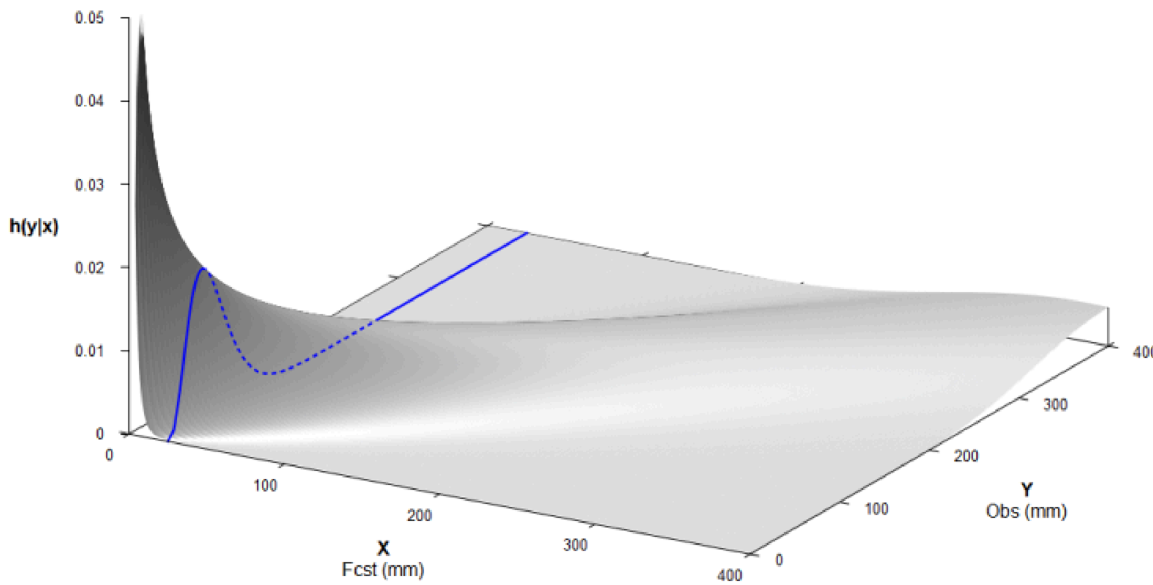
Ensemble Forecasting with the Hydrologic Ensemble Forecast Service (HEFS)

As Implemented at the
California-Nevada River Forecasting Center



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1 Introduction

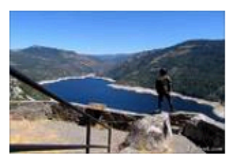
The purpose of this document is to help clarify how National Weather Service (NWS) Hydrologic Ensemble Forecasts are generated at the CNRFC. It is hoped that an increased understanding of the fundamentals, process, and limitations will lead toward (1) more informed and appropriate applications by users and (2) ideas for improvements and refinements by researchers and collaborators.

Hydrologic forecasts provide value to a variety of sectors including flood management, reservoir management, water resources management, hydropower, navigation, and recreation. Historically, hydrologic forecasts have been single-value (deterministic) and of short duration (a day or two) given the uncertainty in the weather forecast. Improvements in weather forecast skill has led to longer forecast durations (e.g. 5 days) in some locations. Probabilistic forecasts (usually regression based) have been restricted to seasonal volume forecasts associated with snowmelt (e.g. April-July volume).

Over the past two decades it has become clear that water resource and emergency managers need more than a single-value forecast. They are managing the risks of their actions (or inactions) and the associated costs. Risk is the product of probability and consequence. They understand the consequences. They need the probability. They need probabilistic hydrologic forecasts for short, medium, and long-range decision making.

- Short-range (hours to days)
  - Watch and warning program
  - Local emergency management activities
  - Reservoir and flood control system management

- Medium-range (days to weeks)
  - Reservoir management
  - Local emergency management preparedness
  - Snowmelt runoff management



- Long-range (weeks to months)
  - Water supply planning
  - Reservoir management

Figure 1 - Forecast use by temporal range

Probabilistic forecasts can be generated in multiple ways. The most common are through error propagation and through ensemble techniques. For reasons associated with feasibility and application, ensemble techniques have been the focus of the National Weather Service's development efforts for some time. Progress has been attributable to a growing acceptance that uncertainty is something that can be leveraged to make more informed decisions (National Research Council of the National Academies 2006) and substantial community support as evidenced through the success of the Hydrological Ensemble Prediction Experiment (Schaake et al. (2007), www.hepex.org).

Sources of uncertainty which contribute to uncertainty in the streamflow forecast include: meteorology, hydrology, and flow regulation. Assuming that the (1) hydrologic model is well-conceived and well-calibrated, (2) observations used to drive the model are representative and quality controlled, (3) the individual running the model is well-trained and experienced, and (4) observed and near-term regulated flows are well-defined, then the majority of uncertainty in CNRFC streamflow forecasts typically arises from the uncertainty in future weather (precipitation and air temperature forecasts).

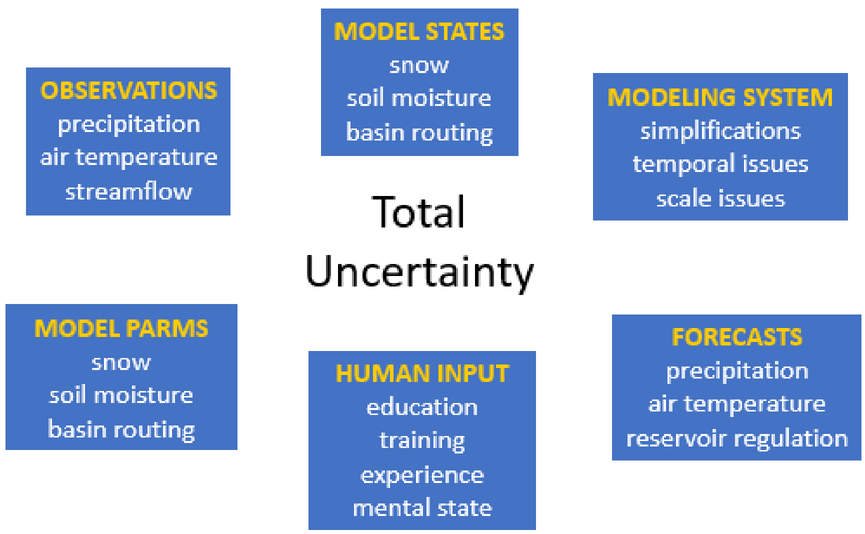


Figure 2 - Sources of streamflow forecast uncertainty

The NWS effort to develop a methodology and toolset capable of generating reliable short, medium, and long-range hydrologic ensembles began in about 2001. Prototype efforts took nearly 10 years to make their way into operations. Today, the CNRFC uses the Hydrologic Ensemble Forecast Service (HEFS) to issue forecasts daily at 353 locations (**Figure 3**). HEFS forecasts are operationally relied upon by water, emergency, environmental, hydropower, and recreation managers to manage risk and improve outcomes.

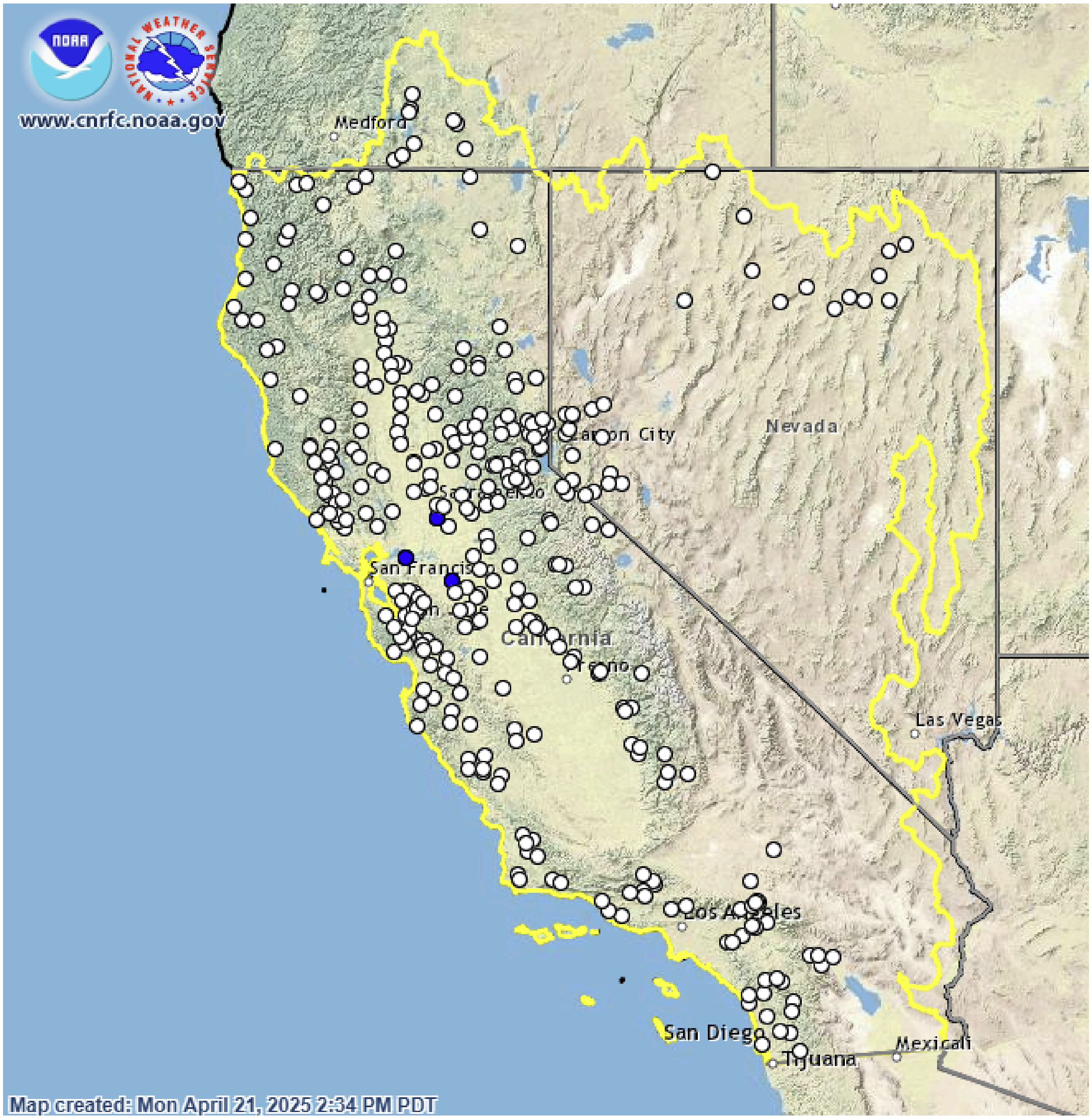


Figure 3 - CNRFC HEFS Forecast Locations

2 Summary points

The CNRFC uses two methods for developing meteorological ensemble forcings for application to hydrologic models to obtain ensemble runoff hydrographs reflecting meteorologic uncertainty. With the first method the statistical post-processing capability of HEFS is used to construct ensemble forcings for forecast days 1 - 14. This method leverages information from the record of past forecasts and observations to leverage conditional probability distributions operationally. With the second method, the CNRFC adopts raw climatology for ensemble forcings for forecast days 15 - 365. Important aspects of these methods as implemented at the CNRFC, and characteristics of the resulting streamflow ensemble forecast, are listed below.

- As of this writing (June, 2025), the number of ensemble members is expected to increase from 43 to 44 in Fall 2025.

- The CNRFC ensemble streamflow forecasts, which result from applying the ensemble forecasts of precipitation and surface air temperature to the hydrologic models, reflect meteorological uncertainty only. Hydrologic uncertainty is not accounted for.

- Work is underway at the CNRFC to configure the HEFS to also generate an ensemble forecast of freezing level for forecast days 1 - 10 (see **Table 6** for context).

- The precipitation and surface air temperature ensembles generated by the HEFS are bias-reduced and exhibit consistent variability with respect to the record of forecasts. Furthermore, the HEFS employs a method known as the Schaake Shuffle (Clark et al., 2004) to ensure that the ensembles are temporally and spatially consistent across locations.

- Operational HEFS consists of two primary components: the Meteorologic Ensemble Forecast Processor (MEFP), and 2) the Ensemble Postprocessor (EnsPost). CNRFC uses the MEFP, but does not use the EnsPost. The EnsPost is designed to modify streamflow forecast ensemble members to minimize bias and incorporate uncertainty attributed to hydrologic modeling. The CNRFC plans to test EnsPost pending completion of planned improvements. A timeline for testing and implementation has not been established.

3 Components of the HEFS

The HEFS has two primary components: 1) MEFP, and 2) the EnsPost. Each of these also has a parameter estimator (PE) component: the MEFPPE and EnsPostPE. These components and their position in the forecast sequence are shown in **Figure 4**. CNRFC does not use EnsPostPE or EnsPost. During HEFS configuration, CNRFC uses MEFPPE to compute historically-based statistical parameters. During forecast operations, CNRFC uses MEFP to construct ensemble forcings for forecast days 1 - 14 of precipitation and air temperature and forecast days 1 - 10 of freezing level (see **Table 5**).

Before MEFP can be run operationally, the MEFPPE is used to extract values from historical time series of past forecasts and their corresponding observations.These values are extracted from a pre-defined set of time-windows (canonical events) relative to the time of forecast. Values of mean and standard deviation are computed for the resulting samples of past forecasts and observations, and the correlation between the two is also computed. These statistical parameters, computed at every basin zone, and for every canonical event, provide the foundation from which the MEFP generates ensemble forcings during operations. Outside of HEFS, ensemble forcings are extended through forecast day 365 using raw climatology. The ensemble forcings are then applied to the hydrologic models to produce ensemble streamflow forecasts. As only meteorologic uncertainty is reflected by the ensemble forcings, the resulting ensemble streamflow forecasts do not reflect hydrologic uncertainty.

Though not presently used at the CNRFC, the EnsPost is designed to be executed once the streamflow ensemble forecast has been created by the MEFP. The EnsPost is designed to adjust streamflow ensembles to reduce bias and incorporate uncertainty (spread) attributed to hydrologic initial states, parameters, and modeled processes. The resulting streamflow ensembles would then reflect minimal bias (both meteorological and hydrologic) and exhibit historically consistent spread reflecting meteorologic and hydrologic uncertainty. Note that the CNRFC plans on testing the EnsPostPE and EnsPost components in the future, once further refinements have been made.

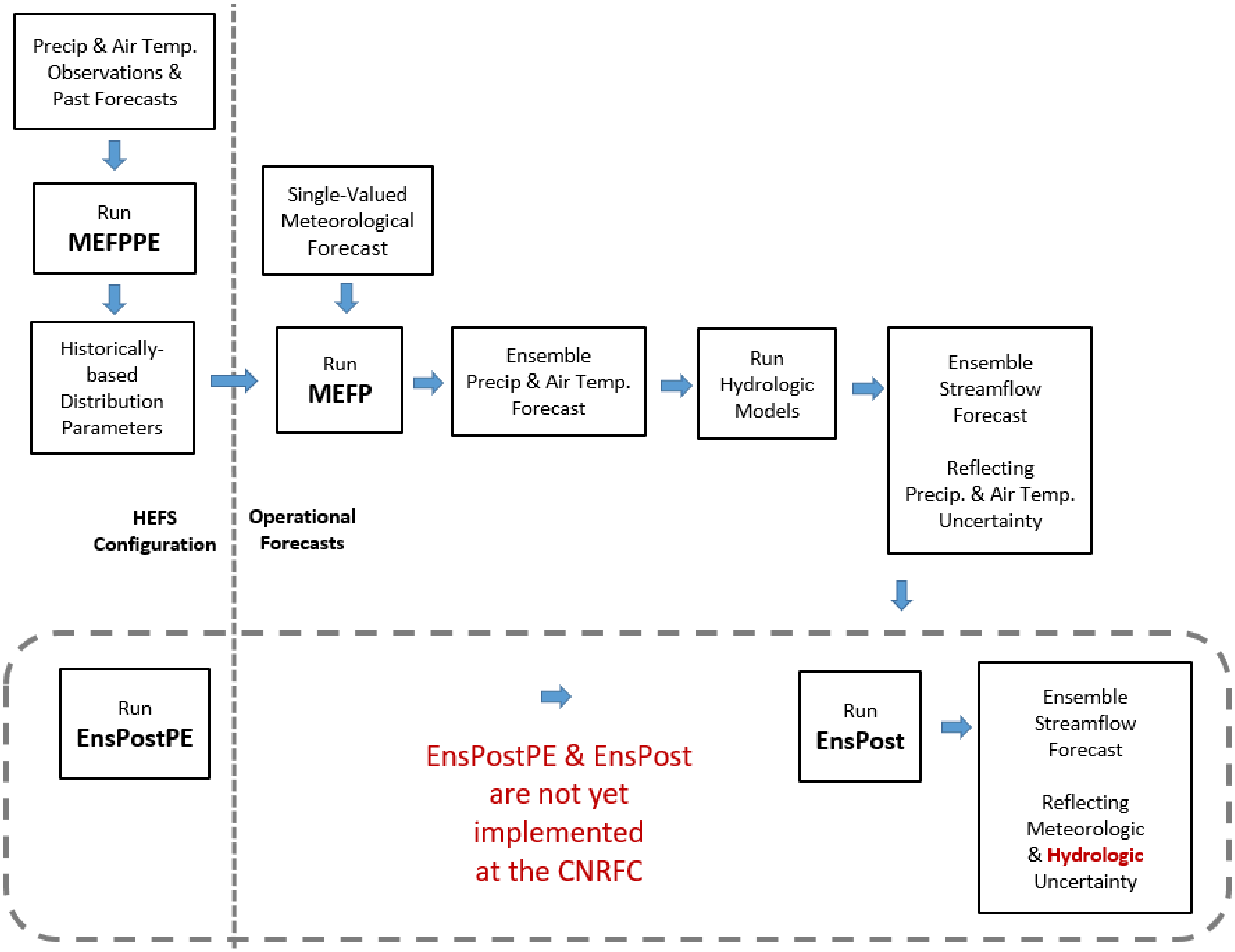


Figure 4 - Components of the HEFS as implemented at the CNRFC (June 2025)

4 Hydrologic models

Description

CNRFC hydrologic models are configured to generate simulated streamflow time series at gaged subbasin outlets. These models represent the physical processes of snow accumulation and ablation, soil moisture storage, and fast and slow runoff. For each area modeled, the two primary modeling components are SNOW-17 (Anderson, 1976) and SAC-SMA (Burnash, 1973). Both models share the following characteristics:

- A conceptual model representing physical processes.
- Model parameters derived from calibration to historical record and guidance.
- Model time step is 6-hours.
- One-dimensional model, that computes area-average depth (not volume) time series.
- Post-model, unit hydrograph applied to convert simulated depth series to1-hour (most locations, 6-hour at some) flow series.
- Operationally used for continuous simulation, with model states being saved after one forecast to provide initial states for the next.

