Impacts of Alternative Climate Information on Hydrologic Processes with SWAT: A Comparison of NCDC, PRISM and NEXRAD Datasets[1]

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Abstract: Precipitation and temperature are two primary drivers that significantly affect hydrologic processes in a watershed. A network of land-based National Climatic Data Center (NCDC) weather stations has been typically used as a primary source of climate input for agro-ecosystem models. However, the network may lack the density to adequately capture spatial climate variability throughout large watersheds. High-resolution weather datasets based on 4 km × 4 km grid, such as Next Generation Weather Radar (NEXRAD) and Parameter–Elevation Regressions on Independent Slopes Model (PRISM), have become increasingly available as alternatives to conventional land-based networks. The goal of this study was to evaluate impacts of the three weather datasets, NCDC, NEXRAD, and PRISM, on hydrologic processes in an agricultural catchment in Kansas. A method of collecting and processing three sets of weather input datasets was developed and applied to a calibrated Soil and Water Assessment Tool (SWAT) model for the Smoky Hill River watershed (SHRW) in west-central Kansas, which is sparsely covered by NCDC weather stations with fair to poor range of NEXRAD coverage. SHRW is a typical agricultural catchment in the Central Great Plains; research findings here may be applicable to large areas of the US with similar

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topography and climate conditions. The SWAT model based on PRISM dataset was able to capture daily streamflow alterations with a greater accuracy compared to NCDC and NEXRAD based SWAT models. With three different weather inputs, SWAT with NCDC consistently overestimated monthly stream discharges, while the SWAT models based on NEXRAD and PRISM datasets tended to underestimate monthly high flows of over 8 $m^3 s^{-1}$ and overestimate monthly low flows of below 1 $m^3 s^{-1}$. In general, all models overestimated streamflow in dry years and underestimated streamflow in wet years, however, the PRISM-based model generated smaller bias than the models utilizing NEXRAD or NCDC. The use of PRISM resulted in better statistical performance metrics for streamflow. The conducted study suggests that gridded weather datasets can significantly improve simulated streamflow at daily, monthly and yearly scales as compared to traditional land-based networks.

Keywords: NEXRAD; PRISM; NCDC; Climate Data; SWAT; Kansas

1. Introduction

Hydrologic observational data are required to conduct implementation and assessment of watershed and water resource management practices, including natural resource planning, flood and drought mitigation, and reservoir operation among other conservation efforts (Moon et al., 2004). Precipitation regimes are predicted to shift to more extreme patterns that are characterized by more events with heavy rainfall and longer dry intervals (Zhang et al., 2013). Moreover, many studies have shown a bias in various rainfall datasets, even in rain gauges during heavy rainfall as there is a tendency for water loss, due to wind and erratic behavior of the mechanical aspects of the gauge during intense rainfall (Molini et al., 2005; Lanza and Stagi, 2008). It was also noticed the complexity of the propagation of seemingly small errors in rainfall fields to much larger errors in predicted streamflow (Ogden et al. 2000). Therefore, the increased number of events with high rainfall intensity could make hydrological predictions less accurate due to difficulties in measuring rainfall peaks. In recent years, the use of hydrologic models to predict future hydrologic trends in response to anthropogenic environmental changes has become a popular topic worldwide because it can provide information on how to mitigate the negative effects of these changes (Yen et al., 2015). In addition, the use of models or multiple models is a cost-effective means to evaluate various management plans at a basin scale (Scavia et al., 2016). However, despite the use of multiple models, overall prediction certainty is still limited by the accuracy of the input data sources (Moon et al., 2004). The reliability of model predictions largely depends on the accuracy of model inputs, especially precipitation and temperature, two of the primary controlling factors for physical processes such as the hydrologic cycle, land surface and air interaction, and forest and agriculture crop growth (Sexton et al., 2010; Xie et al., 2011).

Most hydrologic modeling studies in the U.S. use rain gauge measurements (approximately one gauge per 800 km^2) from National Climatic Data Center (NCDC) for precipitation input data, with the exception of several experimental or research watersheds (Sexton et al., 2010). However, there are relatively new alternatives to rain gauge network, specifically, the high-resolution radar precipitation estimation from systems such as the Next Generation Weather Radar (NEXRAD) of the National Weather Service (NWS) and fine-resolution spatial climate datasets of the Parameter–Elevation Regressions on Independent Slopes Model (PRISM) maps from the PRISM Climate Group of Oregon State University. These estimates from NEXRAD and PRISM capture spatial variability at a much finer scale, and NEXRAD data are available on a near real-time basis. Although these data are vulnerable to sources of error such as ground clutter contamination and incorrect calibration, the radar provides the most spatially distributed precipitation data available with current technologies.

It has been shown that Stage III NEXRAD radar may underestimate total precipitation in specific areas due to the effects of terrain blockage (Westrick et al., 1999) or extremely high precipitation events between the antenna and area of interest which attenuate radar signals and reduce the reflectivity-precipitation rate (Baeck and Smith, 1998), (Lott and Sittel, 1996). However, reflectivity-precipitation rate relationships calibrated by rain gauge data increase the accuracy of precipitation estimates (Legates, 2000). A case study in Tulsa, Oklahoma, implied that Stage III bias-adjusted data could better represent measured rain gauge data (Anagnostou et al., 1998). Another case study conducted in the Texas-Gulf basin, showed that precipitation events can be more accurately captured as compared to rain gauge data alone by combining NEXRAD with improved data processing algorithms (Jayakrishnan, 2001). Additional detailed information on NEXRAD products and processing algorithms can be found in Crum and Alberty (1993), Fulton et al. (1998), and Moon et al. (2004).

