	0.3145	0.3635
03-01	ESP	0.1854	0.1881	0.3306	0.336
	WG ESP	0.1645	0.1657	0.3446	0.3422
	CondESP	0.218	0.2232	0.3907	0.397
04-01	ESP	0.3199	0.2638	0.2539	0.343
	WG ESP	0.3226	0.2627	0.2486	0.3401
	CondESP	0.3676	0.3047	0.2973	0.3932

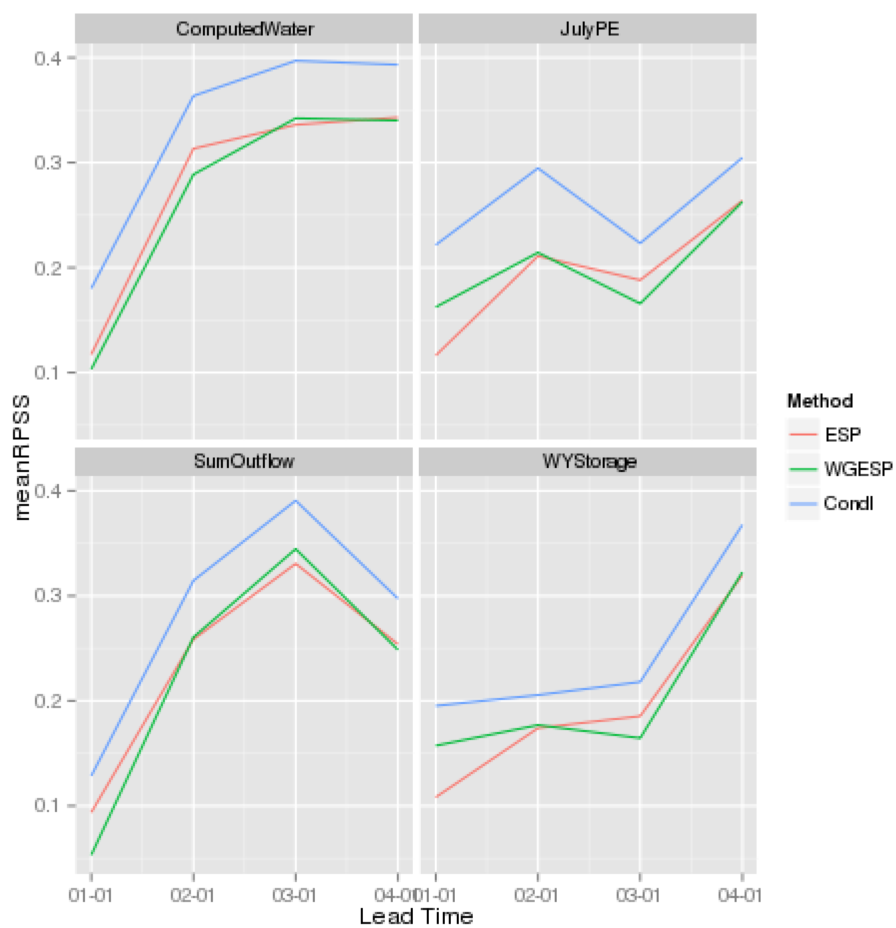


Figure 2.13 RPSS values at each lead time for each operational performance metric from the MTOM.

2.4.2. Operation Metrics Conditioned on Winter Precipitation Forecasts and Spring Temperature Forecasts

Due to data processing constraints, three representative years were chosen for MTOM simulations using the streamflow forecasts conditioned on winter precipitation and spring temperature forecasts, denoted as 'CondII'. Each year represents a different streamflow category: 2002, a dry year, 2004, a normal year, and 2005, a wet year. These years had skillful climate forecasts, except for 2005 which had an inaccurate spring temperature forecast; see Section 2.3.1 and Table 2.1.

Once again, the following results do not include 2004 CondI combination because the winter precipitation forecast for that year was climatology. Therefore the methodology for 2004 CondI and 2004 WGESP is the same and only 2004 WGESP is shown.

Figure 2.14 shows the boxplots for the July pool elevation. For the dry year, 2002, CondII shows an improved forecast over the other methods in that the entire boxplot is closer to the baseline value. The spring temperature forecast was issued on February 1 for MAM, so the lead times run for the MTOM are February, March, and April and does not include January because the climate forecasts would not be available at that time.

The CondII forecasts for 2004 show improvement over the other methods at long lead times. This improvement is shown by CondII for which the interquartiles both capture the baseline value and forecast the July pool elevation to be below the minimum 1 MAF at long lead times. This is contrasted by the other methods (ESP, WGESP, CondI), where the interquartiles of the boxplots are not fully beneath the minimum 1 MAF until the April lead time. The CondII boxplot is also has tighter tails than the other methods, so for 2004, the pool elevation during the February and March lead times is forecasted to be above the NIIP minimum elevation. Although 2004 is forecasted to be a normal winter precipitation year, due to the impacts of the previous dry years of 2002 and 2003, 2004 forecasts to be a low pool elevation year. With this information at earlier lead times, better management planning decisions can be made for the following irrigation season. The PDFs of the July pool elevation, Figure 2.16, also display the shifts towards the baseline value and as very sharp forecasts for the CondII method for both years. July pool elevation is sensitive to dry or drier years, as previously discussed, so for the wet year of 2005 we do not see much difference in forecasts between the different methods.

Figure 2.15 shows end of water-year storage in Navajo forecast boxplots. For the dry and normal years, the CondII forecasts are closer to the baseline value than the other methods. For the wet year, 2005, the CondII forecast performs worse than the other methods, by forecasting values further away from the baseline value. This is due to the inaccurate warm spring temperature forecasts (observed spring temperatures were normal) decreasing the forecasted runoff volume and the water in the system. The PDFs, Figure 2.17, show the CondII improving towards the baseline value for 2002 and 2004. For the wet year, 2005, all the methods perform similarly.

Overall, incorporating spring temperature forecasts seems to improve the operational metric forecasts for the dry year but not enough to capture the baseline value. The normal year, 2004, shows better metric forecasts for CondII at long lead times. The wet year, 2005, that had an inaccurate climate forecast caused the metric forecasts to perform worse than the other streamflow forecasting methods. The other operational metrics performed similarly and can be found in Appendix B.

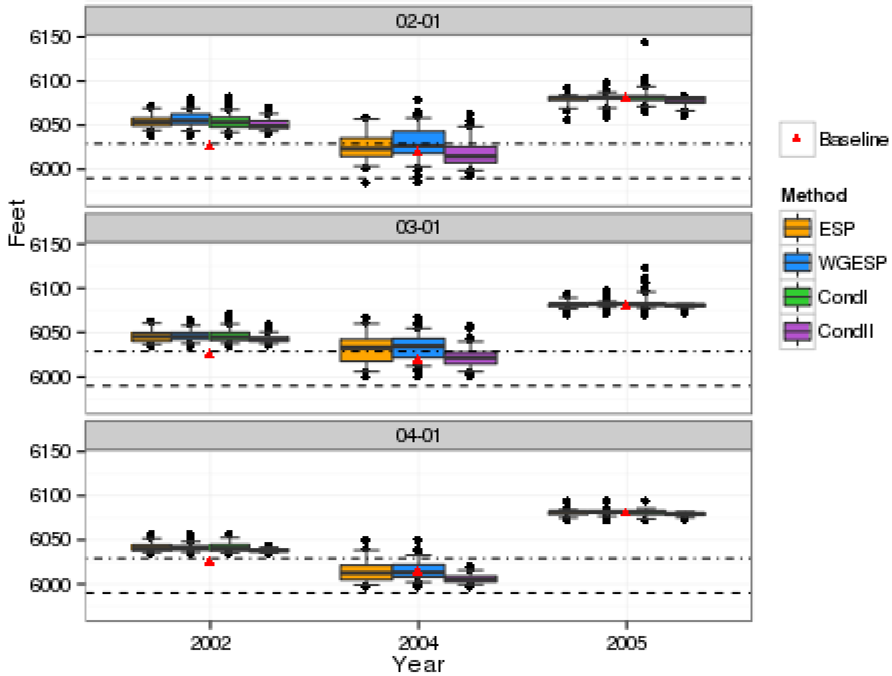


Figure 2.14 July Pool Elevation: The dot-dashed line minimum threshold of 1 MAF (6049.15 ft) and the dashed line is the minimum operating pool elevation for NIIP (5,990 ft).

