Use of nowcaster data in conjunction with a statistical-distributed hydrologic model for flash flood forecasting

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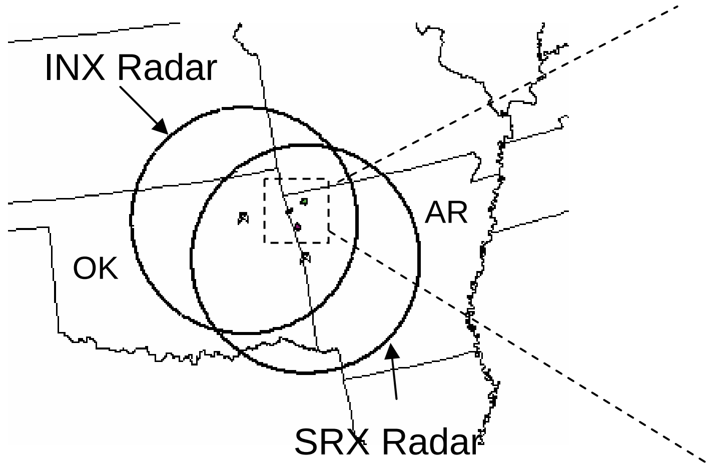
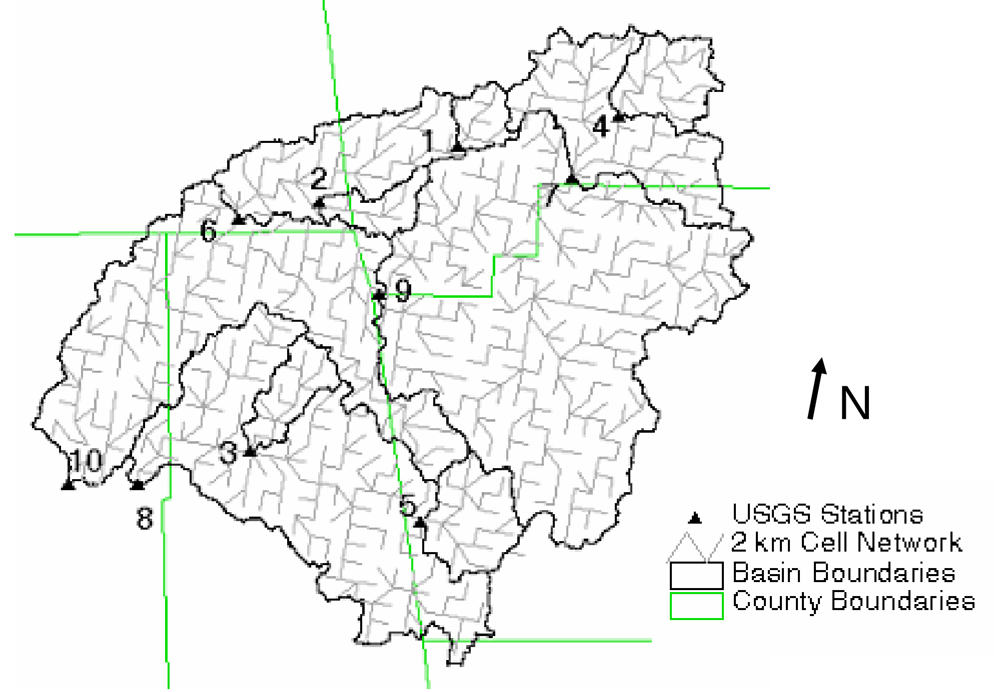
Goals

- Define and validate the statistical-distributed model
  - Understand model errors at flash flood scales
  - Compare a distributed model-based approach to lumped model-based FFG
  - Validate the ability of the statistical-distributed model to inherently correct for model bias
- Understand hydrologic benefits of using short-term QPF (i.e., 1 hour nowcasts)
  - Compare simulated peak flows using several forecasting scenarios:
    - QPF
    - Zero (0) QPF
    - Persistence
    - Radar only vs. multi-sensor

Study Basins





Basins are well covered by either the INX or SRX radar

No	Short Name	Station Name	Area (km2)	Period of record (hourly flow)	Time to peak (hrs)
1	SPRINGT	Flint Ck at Springtown AR	36.8	6/1993-9/2004	3
2	SSILOAM	Sager Ck nr W. Siloam Springs OK	48.9	9/1996-9/2004	3
3	CHRISTI	Peacheater Ck at Christie OK	64.7	5/1993 - 9/2003	6
4	CAVESP	Osage Ck near Cave Springs AR	89.9	4/2000-9/2004	4
5	DUTCH	Baron Fork at Dutch Mills AR	105.1	10/1992-9/2004	2
6	KNSO2	Flint Ck near Kansas OK	284.9	6/1993- 9/2004	6
7	ELMSP	Osage Ck near Elm Springs AR	336.7	10/1995-9/2004	7
8	ELDO2	Baron Fork at Eldon OK	795.1	10/1992 - 9/2004	13
9	ISILOAM	Illinois R. South of Siloam Springs AR	1489.2	7/1995 - 9/2004	17
10	TALO2	Illinois R. near Tahlequah OK	2483.7	6/1993-9/2004	37

