



## RECONSTRUCTIONS OF SOIL MOISTURE FOR THE UPPER COLORADO RIVER BASIN USING TREE-RING CHRONOLOGIES<sup>1</sup>

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**ABSTRACT:** Soil moisture is an important factor in the global hydrologic cycle, but existing reconstructions of historic soil moisture are limited. We used tree-ring chronologies to reconstruct annual soil moisture in the Upper Colorado River Basin (UCRB). Gridded soil moisture data were spatially regionalized using principal components analysis and k-nearest neighbor techniques. We correlated moisture sensitive tree-ring chronologies in and adjacent to the UCRB with regional soil moisture and tested the relationships for temporal stability. Chronologies that were positively correlated and stable for the calibration period were retained. We used stepwise linear regression to identify the best predictor combinations for each soil moisture region. The regressions explained 42-78% of the variability in soil moisture data. We performed reconstructions for individual soil moisture grid cells to enhance understanding of the disparity in reconstructive skill across the regions. Reconstructions that used chronologies based on ponderosa pines (*Pinus ponderosa*) and pinyon pines (*Pinus edulis*) explained more variance in the datasets. Reconstructed soil moisture data was standardized and compared with standardized reconstructed streamflow and snow water equivalent data from the same region. Soil moisture and other hydrologic variables were highly correlated, indicating reconstructions of soil moisture in the UCRB using tree-ring chronologies successfully represent hydrologic trends.

(KEY TERMS: soil moisture; reconstruction; tree-ring chronologies; Upper Colorado River Basin; drought.)

Anderson, SallyRose, Glenn Tootle, and Henri Grissino-Mayer, 2012. Reconstructions of Soil Moisture for the Upper Colorado River Basin Using Tree-Ring Chronologies. *Journal of the American Water Resources Association* (JAWRA) 48(4): 849-858. DOI: 10.1111/j.1752-1688.2012.00651.x

### INTRODUCTION

The water content of soil is an important variable in the global hydrologic cycle. Variations in soil moisture transform the structure, species composition, and abundance of vegetative coverage (Evans and Trevisan, 1995). Changes in runoff rates, driven by

variations in vegetation and transpiration rates, affect streamflow volumes, drought duration, soil erosion, and crop yields (Perry and Niemann, 2007). Soil moisture is a large determining factor of transpiration rates (Briffa and Wigley, 1985). Changes in transpiration rates influence the amount of water interacting with the atmosphere, which alters global climate and the global hydrologic cycle (Evans and

<sup>1</sup>Paper No. JAWRA-11-0145-P of the *Journal of the American Water Resources Association* (JAWRA). Received November 15, 2011; accepted February 8, 2012. © 2012 American Water Resources Association. **Discussions are open until six months from print publication.**

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Trevisan, 1995). Soil moisture is a key component in the surface energy balance because evaporation rates drive the heat fluxes between the surface and the atmosphere (Delworth and Manabe, 1988), making soil moisture an important factor in modeling global climate.

Soil moisture is an indicator of drought severity (Wen *et al.*, 2011) and can be useful in identifying abnormally wet or abnormally dry periods. Several studies found a strong relationship between soil moisture and tree-ring widths during drought conditions (Chang and Anguilar, 1980; Kagawa *et al.*, 2003; Bower *et al.*, 2005). Briffa and Wigley (1985) determined that reconstructions of soil moisture are most successful in arid regions where moisture stress is the growth-limiting factor. These spatial variations in soil moisture properties may be useful in differentiating between local and regional climate signals (Yin *et al.*, 2008).

Streamflow and snowpack have been studied extensively in conjunction with tree-ring chronologies, yet reconstructions of soil moisture are not common because existing soil moisture data are limited both spatially and temporally (Perry and Niemann, 2007). The diversity of soil properties and lack of recorded data have reduced the use of soil moisture data for reconstruction purposes by dendroclimatologists (Yin *et al.*, 2008). The development of methods for estimating regional soil moisture would help increase our understanding of patterns in soil moisture variability. Understanding soil moisture cycles and extremes is important for flood forecasting, agricultural practices, erosion control, and climate modeling (Perry and Niemann, 2007).

