Synthetic Forecast Generation for Forecast Informed Reservoir Operations (FIRO)

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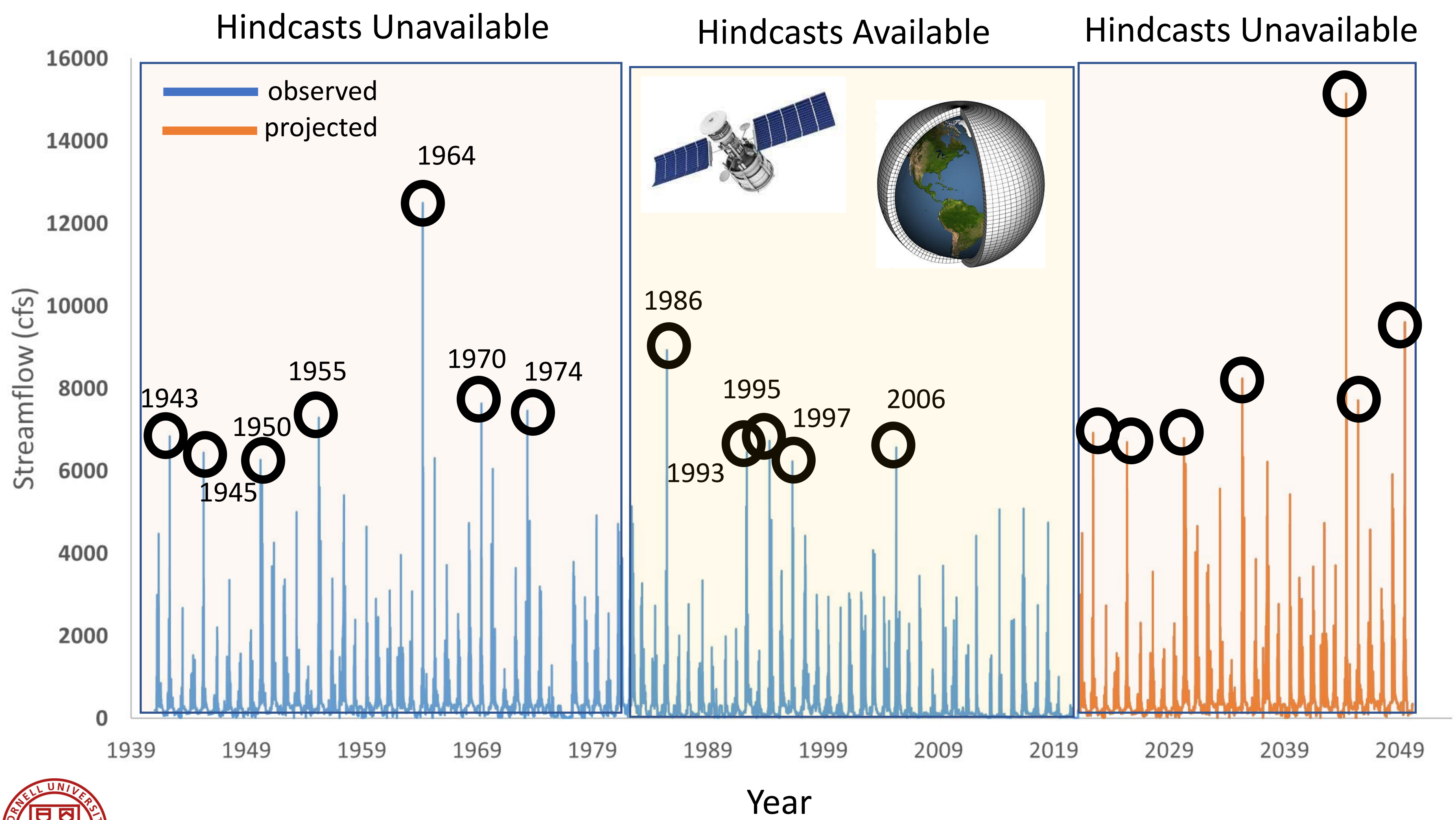
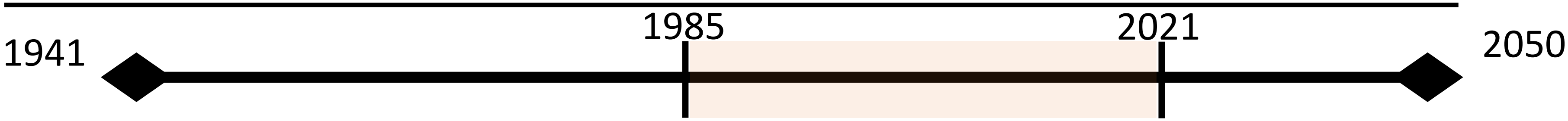
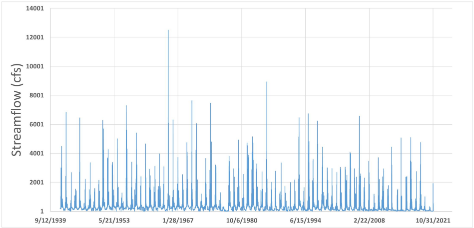
The Problem