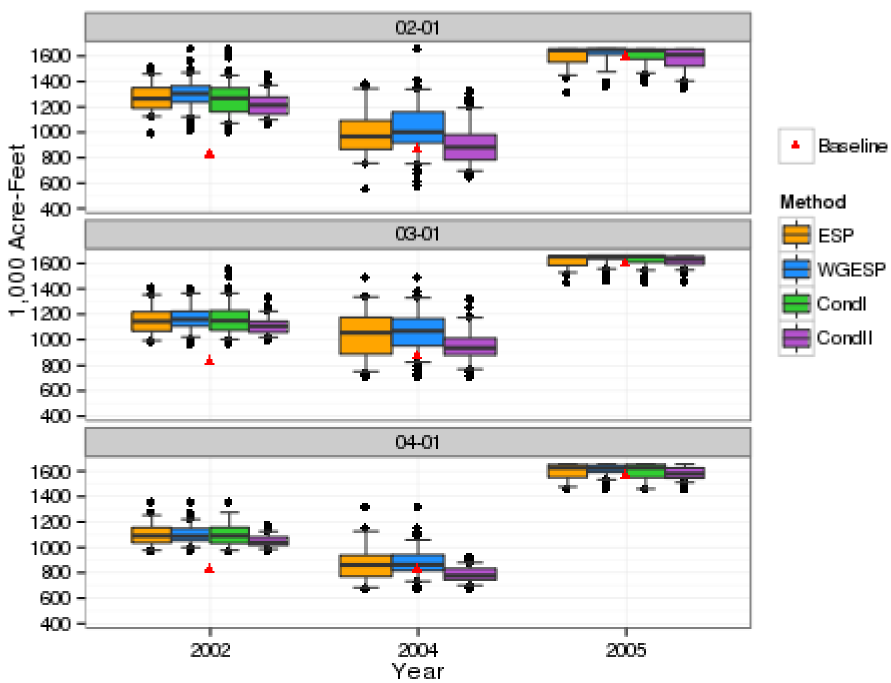


Figure 2.15 End of water year storage in Navajo Reservoir

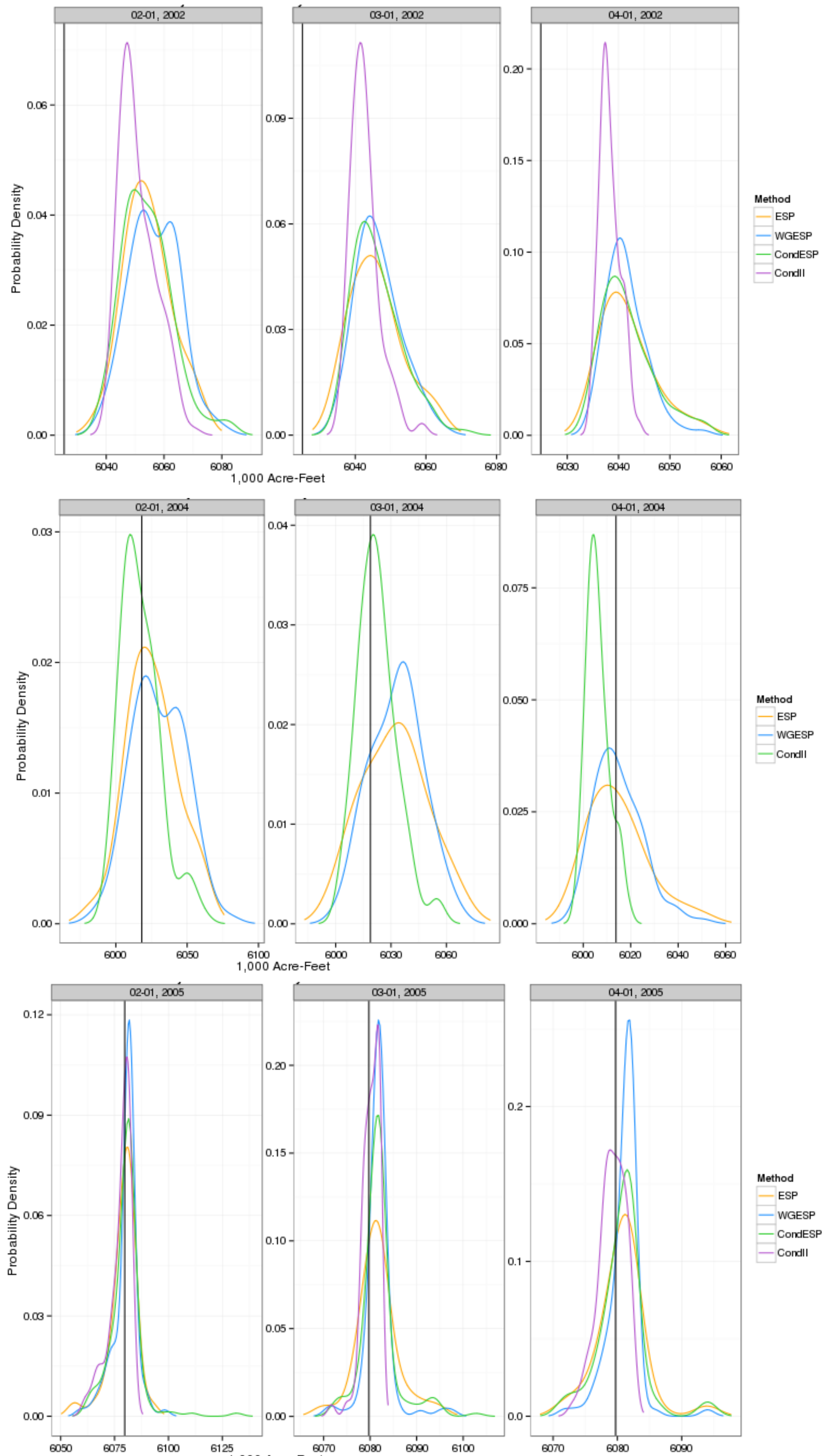


Figure 2.16 July pool elevation PDFs, top to bottom 2002, 2004, 2005.

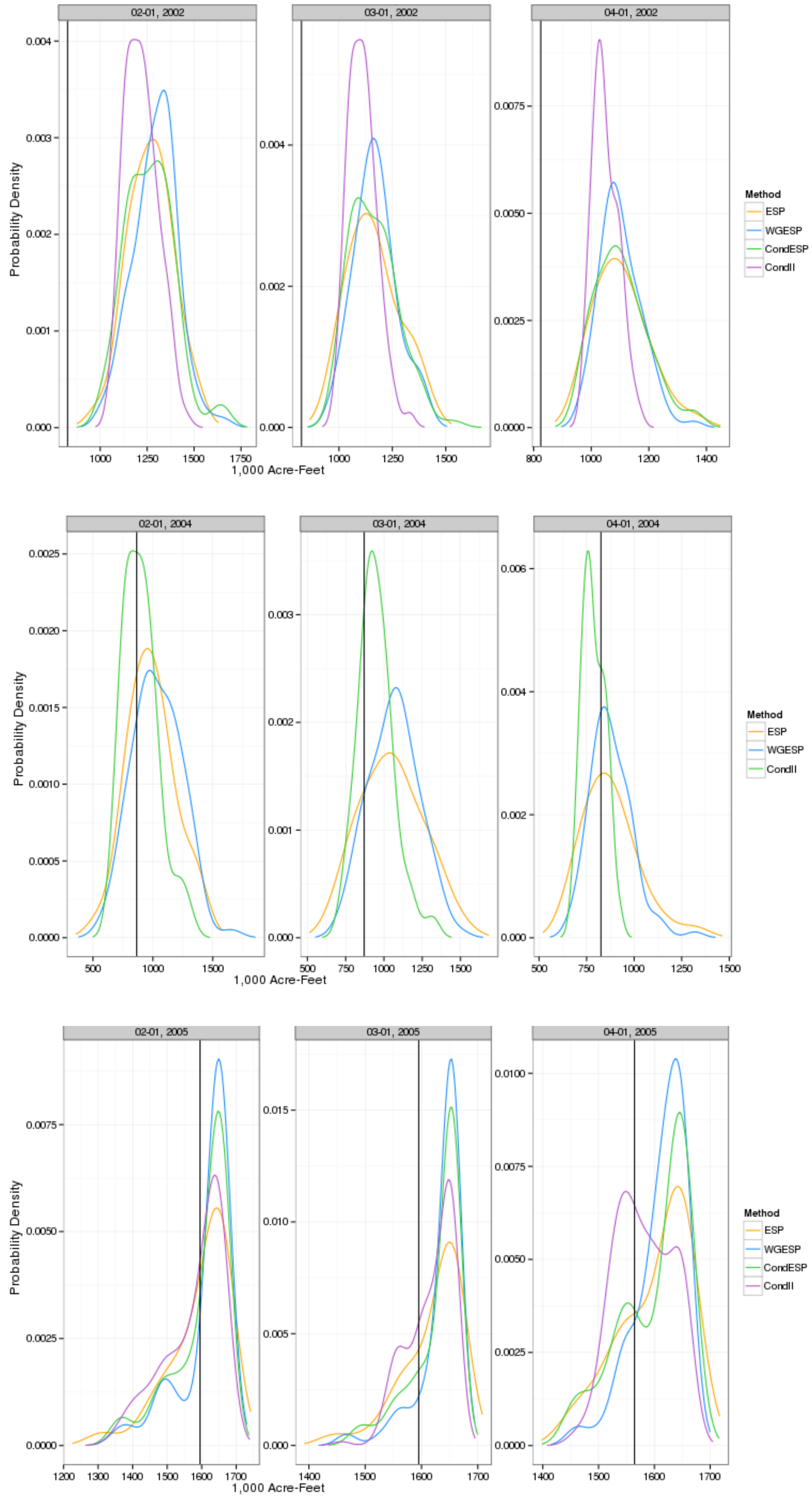


Figure 2.17 End of water year storage PDFs, top to bottom 2002, 2004, 2005.

Table 2.7 shows a final comparison of the operational metrics using the different streamflow forecasting methods by looking at the minimum thresholds. The two thresholds for the July pool elevation are the 1 MAF (converted into 6049.15 ft pool elevation) and the NIIP critical operating pool elevation at 5990 ft. The threshold for the computed available water is 114,000 acre-feet and the values are given in non-exceedance percentages because if the computed available water is below the threshold then a spring release is not made.

Table 2.7 Non-Exceedance Percentages for 3 different operational metric thresholds.