Interior, 'flash flood' basins

Hydrology Laboratory Research Distributed Hydrologic Model (HL-RDHM)

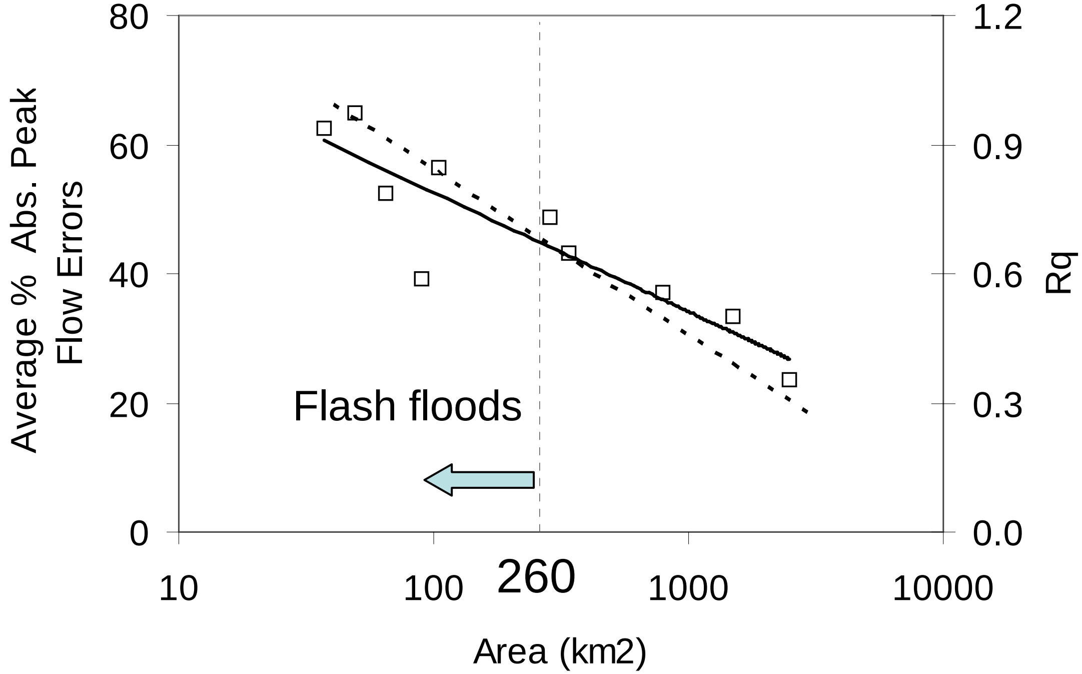
- This implementation of HL-RDHM uses:
  - 2 km grid cell resolution
  - Hourly, 4 km QPE and QPF grids are resampled to 2 km (nearest neighbor resampling)
  - Gridded SAC-SMA
  - Hillslope routing within each model cell
  - Cell-to-cell channel routing
  - **Uncalibrated, a-priori parameters for Sacramento (SAC-SMA) and channel routing models** (Koren et al., 2004)
- Similar HL-RDHM implementations showed good performance in the Distributed Model Inter-comparison Project (DMIP) (Smith et al., 2004; Reed et al., 2004)
- An operational prototype version of HL-RDHM is running at two NWS River Forecast Centers

Multisensor Precipitation Nowcaster (MPN)

- Radar-based extrapolative nowcaster with the capability to:
  - Produce one-hour rainfall forecasts on a 4 km grid with a 5 minute update frequency
  - Use mosaicked WSR-88D radar data (used single radar here)
  - Use real time rain gauge data for radar bias adjustment (not used here)
  - Optionally use:
    - Storm growth/decay accounting (not used)
    - Progressive smoothing with forecast lead time (used)
    - Local (20 km) or area-averaged storm motion vectors (used local)

- MPN is currently running along with the Enhanced Multi-sensor Precipitation Estimator (EMPE) at HL in real-time for a 5 radar test region in the mid-Atlantic states