Meteorologic forcings are the collection of continuous 6-hour time series of precipitation, air temperature, and freezing level required that are required inputs to the hydrologic models. Data types of these three quantities are given in **Table 1**. Air temperature is the value two meters above the ground surface.

Table 1 - Forcings data types

Forcing	Data type	Units
Precipitation	Incremental	mm
Air Temperature	Instantaneous	deg C
Freezing level	Instantaneous	m

Each 6-hour forcing time series is a series of grids, with each grid spanning all of the modeled CNRFC basins. The grids are produced in Hydrologic Rainfall Analysis Project (HRAP) format. Each grid cell is nominally about 4.7 km x 4.7 km, but varies gradually with changes in latitude and longitude. **Figure 5** shows an example of the HRAP grid mesh overlaying CNRFC subbasin boundaries.

The freezing elevation forcing is converted into a rain-snow elevation series for use in SNOW-17. SNOW-17 computes snow accumulation and ablation. It functions as a temperature-index model during non-rain conditions, and as a simple energy budget model during rain on snow events. Two key outputs are the snow water equivalent time (SWE) time series, and the rain plus snow time series. During winter months, the hydrologist may adjust how much SWE is in the model based on observations. The rain plus snow series is the 6-hour area-average series of rain depth (on bare ground) plus melt depth (on snow-covered area), with each component weighted by its portion of total area. This series is provided as input to the SAC-SMA.

SAC-SMA is a soil moisture accounting model. It simulates water movement within the soil as a system of tanks, and flow resistances between those tanks. There are two soil zones. In each zone the upper most tank represents tension water while the other tanks represent free water. The “upper zone” consists of three tanks. These tanks accumulate rain plus melt, allow percolation to the “lower zone”, and are the source of three runoff components: direct runoff, surface runoff, and interflow. Percolation between the two zones is computed using a highly nonlinear equation which uses as inputs the upper zone free water tank contents and lower zone tension water tank contents as inputs. Parameters of the equation are determined by calibration. Also in the lower zone are two free water tanks. One contributes primary (long-term) baseflow, and the other contributes secondary (short-term) baseflow, to runoff. All runoff components are added together to obtain the runoff depth time series for the area.

Basin zone runoff

The CNRFC delineates each subbasin area contributing to each streamgage location. In order to improve modeling of subbasins having a large change in elevation, each subbasin is divided into elevation zones, or “basin zones”, using the 5,000 and 8,000 foot contours. As a result each CNRFC subbasin consists of 1, 2, or 3 basin zones. An example of the delineation of subbasins and basin zones is shown in **Figure 5**. A unique hydrologic model (SNOW-17 and SAC-SMA) is developed for each basin zone, with unique the forcings of precipitation and air temperature for each basin zone. For the freezing level, the highest basin zone forcing is adopted for all basin zones in the subbasin. For subbasins having more than one basin zone, basin zones improve the modeling of snow accumulation and ablation processes, and can also improve modeling of soil moisture.

Subbasin runoff

The simulated runoff depth series from each elevation zone in a subbasin are combined to give the total runoff depth series for the subbasin. This series is then transformed by unit hydrograph into the runoff hydrograph for the total subbasin area. At this point, depending on the specific basin in question, the hydrograph may be routed downstream using the Lag K hydrologic routing method, and channel losses (or gains) determined through calibration may be included. If the subbasin is a “local” subbasin, then a hydrograph representing an upstream location will be routed and added to the local hydrograph. This yields the total simulated flow at the streamgage. The so-called “estimated” flow hydrograph is obtained by merging the observed and simulated hydrographs and defining a time over which to transition, or “blend”, from the last observed value to the simulated series. This series is then routed downstream.

The hydrologic forecaster compares simulated and observed runoff hydrographs to assess hydrologic model performance, and when warranted, will make adjustments to model parameters, states, or related time series.

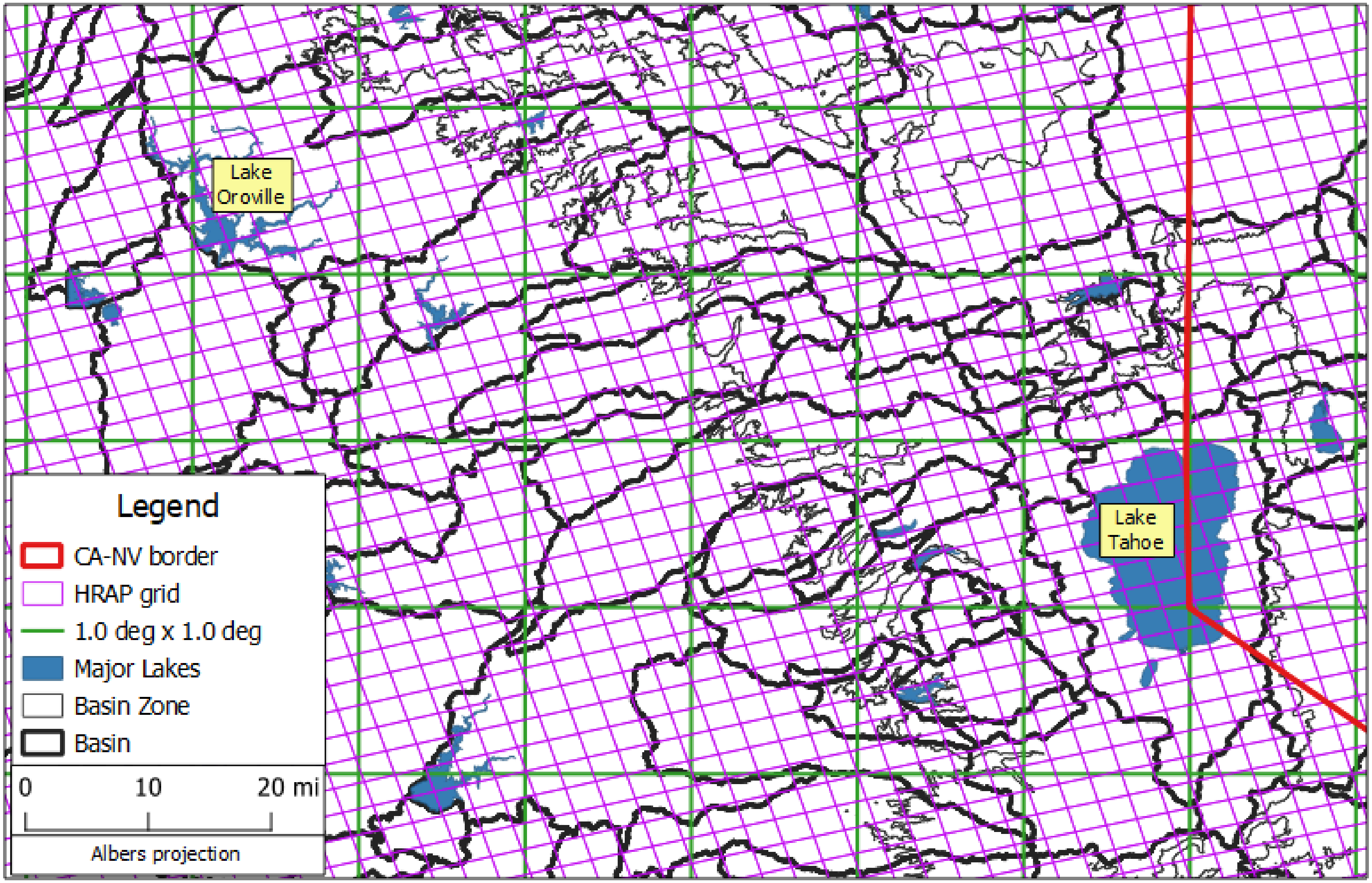


Figure 5 - HRAP grid overlaying subasins and subasin zones

Data sources for hydrologic calibration

Historical data used to calibrate hydrologic models are listed in **Table 2**. The first three rows provide sources of the three observed forcings. As indicated in the third column, more than one source was needed to complete the period of record for precipitation and freezing level. CNRFC creates precipitation grids from Global Historical Climate Network (GHCN) gage data for the early portion of the precipitation record. For the later portion CNRFC uses the archived operational QPE grids. Observed temperature grids from NOAA's Analysis of Record for Calibration (AORC) are used for the full calibration record. Freezing level is shown as "computed" because the majority of the record is based on NWP models. In 2019, CNRFC began using archived operational QZE grids to extend the freezing level record. Observed streamflow data are not used by HEFS, but are listed for completeness as a needed data component for hydrologic models calibration.

Table 2 - Observed Data Sources

(for calibration por = wy 1980 - 2023)

Forcing	Type	Source & POR
precipitation	observed	GHCN 10/1979 - 09/2003 QPE 10/2003 - 09/2023
temperature	observed	AORC 02/1979 - 09/2021
freezing level	computed	ERA5 01/1979 - 12/2018 GFS 01/2019 - 09/2019 QZE 10/2019 - 09/2023
streamflow	observed	USGS varies by site CDWR varies by site OWRD varies by site

QPE - CNRFC Quantitative Precipitation Estimate
ERA5 - ECMWF Reanalysis version 5
GFS - Global Forecast System
QZE - CNRFC Quantitative Freezing Level Estimate
USGS - United States Geological Survey
CADWR - California Department of Water Resources
ORWRD - Oregon Water Resources Department

5 CNRFC forecasts and forcings

Overview of CNRFC forecasts

Each CNRFC forecast is generated with respect to time T0 (pronounced “T zero”). T0 is the time at which the meteorologic forecast begins. Depending on when the forecast is issued, T0 can take on one of 4 values. These values, and corresponding issuance times, are shown in **Table 3**. The difference between T0 and issuance time is 5 or 4 hours depending on whether PST or PDT is in effect. As UTC time is often referred to as “z” (Zulu) time, the T0 times in the first column are often referred to as 12z, 18z, 00z, and 06z. Every day, CNRFC issues a morning forecast with T0=12z. During the rainy season, afternoon forecasts are also issued on weekdays for T0=18z. As needed to support public safety, forecasts can also be issued at T0=00z and 06z.

Table 3 - Forecast T0 and Issuance Times

T0			Issuance Time
UTC	PST	PDT	Local (PST and PDT)
12	4 AM	5 AM	9 AM
18	10 AM	11 AM	3 PM
00	4 PM	5 PM	9 PM
06	10 PM	11 PM	3 AM

When CNRFC issues a forecast for any T0, it issues both deterministic (or “single-valued”) forecasts and ensemble forecasts. Ensemble forecasts are also referred to as probabilistic forecasts as probabilistic products derived from the ensemble are often of interest. As shown in **Table 4**, single-valued forecasts extend 10 days for all T0 forecasts. On the other hand, ensemble forecasts extend 365 days for the 12z forecast and 14 days for the 18z, 00z, and 06z forecasts. Note that the first 14 days of all ensemble forecasts are the result of 14-day forcings developed using statistical sampling and distribution fitting implemented by the MEFPPE and MEFP. Only the 12z ensemble forecast is extended to 365 days by adopting forcings based on raw climatology.

Table 4 - Forecast types and lengths

Forecast	Forecast day (relative to T0)				Forecast
T0	1 - 10	11 - 14	15 - 30	31 - 365	Type
12z	single-valued	n/a			10-day single-valued
	MEFP ensemble		climate-based ens.		365-day ensemble
18z, 00z, 06z	single-valued	n/a			10-day single-valued
	MEFP ens. *	MEFP ens.	climate	n/a	30-day ensemble

* During forecast days 1 - 10, the MEFP ensemble forcing consists of the precipitation and temperature ensembles only, and uses a single-valued forcing for freezing level. This is indicated in **Table 6.**

While the 12z ensemble forecast is the focus of the remainder of this document, it requires a single-valued forcing spanning forecast days 1 through 14 as input. Single-valued forcings are further described in the next section.

Single-valued forcings - for the deterministic forecast

The on-duty hydrologist generates the 10 days of 6-hour precipitation forcing grids for the *observed* portion of the single-valued forcings. This requires reviewing measurements from precipitation gages and snow sensors. This is accomplished by visual inspection of hyetographs, comparing with radar, multi-radar multi-sensor (MRMS) grids, and satellite imagery. Once satisfied, observed precipitation grids are created by normalizing the reviewed point values to a seasonal Parameter-elevation Regressions on Independent Slopes Model (PRISM) grid, applying a distance squared algorithm to populate the target grid, then multiplying by the corresponding PRISM grid cell values. While not considered forcings, the hydrologist also reviews streamflow at this time. As indicated in **Table 5**, these steps are referred to in this document as the RFC QC process. Observed air temperature and freezing level grids grids are adopted without modification from URMA and RTMA, and the HRRR respectively.

The on-duty meteorologist generates the 10-day *forecast* portion of the single-valued forcings. During active weather, the forecaster is likely to apply judgement to adjust days 1 - 6 of precipitation (RFC QPF) and/or days 1 - 6 of freezing level (RFC QZF). These processes include reviewing NWS Weather Prediction Center (WPC) guidance and available model outputs, using the Graphical Forecast Editor to weight, adjust, or use source data without modification. If weather is calm, or there is no precipitation in the forecast, then a single model, such NBM, GFS, ECMWF, or WPC guidance may be adopted. The NBM air temperature forecast is used without modification. This process results in a 10-day set of 6-hour *forecast* grids for the 3 forcing components. These processes and sources are indicated in **Table 5**.

Table 5 - Sources of single-valued forcings for the deterministic forecast

Forcing	Days before T0	Days after T0	
	10 - 1	1 - 6	7 - 10
precipitation	RFC QPE	RFC QPF	NBM
temperature	URMA / RTMA	NBM	
freezing level	HRRR	RFC QZF	GFS / ECMWF

RFC QPE	- CNRFC QC of observed (gage) precipitation data
RFC QPF	- CNRFC review/adjust. of WPC, NBM, and other precipitation sources
RFC QZF	- CNRFC review/adjust. of WPC, NBM, and other freezing elevation sources
GFS	- Global Forecast System
URMA	- UnRestricted Mesoscale Analysis (for 12 hours or more before T0)
RTMA	- Real-Time Mesoscale Analysis (for 6 hours before T0)
HRRR	- High-Resolution Rapid Refresh
NBM	- National Blend of Models

Once the observed and forecast grids are finalized, a shapefile of basin basin zone boundaries is used to extract area-average values. The resulting 6-hour time series span 20 days and are the deterministic forcings applied to each basin modeled in the CNRFC hydrologic model system. Hydrographs from the hydrologic model simulations then define the 10-day forecast portion of the deterministic runoff forecast, while RFC QC'd observed flows define the observed portion. Note that on the CNRFC webpage, that most deterministic graphics show only the first 5 days of forecasted runoff.

Single valued forcings - for generating ensemble forcings

Table 6 provides sources of single-valued forcings used to generate ensemble forcings. Note for forecast days 1 through 10, that **Tables 5** and **6** are *mostly* the same. The difference is in forecast days 7 -10 of the precipitation forcing, in which the single-valued forcing for deterministic forecasts (**Table 5**) uses the NBM while the single-valued forcing for generating ensembles **(Table 6**) uses the GEFS mean. **Table 6** also contains shaded cells indicating additional steps must be taken to obtain the ensemble forcings (see Ensemble forcings development). While the white cells represent single-valued sources, the single-valued series are duplicated to provide an ensemble for that portion of time. Light grey shading indicates a single-valued time series is used as input to the MEFP, which samples statistical distributions to obtain the needed building blocks to construct the forcing ensemble Dark grey shading indicates that there are no single-valued forcing series and the MEFP is not used. Instead, each ensemble member is directly defined by the historical time series for a unique historical water year. Note also that ensemble forcings extend through forecast day 365 for 12z forecasts, but only through forecast day 30 for 18z, 00z and 06z forecasts. provides more details on how the ensemble forcings are constructed.

Table 6 - Sources of single-valued forcings for ensemble forcings

Forcing	Days before T0	Days after T0				
	10 - 1	**1 - 6**	**7 - 10**	**11 - 14**	**15-30**	**31 - 365**
precipitation	RFC QPE	RFC QPF	GEFS mean		raw climatology	
temperature	URMA / RTMA	NBM		GEFS mean	raw climatology	
freezing level	HRRR	RFC QZF	GFS / ECMWF	raw climatology		

General process for obtaining ensemble forcing from single-valued forcing

	1 historical (or forecast) time series --> *n* copies --> ensemble forcing
	1 forecast time series --> MEFP & Schaake Shuffle --> ensemble forcing

GEFS mean - mean of ensemble from the Global Ensemble Forecast Service
ECMWF - European Centre for Medium-Range Weather Forecasts

6 Generating the ensemble forecast

Overview of ensemble forecast

The following sections describe how the MEFPPE and MEFP components of the HEFS are used to generate ensemble forcings spanning forecast days 1 - 14. The ensemble forcings are then extended further using raw climatology, in which each member reproduces a unique historical year. Once generated, a unique set of forcing ensembles (of precipitation, air temperature, and freezing elevation) is applied to each basin zone of the hydrologic models. The resulting ensembles of simulated runoff hydrographs at basin outlets and downstream main stem locations define the ensemble runoff forecast. This allows for computation of useful metrics on the forecasted variability of flow, volume, and timing. For those seeking greater detail on the process, references are provided.

How many ensemble members?

In this document, "*n*" is used to represent the number of ensemble members. **Table 7** shows that since water year 2021, when *n* = 39, n has increased by 1 with the start (roughly) of each new water year. As of this writing (June, 2025) *n* = 44, and is expected to increase to *n* = 45 in Fall 2026. If *n* is not increased one year, possibly due to limited resources in that year, it would likely be increased by 2 when the effort was undertaken the following year.

Table 7 - Number of ensemble members

Approximate dates of implementation	Number of members *n*	Approximate water year *n* members used operationally	Historical water years reflected by members
(date uncertain) through March 10, 2019	59	(uncertain)	1950 - 2008
March 11, 2019 through October 18, 2020	68	2020	1950 - 2017
Starting October 19, 2020	39	2021	1980 - 2018
Starting Fall 2021	40	2022	1980 - 2019
Starting Fall 2022	41	2023	1980 - 2020
Starting Fall 2023	42	2024	1980 - 2021
Starting Fall 2024	43	2025	1980 - 2022
Starting Fall 2025	44	2026	1980 - 2022

Early in the evolution of applying HEFS to generate ensemble forecasts, CNRFC used a historical record starting with water year 1950. In 2020, the starting water year was changed to 1980. This change was made because:

- There was less confidence in the quality of the pre-1980 data datasets.
- The period of 1950 - 1980 was considered less representative of the present climate than the post-1980 period.

Ensemble forcings development

The HEFS employs statistical postprocessing to develop ensembles of 6-hour time series of precipitation and air temperature for the first 14 days of the forecast. The components of HEFS which generate these parts of the ensembles are the MEFPPE and the MEFP. Outside of HEFS, days 15 - 365 of the precipitation and air temperature time series, and days 11 - 365 of the freezing level time series are directly defined by raw climatology.