Forecast Lead Time		Performance Metric Threshold: NIIP Critical Operating Pool Elevation (5990ft)				1MAF Threshold for July Navajo Storage				Computed Available Water (114,000AF)			
			Year				Year				Year		
		Method	2002	2004	2005	**Method**	Dry	Normal	Wet	**Method**	Dry	Normal	Wet
	February	Baseline	0.0%	0.0%	0.0%	Baseline	100.0%	100.0%	0.0%	Baseline	100.0%	100.0%	0.0%
	February	ESP	0.0%	3.3%	0.0%	ESP	0.0%	56.7%	0.0%	ESP	0.0%	63.3%	0.0%
	February	WGESP	0.0%	1.1%	0.0%	WGESP	0.0%	52.2%	0.0%	WGESP	0.0%	54.4%	0.0%
	February	CondI	0.0%	-	0.0%	CondI	0.0%	-	0.0%	CondI	0.0%	-	0.0%
	February	CondII	0.0%	0.0%	0.0%	CondII	0.0%	83.3%	0.0%	CondII	0.0%	86.7%	0.0%
			Year				Year				Year		
		Method	2002	2004	2005	**Method**	Dry	Normal	Wet	**Method**	Dry	Normal	Wet
	March	Baseline	0.0%	0.0%	0.0%	Baseline	100.0%	100.0%	0.0%	Baseline	100.0%	100.0%	0.0%
	March	ESP	0.0%	0.0%	0.0%	ESP	0.0%	43.3%	0.0%	ESP	0.0%	43.3%	0.0%
	March	WGESP	0.0%	0.0%	0.0%	WGESP	0.0%	38.9%	0.0%	WGESP	0.0%	41.1%	0.0%
	March	CondI	0.0%	-	0.0%	CondI	0.0%	-	0.0%	CondI	0.0%	-	0.0%
	March	CondII	0.0%	0.0%	0.0%	CondII	0.0%	76.7%	0.0%	CondII	0.0%	80.7%	0.0%
			Year				Year				Year		
		Method	2002	2004	2005	**Method**	Dry	Normal	Wet	**Method**	Dry	Normal	Wet
	April	WGESP	0.0%	0.0%	0.0%	Baseline	100.0%	100.0%	0.0%	Baseline	100.0%	100.0%	0.0%
	April	CondI	0.0%	0.0%	0.0%	ESP	0.0%	90.0%	0.0%	ESP	10.0%	90.0%	0.0%
	April	CondII	0.0%	0.0%	0.0%	WGESP	0.0%	94.4%	0.0%	WGESP	5.6%	94.4%	0.0%
	April	Baseline	0.0%	-	0.0%	CondI	0.0%	-	0.0%	CondI	10.0%	-	0.0%
	April	ESP	0.0%	0.0%	0.0%	CondII	0.0%	100.0%	0.0%	CondII	10.7%	100.0%	0.0%

2.4.3. Operational Metrics Conditioned on Winter Precipitation Forecasts and Synthetic Spring Temperature Forecasts

The above sections used the enhanced ESP methods developed by Caraway (2012) and Chapter 1 to produce operations forecasts. In Chapter 1, another enhancement was made to the ESP method by creating synthetic spring temperature forecasts to condition the weather generator. The IRI spring temperature forecasts used in this research are fairly conservative, not straying very far from climatology. Snowmelt runoff timing is sensitive to spring temperature and sharper forecasts may produce more hydrograph effects, such as earlier or later runoff timing previously not seen in the forecasts. To test this, synthetic spring temperature forecasts were created and streamflow forecasts were generated for two years, 2002 and 2005 as described in Chapter 1.

The dry year 2002 was chosen to increase the warm spring temperature forecast from the IRI issued 40:35:25 to a warmer forecast of 60:30:10. The wet year 2005 was chosen to decrease the spring temperature forecast from a warm IRI issued 40:35:25 to a cool forecast of 10:30:60. For the dry year, a 'warmer' forecast was able to shift the streamflow timing even earlier in the season than was seen using the conservative forecast. For the wet year, using a 'cooler' forecast, the timing shifted towards later in the season. This indicated that the hydrologic models are sensitive to a sharper weather sequence.

In this chapter, we take the streamflow forecasts and run them through the MTOM and analyze the skill. The results displayed slight improvements in the operation forecasts for the dry year in the direction of the baseline value, but not much more than already displayed by the CondII in the above sections. All the results can be found in Appendix B.

2.5. Conclusions

In this research, we built an end-to-end framework beginning with global climate forecasts used by an enhanced streamflow forecasting method and ending with operational forecasts that can be used in water resource planning and management. Using the flexible stochastic weather generator, streamflow forecasts conditioned on climate forecasts of winter precipitation, spring temperature, and synthetic temperature forecasts were run through a probabilistic operations model, the MTOM, for the San Juan River Basin. The skill of the operations forecasts were analyzed using operational metrics for the basin such as water available to environmental releases, reservoir pool elevation in critical months, total summer releases for meeting downstream demands, and end of water year storage. The skill of the operations forecast generally improved for each of the four lead times when the model was forced with the streamflow forecasts conditioned on winter precipitation, CondI,. The CondI PDFs were sharper forecasts of the operations than either the ESP or WGESP. The skill of the operations forecasts using streamflow forecasts conditioned on winter precipitation and spring temperature varies from outperforming to underperforming the other methods. The spring temperature forecast for all the years was warmer than climatology. We obtained the PDF shifts towards drier conditions in the operational metrics for the dry and normal years by adding the spring temperature forecast, which helps melt the snow sooner and decreases the total runoff volume. The PDFs for the wet year were less sharp than the other methods and widen at the left tail. Both of these results show the inclusion of the spring temperature not only reducing the volume in the streamflow forecasts, but reducing other metrics in the operations model, sharply in drier years and by adding more variability in wet years. So while including the winter precipitation adds skill in the wet years, including the spring temperature adds skill in the dry years.

We have been able to show the translation of skill from streamflow forecasts to operations forecasts by the use of a probabilistic operations model, the MTOM, in reforecasts from 2002-2010. Having probabilistic forecasts gives the forecaster greater ability to produce products that can be then integrated into water resource management decisions and planning.

Future Work

The assumptions made for the reforecasts in the operations model disregards subjective changes made to the model due to demands, short-term forecasts, and current scenarios, which are necessary for real-time forecasting. We have shown that the enhanced streamflow forecasting methods produces an improvement in operational performance metrics with static operation variables. The next step would be to test the streamflow forecasting methods in real-time operation models and could begin by running the MTOM for 2010-2012 with the historical values, such as the computed available water.

This research focused on the San Juan River Basin, but the MTOM encompasses the whole of the CRB. The enhanced streamflow forecasting method and then the operations forecasting should be expanded to include the entire CRB.

Bibliography

Apipattanavis, Somkiat, Guillermo Podestá, Balaji Rajagopalan, and Richard W Katz (2007). A Semiparametric Multivariate and Multisite Weather Generator. Water Resources Research 43 (11): W11401.

Bracken, Cameron W. (2011). Seasonal to Inter-Annual Streamflow Simulation and Forecasting on the Upper Colorado River Basin and Implications for Water Resources Management. Masters thesis, University of Colorado at Boulder.

Caraway, Nina Marie (2012). Stochastic Weather Generator Based Ensemble Streamflow Forecasting. Masters thesis, University of Colorado at Boulder.

Caraway, Nina M.,…., (2013). "Multisite Stochastic Weather Generation Using Cluster Analysis and K-nearest neighbor Time Series Resampling." Journal of Hydrology

Day, Gerald N. (1985). Extended Streamflow Forecasting Using NWSRFS. Journal of Water Resources Planning and Management 111 (2) (April): 157–170. ASCE.

Fulp, Terry (2005). "How Low Can It Go ?" Southwest Hydrology: 16–28.

Grantz, K. (2011, March 21{22). Reclamation mid-term operational modeling. In Seasonal to Year-Two Colorado River Streamow Prediction Workshop, Salt Lake City, Utah. Colorado Basin River Forecast Center.

Hartmann, Holly C, Roger Bales, and Soroosh Sorooshian (2002). Weather , Climate , and Hydrologic Forecasting for the US Southwest : a Survey. Climate Research 21: 239–258.

Miller, W Paul, R Alan Butler, S M Asce, Thomas Piechota, M Asce, James Prairie, Katrina Grantz, and Gina Derosa. (2012). Water Management Decisions Using Multiple Hydrologic Models Within the San Juan River Basin Under Changing Climate Conditions. Journal of Water Resources Planning and Management (September/October): 412–420.

New Mexico Energy, Minerals, and Natural Resources Department. (2004). New Mexico's Natural Resources 2003/2004. Annual Report http://www.emnrd.state.nm.us/MAIN/documents/SER1_electricity.pdf.

Rajagopalan, B. and U. Lall (1999). A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resources Research 35(10), 3089-3101.

USBR (2006). Record of Decision for the Navajo Reservoir Operations, Navajo Unit - San Juan River New Mexico, Colorado, Utah Final Environmental Impact Statement.

Werner, Kevin (2011). NOAA ' s Colorado Basin River Forecast Center : ' Climate Services on the Colorado River : Capabilities , Gaps , and Chasms '. In Climate Test Bed Joint Seminar Serie. Camp Springs, Maryland: U.S. National Oceanic and Atmospheric Administration.

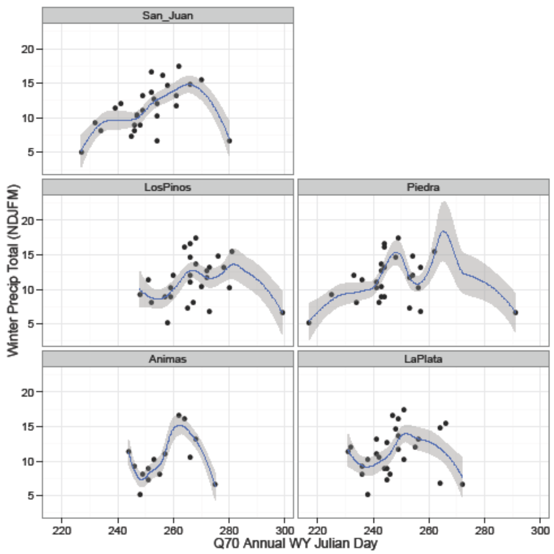
Wilks, D. S. (1995). Statistical Methods in the Atmospheric Sciences. Academic Press, New York.

Yates, D., S. Gangopadhyay, B. Rajagopalan, and K. Strzepek (2003). A technique for generating regional climate scenarios using a nearest-neighbor algorithm. Water Resources Research 39(7), 1199.