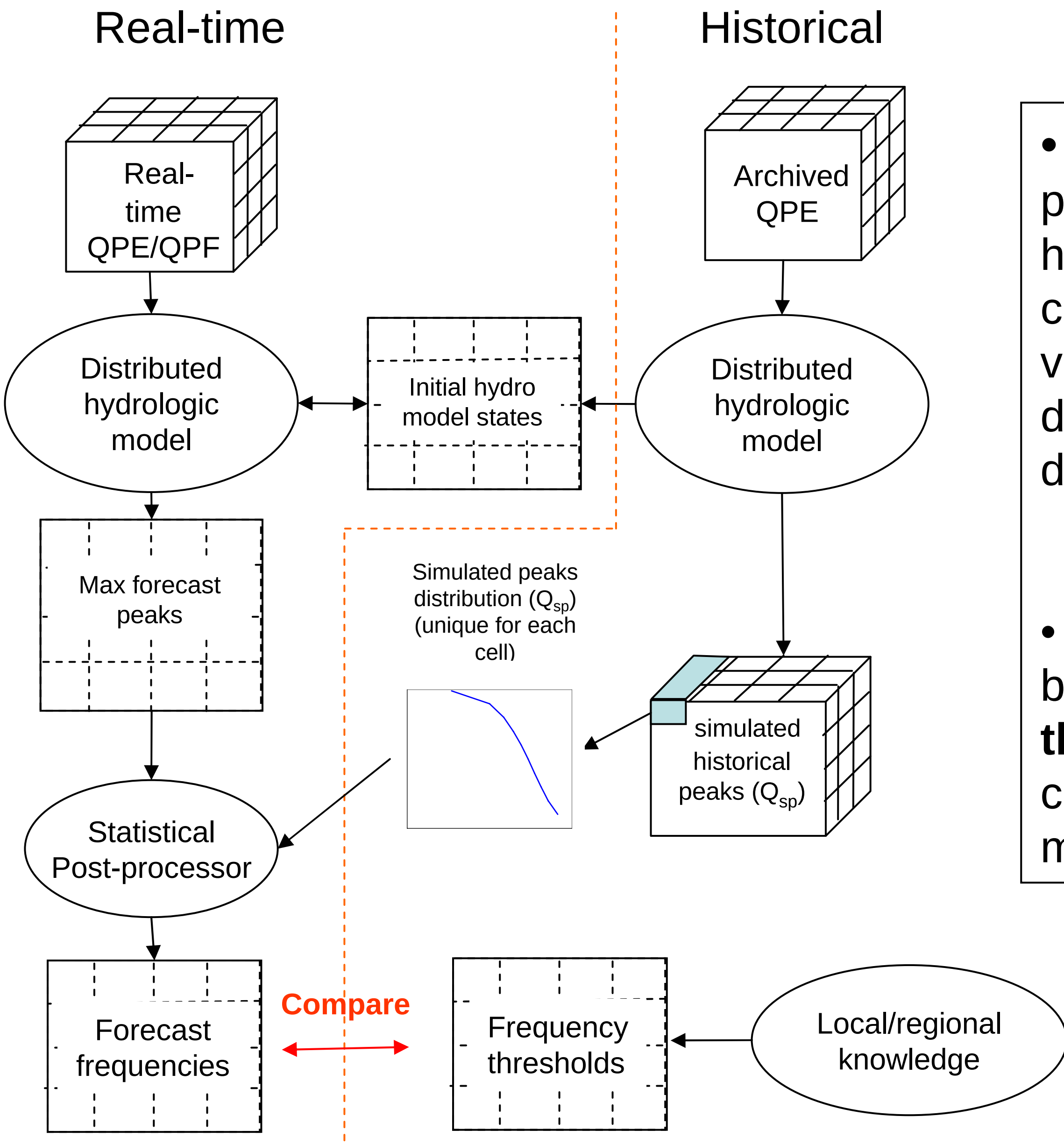
High Resolution Modeling Brings Potential Benefits but Also Increased Uncertainty



□	Distributed model (uncalibrated). Each point is an average peak flow error from approximately 25 events over an eight year study period.
———	Log-linear regression for distributed model data
- - -	Scaling relationship for an uncertainty index (Rq) from Carpenter and Georgakakos (2004) (secondary axis)

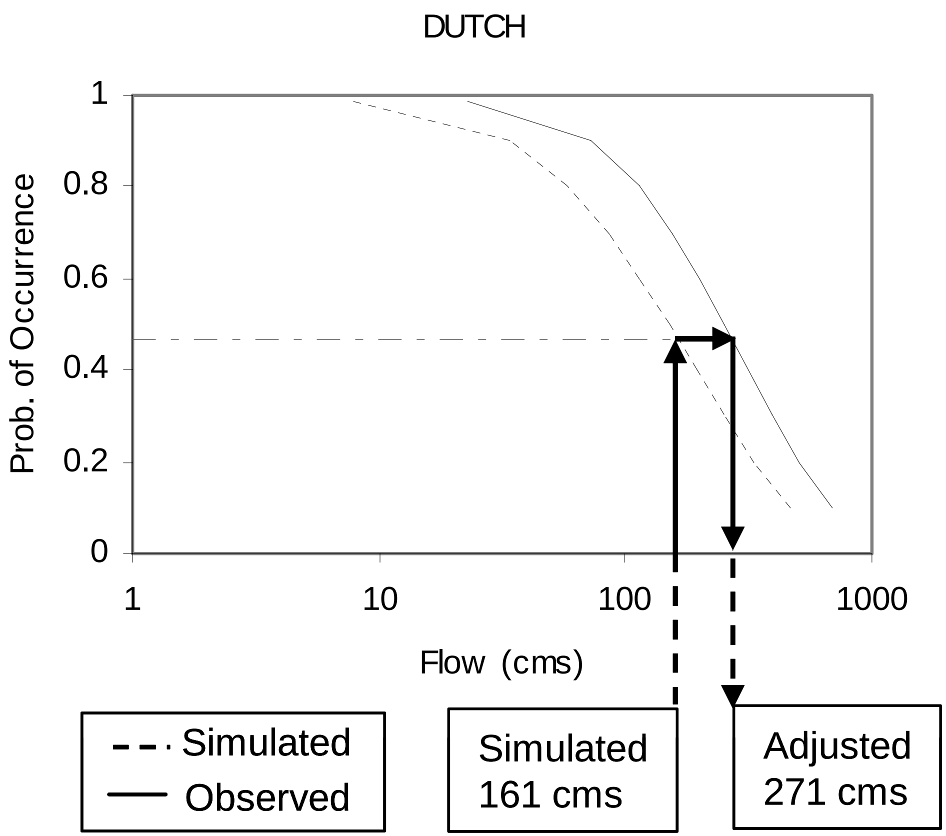
- FFG system uses lumped (260 – 4000 km^2) soil moisture states based on 6 hour models.
- A distributed hydrologic model can make computations at spatial and temporal scales consistent with flash flooding.
- Model errors tend to increase at smaller modeling scales.
- Will increased model errors in small basins mask the benefits of making calculations at the appropriate scales?

