Hydrologic Ensemble Forecasting Service (HEFS)

Seminar D
MEFP Theory

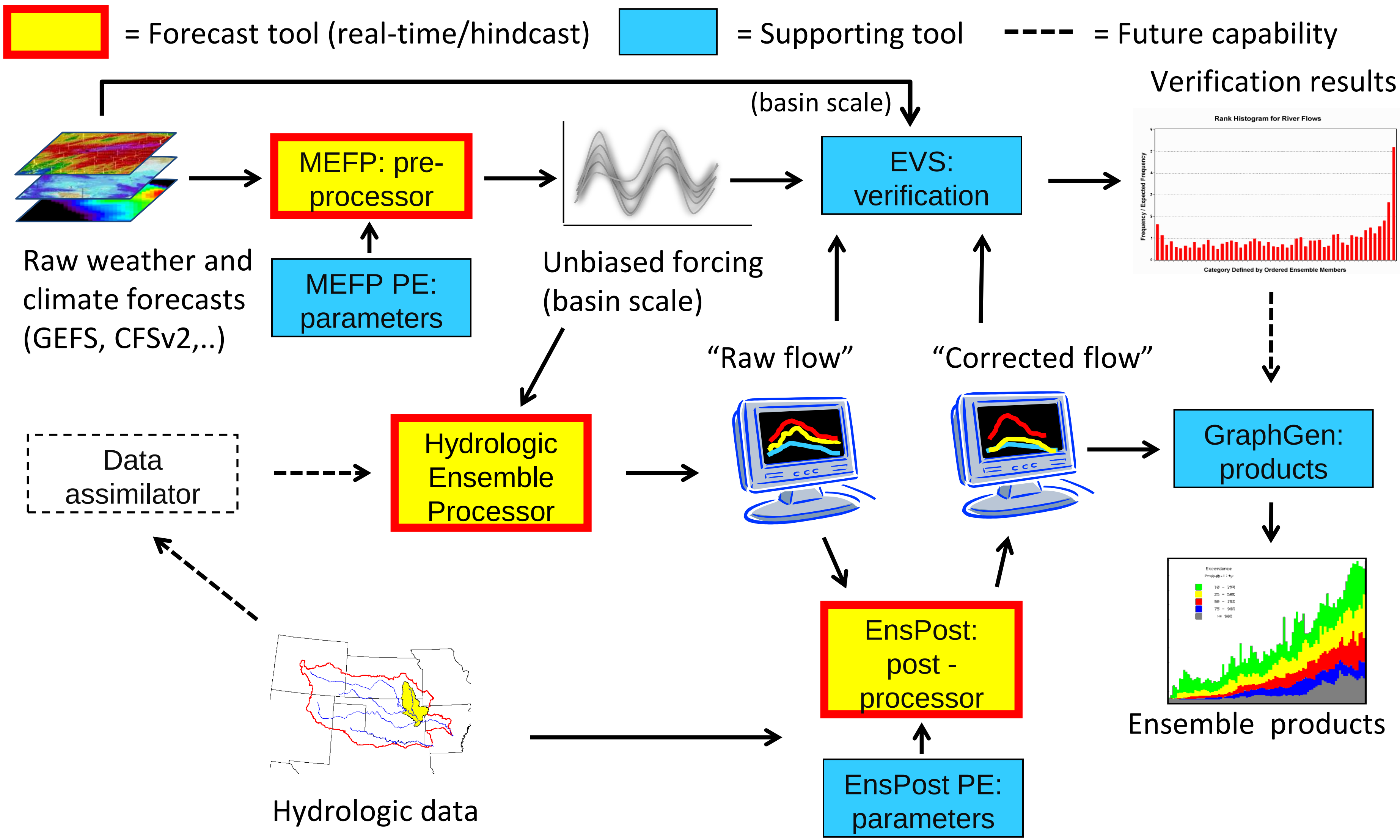
Limin Wu

HEFS Rollout Training Workshop, Kansas City, MO
August 19 – 21, 2014

Outline

- Central idea
- Problems faced
- MEFP's solutions
- General steps in MEFP
- Some examples

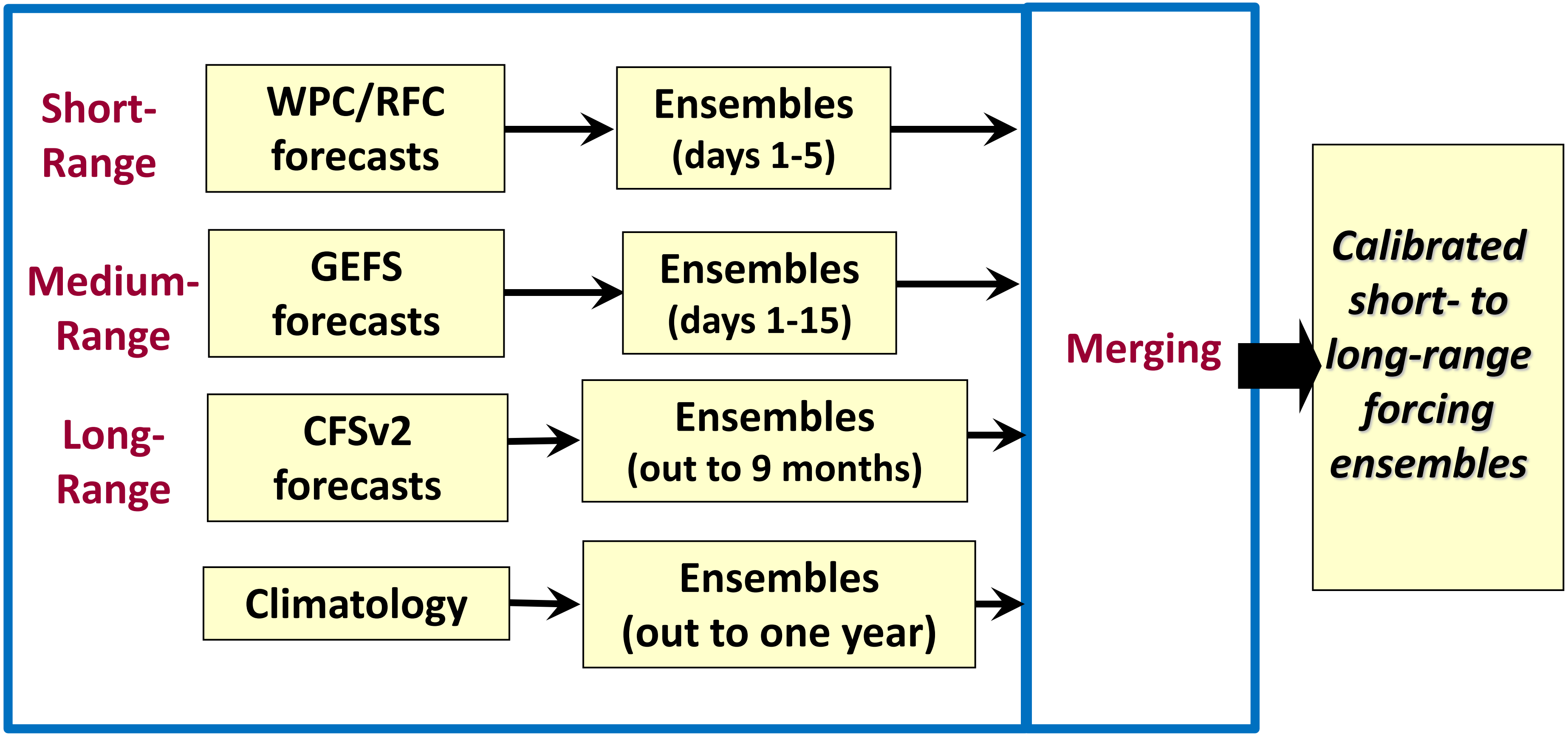
HEFS Components



Central Idea

- History is a guide to the future. Assume recent history represents near future.
- Looking back, given your single-valued forecasts, what were your observations?
- MEFP ensemble forecasts are the past observations conditional on your forecasts.
- Uncertainties are quantified by ensemble members.

MEFP System



Short-Range
WPC/RFC forecasts
Ensembles (days 1-5)
Medium-Range
GEFS forecasts
Ensembles (days 1-15)
Long-Range
CFSv2 forecasts
Ensembles (out to 9 months)
Climatology
Ensembles (out to one year)
Merging
Calibrated short- to long-range forcing ensembles

Hydrologic Forecast Needs

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

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

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

- Problem 1: How to extract skill from short-to-long range meteorological forecasts?

