**Benefits of Using Higher Density Lower Reliability Weather Data from the Global Historical Climatology Network (GHCN) Monitors for Watershed Modelling**

Roja K. Garna1,2, Zachary M. Easton1, Joshua W. Faulkner3, Amy S. Collick4, Daniel R. Fuka1, \*

1 Department of Biological Systems Engineering, Virginia Tech, Blacksburg, VA

2 Stantec Consulting Services Inc., Lexington, KY

3 Department of Plant and Soil Science, University of Vermont, Burlington, VT

4 Department of Agricultural Sciences, Morehead State University, Morehead, KY

**\* Corresponding author**: Virginia Tech, 155 Ag Quad Lane, Blacksburg, VA, 24061, USA; [drfuka@vt.edu](mailto:drfuka@vt.edu)

# Abstract (up to 300 words)

Hydrological models require a complete and accurate time series of weather inputs to adequately represent watershed-scale responses. The Global Historical Climatology Network (GHCN) is the most comprehensive ground-based global weather database and is often used in hydrological modeling studies. Since higher density, lower reliability precipitation measurements from private citizens collected by the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) network data were integrated into the GHCN, hydrological modelers in the U.S. have access to a much greater amount of weather data. However, the benefit of using CoCoRaHS data has not been assessed. The objectives of this work were to develop a method for generating a complete weather data time series based on the combination of data from multiple GHCN monitors and to assess several methods for estimation of missing weather data. Weather data from GHCN monitors located within a specific radius of a watershed were obtained and interpolated using three estimation methods (Inverse Distance Weighting (IDW), Inverse Distance and Elevation Weighting (IDEW), and Closest Station), creating a seamless time-series of weather observations. To evaluate the performance of the methodologies, weather data obtained from each estimation method was used to force the Soil and Water Assessment Tool (SWAT) models of 21 U.S. Department of Agriculture-Conservation Effects Assessment Project watersheds in different climate regions to simulate daily streamflow for 2010-2021. Except for three watersheds, all SWAT models had Nash-Sutcliffe Efficiency above 0.5, the ratio of the root mean square error to the standard deviation of observations below 0.7, and percent bias from -25% to 25% with a satisfactory performance rating. Overall, IDEW and IDW performed similarly, and the Closest Station method resulted in the poorest streamflow simulation. A comparison with published SWAT model results further corroborated improved model performance using newly combined GHCN data with all Closest Station, IDW, and IDEW methods.

**Keywords:** Global Historical Climatology Network, Hydrological models, Inverse Distance Weighting, Interpolation technique, weather forcing data, missing weather data, SWAT, Conservation Effects Assessment Project

# 1. INTRODUCTION

Weather data are critical inputs for hydrological models used to simulate hydrological, geomorphological, and biological processes in watersheds. Complete and accurate weather data is essential for modelers and decision-makers to accurately and efficiently predict, assess, and manage water resources [(Gyau-Boakye & Schultz, 1994)](https://paperpile.com/c/HAeg3w/S5NA) although acquiring representative weather data is often challenging due to the sparse availability of timely, continuous and objective observations with uniform spatial coverage [(Kite & Haberlandt, 1999](https://paperpile.com/c/HAeg3w/4I3V); [Rafii & Kechadi, 2019)](https://paperpile.com/c/HAeg3w/8WOS). Also, if the regional distribution of precipitation is not adequately represented, process-based hydrological models such as the Soil and Water Assessment Tool (SWAT) cannot accurately simulate the hydrological process in a watershed [(Chaplot et al., 2005)](https://paperpile.com/c/4eacFx/b1Qs). The amount of weather data available to hydrological modelers in the US has extensively expanded with the integration of the much higher density (though less reliable) precipitation measurements from private citizens submitted to the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) [(Doesken & Reges, 2011; Reges et al., 2016)](https://paperpile.com/c/HAeg3w/wKmG+yiMa) into the Global Historical Climatology Network (GHCN) [(Menne et al., 2012a; Menne et al., 2012b)](https://paperpile.com/c/HAeg3w/d3rY+c4MC); however, the benefit of the additional data which is less reliable at any given location has not been assessed over multiple climatic regions of the US.

Estimation of weather data to force watershed models is usually accomplished by using the closest weather stations and combining records from neighboring weather stations where weather records are available [(Galván et al., 2014)](https://paperpile.com/c/4eacFx/DPZ6). There are many methods proposed for estimating and combining weather data to obtain representative forcing data [(Thiebaux & Pedder, 1987)](https://paperpile.com/c/HAeg3w/Zj4Q). Many approaches compute missing values from adjacent stations using a weighting function, which could involve everything from simple arithmetic averaging to more complex differential weighting techniques to employing spatial covariance to interpolate values [(Wallis et al., 1991; Willmott & Robeson, 1995](https://paperpile.com/c/HAeg3w/B3wB+R6DD); [DeGaetano et al., 1995; Huth & Nemes̆ová, 1995; Saborowski & Stock, 1994)](https://paperpile.com/c/HAeg3w/Fenl+2ZMa+Jfre). Among all the various methods, the Closest Station [(Wallis et al., 1991)](https://paperpile.com/c/HAeg3w/B3wB), inverse distance weighting (IDW) [(Hubbard, 1994)](https://paperpile.com/c/HAeg3w/c7TL), and inverse distance and elevation weighting (IDEW) techniques [(Masih et al., 2011)](https://paperpile.com/c/HAeg3w/QgHv) are the most commonly used and have shown good performance for the estimation of missing data [(Suhaila et al., 2008; Teegavarapu & Chandramouli, 2005)](https://paperpile.com/c/HAeg3w/auEI+mcCZ).

There are many sources of weather data used in hydrological modeling studies including ground-based [(Faurès et al., 1995)](https://paperpile.com/c/HAeg3w/pgbI), reanalysis-based [(Fuka et al., 2014b)](https://paperpile.com/c/HAeg3w/4iwh), and satellite-based [(Alazzy et al., 2017)](https://paperpile.com/c/HAeg3w/enlw). Weather data from ground-based stations are often considered standard for hydrologic modeling [(Colston et al., 2018; Mistry et al., 2022)](https://paperpile.com/c/HAeg3w/eTKL+P0pn); however, many ground-based stations contain missing data. The Global Historical Climatology Network (GHCN) is the most comprehensive ground-based global weather database consisting of daily weather records [(Menne et al., 2012b)](https://paperpile.com/c/HAeg3w/c4MC), often including precipitation, daily maximum, and minimum temperature, snowfall, humidity, and snow depth managed by the National Oceanic and Atmospheric Administration (NOAA)’s National Centers for Environmental Information (NCEI). GHCN includes data from 107,000 ground stations across the globe [(Jaffrés, 2019; Menne et al., 2012a; Menne et al., 2012b)](https://paperpile.com/c/HAeg3w/c4MC+d3rY+61rs), and is used broadly in multiple hydro-ecological applications [(Muche et al., 2020;](https://paperpile.com/c/HAeg3w/wPze) [Brazel et al., 2000](https://paperpile.com/c/HAeg3w/61zW); [Larkin, 2005](https://paperpile.com/c/HAeg3w/ZCwQ)[)](https://paperpile.com/c/HAeg3w/wPze). GHCN data are derived from several weather networks, including the CoCoRaHS, the National Weather Service’s Cooperative Observers Program (COOP), the European Climate Assessment and Dataset (ECA&D), the World Meteorological Organization (WMOID), the National Meteorological or Hydrological Center (NM/HC), the U.S. Interagency Remote Automatic Weather Station (RAWS), the U.S. Natural Resources Conservation Service (NRCS) SNOwpack TELemtry (SNOTEL), and the Weather Bureau Army Navy channel (WBAN) [(Menne et al., 2012a; Menne et al., 2012b)](https://paperpile.com/c/HAeg3w/c4MC+d3rY). Of the aforementioned eight GHCN weather data sources, five sources (CoCoRaHS, COOP, RAWS, WBAN, and SNOTEL) provide the majority of reporting stations in the continental U.S., where the study is performed.