A Statistical-Distributed Model for Flash Flood Forecasting at Ungauged Locations

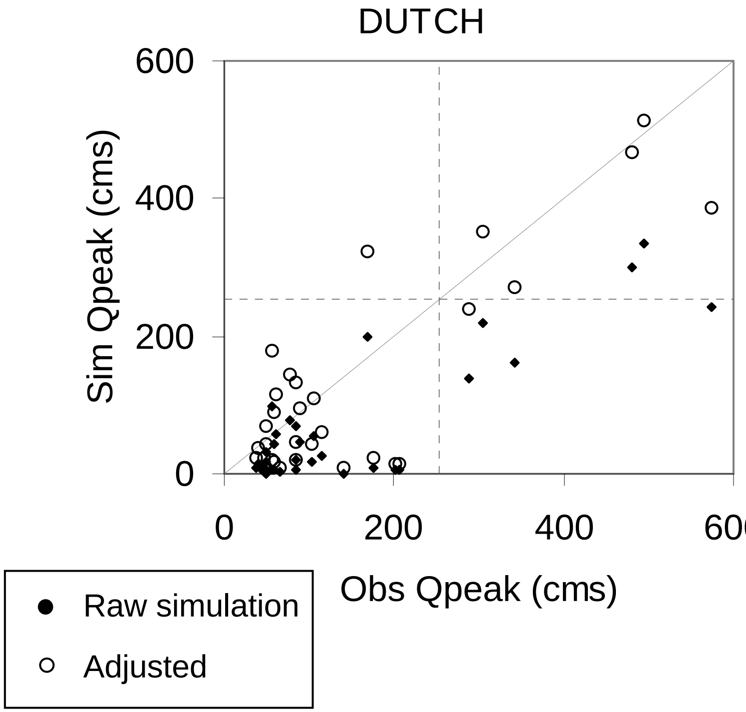


- Forecast frequency grids provide a well-understood historical context for characterizing flood severity; values relate to engineering design criteria for culverts, detention ponds, etc.
- Comparison of simulation-based frequencies to **threshold frequencies (TF)** can inherently correct for model biases.

Validating the Inherent Bias Correction



- To validate the inherent bias correction, we compute adjustments at validation points using **probability matching**. This is only done for validation points because we do not have the techniques and data to make explicit adjustments at ungauged locations.



Peak Simulation Improvements from the Statistical-Distributed Model for 6 Interior Basins

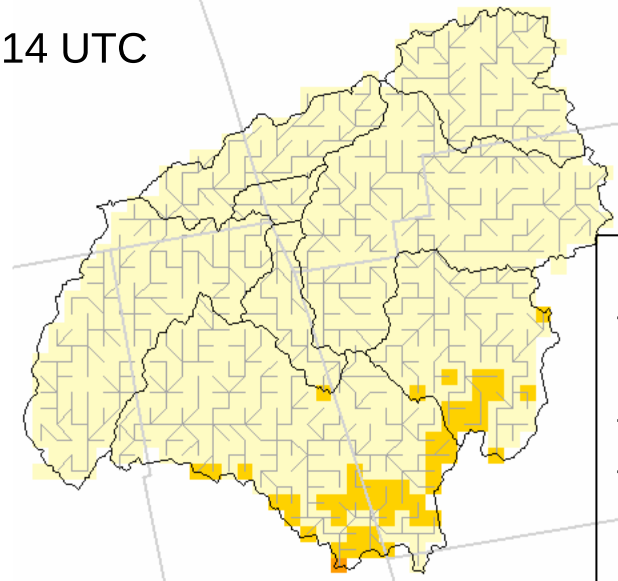
		Average % Absolute Peak Flow Errors			Improvement (decrease in % error)		
	Area (km^2)	*Lumped FFG-like*	*Distributed Uncalib*	*Distributed w/ Statistical Adjustment*	*From lumped to distributed*	*From statistical adjustment*	*Total*
		A	B	C	A-B	B-C	A-C
SPRINGT	37	69	62	63	7	-1	6
SSILOAM	49	67	65	53	2	12	14
CHRISTI	65	54	52	50	1	2	3
CAVESP	90	45	39	30	6	9	16
DUTCH	105	74	57	42	18	14	32
ELMSP	337	44	43	36	1	8	9

- Peak flow errors are averages from approximately 25 events per basin over an eight year study period (Oct. 1996 – Sept. 2004). Errors are computed between simulated and observed peaks for events independent of the peak time.

