Improving seasonal streamflow forecasts using remote sensing

Mingxiu Wang[1], Briana M. Wyatt[1], and Tyson E. Ochsner[2]

[1]Department of Soil and Crop Sciences, Texas A&M University
[2]Department of Plant and Soil Sciences, Oklahoma State University

TEXAS A&M UNIVERSITY
Soil & Crop Sciences

TEXAS A&M AGRILIFE RESEARCH

Introduction

- Seasonal streamflow forecasts, especially in rainfall-dominated watersheds, have strong potential to improve reservoir operations, drought and flood management, sustainable water use, hydropower production, and irrigated agriculture.
- Prior research shows in-situ soil moisture data improve forecast accuracy in rainfall-dominated watersheds.
- A lack of monitoring sites in many areas limits the use of in-situ soil moisture measurements in developing more accurate seasonal streamflow forecasts.
- Current remote sensing technology can provide soil moisture information in areas without in-situ monitoring sites.
- We incorporated remote sensing-based soil moisture and groundwater data as a supplement to precipitation data in three regression models to produce seasonal streamflow forecasts.

Objective

Improve the accuracy of seasonal streamflow forecasts by using remotely sensed soil moisture and groundwater data within regression-based models in rainfall-dominated watersheds.

Materials and Methods

Research site

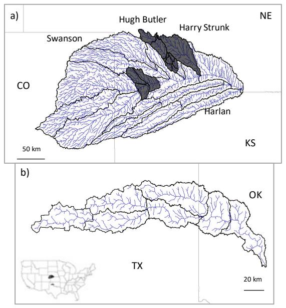

Figure 1. Watershed boundaries of basins (a) draining into the Swanson, Butler, and Strunk reservoirs of the Frenchman Cambridge Irrigation District (FCID) in NE (shaded gray) and the Harlan County reservoir of the Kansas Bostwick Irrigation District (KBID) in KS and (b) draining into the Lugert-Altus reservoir of the Lugert-Altus-Irrigation District (LAID) in OK.

Input data

- Accumulated precipitation data (ΣP) are calculated from the beginning of the water year until the forecast date using the PRISM dataset in Google Earth Engine.
- Mean, minimum, and maximum soil moisture data (SM) between the 0-0.4 m soil depth are from the Soil MERGE (SMERGE) product.
- Monthly total terrestrial water storage anomaly data (GW) from the GRACE (April 2002 - January 2017) and GRACE-FO (June 2018 - present) satellite mission were collected for all available dates in each study watershed using Google Earth Engine.
- As the response variable of each model, reservoir inflow data were used to represent streamflow (Q) for each of the study watersheds.

Regression-based models

- Two step PCR model included a baseline PCR analysis using only antecedent precipitation data to estimate seasonal streamflow volumes, followed by a second PCR analysis using the soil moisture and terrestrial water storage anomaly data to estimate the residuals from the first PCR run.
- One step PCR model used different combinations of predictor variables to estimate seasonal streamflow volumes.
- Multiple linear regression model used different combinations of predictor variables to estimate seasonal streamflow volumes.

Soil moisture averaging period

Table 1. Soil moisture and equivalent thickness anomaly averaging period numbers, associated dates, and a short description of each period.

Averaging period	Dates	Description
1	Feb 28, current year	Day prior to forecast
2	Jan 31, current year	1-month lead time
3	Dec 31, prior year	2-month lead time
4	Nov 30, prior year	3-month lead time
5	Feb 1-Feb 28	Month prior to forecast
6	Oct 1 prior year-Feb 28 current year	Water year prior to forecast
7	Oct 1-Oct 31, prior year	First month of water year
8	Jun 1-Jul 30, prior year	Prior summer

Results

Table 2. Summary of the most accurate forecasts in each watershed from 2-step PCR, 1-step PCR, and MLR models. Nash-Sutcliffe Efficiency (NSE) values are shown for forecasts using antecedent precipitation only (ΣP); antecedent precipitation and soil moisture (ΣP+SM); and antecedent precipitation, soil moisture, and terrestrial water storage anomaly data (ΣP+SM+GW) for a March – June target period. Asterisks indicate forecasts with at least one statistically significant principal component.