This study evaluates whether the combined datasets of GHCN, including the addition of higher-density but perhaps lower-quality citizen science weather data, combined with previously published methods to estimate missing weather data from multiple nearby weather stations better represent the weather forcings over a watershed than the most commonly used methods of using the closest weather stations. To test this, we use the SWAT model for 21 United States Department of Agriculture (USDA)-Agricultural Research Service (ARS)-NRCS-Conservation Effects Assessment Project (CEAP) watersheds [(Sadler et al., 2008; Sadler et al., 2015)](https://paperpile.com/c/HAeg3w/btJg+g2wK) across five Köppen climate classification [(Peel et al., 2007)](https://paperpile.com/c/HAeg3w/wlAD) regions in the United States and compare model predicted streamflow to observed data. To perform the evaluation, we developed a new tool, “FillMissWX”, to automatically download GHCN data (precipitation, maximum temperature, and minimum temperature) from all monitors that are located in a specific radius from the target location and then estimate and interpolate missing data based on three estimation methods; Closest Station, IDW, and IDEW. Then, complete weather data time series from multiple GHCN monitors generated by FillMissWX estimation methods are used to force SWAT models and simulate streamflow. The predicted streamflow of each estimation method is evaluated based on standard statistical measures (Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR)) and evaluation criteria suggested by [Moriasi et al. (2007)](https://paperpile.com/c/HAeg3w/bb4z). The effect of each estimation method on simulated streamflow was further assessed by comparing model results with previously published model results.

# 2. METHODS AND SITE DESCRIPTION

## **2.1 GHCN Weather Data Sources**

CoCoRaHS, with over 20,000 active observers across the United States, Puerto Rico, the U.S. Virgin Islands, and Canada [(Reges et al., 2016)](https://paperpile.com/c/HAeg3w/yiMa), is a collaborative precipitation monitoring network sponsored by NOAA and National Science Foundation (NSF) [(Kelsch, 1998; Reges et al., 2016)](https://paperpile.com/c/HAeg3w/Uq9Y+yiMa). The CoCoRaHS is a network of volunteer observers using inexpensive measurement tools to measure daily precipitation (<https://www.cocorahs.org/>). The National Weather Service (NWS) COOP [(Wuertz et al., 2018)](https://paperpile.com/c/HAeg3w/sB0M) is another network with a mix of contractors and volunteers that provides observational weather data, including snowfall, precipitation, minimum and maximum temperature at more than 8,700 observers. All COOP providers must employ NWS-approved equipment and standards (<https://www.weather.gov/coop/Overview>). Remote Automatic Weather Stations (RAWS) [(Brown et al., 2011)](https://paperpile.com/c/HAeg3w/q19h) are solar-powered stations, both portable and permanent, that collect weather data, primarily by U.S. government agencies such as the U.S. Forest Service and the U.S. National Park Service [(Zachariassen, 2003)](https://paperpile.com/c/HAeg3w/QOl5). RAWS data is transmitted to the National Interagency Fire Center (NIFC) via NOAA’S Geostationary Operational Environmental Satellite (GOES). This network operates nearly 2,200 stations across the United States, primarily owned by the wildland fire agencies (<https://raws.nifc.gov/>). Weather Bureau Army Navy (WBAN), introduced in 1947 as a combination of the Weather Bureau, Air Force Master, and Navy Weather Central Analysis Center [(Vederman, 1949)](https://paperpile.com/c/HAeg3w/J0vi) includes precipitation, temperature, relative humidity, and wind speed data from 237 weather stations over the U.S. (<https://www.epa.gov/ceam/weather-bureau-army-navy-wban-station-locations-and-30-year-normals>). The U.S. Natural Resources Conservation Service SNOTEL observer stations was established in 1978 to transmit high-altitude climate data via telemetry [(Schaefer & Paetzold, 2001)](https://paperpile.com/c/HAeg3w/IwgI) over 650 remote sites that monitor snow water content, precipitation, snow depth, and temperature data [(Schaefer & Paetzold, 2001)](https://paperpile.com/c/HAeg3w/IwgI).

### ***2. 1. 1 Estimation Methods of Missing Weather Data (Interpolation Methods)***

#### ***Closest Station (closest)***

As the name suggests, the Closest Station method (closest) estimates missing data for the target location by imputing data from the nearest station with measurements. If the data needed is missing at the closest station, data from the next closest station are used. This continues to the point that either there is no more missing data in the particular time period or there are no more stations within the maximum station radius with measured data [(Wallis et al., 1991)](https://paperpile.com/c/HAeg3w/B3wB).

#### ***Inverse Distance Weighting (IDW)***

IDW estimates the missing data using distance-weighted average data from stations within the user-defined radius [(Hubbard, 1994)](https://paperpile.com/c/HAeg3w/c7TL). The missing values are calculated by Equation 1:

|  |  |
| --- | --- |
|  | (1) |

Where is the estimated value of the missing data, is the data value of the ith closest station, is the distance between ith closest station and the target location, is the weighting power that ranges from 1 to 6 with the most common value of 2 [(Teegavarapu & Chandramouli, 2005; Vieux, 2001)](https://paperpile.com/c/HAeg3w/mcCZ+XYWy), and n is the total number of GHCN monitors located in a user-defined search radius.

#### ***Inverse Distance and Elevation Weighting (IDEW)***

While IDW considers the influence of the distance between the target and reference locations to estimate missing data, in many areas, elevation also influences the distribution of precipitation. The IDEW method for this study is built based on the methodology presented in [(Liston & Elder, 2006; Zhang et al., 2017)](https://paperpile.com/c/HAeg3w/uIEpl+OSW0) for precipitation () and temperature (), respectively:

|  |  |
| --- | --- |
|  | (2) |
|  | (3) |

Where and are precipitation and temperature values of the ith closest station, is the elevation of target location with missing data, is the elevation of the ith closest station, is a precipitation adjustment factor to vary monthly values, and is the air temperature lapse rate that varies depending on the month of the year. Lapse rates are by default set to those suggested by [Kunkel (1989), Liston & Elder (2006)](https://paperpile.com/c/HAeg3w/g4lz+uIEpl), and Thornton et al. (1997) for precipitation in the Northern Hemisphere. Lapse rates, and can be specified if known.

## **2.2 Tool Development**

To reliably estimate missing weather data we developed FillMissWX, a tool in the EcoHydRology R package [(Fuka et al., 2014a)](https://paperpile.com/c/HAeg3w/HtPk5), to automatically download daily weather data of GHCN monitors and fill and interpolate missing data using data from neighboring monitors based on three estimation methods: IDW, IDEW, and Closest Station. The tool assimilates precipitation and maximum and minimum temperature from monitors that are located within the user-defined distance of a location of interest using the “rnoaa” R package library [(Edmund et al., 2016)](https://paperpile.com/c/HAeg3w/r7E1). The tool will also automatically generate plots of weather variables including the sources and numbers of GHCN monitors used (CoCoRaHS, COOP, ECA&D, WMOID, NM/HC, RAWS, SNOTEL) and their distances from the target location. The required inputs to run the FillMissWX function are latitude (declat) and longitude (declon) of the location of interest, the radius within which to search for monitors from the target location in kilometers (StnRadius), the minimum number of monitors from which data need to be downloaded (minstns), the earliest (date\_min) and latest (date\_max) date of interest, the elevation of the target location (km) in IDEW method (targElev), the method to use to fill missing weather data including “closest”, “IDW”, and “IDEW” (method), the weighting power in IDW and IDEW methods with the default value of 2 (alfa, 1-6), and the print format “png” or “pdf” format (printinto). The outputs of the FillMissWX function include a data frame containing filled precipitation (P) (mm), maximum temperature (MaxTemp) and minimum temperature (MinTemp) (°C), the weighted-average elevation of monitors used for precipitation (prcpElev), maximum temperature (tmaxElev), and minimum temperature (tminElev).

## **2. 3 Study Watersheds**

To evaluate whether combined and complete GHCN weather data from estimation methods adequately represent regional weather distribution as a major driving force of hydrological processes, we initialized SWAT models for each of the 21 USDA-ARS-NRCS-CEAP [(Sadler et al., 2008; Sadler et al., 2015)](https://paperpile.com/c/HAeg3w/g2wK+btJg) benchmark watersheds (Figure 1 and Table 1). The relevant properties of the 21 watersheds are shown in Table 1, including the ARS-NRCS-CEAP benchmark watershed name, U.S. Geological Survey (USGS) gage name [(U.S. Geological Survey, 2022)](https://paperpile.com/c/HAeg3w/GXjP), drainage area (km2), latitude and longitude of watershed centroid, the search radius, number and type of reporting weather station, and average annual weather characteristics including precipitation, maximum and minimum temperature. USGS gages, listed in Table 1, are the portion of ARS-NRCS-CEAP watersheds used as test watersheds in this study that had daily measured streamflow data for 2010-2021 and were used for model calibration. The search radius, a user-defined parameter, is the distance from which to draw missing data and can be varied based on user knowledge of data completeness and density of stations. The initial search radius was set to 30 km as has been shown to be a suitable first estimate in many locations [(](https://paperpile.com/c/HAeg3w/SjQf+61CrZ)[Chen & Liu, 2012; Fuka et al., 2014b](https://paperpile.com/c/u0UAFs/Zo3W+CHm6)). In some cases, 30 km was inadequate to provide suitable station density; therefore, search radii greater than 30 km in Table 1 were increased iteratively until sufficient station numbers were identified. Figure 1 shows the watershed locations and their corresponding climate types based on the Köppen climate classification [(Köppen et al., 2011; Rubel & Kottek, 2011)](https://paperpile.com/c/HAeg3w/BFLqz+iUj91).