In the past two decades, the Soil and Water Assessment Tool (SWAT), a widely used hydrologic model, has been applied to numerous watersheds around the world (Arnold et al., 2015). In addition to the development of data sources for hydrologic models, applications of alternative weather datasets to SWAT have drawn great attention in the field of water and environmental engineering (Gassman et al., 2007). The general approach is to utilize a single weather dataset in the model for conducting hydrologic simulations. However, the impact of different weather datasets applied to the same complex watershed model on various hydrologic outputs has not been fully explored. A few studies have used NEXRAD gridded data and NCDC single-station gauged data in SWAT by using one of the following two methods: (1) an area-weighted average value of NEXRAD precipitation from grid cells that overlay a subbasin (Gali et al., 2012; Moon et al. 2004), and (2) precipitation from a single NEXRAD grid cell closest to the subbasin by the nearest-neighbor approach (Guo et al., 2004; Johnson et al. 1999; Kalin and Hantush, 2006; Sexton et al., 2010; Tobin and Bennett, 2009; Tuppad et al., 2010). These studies found that the use of NEXRAD improved hydrological simulations as compared to the NCDC gauge data, but further validation with different spatial datasets was needed to assess hydrologic response to spatially averaged subbasin-specific rainfall estimates. Due to additional processing being required to develop area-weighted averages for subbasin-specific spatial rainfall coverage, the nearest-neighbor approach was adopted more often when NEXRAD gridded dataset was used.

Gridded PRISM rainfall was developed utilizing (Daly, 2006) (i) land-based rain gauge data, (ii) specifics of digital elevation model (DEM), and (iii) geographic datasets that use an interpolation method, are adjusted for orography (Tobin and Bennett, 2013). The PRISM methodology has been used extensively to map precipitation, temperature, weather-generator parameters, and other climate elements worldwide (Hannaway and Daly, 2005; Johnson et al., 2000; Simpson et al., 2005). As PRISM is a high resolution gridded data product like NEXRAD, the application in hydrologic models is similar. The generally adopted approach is to summarize spatially averaged values for monthly weather data over each basin with a time series of PRISM grids and watershed boundaries (Fernandez et al., 2000; Price et al., 2014). Alternatively, the center of each 4-km PRISM grid has been taken as a weather station to be assigned to the closest subbasins (Radcliffe and Mukundan, 2016). Srinivasan et al. (2010) attempted to aggregate the gridded daily weather variables to the eight-digit subbasins using standard ArcGIS aggregation procedures, and obtained better streamflow simulation prior to calibration. Although the approach of using NEXRAD and PRISM climate datasets in watershed modeling is available, only few studies have implemented both datasets based on an area-weighted method at daily scale with SWAT, and it remains unclear how SWAT model would be affected by different weather datasets, especially from gauge-based and spatially distributed ones, or from different types of spatial grid datasets. The availability of NCDC, NEXRAD, and PRISM datasets for the Central Great Plains of the U.S. presented a unique opportunity to evaluate the SWAT model performance and impacts on watershed hydrology by using three alternative weather datasets, which composes a main goal of this study.

Weather data is of critical importance to simulate surface water, base flow and nutrients in hydrologic models. However, insufficient research incorporating various weather data in the simulation of streamflow with SWAT model is available. A few research articles have attempted to solely adopt land-based gauged data or spatial gridded data to estimate streamflow. In this study, three sources of datasets (NCDC, NEXRAD, and PRISM) were developed and implemented in the SWAT model, with a primary emphasis to evaluate changes in streamflow resulting from each weather dataset.

The primary goal of this study was to investigate the potential impact of alternative weather datasets on watershed model responses. The specific objectives were: (i) to develop a subbasin level framework of climate data input for the SWAT model by an area-weighted average approach; (ii) to examine the performance of the SWAT model by using each of three weather datasets; (iii) to evaluate the potential bias of high and low flows among different datasets; and (iv) to explore impacts of implementing alternative climate datasets on hydrologic components in water balance.

2. Materials and methods

2.1. Study area

The SHRW, a 6,310 km^2 (1,559,338 acres) sub-watershed of the Arkansas Red River Basin, is located within 11 counties in western Kansas (Fig.1). Two federal reservoirs are located at the inlet (Cedar Bluff Reservoir) and outlet (Kanopolis Reservoir) of the SHRW. Both reservoirs are maintained by the U.S. Army Corps Engineers and control inflow and outflow of Smoky Hill River. The SHRW is comprised of two eight-digit Hydrologic Unit Code (HUC: 10260006 and 10260007) watersheds. The relief is typical to western Kansas within the High Plains ecoregion of the Central Great Plains of the U.S. Two primary land use types are cropland (47%) and rangeland (47%), with 6% of the watershed in the other land use types (forest, developed area, water, etc.). The primary crop is winter wheat, typically planted in autumn and harvested in late spring or early summer, other crops include sorghum and corn, both of which are planted in the spring and harvest in the fall of the same year. Highly variable precipitation with extreme summer temperatures was observed in the watershed, with over a 40-year period from 1950 to 1990 annual precipitation ranged from 381 mm (15 in.) to 635 mm (25 in.) while average annual temperature was between 10 ºC to 12 ºC (Goodin et al., 1995). Topography generally consists of gentle slope (mean 3.2%), however, elevation increases from 441 m to 924 m from east to west. Soils are generally silt loam type with mean permeability of approximately 0.5 cm h^{-1}, and mostly of hydrologic soil group B (USDA-NRCS, 2005 and 2007).