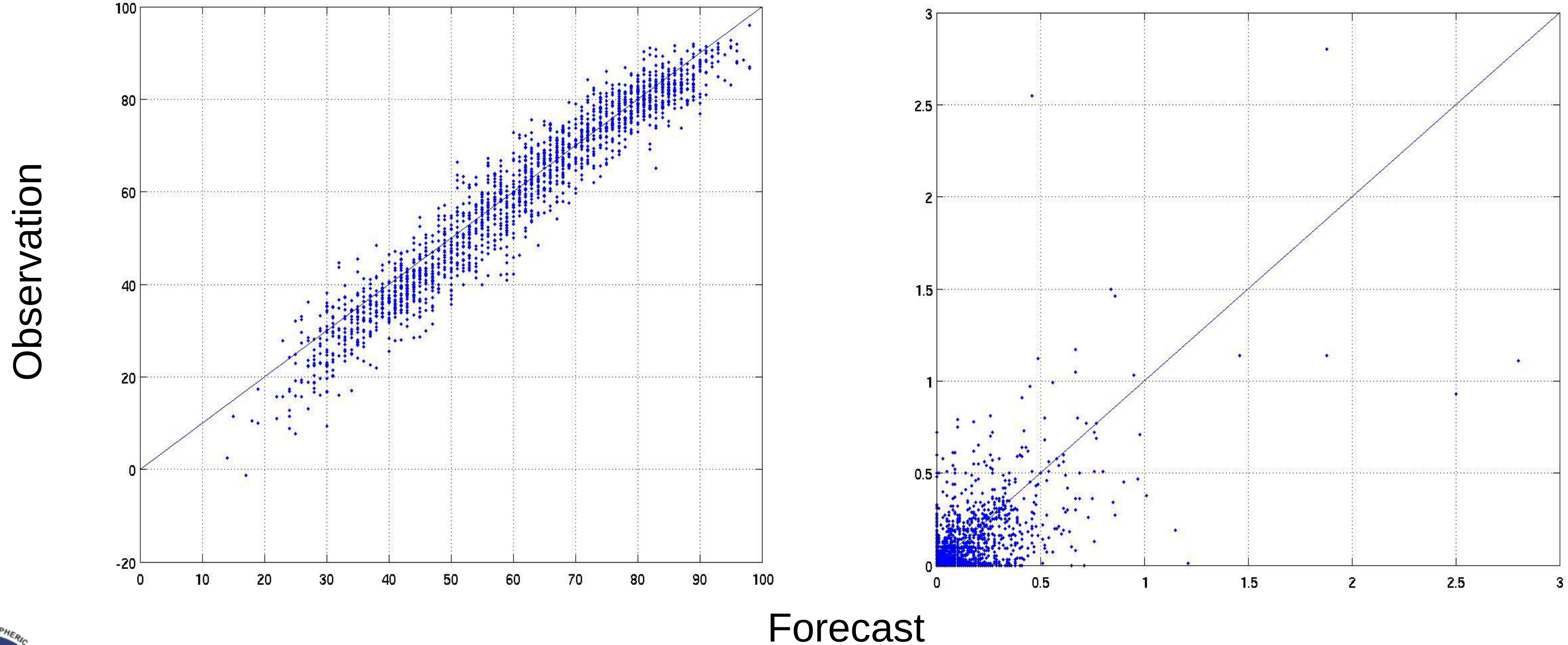
Modeling Forcing Variables

- Linear regression model may be good for temperature.
- Precipitation is skewed and intermittent.
- Problem 2: What models to choose for the forcing variables?

Joint distribution between forecast and observation

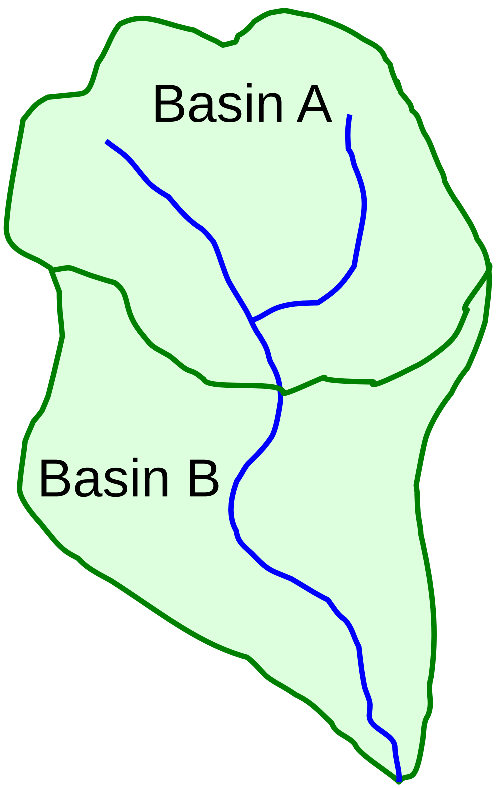
Huntingdon in Juniata River Basin

Tmax (deg. F) Precipitation (in.)



Spatial and Temporal Consistency

- Problem 3: Can the spatial correlation between two neighboring basins be preserved? How about temporal correlation? How about the relationship between temperature and precipitation?



For a given time step

Basin A

year	historical obs	ensemble fcst
1958	*	*
…		
1996	y_{Ai}	x_{Ai}
…		
2007	*	*

Basin B

Year	historical obs	ensemble fcst
1958	*	*
…		
1996	y_{Bi}	x_{Bi}
…		
2007	*	*

Close

Also close ?

Meteorological Forecasts Used

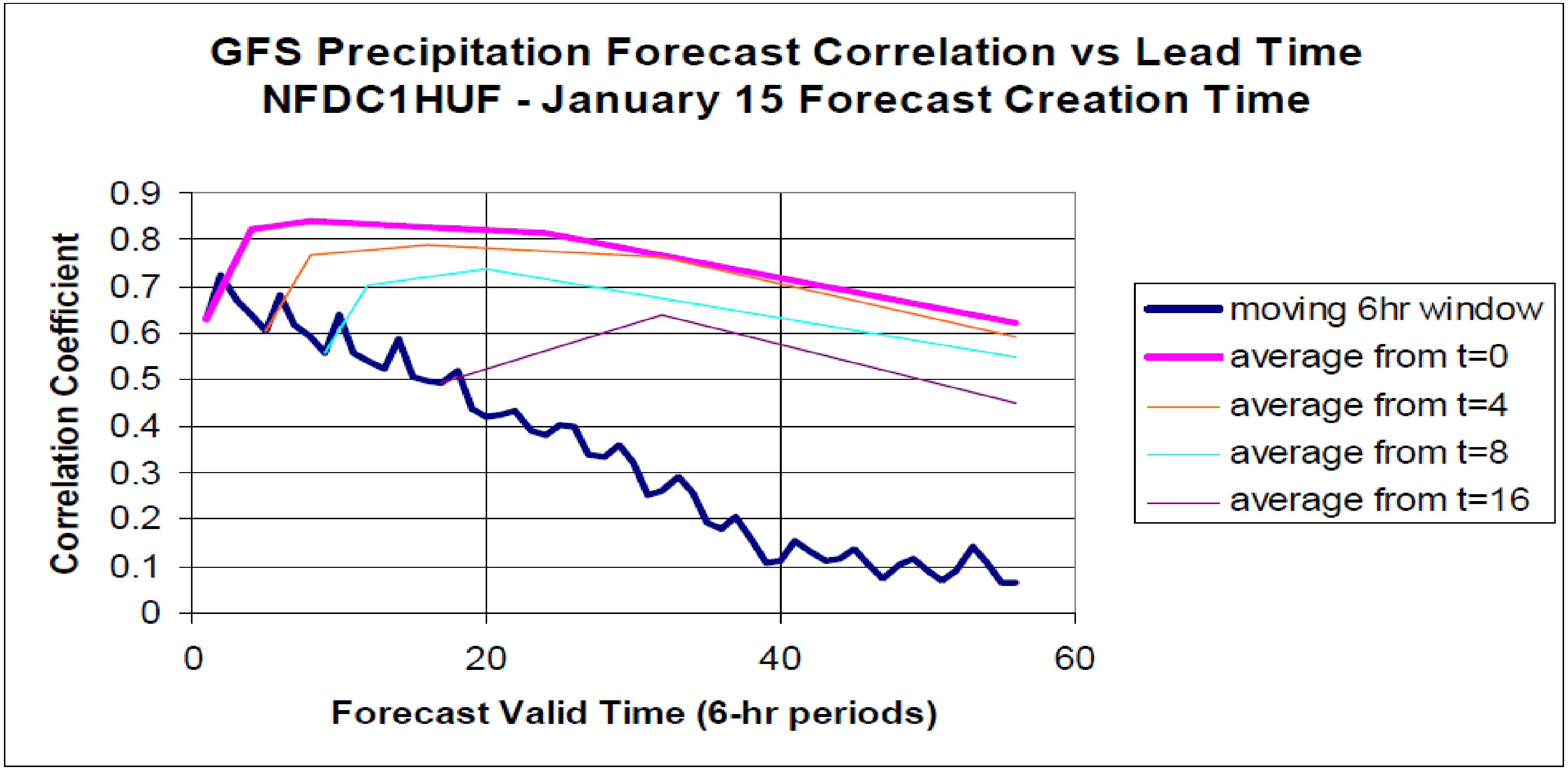
- WPC/RFC single-valued forecasts
  - QPF for days1-5 and QTF1-7
  - Additional skill from human forecasters, particularly in Day 1
- GEFS ensemble forecasts
  - Gridded forecasts out to 16 days
  - Horizontal resolution about 1 degree
  - Reforecasts available for 1985-2010
  - Moderate forecast skill
  - Ensemble mean is used
- CFSv2
  - Gridded forecasts out to 9 months
  - Horizontal resolution about 1 degree
  - Reforecasts available for 1982-2011
  - Skill is limited
  - Mean of lagged ensemble of the forecasts is used