Based on this methodology, three weather datasets for each of the 21 watersheds were developed for testing. For each watershed, we investigated the types of GHCN networks and the number of monitors per type that were used to generate the complete weather data time series used within the SWAT model.

Table 1. Table of study area information including ARS-NRCS-CEAP benchmark watershed names, the name of experimental (test) USGS gage as a portion of ARS-NRCS-CEAP watershed, the area of watershed above USGS gage (km2), longitude and latitude of watershed centroids, the search radius (R) in km to interpolate all missing data from center of the watershed, number and platform type of precipitation, maximum and minimum temperature GHCN stations in a circle with a center of latitude and longitude of watershed’s centroid and the radius of R, average annual precipitation (mm), and annual maximum and minimum temperature (℃) using FillMissWX tool for each of Closest Station (Closest), IDW, and IDEW interpolation methods

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Basin #** | **CEAP watershed name** | **USGS gage** | **Watershed area (km2)** | **Watershed centroid** | **Search radius (km)** | **Station type and density (precipitation)a** | **Station type and density (temperature)a** | **Average annual precipitation (mm)b** | **Average annual maximum/minimum temperature (℃)b** |
| 1 | Mahantango Creek Watershed, Pennsylvania | USGS 01555500-East Mahantango Creek near Dalmatia, PA | 414.72 | -76.60791  /40.6619 | 42.42 | Total=29  CoCoRaHS=18  COOP=10  WBAN=1 | Total=10  CoCoRaHS=1  COOP=8  WBAN=1 | Closest=1273  IDW=1237  IDEW=1322 | Closest=15.69 /5.03  IDW=16.20 /4.97  IDEW=16.34/5.09 |
| 2 | Choptank River, Maryland | USGS 01491000-Choptank River near Greensboro, MD | 289.28 | -75.70502  /39.07633 | 60 | Total=111  CoCoRaHS=98  COOP=11  WBAN=2 | Total=13  CoCoRaHS=1  COOP=9  RAWS=1  WBAN=2 | Closest=1367  IDW=1324  IDEW=1333 | Closest=19.39 /9.07  IDW=19.14 /9.04  IDEW=19.38/9.26 |
| 3 | Upper Big Walnut Creek, Ohio | USGS 03228300-Big Walnut Creek at Sunbury, OH | 258.56 | -82.77789  /40.33008 | 30 | Total=26  CoCoRaHS=21  COOP=5 | Total=4  CoCoRaHS=1  COOP=3 | Closest=1260  IDW=1199  IDEW=1226 | Closest=15.83 /4.74  IDW=16.09 /4.97  IDEW=16.33/5.20 |
| 4 | St. Joseph River, Indiana | USGS 04180000-Cedar Creek near Cedarville, IN | 691.2 | -85.10909  /41.39034 | 30 | Total=65  CoCoRaHS=56  COOP=9 | Total=2  COOP=2 | Closest=976  IDW=962  IDEW=973 | Closest=15.23 /4.26  IDW=15.17 /4.25  IDEW=15.39/4.47 |
| 5 | Topashaw Canal Watershed, Mississippi | USGS 07283000-Skuna River at Bruce, MS | 650.2 | -89.19086  /34.09643 | 60 | Total=31  CoCoRaHS=15  COOP=15  WBAN=1 | Total=12  COOP=9  RAWS=2  WBAN=1 | Closest=1485  IDW=1487  IDEW=1465 | Closest=22.73 /10.41  IDW=23.12 /10.41  IDEW=23.31/10.69 |
| 6 | Goodwin Creek, Mississippi | USGS 07274000-Yocona River near Oxford, MS | 670.7 | -89.34907  /34.27514 | 60 | Total=34  CoCoRaHS=17  COOP=16  WBAN=1 | Total=13  COOP=10  RAWS=2  WBAN=1 | Closest=1519  IDW=1504  IDEW=1492 | Closest=23.23 /10.09  IDW=23.08 /10.28  IDEW=23.27/10.50 |
| 7 | Beasley Lake, Mississippi | USGS 07288500-Big Sunflower River at Sunflower, MS | 1963.5 | -90.64328  /33.9998 | 85 | Total=56  CoCoRaHS=27  COOP=27  WBAN=2 | Total=22  CoCoRaHS=1  COOP=18  RAWS=1  WBAN=2 | Closest=1456  IDW=1475  IDEW=1466 | Closest=22.81 /10.95  IDW=22.97 /11.35  IDEW=23.172 /11.58 |
| 8 | Little River Ditches, Arkansas | USGS 07043500-Little River Ditch No. 1 near Morehouse, MO | 1152 | -89.84413  /37.05175 | 42.42 | Total=21  CoCoRaSH=15  COOP=5  WBAN=1 | Total=16  COOP=5  WBAN=1 | Closest=1327  IDW=1377  IDEW=1381 | Closest=20.41 /9.02  IDW=20.19 /8.59  IDEW=20.43/8.80 |
| 9 | Lower St. Francis, Arkansas | USGS 07047855-Whiteman's Crk Jonesboro, AR | 16.9 | -90.67069  /35.82797 | 60 | Total=38  CoCoRaSH=26  COOP=11  WBAN=1 | Total=9  COOP=8  WBAN=1 | Closest=1325  IDW=1389  IDEW=1382 | Closest=21.43 /10.54  IDW=21.31 /9.98  IDEW=21.56/10.20 |
| 10 | Salt River/Mark Twain Reservoir, Missouri | USGS 05506800-Elk Fork Salt River near Madison, MO | 512 | -92.30355  /39.37527 | 50 | Total=60  CoCoRaSH=49  COOP=11 | Total=7  CoCoRaSH=1  COOP=6 | Closest=1095  IDW=1088  IDEW=1084 | Closest=17.54 /6.56  IDW=17.65 /6.62  IDEW=17.92/6.85 |
| 11 | Goodwater Creek, Missouri | USGS 05506100-Long Branch near Santa Fe, MO | 460.8 | -92.0785  /39.28779 | 50 | Total=64  CoCoRaSH=55  COOP=9 | Total=7  CoCoRaSH=1  COOP=6 | Closest=1064  IDW=1090  IDEW=1089 | Closest=18.01 /6.95  IDW=17.80 /6.58  IDEW=18.06/6.80 |
| 12 | South Fork of the Iowa River, Iowa | USGS 05451210-South Fork Iowa River NE of New Providence, IA | 573.4 | -93.42387  /42.43898 | 60 | Total=50  CoCoRaSH=27  COOP=21  WBAN=2 | Total=12  COOP=10  WBAN=2 | Closest=982  IDW=984  IDEW=1023 | Closest=13.87 /2.34  IDW=14.15 /2.50  IDEW=14.40/2.73 |
| 13 | Walnut Creek, Iowa | USGS 05471000-South Skunk River below Ioway Creek near Ames,  IA | 1423.3 | -93.67975  /42.22596 | 42.42 | Total=35  CoCoRaSH=26  COOP=8  WBAN=1 | Total=5  COOP=4  WBAN=1 | Closest=951  IDW=964  IDEW=988 | Closest=15.43 /4.18  IDW=14.88 /3.14  IDEW=15.14/3.39 |
| 14 | Riesel Watersheds, TEXAS (TXRI) | USGS 08096500-Brazos Rv at Waco, TX | 75671 | -99.89573  /33.02752 | 60 | Total=31  CoCoRaSH=23  COOP=8 | Total=5  COOP=5 | Closest=658  IDW=660  IDEW=655 | Closest=25.17 /10.55  IDW=25.14 /10.49  IDEW=25.41/10.73 |
| 15 | Leon River, Texas | USGS 08100500-Leon Rv at Gatesville, TX | 5995.5 | -98.4981  /31.98979 | 60 | Total=32  CoCoRaSH=21  COOP=10  WBAN=1 | Total=6  COOP=5  WBAN=1 | Closest=830  IDW=818  IDEW=816 | Closest=25.44 /11.92  IDW=25.50 /11.87  IDEW=25.75 /12.05 |
| 16 | Upper Washita River, Oklahoma | USGS 07327442-Little Washita River near Cyril, OK | 34 | -98.25425  /34.91768 | 42.42 | Total=35  CoCoRaSH=23  COOP=12 | Total=9  COOP=9 | Closest=802  IDW=841  IDEW=854 | Closest=22.47 /9.46  IDW=22.50 /9.45  IDEW=22.76/9.70 |
| 17 | Ft. Cobb Reservoir watershed, Upper Washita River, OK | USGS 07325840-Lake Creek near Sickles, OK | 48.8 | -98.51569  /35.43215 | 60 | Total=44  CoCoRaSH=27  COOP=17 | Total=11  COOP=11 | Closest=716  IDW=762  IDEW=780 | Closest=21.96 /9.03  IDW=22.0 /9.03  IDEW=22.26/9.26 |
| 18 | Upper Snake Rock Watershed, Idaho | USGS 13090000-Snake River near Kimberly, ID | 57190.4 | -111.7734  /43.25814 | 60 | Total=20  CoCoRaSH=8  COOP=8  SNOTEL=3  WBAN=1 | Total=26  COOP=8  RAWS=4  SNOTEL=3  WBAN=1 | Closest=683  IDW=565  IDEW=579 | Closest=11.11 /0.31  IDW=12.01 /-0.16  IDEW=12.21/-0.0043 |
| 19 | Little River, Georgia | USGS 02317797-Little River At Upper Ty Ty Road, Near Tifton, GA | 330.2 | -83.65937  /31.61125 | 60 | Total=36  CoCoRaSH=23  COOP=12  WBAN=1 | Total=14  CoCoRaSH=1  COOP=11  RAWS=1  WBAN=1 | Closest=1300  IDW=1312  IDEW=1303 | Closest=25.18 /12.19  IDW=25.39 /12.69  IDEW=25.54/12.86 |
| 20 | Lake Champlain Watershed, Vermont | USGS 04282650-Little Otter Creek at Ferrisburg, VT | 146.1 | -73.17117  1/44.16641 | 30 | Total=32  CoCoRaSH=23  COOP=9 | Total=8  COOP=8 | Closest=1052  IDW=1091  IDEW=1042 | Closest=13.18 /1.87  IDW=13.25 /1.92  IDEW=13.55/2.20 |
| 21 | Kaweah River, California | USGS 11208600-Kaweah R BL Conduit NO. 2 near Hammond, CA | 422.4 | -118.6931  /36.55537 | 60 | Total=17  CoCoRaSH=8  COOP=9 | Total=20  COOP=9  RAWS=11 | Closest=1035  IDW=862  IDEW=988 | Closest=13.78 /-0.44  IDW=17.62 /4.10  IDEW=17.76/4.24 |