Hindcasts Unavailable
Hindcasts Available
Hindcasts Unavailable
observed
projected
16000
14000
12000
10000
8000
6000
4000
2000
0
Streamflow (cfs)
1964
1943
1945
1950
1955
1970
1974
1986
1993
1995
1997
2006
1939
1949
1959
1969
1979
1989
1999
2009
2019
2029
2039
2049
Year

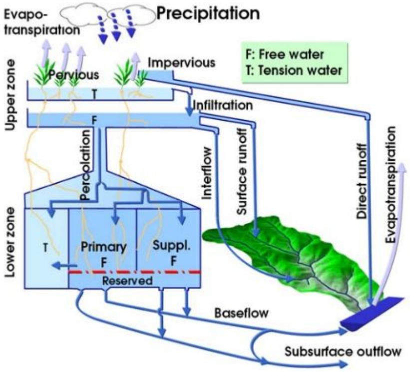
A Possible Solution



Observations



GEFS/HEFS



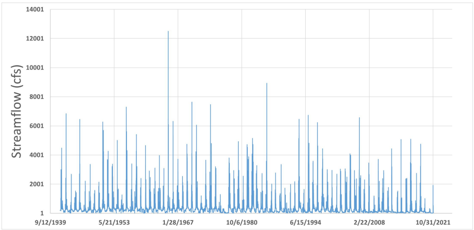
Hindcast Period

Error = Observations - Forecast

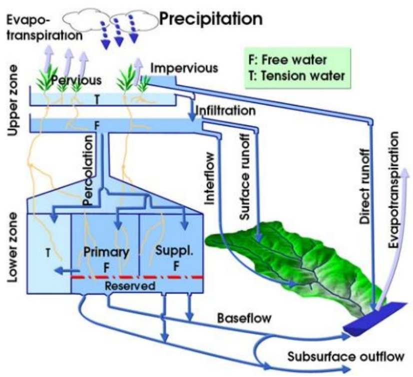
Statistical Model of Errors

A Possible Solution

Observations



GEFS/HEFS



Hindcast Period

Error = Observations - Forecast

Statistical Model of Errors

Non-Hindcast Period

Synthetic Forecasts = Observations – Synthetic Error

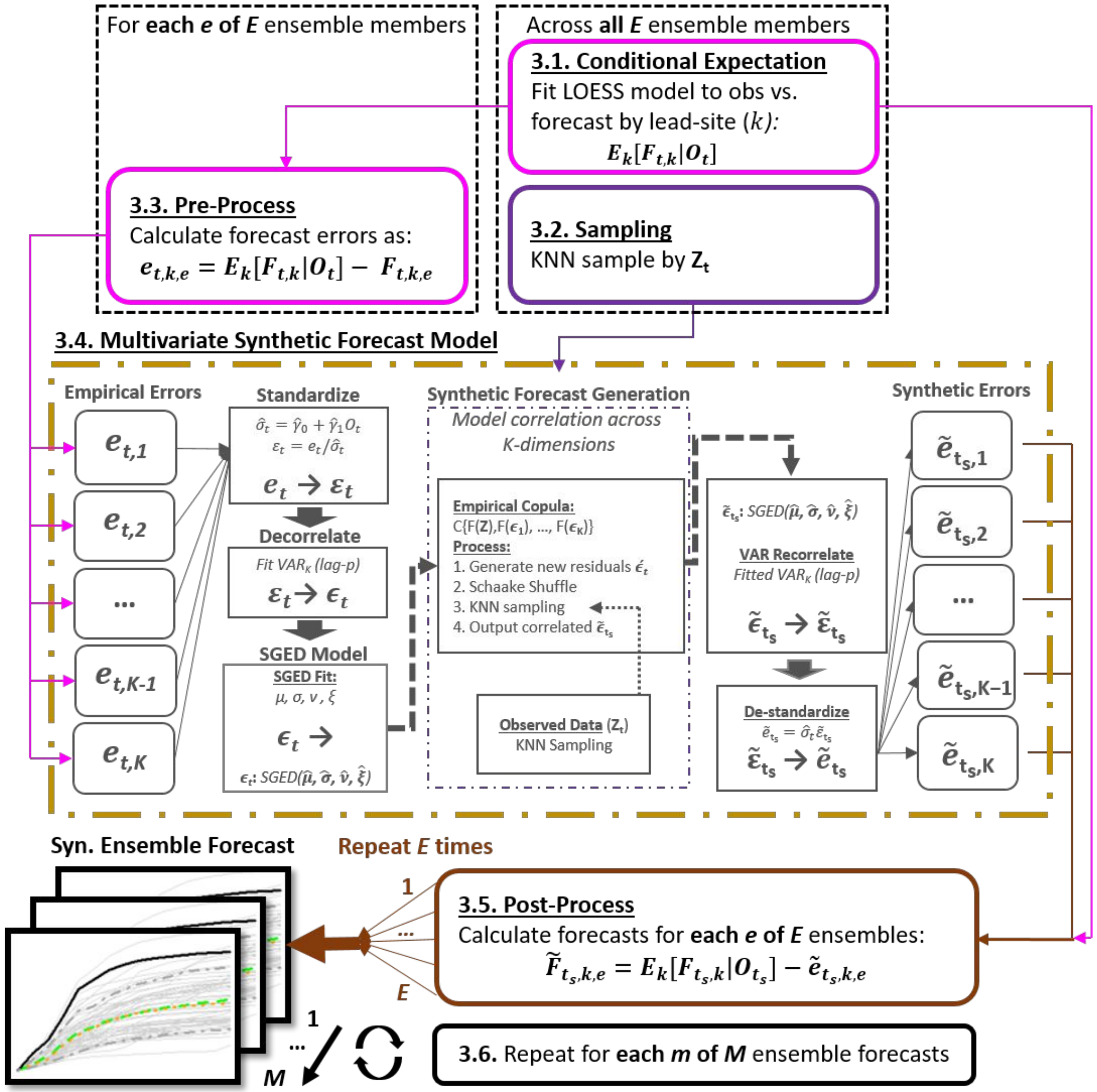
Challenges