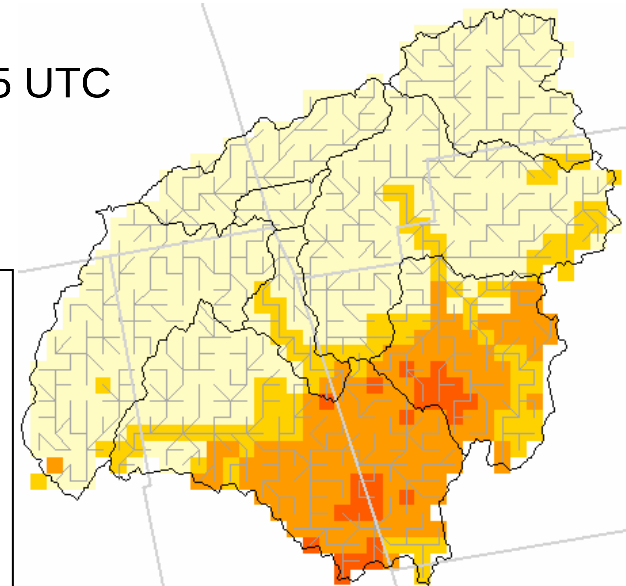
Case Study: 1/4/1998

- The maximum forecast value during the next 96 hours is displayed in each cell.

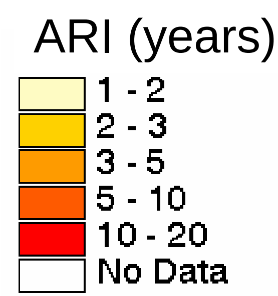
14 UTC



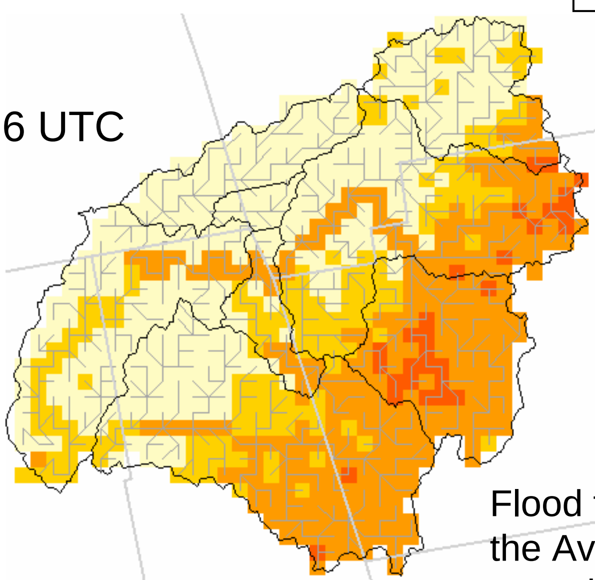
15 UTC



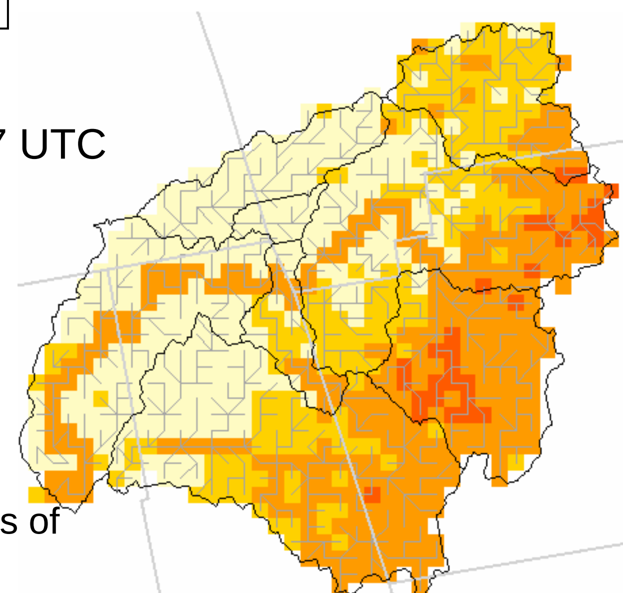
In these examples, frequencies are derived from routed flows, demonstrating the capability to forecast floods in locations downstream of where the rainfall occurred.