MEFP's solution to Problem 1

Canonical Events

Capture Forecast Skill through Aggregation

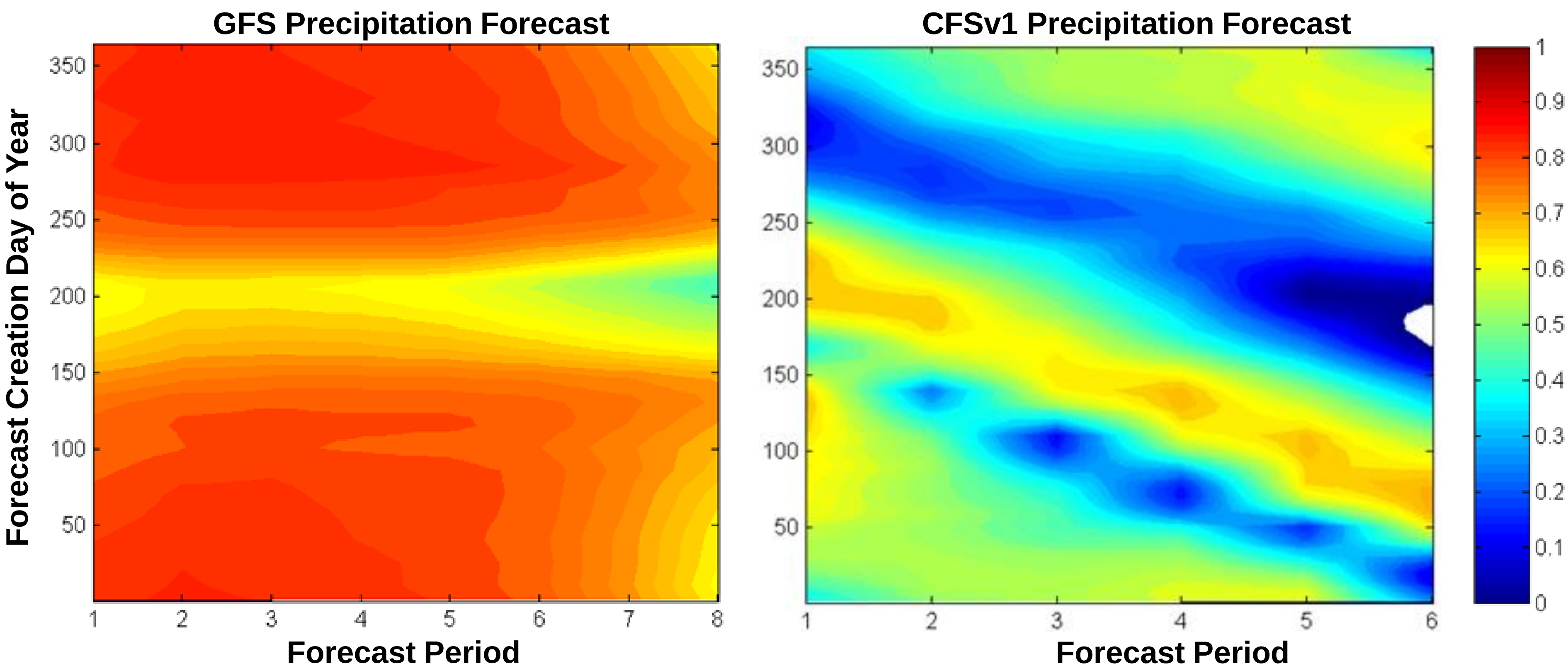
An example for winter precipitation events in the upper zone of the North fork of the American River, CA.



Forecast skill for events of fixed duration tends to decrease as forecast lead time increases. But forecast skill may be maintained as the duration of events increases (at the expense of reduced resolution).

Capture Forecast Skill through Aggregation

Correlation Coefficient of Forecast and Observation



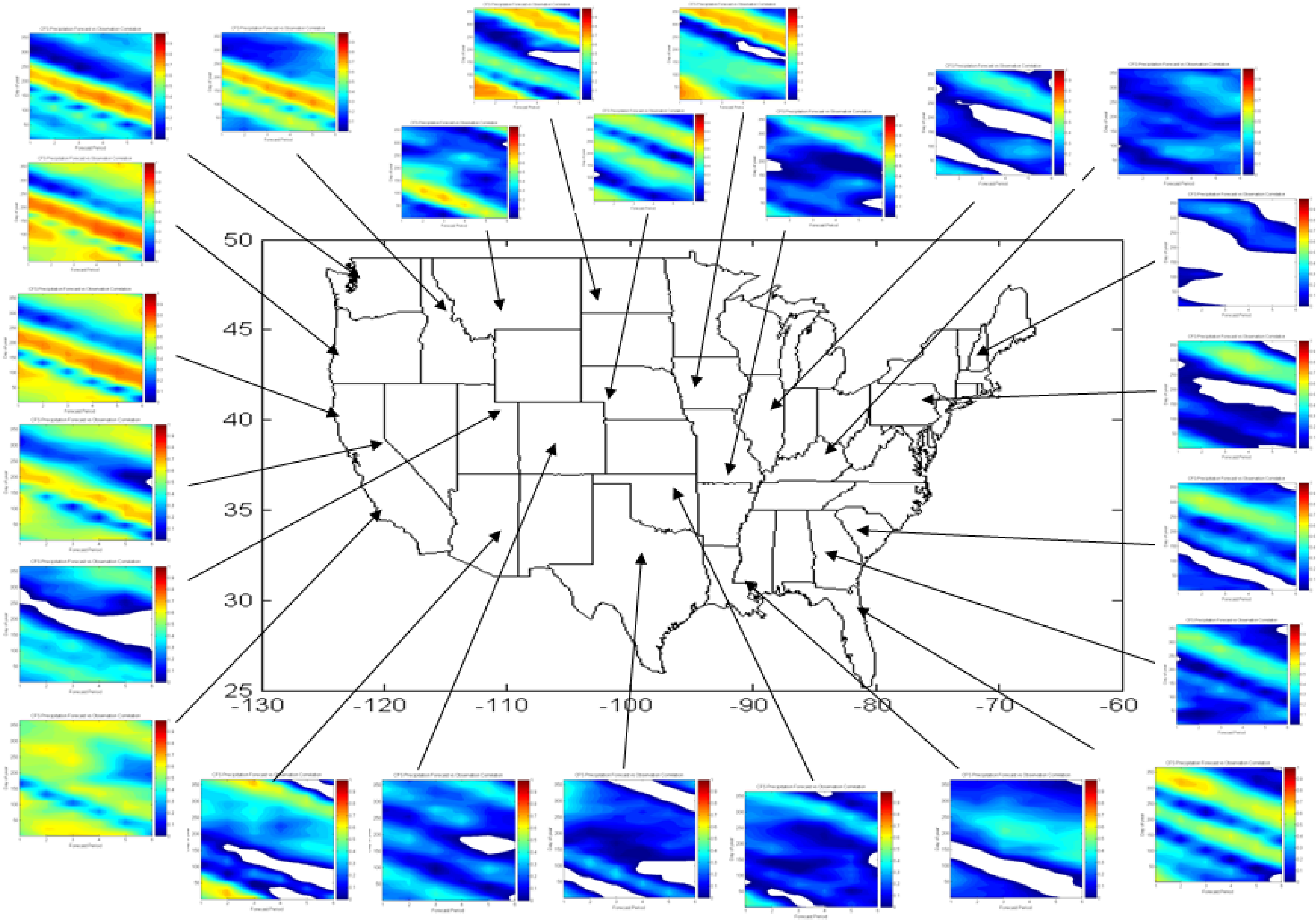
Period	1	2	3	4	5	6	7	8
Days	1	1-2	1-3	1-4	1-5	1-7	1-10	1-14

Period	1	2	3	4	5	6
Months	1-3	2-4	3-5	4-6	5-7	6-8

Potential skill of GFS and CFSv1 precipitation forecast for NFDC1 in CNRFC

CFSv1 Forecast Skill

Correlation Coefficient of Forecast and Observation
CFSv1 Precipitation Forecast



Potential skill of CFSv1 precipitation forecast for 24 basins

Canonical Events

Introducing Canonical Event: For a given forecast, a canonical event is a time scale in the forecast horizon, over which a time series of the forecast and corresponding observed are aggregated.