Tree-ring chronologies have proven to be reliable predictors in reconstructions of hydrologic variables. Several studies have used chronologies to reconstruct streamflow (Woodhouse *et al.*, 2006; Barnett *et al.*, 2010) and snowpack (Woodhouse, 2003; Timilsena and Piechota, 2008) in the Upper Colorado River Basin (UCRB). Tree-ring widths have been shown to be statistically correlated with regional soil moisture in the United Kingdom (Briffa and Wigley, 1985) and in China (Yin *et al.*, 2008). Given these successful reconstructions of soil moisture using tree-ring chronologies and the successful use of tree-ring chronologies to reconstruct hydrologic variables in the UCRB (Woodhouse, 2003; Woodhouse *et al.*, 2006; Timilsena and Piechota, 2008; Tang and Piechota, 2009; Barnett *et al.*, 2010), we hypothesize that regional tree-ring chronologies can be used to reconstruct soil moisture in the UCRB. A better understanding of soil moisture variation in the UCRB could augment existing hydrologic reconstructions and improve understanding of the hydrologic cycle.

## DATA AND METHODS

### Study Area

The UCRB spans five states and covers 283,811 square kilometers (109,580 square miles) (Figure 1). The Colorado River is fed by most mountain ranges west of the continental divide (Hayward *et al.*, 1958). Approximately 90% of the water in the Colorado River system originates in the UCRB. Water from the Colorado River is supplied to over 28 million people. The soils in the UCRB are very diverse, due to the highly varied geology. The UCRB is composed of igneous, metamorphic, and sedimentary rock, resulting in a varied topography (Patrick, 2000). Elevations throughout the basin range from approximately 1,000-4,500 m. The winter climate is characterized by cold, dry, and windy days, while summer days are warm with cool nights. Moisture is provided primarily by winter snowpack and spring showers with late-summer thunderstorms providing precipitation to the mountains and high plateaus, but rarely to the desert regions (Hayward *et al.*, 1958). The forests in the UCRB are primarily coniferous (Patrick, 2000).

### Soil Moisture Data

Fan and van den Dool (2004) modeled single-layer soil moisture data from 1948 to present. These data are model calculated and not measured directly. Data are available in 0.5-degree latitude by 0.5-degree longitude cells and extends from 89.75S to 89.75N

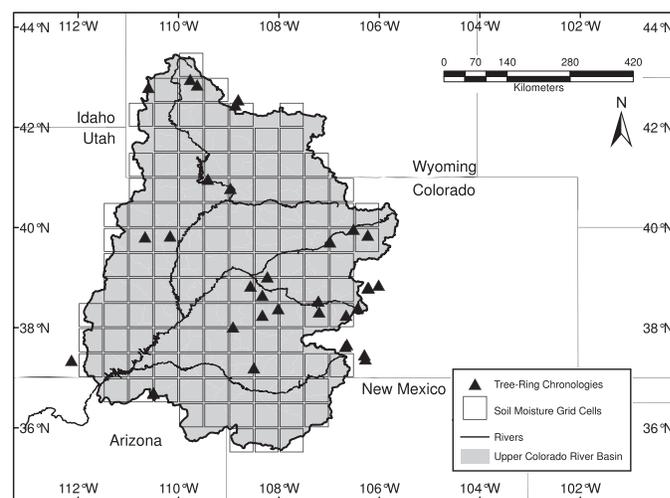


FIGURE 1. Location of the Upper Colorado River Basin with Selected Soil Moisture Grid Cells and Locations of Moisture-Sensitive Regional Tree-Ring Chronologies.

latitude and from 0.25E to 359.75E longitude (van den Dool *et al.*, 2003). The single-layer approach calculates soil moisture using a “bucket” water balance model. Monthly global precipitation data, supplied by the National Weather Service Climate Prediction Center, and monthly global temperature, supplied by the Climate Data Assimilation System, jointly run by the National Center for Environmental Protection and the National Center for Atmospheric Research, were the driving inputs behind the model (Fan and van den Dool, 2004). Modeled data were validated by comparing the annual cycle and interannual variability with observed data from China, India, Russia, Mongolia, and Illinois (Fan and van den Dool, 2004). Monthly soil moisture values for individual cells were summed to obtain annual soil moistures. The UCRB was transposed onto the gridded data. Cells with 50% or greater of their spatial area contained within the UCRB and with their center point located within the boundary of the UCRB were retained (Figure 1).

### Principal Components Analysis and k-Nearest Neighbor Technique.

Data from the retained soil

TABLE 1. Tree-Ring Chronologies in and Adjacent to the Upper Colorado River Basin.