Ensemble forecasts (and ensemble forecast error) are:

- Needed for multiple lead times and locations
- Correlated across lead times
- Correlated across locations
- Autocorrelated in time
- Distributed in funky ways
- Correlated with the observations
- Correlated across ensemble members

Approach

Statistical model of forecast errors 😊



Approach

Method 1 (syn-HEFS):
direct synthetic forecasts of streamflow

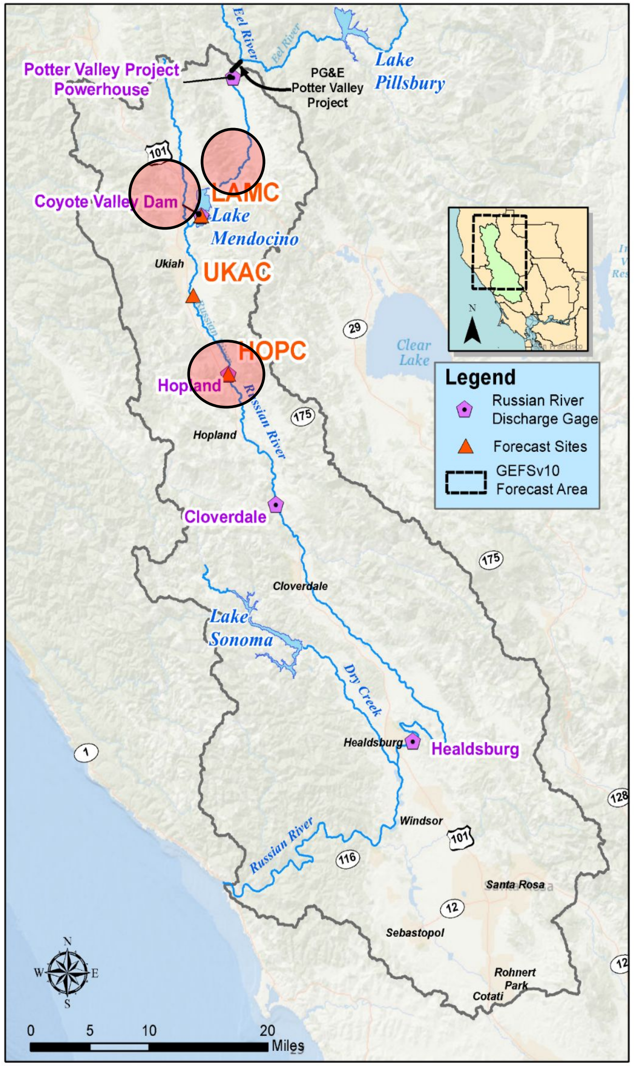
Method 2 (syn-GEFS):
synthetic forecasts of GEFS prcp/temp, then pass through HEFS

Approach

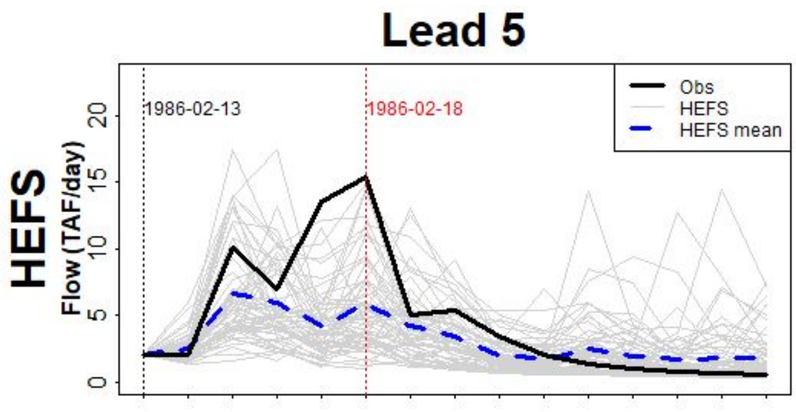
Lake Mendocino + Russian River

- 3 locations
- 14 lead times

- Climate Forecasts – Global Ensemble Forecast System (GEFS v10)
- Hydrologic Forecasts – Hydrologic Ensemble Forecast System (HEFS)