Examples of canonical events

6-hr events for Days 1-5	RFC/GEFS
1-day events for Days 6-8	GEFS
2-day events for Days 9-12	GEFS
3-day event for Days 13-15	GEFS
30-day events for Months 2-9	CFS
90-day events for Months 1-9	CFS

During calibration, correlations for canonical events between forecast and the corresponding observed are calculated.

MEFP's solution to Problem 2

Meta-Gaussian Distribution

Meta-Gaussian Model

- Consider the joint distribution of forecast and observation:

$F(x,y) = P(X \le x, Y \le y)$ *X*: Forecast *Y*: Observation

- The meta-Gaussian distribution constructed from the forecast and observation (Kelly and Krzysztofowicz, 1997):

$H(x, y) = B(Z, W; \rho)$, where

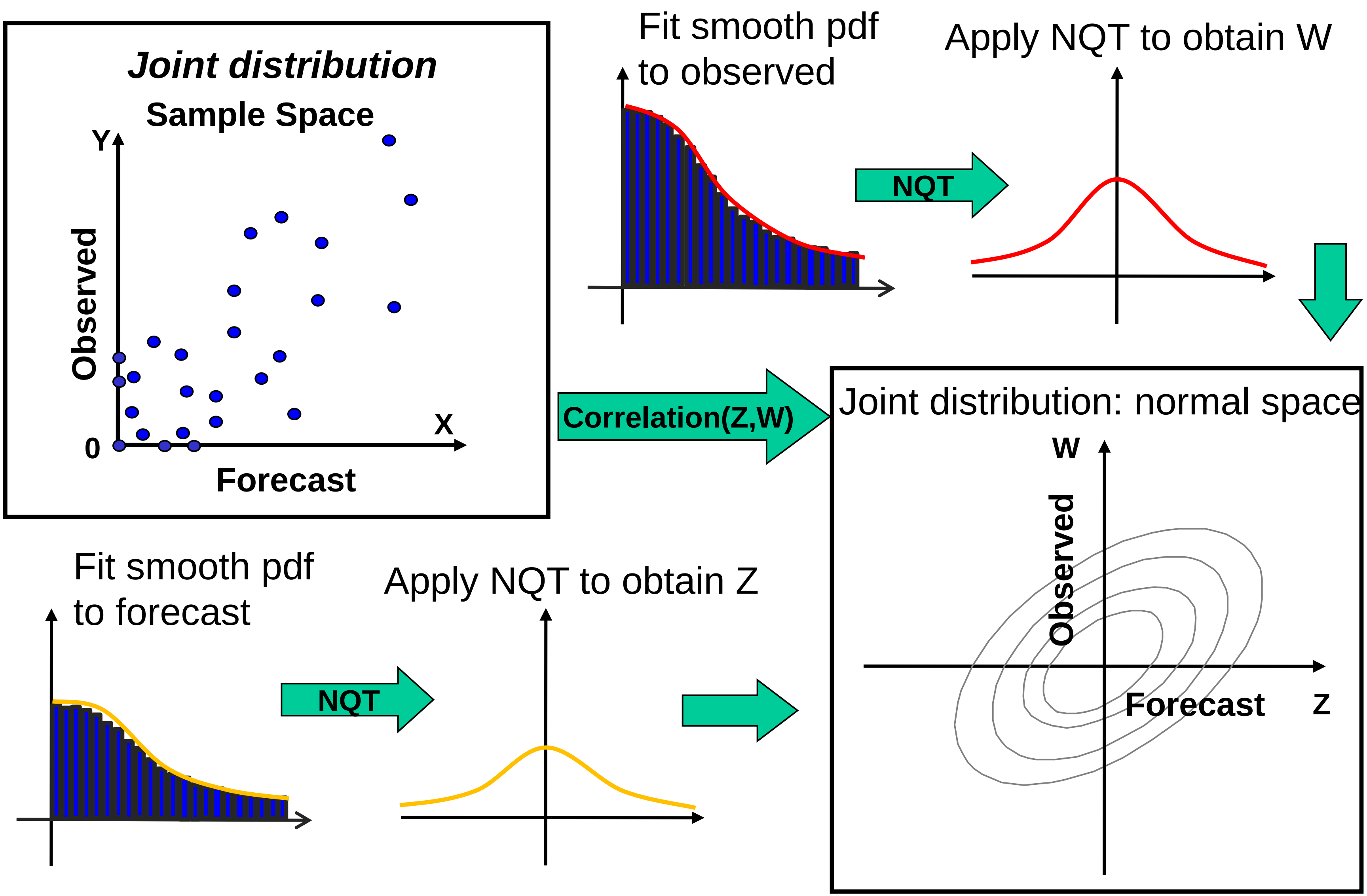
$$\left.\begin{aligned} Z &= Q^{-1}(F_X(X)) \\ W &= Q^{-1}(F_Y(Y)) \end{aligned}\right\}$$ Normal Quantile Transformation (NQT)

B is bivariate standard normal distribution function.
Q is standard normal distribution function.
ρ is correlation coefficient between *Z* and *W*.

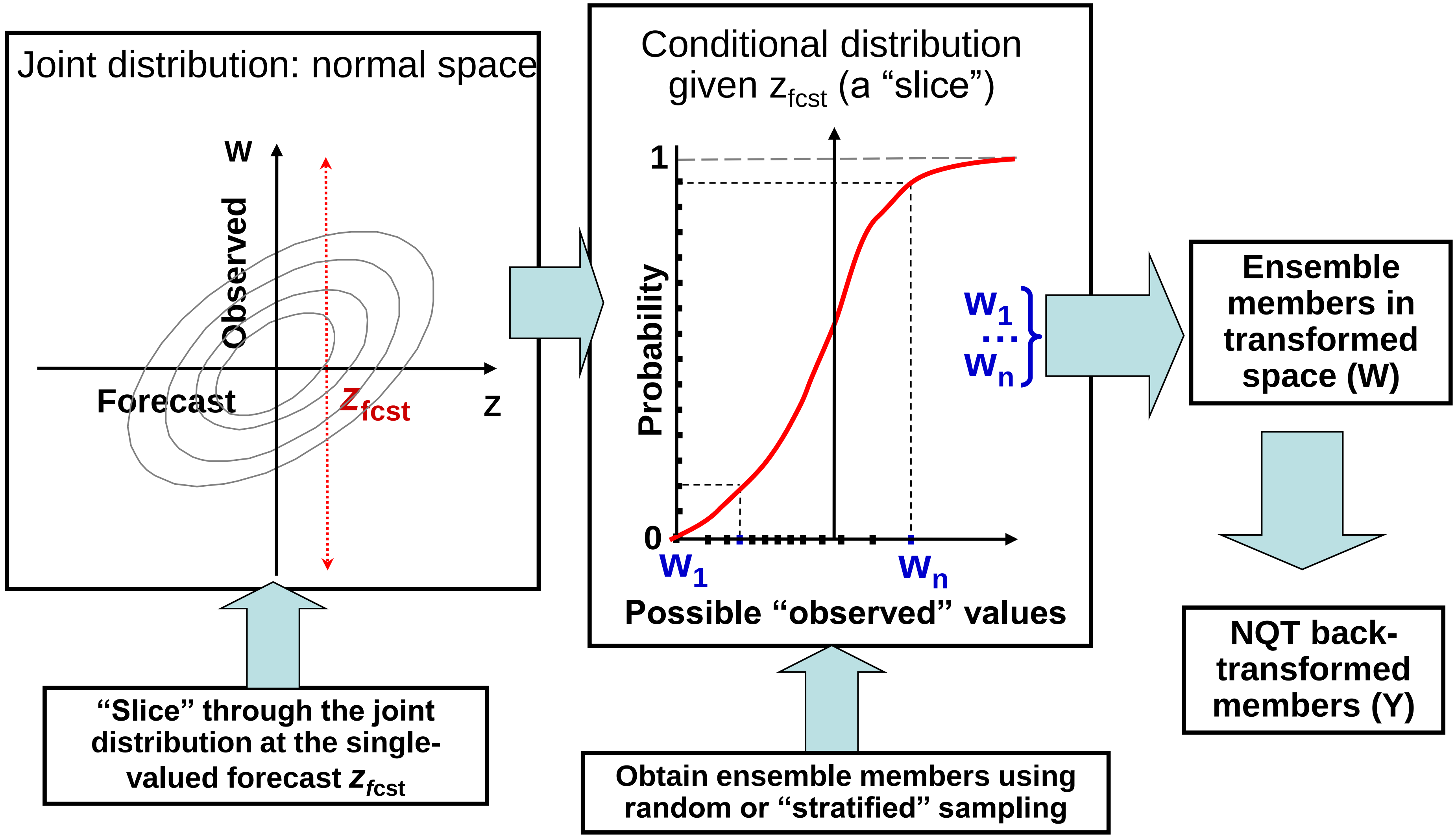
- Our hope is that $F(x,y)$ can be well approximated by $H(x,y)$.