16 UTC

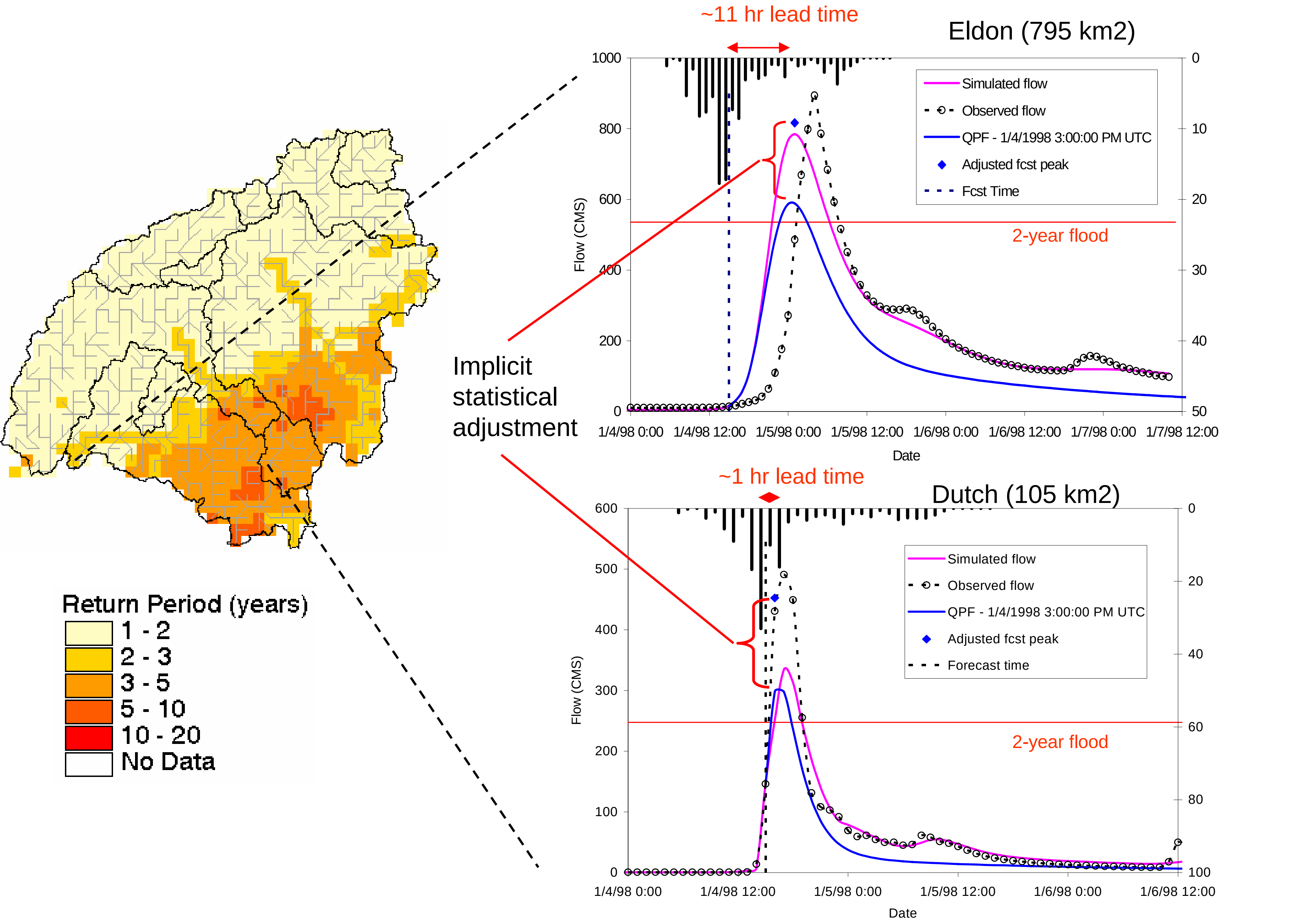


17 UTC



Flood frequencies are expressed in terms of the Average Recurrence Interval (ARI) associated with the annual maximum flood.

Example Forecast Grid and Corresponding Forecast Hydrographs for 1/4/1998 15z



8 MPN to HL-RDHM Case Studies

		No. Hours	Areal Average Storm Total Precipitation in mm: MPE	DPA	QPF	Biases relative to MPE: DPA %bias	QPF % bias
1	1/4/1998	35	76	58	63	-23	-18
2	10/5/1998	20	102	75	80	-26	-21
3	6/17/2000	25	63	60	53	-5	-17
4	6/21/2000	15	106	90	85	-15	-19
5	6/28/2000	11	55	52	44	-7	-20
6	8/14/2002	25	129	103	108	-20	-16
7	4/24/2004	42	110	112	112	2	2
8	7/3/2004	34	104	76	72	-27	-31
					Average	-15	-18