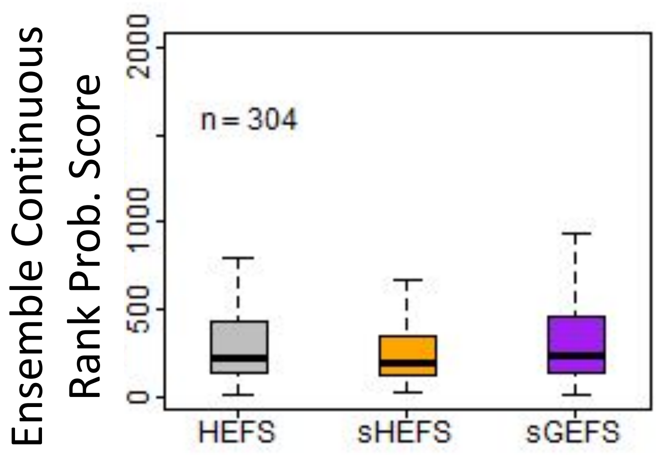


Results


Lead 5
HEFS
Flow (TAF/day)
0
5
10
15
20
1986-02-13
1986-02-18
Obs
HEFS
HEFS mean

Results

1-Day Lead



Results

Synthetic Forecasts
(3 locations, 14 lead times)