Developing the ensemble forecasts begins with the MEFPPE, which computes statistical distribution parameters relating *past* forecast values to observations for a collection of forecast time windows (canonical events). This is done only once as part of configuration of the HEFS. Operationally, the MEFP computes for days 1 - 14 the ensemble of basin zone forcings required by the hydrologic models. For each canonical event, the MEFP extracts from the *current* single-valued forecast its value, which is the *condition* for which the conditional probability distribution of historical values is generated and sampled. For each canonical event, the MEFP draws *n* samples from the corresponding conditional distribution. At this step in the process the bias in the single-valued forecast series is minimized because the sampled distributions represent observations, not past forecasts. The MEFP then applies the Schaake Shuffle. This process scales and re-sorts the canonical events based on previously computed correlation values, then “stitches” the canonical events together based on their historical ranking to reveal the *n* ensemble forcings for forecast days 1 - 14. Outside of HEFS, the forcings are then extended using raw climatology.

Steps are provided below for developing ensemble forcings from the single valued forcing. Each step is described in greater detail in the following sections.

As part of HEFS configuration, run the MEFPPE to compute the sets of statistical parameters relating past forecasts to corresponding observations.

A. Collect observed and past forecast data
B. Define canonical events
C. Extract canonical event historical data pairs
D. Compute statistical parameters

During operations, run the MEFP to create the single-valued forecast, and leverage this with the statistical parameter sets generated by the MEFPPE, to generate ensemble forcings for forecast days 1 - 14. Extend the ensemble forcings using raw climatology.

E. Extract current forecast canonical events
F. Generate joint probability distributions and conditional probability surfaces
G. Generate and sample conditional probability distributions
H. Generate ensemble forcings (Schaake Shuffle)
I. Extend ensemble forcings using raw climatology

Steps A, B, C, & D - HEFS configuration with MEFPPE

A - Collect observed and past forecast data

Tables 8 and 9 list sources of observed and past forecast time series inputs to the MEFPPE. Each table spans past forecast days 1 through 14, which is consistent with the grey-shaded region in **Table 6**. From these time series the MEFPPE extracts historical data pairs for all canonical event time windows (see upcoming **Tables 10** and **11**). Past forecasts can be historical forecasts or hindcasts depending on data source. In **Tables 8** and **9** the column “Past-forecast days” indicates which days of the past-forecast are described by the columns to the right.

The second column “MEFPPE Initial Year” lists the first water year from which data pairs were extracted. A larger sample size is generally desirable which implies that the initial data year used by the MEFPPE should be the first available in the record. However, the following considerations also contributed to the selection of the initial year:

- Differences in data variables - Air temperature data are generally available 24 hours a day, 365 days a year, while non-zero precipitation data are only available during precipitation events. As a result much less precipitation data is available for sampling than temperature data. In order to increase precipitation sample sizes the MEFPPE begins extracting precipitation data pairs 10 years (days 1 - 6) and 16 years (days 7 - 14) earlier than is done for air temperature data pairs.

- Short-term precipitation - Hindcasts of short-term (days 1 - 6) precipitation are challenging to develop because the forecast process can be complex for active weather situations and involve expert judgment that cannot be replicated by a computer program. In order to at least partially address this challenge, CNRFC uses historical NBM precipitation forecasts for 2010 - current for the first 6 days of the forecast.

- Short-term temperature - Analysis at CNRFC showed that configuring MEFPPE and MEFP to use historical forecasts of air temperature, instead of the GEFS mean hindcasts of air temperature, reduced bias in the resulting ensemble forecast. The NBM temperature forecast has now been implemented operationally as a result for forecast days for days 1 through 10. Since the NBM forecast is only available for days 1 through 10, the GEFS mean temperature forecast remains in use for days 11 through 14.

Table 8 - MEFPPE sources for past precipitation time series

Past-forecast days	MEFPPE Initial Year	Data Type	Data Source	Available POR
1 - 6	2010	observed	RFC QPE	2004 - current
		historical forecast	RFC QPF	2000 - current
7 - 14	2000	observed	GHCN RFC QPE	1980 - 2003 2004 - current
		mean of GEFS hindcast mean of GEFS hist. forecast	GEFS	1990 - 2019 2021 - current

Table 9 - MEFPPE sources for past air temperature time series

Past-forecast days	MEFPPE Initial Year	Data Type	Data Source	Available POR
1 - 10	2020	observed	AORC	1980 - current
		historical forecast	RFC QTF (NBM)	2020 - current
11 - 14	2016	observed	AORC	1980 - current
		historical forecast	RFC QTF	2020 - current
		mean of GEFS hindcast mean of GEFS hist. forecast	GEFS	1990 - 2019 2021 - current

B - Define canonical events

Canonical events are sets of time windows within forecast days 1 - 14. The motivation for using canonical events is to capture the skill in the forecast precipitation and temperature at different temporal scales. The MEFPPE uses canonical events to compute statistical parameters relating past forecasts to observations. The MEFP uses canonical events to extract canonical event values from the current single-valued forecast, and ultimately to generate the ensemble forcings.

A unique set of canonical events is defined for precipitation, and another for air temperature. Each canonical event is defined by a duration (aggregation period) and a lead time relative to T0. The value assigned to a precipitation canonical event is simply the total precipitation amount during the event. For air temperature canonical events, two values are of interest: the maximum value (Tmax) and the minimum value (Tmin). Tmax and Tmin are described further in E1.

There are two types of canonical events: base events and modulation events. Base events do not overlap and have no gaps in between. Modulation events span multiple base events and can overlap one another. At the CNRFC, precipitation is represented by 33 base and 7 modulation events. Temperature is represented by 12 base events and 0 modulation events. The total number of canonical events used to represent precipitation and temperature for the first 14 days of the ensemble forecast is therefore 52. The sequence and duration of these events are shown in **Tables 10** and **11**.

Table 10 - Canonical events for precipitation

Day of forecast	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Base Events (numbered)	1, 2, 3, 4	5, 6, 7, 8	9, 10, 11, 12	13, 14, 15, 16	17, 18, 19, 20	21, 22, 23, 24	25, 26, 27, 28	29	30	31	32		33	
Modulation Events (numbered)	1													
		2												
				3										
					4									
							5							
										6 (3 days)				
								7 (6.5 days))						

Table 11 - Canonical events for air temperature

Day of forecast	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Base Events (numbered)	1	2	3	4	5	6	7	8	9	10	11		12	

C - Extract historical canonical data pairs

A historical canonical data pair consists of one past forecast canonical event value and its corresponding observed value. The MEFPPE extracts. For each past forecast, one data pair is extracted for each canonical event. Because precipitation is intermittant, it is necessary to pool data pairs from multiple forecasts to obtain sufficient sample sizes from which to compute statistical distribution parameters. The MEFPPE creates a pool of data pairs on every 5th calendar day, using 61-day windows. If the first calendar day for which parameters are to be computed is January 1, then for each canonical event, the MEFPPE pools all data pairs having forecast calendar days within plus or minus 30 days (a 61-day window) on January 1. If a past forecast is available for each day, then the number of data pairs for each canonical event will be equal to 61 times the number of years of past forecasts. The MEFPPE then advances the 61-day time window by 5 days, and repeats the process to obtain data pairs associated with January 6. The process is repeated until data pairs have been computed and stored for every 5th day of the calendar year. In addition to increasing sample sizes this process yields statistical parameters which vary gradually through the year. Operationally, the MEFP adopts the parameter set corresponding to the “5th day” nearest to the current forecast day.

For precipitation, the extraction of historical data pairs from the source time series is fairly straightforward. For each time window defined by the canonical events in **Table 10**, the extracted value is simply the accumulated value over the duration of the canonical event.

For air temperature, values are extracted for each base event in **Table 11**. The strategy for developing the air temperature forcings is to first compute values representing the warmest and coldest 6-hour periods (four 6-hour periods, beginning at 12z), then as one of the last steps of the ensemble generation process, interpolate to obtain values for the two remaining 6-hour periods. The warmest 6-hour period is 06z - 12z, and the coldest 6-hour period is 18z - 00z. The method for computing the representative maximum and minimum values for the canonical events depends on the data source, and therefore also on the forecast day. For both observed (forecast days 1 - 14) and NBM data (forecast days 1 - 10), the average value over the 6-hour period is used. For GEFS mean data (forecast days 11 - 14), the maximum (or minimum) value over the 6-hour period is used. **Tables 12** and **13** provide additional detail, including differences between how these values are computed for 1-day (forecast days 1 -10) versus 2-day canonical events.

Table 12 - Base event data pairs - Tmax

a - forecast days 1 - 10 (1-day base events)

		6-hour periods			
Variable	Source	12z-18z	18z-00z	00z-06z	06z-12z
observed	AORC	--	Tavg	--	--
past forecasts	NBM	--	Tavg	--	--

Base event data pairs
18z - 00z
Tavg
Tavg

b - forecast days 11 - 14 (2-day base events)

		6-hour periods (day 1)				6-hour periods (day 2)			
Variable	Source	12z-18z	18z-00z	00z-06z	06z-12z	12z-18z	18z-00z	00z-06z	06z-12z
observed	AORC	--	Tavg1	--	--	--	Tavg2	--	--
past forecasts	GEFS mean	--	Tmax1	--	--	--	Tmax2	--	--

Base event data pairs
18z - 00z
Tavg = Avg(Tavg1, Tavg2)
Tmax = Avg(Tmax1, Tmax2)

Table 13 - Base event data pairs - Tmin

a - forecast days 1 - 10 (1-day base events)

		6-hour periods			
Variable	Source	12z-18z	18z-00z	00z-06z	06z-12z
observed	AORC	--	--	--	Tavg
past forecasts	NBM	--	--	--	Tavg

Base event data pairs
06z - 12z
Tavg
Tavg

b - forecast days 11 - 14 (2-day base events)

		6-hour periods (day 1)				6-hour periods (day 2)			
Variable	Source	12z-18z	18z-00z	00z-06z	06z-12z	12z-18z	18z-00z	00z-06z	06z-12z
observed	AORC	--	--	--	Tavg1	--	--	--	Tavg2
past forecasts	GEFS mean	--	--	--	Tmin1	--	--	--	Tmin2

Base event data pairs
06z - 12z
Tavg = Avg(Tavg1, Tavg2)
Tmin = Avg(Tmin1, Tmin2)

D - Compute historically-based statistical parameters

The MEFPPE computes the sample statistics for each pool of data pairs (for each location, canonical event, and both precipitation and temperature). These parameters are:

μ_x = sample mean of observations
σ_x = sample standard deviation of observations
μ_y = sample mean of past forecasts
σ_y = sample standard deviation of past forecasts
γ = correlation coefficient between observations and past forecasts

The method used to compute joint probability assumes normally distributed data. However for the case of precipitation, the normal distribution does not describe the data well, while the Gamma distribution does. In order to address this issue, precipitation data values are first transformed using the Normal Quantile Transformation (NQT), which is defined by **Equations 3a** and **3b**. The above-listed sample statistics for precipitation are then computed for the NQ-transformed samples. For air temperature, the samples are distributed normally, and no transform is necessary.

Together, the 5 parameters can be used to define a joint probability surface, with the first pair of parameters defining the marginal distribution of observations and the second pair defining the marginal distribution of past forecasts. The fifth parameter defines how well observations are predicted by forecasts. Note that the above set of parameters is unique for each basin zone, and is defined for every 5th day of the year. Operationally, the MEFP uses the parameter sets representing the 5th day nearest to the day of forecast.

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Steps E, F, G, H, & I - Operational forecasting with HEFS/MEFP

E - Extract canonical values from single-valued forcing series

For each basin zone, three 6-hour single-valued series representing the current forecast are required by the MEFP: precipitation, maximum air temperature, and minimum air temperature. These series are created by spatially extracting values from the 6-hour forecast grids. Sources for the current single-valued forecast series are listed in **Table 6**. **Table 10** shows for precipitation the temporal position of base (grey shading) and modulation (yellow shading) canonical events. **Table 11** shows for maximum and minimum temperature the temporal position of base events (grey shading). For temperature there are no modulation events. For each canonical event, the MEFP extracts values for all canonical events from the 6-hour single-valued input series.

F - Generate joint probability and conditional probability surfaces

In this document, the term "conditional probability surface" refers to the mathematical surface obtained when the joint probability surface (having a volume of 1.0) of observations vs. forecasts is divided by the marginal distribution of forecasts. The resulting surface, when sliced at a forecast value, produces a conditional probability distribution (with area of 1.0). The shape of the surface reveals the effect of forecast magnitude on conditional distribution of observations.

A detailed mathematical description of the procedures implemented by MEFP is provided by Herr and Krzysztofowicz (2005) and Lu et al (2011). This section applies parts of that procedure to example data sets of temperature and precipitation, and intentionally tries to avoid the more advanced topics in the reference paper. The description here is intended to visually illustrate how conditional probability surfaces for temperature and precipitation are created.

F1 - Precipitation (example)

Precipitation is intermittent. Properly accounting for the probability of both rain and non-rain conditions is a mixed distribution problem. The MEFP provides two options for computing mixed distribution statistics: 1) Explicit Precipitation Intermittency Treatment (EPT) described in Herr and Krzysztofowicz (2005) and Wu et al. (2011), and 2) Implicit Treatment (IPT) described in Wu et al. (2011). For short lead times the differences between IPT and EPT methods are small, while EPT is much more skillful for longer lead times. For this reason, the EPT method is used at the CNRFC.

For simplicity, this document does not attempt to describe the details of mixed distribution computations, but instead focuses on the "wet-wet" case. In this example, the CNRFC configured a value of 0.254 mm as the minimum 3-day precipitation value considered non-zero.

In order to provide an example demonstration of computations undertaken by the MEFPPE and MEFP, an example dataset for the North Fork Dam of the American River is used in the following sections. The dataset consists of 952 3-day “wet-wet” precipitation data pairs. Each data pair reflects December 7 precipitation over a 3-day time period starting at T0. These data pairs can be seen as plotted points in **Figures 6 and 10**.

Marginal distributions

The CNRFC configures MEFP to use the gamma distribution to describe each of the two marginal distributions: $f(x)$ for forecast values (x), and $g(y)$ for observations (y). Each gamma distribution is defined by two parameters: the shape factor (α) and the scale factor (β). The density function form of the gamma distribution $f(x)$ is shown in **Equation 1**.

Equation 1

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \cdot x^{\alpha-1} e^{-\frac{x}{\beta}}$$

in which:
- x = forecast value
- α = shape factor
- β = scale factor
- $\Gamma(\alpha)$ = gamma function

Estimates of α and β are computed from the sample mean (μ) and sample standard deviation (σ). Values used to support the computation were: μ_x = 22.4, σ_x = 30.5, μ_y = 40.9, and σ_y = 44.0 and Υ= 0.882. From **Equations 2a** and **2b**, α_x = 0.54, β_x = 41.6, α_y= 0.86, and β_y = 47.3.

Equations 2a and 2b

$$\alpha_x = \frac{\mu_x}{\beta_x} \quad \text{= shape factor for } f(x)$$

$$\beta_x = \frac{{\sigma_x}^2}{\mu_x} \quad \text{= scale factor for } f(x)$$

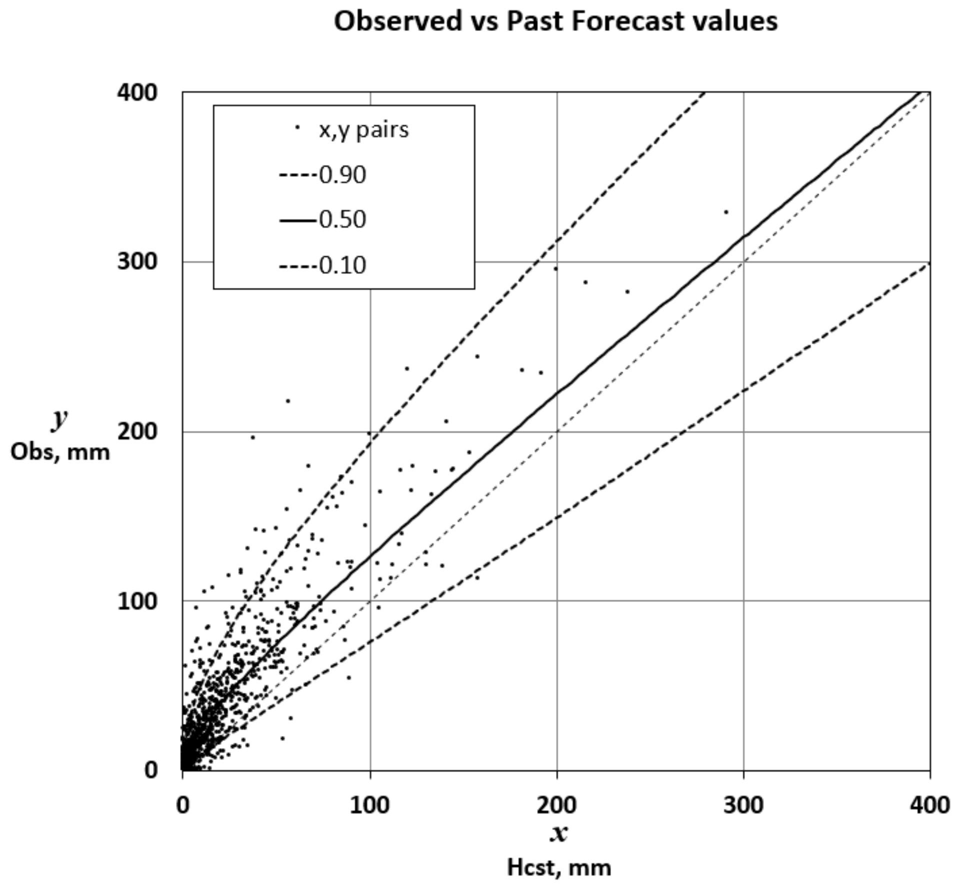


Figure 6 - Data pairs and confidence intervals (precipitation)

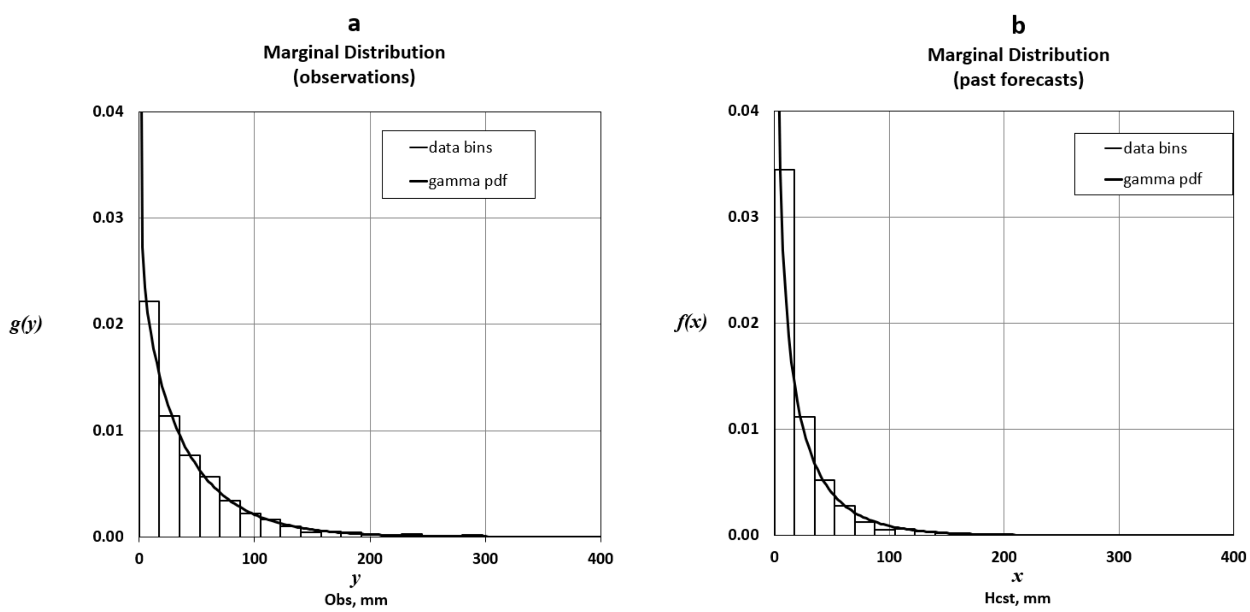


Figure 7 - Marginal distributions (precipitation)

The resulting two marginal distributions, $f(x)$ and $g(y)$, are shown in **Figures 7a** and **7b**. Data bins are also shown for comparison.