2.2. Weather datasets

Three weather datasets were used in this study for the period from 2002 to 2014. The first dataset was derived from observations at land-based weather stations from the NOAA NCDC. A second weather dataset was a simulated data from the PRISM. A third was a NEXRAD dataset of the NOAA National Weather Service (NWS).

2.2.1. NCDC dataset

The NCDC dataset (Menne et al., 2012a, b) includes daily records of temperature, precipitation, wind speed, solar radiation, and atmospheric pressure from the Global Historical Climatology Network (GHCN) of land-based weather stations. The dataset has gone through major processing steps of data collection, quality control, archive, and removal of biases associated with factors such as urbanization and changes in instrumentation through time. For SHRW, the daily data from 2002 to 2014 were obtained from eleven stations for precipitation and four stations for temperature (minimum and maximum) in or within a 8-km buffer of the SHRW (Fig.1; Table 1).

2.2.2. PRISM dataset

PRISM was developed by the PRISM Climate Group at Oregon State University and is recognized as the USDA official climatological dataset (Schneider and Ford, 2011; Wang et al., 2006). PRISM products were created to address spatially sparse location climatology of GHCN (Daly, 2006; Daly et al., 2008) by generating spatially and temporally continuous climate data throughout the contiguous United States. PRISM data is defined on a 2.5 minute degree grid with a grid-cell size of approximately 4×4 km^2 (Schneider and Ford, 2011). The PRISM dataset uses a model that fits local linear regression curves of climate versus elevation, with slopes that vary with elevation, in which local regression accounts for spatially varying elevation relationships, effectiveness of terrain as barriers, terrain-induced climate transitions, cold air drainage and inversions, and coastal effects. The study area of SHRW was covered by 1,375 PRISM grid-cells (Fig.1). Daily PRISM data (minimum temperature, maximum temperature and precipitation) was available online from PRISM Climate Group repository (Daly, 2006; Daly et al., 2008).

2.2.3. NEXRAD dataset

NEXRAD data is developed from a network of 160 high-resolution S-band Doppler weather radars in the U.S. that detects precipitation and atmospheric movements or wind, and returns estimated rainfall depth. After raw data is processed, it is displayed in a gridded format similar to that of PRISM data. The radar system operates in two basic modes, a slow-scanning clear-air mode for analyzing air movements when there is little or no activity in the area, and a precipitation mode, with a faster scan for tracking active weather. NEXRAD has an increased emphasis on automation, including the use of algorithms and automated volume scans. Multi-sensor Stage III adjusted NEXRAD data (derived from Stage I data corrected by a bias adjustment factor based on available one-hour rain gauge reports, and Stage II data comprised of all radars combined into one map with ground truth data from gauge stations), was used to extract precipitation for a typical watershed (Smoky Hill River Watershed, SHRW) in the western Kansas, USA. Additional detailed information about NEXRAD products and processing algorithms can be found in literature (Crum and Alberty, 1993; Fulton et al., 1998; Moon et al., 2004).

In order to establish a long-term GIS-based rainfall database for the study area, two portions of NEXRAD datasets were included in the study. The first part is gage-corrected, mosaicked Stage III NEXRAD rainfall estimate data (2002-2004), derived from hourly NEXRAD precipitation data (in compressed binary format). Stage III data is provided in a grid format with grid-cells of approximately 4×4 km^2, which is referred as Hydrologic Rainfall Analysis Project grid (Reed and Maidment, 1999). The Stage III data includes 1,324 grid cells within the study area similar to PRISM grid shown in Fig.1 and were obtained from the Arkansas-Red Basin River Forecast Center of the NWS (http://water.weather.gov/precip/download.php). In order to obtain daily NEXRAD data, the hourly rain gauge data were summed from 6:00 AM of the first day to 6:00 AM the following day for each NEXRAD grid cell. Hourly NEXRAD Stage III data was utilized in a multi-tarred (or compressed) format distributed by NWS. Compressed hourly rainfall files for a region throughout a rain forecast center (RFC) were tarred into daily files and subsequently tarred into monthly files. The data processing was conducted using computer programs by Zhang et al. (2009). Specifically, the rainfall products were extracted from the distributed archived bundles (in tar format) using a multi-step file extracting procedure in Linux. The resulting hourly files in a binary XMRG format were converted into an ASCII grid format, and then aggregated into daily data that was subsequently transferred into a common coordinate system using Python scripts. A set of algorithms was implemented to automatically select, retrieve, and extract spatial radar precipitation for each grid cell in SHRW (Fig.2). The remaining portion of daily NEXRAD data from 2005 to 2014 was available throughout the conterminous USA in shapefile format from the NOAA NWS online repository (http://www.ncdc.noaa.gov/).