Chronology	Latitude	Longitude	Species
Anderson Ridge East	42.45	-108.87	Limber pine
Beef Basin	36.70	-110.50	Douglas-fir
Boulder Lake	42.85	-109.63	Douglas-fir
Cochetopa Dome	38.25	-106.67	Ponderosa pine
Dry Park	38.25	-108.33	Pinyon pine
Dutch John Mtn.	40.97	-109.42	Pinyon pine
Escalante Forks II	38.65	-108.33	Pinyon pine
Freemont Lake	42.96	-109.77	Douglas-fir
Green Mtn. Res.	39.85	-106.23	Douglas-fir
Harmon Canyon	36.70	-110.50	Douglas-fir
Louis Lake Road	42.55	-108.81	Limber pine
McDougal Pass	42.80	-110.60	Limber pine
McGee Gulch	38.85	-106.02	Douglas-fir
Montrose	38.38	-108.02	Pinyon pine
Navajo Canyon	37.20	-108.50	Douglas-fir
No Man's Mesa	37.35	-112.13	Pinyon pine
Nutter's Ridge	39.82	-110.67	Pinyon pine
Platt Bradbury	37.46	-106.30	Ponderosa pine
Plug Hat Butte	40.78	-108.97	Pinyon pine
Princeton Douglas-fir	38.80	-106.23	Douglas-fir
Princeton Pinyon	38.80	-106.22	Pinyon pine
Pump House	39.97	-106.52	Pinyon pine
Red Creek	38.53	-107.22	Douglas-fir
Sapinero Mesa	38.32	-107.20	Ponderosa pine
Sargents	38.40	-106.43	Douglas-fir
Slickrock	38.02	-108.92	Pinyon pine
South Fork	37.67	-106.65	Ponderosa pine
Terrace Lake Pines	37.38	-106.28	Ponderosa pine
Trail Gulch	39.72	-106.98	Pinyon pine
Unawep Canyon	38.83	-108.57	Pinyon pine
Well's Draw	39.83	-110.17	Pinyon pine
Wild Rose	39.02	-108.23	Douglas-fir
Wilson Ranch	37.63	-106.68	Ponderosa pine

moisture grid cells were analyzed using varimax rotated principal components analysis (PCA) to identify similar regions within the UCRB. PCA is a tool to reduce the size of the dataset while retaining critical information (Richman, 1986; Knapp *et al.*, 2002). We used an eigenvalue cutoff of 1.0 to identify the principal components, retained components that explained 10% or greater variance in the soil moisture dataset, and used a factor-loading cutoff of 0.6 (Timilsena and Piechota, 2008) to select relevant cells. Spatial incongruities were addressed using the non-parametric k-nearest neighbor (k-NN) technique (Dasarathy, 1991), using a k-value of eight. k-NN uses pattern recognition to identify data points with similar attributes and is a useful method of grouping soil moisture data (Nemes *et al.*, 2007). Grid cells identified in each region were averaged to create regional soil moisture indices, similar to the process used by Woodhouse (2003) to create regional snowpack indices.

### Tree-Ring Chronologies

Pederson *et al.* (2011) reconstructed snowpack for the North American cordillera and identified 66 moisture sensitive tree-ring chronologies in the area. The UCRB is located within the North American cordillera. Thirty-three of the 66 chronologies are located within or tangent to the UCRB (Figure 1; Table 1). We obtained these chronologies from the International Tree-Ring Data Bank website (ITRDB. Accessed September 2011, <http://www.ncdc.noaa.gov/paleo/treering.html>). Of the 33 chronologies, 13 were created from pinyon pine (*Pinus edulis*), 11 from Douglas-fir (*Pseudotsuga menziesii*), 6 from ponderosa pine (*Pinus ponderosa*), and 3 from limber pine (*Pinus flexilis*). These four species are moisture sensitive (Fritts, 1976). The standard tree-ring chronology type was used (Pederson *et al.*, 2011) for all 33 chronologies.

Pinyon pines grow in the lower elevations of the UCRB and are resistant to changes in temperature (Anderson, 2002) while ponderosa pines grow at lower elevations, where temperature variability is limited (Howard, 2003). Pinyon pines and ponderosa pines are able to grow in very dry conditions because growth for these species is limited by moisture availability, not temperature (Anderson, 2002; Howard, 2003). Limber pines are very abundant in the UCRB and can prosper in very dry climates (Johnson, 2001). Limber pine growth is limited by both moisture availability and temperature. Douglas-firs grow at high and low elevations and are plentiful across many different slopes, landforms, and soil conditions (Steinberg, 2002).

TABLE 2. Soil Moisture Regression Statistics for Regions in the Upper Colorado River Basin (UCRB).

Region	Predictors	Retained	VIF	D-W	R <sup>2</sup>	R <sup>2</sup> (predicted)
R1	15	3	3.1	Pass	0.69	0.62
R2	10	1	1.0	Inconclusive	0.42	0.37
R3	24	4	3.1	Pass	0.78	0.74
R4	5	2	1.3	Inconclusive	0.46	0.40
UCRB	20	4	2.8	Pass	0.76	0.71

Notes: VIF, Variance Infiltration Factor; D-W, Durbin-Watson.