Watershed	Model	SM Averaging Period	GRACE Averaging Period	NSE		
				ΣP	ΣP+SM	ΣP+SM+GW
FCID BUTLER	2-step PCR	1	water year	0.03	0.48*	0.48*
	1-step PCR	1	water year	0.03	0.68*	0.76*
	MLR	1	water year	0.03	0.68	0.76
FCID SWANSON	2-step PCR	3	same as SM	0.03	0.20	0.56*
	1-step PCR	3	same as SM	0.03	0.26	0.60*
	MLR	3	same as SM	0.03	0.26	0.60
FCID STRUNK	2-step PCR	5	same as SM	0.05	0.52*	0.54*
	1-step PCR	5	same as SM	0.05	0.77*	0.79*
	MLR	5	same as SM	0.05	0.77	0.79
KBID	2-step PCR	1	same as SM	0.14	0.68*	0.70*
	1-step PCR	1	same as SM	0.14	0.92*	0.93*
	MLR	1	same as SM	0.14	0.92	0.93
LAID	2-step PCR	4	water year	0.00	0.26	0.45*
	1-step PCR	4	water year	0.00	0.35*	0.63*
	MLR	4	water year	0.00	0.35	0.63

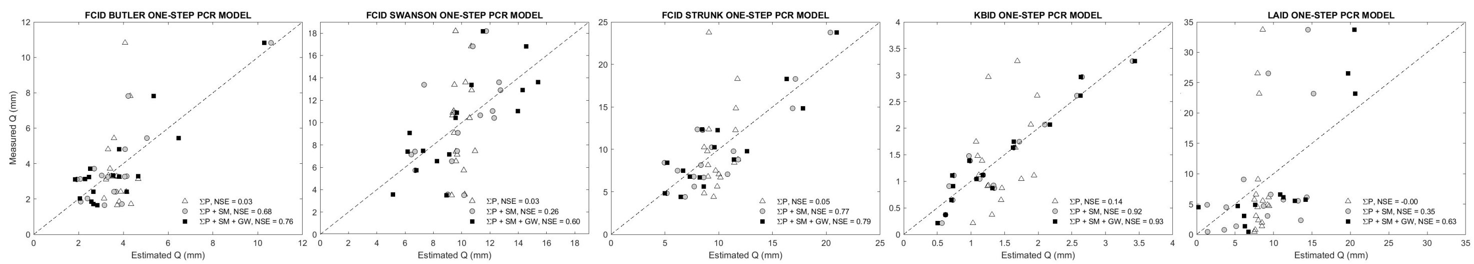

Figure 2. Measured versus estimated seasonal streamflow (Q) corresponding to the most accurate one-step PCR forecast results (Table 2) for each of the five study watersheds. Forecasts developed using antecedent precipitation only (ΣP) are shown by triangles, forecasts using antecedent precipitation and soil moisture (ΣP+SM) are shown by gray circles, forecasts using antecedent precipitation, soil moisture, and terrestrial water storage anomaly data (ΣP+SM+GW) are shown by black squares. NSE values are also shown for each forecast type.

Discussion

- Incorporating remote sensing soil moisture and terrestrial water storage anomaly data improves the accuracy of seasonal streamflow forecasts.
- For all five study watersheds, the one-step PCR model and MLR model have similar forecast accuracies that are higher than that of the two-step PCR model.
- Forecasts with at least one statistically significant principal component have more accurate results.

Future work

- The future work will include introducing the minimum and maximum GRACE terrestrial water storage anomaly data as supplement forecast inputs to test if it is possible to further improve the seasonal streamflow forecasts.

Acknowledgements

- Support for this work was provided by the US Bureau of Reclamation WaterSMART grant #R21AP10100.