2.3. The SWAT model

The SWAT model is a large-scale hydrologic model, developed and maintained by the Agricultural Research Service (ARS) of the U.S. Department of Agriculture (USDA) (Arnold et al., 2012). SWAT is a process-based, continuous watershed-scale simulation model that was extensively applied to worldwide applications of hydrologic, sediment and nutrient processes (Douglas-Mankin et al., 2010; Sheshukov et al., 2011). In SWAT, a watershed is geospatially divided into subwatersheds according to flow accumulation and stream network delineation procedures. Within each subwatershed, geo-referenced units of homogeneous slope, land use, and soil type are identified and aggregated into Hydrologic Response

Units (HRUs). Within each HRU, the modeling components include hydrological budget, sediment transport, nutrient transformation, plant growth, soil percolation, and agricultural management. In each subbasin, SWAT uses a single time series for daily weather inputs, thus all HRUs within the same subbasin receive the same precipitation.

SWAT incorporates a set of physically- and empirically-based equations to simulate various hydrologic and water quality processes and was applied to predict management impact on water, sediment, and agricultural chemical yields in large ungauged river basins (Neitsch et al., 2011; Wang et al., 2016). Soil water content at a specific day *j* within each HRU is tracked based on the daily water balance equation (all variables having units of mm) from all days prior to day *j*:

$$SW_j = SW_0 + \sum_{i=1}^{j}(PR_i - RO_i - ET_i - DP_i - BF_i) \quad (1)$$

where, subscript 0 specifies initial values at the beginning of simulations, *SW* is soil water content, *PR* is precipitation depth, *RO* is surface runoff, *ET* is evapotranspiration, *DP* is the depth of water exiting the root zone to the vadose zone, and *BF* is the baseflow to the stream (Neitsch et al., 2011).

2.4. Watershed model for SHRW

In this study, a SWAT model was built for SHRW with ArcSWAT ver. 2012. At the west end of the watershed, the inlet was introduced in the model to account for daily releases from Cedar Bluff Reservoir to SHRW. The main watershed outlet was placed at the dam of Kanopolis Reservoir on the east end of SHRW. Fifty-Four twelve-digit HUC subwatersheds ranged in size from 5,520 to 16,400 ha were delineated using 10-meter Digital Elevation Model (DEM) (Fig.1; USDA-NRCS, 2007). A stream network representing Smoky Hill River, Big Creek and their major tributaries was created during the delineation process.

2.4.1 Soil database

Twenty-six unique soil types and 45 associated soil specific map units were identified in SHRW using data from the State Soil Geographic (STATSGO) (USDA-NRCS, 2005, 2007). STATSGO was designed to support regional, multi-state, state, or river basin resource planning, management, and monitoring and was created by generalizing detailed soil survey maps or using auxiliary data and remote sensing imagery. The dominant soil component was assumed to be representative of each map unit.

2.4.2 Land use and crop rotation

The land use/land cover data was created from custom multi-year (2003-2012) spatial dataset developed as a part of Kansas NSF EPSCoR project (https://kars.ku.edu/products/maps/). The LULC dataset used annual raster-based USDA-NASS datasets (USDA-NASS, 2012) as base maps refined with Common Land Unit (CLU) dataset of field boundaries and irrigation parcel data. The LULC dataset from 2008 was used to define land use coverage in the SWAT model with 12 LULC classes. The multi-year coverages of cultivated crops in SHRW from 2006 to 2012 in LULC dataset were used to identify 20 dominant three-year crop rotations that included winter wheat, grain sorghum, fallow, corn and soybeans. Dates of crop planting and harvesting, amounts and dates of fertilizer applications, main irrigation scheduling and tillage applications were specified in the model according to agronomical guidelines and after consultations with watershed specialists.

2.4.3 Weather database

Solar radiation, relative humidity, and wind speed were generated by SWAT, based on local monthly statistics. Three sets of weather inputs (NCDC, PRISM and NEXRAD) were applied to the SWAT model. With a set of provided NCDC weather stations, ArcSWAT extension in ArcGIS selects the station that is closest to subbasin centroid and assigns weather records stored in a text format from that station to that subbasin (Neitsch et al., 2011).

In order to use the gridded data from NEXRAD and PRISM in ArcSWAT, a procedure was developed in Python to create single daily weather series for each subbasin by applying an area-weighted average approach to all grid-cells overlaying a subbasin (Enfield et al., 2001) (Fig.3). Following this approach, the precipitation P_i^{sub} and temperature T_i^{sub} for subbasin i $(1 \leq i \leq 54)$ were calculated from PRISM and NEXRAD datasets according to the following formulas:

$$P_i^{sub} = (\sum_{k=0}^{n} P_{k,i}^{PN} \times A_{k,i}^{PN})/A_i^{sub} \quad (2)$$

$$T_i^{sub} = (\sum_{k=0}^{n} T_{k,i}^{PRISM} \times A_{k,i}^{PRISM})/A_i^{sub} \quad (3)$$

where, A_i^{sub} is area of the i^{th} subbasin, $P_{k,i}^{PN}$ is PRISM or NEXRAD precipitation value from grid-cell k in the i^{th} subbasin, $T_{k,i}^{PRISM}$ is the PRISM temperature value from grid-cell k in the i^{th} subbasin, $A_{k,i}^{PN}$ is the area for PRISM or NEXRAD grid k intersected with the i^{th} subbasin, $A_{k,i}^{PRISM}$ the area for PRISM grid k intersected with the i^{th} subbasin, and n is the total number of PRISM or NEXRAD grid cells intersected with the i^{th} subbasin.