Joint Probability Distribution

If precipitation data were fairly normally distributed, then the same approach as for temperature could be taken for generating the joint probability surface $h(x, y)$ and conditional probability surface $h(y|x)$. Instead, the HEFS uses the normal quantile transform (NQT) to transform the forecast (x) and observed (y) values into more normally distributed data sets of u and v. The NQT is defined by **Equations 3a** and **3b**.

Equations 3a and 3b

$$u = NQT(x) = Q^{-1}(F(x)) \qquad \text{and} \qquad v = NQT(y) = Q^{-1}(G(y))$$

in which

$NQT()$ = normal quantile transform
$Q^{-1}()$ = inverse of cumulative standard normal distribution
$F(x)$ = cumulative marginal distribution of x
$G(y)$ = cumulative marginal distribution of y
x = forecast value
y = observed value

u-v data pairs are plotted in **Figure 8**, and marginal distributions of u and v are plotted in **Figures 9a** and **9b**.

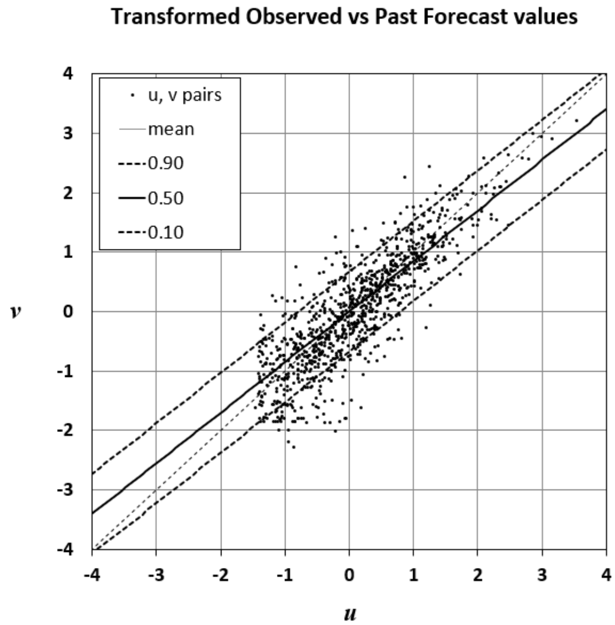


Figure 8 - Data pairs and confidence intervals (transformed precipitation)

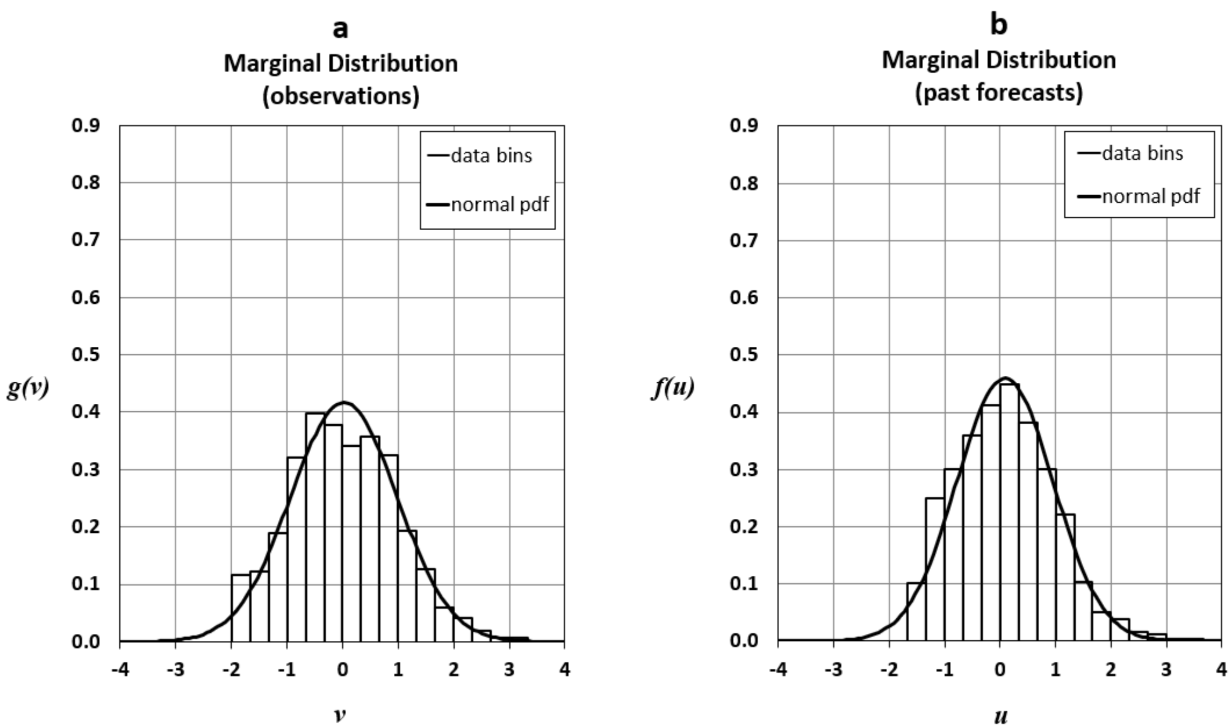


Figure 9 - Marginal distributions (transformed precipitation)

The bivariate standard normal distribution (**Equation 4**) is then fit to the collection of u-v data pairs. The distribution has only one parameter, Pearson's product-moment correlation coefficient, γ, computed from transformed values. For this example γ = 0.851.

Equation 4

$$h(u,v) = \frac{1}{2\pi\sqrt{1-\gamma^2}} \cdot exp\left[-\frac{u^2+v^2-2\gamma uv}{2(1-\gamma^2)}\right]$$

The resulting bivariate standard normal distribution for this example is shown in **Figure 10**.

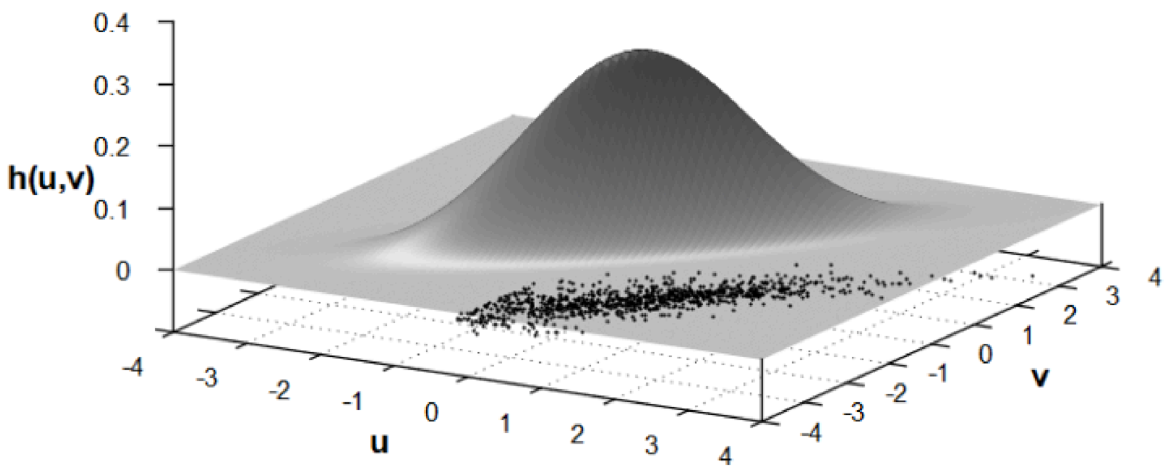


Figure 10 - Joint probability surface (transformed precipitation)

The linear dependence structure between v as a function of u is given by:

Equations 5a and 5b

$$\mu_{v|u=u_o} = \gamma \cdot u$$

$$\sigma_{v|u=u_o} = \sqrt{1-\gamma^2}$$

in which:

$\mu_{v|u=u_o}$ = mean of observed values v given that forecast $u = u_o$

$\sigma_{v|u=u_o}$ = standard deviation of observed values v given that forecast $u = u_o$

The surface $h(u,v)$ is then back-transformed from u-v space to x-y space to obtain the bivariate meta-Gaussian distribution $h(x,y)$. This is done using **Equation 6** below, which is equation 19 in Herr and Krzysztofowicz (2005). In doing so, the original marginal distributions are enforced, and the dependence structure, linear in the u-v domain, becomes non-linear in the x-y domain.

Equation 6

$$h(x,y) = \frac{f(x)g(y)}{\sqrt{1-\gamma^2}\,q\left(Q^{-1}\left(G(y)\right)\right)} \times q\left(\frac{Q^{-1}\left(G(y)\right) - \gamma Q^{-1}\left(F(x)\right)}{\sqrt{1-\gamma^2}}\right)$$

in which:

$h(x,y)$ = joint probability distribution
$mg(x,y)$ = bivariate meta-Gaussian distribution
$q(\,)$ = standard normal density function
$Q^{-1}(\,)$ = inverse of cumulative standard normal distribution function
$F(x)$ = cumulative marginal distribution of forecast value (x)
$G(y)$ = cumulative marginal distribution of observed value (y)
$f(x)$ = marginal probability density function of forecast value (x)
$g(y)$ = marginal probability density function of observed value(y)

In **Equation 6**, as the gamma functions $f(x)$ and $g(y)$ are each defined by shape and scale parameters, the total number of parameters required to define $h(x,y)$ is five: α_x , β_x , α_y , β_y , and γ. The computed values of these parameters for this example are: α_x = 0.54, β_x = 41.6, α_y = 0.86, β_y = 47.3, and Υ = 0.882 (0.851 in u-v space). The resulting surface, $h(x,y)$, is shown in **Figure 11**.

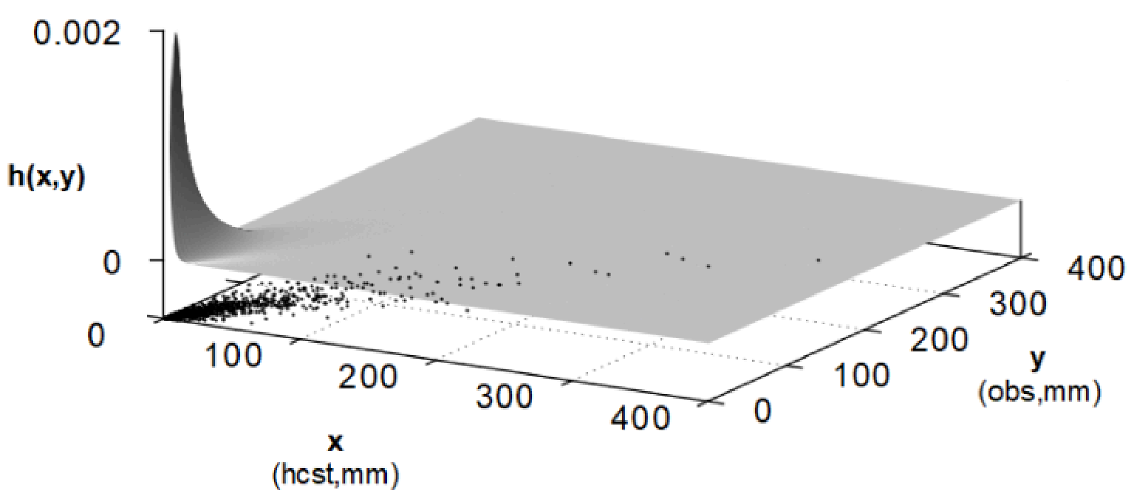


Figure 11 - Joint probability surface (precipitation)

The conditional probability surface $h(y|x)$ for the canonical event is obtained from **Equation 7**, and the resulting surface is shown in **Figure 12**.

Equation 7

$$h(y|x) = \frac{h(x,y)}{f(x)}$$

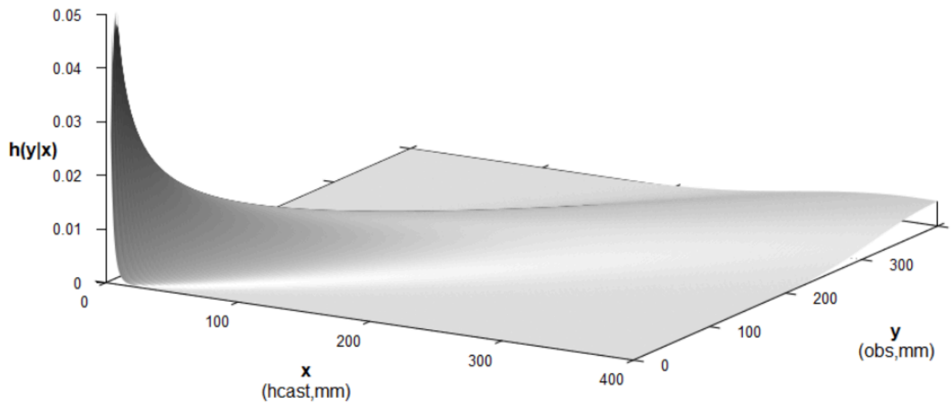


Figure 12 - Conditional probability surface (Precipitation)

This surface reflects the back-transformed dependence structure defined by **Equations 5a** and **5b** (confidence intervals are shown **Figure 6**). Note that when the surface was developed, the x axis represented the *past* forecast value, but when used operationally, the x axis represents the *current* forecast value. For this reason, consistency between current and past forecast sources is essential.

F2 - Air temperature (example)

In this example, a 1-day (no lead time) canonical event temperature hindcast data set of 594 data pairs for the upper basin of North Fork Dam of the American River is plotted in **Figure 13**. The extracted data are for December 27 (12z to 12z). The method for extracting the observed and past forecast values is shown in **Table 10b**.

Marginal Distributions

A normal distribution is fit to each sample group to obtain the two resulting marginal distributions, $f(x)$ and $g(y)$. These are shown in **Figures 14a and 14b**. Data bins are also shown for comparison.

Joint Probability Distribution

For one canonical event, the bivariate normal density function (**Equation 8**) is used to estimate the joint probability distribution $h(x,y)$ of observations (y) and past forecast canonical event inputs (x). $h(x,y)$ is completely defined by the four marginal parameters: μ_x , σ_x , μ_y , σ_y , and correlation coefficient γ. The five parameters are computed directly from the samples.

Equation 8

$$h(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\gamma^2}} exp\left[\frac{1}{2\sqrt{1-\gamma^2}}\left[\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 + 2\gamma\left(\frac{x-\mu_x}{\sigma_x}\right)\left(\frac{y-\mu_y}{\sigma_y}\right)\right]\right]$$

in which:

$h(x,y)$ = joint probability distribution (in this case bivariate normal)
μ_x = sample mean of past forecasts (x)
σ_x = sample standard deviation of past forecasts (x)
μ_y = sample mean of observations (y)
σ_y = sample standard deviation of observations (y)
γ = Pearson's product-moment correlation coefficient

Computed values of the 5 parameters for this example are μ_x = -3.37, σ_x = 4.17, μ_y = -1.48, σ_y = 3.84, and γ = 0.80. The resulting joint probability surface, $h(x,y)$, is shown in **Figure 15**.