**Correlation and Stability.** Soil moisture was correlated with each of the 33 tree-ring chronologies using Pearson's correlation method. Chronologies that were positively and significantly ( $p < 0.05$ ) correlated with soil moisture were retained (Timilsena and Piechota, 2008). To test for temporal stability between tree-ring and soil moisture data, correlation coefficients between the two were calculated for a 25-year moving window (Biondi and Waikul, 2004). We retained chronologies that were positively correlated with soil moisture at a confidence of 90% or greater for all windows, indicating a temporally stable relationship.

### Regressions

Stepwise linear regression (SLR) is a common approach for reconstructing hydrologic variables using tree-ring chronologies (Woodhouse, 2003; Gray *et al.*, 2004; Barnett *et al.*, 2010). SLR uses a forward selection and backward elimination approach for creating regressions. Following Woodhouse *et al.* (2006), parameters were set with an alpha-to-enter value of 0.05 and an alpha-to-remove value of 0.10. Forward selection enters predictor variables (tree-ring chronologies) into the model and retains the predictors that are statistically significant, using a threshold alpha value of 0.05. Backward elimination determines which predictors are not statistically significant, using a threshold alpha value of 0.10. These predictors are rejected from the model. The forward and backward processing of predictors continues until the model has selected the predictors that are the most statistically significant. After identifying the best predictor variables for each model, we performed a standard regression that reconstructed soil moisture data from the tree-ring chronology datasets. Validation statistics were calculated to determine the statistical skill of each model.

The Variance Infiltration Factor (VIF) is a measure of multicollinearity. Each retained predictor variable has a VIF. For models with more than one retained predictor, the largest VIF value is analyzed. A VIF of

1.0 indicates that no multicollinearity is present in the model. VIF values greater than 5.0 are cause for concern.

The Durbin-Watson (D-W) statistic tests for autocorrelation among residuals generated by a regression model, as significant autocorrelation in the residuals can indicate a model that likely excluded necessary predictors. The D-W statistic can vary between zero and four. The bounds for an acceptable D-W statistic vary based on sample size and number of retained variables and can be interpreted based on the significance table developed by Savin and White (1977) for models with an intercept.

Predicted R<sup>2</sup> is an indicator of how well the model predicts future responses for new observations. Predicted R<sup>2</sup> helps identify overfitting of the model and is calculated using drop-one cross-validation where one observation is removed from the model and the remaining observations are used to predict the missing value. This process is repeated for each observation. A predicted R<sup>2</sup> value drastically less than the R<sup>2</sup> value indicates that the regression model generated will not predict future responses based on new observations as well as the model fits the existing data.

## RESULTS

### Data Preparation

Varimax rotated PCA identified 12 components with eigenvalues greater than 1.0. Of these 12 components, 4 explained greater than 10% of the variance from the dataset. The explained variances for the four components were 22.0, 16.4, 27.3, and 14.7%, for a combined variance explained of 80.4%. Relevant cells were identified for each region with the application of a factor-loading cutoff value of 0.6 and k-NN with a k-value of eight (Figure 2). Four regional soil moisture indices were created by averaging the contained cells (Woodhouse, 2003). A composite UCRB

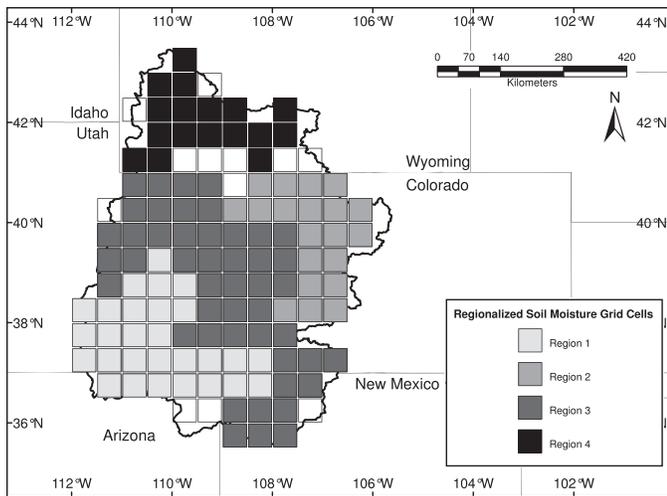


FIGURE 2. Regions in the Upper Colorado River Basin Identified by Principal Components Analysis and k-Nearest Neighbor.

soil moisture index containing all 124 cells was also created.