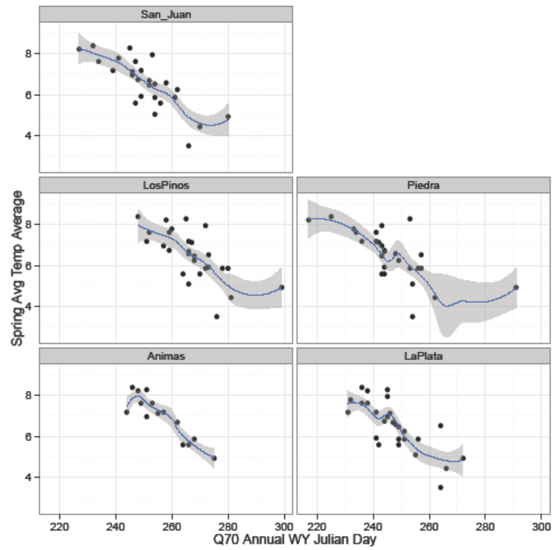
Zagona, Edith A., T.J. Fulp, R. Shane, T. Magee, H.M. Goranflo (2001). Riverware: A Generalized Tool For Complex Reservoir System Modeling. Journal of the American Water Resources Association 37(4), 913-929.

Appendix A

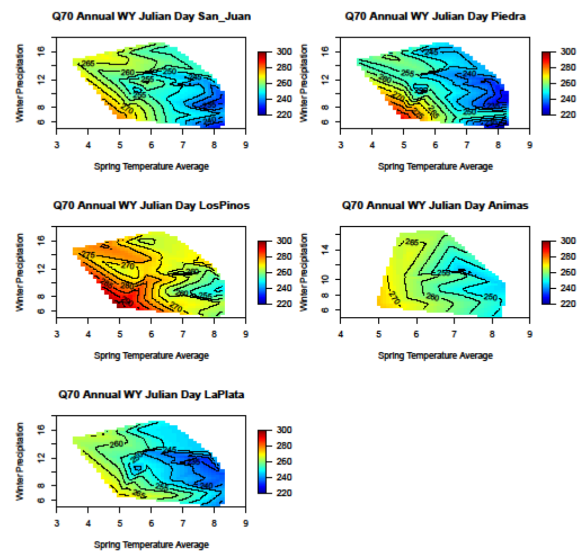
Additional Scatterplot Figures



a) Winter Precipitation NDJFM

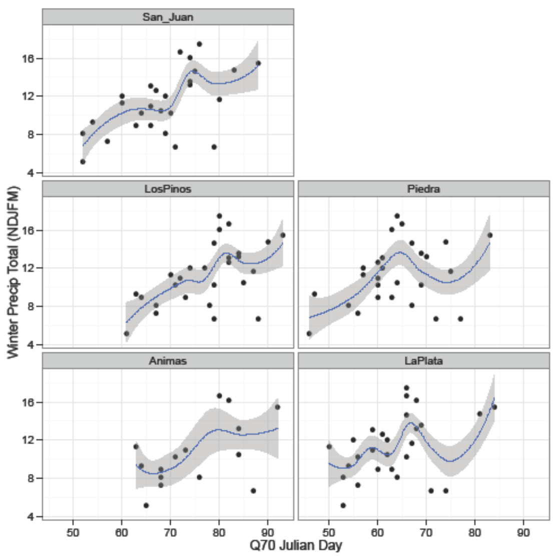


b) Spring Average Temperature AM

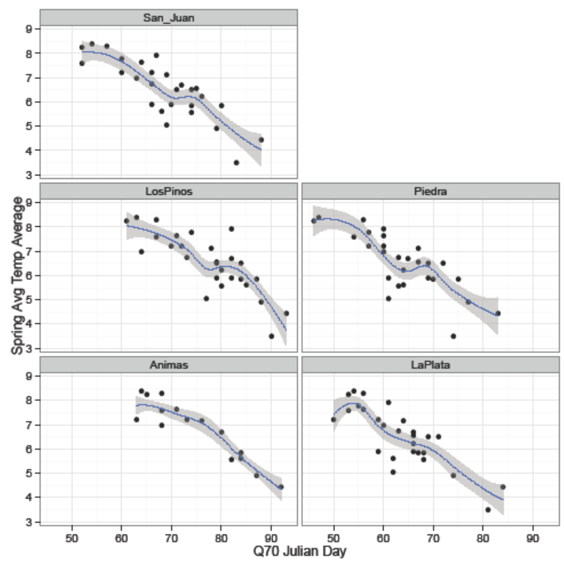


c) Winter Precipitation NDJFM and Spring Average Temperature AM

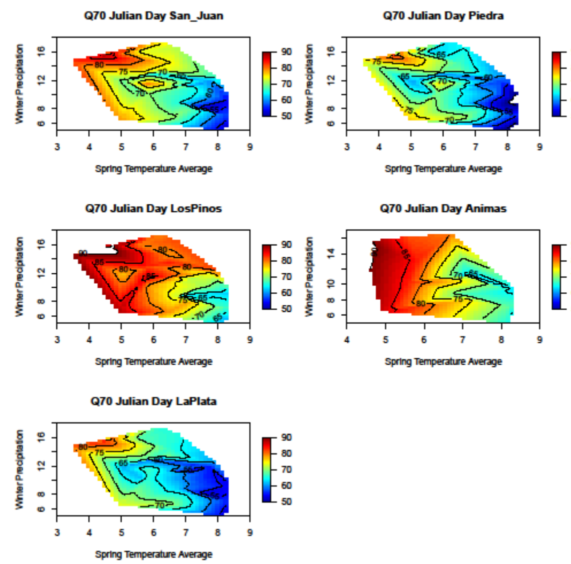
Figure A.1 Annual WY Historical Q50



a) Winter Precipitation NDJFM

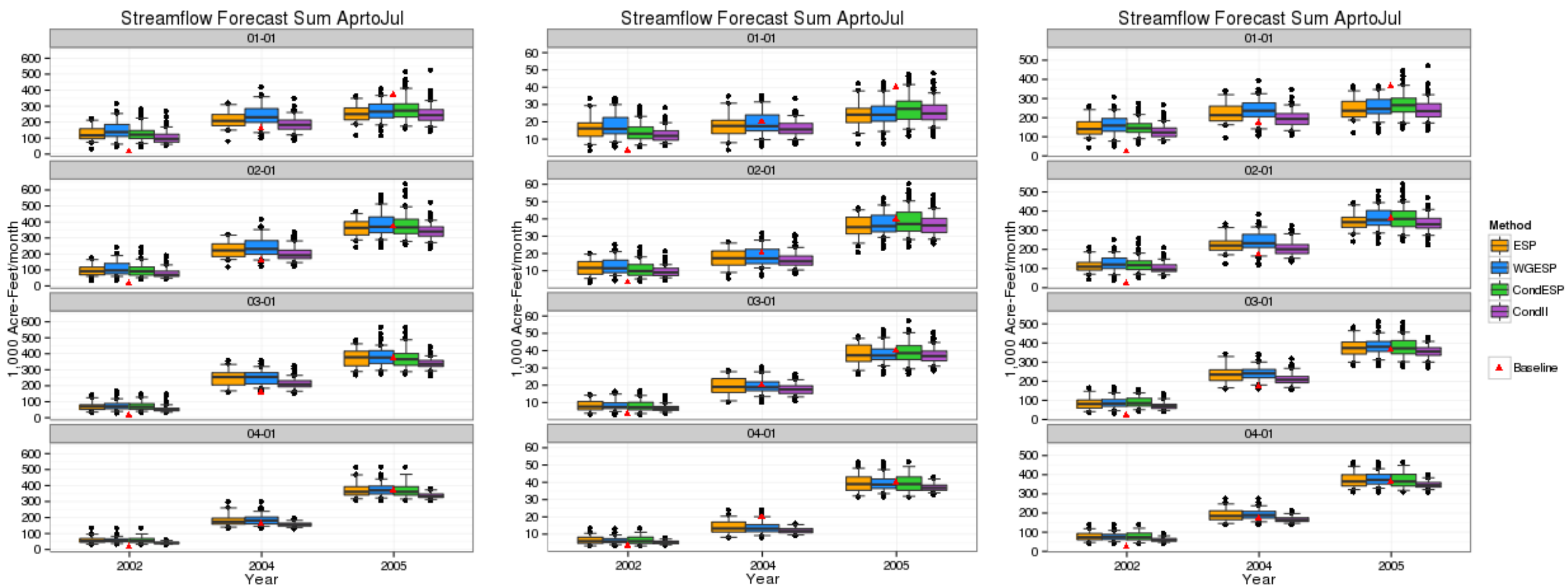


b) Spring Average Temperature AM



c) Winter Precipitation NDJFM and Spring Average Temperature AM

Figure A.2 Seasonal (AMJJ) WY Historical Q50



a) PIDC b) LPHC2 c) PSPC

Figure A.3 Additional Total Volume Flow for Gages PIDC2, LPHC2, PSPC2 using winter precipitation and spring temperature forecasts.

Appendix B

Chapter 2 Supporting Materials

B.1 Winter Precipitation Forecast conditioned Streamflow Forecasts Figures for 2002-2010. (Extension of Caraway 2012 work)

Caraway (2012) conditioned the weather generator with winter precipitation for two years, 2005 and 2006. For this research, we extended the conditional runs to 2002-2010 and Table B.1 shows the winter precipitation forecasts used to do these runs.

B.1.1 Seasonal Climate Forecasts

Forecasts for the San Juan River Basin were visually obtained from the forecast maps around the U.S. Four Corners location. For winter precipitation forecasts, we combine the forecasts issued in December and January for January-February-March (JFM) and February-March-April (FMA), respectively, into one forecast to use as input to the SWG. Verification of the forecasts was done by visually inspecting the IRI verification maps. Figure B.1 shows an example of forecast.