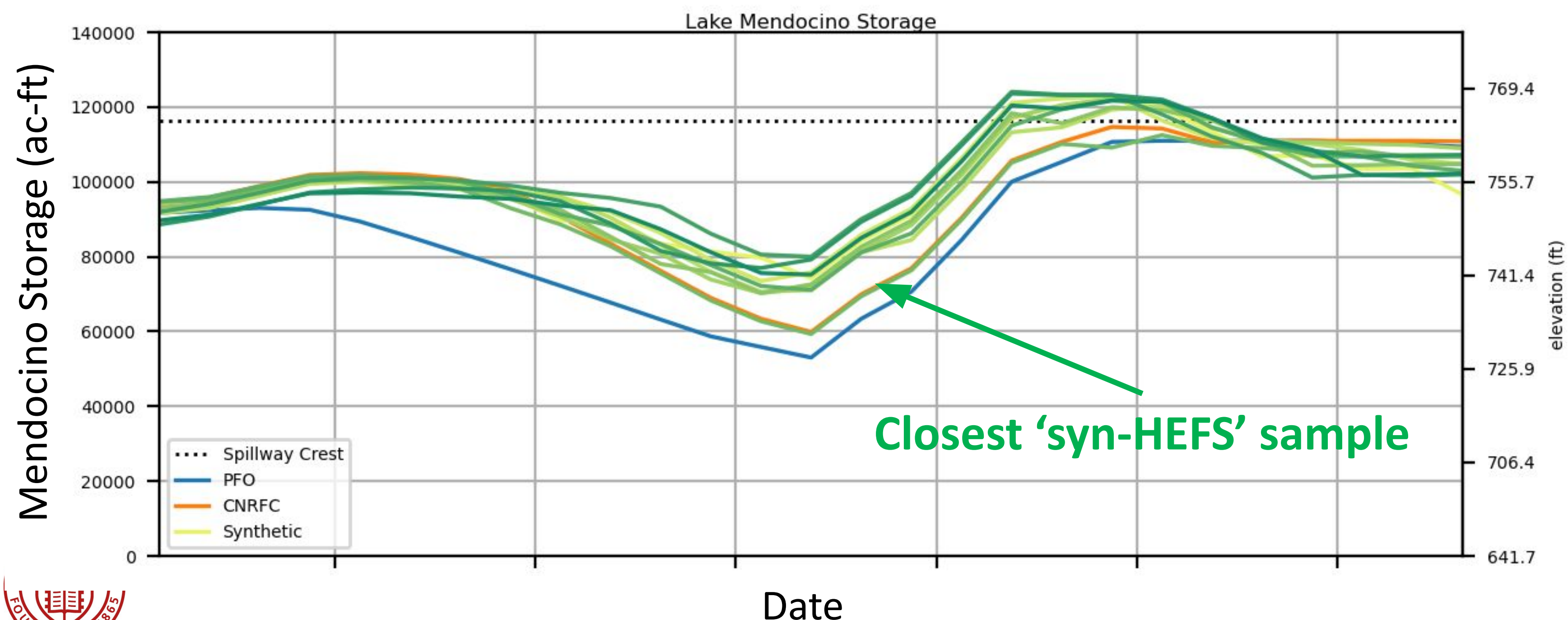
→

Lake Mendocino
FIRO-based Systems Model

→

Forecast Informed System
Operations

February 1986 Flood



Next Steps and New Directions

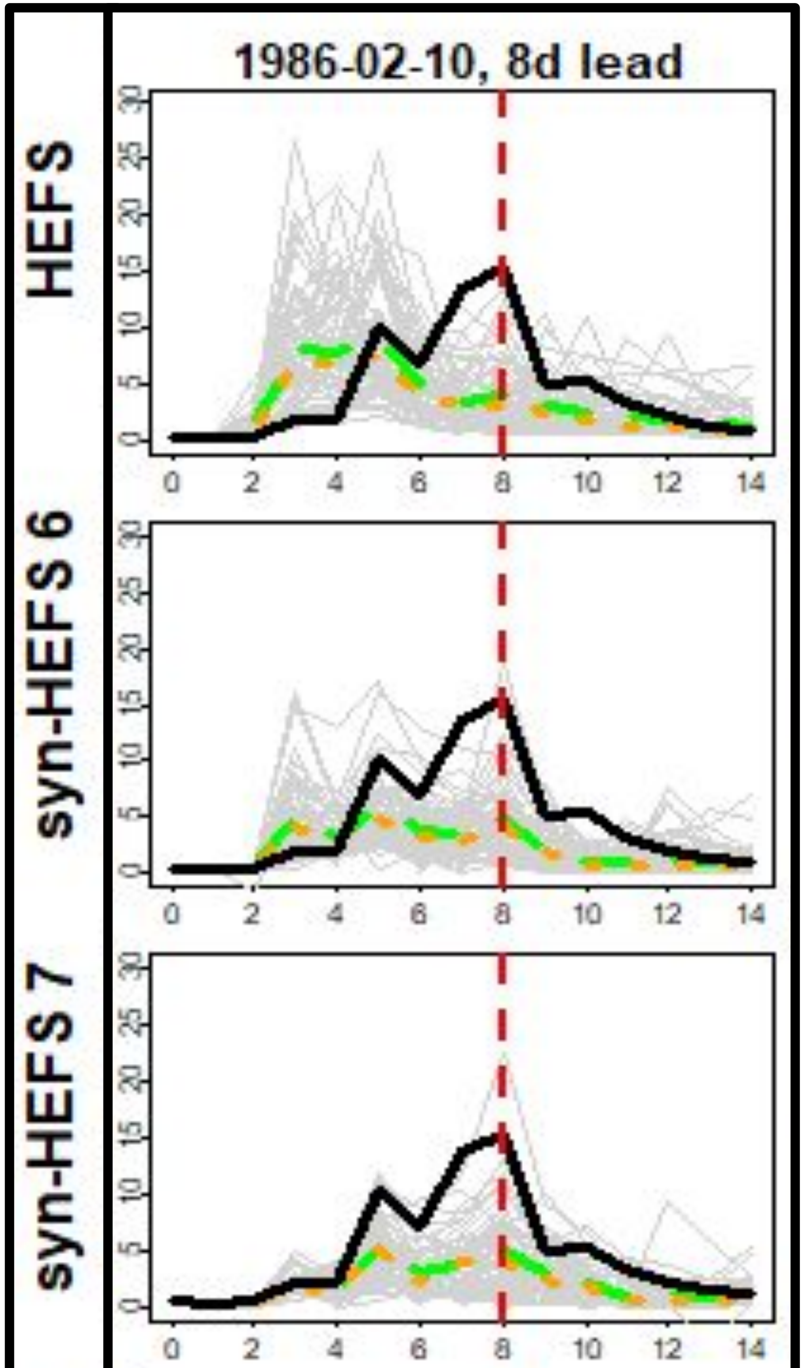
1. **Algorithmic Improvements**: Focus on synthetic forecast fidelity during the largest extremes, especially to replicate ‘false positives’ seen in HEFS

2. **Testing FIRO policies**: Calibrate and validate FIRO policies to synthetic forecasts over different periods to evaluate robustness

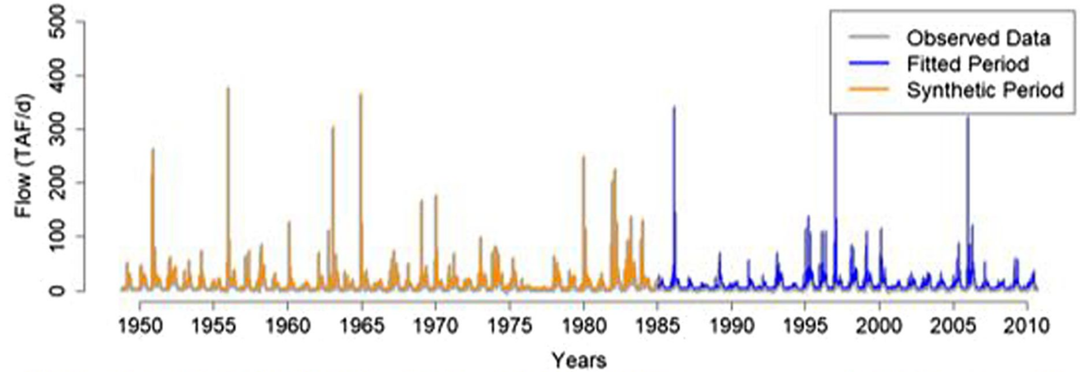
3. **FIRO for Climate Resilience**: Couple synthetic forecasts with climate projections to enable FIRO evaluation under climate change.

Thanks!