The resulting weather series were generated for 54 subbasins in SHRW and assigned as weather stations with geographical coordinates of the centroid of the corresponding subbasin. This approach forced the model to pair each subbasin with the corresponding weather series during the weather input step in ArcSWAT.

2.4.4 Other inputs

Daily releases from Cedar Bluff reservoir for the studied period from 2002 to 2014 were obtained from the U.S. Army Corps of Engineers. Volume and surface area at emergency and principal spillways for the Kanopolis reservoir, was derived from the previous research for SHRW (Sinnathamby, 2014). An intersection of geospatial datasets of slope range, land use, and soil in ArcSWAT generated 7,179 HRUs. This study used the soil moisture-dependent USDA-SCS curve number method for *RO*, the Penman-Monteith method for *ET*, and the variable storage method for channel routing.

2.5. Statistical methods

Three statistical criteria were used to evaluate and analyze the performance of the SWAT model at daily, monthly, and yearly scales. Following Santhi et al. (2001) and Moriasi et al. (2007), the statistics of Nash-Sutcliffe Efficiency (NSE), percent Bias (pBias), and Root Mean Square Error (RMSE)-observations standard deviation ratio (RSR) were used to evaluate streamflow prediction. NSE ranges from -∞ to 1 (Nash and Sutcliffe, 1970); the larger the value, the better the model performance. The second criterion, *pBias*, measures the average tendency of the simulated data to be larger or smaller than their observed counterparts (Gupta et al., 1999). The *pBias* values with smaller magnitudes are preferred. Positive pBias means overestimation, while negative means underestimation (Gupta et al., 1999). The RSR statistics were selected as the third statistical criterion based on the recommendation of Singh et al. (2005). The RSR standardizes RMSE using the observations standard deviation, combining an error index recommended by Legates and McCabe (1999). The RSR is calculated as the ratio of RMSE and standard deviation of measured data.

2.6. Model calibration

The SWAT model of SHRW was calibrated using daily streamflow at the two outlets corresponding to two USGS gauge stations: Smoky Hill R NR Bunker Hill (henceforth called Bunker) [USGS 06864050], and Smoky Hill R Ellsworth (Ellsworth) [USGS 06864500] (USGS, 2014). The observed discharge data were from 2002 to 2011 at Bunker, and from 2002 to 2014 at Ellsworth. The SWAT model was run from 2002 to 2014 and calibrated for daily streamflow from 2008 to 2010 using NSE, pBias, and RSR statistics (Moriasi et al., 2007). The calibration periods included wet, moderate, and dry periods (Arnold et al., 2012). According to previous work (Sexton et al., 2010; Sheshukov et al., 2011; Van Liew et al., 2007; Zhang et al., 2009) on sensitive hydrology parameters in streamflow simulation for calibrating SWAT model, 16 model parameters representing surface and groundwater hydrology were selected for calibration as listed in Tab. 2. Specifically, total flow was adjusted by changing the soil evaporation compensation factor (ESCO) and the curve number for moisture condition II (CN2), plant evaporation compensation factor (EPCO), and maximum canopy storage (CANMX) from the default values. Surface runoff and base flow were calibrated by changing the surface runoff lag factor (SURLAG), and Manning's n value for the main channel (CH_N2), Manning's coefficient value for overland flow (OV_N), available soil water capacity (SOL_AWC), and saturated hydraulic conductivity (SOL_K). In order to adjust seasonal flow balance, snow pack temperature lag factor (TIMP) was also considered during calibration. The SWAT model calibration software, Integrated Parameter Estimation and Uncertainty Analysis Tool (IPEAT) was used to auto-calibrate the model at the daily time step for streamflow (Yen et al., 2014b). IPEAT is a framework for both auto-calibration and uncertainty analysis involving Dynamically Dimensioned Search (DDS) as the major parameter estimation approach. In addition, DDS has been displayed to have superior performance (in terms of convergence speed and the ability to find better solutions) over other commonly implemented auto-calibration techniques such as Shuffle Complex Evolution (SCE-UA) and DiffeRential Evolution Adaptive Metropolis (DREAM) (Yen et al., 2014a). The SWAT model was first calibrated with NCDC weather data. The parameter set of the best simulation for streamflow as listed in Table 2, NCDC was then replaced with PRISM and NEXRAD data in turn. Ranges and final calibrated values of model parameters are presented in Table 2. With this procedure, the uncertainty introduced by SWAT calibration with different weather datasets could be avoided, which will be more effective to assess the uncertainty caused by various weather inputs. Additionally, the parameter set of the optimal simulated result for NCDC was obtained by the first step for calibrating the SWAT with NCDC data.