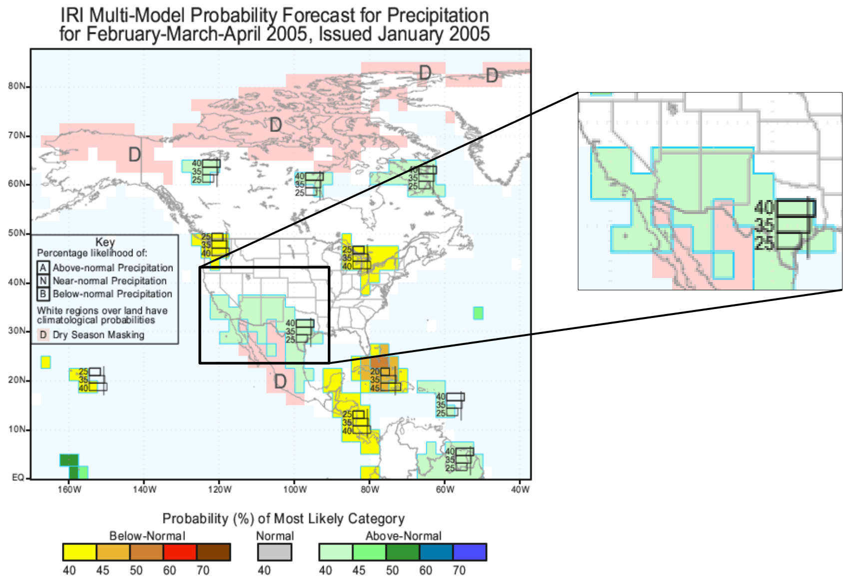


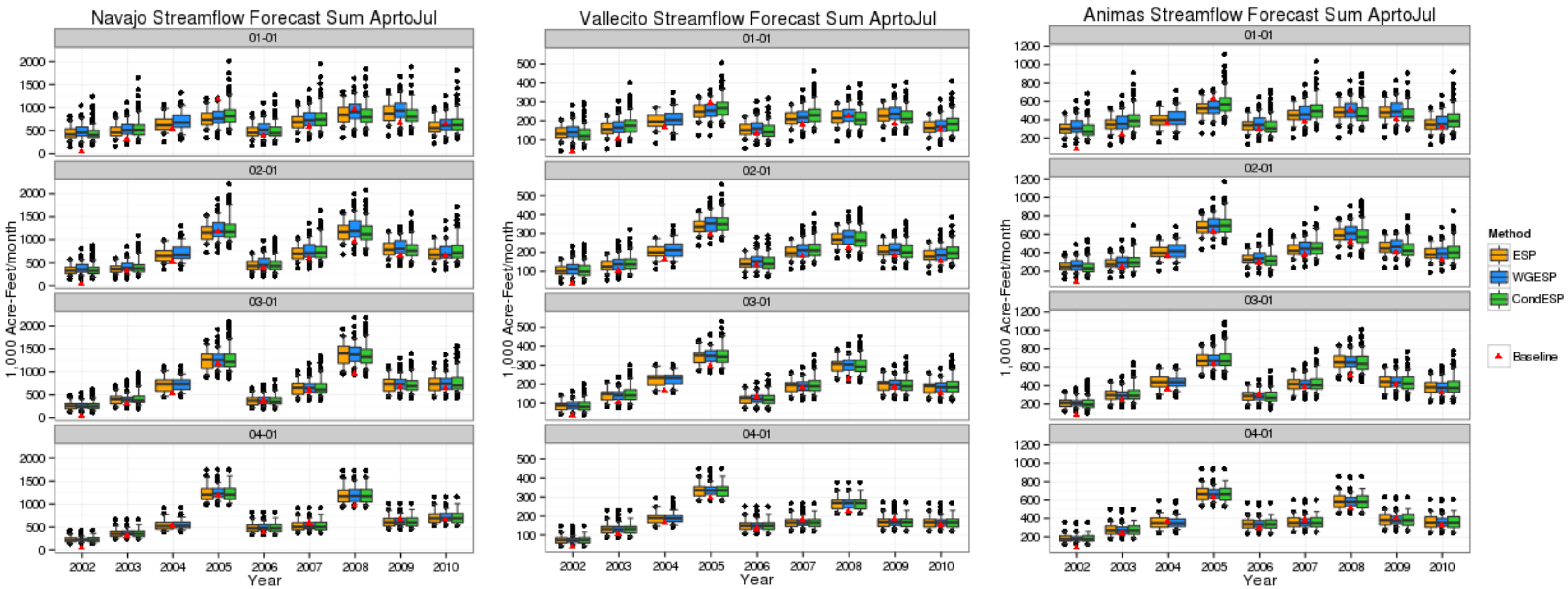
Figure B.1 IRI precipitation forecast issued in January 2005 for the FMA months in North America.

Table B.1 - IRI Seasonal Forecasts for 2002-2010

Winter Precipitation Forecasts					
Year	A	N	B	Forecast	Actual
2002	25	35	40	Dry	Dry
2003	40	35	25	Wet	Wet
2004	33	33	33	Normal	Normal
2005	40	35	25	Wet	Wet
2006	25	35	40	Dry	Normal
2007	40	35	25	Wet	Normal
2008	25	35	40	Dry	Dry
2009	25	35	40	Dry	Dry
2010	40	35	25	Wet	Wet

B.1.2 Streamflow Forecasts

Streamflow forecasts were generated for the MTOM's three input gage locations: at above Navajo Reservoir (NVRN5), on Los Pinos above Vallecito Reservoir (VCRC2), and on the Animas at Durango (DRGC2).



.a) b) c)

Figure B.2 Boxplots of CHPS Streamflow Forecasts for a) ESP, b) WGESP, and c) CondESP for each year from 2002-2010. CondESP means the SWG was conditioned using the winter precipitation forecast.

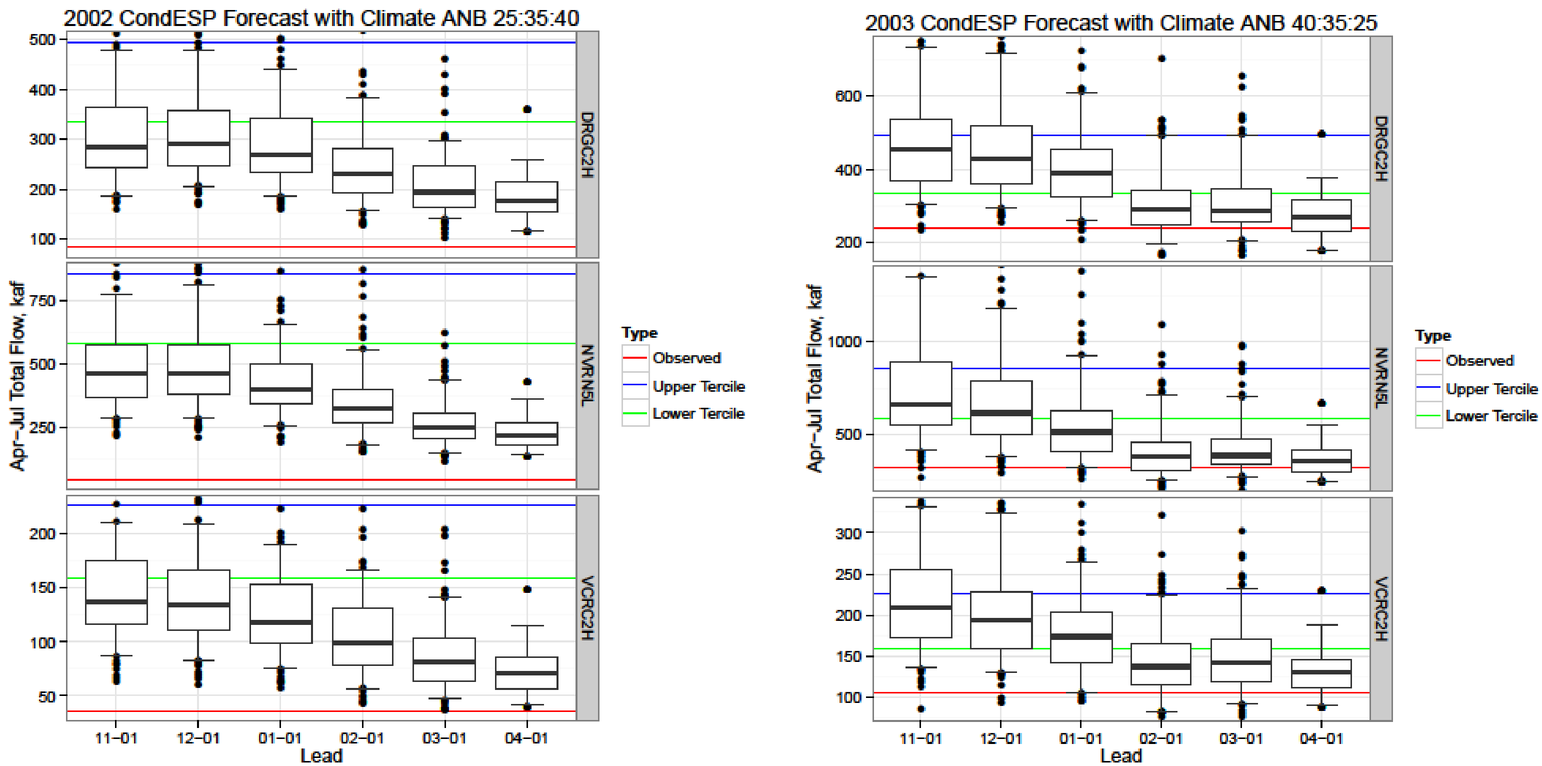


Figure B.3 Boxplots of Seasonal Volume Totals for the CondESP streamflow forecasts for 2002 and 2003. The observed value for each year is the red line, while the climatological upper and lower terciles are shown in blue and green, respectively.