- Uncertainty in the forecast can be estimated by the conditional distribution *of* $H(x, y)$ given *x*.

Meta-Gaussian model: calibration



Meta-Gaussian Model: ensemble generation



Why meta-Gaussian model

- The X and Y can be modeled by any continuous distributions that fit the data well (normal, Weibull, Gamma, …).
- The meta-Gaussian distribution can be constructed easily.
- If $P(Z \leq z, W \leq w)$ is standard normal, the modeling is exact:

  $F(x,y) = H(x,y)$.

- Conditional distribution has an analytical form and can be easily computed.

$$H_{Y|X}(y|x) = Q\left(\frac{Q^{-1}(F_Y(\mathrm{y})) - \rho\, Q^{-1}\,(F_X(\mathrm{x}))}{\sqrt{1-\rho^2}}\right)$$

Precipitation Intermittency

- Problem: Meta-Gaussian model requires continuous variables. For short time scales, precipitation is not continuous.

  Solution: “explicit” or “implicit” treatment of precipitation.

- Implicit precipitation treatment (IPT): similar to original meta-Gaussian model. Defines a positive threshold above which continuous modeling occurs. Initial technique with inconsistent performance.

- Explicit precipitation treatment (EPT): Mixed-type bivariate joint distribution with meta-Gaussian model embedded. Works well for both short and long aggregation periods, or wet and dry conditions. Recommended.

MEFP’s solution to Problem 3

Schaake Shuffle

Preserve Space-time Coherence

- Meteorological events are correlated in space and time.
  - Temperatures tend to be correlated from basin to basin and from one day to the next, as well as during the day.
  - Large-scale storms can be more persistent in space and time than rain showers.
  - There are also relationships between meteorological variables.

- These correlations can be captured by the **rank structure** of historical observations over any relevant spatial domain and for any time period.

- A rank structure can be thought as a table where past observations, their associated years, and their ranks are tabulated.

- **Schaake Shuffle (SS)**: A scheme that arranges ensemble members to have the same rank structure as that of the historical observations.

Schaake Shuffle

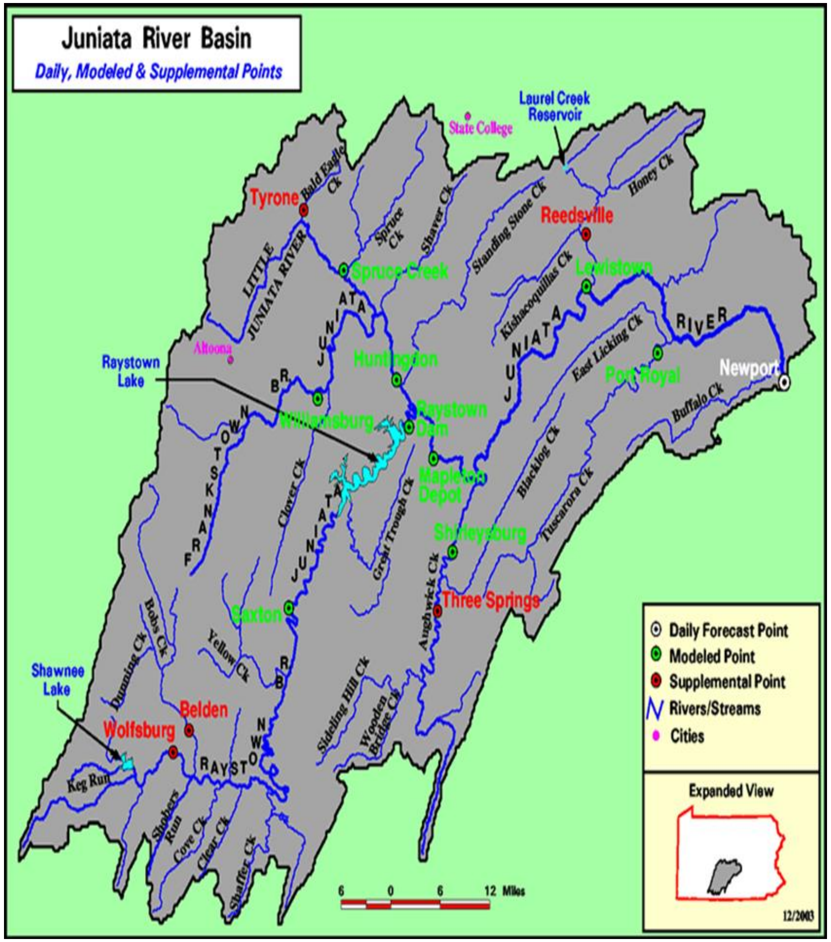
- The scheme: The members of the ensemble are arranged in such a way that the ordering of the members matches the ordering of the corresponding historical observed values in magnitude and associated years, as illustrated in the table below.

- The effect: The ensemble members are ordered according to the historical realization of the observed.

Year	1948	1949	1950	…		1978	…		1998
Observed	xxx	xxx	max	…		min	…		xxx
Ensemble	xxx	xxx	max	…		min	…		xxx

A Schaake Shuffle example

- Locations: 3 sub-areas in the upper part of the Juniata river basin, “hunp1jun”, “wibp1jun” and “spkp1jun”.
- Calibration of MEFP with frozen GFS forecasts (1979-1998) and gage-based MAPs.
- Forecast period of interest: the 12z-12z (24-hr) period beginning on November 7, 1997.
- Forecast amounts: the GFS ensemble mean precipitation total for this 24-hr period is 24.2 mm for all three basins (GFS has 2.5° grid)
- Ensembles were created for each of the four 6-hr sub-periods in the 24-hr period and for each sub-area.



A Schaake Shuffle Example

Spatial and temporal correlations of the observed 6-hr MAP between the sub-basins and sub-periods for the historical years of 1987 through 1998.

Spatial Pearson's correlation between the sub-basins computed with the four sub-periods pooled.

	hunp1jun	wibp1jun	spkp1jun
hunp1jun	1	0.992	0.959
wibp1jun		1	0.925
spkp1jun			1

Temporal Pearson's correlation between the four sub-periods for hunp1jun.

	p1(12-18z)	p2(18-0z)	p3(0-6z)	p4(6-12z)
p1	1	0.996	0.948	0.811
p2		1	0.948	0.810
p3			1	0.842
p4				1

A Schaake Shuffle Example

Comparison of spatial correlation of the observations and ensemble forecasts between the sub-basins. Results were obtained with p1-p4 pooled for years 1987-1998.

Obs	hunp1jun	wibp1jun	spkp1jun
hunp1jun	1	0.992	0.959
wibp1jun		1	0.925
spkp1jun			1

Ens w/o SS	hunp1jun	wibp1jun	spkp1jun
hunp1jun	1	0.042	-0.144
wibp1jun		1	-0.064
spkp1jun			1

Ens w/ SS	hunp1jun	wibp1jun	spkp1jun
hunp1jun	1	0.953	0.927
wibp1jun		1	0.911
spkp1jun			1

- Ens w/o SS (middle table) – Ensemble members were obtained via random sampling in the computation before SS.
- Ens w/ SS (bottom table) - - Ensemble members were obtained via random sampling in the computation with SS applied.

A Schaake Shuffle Example

Comparison of temporal correlation of the observations and ensemble forecasts between the sub-periods. Results were obtained from years 1987-1998 for hunp1jun.