3. Results and discussion

3.1 Comparison of PRISM, NEXRAD, and NCDC at locations of land-based weather stations

Daily values of temperature and precipitation in PRISM and NEXRAD datasets were compared with NCDC data at eleven weather stations (temperature was available at four stations) in SHRW from 2002 to 2014 (Fig.1). For each NCDC station, an overlaying PRISM and NEXRAD grid-cell was identified and the data was extracted. Slope and coefficient of determination R^2 calculated from linear regression fit equation, and statistics NSE and pBias were selected for evaluation of dataset comparison (Table 1). The statistics showed a wide variation of R^2 values across all stations in SHRW. The determination coefficient R^2 ranged from poor (0.31) to excellent (0.96) for PRISM derived precipitation, was above 0.98 for PRISM minimum and maximum temperature, while was in the range from 0.25 to 0.78 for NEXRAD precipitation (Fig.1). The linear regression curves showed that PRISM dataset fitted NCDC data better than NEXRAD with the average slope of 0.82 for PRISM versus 0.78 for NEXRAD, and confirmed by other statistics presented in Table 1. Scatter plots of NCDC versus NEXRAD (precipitation) and PRISM (precipitation, temperature) data for Ellsworth indicated that the slopes of regression curves were less than unity with pBias values showing overestimation of NEXRAD (3.14%) and underestimation of PRISM (-1.49%) data as compared with NCDC. It was evident in Figs. 4c and 4d that minimum temperature had less scatter than maximum temperature confirmed by smaller pBias values in Table 1 (0.17% for maximum temperature, -4.9% for minimum temperature). The graphs in Fig.4 were typical to all eleven NCDC sites in SHRW.

Generally, a positive bias (overestimation) of gridded datasets was prevalent in SHRW, with NEXRAD showing larger distinction than PRISM. For the four stations with higher pBias values in NEXRAD (Gove, Colby, Cedar and Ellis), the bias of PRISM data was also higher (Fig.1). This larger difference of NEXRAD from NCDC data was likely caused by the distance-related effects, such as beam overshooting and spreading to the stations (Habib et al., 2009). The SHRW was 120 km away from the nearest radar site in Wichita, KS, resulting in ten of eleven NCDC stations in fair to poor NEXRAD radar coverage with only one (Alexander, KS) in good coverage.

Another critical reason for higher bias of NEXRAD dataset related to the fact that bias caused by beam spreading becomes more significant with the increase in beam elevation and degradation of resolution (Austin, 1987; Joss et al., 1990; Wilson and Brandes, 1979). The impact of increase in elevation in SHRW was evident in higher positive pBias values in five stations in the western part of SHRW (Gove, Gunter, Colby, Cedar, Ellis) compared to other stations (Fig.1). The effects of changing elevation and other terrain-related factors were accounted in PRISM dataset development, thus a smaller bias was observed (Daly et al., 1994; Small et al., 2006).

3.2. SWAT model performance evaluation for three weather datasets

3.2.1 Streamflow comparisons

A SWAT model for SHRW developed with three weather dataset inputs (SWAT-NCDC, SWAT-NEXRAD, SWAT-PRISM) was calibrated for streamflow at two USGS station locations at Bunker (USGS 06864050) and Ellsworth (USGS 06864500). The SWAT model was run for 13 years (2002-2014), and daily streamflow at two outlets corresponded to two USGS locations was aggregated at monthly and yearly scales. The observed average annual streamflow rates for 13 years of the simulation period were 72.3 $m^3 s^{-1}$ for Bunker and 131.1 $m^3 s^{-1}$ for Ellsworth. Lower streamflow at Bunker corresponds to a smaller drainage area and dryer climate (Fig.1).

After NCDC was replaced with PRISM data, the SWAT estimated streamflow value was even more precise than before. The more accurate simulation would likely be possible if SWAT with PRISM is calibrated further. However, it is sufficient enough with current calibrated parameters to demonstrate the effects of different weather dataset inputs on streamflow. Therefore, our strategy indirectly not only avoids model calibration with specific weather input, but also reduces the uncertainty caused by various parameter combinations for SWAT, due to the similar simulated results by the different parameter sets in a hydrological model.