The number of tree-ring chronologies selected for the predictor pool varied by region. Of the 33 tree-ring chronologies tested, 15 were positively correlated with soil moisture and stable over the entire period of record for region 1. The number of chronologies that passed pre-screening for regions 2, 3, 4, and the composite index were 10, 24, 5, and 20, respectively.

### Regressions

Stepwise linear regression was performed and regression models were developed for each of the four regions and the composite UCRB index. The number of retained predictors varied from one to four (Table 2). Regression models for regions 1, 3, and for the composite UCRB explained 69, 78, and 76% of soil moisture variance, respectively. Regression models for regions 2 and 4 only explained 42 and 44% of soil moisture variances, respectively.

The maximum VIF values for the five models were below 5.0, suggesting the models are statistically valid. Regions 1, 3, and the composite UCRB had D-W values that indicate no autocorrelation was present. The D-W test was inconclusive for regions 2 and 4. Similar to Graumlich *et al.* (2003), we then examined the autocorrelation function (ACF) for these regions. ACF (lag 1) was not significant at  $p < 0.05$  for region 2, suggesting the regression is not biased by autocorrelation. The ACF (lag 1) is significant at  $p < 0.05$  for region 4, indicating the regression is not statistically sound. This region was not included in further analyses. For the five models, the predicted

$R^2$  is within 4-7% of the  $R^2$  value, indicating the models were not overfitted.

## DISCUSSION

### Variability Across the Regions

The reconstructions for regions 1, 3, and the composite UCRB explain a high amount of variance, whereas the reconstruction for region 2 is less informative. Because of this regional discrepancy, we elected to reconstruct each of the 124 grid cells individually to gain a higher level of understanding of the data. The same regression technique was followed for the individual cell reconstructions. The chronologies were individually tested for correlation and stability against soil moisture and only the statistically significant chronologies were retained for each cell. SLR was performed and  $R^2$  values were obtained (Figure 3). A review of validation statistics revealed that all 124 regressions exhibited maximum VIF values less than 5.0. D-W statistics were compared with the significance table developed by Savin and White (1977) and 48 cells had inconclusive D-W statistics. We rejected regressions for cells with an ACF (lag 1) significant at  $p < 0.05$  and retained regressions for cells with an ACF (lag 1) not significant at  $p < 0.05$  (Graumlich *et al.*, 2003), ensuring retained cellular level regressions were statistically valid. Of the 48 cells with inconclusive D-W statistics, we found 19 of

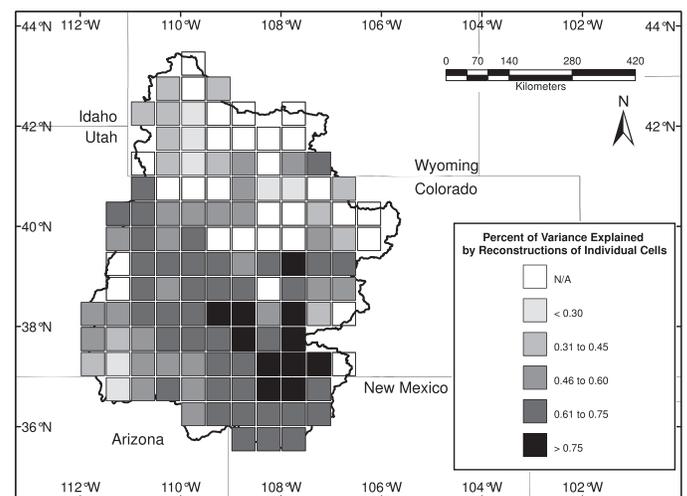


FIGURE 3. Map of the Upper Colorado River Basin, Color-Coded to Show Percent of Variance Explained by Reconstructions of the 124 Individual Grid Cells.

them to be statistically valid. The regressions for the remaining 29 cells were rejected.

### *Reasons for This Variability*

After completing regressions for the individual cells, we were able to analyze the data at a finer level. We explored potential contributors to the discrepancy in regressive skill across the UCRB.

**Topography.** Given that the soil moisture data are model calculated and not measured directly, inaccurate data values may be the cause of the variability we are seeing in our results. The UCRB has a diverse topography. The model used to create the gridded soil moisture data was calibrated with small river basins in eastern Oklahoma (Fan and van den Dool, 2004), which has consistently flat topography. Elevation change is the primary factor for determining soil runoff quantities (Yu and Schwartz, 1998), a factor closely related to soil moisture. Topographical variations could contribute to the inconsistent reconstructive skill seen across the UCRB. Western *et al.* (2004) studied soil moisture in Australia and New Zealand and determined that water content varies based on one or more of the following reasons: regional soil properties, regional hydraulic properties, and site topography. Yin *et al.* (2008) and Briffa and Wigley (1985) determined that soil moisture is a controlling factor of tree growth in arid and semi-arid regions.