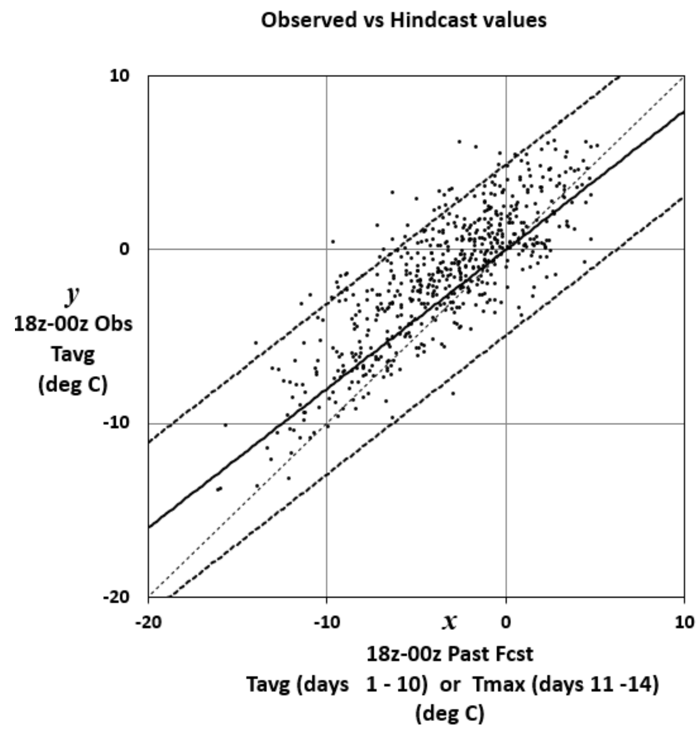
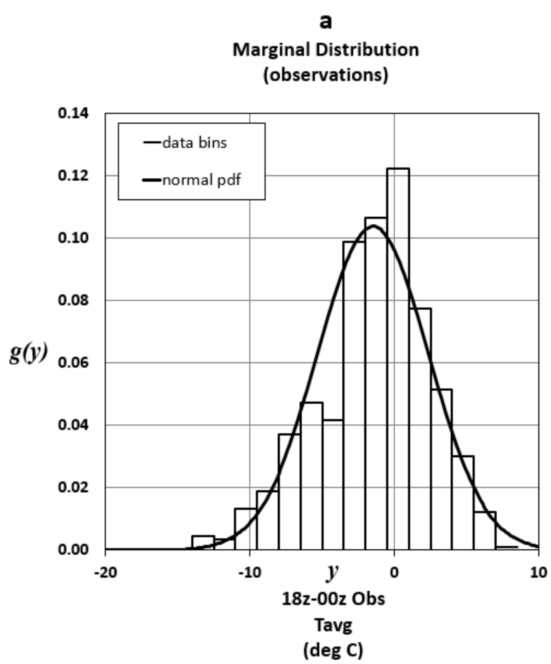


Figure 13 - Data pairs and confidence intervals (Tmax)



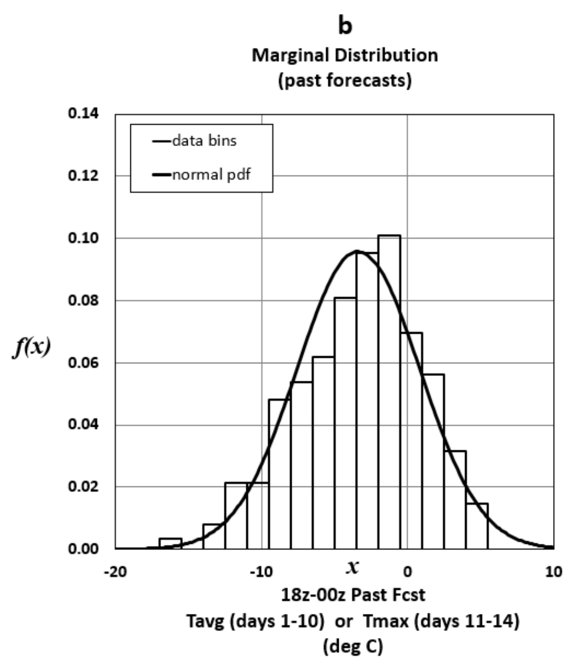


Figure 14 - Marginal distributions and data bins (Tmax)

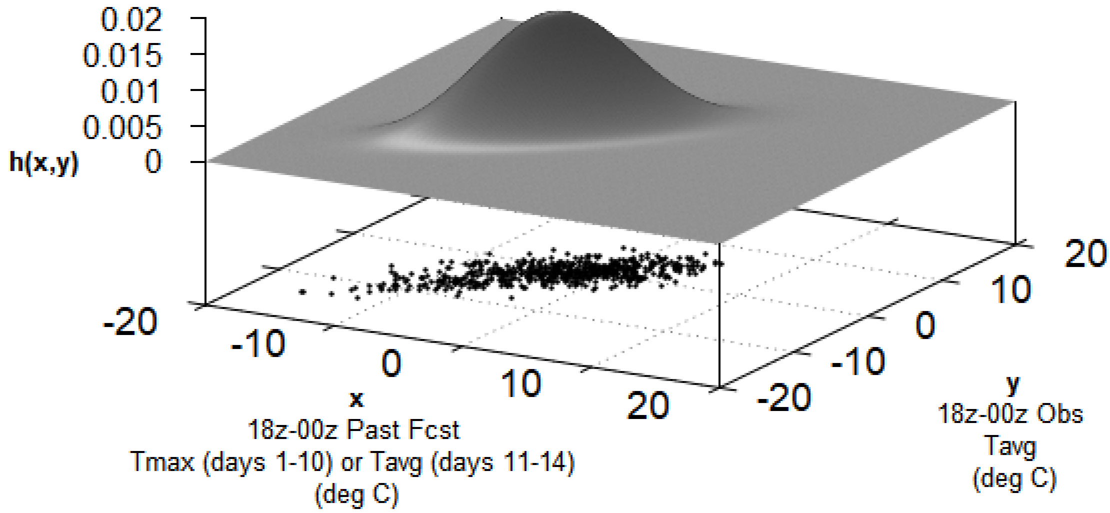


Figure 15 - Joint probability surface (Tmax)

A useful property of the bivariate normal distribution is that the dependence structure between x and y is linear and requires computation of only one additional parameter, γ, from the data. As shown by **Equations 9a** and **9b**, the conditional mean value of y is a straight line, and the conditional standard deviation of y is a constant. These properties represent the change in distribution of observations with respect to forecast value for one canonical event.

Equations 9a and 9b

$$\mu_{y|x=x_o} = \mu_y + \gamma \cdot \sigma_y \cdot \frac{(x-\mu_x)}{\sigma_x}$$

$$\sigma_{y|x=x_o} = \sigma_y \cdot \sqrt{1-\gamma^2}$$

in which:

$\mu_{y|x=x_o}$ = mean of observed values y given that forecast $x = x_o$,

$\sigma_{y|x=x_o}$ = standard deviation of observed values y given that forecast $x = x_o$.

Conditional probability surface

While the joint probability surface is informative, it is the conditional probability surface, given by **Equation 7**, that we are most interested in.

Equation 7 (repeated)

$$h(y|x) = \frac{h(x,y)}{f(x)},$$

In **Equation 7**, $f(x)$ is the marginal distribution of past forecast samples. We are in effect normalizing the joint probability surface to the marginal distribution of past forecasts. The resulting conditional probability surface for this example is shown in **Figure 16**.

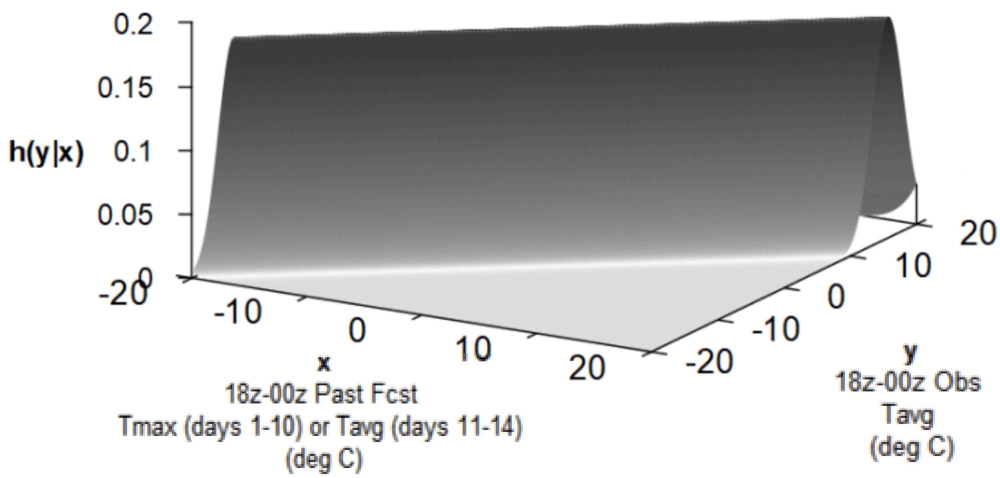


Figure 16 - Conditional probability surface (Tmax)

This surface clearly reflects the dependence structure defined by **Equations 9a** and **9b** (see confidence intervals in **Figure 13**). When this surface is "sliced" with a y-z plane at a selected x value, the resulting intersection is a normal distribution. If a different value of x is chosen for the slice, the same distribution will result, but will be shifted in the y direction. Note that when the surface was developed, the x axis represented the *past* forecast canonical input value, but when used operationally, the x axis represents the *current* forecast canonical input value. For this reason, consistency between current and past forecast sources is essential, as indicated in **Table 10**.

For the canonical event represented by **Figure 13**, if the current forecast canonical input value were a maximum temperature (Tmax) of 10 deg C, then the conditional normal distribution associated with that value defines the corresponding range of uncertainty of the 18z-00z average temperature (Tavg) forecast. Following the above steps, another surface for the Tmin case would also be developed from data pairs of Tmin and 06z-12z Tavg.

G - Generate and sample conditional probability distributions

With conditional probability surfaces defined (**Figures 12 and 16**), the MEFP "slices" each surface at the corresponding current forecast canonical input value. The slice reveals the conditional distribution of observations associated with the current forecast value. The conditional distribution is inherently bias-corrected and reflects historically consistent spread, because it is a distribution of observations (not past forecasts).

Sampling is done using equally spaced increments of cumulative probability along the vertical H(y|x) axis. The values of non-exceedance probability (NEP) used for sampling are given by Weibull plotting positions, which are defined by :

Equation 10

$$NEP = r / (n + 1)$$

where: NEP = non-exceedance probability (Weibull plotting position)
r = rank of sample (from largest to smallest)
n = sample size = number of ensemble members needed

Note that the maximum value of NEP is less than 1.0 and the minimum value of NEP is greater than 0. This allows for the possibility of extreme events in the population that are not reflected in the sample.

G1 - Precipitation (example)

Using the conditional probability surface developed for precipitation in the previous section, **Figure 17a** shows the conditional probability surface for precipitation from **Figure 12**, with two colored curves indicating slicing the surface at two hypothetical current forecast canonical input values of 25 and 200 mm on the x axis. The resulting magenta curve is the conditional probability distribution given a current forecast value of 25 mm, and the resulting blue curve is the conditional probability distribution given a current forecast value of 200 mm. The resulting difference in mean and spread of the conditional distributions is seen in **Figure 17b**. **Figure 17c** shows the cumulative form, H(y|x), of the same distributions. Note that during operations, only one current forecast canonical input value, and therefore only one conditional probability distribution, is produced for each canonical event.

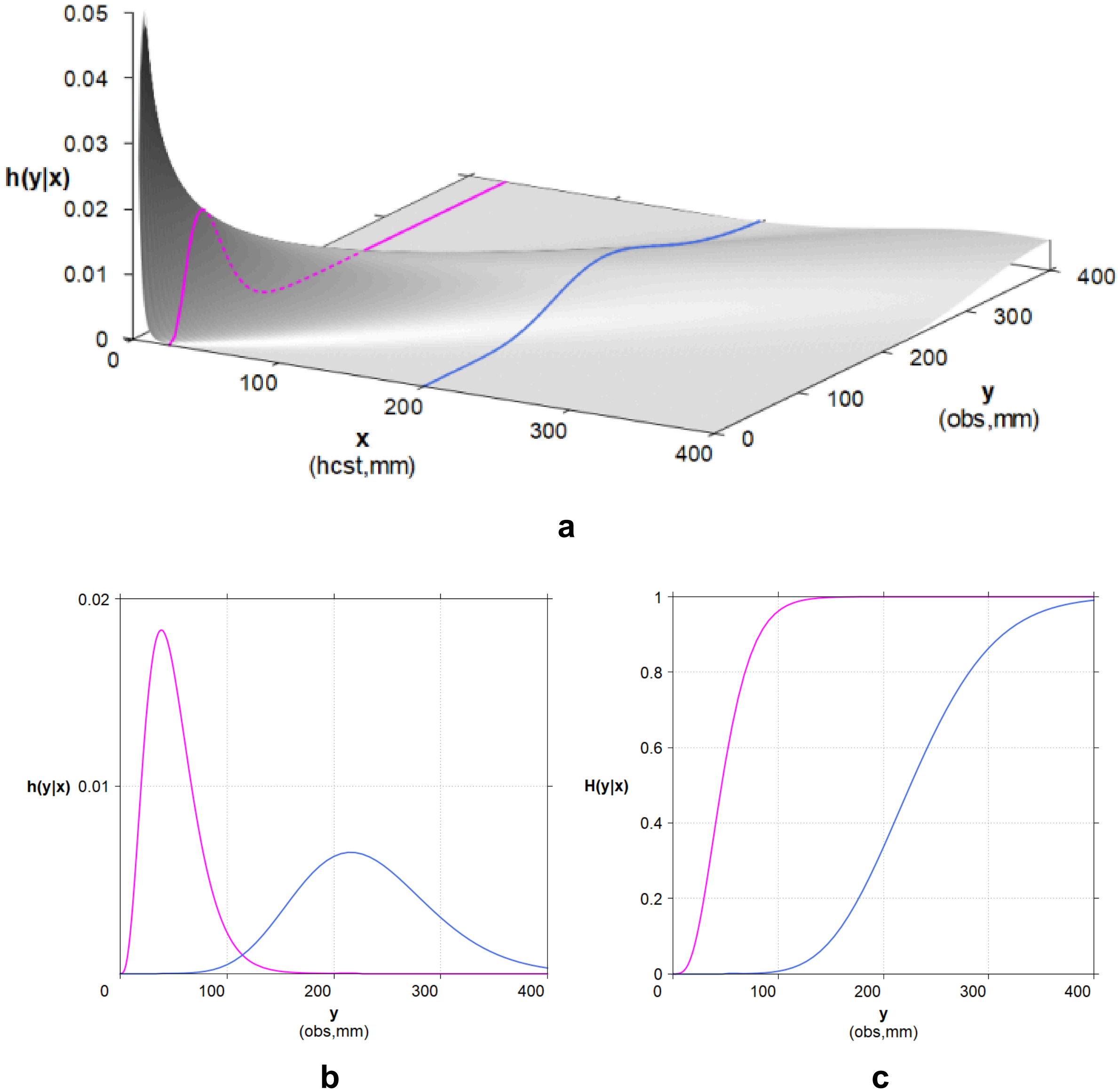


Figure 17 - Conditional probability distributions (precipitation)

The samples must be drawn so as to be unbiased, in order that the resulting distribution of samples is reflective of the original continuous distribution. It is also desirable that the sampling method is repeatable. To satisfy these requirements, the MEFP draws samples from the cumulative form of the conditional probability distribution $H_{Y|X}(y|x)$. This is given by **Equation 11**, which is Equation 20 in Herr and Krzysztofowicz (2005).

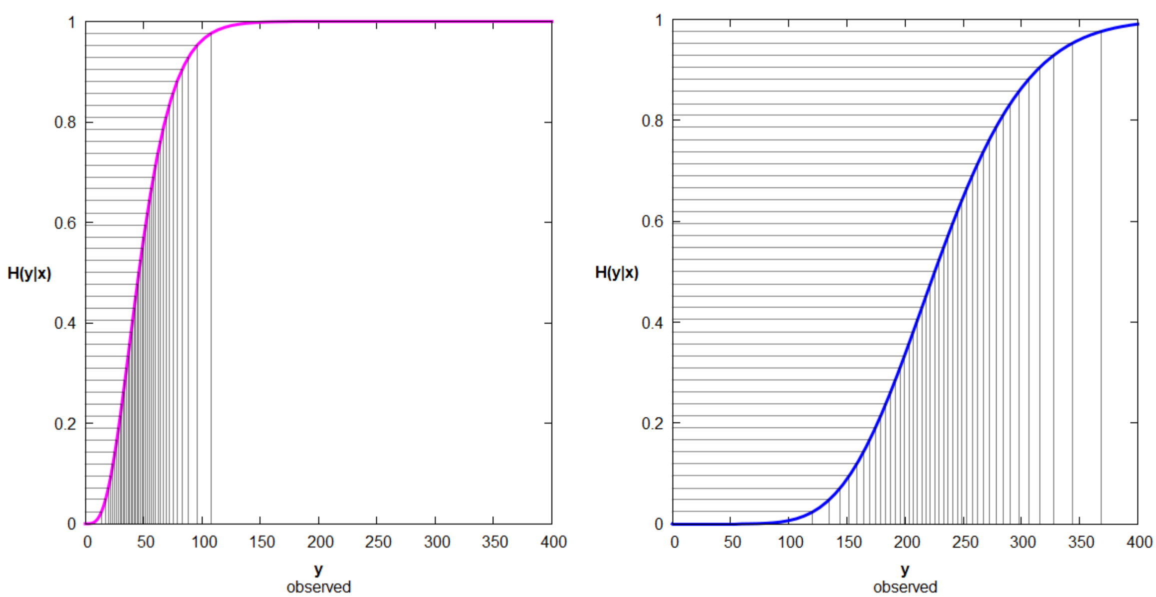
Equation 11

$$H_{Y|X}(y|x) = Q\left(\frac{Q^{-1}(G(y)) - \gamma Q^{-1}(F(x))}{\sqrt{1-\gamma^2}}\right)$$

in which:

- $H_{Y|X}(y|x)$= cumulative conditional probability distribution
- $Q(\ )$ = cumulative standard normal distribution function
- $Q^{-1}(\ )$ = inverse of cumulative standard normal distribution function
- $F(x)$ = cumulative (gamma) distribution of forecast value (x)
- $G(y)$ = cumulative (gamma) distribution of observed value (y)

Figures 18a and 18b illustrate drawing *n* samples from cumulative probability distributions corresponding to hypothetical current forecast canonical input values of 25 mm and 200 mm. The resulting sample values are indicated on the horizontal axes.



Forecast = 25 mm

a

Forecast = 200 mm

b

Figure 18 - Sampling of conditional probability distributions (precipitation)

G2 - Air temperature (example)

The process for generating conditional probability distributions for temperature is fundamentally the same as for precipitation, but for each canonical event two surfaces are required:

- Tmax forecast vs 18z-00z Tavg observed (**Figure 16**).
- Tmin forecast vs 06z-12z Tavg observed.

Operationally, MEFP would "slice" each surface at their respective forecast values, and two samples drawn by stratified sampling: one sample of *n* Tmin values and one sample of *n* Tmax values. (Improved illustrations for this section have not yet been developed.

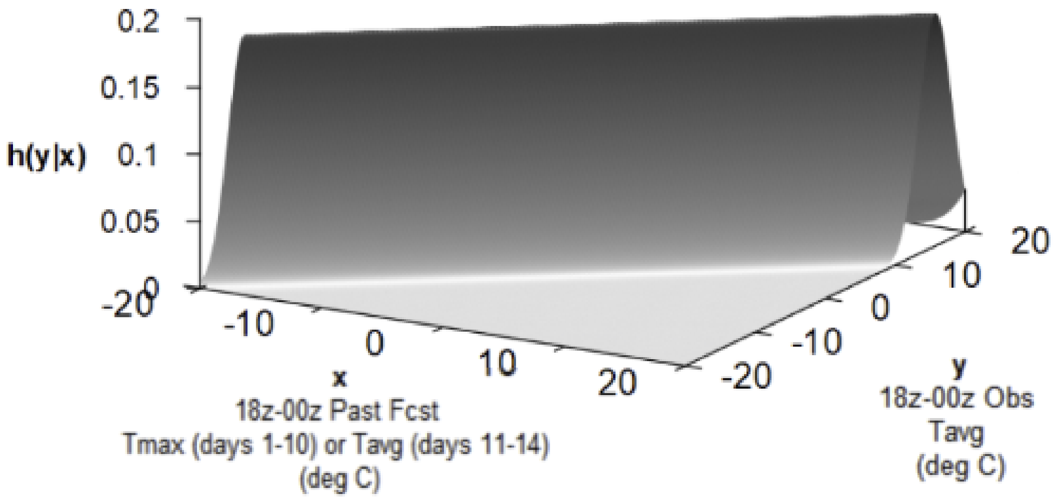


Figure 16 (repeated) - Conditional probability surface (Tmax)

H - Create ensemble forcings (Schaake Shuffle)

Samples drawn from the conditional probability distributions for all canonical events are input to a procedure known as the Schaake Shuffle. The procedure is a simple and efficient method used to preserve the space-time statistical properties of climatology among multiple hydro-meteorological variables across multiple forecast locations for ensemble forecasting. For this application at CNRFC, once MEFP has drawn the *n* samples from each conditional probability distribution for each canonical event for a forcing type, the Schaake Shuffle uses the historically-based correlation values associated with each canonical event as a basis for sorting and scaling. The modified events are then stitched together based on common year ranking. This generates the desired *n*-member ensemble spanning 14 days.