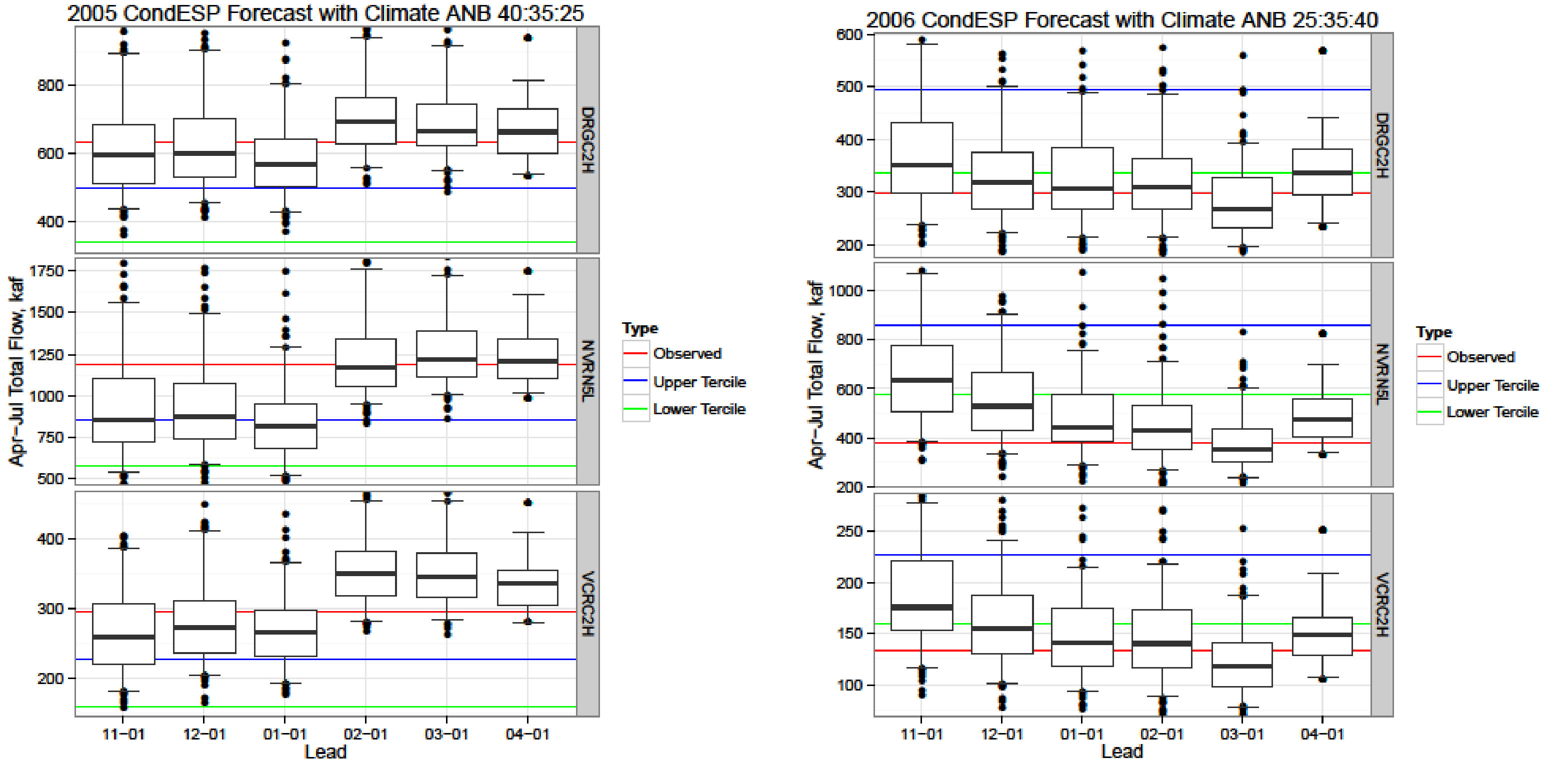


Figure B.4 Boxplots of Seasonal Volume Totals for the CondESP streamflow forecasts for 2005 and 2006. The observed value for each year is the red line, while the climatological upper and lower terciles are shown in blue and green, respectively.

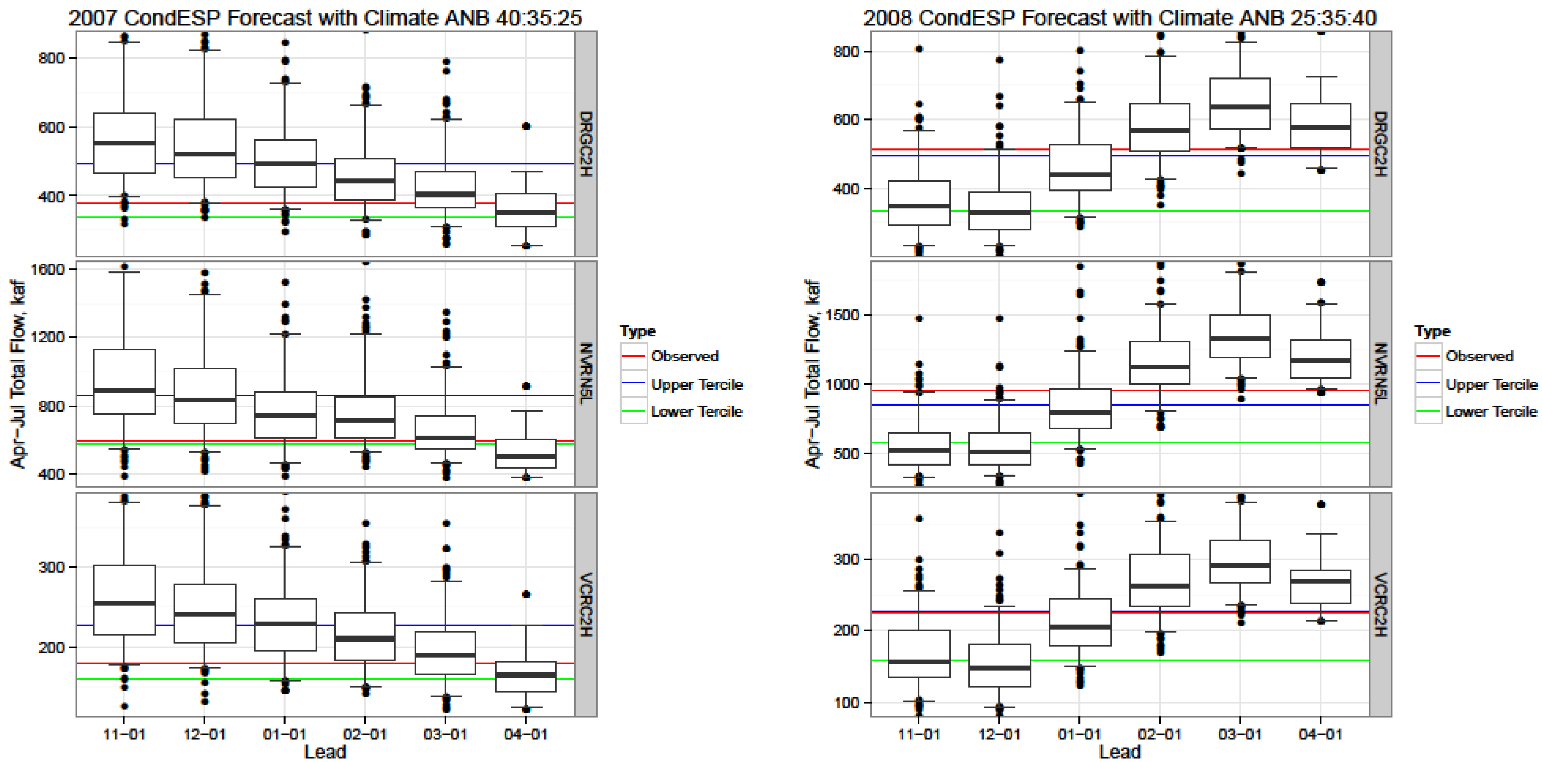


Figure B.5 Boxplots of Seasonal Volume Totals for the CondESP streamflow forecasts for 2007 and 2008. The observed value for each year is the red line, while the climatological upper and lower terciles are shown in blue and green, respectively.

