# CW3E Hydrologic Modeling/Forecasting Efforts: From Process-Based to Data-Driven

#### Ming Pan, CW3E (CW3E Hydrology/S2S/Weather Teams and Partners)

Session: Improving Inflow Forecasts - Progress on Hydrologic Forecasting

Wednesday 3 August 2022

2022 FIRO Workshop 2-4 August 2022 Hosted by the Center for Western Weather and Water Extremes



Center for Western Weather and Water Extremes

### Background: role of hydrologic modeling in FIRO

#### Weather/Climate



#### Hydrology



#### **Engineering/App**





### **CW3E Hydrologic Monitoring/Forecasting: Basic Framework**





### **CW3E Hydrologic Monitoring/Forecasting: Forcing Data Engine**



# **CW3E Hydrologic Monitoring/Forecasting: Forcing Data Engine**



# **CW3E Hydrologic Monitoring/Forecasting: Forcing Data Engine**

#### **QPE** improvement (work in progress):

- Hourly gauge-based estimates with site QC
- Sampling bias
- Orographic
- Snow undercatch
- Freezing level (precip phase)



### **CW3E Hydrologic Monitoring/Forecasting: Reanalysis**



#### **CW3E Hydrologic Monitoring/Forecasting: Reanalysis**



#### **CW3E Hydrologic Monitoring/Forecasting: NRT Monitoring**





#### **CW3E Hydrologic Monitoring/Forecasting: NRT Monitoring**











#### **CW3E Hydrologic Monitoring/Forecasting: NRT Monitoring**







EnKF

EnKF state update is a weighted sum of inputs:

$$\mathbf{x}_{t}^{\prime\prime(i)} = \mathbf{x}_{t}^{\prime(i)} + \mathbf{K}_{t} (\mathbf{z}_{t} - \mathbf{H}_{t} \mathbf{x}_{t}^{\prime(i)})$$
$$= w_{x} \mathbf{x}_{t}^{\prime(i)} + w_{z} \mathbf{z}_{t}$$

 $\mathbf{x'}_{t}^{(i)}$ :prior estimate (ESP) $\mathbf{x''}_{t}^{(i)}$ :posterior estimate (merged) $\mathbf{z}_{t}$ :additional forecast info



How to determine weights: if CCA forecast explains  $r^2$  of the variability, then the combined (fused) forecast ensemble should have its spread reduced by  $r^2$ , therefore:

$$w_x = 1 - r^2$$
 and  $w_z = r^2$ 



Station	50%	0	90%	6	10%	AVG		
Month	KAF	%AVG	KAF	%AVG	KAF	%AVG	KAF	
Feather River at Oroville								
June 2022	95	32	94	32	107	36	298	
July 2022	80	55	80	55	89	62	144	
August 2022	70	72	68	70	92	95	97	
September 2022	65	76	62	72	92	107	86	
October 2022	99	101	74	74	245	248	99	
November 2022	338	184	123	67	739	403	183	
April-July total 2022	897	54	895	54	913	55	1666	
Yuba River near Smartsville								
June 2022	44	24	44	24	64	35	185	
July 2022	19	34	16	28	28	50	56	
August 2022	13	62	12	58	23	110	21	
September 2022	20	113	16	92	33	185	18	
October 2022	121	378	29	91	243	761	32	
November 2022	215	250	147	170	477	554	86	
April-July total 2022	532	55	531	55	573	59	973	
American River below Folsom Lake								
June 2022	87	35	86	35	113	46	245	
July 2022	22	32	20	29	23	34	69	
August 2022	5	31	5	31	12	72	16	
September 2022	10	81	8	65	12	98	12	
October 2022	20	74	19	69	177	660	27	
November 2022	201	236	80	93	836	982	85	
April-July total 2022	741	61	735	60	781	64	1223	



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#### Monthly monitor/forecast updates:





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April 2022	May 2022	Figure 1.3 WRP-Hs and May 31, 2

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# Data-Driven Alternative Modeling: Machine Learning (ML)

#### Machine Learning: statistics on steroids

- Any inputs, any predictive connections, any functional relationships, exhaustive extraction, ...
- Requires data for training, over-fitting, curse of dimensionality, ...



Are you sure? Can you verify? Why so dependent on training?

# **Runoff Hydrology:**

- Many processes at many spatial and temporal scales – what matters at what time/location/scale/circumstance?
- Low dimensionality: watershed runoff is the primary target)
- Lack measurements to verify assumed physical processes
- Still need tuning against data

# Data-Driven Alternative Modeling: Machine Learning (ML)



Long Short Term Memory (LSTM)

State-space (Markovian) type of dynamic processes





(Kratzart et al., 2018)

#### How we're trying to improve inflow modeling:

Data

- Better QPE/QPF (orographic, undercatch, sampling bias, phase, etc.)
- Long-term consistency (bias correction, data-driven approaches)
- Modeling
  - Physical process based modeling (at fine scales)
  - Data driven modeling like ML (at watershed and daily scales)
- Assimilation/fusion (snow, soil moisture, groundwater, etc.)
  - Traditional DA
  - Differentiable ML



## Data-Driven Alternative Modeling: Machine Learning (ML)







**Regression Trees** 



Many many more ...



#### Ming Pan:

- Lead hydrologic modeling/forecasting research at CW3E since 2021
- Background in hydrologic modeling, remote sensing, data assimilation
- Research scholar at Princeton University before joining CW3E
- PhD in hydrology from Princeton University (2006)