H1 - Precipitation

Beginning with precipitation, it is useful to organize the sample as shown in **Table 14**. Note that column width does not reflect canonical event duration. The top row provides an arbitrary id number for each canonical event. Precipitation is represented by 33 base events and 7 modulation events. The first column contains an arbitrary number id for each sample. Each column represents the individual sample values drawn from the conditional probability distribution for the canonical event represented by the column. Data values, shown as “b” and “m”, represent base event and modulation event sample values. The last row contains the correlation coefficients (between observed and past forecast samples) for each canonical event. These values are indicated by “c”. The canonical event values represent accumulated precipitation during each canonical event.

Table 14 - Precipitation samples for Schaake Shuffle (forecast Days 1 - 14)

	Precipitation Base Events																																
Sample	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
2	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
3	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
4	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
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44	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b
Corr. Coeff.	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c	c

	Precipitation Modulation Events						
Sample	1	2	3	4	5	6	7
1	m	m	m	m	m	m	m
2	m	m	m	m	m	m	m
3	m	m	m	m	m	m	m
4	m	m	m	m	m	m	m
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
44	m	m	m	m	m	m	m
Corr. Coeff.	c	c	c	c	c	c	c

The Schaake Shuffle ranks base events extracted from the *n*-year historical record, and assigns year labels to the base events of corresponding rank. A detailed example of the Schaake Shuffle applied to precipitation is provided in the attachment “Schaake Shuffle Step-by-Step Example”. If there were no modulation events, each set of base events having matching year labels would be merged to form the set of ensemble members (this is how it is done for temperature). However, precipitation has modulation events, which overlap base events and sometimes other modulation events. To handle this, the Schaake Shuffle considers all (base and modulation) events, in order from lowest correlation to highest. Typically, modulation events will have higher correlation, and will apply after base events, thus “modulating” the base events. When a modulation event is considered, base events contained by the modulation event are adjusted to be consistent with the modulation event.

H2 - Air temperature

As described in E1 - Temperature, conditional probability distributions that relate Tmax forecasts and Tmin forecasts to Tavg (18z to 00z) and Tavg (06z to 12z) observations respectively, for each day of the forecast, are used to construct the temperature ensemble. For the two 6-hour periods not addressed (00z to 06z, 12z to 18z), the MEFP interpolates to fill gaps. This is shown in **Table 15**.

Table 15 - HEFS processing of temperature (Tmin and Tmax)

	MEFPPE		MEFP	
Time Period	**Observed**	**Past Forecast**	**Current Forecast**	**Source of Ensemble Member 6-hour Tavg value**
12z to 18z	--	--	--	interpolation
18z to 00z	Tavg	Tmax	Tmax	sample from distribution
00z to 06z	--	--	--	interpolation
06z to 12z	Tavg	Tmin	Tmin	sample from distribution

Temperature is represented by 12 base events, and no modulation events. The first 10 base events are 1-day periods. The last 2 are 2-day periods. From each base event the Tmin and Tmax values are extracted from past forecasts and the current forecast. Samples of 6-hour Tavg are drawn from the corresponding conditional probability distributions. **Tables 16a** and **16b** show how the sampled values can be organized, with "b" and "c" indicating base event sample and correlation values respectively.

Tables 16a and 16b - Temperature samples for Schaake Shuffle (forecast days 1 - 14)

16a

Tavg (06z - 12z)

Base Events

Sample	1	2	3	4	5	6	7	8	9	10	11	12
1	b	b	b	b	b	b	b	b	b	b	b	b
2	b	b	b	b	b	b	b	b	b	b	b	b
3	b	b	b	b	b	b	b	b	b	b	b	b
4	b	b	b	b	b	b	b	b	b	b	b	b
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
44	b	b	b	b	b	b	b	b	b	b	b	b
Corr. Coeff.	c	c	c	c	c	c	c	c	c	c	c	c

16b

Tavg (18z - 00z)

Base Events

Sample	1	2	3	4	5	6	7	8	9	10	11	12
1	b	b	b	b	b	b	b	b	b	b	b	b
2	b	b	b	b	b	b	b	b	b	b	b	b
3	b	b	b	b	b	b	b	b	b	b	b	b
4	b	b	b	b	b	b	b	b	b	b	b	b
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:
44	b	b	b	b	b	b	b	b	b	b	b	b
Corr. Coeff.	c	c	c	c	c	c	c	c	c	c	c	c

The Schaake Shuffle treats the values in **Tables 16a** and **16b** separately. With **Table 16a**, base events are extracted from the *n*-year historical record, and year labels are assigned to the base events of corresponding rank. There are no modulation events, so no further adjusting of values is necessary. The process is repeated for the values in **Table 16b**. The temperature ensembles are created by merging (alternating 06z-12z and 18z-00z) Tavg values having the same year label, and then interpolating in time between those values to obtain the missing 00z-06z and 12z-18z Tavg values. Each resulting set of values having matching year labels is an ensemble member.

I - Extend ensemble forcings with raw climatology

For the CNRFC morning forecast (T0 = 12z), the ensemble is extended to span days 25 - 365 of the forecast. This part of the ensemble is defined *outside* of the HEFS using raw climatology, in which each member corresponds to one year in the *n*-year historical record. Raw climatology is also used to define ensemble members for freezing level for days 11 through 365. The resulting 365-day *forecasts* are then merged with the 10-day single-valued *observed* forcings (QPE, QTE, and QZE) to create the 375-day (from T0 - 10 days to T0 + 365 days) forcing series required to execute the hydrologic models. A summary of the resulting forcings is provided in **Table 6**. Note that work is underway at CNRFC to configure MEFP to generate a freezing level ensemble for days 1 through 10.

Table 6 (repeated) - Single-valued forcings for ensemble forecasts

Forcing	Days before T0	Days after T0				
	10 - 1	1 - 6	7 - 10	11 - 14	15-30	31 - 365
precipitation	RFC QPE	RFC QPF	GEFS mean		raw climatology	
temperature	URMA / RTMA	NBM		GEFS mean	raw climatology	
freezing level	HRRR	RFC QZF	GFS / ECMWF	raw climatology		

General process for obtaining ensemble forcing from single-valued forcing

1 historical (or forecast) time series --> *n* copies --> ensemble forcing

1 forecast time series --> MEFP & Schaake Shuffle --> ensemble forcing

Apply ensemble forcings to the hydrologic models

The ensemble forcings are applied across all subbasins (3 forcings for each subbasin elevation zone) one member at a time. This ensures that historically-based spatial and temporal patterns embedded by the Schaake Shuffle are preserved. The results of applying the ensemble forcings to the hydrologic models are ensemble streamflow forecasts, reflecting only meteorologic uncertainty. At each ensemble forecast location, the ensemble streamflow forecast consists of *n* members.

7 MEFP Limitations

This section is intended to list the more significant limitations of MEFP. Some limitations, particularly those relating to issues of consistency, are not limitations of the HEFS methodology, but are limitations on data availability. Other limitations, particularly those contributing to underprediction of rare events, will be addressed to some extent with the release of the HEFS version 2.

Only meteorological uncertainty is considered

The MEFP system is a very robust and stable system that can be implemented easily into an operational environment. Verification studies done by the CNRFC have shown that the MEFP program provides statistically reliable spread across seasons, lead times, and event size. However, the uncertainty is limited to that associated with forecasted precipitation and temperature. The HEFS does have hydrologic uncertainty components (EnsPostPE and EnsPost), but these have not yet been implemented at the CNRFC. This is because previous testing on an early version of HEFS indicated additional refinement of these components would be appropriate before testing further.

The MEFP does not generate freezing level ensembles

Another MEFP limitation is the quality of temperature estimates during winter storms. Since MEFP can only be parameterized for temperature and precipitation, uncertainty in rain-snow elevation estimates is derived within SNOW-17 when the lapsed temperature forecast is used to estimate the rain-snow elevation. MEFP creates 6-hour temperature ensembles derived from daily maximum and minimum forecasts. This method works well when describing the daily diurnal pattern during clear sky situations. But it does not work well for precipitation events when variations between daily maximum and minimum temperature are compressed or even non-existent. This occurs when storm attributes, such as frontal passage, overwhelm the normal diurnal pattern. In these situations, the diurnal pattern forecast can be overstated and result in incorrect precipitation typing (rain or snow). This can be problematic for basins where watershed area changes dramatically with just a slight change in elevation. In these cases, a very large area of the watershed could be modeled as snow falling due to unreasonable low temperature estimates from the diurnal temperature estimates. This issue could be improved by adding a third parameter to the MEFP - freezing level. Also, parameterizing temperatures based on 6-hour records rather than daily maximums and minimums would also be an improvement. Because of this, CNRFC has configured HEFS to use the single-valued freezing level estimate (HAS-QZF) for all ensemble members for the first 10 days of the forecast. This change eliminates any uncertainty in precipitation typing, but does provide a more realistic estimate of where it is raining and snowing in a watershed. So MEFP temperature uncertainty impacts are limited to snowmelt processes modeled by SNOW-17 during the first 10 days of the forecast run.

CNRFC notes that other RFCs are using the two temperature slots in the MEFPPE to forecast two of the synoptic times and then interpolating the other two. So there is a mitigation/workaround for situations where the diurnal-cycle modeling is inappropriate.

Conditionality of meteorological uncertainty

In addition, as described above, the MEFP is calibrated using samples across a moving 61-day window. The samples likely represent a diverse set of atmospheric conditions that do not have the same predictability. As such, it is possible that MEFP provides over-dispersed ensembles when atmospheric conditions are more predictable (strongly forced frontal system) and under-dispersed ensembles when atmospheric conditions are less predictable (a cut-off low or convective). However, deriving conditional distributions could run into issues related to inadequate sample sizes.

Limited ensemble spread in late season snowmelt forecasts

While HEFS forecasts generated by MEFP reflect uncertainty in meteorology, uncertainty in the current state of the hydrologic models is not reflected. With respect to snowmelt forecasts, it is important to recognize that uncertainty in the modeled snowpack is not reflected. While hydrologic models are periodically updated to reflect latest available snow course measurements, the resulting values of basin zone snow-water equivalent (SWE) are single-valued best estimates. Uncertainty about these estimates is not modeled.

Consistency in forecast models and methods

Current and past forecast data sets should be as consistent as possible to avoid introducing errors in bias or spread into the ensemble forecast. Ideally, the current operational forecast model, and associated forecast methods, would be exactly consistent with the model and methods reflected in past forecasts. However, the operational forecast model and methods are adjusted with time in order to provide a best forecast. Past forecasts in the form of reforecasts will typically reflect a single “frozen” version of the model, and past forecasts in the form of archived forecasts will reflect any changes in models or methods during the record. Efforts are made to build data sets that are as consistent as possible, but they are not perfectly consistent.

An example of a known inconsistency at the CNRFC is described here. At the CNRFC, the NBM can comprise a significant component of the QPF for days 1 - 6, which is the single-valued precipitation input to the MEFP. Archived forecasts for the period of record WY 2010 - 2023 were supplied to the MEFPPE for computation of statistical parameters. However, the National Blend of Models (NBM), which is a component of the current NBM QPF, is only reflected in the NBM QPF forecast archive for the last few years of the record. Through testing, the CNRFC determined that ensembles computed using the NBM QPF for days 1 - 6, still out performed GEFSv12 even with the inconsistent representation of the NBM.

Consistency in period of record

The HEFS computations can also be affected by inconsistencies in period of record. There is a period of record of historical data that the Schaake shuffle draws upon to rank historical canonical events. This period of record should equal that from which canonical events are drawn for the MEFPPE to compute statistical parameters. Computations to create ensembles beyond the MEFP period (14 days at the CNRFC), which can be based on raw or sampled climatology, should also reflect the same period of record to prevent sudden changes at the transition.

Only one parametric distribution option

The MEFP is limited to the gamma distribution for fitting the marginal distributions of observations and forecasts. This can be an issue when trying to get a good fit at the tails of a distribution. The quantile-quantile plots in **Figures 19 and 20** show how observations and forecasts for an example location, French Meadows (FMDC1), do not have a good fit in the upper tail of the distribution. Verification studies at the CNRFC have shown that this issue can adversely affect the reliability of the ensemble forecast associated with a large event (greater than about 200 mm over 3 days at FMDC1), resulting in a low bias.

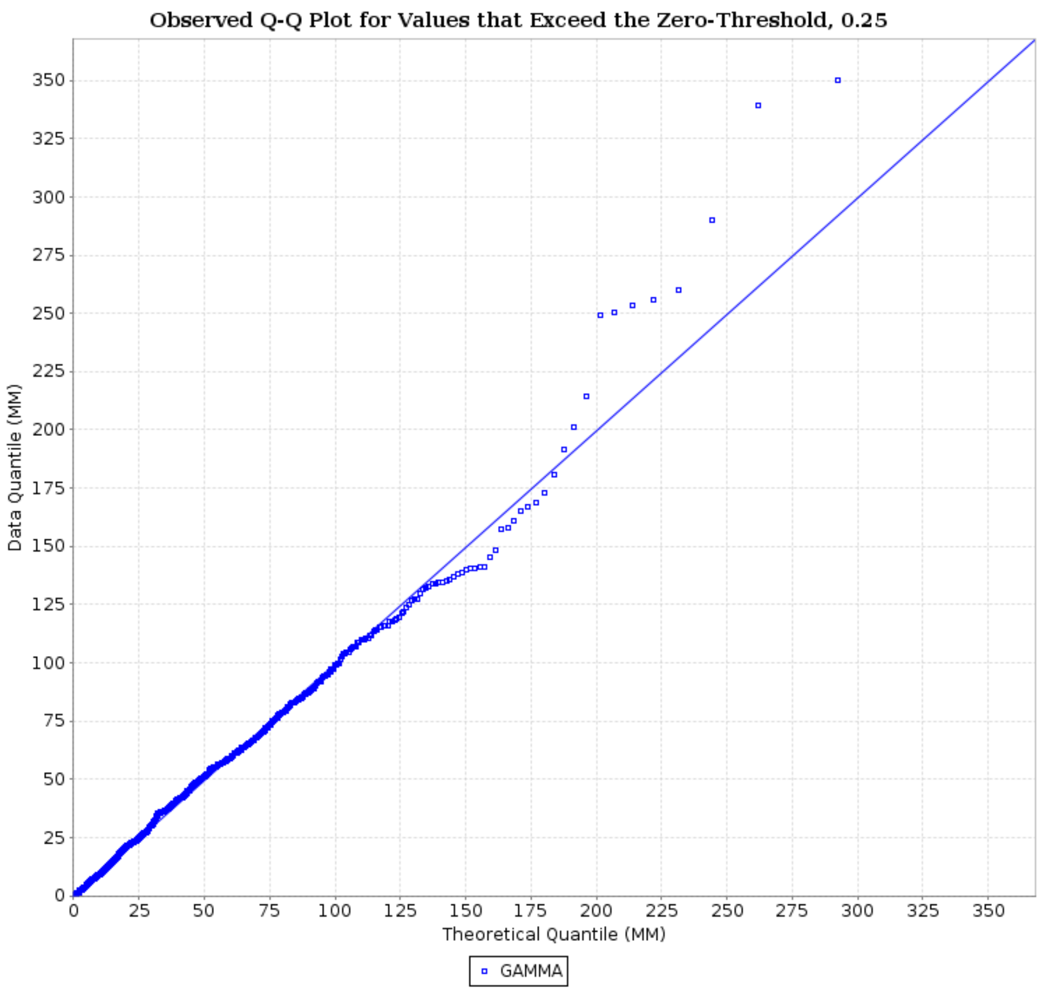


Figure 19 - French Meadows *Observed* Data & Theoretical Quantiles for 3-day Total Precipitation for January 26th 60-day Window Sample Size

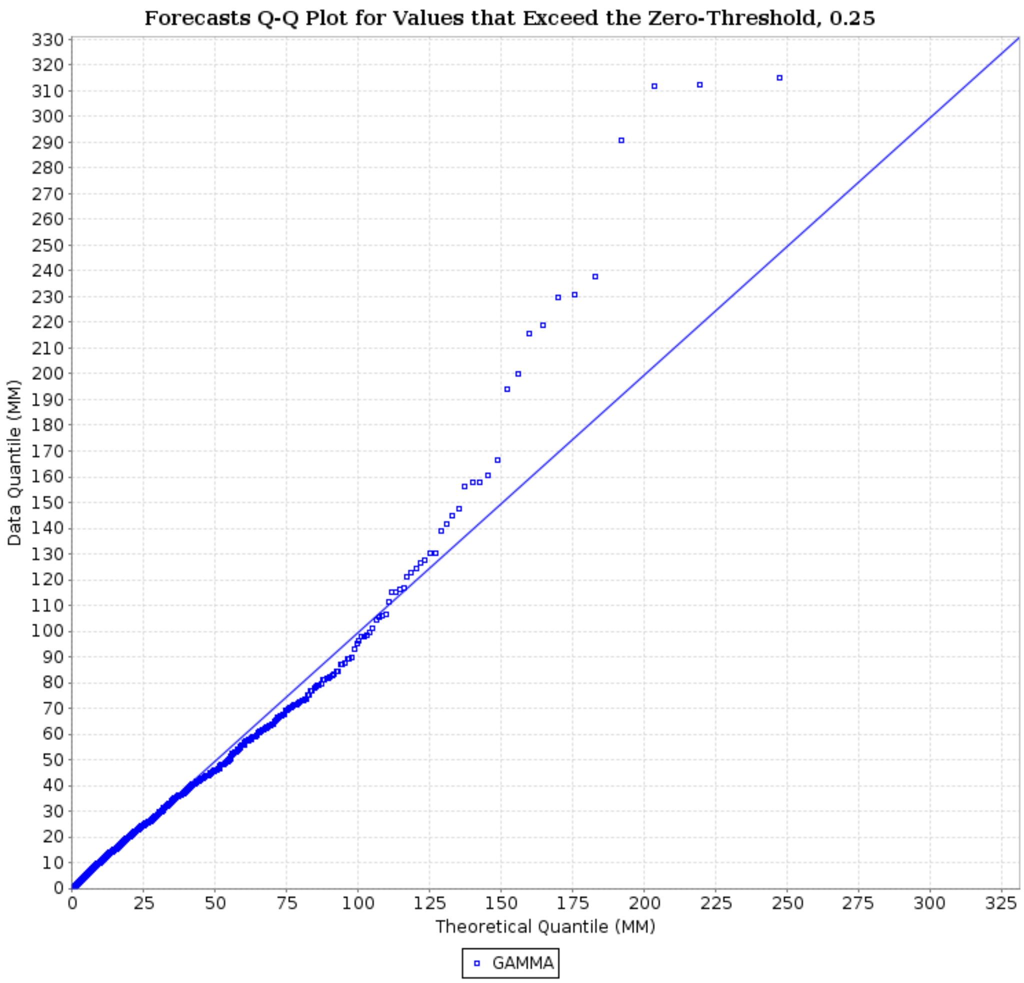


Figure 20 - French Meadows *Forecast* Data & Theoretical Quantiles for 3-day Total Precipitation for January 26th 60-day Window Sample Size

Type-II conditional bias

Type-II conditional bias (T2CB) in this case refers to the tendency of MEFP to systematically underestimate the most extreme observed precipitation amounts. In contrast, smaller forecasts are reasonably unbiased, conditional upon the forecast amount (aka small Type-I conditional bias or good "reliability"). The main reason for this is a “regression dilution” or “attenuation effect” (see Wikipedia for description), which is common with regression-type statistical post-processors, such as the MEFP. Methods for reducing the effect of T2CB are under consideration for implementation in the HEFS v2.