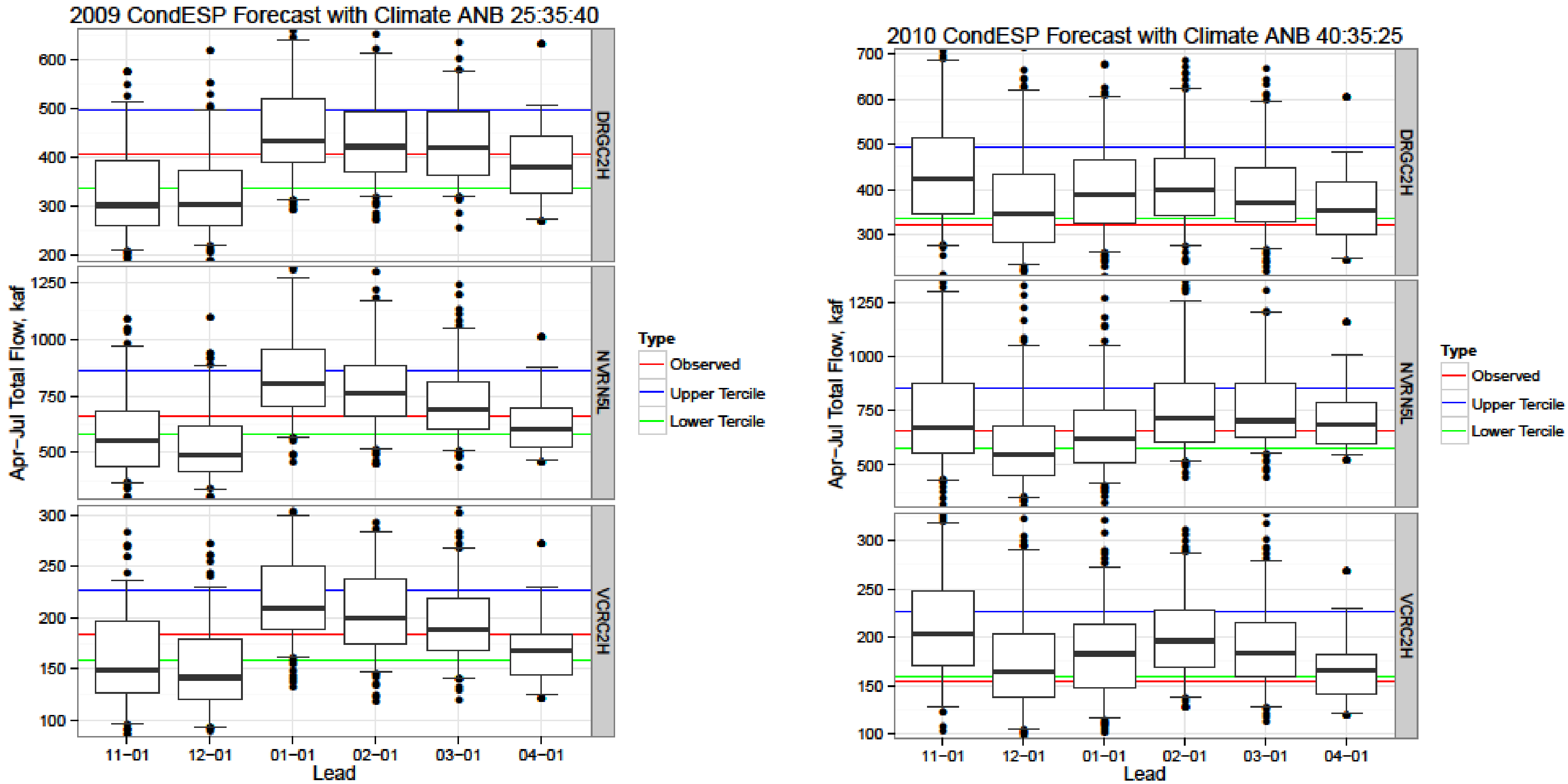


Figure B.6 Boxplots of Seasonal Volume Totals for the CondESP streamflow forecasts for 2009 and 2010. The observed value for each year is the red line, while the climatological upper and lower terciles are shown in blue and green, respectively.

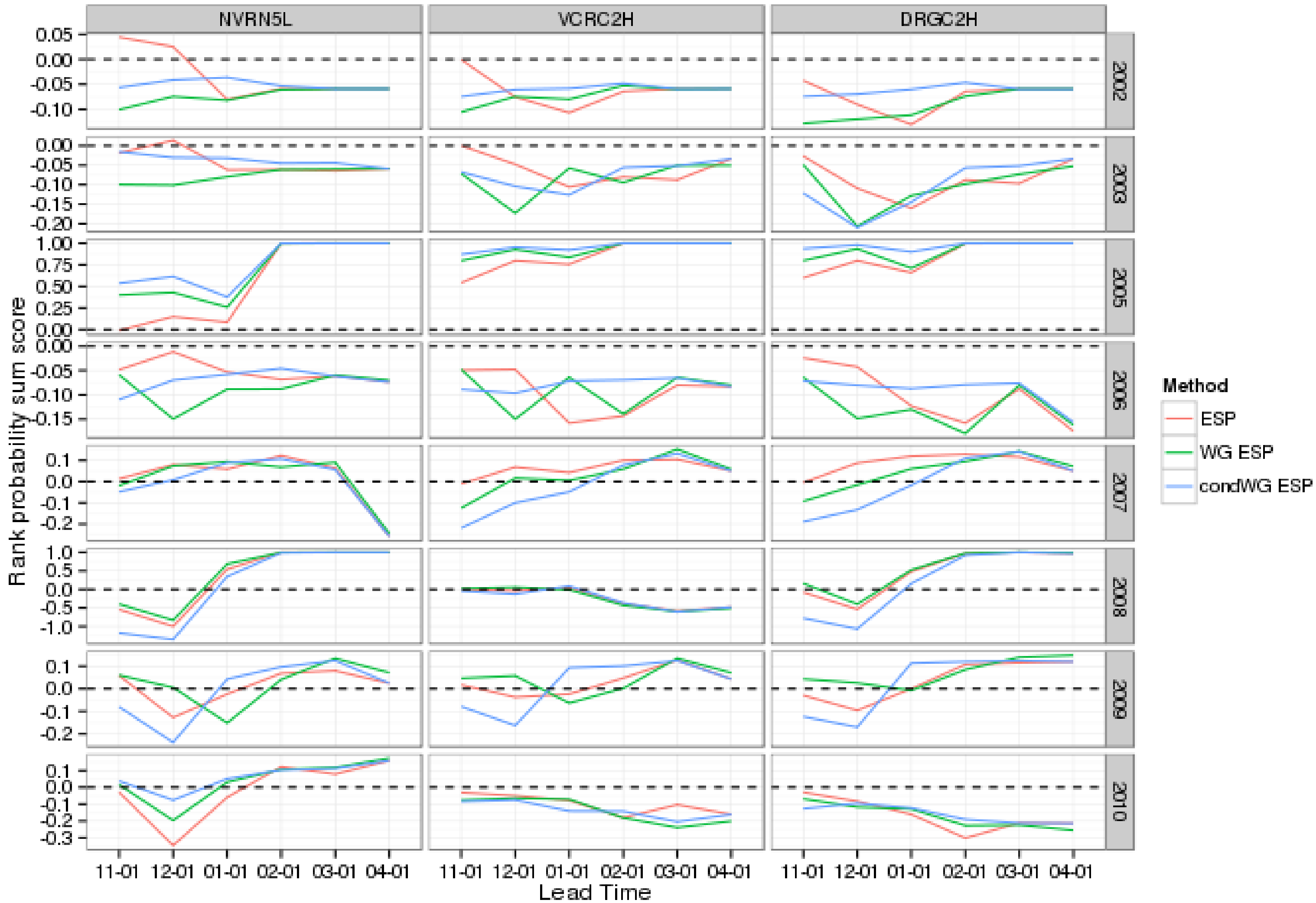
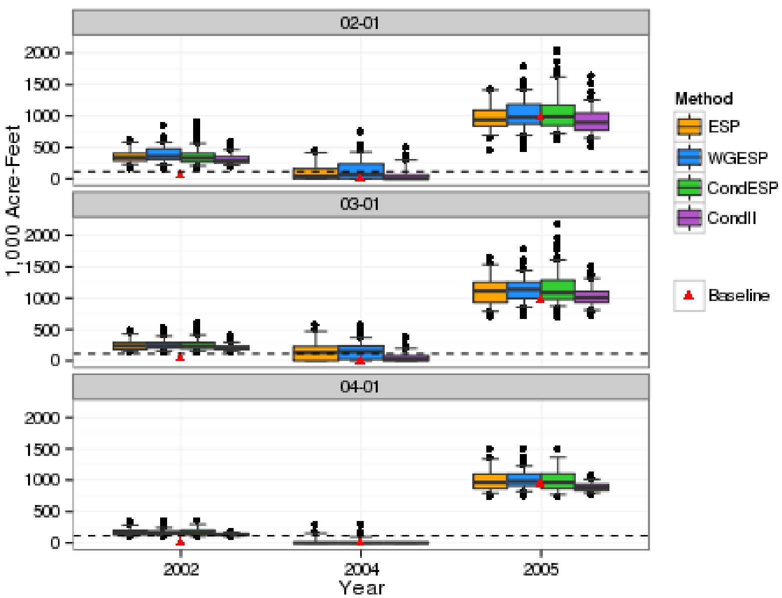
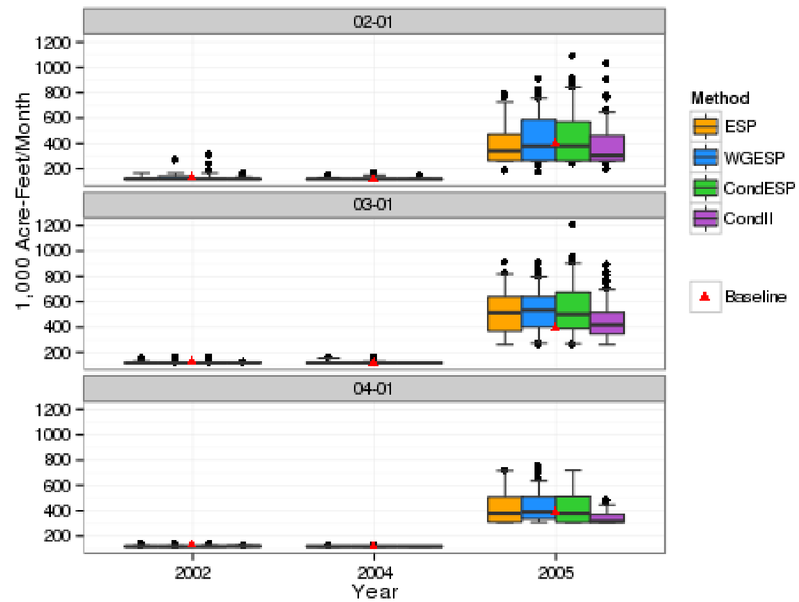


Figure B.7 RPSS values for each gage at each lead time for each year from 2002-2010. CondESP streamflow forecasting method performs better than the other methods for most of the years at early lead times.