Of the 29 soil moisture cells that could not be reconstructed, 17 are located on flat topography and 12 are located in mountainous regions. Reconstructions for seven soil moisture cells explained a variance of less than 30%. All seven of these cells are located on flat topography. Of the 11 cells that explained greater than 75% of variance in soil moisture, 9 are located in mountainous regions and 2 are located on flat topography, suggesting soil moisture cells in mountainous regions can be reconstructed with a higher degree of reconstructive skill. However, a reconstruction of region 2 explained only 42% of soil moisture variance. Approximately 75% of the cells contained in region 2 are located in mountainous regions, suggesting reconstructions in mountainous regions are not always statistically skillful. This contradiction can be explained by examining the distribution of tree species present in the different regions.

**Retained Tree-Ring Chronologies.** Differences in regional elevations determine which species of trees are able to prosper in the regions. The physical location and varying moisture sensitivity of different tree species is a contributing factor to the variability

of reconstructive skill seen across our soil moisture regions. The physical location of the tree-ring chronologies determines how responsive they are to soil moisture in a given region. Of the 33 regional chronologies, the three chronologies from limber pines are all located in the northern portion of region 4. The six chronologies from ponderosa pines are clustered on the eastern edge of the UCRB, at the junction of regions 2 and 3. The chronologies created from Douglas-firs and pinyon pines are well distributed across the basin.

The regression of region 3 yielded the highest amount of explained variance of all four regions and retained two ponderosa pine chronologies, one Douglas-fir chronology, and one pinyon pine chronology. When looking at all of the retained chronologies for the individual cells that compose region 3, 29% are ponderosa pine chronologies and 51% are pinyon pine chronologies. These percentages suggest that ponderosa pines and pinyon pines are preferred species for reconstructing soil moisture. None of the cells in the other three regions retained chronologies from ponderosa pines, potentially due to the limited physical location. All regions retained chronologies from pinyon pines. Chronologies from pinyon pines are distributed evenly across the basin. Developing additional chronologies from ponderosa pines across the UCRB could improve the skill of soil moisture regressions.

Regression in region 2 relied heavily on Douglas-fir chronologies. Thirty-five percent of the chronologies retained in individual cell reconstructions in region 2 were from Douglas-firs, whereas Douglas-fir chronologies comprised only 17 and 18% of chronologies used in regressions for regions 1 and 3, respectively. Chronologies using Douglas-firs are spatially diverse across the basin, yet these chronologies were not often retained in individual reconstructions with higher levels of explained variance, indicating Douglas-firs may not be a strong predictor variable for soil moisture.

Four of the 124 individual regressions retained chronologies from limber pines. Limber pines are located exclusively in region 4. The Green River Basin (GRB) coincides with region 4 identified in our study. Previous research efforts have expressed difficulty reconstructing hydrologic variables in the GRB (Timilsena and Piechota, 2008) and the adjacent Wind River Basin (Watson *et al.*, 2009) because of a lack of moisture sensitive tree-ring chronologies. The development of additional chronologies in this region could allow for the successful reconstruction of soil moisture. In general, reconstructions that used chronologies based on ponderosa pines (*P. ponderosa*) and pinyon pines (*P. edulis*) explained more variance in the datasets. These species grow at lower elevations

and are highly moisture sensitive. Limber pines grow at higher elevations and are sensitive to both moisture and temperature.

#### *Comparison with Snow Water Equivalent and Streamflow*

A direct relationship exists between soil moisture and streamflow (Aubert *et al.*, 2003). Snowpack provides 50-80% of yearly streamflow in the UCRB (Timilsena and Piechota, 2008). Given these relationships, a comparison of soil moisture reconstructions with existing regional snowpack and streamflow reconstructions could provide an additional validation check for the soil moisture reconstructions. Yin *et al.* (2008) verified soil moisture reconstructions in northwestern China by comparing regressions with other proxy data.

**Upper Green Watershed.** Barnett *et al.* (2010) reconstructed annual water-year streamflow for nine unimpaired gages in the northern portion of the UCRB, including US Geological Survey gage #09234500. This gage is located on the Green River at the lower boundary of the Upper Green watershed (UGW). Pederson *et al.* (2011) reconstructed snow water equivalent (SWE) in the UGW. Both Pederson *et al.* (2011) and Barnett *et al.* (2010) identified the UGW as the region containing the eight smaller watersheds identified by hydraulic unit codes (HUCs) 14040101-14040109 (Figure 4).