The statistics of NSE, pBias, and RSR were calculated for the SWAT model with three weather datasets at each temporal scale as shown in Fig.5. At the daily scale, SWAT-NCDC and SWAT-NEXRAD models showed poor calibration results while the statistics for SWAT-PRISM model was satisfactory at either calibration site (Figs. 5a, d and g). Upscaling to monthly and yearly scales from daily scale improved the statistics of NEXRAD and PRISM based models, however, disproportionally with regards to locations of Bunker and Ellsworth. NSE gradually increased from 0.4 to 0.8 and RSR gradually decreased from 0.7 to 0.4 of the SWAT-PRISM model at both locations with upscaling, while pBias stayed unchanged at about 20%. This proved excellent performance of the SWAT-PRISM in SHRW. The statistics for SWAT-NEXRAD were sensitive to location and showed better results for Bunker than Ellsworth. For that model, the values of NSE were negative at both locations at the daily scale, but improved to good (NSE=0.6, RSR=0.6 at Bunker and NSE=0.4, RSR=0.8 at Ellsworth) at monthly and to excellent (NSE=0.95, RSR=0.45 at Bunker and NSE=0.6, RSR=0.4 at Ellsworth) at yearly scales (Figs. 5,b, c, h, i). It is interesting to note that pBias values for SWAT-NEXRAD did not change significantly at all time scales, staying excellent at Bunker and at 40% at Ellsworth (Figs. 5,d, e, f). Research by Price et al. (2014) on a large watershed in North Carolina found out that the radar-based data overestimated the rainfall collected at rain gauges during large storm events, however, total rainfall was higher in rain gauges, due to most of the rain occurring during small storms. For SWAT-NEXRAD model in PBIAS, it indicated that the errors (underestimation) caused by daily high flow events were compensated by the errors (overestimation) at low flows, forcing pBias to be insensitive to intra-annual flow dynamics. All statistics produced by the SWAT-NCDC model were worse than the ones by the SWAT-PRISM and the SWAT-NEXRAD models. As mentioned in Gali et al. (2012), measured precipitation depth at a rain gauge is considered as “observed” data for a given gauge location, but these data may become less accurate as distance from the gauge increases. In addition, multiple researchers have demonstrated a conditional negative bias of rain gauges during large rainfall events, as there is a tendency for water loss caused by wind and erratic behavior of the mechanical aspects of the gauge during intense rainfall (Molini et al., 2005; Lanza and Stagi, 2008).

3.2.2 Comparison of observed and simulated streamflow

Monthly streamflow for the SWAT model with three weather datasets were compared against observed flows at the USGS station in Ellsworth from 2002 to 2014. The scatterplot in Fig.6 showed that for flow less than 1 m^3 s^{-1}, simulated values were consistently higher than the observation by USGS, while streamflow fit well for flow greater than 8 m^3 s^{-1} (similarly reported by Radcliffe and Mukundan (2016)). For high flows, underestimation can be found in the SWAT-NEXRAD and the SWAT-PRISM models but overestimation for SWAT-NCDC. It is similar to the previously conducted research that SWAT-NEXRAD under-predicted high flow events and over-predicted low flow events (Moon et al., 2004). The simulated flows exhibited higher variation in values for low flows (less than 1 m^3 s^{-1}) while clustering close to 1x1 line for higher flows (greater than 8 m^3 s^{-1}). The linear regression equations showed the determination of 0.8 for SWAT-PRISM, while R^2 was lower for SWAT-NCDC (0.53). As mentioned previously that Price et al. (2014) found that radar simulations demonstrated greater underestimation of low and median flows than simulating high flows. The major reason is that gauges generally measured greater rainfall during light rainfall events (corresponding to low and median flows), whereas radar tended to record greater rainfall during heavier events (corresponding to high flow).

The model behavior of overestimating flows in Fig.6 was consistent with positive pBias exhibited by all models in Fig.5. However, it can be seen that SWAT-PRISM outperformed SWAT-NCDC and SWAT-NEXRAD in simulating monthly flows. SWAT-NCDC showed the worst statistics in Figs. 5 and 6. In 13-year simulation period, the observed streamflow at Ellsworth was higher than 6.8 $m^3 s^{-1}$ at 10% times, but that value increased to 7.8 $m^3 s^{-1}$ for SWAT-PRISM, 7.9 $m^3 s^{-1}$ for SWAT-NEXRAD, and 12.4 $m^3 s^{-1}$ for SWAT-NCDC. This indicates that there was an overestimation of high flow events by SWAT-NCDC. Higher variation of small precipitation events by NEXRAD (Fig.4a) caused the SWAT-NEXRAD model to overestimate the observed flows at flow rates lower than 1 $m^3 s^{-1}$.

From the analysis of simulated flows in Fig.6 and calibration statistics in Fig.5, it was apparent that gridded PRISM dataset and the corresponding SWAT-PRISM model were superior in matching observed flow at two locations and three time scales than NCDC and NEXRAD based SWAT models, which was consistent with the results reported by Radcliffe and Mukundan (2016). Although only few studies reported the comparisons of PRISM and NEXRAD data on streamflow simulations using SWAT, PRISM was undoubtedly a better choice of alternative weather inputs for hydrological simulation due to its superiority compared to NEXRAD.

3.2.3 Subbasin weather aggregation in SWAT

Subbasin distribution of weather input by three datasets played an important role in SWAT model performance, especially, the precipitation input. For NCDC dataset, the subbasin centroid based approach in SWAT aggregated weather data from the same NCDC station to more than one subbasin. It resulted in data becoming less accurate as distance from the gauge site increases (Gali et al., 2012). For NEXRAD and PRISM, an area-weighted approach was utilized in Eqs. (2) and (3) to distribute gridded weather input to SWAT subbasins, with multiple grid-cells for each subbasin. The quality of NEXRAD data was based on atmospheric radar reflectivity primarily recorded by water droplets and maybe affected by proximity to radar location (Gali et al., 2012), while PRISM data was created by interpolation involving many factors such as location, elevation, topographic and atmospheric environment, and terrain (Daly et al., 2008).