Lack of smoothness between canonical event boundaries

Each canonical event is a separate statistical model. When these models are brought together in a forecast horizon, without any kind of smoothing (as is the case with the MEFP), then any differences in the statistical behavior between these events (e.g., merely due to sampling uncertainty) will translate into discontinuities in the forecast horizon. They are generally most prominent for temperature because it is a smoothly varying time-series. At the CNRFC, this lack of smoothness can also occur when transitioning from the last day of the MEFP-generated ensemble forecast (day 14) to the first day of the ensemble forecast developed outside of MEFP using raw climatology. This occurs when there is an inconsistency between the “no-skill” baseline adopted by the MEFP for periods of forecast forcing, which is known as “resampled climatology”, and the raw climatology used after the period of forecast forcing. This typically occurs when the period of record for the forecast forcing (and hence resampled climatology) is different from the period of record used for raw climatology.

The Schaake Shuffle is not flow dependent

The MEFP uses observed time-series that begin on the same historical month/day/hour in each of N historical years. It is purely conditional upon the month, day and hour at which the forecast is issued, nothing else. For example, if there is an extreme atmospheric river on 21 January 2024 at location XYZ, but there are no similar cases on or near that calendar day in the historical record, then the Schaake shuffle will provide a poor representation of the space time patterns because it will use largely dry conditions to shuffle an extremely wet forecast. In that case the Schaake shuffle will effectively randomize the inputs (since dry values all have tied ranks). Alternatives to the Schaake shuffle exist, each with unique strengths and weaknesses. One such alternative under consideration is adopting a “flow dependent” approach, in which shuffling is conditioned on the current forecast (GEFS for example) state of the atmosphere. This has the potential benefit of being more likely to capture extreme conditions if the forecasting model is more skillful than climatology (which is, effectively, what the Schaake shuffle relies on), but also has limitations which are beyond the scope of this document.

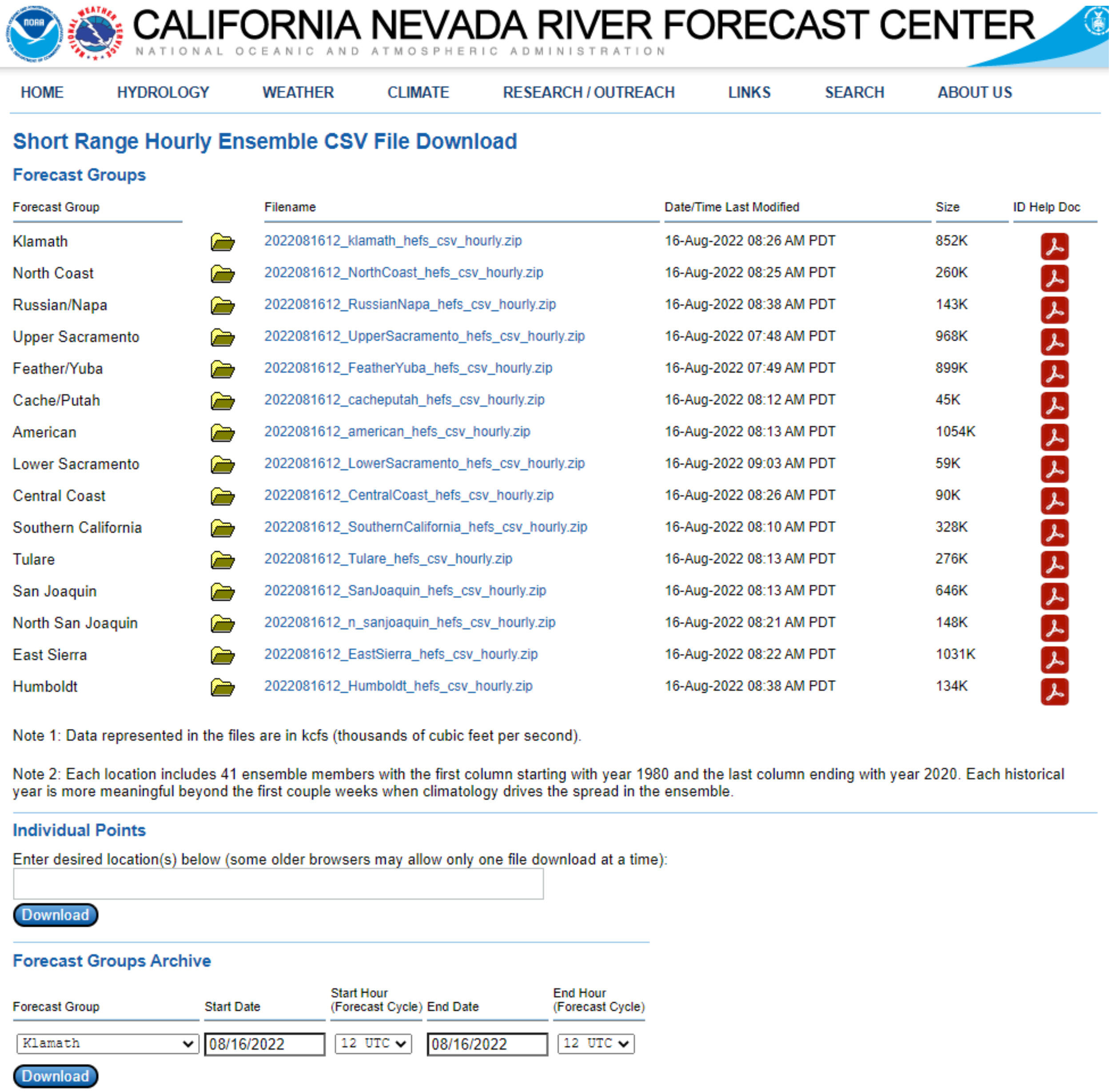
8 HEFS Products

The phrase "HEFS products", as used in this section, refers to the streamflow forecast ensembles and the variety of probabilistic products derived from them. A variety of HEFS products are disseminated through the CNRFC website. The simplest are the actual streamflow forecast ensemble time series, which can be downloaded in csv format. Hourly ensemble csv data include regulation effects and are provided out to 30 days. Daily ensemble csv data which do not include regulation effects are provided out to 365 days.

The hourly 30-day HEFS forecasts can be downloaded for an entire forecast group in csv format at: 30-day HEFS (**Figure 21**). Through this website, a user can also obtain older ensemble forecast csv files through the "Forecast Groups Archive" at the bottom of the page. There is also an option to obtain the current ensemble forecast in csv format for a single location by entering in the five character ID in the "Individual Points" section.

Ensemble traces can also be viewed and downloaded in csv format for a given location in the interactive short-range peak exceedance plot for every location where HEFS results are available. **Figure 22** shows an example for the West Walker River. All of the traces can be displayed on the plot by clicking the "View Model Traces" button to the right of the graph. The hourly csv data can be obtained by clicking on the 5 letter ID above the graphic where it says "CSV Ensemble File Download". There are other short-range graphics that can be viewed on the CNRFC website, such as probabilistic accumulated volumes, and daily box plots and histograms.

There are also a number of long-range volume plots for many HEFS locations as well. There are graphical displays for forecast monthly, seasonal (April-July), water year, and multi-year volumes. Above the water year accumulation plots (**Figure 23**) the daily 365-day ensemble time series can be accessed by clicking on the five letter ID next to the "CSV Ensemble File Download" text. There is also a 365-day HEFS csv download site similar to the hourly one where a user can download an HEFS forecast csv file for all locations in a given forecast group, obtain older HEFS forecasts for a given date, and also get a current 365-day HEFS forecast for a specified location. This site can be accessed by clicking on the "Forecast Group" text to the right of the "CSV Ensemble File Download".



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NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

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Short Range Hourly Ensemble CSV File Download

Forecast Groups

Forecast Group	Filename	Date/Time Last Modified	Size	ID Help Doc
Klamath	2022081612_klamath_hefs_csv_hourly.zip	16-Aug-2022 08:26 AM PDT	852K	
North Coast	2022081612_NorthCoast_hefs_csv_hourly.zip	16-Aug-2022 08:25 AM PDT	260K	
Russian/Napa	2022081612_RussianNapa_hefs_csv_hourly.zip	16-Aug-2022 08:38 AM PDT	143K	
Upper Sacramento	2022081612_UpperSacramento_hefs_csv_hourly.zip	16-Aug-2022 07:48 AM PDT	968K	
Feather/Yuba	2022081612_FeatherYuba_hefs_csv_hourly.zip	16-Aug-2022 07:49 AM PDT	899K	
Cache/Putah	2022081612_cacheputah_hefs_csv_hourly.zip	16-Aug-2022 08:12 AM PDT	45K	
American	2022081612_american_hefs_csv_hourly.zip	16-Aug-2022 08:13 AM PDT	1054K	
Lower Sacramento	2022081612_LowerSacramento_hefs_csv_hourly.zip	16-Aug-2022 09:03 AM PDT	59K	
Central Coast	2022081612_CentralCoast_hefs_csv_hourly.zip	16-Aug-2022 08:26 AM PDT	90K	
Southern California	2022081612_SouthernCalifornia_hefs_csv_hourly.zip	16-Aug-2022 08:10 AM PDT	328K	
Tulare	2022081612_Tulare_hefs_csv_hourly.zip	16-Aug-2022 08:13 AM PDT	276K	
San Joaquin	2022081612_SanJoaquin_hefs_csv_hourly.zip	16-Aug-2022 08:13 AM PDT	646K	
North San Joaquin	2022081612_n_sanjoaquin_hefs_csv_hourly.zip	16-Aug-2022 08:21 AM PDT	148K	
East Sierra	2022081612_EastSierra_hefs_csv_hourly.zip	16-Aug-2022 08:22 AM PDT	1031K	
Humboldt	2022081612_Humboldt_hefs_csv_hourly.zip	16-Aug-2022 08:38 AM PDT	134K	

Note 1: Data represented in the files are in kcfs (thousands of cubic feet per second).

Note 2: Each location includes 41 ensemble members with the first column starting with year 1980 and the last column ending with year 2020. Each historical year is more meaningful beyond the first couple weeks when climatology drives the spread in the ensemble.

Individual Points

Enter desired location(s) below (some older browsers may allow only one file download at a time):

Download

Forecast Groups Archive

Forecast Group	Start Date	Start Hour (Forecast Cycle)	End Date	End Hour (Forecast Cycle)
Klamath	08/16/2022	12 UTC	08/16/2022	12 UTC

Download

Figure 21 - Hourly 30-day Ensemble Streamflow Forecasts

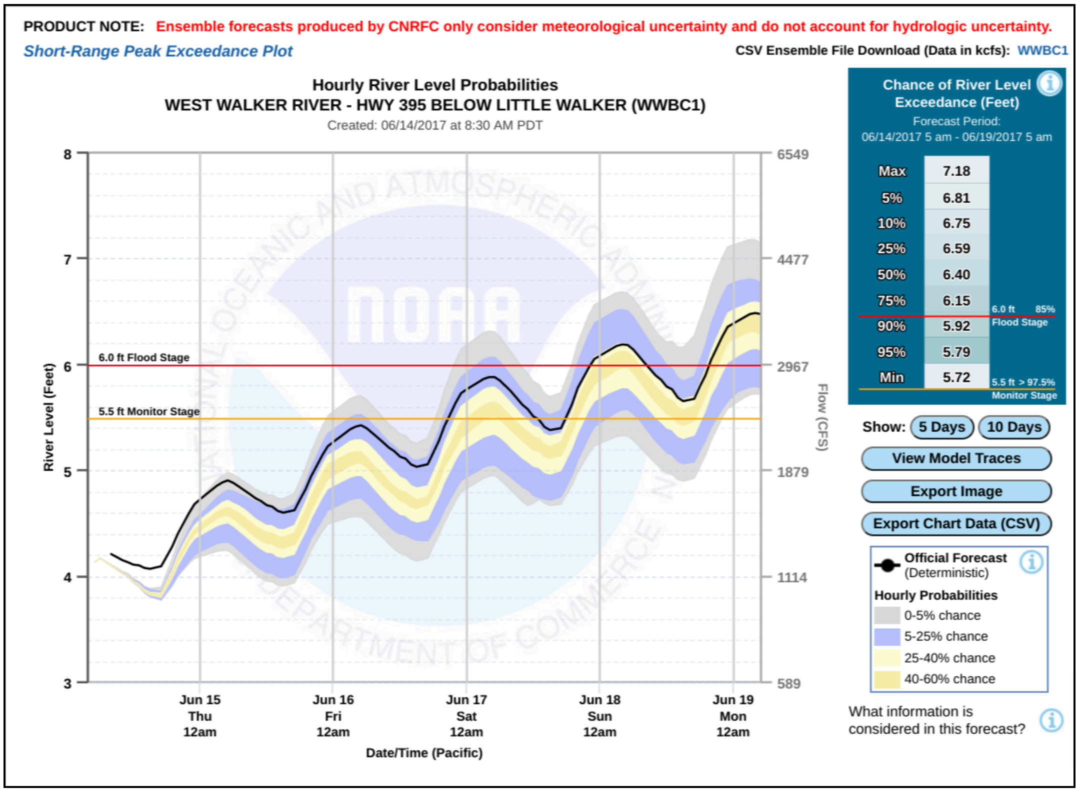

Figure 22 - Short-Range Ensemble Graphic

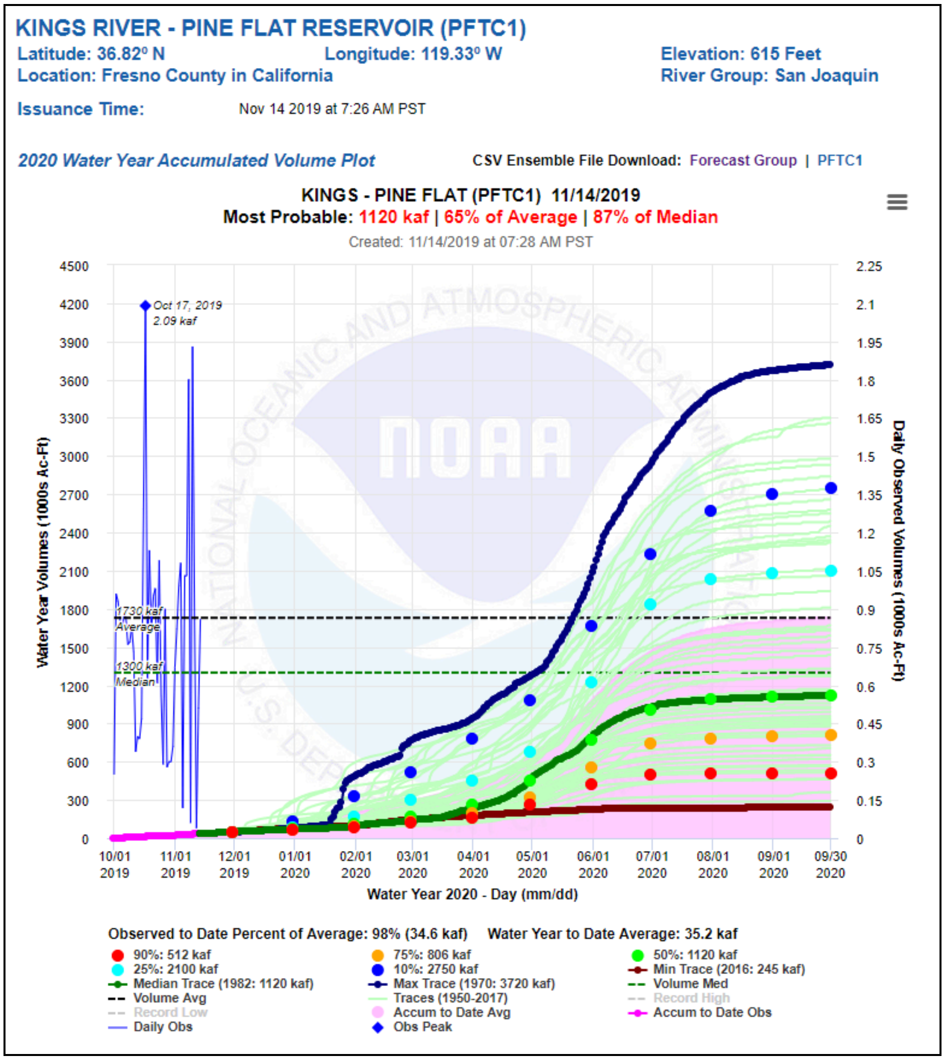

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Figure 23 - Long-Range Water Year Accumulation Plot

9 References

Anderson, E.A., 'A Point Energy and Mass Balance Model of a Snow Cover', NOAA Technical Report NWS 19, 150 pp, February 1976.

Burnash, R. J. C., Ferral, R. L., and McGuire, R. A. 'A Generalized Streamflow Simulation System, Conceptual Modeling for Digital Computers', National Weather Service, California Department of Water Resources, March 1973.

Clarke, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., Wilby, R., 2004. The Schaake Shuffle: A Method for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields. Journal of Hydrometeorology, 5 (1), 243-262.

Demargne, j., Wu, L., Regonda, S. K., Brown, J. D., Lee, H., He, M., Seo, D., Hartman, R., Herr, H., Fresch, Schaake, J., and Zhu, Y., The science of NOAA's operational hydrologic ensemble forecast service., Bull. Amer. Meteor. Soc., 2014, Jan., 79-98.

Herr, H.D., Krzysztofowicz, R., 2005. Generic probability distribution of rainfall in space: the bivariate model. J. Hydrol., 306, 234–263.

Wu, L., Seo, D., Demargne, J., Brown, J., Cong, S., Schakke, J., 2011. Generation of ensemble precipitation forecast from single-valued quantitative precipitation forecast for hydrologic ensemble prediction. J. Hydrol., 399, 281-298.

10 Attachment "Schaake Shuffle Step-by-Step Example"

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Schaake Shuffle Step-by-Step Example

- Assume we have a 24 hour precipitation forecast. We have 4 6-hour base events and one 24 hour total modulation event – 5 canonical events.
- Assume we have 10 ensemble members that matches the number of years we have in our climatology.
- The Schaake Shuffle will compute the mapping of the ensemble members one canonical event at a time starting from lowest correlation, and ending with the highest correlated canonical event.
- Base and modulation event precipitation amounts will be shuffled based on the climatological ordering technique.