Examination of watershed maps allowed us to select the soil moisture grid cells contained within the UGW. These 19 cells were averaged to form a

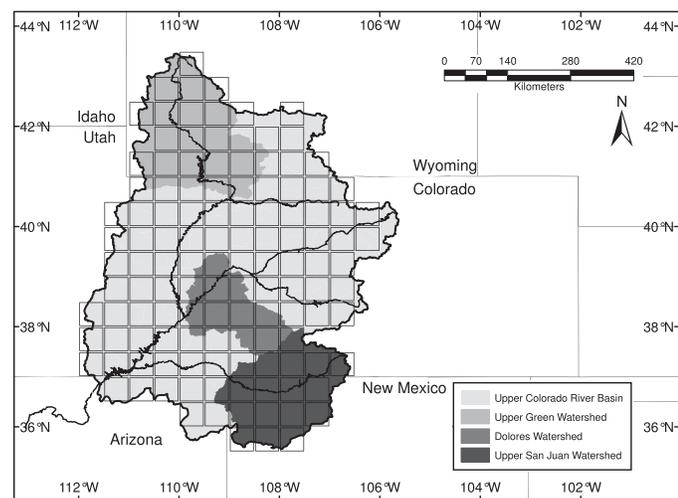


FIGURE 4. Map of Watersheds Selected for Comparison of Hydrologic Reconstructions.

soil moisture index for the UGW. The index was correlated with tree-ring chronologies and the remaining chronologies were tested for stability. These chronologies were used as the predictor variables in SLR. Once the regression equation was determined, soil moisture was reconstructed for the region with an  $R^2$  of 0.54. The  $R^2$  value for the streamflow reconstruction is 0.65 (Barnett *et al.*, 2010) and the  $R^2$  value for the SWE reconstruction is 0.51 (Pederson *et al.*, 2011). Our reconstructed soil moisture was correlated with reconstructed streamflow (Barnett *et al.*, 2010) and reconstructed SWE (Pederson *et al.*, 2011) for the UGRB for the period from 1632 to 1947. The resulting  $r$ -values were 0.74 and 0.55, respectively. All three datasets were standardized (mean of zero, standard deviation of one) and a five-year (end year) filter was applied (Figure 5).

A visual inspection of the two graphs reveals that soil moisture is closely aligned with streamflow. Soil moisture occasionally exceeds high values of streamflow. Soil moisture and streamflow agree for low- and mid-range moisture levels. The two datasets show no lagging. A clear relationship exists between soil moisture and SWE, yet the two datasets are visibly less related than soil moisture and streamflow. Decades of congruity exist (1790-1860), but are often followed or preceded by extended periods of disagreement (1750-1790). In the UGW, soil moisture is more closely aligned with reconstructed streamflow than reconstructed SWE.

**Dolores Watershed and Upper San Juan Watershed.** The UGW is one of the regions that yielded regression equations with the lowest explained variance. The Dolores watershed (DW) and the Upper San Juan watershed (USJW) are located in the southeastern portion of the UCRB and contain the soil moisture cells that yielded regression equations with the highest explained variance. Pederson *et al.* (2011) reconstructed SWE in the DW and the USJW. The DW encompasses HUCs 14030001-14030005 and the USJW encompasses HUCs 14080101-14080107 (Figure 4).

We created soil moisture indices for the DW and the USJW, identifying 10 cells in the DW and 17 cells in the USJW. The same process was followed to create regression equations for these new indices. Validation statistics were analyzed to ensure statistical strength. Reconstructed soil moisture for the two regions was correlated with reconstructed SWE (Pederson *et al.*, 2011) for the period from 1632 to 1947. The resulting correlations were 0.67 for the DW and 0.74 for the USJW. The datasets were standardized (mean of zero, standard deviation of one) and a five-year (end year) filter was applied (Figure 5). The soil