Obs	p1	p2	p3	p4
p1	1	0.996	0.948	0.811
p2		1	0.948	0.810
p3			1	0.842
p4				1

Ens w/ SS	p1	p2	p3	p4
p1	1	0.820	0.786	0.745
p2		1	0.734	0.736
p3			1	0.698
p4				1

Schaake Shuffle: Summary

- Precipitation and temperature events tend to be correlated in space and time.
- The correlations can be captured by a rank structure derived from the historical observed values over a relevant spatial domain and time period.
- The rank structure is used to arrange MEFP ensemble members so that the final ensemble forecasts can possess the same rank structure and similar correlations over the same spatial domain and time period. To construct a consistent rank structure, identical historical years for observed values must be used across a forecast group.
- Schaake shuffle has known limitations: uses historical data only, not state of atmosphere at forecast time; many tied ranks for zero precipitation amounts, which can reduce correlations.

Putting All Together -- General Steps

Goal: Produce reliable forcing ensembles that capture the inherent skill of the raw meteorological forecasts.

1. Use met forecasts from multiple NCEP products to cover short- to long range.
2. Define canonical events.
3. For each canonical event, calibrate the meta-Gaussian model.
4. Sample from the conditional probability distribution of the model given the single-valued forecast.
5. Form an ensemble of historical observations to provide the rank structure.
6. Recover space-time relationships using Schaake Shuffle.
7. Join the shuffled short-to-long range ensembles.

Putting All Together -- Temperature

1. Convert 6-hour observed time series to daily maximum and minimum time series using a diurnal relationship.

2. Work on the daily maximum and minimum time series to produce daily maximum and minimum ensembles (using a similar procedure described in the previous slide).

3. The daily maximum and minimum ensembles are transformed to instantaneous 6-hour values using the inverse of the diurnal relationship.

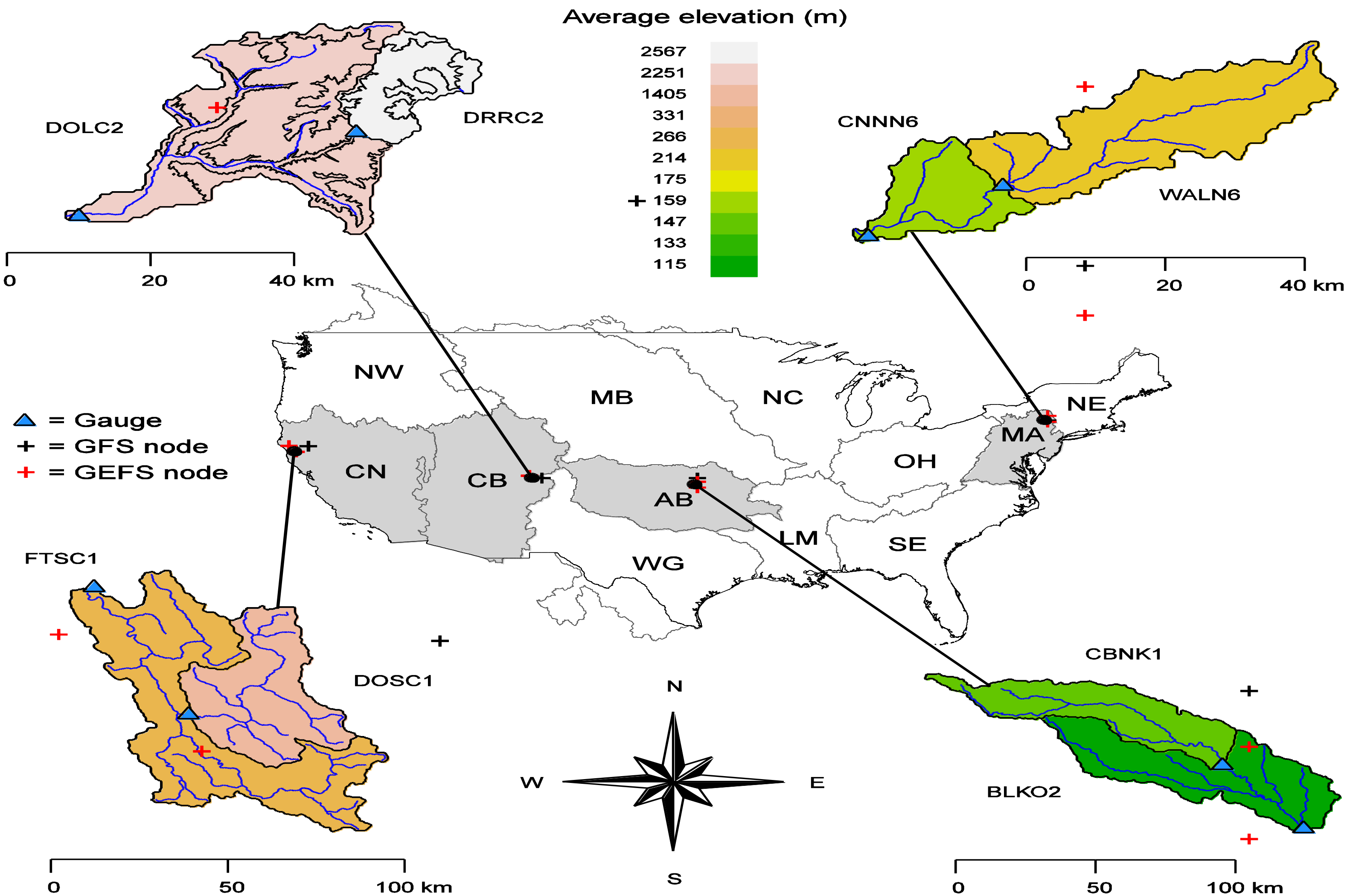
Other MEFP Capabilities

- Seasonality: accounted for by using moving window of user-specified size to pool data points in calibration.

- Parameters: estimated for days-of-the-year at 5-day increments (default).

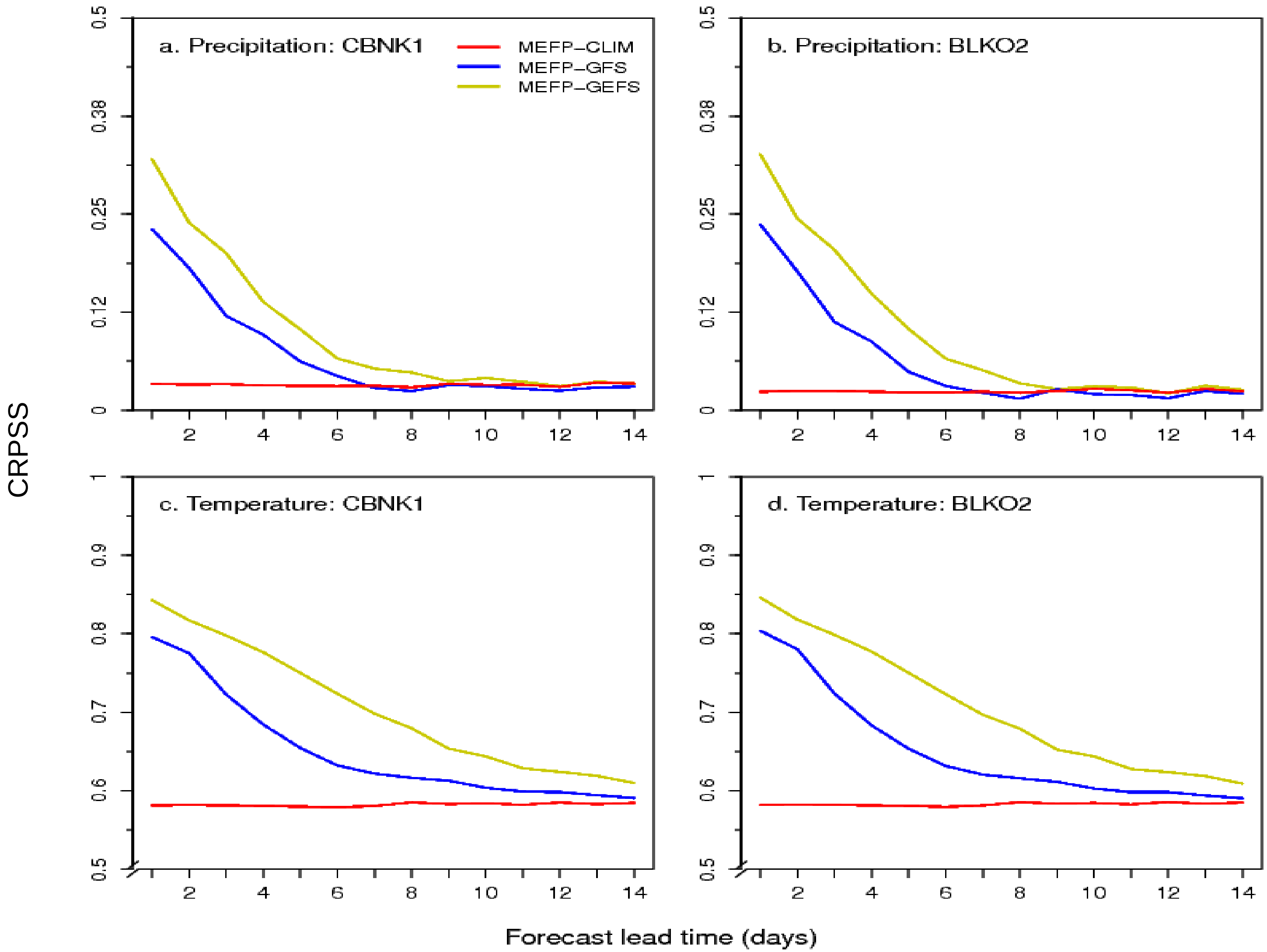
- Operation modes: forecasting and hindcasting.