Here are the raw ensemble member precipitation values generated by MEFP prior to being shuffled by the Schaake Shuffle method

6-hour base event periods

24 aggregation modulation event

	0-6	6-12	12-18	18-24	0-24
ens #	FMAP (in)	FMAP (in)	FMAP (in)	FMAP (in)	FMAP (in)
1	0.60	1.00	0.85	0.20	3.08
2	0.44	0.55	0.24	0.40	1.83
3	0.35	0.40	0.17	0.13	1.23
4	0.47	0.65	0.32	0.17	1.80
5	0.30	0.32	0.21	0.09	1.09
6	0.38	0.53	0.73	0.10	1.81
7	0.33	0.35	0.25	0.05	1.13
8	0.49	0.75	0.38	0.15	2.13
9	0.41	0.64	0.21	0.16	1.67
10	0.40	0.44	0.30	0.11	1.48
	0.78	0.72	0.68	0.63	0.82

correlation values

	0-6	6-12	12-18	18-24
ens #	FMAP (in)	FMAP (in)	FMAP (in)	FMAP (in)
1	0.60	1.00	0.85	0.20
2	0.44	0.55	0.24	0.40
3	0.35	0.40	0.17	0.13
4	0.47	0.65	0.32	0.17
5	0.30	0.32	0.21	0.09
6	0.38	0.53	0.73	0.10
7	0.33	0.35	0.25	0.05
8	0.49	0.75	0.38	0.15
9	0.41	0.64	0.21	0.16
10	0.40	0.44	0.30	0.11
	0.78	0.72	0.68	0.63
	4	3	2	1

0-24
FMAP (in)
3.08
1.83
1.23
1.80
1.09
1.81
1.13
2.13
1.67
1.48
0.82
5

Based on the correlation values, the 18-24 hour period will get shuffled first because it has the lowest correlation. The modulation event will be applied last because it has the highest correlation.

- Let's start with the Schaake Shuffle being applied to the lowest correlated period: 18-24 hr.
- We want to map these 10 members to historical years as part of the Schaake Shuffle.
- We apply the Schaake Shuffle method to each base event, one at a time.
- We will step through this example step by step for base event 18-24hr.
- The shuffling for the 18-24 hour period is associated with the corresponding historical precipitation amount ordering.

MEFP unshuffled precipitation 6-hr precipitation values

	0-6	6-12	12-18	18-24
ens #	FMAP (in)	FMAP (in)	FMAP (in)	FMAP (in)
1	0.60	1.00	0.85	0.20
2	0.44	0.55	0.24	0.40
3	0.35	0.40	0.17	0.13
4	0.47	0.65	0.32	0.17
5	0.30	0.32	0.21	0.09
6	0.38	0.53	0.73	0.10
7	0.33	0.35	0.25	0.05
8	0.49	0.75	0.38	0.15
9	0.41	0.64	0.21	0.16
10	0.40	0.44	0.30	0.11

Historical precipitation values for corresponding forecast periods

	0-6	6-12	12-18	18-24
year	MAP (in)	MAP (in)	MAP (in)	MAP (in)
1990	0.05	0.52	0.26	0.09
1991	0.37	0.33	0.43	0.62
1992	0.27	0.18	0.30	0.42
1993	0.07	0.49	0.11	0.04
1994	0.48	0.70	0.52	0.24
1995	0.54	1.30	0.83	0.32
1996	0.35	0.25	0.09	0.03
1997	0.11	0.27	0.13	0.06
1998	0.02	0.61	0.45	0.20
1999	0.51	0.90	0.72	0.66

Ensemble Member (18-24 hour period)	
ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked **Ensemble** (18-24 hour period)	
ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

First, the 10 ensemble values are ranked by forecast value for the base event of interest.

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked **Ensemble** (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

The 10 historical precipitation amounts are determined for the given forecast period.

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked **Ensemble** (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked **Historical**

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

The 10 historical precipitation amounts are then ranked.

The highest ranked precipitation ensemble value is assigned the historical year with the largest precipitation amount.

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	**0.40**

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	**1**	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	**1**	2	**0.4**

The second highest ranked precipitation ensemble value is assigned the historical year with the second largest precipitation amount.

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	**0.20**
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	**2**	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	**2**	1	**0.2**
1999	1	2	0.4

This process is repeated for all ensemble values.

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	**0.17**
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	**3**	4	**0.17**
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	**0.16**
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	**0.15**
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member
(18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble
(18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	**0.15**
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values
(18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	**0.32**
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	**5**	**0.24**
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	**5**	**8**	**0.16**
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	**0.13**
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	**0.13**
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	**0.11**
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	**0.11**
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	**0.10**
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	**0.1**
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member
(18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble
(18-24 hour period)

ens #	FMAP (in)
7	0.05
5	**0.09**
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values
(18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	**0.09**
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

Ensemble Member
(18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked Ensemble
(18-24 hour period)

ens #	FMAP (in)
7	**0.05**
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values
(18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked Historical

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	**0.05**
1993	9	5	0.09
1997	8	6	0.1
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.2
1999	1	2	0.4

- Now let's look at the ensemble members for the second lowest correlated base event: 12-18 hour forecast period.
- Ensemble members are ranked just like for the 18-24 hour base event

Ensemble Member (12-18 hour period)

ens #	FMAP (in)
1	0.85
2	0.24
3	0.17
4	0.32
5	0.21
6	0.73
7	0.25
8	0.38
9	0.21
10	0.30

Ranked **Ensemble** (12-18 hour period)

ens #	FMAP (in)
3	0.17
5	0.21
9	0.21
2	0.24
7	0.25
10	0.30
4	0.32
8	0.38
6	0.73
1	0.85

Historical values for the base event are selected and ranked just like for the 18-24 base event

Ensemble Member (12-18 hour period)

ens #	FMAP (in)
1	0.85
2	0.24
3	0.17
4	0.32
5	0.21
6	0.73
7	0.25
8	0.38
9	0.21
10	0.30

Ranked **Ensemble** (12-18 hour period)

ens #	FMAP (in)
3	0.17
5	0.21
9	0.21
2	0.24
7	0.25
10	0.30
4	0.32
8	0.38
6	0.73
1	0.85

Historical Values (12-18 hour period)

year	MAP (in)
1990	0.26
1991	0.43
1992	0.30
1993	0.11
1994	0.52
1995	0.83
1996	0.09
1997	0.13
1998	0.45
1999	0.72

Ranked **Historical**

year	Hist Rank	MAP (in)
1996	10	0.09
1993	9	0.11
1997	8	0.13
1990	7	0.26
1992	6	0.30
1991	5	0.43
1998	4	0.45
1994	3	0.52
1999	2	0.72
1995	1	0.83

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	3	0.17
1993	9	5	0.21
1997	8	9	0.21
1990	7	2	0.24
1992	6	7	0.25
1991	5	10	0.30
1998	4	4	0.32
1994	3	8	0.38
1999	2	6	0.73
1995	1	1	0.85

Results from Base Event 18-24 hr

Ensemble Member (18-24 hour period)

ens #	FMAP (in)
1	0.20
2	0.40
3	0.13
4	0.17
5	0.09
6	0.10
7	0.05
8	0.15
9	0.16
10	0.11

Ranked **Ensemble** (18-24 hour period)

ens #	FMAP (in)
7	0.05
5	0.09
6	0.10
10	0.11
3	0.13
8	0.15
9	0.16
4	0.17
1	0.20
2	0.40

Historical Values (18-24 hour period)

year	MAP (in)
1990	0.09
1991	0.62
1992	0.42
1993	0.04
1994	0.24
1995	0.32
1996	0.03
1997	0.06
1998	0.20
1999	0.66

Ranked **Historical**

year	Hist Rank	MAP (in)
1996	10	0.03
1993	9	0.04
1997	8	0.06
1990	7	0.09
1998	6	0.20
1994	5	0.24
1995	4	0.32
1992	3	0.42
1991	2	0.62
1999	1	0.66

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	7	0.05
1993	9	5	0.09
1997	8	6	0.10
1990	7	10	0.11
1998	6	3	0.13
1994	5	8	0.16
1995	4	9	0.15
1992	3	4	0.17
1991	2	1	0.20
1999	1	2	0.40

Results from Base Event 12-18 hr

Ensemble Member (12-18 hour period)

ens #	FMAP (in)
1	0.85
2	0.24
3	0.17
4	0.32
5	0.21
6	0.73
7	0.25
8	0.38
9	0.21
10	0.30

Ranked **Ensemble** (12-18 hour period)

ens #	FMAP (in)
3	0.17
5	0.21
9	0.21
2	0.24
7	0.25
10	0.30
4	0.32
8	0.38
6	0.73
1	0.85

Historical Values (12-18 hour period)

year	MAP (in)
1990	0.26
1991	0.43
1992	0.30
1993	0.11
1994	0.52
1995	0.83
1996	0.09
1997	0.13
1998	0.45
1999	0.72

Ranked **Historical**

year	Hist Rank	MAP (in)
1996	10	0.09
1993	9	0.11
1997	8	0.13
1990	7	0.26
1992	6	0.30
1991	5	0.43
1998	4	0.45
1994	3	0.52
1999	2	0.72
1995	1	0.83

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1996	10	3	0.17
1993	9	5	0.21
1997	8	9	0.21
1990	7	2	0.24
1992	6	7	0.25
1991	5	10	0.30
1998	4	4	0.32
1994	3	8	0.38
1999	2	6	0.73
1995	1	1	0.85

Results from Base Event 6-12 hr

Ensemble Member (6-12 hour period)

ens #	FMAP (in)
1	1.00
2	0.55
3	0.40
4	0.65
5	0.32
6	0.53
7	0.35
8	0.75
9	0.64
10	0.44

Ranked **Ensemble** (6-12 hour period)

ens #	FMAP (in)
5	0.32
7	0.35
3	0.40
10	0.44
6	0.53
2	0.55
9	0.64
4	0.65
8	0.75
1	1.00

Historical Values (6-12 hour period)

year	MAP (in)
1990	0.52
1991	0.33
1992	0.18
1993	0.49
1994	0.70
1995	1.30
1996	0.25
1997	0.27
1998	0.61
1999	0.90

Ranked **Historical**

year	Hist Rank	MAP (in)
1992	10	0.18
1996	9	0.25
1997	8	0.27
1991	7	0.33
1993	6	0.49
1990	5	0.52
1998	4	0.61
1994	3	0.70
1999	2	0.90
1995	1	1.30

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1992	10	5	0.32
1996	9	7	0.35
1997	8	3	0.40
1991	7	10	0.44
1993	6	6	0.53
1990	5	2	0.55
1998	4	9	0.64
1994	3	4	0.65
1999	2	8	0.75
1995	1	1	1.00

Results from Base Event 0-6 hr

Ensemble Member (0-6 hour period)

ens #	FMAP (in)
1	0.60
2	0.44
3	0.35
4	0.47
5	0.30
6	0.38
7	0.33
8	0.49
9	0.41
10	0.40

Ranked **Ensemble** (0-6 hour period)

ens #	FMAP (in)
5	0.30
7	0.33
3	0.35
6	0.38
10	0.40
9	0.41
2	0.44
4	0.47
8	0.49
1	0.60

Historical Values (0-6 hour period)

year	MAP (in)
1990	0.05
1991	0.37
1992	0.27
1993	0.07
1994	0.48
1995	0.54
1996	0.35
1997	0.11
1998	0.02
1999	0.51

Ranked **Historical**

year	Hist Rank	MAP (in)
1998	10	0.02
1990	9	0.05
1993	8	0.07
1997	7	0.11
1992	6	0.27
1996	5	0.35
1991	4	0.37
1994	3	0.48
1999	2	0.51
1995	1	0.54

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1998	10	5	0.30
1990	9	7	0.33
1993	8	3	0.35
1997	7	6	0.38
1992	6	10	0.40
1996	5	9	0.41
1991	4	2	0.44
1994	3	4	0.47
1999	2	8	0.49
1995	1	1	0.60

Results from Modulation Event 0-24hr Total

Ensemble Member (24 hour period)

ens #	FMAP (in)
1	3.73
2	3.03
3	1.57
4	2.18
5	1.39
6	1.24
7	1.46
8	1.80
9	1.39
10	1.32

Ranked **Ensemble** (24 hour period)

ens #	FMAP (in)
6	1.24
10	1.32
5	1.39
9	1.39
7	1.46
3	1.57
8	1.80
4	2.18
2	3.03
1	3.73

Historical Values (24 hour period)

year	MAP (in)
1990	0.92
1991	1.75
1992	1.17
1993	0.71
1994	1.94
1995	2.99
1996	0.72
1997	0.57
1998	1.28
1999	2.79

Ranked **Historical**

year	Hist Rank	MAP (in)
1997	10	0.57
1993	9	0.71
1996	8	0.72
1990	7	0.92
1992	6	1.17
1998	5	1.28
1991	4	1.75
1994	3	1.94
1999	2	2.79
1995	1	2.99

Historical Year Label Mapping

year label	Ens# rank	Orig Ens #	FMAP (in)
1997	10	6	1.24
1993	9	10	1.32
1996	8	5	1.39
1990	7	9	1.39
1992	6	7	1.46
1998	5	3	1.57
1991	4	8	1.80
1994	3	4	2.18
1999	2	2	3.03
1995	1	1	3.73

Sorted Base Events are Combined into shuffled ensemble time series

0-6 hr

year label	FMAP (in)
1990	0.33
1991	0.44
1992	0.40
1993	0.35
1994	0.47
1995	0.60
1996	0.41
1997	0.38
1998	0.30
1999	0.49

6-12 hr

year label	FMAP (in)
1990	0.55
1991	0.44
1992	0.32
1993	0.53
1994	0.65
1995	1.00
1996	0.35
1997	0.40
1998	0.64
1999	0.75

12-18 hr

year label	FMAP (in)
1990	0.24
1991	0.30
1992	0.25
1993	0.21
1994	0.38
1995	0.85
1996	0.17
1997	0.21
1998	0.32
1999	0.73

18-24 hr

year label	FMAP (in)
1990	0.11
1991	0.20
1992	0.17
1993	0.09
1994	0.15
1995	0.16
1996	0.05
1997	0.10
1998	0.13
1999	0.40

Combined Results for the 4 base events

	FMAP (in)				
year label	0-6 hr	6-12 hr	12-18 hr	18-24 hr	total
1990	0.33	0.55	0.24	0.11	1.23
1991	0.44	0.44	0.30	0.20	1.38
1992	0.40	0.32	0.25	0.17	1.14
1993	0.35	0.53	0.21	0.09	1.18
1994	0.47	0.65	0.38	0.15	1.65
1995	0.60	1.00	0.85	0.16	2.61
1996	0.41	0.35	0.17	0.05	0.98
1997	0.38	0.40	0.21	0.10	1.09
1998	0.30	0.64	0.32	0.13	1.39
1999	0.49	0.75	0.73	0.40	2.37

- **Now we apply the modulation event last since it has the highest correlation**
- **The 24-hour modulation event is shuffled like the base events (see previous graphic)**
- **6-hour values are summed up over 24 hours**

6-hour values aggregated over 24 hour period

	FMAP (in)				
year label	0-6 hr	6-12 hr	12-18 hr	18-24 hr	total
1990	0.33	0.55	0.24	0.11	1.23
1991	0.44	0.44	0.30	0.20	1.38
1992	0.40	0.32	0.25	0.17	1.14
1993	0.35	0.53	0.21	0.09	1.18
1994	0.47	0.65	0.38	0.15	1.65
1995	0.60	1.00	0.85	0.16	2.61
1996	0.41	0.35	0.17	0.05	0.98
1997	0.38	0.40	0.21	0.10	1.09
1998	0.30	0.64	0.32	0.13	1.39
1999	0.49	0.75	0.73	0.40	2.37

Shuffled 24 hour Modulation Event Values

year label	FMAP (in)
1990	1.39
1991	1.80
1992	1.46
1993	1.32
1994	2.18
1995	3.73
1996	1.39
1997	1.24
1998	1.57
1999	3.03

A factor is calculated that will be applied uniformly to the individual 6-hour precipitation values so that the 6-hr summations equal the modulation event totals

24-hour totals from 6-hour values

year label	total
1990	1.23
1991	1.38
1992	1.14
1993	1.18
1994	1.65
1995	2.61
1996	0.98
1997	1.09
1998	1.39
1999	2.37

Modulation event shuffled totals

FMAP (in)
1.39
1.80
1.46
1.32
2.18
3.73
1.39
1.24
1.57
3.03

Ratio of modulation event values to 6-hr aggregations over 24-hr period

Scale Factor
1.13
1.30
1.28
1.12
1.32
1.43
1.42
1.14
1.13
1.28

A factor is calculated that will be applied uniformly to the individual 6-hour precipitation values. In this case, since the modulation event is applied last, the scaled 6-hour precipitation 24 hour totals equals the shuffled modulation event totals.

Ratio of modulation event values to 6-hr aggregations over 24-hr period

New 6-hr totals equal modulation event totals

	FMAP (in)				
year label	0-6 hr	6-12 hr	12-18 hr	18-24 hr	total
1990	0.33	0.55	0.24	0.11	1.23
1991	0.44	0.44	0.30	0.20	1.38
1992	0.40	0.32	0.25	0.17	1.14
1993	0.35	0.53	0.21	0.09	1.18
1994	0.47	0.65	0.38	0.15	1.65
1995	0.60	1.00	0.85	0.16	2.61
1996	0.41	0.35	0.17	0.05	0.98
1997	0.38	0.40	0.21	0.10	1.09
1998	0.30	0.64	0.32	0.13	1.39
1999	0.49	0.75	0.73	0.40	2.37

X

Scale Factor
1.13
1.30
1.28
1.12
1.32
1.43
1.42
1.14
1.13
1.28

=

	FMAP (in)				
year label	0-6 hr	6-12 hr	12-18 hr	18-24 hr	total
1990	0.37	0.62	0.27	0.12	1.39
1991	0.57	0.57	0.39	0.26	1.80
1992	0.51	0.41	0.32	0.22	1.46
1993	0.39	0.59	0.24	0.10	1.32
1994	0.62	0.86	0.50	0.20	2.18
1995	0.86	1.43	1.21	0.23	3.73
1996	0.58	0.50	0.24	0.07	1.40
1997	0.43	0.45	0.24	0.11	1.24
1998	0.34	0.73	0.36	0.15	1.58
1999	0.63	0.96	0.93	0.51	3.03

- In this example, the modulation event had the highest correlation, so it was ordered and applied last after all base events.
- If the modulation event had a lower correlation than one of the 6-hour base events, the modulation event would be applied before the 6-hour base event with the higher correlation.
- So the modulation event would be applied prior to all of the 6-hour base events being shuffled, and assigned historical year labels.
- In this case, climatological values are used for the base events that have not gone through the Schaake Shuffle when computing the modulation scale factor.
- The climatological values for the 6-hour base event with the higher correlation are replaced with shuffled MEFP values after the modulation event has been applied.