Improving seasonal streamflow forecasts by incorporating soil moisture data

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Surface water vulnerability

- Growing water demands
- Increasingly variable climate
- Low streamflow forecast accuracy
- Limited streamflow forecast availability



Figure 1. Fish kill at Altus-Lugert Lake in 2013 resulting from a golden algae bloom caused by prolonged drought conditions and increasing upstream groundwater use.

Current forecasting methods in Oklahoma

- National Weather Service (NWS) provides river flood forecasts at ≤ 6-day lead times
- Experimental long-range forecast gives probability of flooding for next two months
- No publicly available information on future streamflow volumes



Figure 2. Screenshot of experimental NWS Arkansas Red-Basin River Forecast Center exceedance probability forecast for April-June 2019 for the Cimarron River in Payne County, OK.

Current forecasting methods in Western U.S.

- Made by Natural Resources Conservation Service (NRCS) in snow-dominated Western U.S.
- Principle components analysis and regression (PCR)
- Linear combination(s) of predictor variable(s) used to estimate response variable



Figure 3. Locations of operational streamflow forecasts made by the NRCS in the Western U.S.

Research Objective

The objective of this research is to determine the extent to which soil moisture data can improve seasonal streamflow forecasts in regions where rainfall is the primary driver of surface runoff.

Fort Cobb Watershed

- 786 km² area
- 816 mm yr⁻¹ precipitation
- Sandy clay and sandy loam
- >90% agricultural land
- Fort Cobb Lake
 - Municipal water supply for Chickasha and Anadarko



Figure 4. Location of Fort Cobb watershed.

Fort Cobb Micronet

- 15 stations, 2005-present
- Precipitation and soil moisture
 - Soil moisture sensors at 5, 25, and 45 cm
- Daily change in storage at Fort Cobb reservoir
 - U.S. Army Corps of Engineers



Forecasting Model

- Scenario 1 (baseline)
 - Step 1: antecedent precipitation \rightarrow April-July streamflow
- Scenario 2 (two-step)
 - Step 1: antecedent precipitation \rightarrow streamflow
 - Step 2: antecedent soil moisture \rightarrow residuals (observed-estimated streamflow)
 - Step 3: Step 1 streamflow + Step 2 residuals → final April-July streamflow estimate
- Water years 2006-2018
- 0-, 1-, 2-, and 3-month lead times
- Evaluation
 - root mean square error (RMSE)
 - coefficient of determination (R²)

Scenario 1

Predictor

 Mean cumulative water year antecedent precipitation (mm)





<u>Response</u>

 Total April-July streamflow (mm)



Scenario 1 Results

Table 1. RMSE and R² of precipitation-based forecasts at all lead times.

Lead Time	RMSE	R ²
(months)	(mm)	—
0	18.06	0.28
1	_	—
2	—	—
3	_	—

- Only able to make forecast at 0-month lead time
- Explains very little variability in observed streamflow



Figure 7. Observed versus predicted streamflow for baseline forecasts at 0-month lead time. Dotted line is a 1:1 line.

Scenario 2

Predictors

- Mean antecedent soil moisture
 - Volumetric water content (cm³ cm⁻³)
 - Percent saturation (%)
 - Storage (mm)
 - Available storage (mm)
 - Soil moisture index (-)





<u>Response</u>

 Residuals of scenario 1 April-July streamflow predictions (mm)



Testing soil moisture averaging periods

Table 2. RMSE and R² values for 0-month lead time forecasts made using different soil moisture averaging periods (FD = forecast date). Baseline forecast statistics are shown in the bottom row.

SM period	RMSE	R ²
	(mm)	_
Apr 1	11.68	0.70
Mar	13.18	0.62
Feb-Mar	12.97	0.63
Jan-Mar	14.86	0.51
Oct-Mar	15.31	0.48
Sep-Oct	14.44	0.54
Sep-Nov	8.42	0.84
Oct 1-FD	15.31	0.48
 baseline	18.02	0.28

Scenario 2 Results

Table 3. RMSE and R² for forecasts made using precipitation and September-November soil moisture data at all lead times.

Lead Time	RMSE	R ²
(months)	(mm)	_
0	8.42	0.84
1	10.66	0.75
2	11.34	0.72
3	11.93	0.69

- Highest accuracy at shortest lead time
- Accuracy decreases as lead time increases



Figure 8. Observed versus predicted streamflow for baseline (black squares) and two-step (triangles) forecasts at 0-month lead time using soil moisture data from September-November of the prior year.

Impact of soil moisture data

- Forecasts improve at all lead times
- On average, 68% more variability in streamflow explained by two-step forecasts
- Forecasts can be made up to three months in advance of target period

Key points

- Any soil moisture data improves streamflow forecast accuracy
- Best performance at decreasing lead times
- Demonstrates the importance of long-term in-situ precipitation and soil moisture monitoring
- Strong potential for use in water resource planning and allocation

Ongoing and future work

- Sensitivity analysis
 - Number of soil moisture monitoring locations?
- Expand to two additional watersheds
 - Little Washita, OK
 - Little River, GA
- Human influences?



Figure 9. Locations of Little Washita, OK and Little River, GA watersheds.

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"...records of soil moisture should be maintained... both because of their direct economic value and because of the need of such data as a basis for scientific researches in hydrology, particularly with reference to the solution of the rainfall-runoff problem."

- Robert Horton, 1931



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Forecast period



Figure 6. Median, mean, and standard deviation (σ) of monthly inflow to Fort Cobb Lake versus month of year (MOY) from Nov. 1994 - July 2018.