Validation


Average elevation (m)
2567
2251
1405
331
266
214
175
159
147
133
115
DOLC2
DRRC2
CNNN6
WALN6
FTSC1
DOSC1
CBNK1
BLKO2
0 20 40 km
0 50 100 km
NW
MB
NC
NE
MA
OH
CN
CB
AB
LM
SE
WG
= Gauge
= GFS node
= GEFS node
N
S
W
E

Validation

CRPSS measures the overall quality of probabilistic forecasts against reference forecasts. The larger the value, the better.



References

- Clark, 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.
- Herr, H.D., Krzysztofowicz, R., 2005. Generic probability distribution of rainfall in space: the bivariate model. Journal of Hydrology 306, 234–263.
- Brown, J. D., Wu, L, He, M., Regonda, S., Lee, H., and Seo, D.J., Verification of temperature, precipitation and streamflow forecasts from the NOAA/NWS Hydrologic Ensemble Forecast Service (HEFS): 1. Experimental design and forcing verification, in press, DOI: 10.1016/j.jhydrol.2014.05.028, Journal of Hydrology.
- Brown, J.D. (2014) Verification of temperature, precipitation and streamflow forecasts from the Hydrologic Ensemble Forecast Service (HEFS) of the U.S. National Weather Service: an evaluation of the medium-range forecasts with forcing inputs from NCEP's Global Ensemble Forecast System (GEFS) and a comparison to the frozen version of NCEP's Global Forecast System (GFS). Technical Report prepared by Hydrologic Solutions Limited for the U.S. National Weather Service, Office of Hydrologic Development, 139pp.
- Kelly, K.S., Krzysztofowicz, R., 1997. A bivariate meta-Gaussian density for use in hydrology. Stochastic Hydrology and hydraulics 11, 17–31.

References

- Kelly, K.S., Krzysztofowicz, R., 1997. A bivariate meta-Gaussian density for use in hydrology. Stochastic Hydrology and hydraulics 11, 17–31.
- Schaake, J.C., Demargne, J., Hartman, R., Mullusky, M., Welles, E., Wu, L., Herr, H., Fan, X., Seo, D.-J., 2007. Precipitation and temperature ensemble forecasts from single-value forecasts. Hydrology and Earth System Sciences Discussions 4, 655–717.
- Wu, L., Seo, D.J., Demargne, J., Brown, J.D., Cong, S., Schaake C., 2011: Generation of ensemble precipitation forecast from single-valued quantitative precipitation forecast for hydrologic ensemble prediction. Journal of Hydrology 399 (2011) 281-298.

Questions?

Thank You !

Extra slides

A Schaake Shuffle Example

Observed 6-hr MAP values (mm) for sub-periods 12-18z (P1), 18-0z (P2), 0-6z (P3), and 6-12z (P4) beginning on Nov. 7 for the three sub-basins. Can you see any patterns?

		hunp1jun				Wibp1jun				Spkp1jun			
Index	Year	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
1	1948	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1949	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	1950	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	1951	5.5	0.0	0.0	0.0	4.3	0.1	0.0	0.0	7.0	0.0	0.0	0.0
5	1952	0.0	0.4	0.1	0.1	0.0	0.8	0.3	0.1	0.1	0.2	0.1	0.0
6	1953	1.0	0.8	0.3	0.1	0.0	0.5	0.4	0.1	0.3	0.6	0.2	0.0
7	1954	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
…	…	…	…	…	…	…	…	…	…	…	…	…	…
40	1987	0.8	0.6	0.0	0.0	0.1	1.2	0.0	0.0	1.7	0.4	0.0	0.0
41	1988	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42	1989	0.0	0.1	1.0	0.0	0.0	0.2	0.8	0.0	0.0	0.1	0.4	0.0
43	1990	0.0	0.0	0.4	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.7	0.0
44	1991	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45	1992	0.0	0.3	0.0	0.0	0.0	0.4	0.1	0.0	0.0	0.7	0.0	0.0
46	1993	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
47	1994	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0
48	1995	1.4	0.1	1.8	1.0	2.3	0.2	0.3	1.9	0.8	0.1	3.8	1.0
49	1996	0.0	0.2	0.1	11.7	0.0	0.2	0.1	11.1	0.0	0.0	0.0	14.8
50	1997	29.9	15.7	30.5	21.2	39.3	22.4	35.8	21.4	19.2	11.0	37.0	21.6
51	1998	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

A Schaake Shuffle Example: Ranks

Ranks for chronologically ordered historical MAP values (mm) corresponding to the 1st 6-hr period (12z-18z) on November 7, 1997 for “hunp1jun”.

Year	MAP	Rank
1948	0.0	27
1949	0.0	34
1950	0.0	1
1951	5.5	50
1952	0.0	21
1953	1.0	41
1954	0.0	22
…	…	…
1987	0.8	40
1988	0.0	14
1989	0.0	15
1990	0.0	16
1991	0.0	17
1992	0.0	18
1993	0.1	35
1994	0.0	19
1995	1.4	44
1996	0.0	26
1997	29.9	51
1998	0.0	20

- A multi-year historical record of observed MAP for each basin is needed to provide the **ranks** for each 6-hr sub-period.

- The observed MAP values can be sorted in increasing order. The position of a given value in that order is its **rank**. The rank is assigned to this value with its associated year given as reference.

- In the ranking, if multiple equal values are encountered, the next rank will be randomly assigned to one of the values. The random ranking for tied values may lead to loss of correlation strength in SS.

A Schaake Shuffle Example: Rank Structure

Rank structure for the historical observed 6-hr MAP values.

		hunp1jun				wibp1jun				spkp1jun			
Ind	Year	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
1	1948	27	28	1	32	32	21	23	34	29	29	32	37
2	1949	34	18	27	1	37	26	1	1	1	1	26	1
3	1950	1	1	28	27	1	1	2	2	2	2	1	2
4	1951	50	35	2	2	50	38	3	3	48	21	33	3
5	1952	21	39	32	35	2	44	37	35	34	38	36	38
6	1953	41	45	35	31	30	43	40	33	41	43	39	36
7	1954	22	22	3	3	28	22	4	4	3	25	2	4
…	…	…	…	…	…	…	…	…	…	…	…	…	…
40	1987	40	44	17	20	34	45	27	27	46	42	19	34
41	1988	14	14	18	21	16	16	21	22	16	16	20	29
42	1989	15	33	45	29	17	34	46	23	17	37	41	23
43	1990	16	15	44	22	18	17	44	29	18	24	43	24
44	1991	17	16	30	23	19	18	22	39	19	30	21	33
45	1992	18	42	31	24	29	41	31	24	26	44	22	25
46	1993	35	19	19	34	31	30	26	25	27	17	30	26
47	1994	19	32	20	25	20	19	29	26	33	18	29	27
48	1995	44	30	47	41	46	35	38	44	44	36	47	42
49	1996	26	38	34	48	21	39	34	46	20	35	28	49
50	1997	51	49	50	49	51	51	50	49	51	51	51	51
51	1998	20	17	21	26	22	20	25	31	21	19	23	32

A Schaake Shuffle Example

For each sub-basin and sub-period, 51 forecast values (ensemble members) are sampled from the conditional PDF of the meta-Gaussian model, given the GFS ensemble mean forecast. The values are sorted in increasing order to get ranks.