Abbreviations: ARS, agricultural research service; NRCS, natural resources conservation service; USGS, U.S. geological survey; CEAP, conservation effects assessment project; GHCN, global historical climatology network; IDW, inverse distance weighting; IDEW, inverse distance and elevation weighting; CoCoRaHS, community collaborative rain, hail, and snow; COOP, cooperative observers program; WBAN, weather bureau army navy; RAWS, remote automatic weather station; SNOTEL, U.S. natural resources conservation service SNOwpack TELemtry.

aThe platform types of GHCN network for ARS-NRCS-CEAP watersheds include CoCoRaHS, COOP, WBAN, RAWS, SNOTEL.

bAverage annual precipitation, maximum and minimum temperatures obtained by three methods in FillMissWX tool including Closest Station, IDW, IDEW.

[Insert Figure 1]

## **2. 4 Hydrologic Model Initialization and Calibration**

The SWATmodel package, an R-based distribution of the SWAT model, was used for this study (Fuka et al., 2014c). The SWATmodel R package offers a linear model-like interface with the SWAT modeling system in R, transforming weather data into hydrological output responses. The SWATmodel initialization for each CEAP watershed includes two steps. First, we obtained the required data to represent the various watersheds, including basin characteristics (size, centroid, location), the weather forcing data, and the hydrological response data used for calibration. As described in section 2.3, a 30-km search radius was initially set and increased until a sufficient number of stations was found to fill in the missing data. Second, models of the 21 watersheds were initialized for the 2010-2021 period and calibrated against USGS measured data using the DEoptim algorithm [(Ardia et al., 2007; Mullen et al., 2011)](https://paperpile.com/c/HAeg3w/3HxZ3+EN8ao). DEoptim is coupled to the SWATmodel package in R and performs evolutionary global optimization using the differential evolution algorithm. Note that three SWAT models were initialized for each of the 21 watersheds based on Closest Station, IDW, and IDEW weather data time series.

After model initialization in each of the 21 ARS-NRCS-CEAP watersheds, 19 parameters, previously shown as important SWAT streamflow parameters were calibrated [(Cibin et al., 2010; Khorashadi Zadeh et al., 2017; Leta et al., 2015; Nossent & Bauwens, 2012)](https://paperpile.com/c/HAeg3w/OcHl+ge8l+3Pyp+NWqy) (Table S1). The simulated streamflow using each of the Closest Station, IDW, and IDEW methods was assessed for the goodness of fit against observations using three statistical measures (Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR)) as recommended by [Moriasi et al. (2007)](https://paperpile.com/c/HAeg3w/bb4z) for each watershed.

The NSE shows how well the simulated versus observed data plot falls along the 1:1 line, ranges between -∞ and 1, and is a good estimator of overall mass balance adherence [(Nash & Sutcliffe, 1970)](https://paperpile.com/c/HAeg3w/k8eCJ). RSR is another statistic for model evaluation, ranging from 0 to positive values, where 0 indicates the perfect fit [(Singh et al., 2005)](https://paperpile.com/c/HAeg3w/epeUF). PBIAS is a measure of how much the model over-(>0) or under-(<0) estimates observed values [(Gupta et al., 1999)](https://paperpile.com/c/HAeg3w/AE9eM). Based on the reported statistical metrics, [Moriasi et al. (2007)](https://paperpile.com/c/HAeg3w/bb4z) suggested that models for streamflow simulation are satisfactory when NSE > 0.5, RSR ≤ 0.70, and -25 ≤ PBIAS ≤ 25. Although PBIAS indicates whether the simulated data of a model tend to be larger or smaller than their observed counterparts, comparing different estimation models based on PBIAS values for each watershed is misleading as even a model underestimates or overestimates the observed data it will still have a PBIAS close to zero, regardless of the model's poor performance [(Moriasi et al., 2015)](https://paperpile.com/c/HAeg3w/TuTP). Thus, in addition to evaluating the goodness of fit based on the PBIAS metric, we calculated the percent absolute bias (APBIAS).

A one-way analysis of variance (ANOVA) test and the post hoc of Tukey’s Honest Significant Difference were used individually for each of the statistical measures (NSE, RSR, APBIAS) to identify statistically significant differences between the means of the estimation methods. The effects of estimation methods, climate classifications, and their interactions on calculated statistical metrics (NSE, RSR, and PBIAS) were analyzed using a general fitted linear model and evaluated at a significance level of 0.10 ([Kim & Choi, 2021)](https://paperpile.com/c/HAeg3w/UetiC). In the model, all variables were treated as fixed effects as we were only interested in the three estimation methods tested and the five levels of climate classifications associated with 21 watersheds.

## **2.5 Model Evaluation**

To test the performance of these methods beyond the basins used for development, we evaluated the three weather forcing estimation methods for four previously published SWAT modeling studies that were performed in CEAP watersheds including Mahantango Creek Watershed ([Wagena et al., 2018](https://paperpile.com/c/HAeg3w/QlQE+ukoH+V9Qn+rR6a)), Choptank River ([Lee et al., 2018](https://paperpile.com/c/HAeg3w/QlQE+ukoH+V9Qn+rR6a)), Ft. Cobb Reservoir watershed ([Guzman et al., 2015](https://paperpile.com/c/HAeg3w/QlQE+ukoH+V9Qn+rR6a)), and Goodwater Creek [(Ghidey et al., 2007)](https://paperpile.com/c/HAeg3w/QlQE+ukoH+V9Qn+rR6a) (Table 2). These studies were selected because they had previously published SWAT model results and employed weather data from four different research groups using traditional weather data aggregation methods. To compare streamflow simulations, SWAT model performance from previous studies was compared to SWAT model results using the Closest Station, IDW, and IDEW methods. Based on these prior studies, daily simulated streamflows for Mahantango Creek Watershed, Ft. Cobb Reservoir watershed, and Goodwater Creek and monthly simulated streamflows for Choptank River (the Lee et al. 2018 model was run on a monthly time step) were initialized and run for the same time periods. The streamflow calibration periods for Mahantango Creek Watershed, Choptank River, Ft. Cobb Reservoir watershed, and Goodwater Creek were 1989-1998, 2001-2008, 2006-2012, and 1995-2003, respectively. The evaluation periods for Mahantango Creek Watershed and Choptank River were 1999-2007 and 2009-2014, respectively. The Ft. Cobb Reservoir watershed and Goodwater Creek studies did not report model evaluation. In order to determine whether the newly developed complete GHCN weather data were as reliable as the previously used weather data in representing hydrological processes, we compared the resulting NSEs with the previous studies.