Additional Slides



1986-02-10, 8d lead
HEFS
syn-HEFS 6
syn-HEFS 7
0
2
4
6
8
10
12
14



1) Empirical (a_t) Copula [RANK]

t	Z_t	$a_{t,1}$	...	$a_{t,K}$
1	.45 [32]	.34 [22]	...	.38 [25]
2	.33 [14]	.55 [52]	...	.81 [77]
...	...	...	...	...
n-1	.78 [80]	.43 [39]	...	.47 [49]
n	.65 [57]	.58 [54]	...	.61 [53]

2) Generate new a_t ($\acute{a}_t$)

Z_t	$\acute{a}_{t,1}$	...	$\acute{a}_{t,K}$
.45 [32]	.88 [83]	...	.44 [49]
.33 [14]	.32 [22]	...	.38 [27]
...	...	...	...
.78 [80]	.71 [63]	...	.36 [25]
.65 [57]	.46 [39]	...	.65 [57]

Schaake Shuffle (SS)

3) SS Empirical Copula

Z_t	$\acute{a}_{t,1}$	...	$\acute{a}_{t,K}$
.45 [32]	.32 [22]	...	.36 [25]
.33 [14]	.56 [52]	...	.82 [77]
...	...	...	...
.78 [80]	.46 [39]	...	.44 [49]
.65 [57]	.57 [54]	...	.59 [53]

4) Synthetic Period Observations ($\tilde{Z}_t$)

t	$\tilde{Z}_t$
1	.32
2	.69
...	...
n_s-1	.45
n_s	55

4a.

SS Empirical Copula
KNN resample

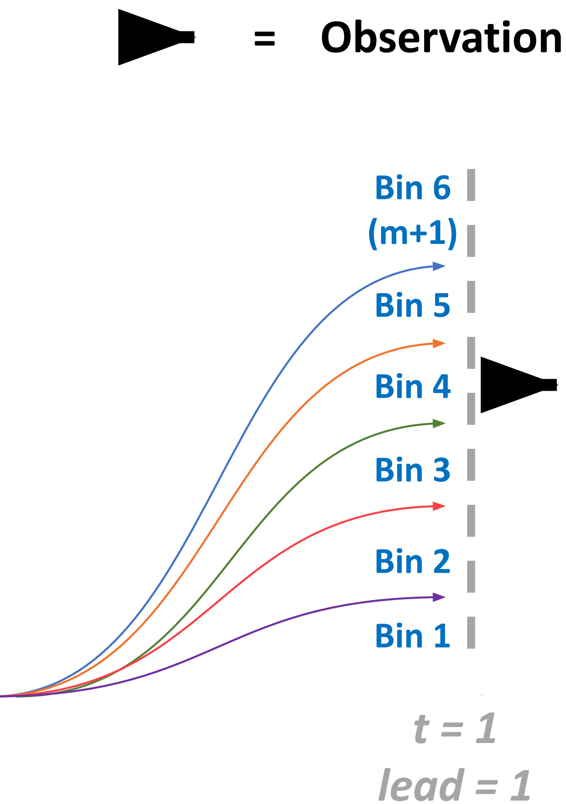
Z_t	$\acute{a}_{t,1}$	...	$\acute{a}_{t,K}$
.45 [32]	.32 [22]	...	.36 [25]
.33 [14]	.56 [52]	...	.82 [77]
...	...	...	...
.78 [80]	.46 [39]	...	.38 [49]
.65 [57]	.57 [54]	...	.55 [53]

4b.

Synthetic Period ($\tilde{a}_t$)

t	$\tilde{Z}_t$	$\tilde{a}_{t,1}$	...	$\tilde{a}_{t,K}$
1	.32	.56	...	.82
2				
...				
n_s-1				
n_s				

Rank Histograms



Repeat for each lead…

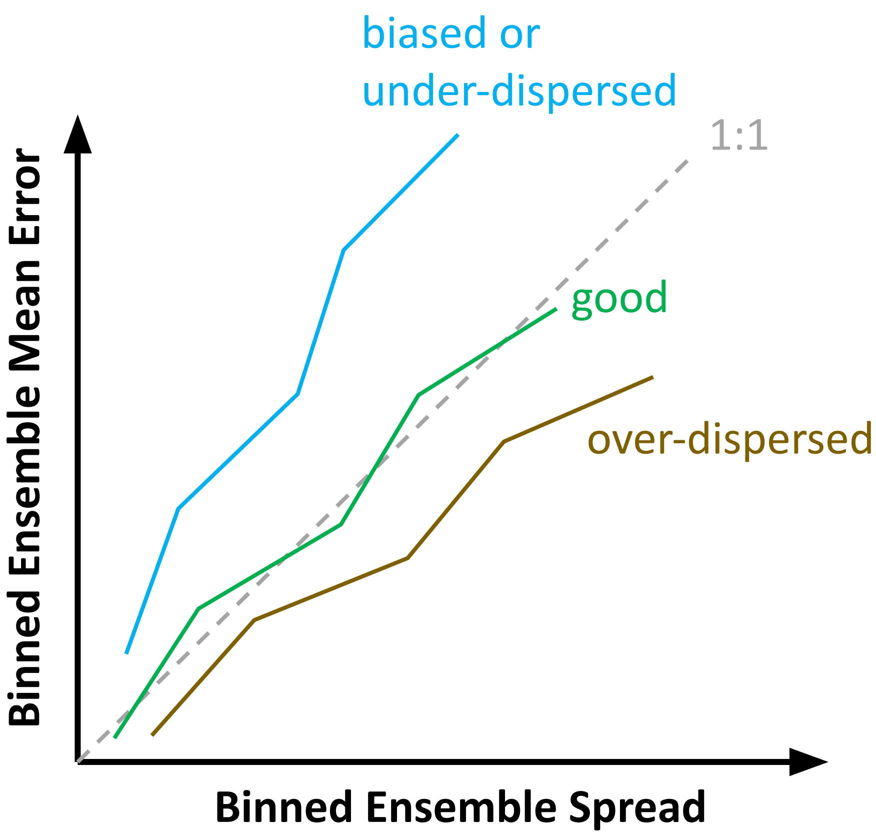
‘Ideal’ ensemble = observation equally likely to fall in any bin
In other words, each bin has ~ same number of observations