B.2 Operational Performance Metrics using Conditioned Streamflow Forecasts (CondII) using Winter Precipitation Forecasts and Spring Temperature Forecasts



a) Computed Available Water: The dashed line is the 114,000 acre-feet threshold that if exceeded will allow for spring release from Navajo.



b) Seasonal Release Volume (April-July)

Figure B.8 Operational metrics showing each year from 2002 to 2010

B.3 Operational Performance Metrics using Conditioned Streamflow Forecasts (CondIIS) using Winter Precipitation Forecasts and Synthetic Spring Temperature Forecasts

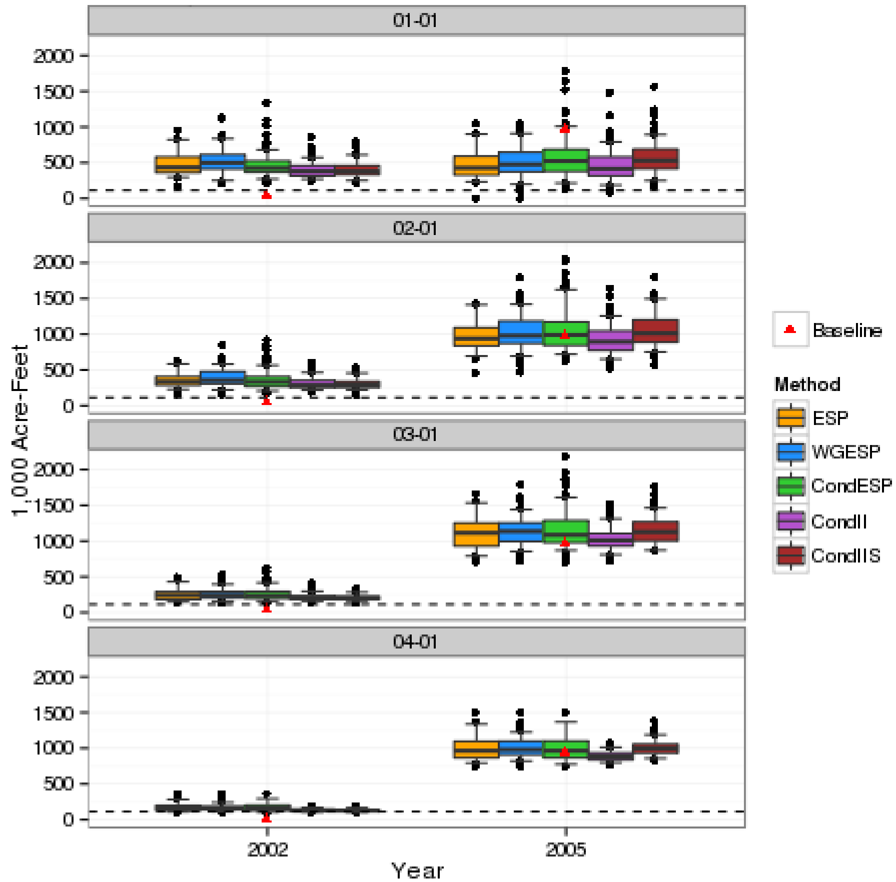


Figure B.9 Computed Available Water for the dry (2002) and wet (2005) years.

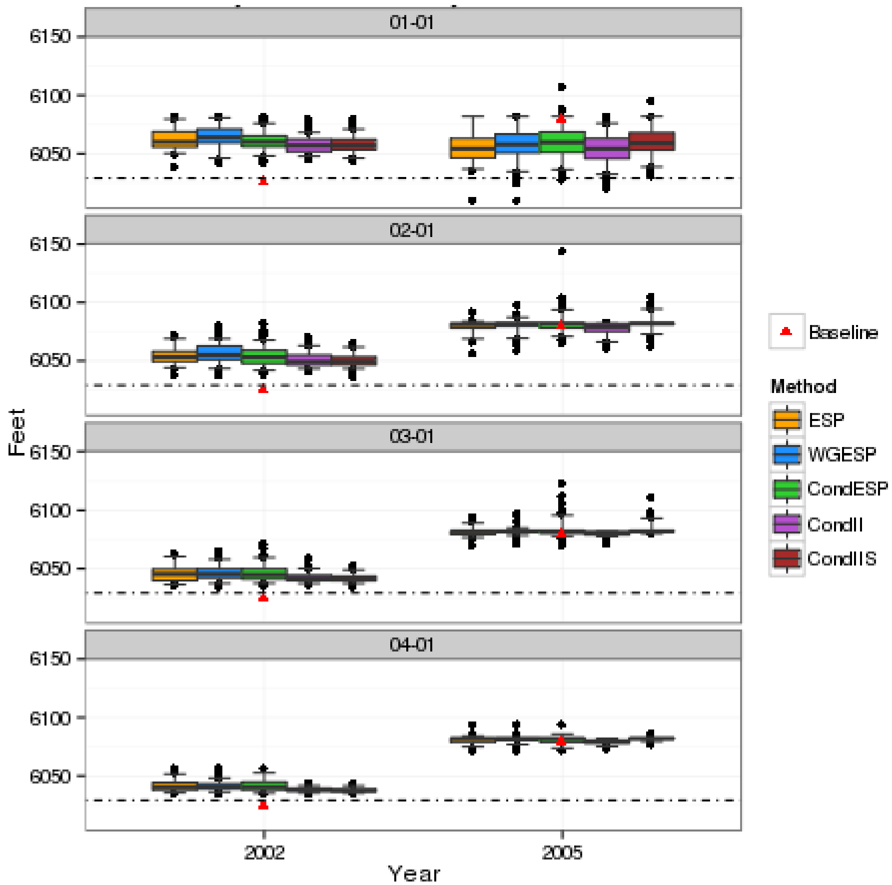


Figure B.10 July pool elevation for the dry (2002) and wet (2005) years.

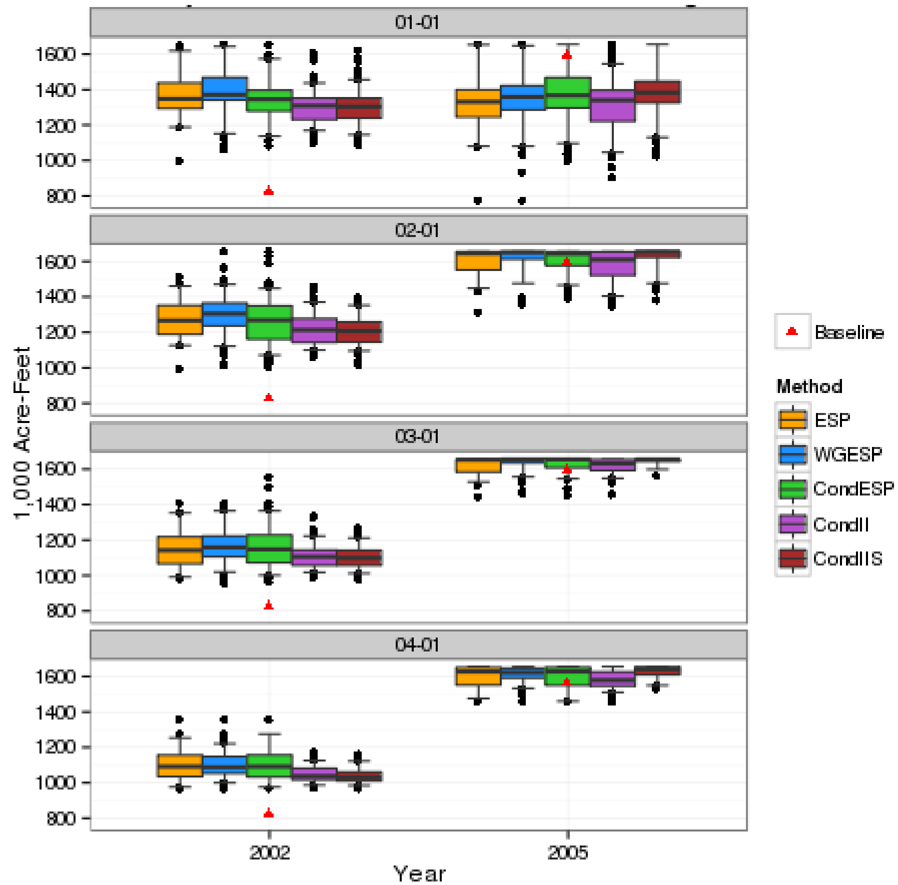


Figure B.11 End of Water Year Storage for the dry (2002) and wet (2005) years.

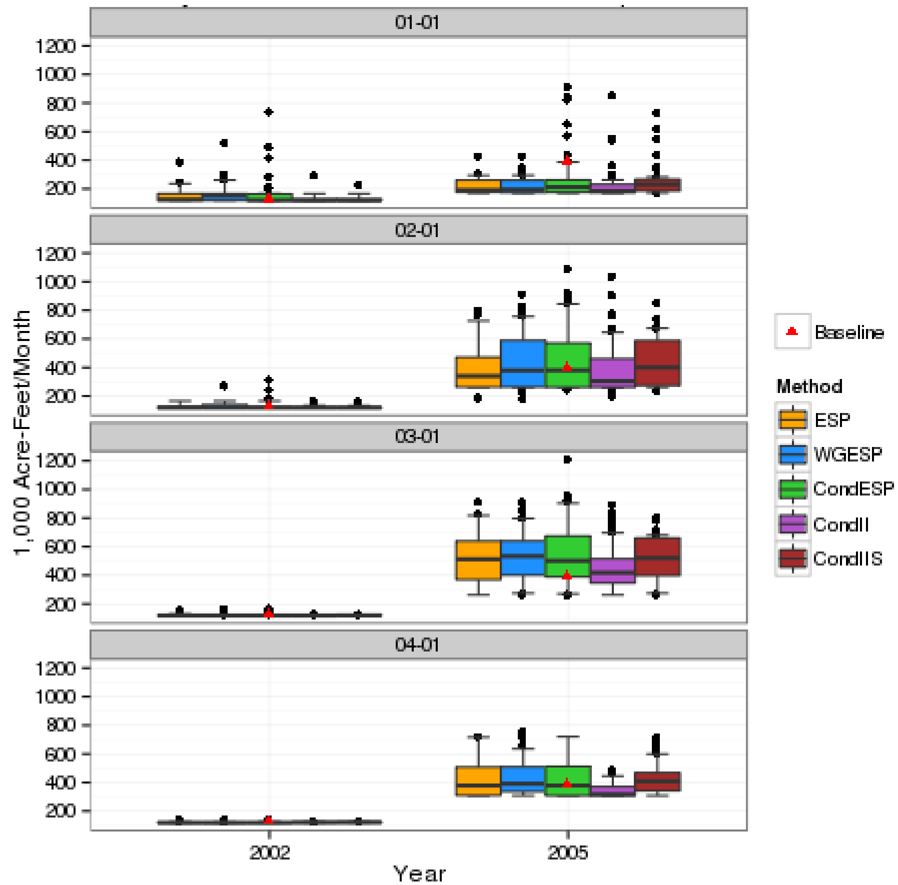


Figure B.12 Seasonal Release Volume (April-July) for the dry (2002) and wet (2005) years.