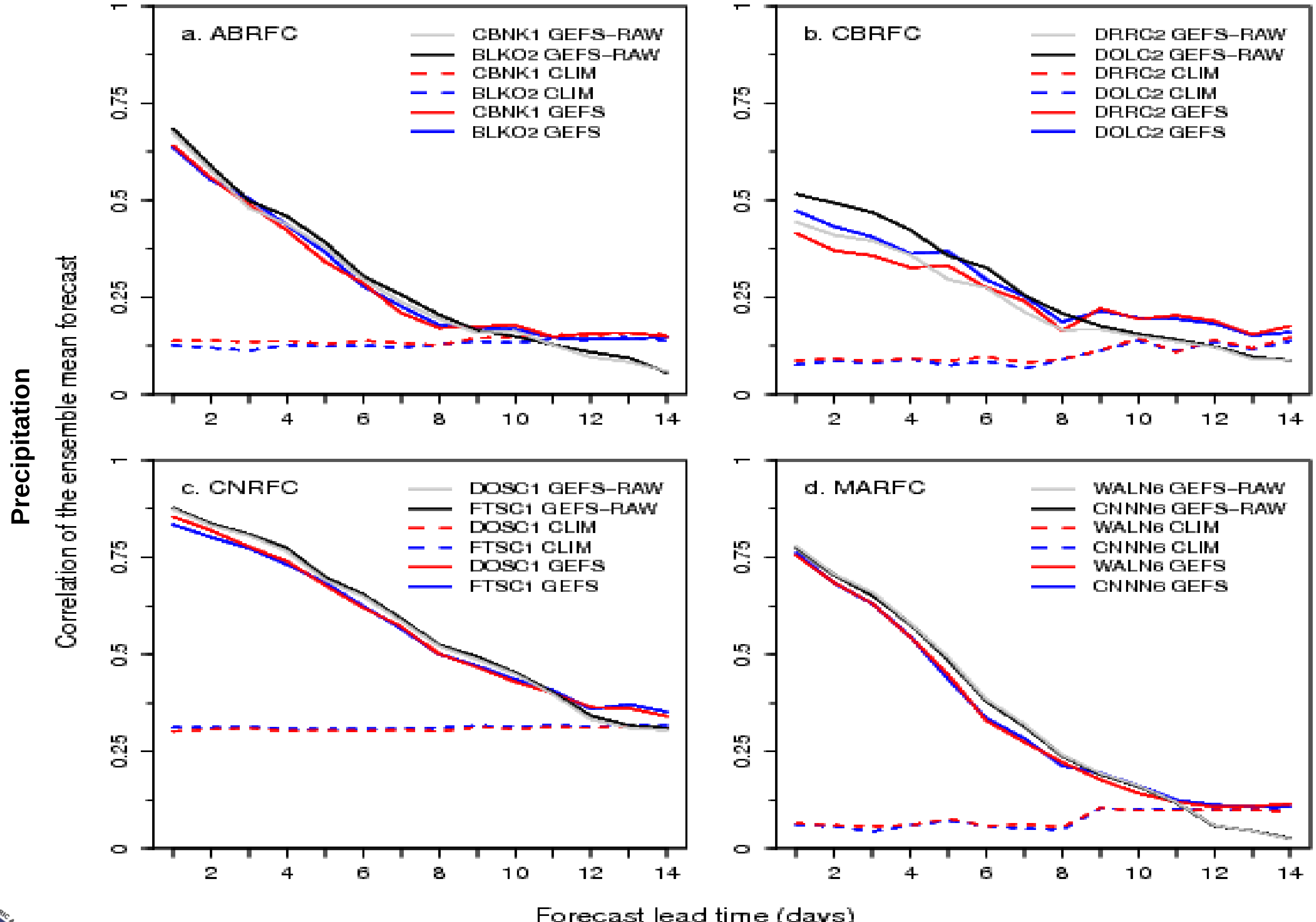
	hunp1jun				wibp1jun				spkp1jun			
Rank	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
…	…	…	…	…	…	…	…	…	…	…	…	…
40	7.8	7.8	7.9	3.9	7.0	6.9	6.1	4.6	5.0	5.2	5.6	3.4
41	8.8	8.0	8.2	4.9	7.1	7.2	7.0	6.0	5.5	5.7	6.4	4.0
42	9.2	8.3	8.3	7.2	7.3	8.2	7.4	7.6	6.1	6.3	7.2	4.5
43	9.6	8.4	8.9	7.6	8.2	8.4	8.6	7.8	6.8	7.0	8.1	5.2
44	9.8	9.1	10.5	7.9	10.5	8.5	10.3	8.1	7.6	7.7	9.2	6.0
45	9.9	9.6	12.6	10.2	11.4	12.0	11.9	13.1	8.5	8.5	10.5	6.8
46	10.2	9.8	12.9	15.3	12.9	12.5	12.6	17.6	9.6	9.5	12.0	7.9
47	11.5	12.7	13.5	16.3	13.5	13.8	13.3	19.8	10.8	10.7	13.9	9.2
48	15.8	13.2	14.5	17.3	13.6	14.1	14.0	22.2	12.5	12.2	16.3	10.8
49	17.0	17.1	15.4	21.4	19.5	14.7	14.3	22.8	14.7	14.2	19.7	13.1
50	20.2	17.8	24.0	21.5	22.6	17.0	24.3	23.7	18.2	17.4	25.1	16.7
51	26.2	17.9	29.2	27.8	23.5	18.0	31.3	28.1	27.8	25.9	40.4	26.6

A Schaake Shuffle Example

Final 6-hr ensemble forecasts (mm) for each sub-basin for the 24-hr period beginning 12z on November 7, 1997. The ensemble members are ordered following the same rank structure associated with the historical observed MAP values.

		hunp1jun				wibp1jun				spkp1jun			
Ind	Year	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
1	1948	1.5	3.0	0.0	2.8	2.8	0.3	0.0	3.4	1.2	1.5	1.8	2.1
2	1949	4.6	0.2	2.0	0.0	6.1	1.5	0.0	0.0	0.0	0.0	0.3	0.0
3	1950	0.0	0.0	2.5	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	1951	20.2	5.6	0.0	0.0	22.6	6.4	0.0	0.0	12.5	0.1	2.1	0.0
5	1952	0.0	7.7	3.8	3.4	0.0	8.5	4.9	3.5	2.5	4.3	3.3	2.5
6	1953	8.8	9.6	4.2	2.2	1.6	8.4	6.1	2.6	5.5	7.0	5.0	1.8
7	1954	0.3	1.1	0.0	0.0	0.7	0.9	0.0	0.0	0.0	0.7	0.0	0.0
…	…	…	…	…	…	…	…	…	…	…	…	…	…
40	1987	7.8	9.1	0.0	0.0	4.5	12.0	1.1	0.2	9.6	6.3	0.0	1.2
41	1988	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
42	1989	0.0	4.6	12.6	0.6	0.0	4.8	12.6	0.0	0.0	3.9	6.4	0.0
43	1990	0.0	0.0	10.5	0.0	0.0	0.0	10.3	0.9	0.0	0.5	8.1	0.0
44	1991	0.0	0.0	3.3	0.0	0.0	0.0	0.0	4.4	0.0	1.8	0.0	0.9
45	1992	0.0	8.3	3.7	0.0	1.0	7.2	2.7	0.0	0.6	7.7	0.0	0.0
46	1993	4.9	0.5	0.0	3.1	2.2	3.1	0.7	0.0	0.8	0.0	1.2	0.0
47	1994	0.0	4.2	0.0	0.0	0.0	0.0	2.1	0.0	2.2	0.0	0.9	0.0
48	1995	9.8	3.4	13.5	4.9	12.9	4.9	5.3	8.1	7.6	3.5	13.9	4.5
49	1996	1.2	7.3	4.1	17.3	0.0	6.5	4.4	17.6	0.0	3.2	0.7	13.1
50	1997	26.2	17.1	24.0	21.4	23.5	18.0	24.3	22.8	27.8	25.9	40.4	26.6
51	1998	0.0	0.0	0.0	0.0	0.0	0.0	0.5	2.0	0.0	0.0	0.0	0.7

Validation



Precipitation
Correlation of the ensemble mean forecast
Forecast lead time (days)
a. ABRFC
CBNK1 GEFS-RAW
BLKO2 GEFS-RAW
CBNK1 CLIM
BLKO2 CLIM
CBNK1 GEFS
BLKO2 GEFS
b. CBRFC
DRRC2 GEFS-RAW
DOLC2 GEFS-RAW
DRRC2 CLIM
DOLC2 CLIM
DRRC2 GEFS
DOLC2 GEFS
c. CNRFC
DOSC1 GEFS-RAW
FTSC1 GEFS-RAW
DOSC1 CLIM
FTSC1 CLIM
DOSC1 GEFS
FTSC1 GEFS
d. MARFC
WALN6 GEFS-RAW
CNNN6 GEFS-RAW
WALN6 CLIM
CNNN6 CLIM
WALN6 GEFS
CNNN6 GEFS
0
0.25
0.5
0.75
1
2
4
6
8
10
12
14