Table 2. Watershed name, calibration and evaluation period, and weather data sources for four watersheds: Mahantango Creek Watershed, Choptank River, Ft. Cobb Reservoir watershed, and Goodwater Creek. Ft. Cobb Reservoir watershed and Goodwater Creek watersheds did not report any evaluation periods

|  |  |  |  |
| --- | --- | --- | --- |
| **Name** | **Calibration period** | **Evaluation period** | **Weather data source** |
| Mahantango Creek Watershed | 1989-1998 (daily) | 1999-2007 (daily) | Three land-based stations in the watershed |
| Choptank River | 2001-2008 (monthly) | 2009-2014 (monthly) | Three NOAA-NCDC (COOP) stations |
| Ft. Cobb Reservoir watershed | 2006-2012 (daily) | - | A network of fifteen USDA-ARS climate observation sites (MICRONETa ) |
| Goodwater Creek | 1995-2003 (daily) | - | Seven rain gages installed in the watershed |

Abbreviations: NOAA, national oceanic and atmospheric administration; NCDC, national climate data center; COOP, cooperative observers program; USDA, U.S. department of agriculture; ARS, agricultural research service.

aThe description of MICRONET is detailed in [(Guzman et al., 2014)](https://paperpile.com/c/HAeg3w/1lBF).

# 3. RESULTS

## **3.1 Weather Data**

For the Closest Station, IDW, and IDEW weather data time series the search radius from which the weather variables were filled varied from 30 km for most watersheds to 85 km for Big Sunflower River at Sunflower, MS, as shown in Table 1. The watershed above USGS number 04282650 is shown in Figure S1 to give an example of how the automatically generated plots by FillMissWX that show the types of GHCN monitors and their distances from the watershed centroid, while scatter plots of precipitation, maximum, and minimum temperatures data obtained by IDW and IDEW against the Closest Station method are shown in Figure S2.

Figure 2 shows the number of stations by GHCN platform type used to acquire and interpolate precipitation data for 21 basins. Table 1 and Figure 2 show that among all GHCN sources, and for nearly every watershed, data from the CoCoRaH observer network contributes at least 50% of the precipitation data, with COOP data the next most common source, and WBAN and SNOTEL contributing less than 10% of the observations.

[Insert Figure 2]

## **3.2 Evaluation of Closest Station, IDW, and IDEW Estimation Methods for Streamflow Simulation**

Simulated streamflow from the SWAT model runs were calibrated individually against observed data for the 2010-2021 period. In Table 3, simulated streamflow in 18 out of 21 watersheds showed satisfactory agreement, as suggested by [Moriasi et al. (2007)](https://paperpile.com/c/HAeg3w/bb4z), with measured data across all three metrics, NSE > 0.5, RSR ≤ 0.70, and -25 ≤ PBIAS ≤ 25. Two lower-performing simulations (Riesel and Leon River watersheds, both in Texas) had NSE values of 0.30 to 0.41, RSR values of 0.77 to 0.83 across estimation methods, and the PBIAS of 31 for the Closest Station method for Leon River watershed simulations also suggest poor performance (Table 3). For the Upper Washita River watershed in Oklahoma, the Closest Station and IDW simulations indicated poor performance with PBIAS values of -36 and -40, respectively.

The results of the one-way ANOVA test showed significant difference among estimation methods for all statistical metrics with probability values (p-value) less than 0.1. Tukey test revealed that this significant difference in the estimation methods was caused by Closest Station method (Table 4). For all watersheds, the IDW and IDEW methods resulted in greater NSE, lower RSR, and lower APBIAS values, in most cases substantially, than the Closest Station method (Table 3), demonstrating the better performance of IDW and IDEW to represent hydrological processes than the Closest Station method.

Table 3. Table of NSE, RSR, PBIAS, and APBIAS values obtained from Closest Station, IDW, and IDEW methods for SWAT models of ARS-NRCS-CEAP watersheds with their watershed area (km2) and climate classification

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | **NSE** | | | **RSR** | | | **PBIAS** | | | **APBIAS** | | |
| **USGS Gage** | **Watershed area (km2)** | **Climate Classification** | **Closest Station** | **IDW** | **IDEW** | **Closest Station** | **IDW** | **IDEW** | **Closest Station** | **IDW** | **IDEW** | **Closest Station** | **IDW** | **IDEW** |
| USGS 01555500-East Mahantango Creek near Dalmatia, PA | 414.72 | Dfb | 0.69 | 0.83 | 0.83 | 0.55 | 0.40 | 0.40 | -18.8 | -19.9 | -12.7 | 47.52 | 44.85 | 40.90 |
| USGS 01491000-Choptank River near Greensboro, MD | 289.28 | Dfa | 0.72 | 0.77 | 0.77 | 0.53 | 0.49 | 0.51 | -23 | -20.2 | -1.3 | 44.41 | 43.23 | 41.42 |
| USGS 03228300-Big Walnut Creek at Sunbury, OH | 258.56 | Dfa | 0.66 | 0.75 | 0.75 | 0.58 | 0.49 | 0.49 | -18.3 | -9.7 | -8.8 | 56.93 | 51.59 | 50.77 |
| USGS 04180000-Cedar Creek near Cedarville, IN | 691.2 | Dfa | 0.73 | 0.79 | 0.80 | 0.54 | 0.45 | 0.44 | -23.3 | -21.6 | -5.9 | 48.84 | 42.37 | 37.52 |
| USGS 07283000-Skuna River at Bruce, MS | 650.2 | Cfa | 0.67 | 0.79 | 0.79 | 0.57 | 0.45 | 0.45 | 1.9 | -18.4 | -8.4 | 66.94 | 53.17 | 50.68 |
| USGS 07274000-Yocona River near Oxford, MS | 670.7 | Cfa | 0.74 | 0.84 | 0.83 | 0.52 | 0.40 | 0.40 | -18 | 0.3 | -1.3 | 55 | 39.95 | 41.41 |
| USGS 07288500-Big Sunflower River at Sunflower, MS | 1963.5 | Cfa | 0.73 | 0.79 | 0.80 | 0.56 | 0.45 | 0.44 | 19 | -5.3 | -0.7 | 58.00 | 40.80 | 40.80 |
| USGS 07043500-Little River Ditch No. 1 near Morehouse, MO | 1152 | Cfa | 0.67 | 0.80 | 0.81 | 0.56 | 0.44 | 0.43 | -20.6 | -1.9 | -3.9 | 52.55 | 38.19 | 37.12 |
| USGS 07047855-Whiteman's Crk at Ind Dr at Jonesboro, AR | 16.9 | Cfa | 0.77 | 0.78 | 0.78 | 0.47 | 0.47 | 0.46 | -6.6 | -11.4 | -2 | 56.54 | 51.70 | 52.32 |
| USGS 05506800-Elk Fork Salt River near Madison, MO | 512 | Dfa | 0.62 | 0.74 | 0.73 | 0.61 | 0.50 | 0.51 | -9.3 | -14.5 | -15.2 | 73.38 | 58.82 | 58.35 |
| USGS 05506100-Long Branch near Santa Fe, MO | 460.8 | Dfa | 0.63 | 0.72 | 0.71 | 0.60 | 0.52 | 0.53 | -23.6 | -7.4 | -10.6 | 60.86 | 54.35 | 57.67 |
| USGS 05451210-South Fork Iowa River NE of New Providence, IA | 573.4 | Dfa | 0.52 | 0.60 | 0.58 | 0.68 | 0.63 | 0.66 | -3.4 | -12.9 | -11.6 | 58.05 | 56.55 | 58.36 |
| USGS 05471000-South Skunk River below Ioway Creek near Ames, IA | 1423.3 | Dfa | 0.62 | 0.67 | 0.66 | 0.61 | 0.59 | 0.57 | -18.7 | -15.6 | -22.2 | 59.82 | 58.76 | 58.56 |
| USGS 08096500-Brazos Rv at Waco, TX | 75671 | Cfa | 0.33 | 0.41 | 0.41 | 0.81 | 0.77 | 0.79 | -1.1 | -5.3 | -16.7 | 89.57 | 83.16 | 82.59 |
| USGS 08100500-Leon Rv at Gatesville, TX | 5995.5 | Cfa | 0.30 | 0.37 | 0.39 | 0.83 | 0.78 | 0.80 | 31 | -23.1 | -17.4 | 89.63 | 82.35 | 80.32 |
| USGS 07327442-Little Washita River near Cyril, OK | 34 | Cfa | 0.50 | 0.56 | 0.59 | 0.70 | 0.65 | 0.63 | -36 | -40 | -24 | 91.44 | 86.74 | 80.49 |
| USGS 07325840-Lake Creek near Sickles, OK | 48.8 | Cfa | 0.71 | 0.77 | 0.77 | 0.53 | 0.47 | 0.47 | 10.7 | -11.6 | -18.8 | 74.49 | 60.74 | 57.11 |
| USGS 13090000-Snake River Nr Kimberly, ID | 57190.4 | BSk | 0.55 | 0.55 | 0.60 | 0.67 | 0.64 | 0.61 | 11.5 | -22 | -4.6 | 67.68 | 61.11 | 59.91 |
| USGS 02317797-Little River at Upper Ty Ty Road, Near Tifton, GA | 330.2 | Cfa | 0.65 | 0.71 | 0.73 | 0.59 | 0.55 | 0.51 | -3 | -21.7 | 11.6 | 74.49 | 73.82 | 63.55 |
| USGS 04282650-Little Otter Creek At Ferrisburg, VT | 146.1 | Dfb | 0.52 | 0.62 | 0.63 | 0.69 | 0.61 | 0.63 | -2.7 | 4.9 | -23 | 60.33 | 54.12 | 52.96 |
| USGS 11208600-Kaweah R BL Conduit NO. 2 near Hammond, CA | 422.4 | Csa | 0.71 | 0.78 | 0.78 | 0.53 | 0.45 | 0.48 | -5.2 | -2.8 | -10.3 | 45.83 | 42.65 | 42.68 |