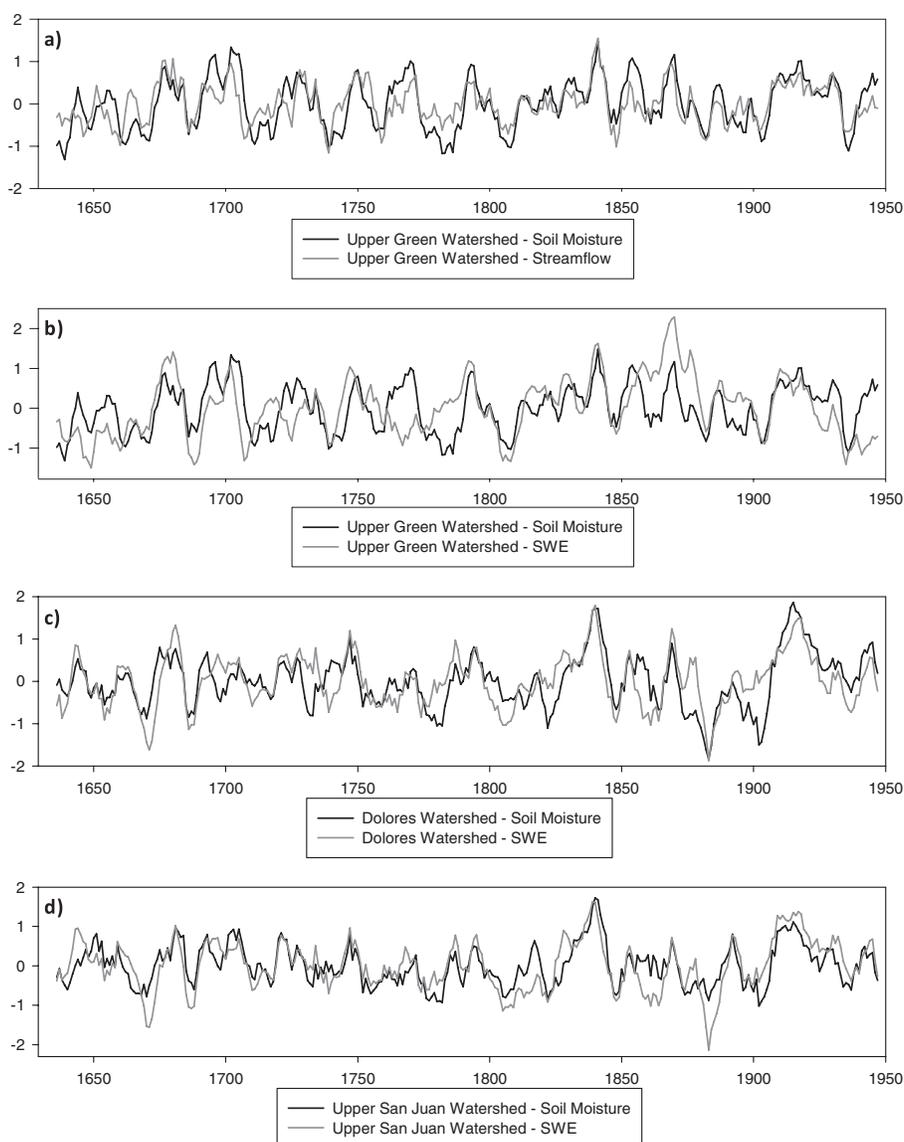


FIGURE 5. Comparison of Hydrologic Reconstructions with a Five-Year (end-year) Filter. (a) Soil moisture and streamflow in the Upper Green watershed, (b-d) soil moisture and snow water equivalent (SWE) in the Upper Green watershed, the Dolores watershed, and the Upper San Juan watershed.

moisture reconstructions explained 78% of variance in the DW and 82% of variance in the USJW. The SWE reconstructions explained 63% of variance in the DW and 58% of variance in the USJW (Pederson *et al.*, 2011).

From a visual inspection, soil moisture and SWE agree for both watersheds. The  $R^2$  values for the explained variance between soil moisture and SWE in these two watersheds are 0.45 (DW) and 0.55 (USJW), as opposed to 0.30 for the UGW. Soil moisture and SWE match well at low-, mid-, and high-moisture levels for the DW and the USJW. Annual soil moisture patterns are aligned with hydrologic trends in snowpack.

## CONCLUSIONS

Our results suggest that tree-ring chronologies can be used as proxy records of past soil moisture. Soil moisture is an important component in the hydrologic cycle and a critical variable in reconstructing global climate. Reconstructed soil moisture could augment understanding of paleoenvironments and improve understanding of the relationship between surface moisture and the atmosphere. However, few reconstructions of soil moisture exist. Given the importance of water in the Colorado River Basin, coupled with the recent ecological

changes brought about by the pine beetle, future research should focus on determining what drives variation in soil moisture. Our results indicate a strong relationship between soil moisture and other hydrologic variables (streamflow, snowpack). Soil moisture reconstructions could help verify existing hydrologic reconstructions in the UCRB and around the world.

#### ACKNOWLEDGMENTS

This research is supported by the National Science Foundation Paleo Perspectives on Climate Change award (AGS1003393).

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