QPF bias is comparable to DPA bias

MPE = Multisensor Precipitation Estimate

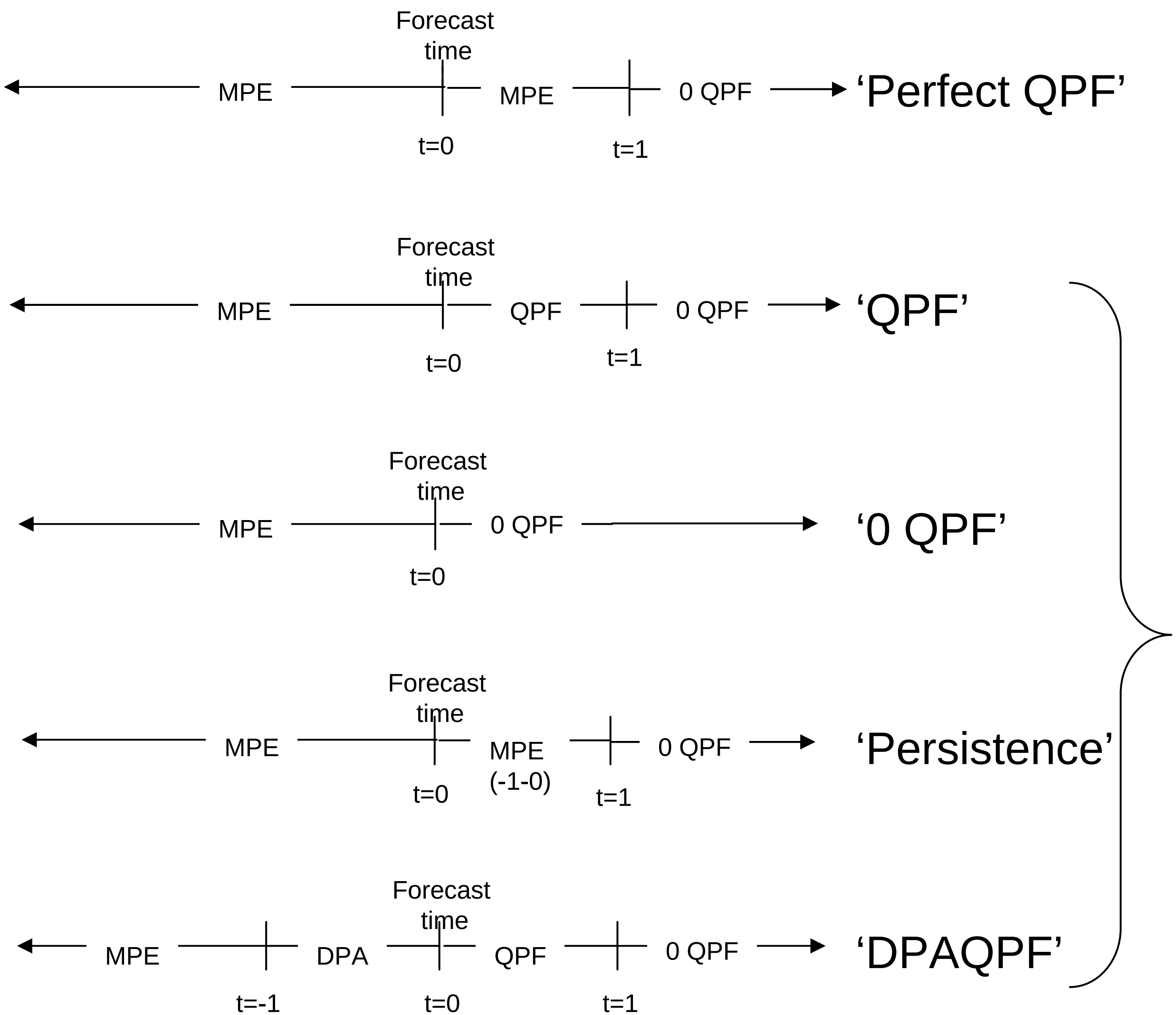
This is the best available precipitation estimate from ABRFC based on analysis with multiple radars, gauge adjustments, and human quality control

DPA = Digital Precipitation Array

This is a radar only (1 hour, 4 km) product with no bias correction.

QPF = Quantitative Precipitation Forecast from MPN

Forecast Scenarios Considered

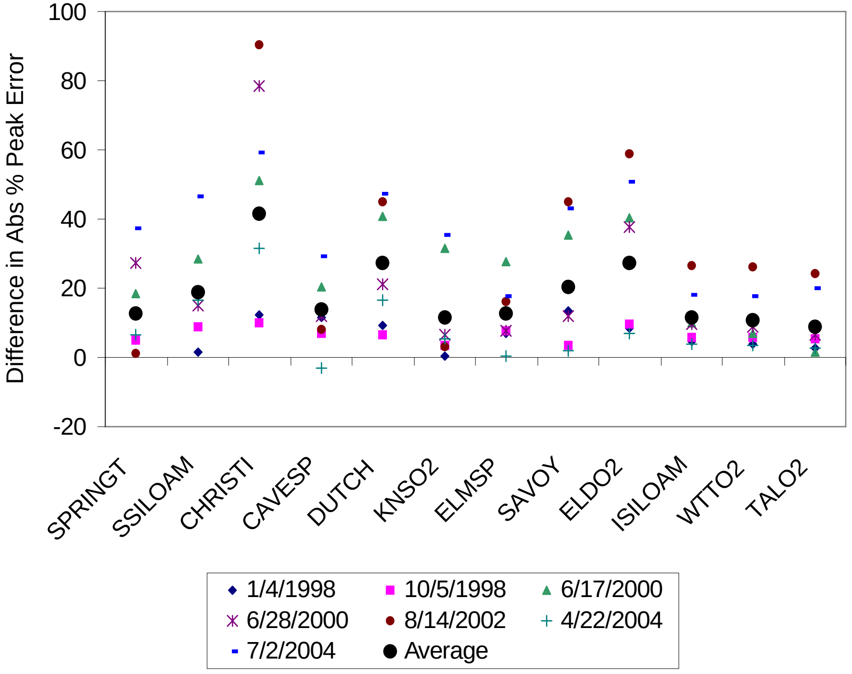


Absolute % peak errors are computed relative to the 'Perfect QPF' case for each hour during the selected events, e.g., for QPF:

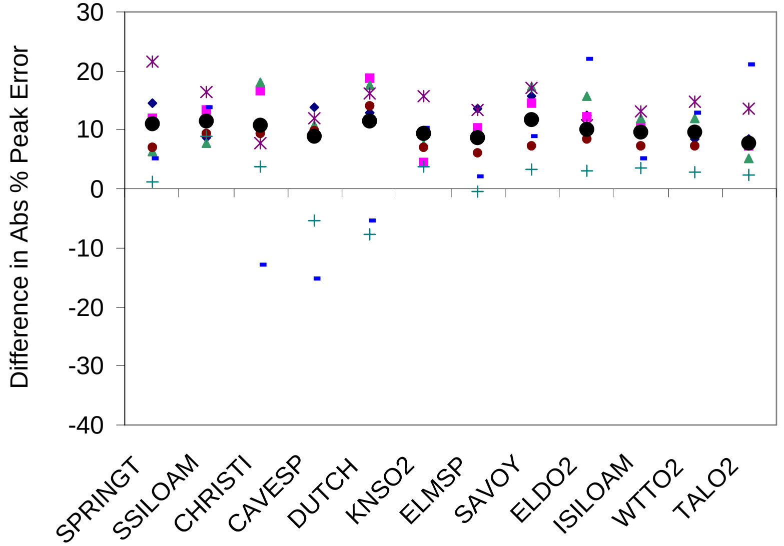
$$\frac{\sum_{t=1}^{n} \frac{\left| Q_{QPF} - Q_{PerfQPF} \right|}{Q_{PerfQPF}} * 100}{n}$$

Forecast Scenario Comparisons

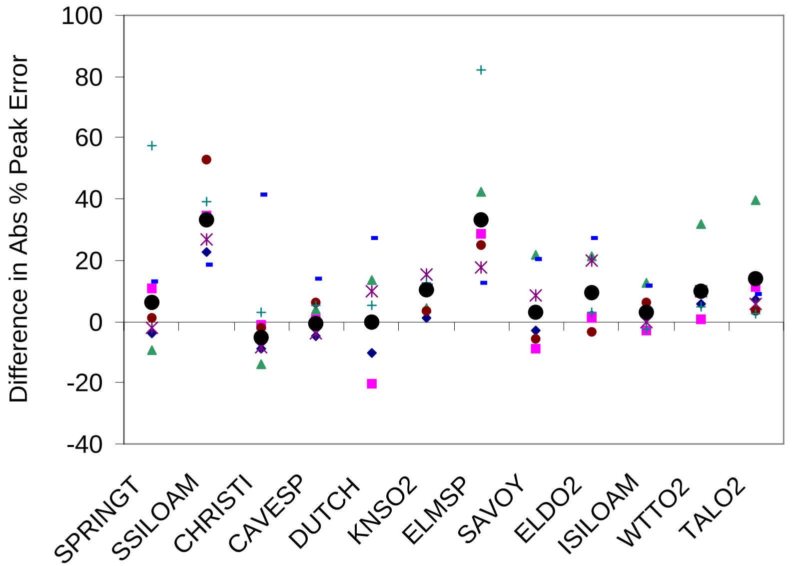
Persist Abs % Error – QPF Abs % Error
(both errors relative to Perfect QPF case as defined on the previous slide)



0 QPF Abs % Error – QPF Abs % Error



DPA QPF Abs % Error – QPF Abs % Error



Over all basins, all events, and all time steps:

- Average relative error for persistence is 18.2% higher than for QPF.
- Average relative error for 0 QPF is 10.1% higher than for QPF
- Average relative error for DPAQPF is 9.7% higher than QPF

Conclusions

- At scales down to 40 km^2, even an uncalibrated distributed model improves upon a lumped model-based approach
- Inherent bias adjustment in the statistical-distributed model further improves results
- For eight case studies, 1-hour nowcasts based on reflectivity had similar biases to reflectivity based rain rate observations (DPA)
- Nowcaster-distributed hydrologic model case studies showed that use of 1-hour QPF produces better simulated flow peaks relative to the case of ‘Perfect QPF’ than ‘0 QPF’, ‘Persistence’, and ‘DPAQPF’ scenarios.
- A proposed next step is couple the statistical-distributed model to EMPE/MPN runs in real-time over a portion of the mid-Atlantic test region currently being used for EMPE/MPN