Abbreviations: ARS, agricultural research service; NRCS, natural resources conservation service; USGS, U.S. geological survey; SWAT, soil and water assessment tool;CEAP, conservation effects assessment project; IDW, inverse distance weighting; IDEW, inverse distance and elevation weighting; NSE, Nash-Sutcliffe efficiency; RSR, ratio of the root mean square error to the standard deviation of measured data; PBIAS, percent bias; APBIAS, absolute percent bias.

Table 4. Table of probability values (p-values) obtained from the post hoc of Tukey’s Honest Significant Difference test to determine if there is a significant difference between the means of Closest Station and IDW (Closest Station-IDW), Closest Station and IDEW (Closest Station-IDEW), and IDW and IDEW (IDW-IDEW) for each of NSE, RSR, and APBIAS statistical measures

|  |  |  |  |
| --- | --- | --- | --- |
| **Statistical measure** | **p-value** | | |
| **Closest Station-IDW** | **Closest Station-IDEW** | **IDW-IDEW** |
| NSE | 0.06 | 0.04 | 0.90 |
| RSR | 0.02 | 0.03 | 0.98 |
| APBIAS | 0.09 | 0.04 | 0.71 |

Abbreviations: ANOVA, analysis of variance; IDW, inverse distance weighting; IDEW, inverse distance and elevation weighting; NSE, Nash-Sutcliffe efficiency; RSR, the ratio of the root mean square error to the standard deviation of measured data; APBIAS, absolute percent bias.

Climate classification had a significant effect only on the APBIAS values (Table 5) There was no significant effect found from the interaction of the estimation method and climate classification on the studied statistical measures (Table 5).

Table 5. Table of p-value obtained for the fitted linear model. In the model, statistical metrics (NSE, RSR, APBIAS) were response variables with the fixed effects of estimation method, climate classification, and interaction between them (Interaction)

|  |  |  |  |
| --- | --- | --- | --- |
| **Response variable** | **p-value** | | |
| **Estimation Method** | **Climate Classification** | **Interaction** |
| NSE | 210-16 | 0.47 | 1 |
| RSR | 210-16 | 0.57 | 1 |
| APBIAS | 210-16 | 0.03 | 0.99 |

Abbreviations: IDW, inverse distance weighting; IDEW, inverse distance and elevation weighting; NSE, Nash-Sutcliffe efficiency; RSR, the ratio of the root mean square error to the standard deviation of measured data; APBIAS, absolute percent bias.

Figure 3 shows the distribution of NSE, RSR, and APBIAS values for the watersheds categorized by Köppen climate classification. For NSE, the median for the Closest Station method simulations were lower than both IDW and IDEW simulations for all climate classifications. Across all climate classes, the median of RSR values for the Closest Station method were higher than IDW and IDEW simulations. For APBIAS, the median IDW and IDEW values for all climate classifications were lower than the Closest Station method. Thus, given the lowest NSE, highest RSR and APBIAS values, the Closest Station method resulted in the poorest performance. For IDW and IDEW, median NSE, RSR, and APBIAS values for the Dfa, Dfb, Cfa, and Csa were approximately similar. However, for the BSk climate region (Snake River near Kimberly, ID) the IDEW methodology resulted in higher NSE, lower RSR, and lower APBIAS values, although because there was only one BSk watershed, no statistical test was performed.

[Insert Figure 3]

## **3.3 Model Corroboration**

Models of daily streamflows for the Mahantango Creek Watershed, Ft. Cobb Reservoir watershed, and Goodwater Creek and monthly streamflows for the Choptank River for each estimation method were calibrated and corroborated. Table 6 shows the SWAT models initialized with GHCN datasets developed with the FillMissWX estimation methods outperformed the SWAT models of the previous study's initializations for both Mahantango Creek Watershed (NSE=0.6 for both calibration and evaluation) and Goodwater Creek (NSE=0.45 for calibration). Although all interpolation methods in the Choptank River and Ft. Cobb Reservoir watersheds for the calibration period resulted in lower NSEs than in the previous studies (0.68 for Choptank River and 0.69 for Ft. Cobb Reservoir watershed), the NSE values were above 0.5 and still in a satisfactory range recommended by [Moriasi et al. (2007)](https://paperpile.com/c/HAeg3w/bb4z). In the Choptank River watershed, IDW, IDEW, and Closest Station models outperformed the previous study for the evaluation period (NSE=0.79). The results demonstrated that integrated weather data from multiple GHCN sources were as reliable as commonly used weather aggregation techniques used in previous studies to predict hydrological responses in a watershed.

Table 6. Comparison of calibration and evaluation NSE values of daily (for Mahantango Creek Watershed-[(Wagena et al., 2018)](https://paperpile.com/c/HAeg3w/QlQE), Ft. Cobb Reservoir watershed-[(Guzman et al., 2015)](https://paperpile.com/c/HAeg3w/V9Qn), and Goodwater Creek-[(Ghidey et al., 2007)](https://paperpile.com/c/HAeg3w/rR6a)) and monthly (for Choptank River-[(Lee et al., 2018)](https://paperpile.com/c/HAeg3w/ukoH)) streamflow simulation of SWAT models initialized by three estimation methods (Closest Station, IDW, and IDEW) with NSE of previous studies

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Watershed** | **NSE of calibration** | | | | **NSE of evaluation** | | | |
| Previous study | Closest Station | IDW | IDEW | Previous study | Closest Station | IDW | IDEW |
| Mahantango Creek Watershed | 0.60 | 0.68 | 0.66 | 0.68 | 0.60 | 0.71 | 0.67 | 0.70 |
| Choptank River | 0.68 | 0.51 | 0.66 | 0.64 | 0.79 | 0.83 | 0.84 | 0.83 |
| Ft. Cobb Reservoir watersheda | 0.69 | 0.63 | 0.65 | 0.63 | - | - | - | - |
| Goodwater Creeka | 0.45 | 0.60 | 0.68 | 0.68 | - | - | - | - |

Abbreviations: IDW, inverse distance weighting; IDEW, inverse distance and elevation weighting; NSE, Nash-Sutcliffe efficiency; SWAT, soil and water assessment tool.

a The study did not report model fit for an evaluation period.