Binned Spread Error Diagram

Ensemble spread should be reflective of the ensemble mean error

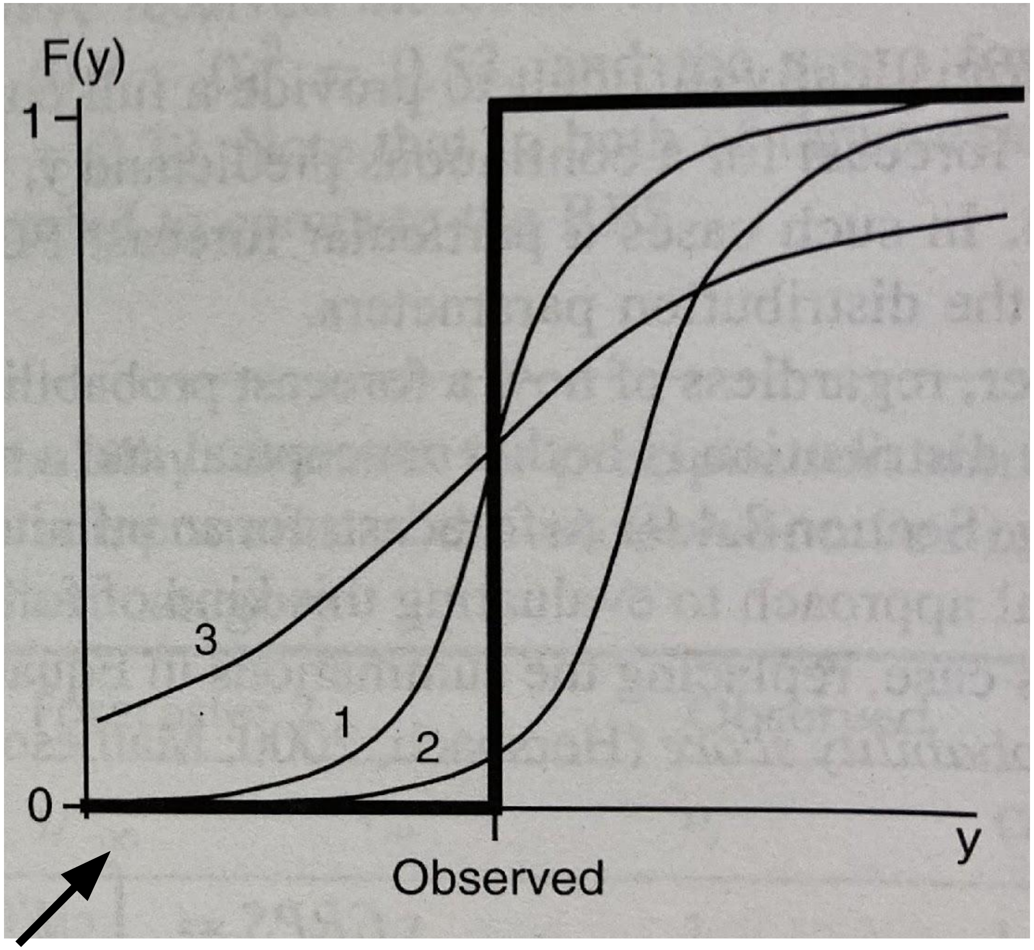
In a well calibrated forecast, spread = error (1:1 line)

Can more directly show conditional issues with dispersion or bias



Ensemble Continuous Ranked Probability Score (eCRPS)

- Lower is better
- Best possible score is 0



eCRPS is a discrete ensemble representation of this

Wilks, D. S. (2019)