# 4. DISCUSSION

While 18 of the 21 CEAP watersheds had satisfactory model performance using our weather estimation methods, there were two watersheds that had poorer performance, Riesel and Leon River watersheds, both located in Texas. Both watersheds are relatively large (76,671 and 5,995.5 km2) compared to other watersheds listed in Table 1. As watersheds become larger, utilizing only the centroid of the basin may misrepresent the spatial variability of precipitation events over the watersheds. Both watersheds also have features that add complexity to the model development: the Leon River watershed has three reservoirs and complex soil types ([Rossi et al., 2008), and the](https://paperpile.com/c/HAeg3w/hrCxI) Riesel watershed is dominated by swelling-cracking clay soils ([Arnold et al., 2005)](https://paperpile.com/c/HAeg3w/Yp8hQ), both of which have previously confounded modeling efforts. Another watershed with an unsatisfactory PBIAS value was the Upper Washita River watershed in Oklahoma, where Liew [& Garbrecht (2003)](https://paperpile.com/c/HAeg3w/Mv1p) state that numerous farm ponds and 45 flood-retarding structures constructed by the Soil Conservation Service (SCS) complicate the modeling effort.

Table 3 shows that NSE, RSR, and APBIAS have similar performance ratings for each estimation method (e.g., Closest Station resulted in the poorest model performance), while PBIAS tended to indicate different performance across all estimation methods (although in 66% of simulations, IDEW and IDW outperformed the Closest Station method for PBIAS). In some watersheds (e.g., Mahantango Creek Watershed, Topashaw Canal Watershed, Salt River/Mark Twain Reservoir), the results of PBIAS evaluation did not align with NSE and RSR results across estimation methods. This is perhaps not surprising as PBIAS does not consider measured data variance [(Moriasi et al., 2015)](https://paperpile.com/c/HAeg3w/TuTP) and therefore relying solely on PBIAS to evaluate performance can be misleading in situations where the model equally overpredicts and underpredicts.

Across climate classification, the Closest Station method generally had the lowest accuracy among estimation methods, unsurprising given the simplicity of this method. Limiting weather data to the closest station can bias model results ([Sattari et al. 2017)](https://paperpile.com/c/HAeg3w/2oxL), especially in large watersheds (Table 3). The IDW and IDEW estimation methods were similar across climate classification, with the exception of the BSk climate region. The improvements to model performance using IDEW in the BSk region were likely due to the considerable elevation changes between the target and nearby weather stations located in a mountainous region where there is a high correlation between precipitation and elevation [(Zhang et al., 2017)](https://paperpile.com/c/HAeg3w/OSW0).

The results of model corroboration (Table 6) using previously published SWAT model results for four watersheds revealed that combined GHCN weather data generally provided similar streamflow prediction to the weather data sources that were used in the individual watershed studies [(Ghidey et al., 2007; Guzman et al., 2015; Lee et al., 2018; Wagena et al., 2018)](https://paperpile.com/c/HAeg3w/QlQE+ukoH+V9Qn+rR6a). Interestingly, all three estimation methods provided better model performance in the Mahantango Creek Watershed and Goodwater Creek watersheds, which both employ custom USDA research weather stations, and more sophisticated SWAT models. In the Choptank River and Ft. Cobb Reservoir watersheds, all three estimation methods resulted in poorer model performance for the calibration period, although IDW and IDEW NSE values were similar to the results of Lee et al. (2018) in the Choptank watershed. The previous studies initialized their models with multiple time series of weather data which would result in more degrees of freedom and better calibration results than our models where a single weather time series was used. For the evaluation period in the Choptank watershed, Closest Station, IDW, and IDEW models outperformed the previous study result. These results indicate that employing the open source GHCN datasets to force the models achieve similar results and is much cheaper than deploying custom weather stations.

Our results are in agreement with several studies that assessed sources and methods of weather data to drive hydrological models. [Auerbach et al. (2016) and](https://paperpile.com/c/HAeg3w/enrJV+4iwh) Fuka et al. (2014b[)](https://paperpile.com/c/HAeg3w/enrJV+4iwh) evaluated reanalysis-based Climate Forecast System Reanalysis weather data (which integrates all available higher density climate stations), either gridded or interpolated at various densities almost exclusively resulted in better hydrologic model results, at least for streamflow, than using the closest land-based weather station. Others [(Tan et al., 2015; Vu et al., 2018; and Worqlul et al., 2014) have used](https://paperpile.com/c/HAeg3w/VX0V6+UYPyD+CXFgD) satellite-based weather data which were also shown to provide better estimates of weather occurring over a watershed, as estimated by the hydrological model response. This study demonstrates that using GHCN stations and specifically including CoCoRaHS volunteer monitors result in similar levels of hydrological model performance across diverse watersheds.

# 5. CONCLUSIONS

This study demonstrates that for watershed modeling across a variety of hydroclimate regimes and watershed types, using higher-density, but perhaps lower-quality weather data can improve model performance. Incorporation of the citizen science based CoCoRaHS weather monitors and integrated into the GHCN better represent weather forcings over a watershed. As hypothesized, the integration of all available weather measurements, even if of lower "quality" resulted in as good or better streamflow predictions as the best (often nearest) weather station to a watershed centroid. This is because the higher station density is able to capture more information than an individual weather station. The addition of higher-density, lower-quality, citizen weather measurements to the suite of hydrological modeling tools provides opportunities for improving hydrological understanding, including for modeling ungauged watersheds. As citizen science data is made available more rapidly, these data have the potential to advance real-time hydrological modeling and prediction.

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# CONFLICTS OF INTEREST

The authors declare no conflict of interest.

# DATA AVAILABILITY

The scripts and data that support the findings of this study are openly available in <https://doi.org/10.5281/zenodo.7013185>