Validation of Synthetic Forecasts with FIRO

Synthetic Forecasts
(3 locations, 14 lead times)
1985-2010

↓

Lake Mendocino
FIRO-based Systems Model

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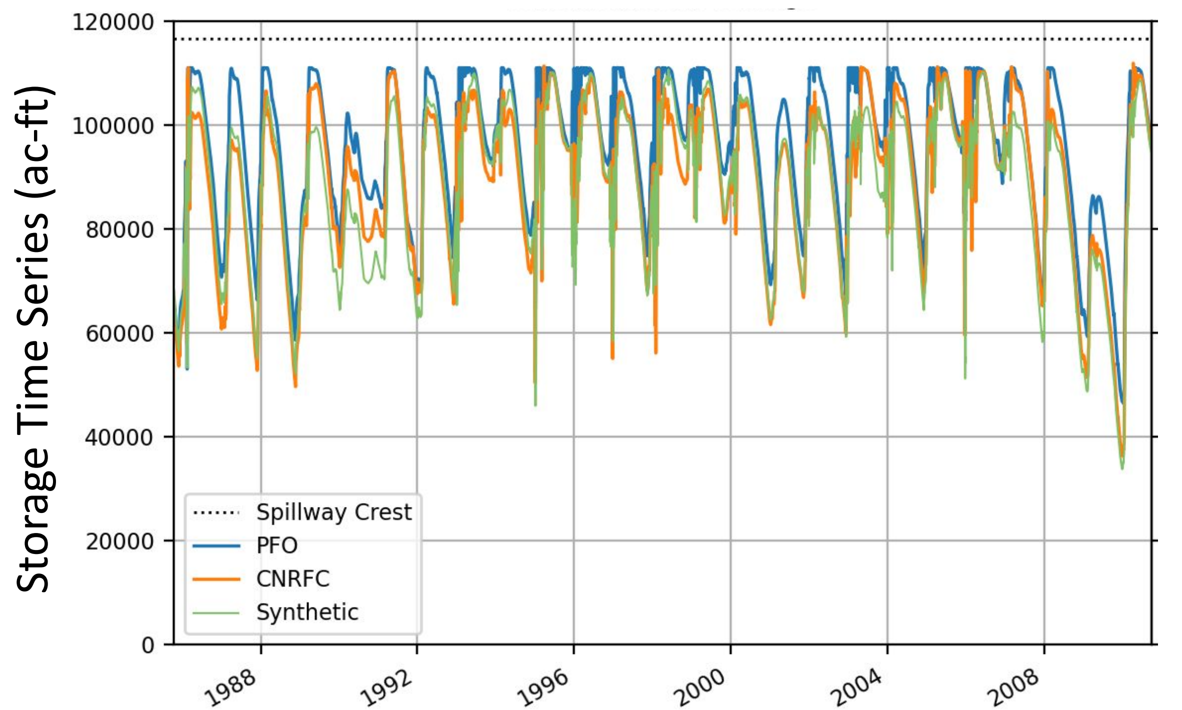
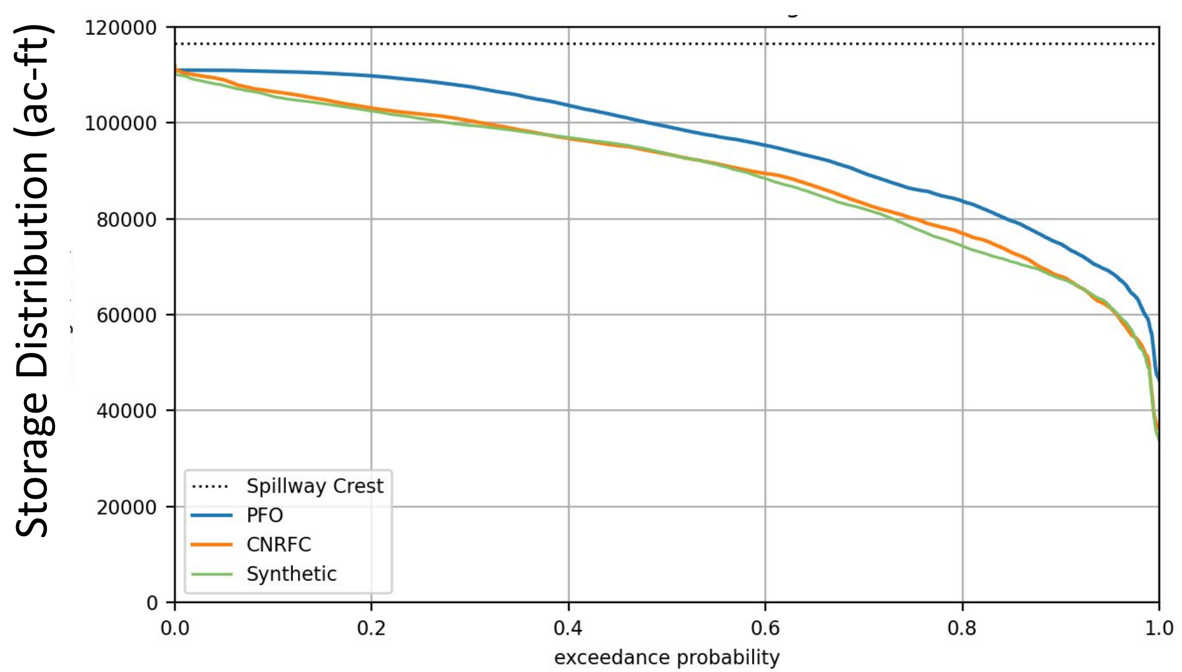
Forecast Informed System Operations





Extension of FIRO with Synthetic Forecasts