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# FIGURES

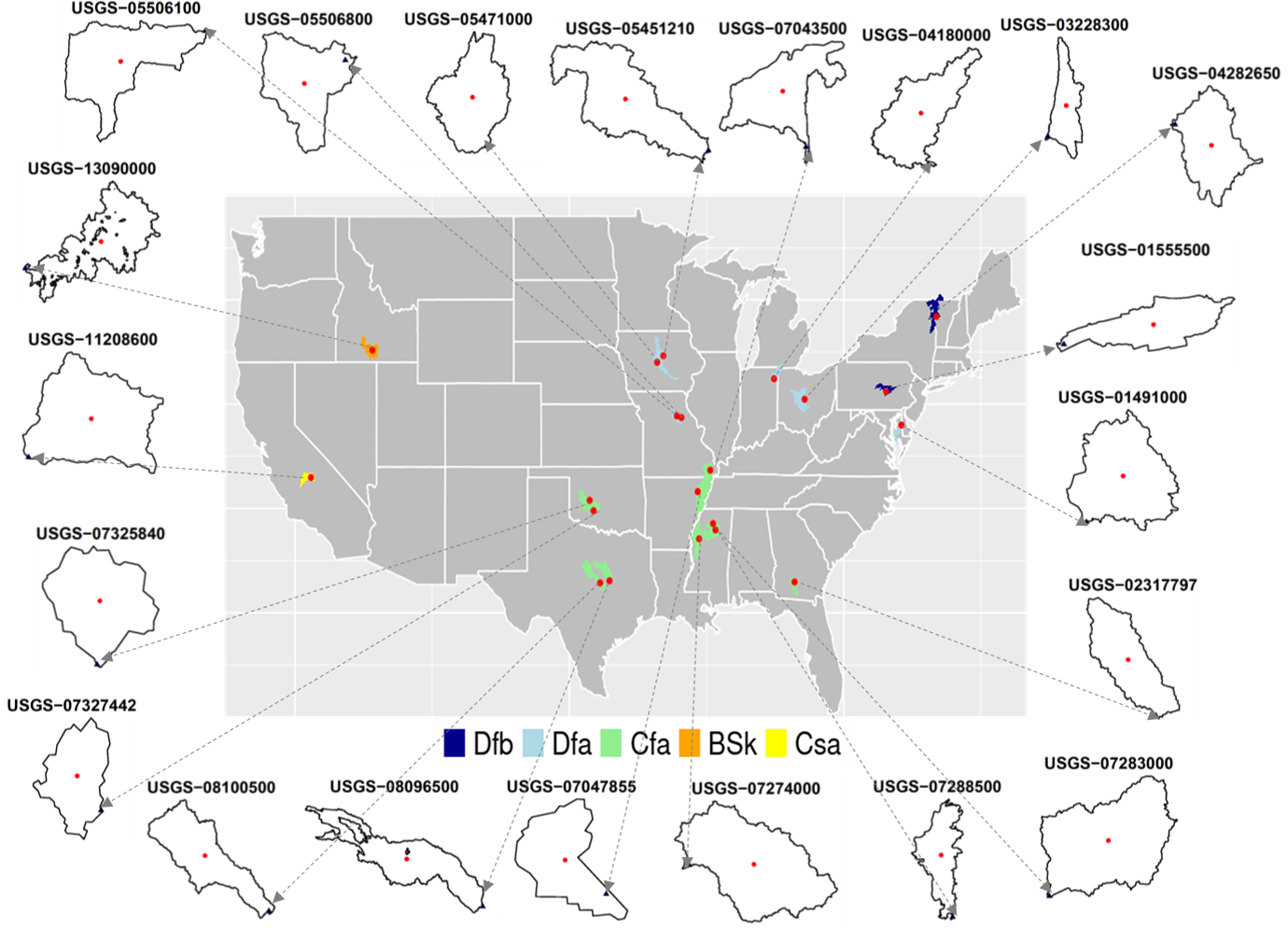


Figure 1. Locations and climate classifications of 21 ARS-NRCS-CEAP watersheds and test USGS watersheds. Red dots show area-weighted USGS watershed centroids. Climate of the watersheds is grouped based on Köppen climate classification [(Beck et al., 2018)](https://paperpile.com/c/HAeg3w/F87j) into Dfa=Hot summer continental climates (light blue); Dfb=Warm summer continental or hemiboreal climates (dark blue); Cfa=Humid subtropical climates (light green); BSk=Cold semi-arid (orange); Csa=Mediterranean hot summer climates (yellow).

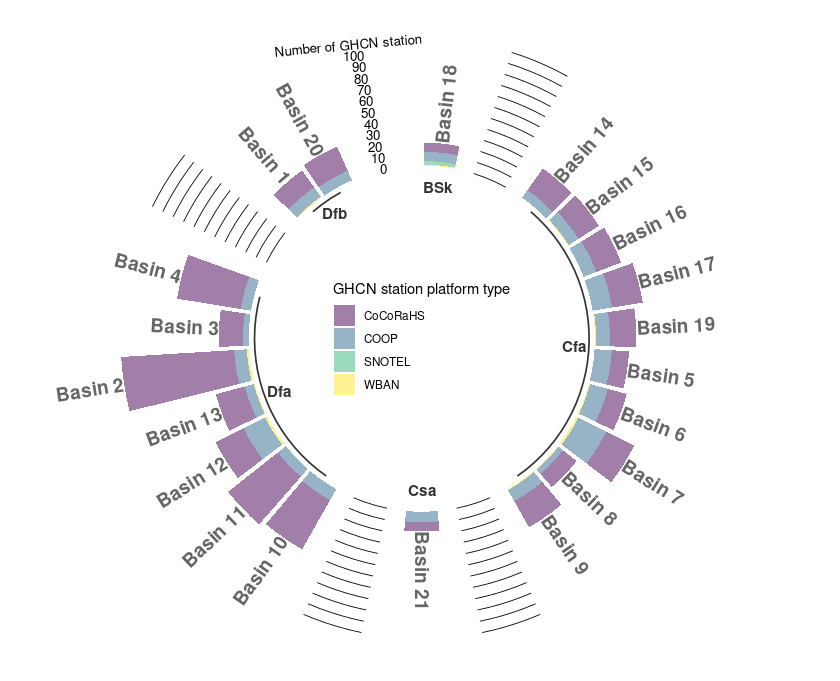


Figure 2. The stacked barplot of the number and type of GHCN stations used to obtain and fill in missing precipitation data of 21 USGS gages. Each bar represents the numbers and types of precipitation GHCN stations, including CoCoRaHS (purple), COOP (blue), SNOTEL (aqua), and WBAN (yellow) for a basin with the associated number from Table 1. The basins are grouped based on climate classification, including Dfa=Hot summer continental climates; Dfb=Warm summer continental or hemiboreal climates; Cfa=Humid subtropical climates; BSk=Cold semi-arid; Csa=Mediterranean hot summer climates. The black lines that range from 0-110 show the y-axis scales (number of GHCN stations).

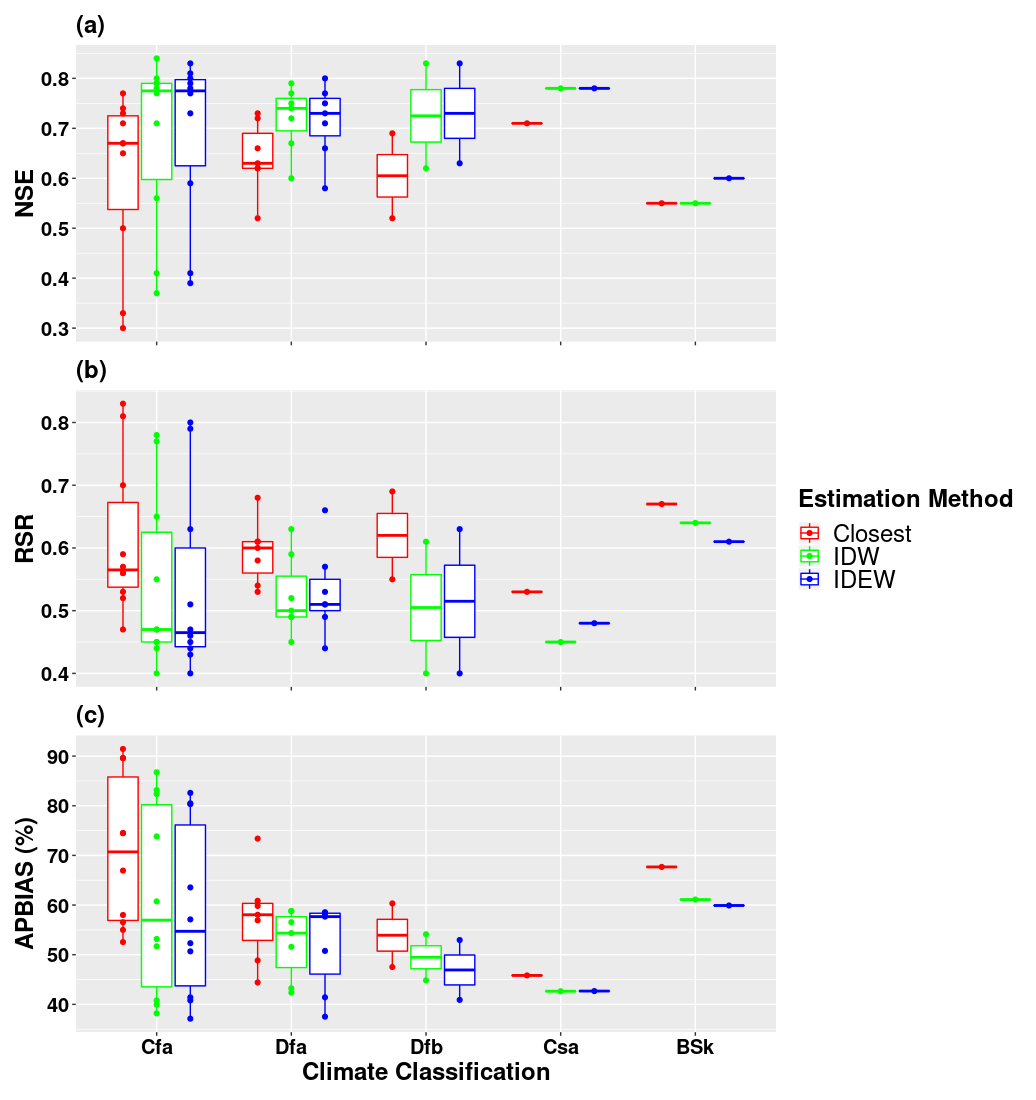


Figure 3. The boxplot of NSE (a), RSR (b), and APBIAS (c), values (dots) of ARS-NRCS-CEAP watersheds obtained from Closest Station, IDW, and IDEW were grouped based on climate classification(Dfa=Hot summer continental climates; Dfb=Warm summer continental or hemiboreal climates; Cfa=Humid subtropical climates; BSk=Cold semi-arid; Csa=Mediterranean hot summer climates). Red, green, and blue dots show the statistical metrics obtained from Closest Station, IDW, and IDEW methods, respectively. Note that we only have one watershed for each of BSk and Csa. The boxplot shows the first and third quartiles, median, minimum, and maximum values. The model with higher NSE, lower RSR, and lower APBIAS shows better performance.