The 13-year average precipitation over SHRW from NCDC and PRISM were close at 611 mm and 617 mm, respectively, while it was 630 mm for NEXRAD (see Supplemental Material). The minimum annual NCDC precipitation of 475 mm was at the station Cedar near Cedar Bluff Reservoir, and it was assigned to six subbasins (9, 18, 26, 30, 52, 54). At those six subbasins, annual precipitation by NEXRAD and PRISM was higher than by NCDC on average by 80 and 111 mm, respectively. The fact that rain gauges underestimated rainfall in large storms compared to radar data, can also be found by Price et al. (2014). This indicates strong underestimation of rainfall rates by NCDC causing lower flow rates by the SWAT-NCDC model and poor agreement with USGS data at Bunker in Fig.5.

The highest overestimation of annual precipitation by NCDC as compared to PRISM was observed for 13 subbasins with weather from Ellsworth station. While at the location of Ellsworth station the difference was small for PRISM and NEXRAD, the average difference for 13 subbasins, with two located more than 30 km west from the station, was 68 mm for PRISM and 46 mm for NEXRAD. This rainfall overestimation by NCDC for the area close to the streamflow calibration location at Ellsworth led to significant positive bias by SWAT-NCDC model (Fig.5).

We notice that streamflow-based evaluation of the SWAT model performance with three different weather inputs indicated that higher spatial resolution of radar data from NEXRAD did not provide significantly better SWAT model performance than NCDC, especially at the daily scale. This is probably due to having a poor network of radar grid cells located within the watershed boundaries as shown in Fig. 1, not allowing NEXRAD to better explain spatial variability of rainfall (Sexton et al., 2010). In 54 subbasins of SHRW, the annual precipitation in PRISM had higher standard deviations from NCDC than NEXRAD, 75 mm versus 40 mm, but smaller differences in average annual precipitation, 8.6 mm versus 20.6 mm. The

NEXRAD grid-cells in SHRW were located mainly (in 48 of 54 subbasins) in fair radar coverage that led to bias in daily precipitation in SWAT which resulted in poor streamflow calibration (Fig.1; Supplement Material). Additionally, the increase of elevation in areas of fair to poor NEXRAD coverage negatively affected precipitation estimation in streamflow simulations.

3.3. Evaluation of impacts of weather datasets on hydrologic components

Main components of hydrologic cycle were extracted from SWAT models to evaluate the impacts of three weather input datasets. Within each HRU, the water balance was based on Eq. (1), while each component in Eq. (1) was aggregated daily for all HRUs in SHRW to obtain watershed average annual depths of surface runoff *RO*, evapotranspiration *ET*, and baseflow *BF*. The values of *RO*, *ET*, and *BF* for a 13-year simulation period along with average streamflow rates at Ellsworth USGS station are shown in Fig.7 for three SWAT models.

Of 13 years of simulation, the years 2002, 2003, and 2012 had annual precipitation less than 90% of the average annual by all three weather datasets, and thus were considered dry years, whereas the years 2007, 2008, and 2014 were wet with annual precipitation above 110% of the average annual. At Ellsworth, the average annual flow in dry years decreased relative to 13-year averages by 53% for USGS observations, and by 29%, 36%, and 52% for the SWAT-NCDC, SWAT-PRISM, and SWAT-NEXRAD models, respectively. In contrast, in wet years, the flows for USGS observations increased by 141%, while the increase was 84%, 103%, and 126% for the SWAT-NCDC, SWAT-PRISM, and SWAT-NEXRAD models, respectively. These results indicate that all models overestimated streamflow in dry years and underestimated in wet years, with PRISM exhibiting the smallest bias. The work conducted in southern Kansas also revealed similar results that simulations of implementing NEXRAD and NCDC in SWAT overestimated streamflow in dry years and underestimated in wet years, except for extremely wet years (Gali at al. 2014).

Among the models, BF and RO were higher for SWAT-NCDC, which primarily resulted from overestimating precipitation in the entire watershed by adopting sparse land-based stations (see Supplement Material for details on subbasin precipitation). As a result, ET was higher for the SWAT-PRISM and SWAT-NEXRAD models than for the SWAT-NCDC model. The SWAT-PRISM and SWAT-NEXRAD models predicted lower BF and RO in dry years, while SWAT-NCDC simulated higher BF and RO in wet years. The NCDC based model generated lower ET in dry years with SWAT-NEXRAD and SWAT-PRISM projecting higher ET in wet years. The different effects of three sets of weather datasets on hydrologic components indicated that SWAT models with gridded weather datasets estimated higher BF and RO and lower ET in dry years, while lower BF and RO and higher ET in wet years, than the SWAT-NCDC model with eleven land-based weather stations distributed weather to 54 SWAT subbasins. During the simulation period, the most significant changes of BF, RO, and ET, all decreased by 17%, 46%, and 14%, respectively, were observed in dry years for the SWAT-PRISM model. Similarly, the increases in BF (19%) and RO (138%) were observed in wet years for the SWAT-PRISM model, while ET increased by 14% for the SWAT-NEXRAD model.

4. Summary and Conclusions

In this study, two spatial weather datasets, PRISM and NEXRAD, developed at 4×4 km^2 grid-cells were used as alternatives to NCDC dataset of permanently established land-based weather stations. The SWAT model was developed for Smoky Hill River watershed in west-central Kansas and used to evaluate the impacts of two gridded NEXRAD and PRISM datasets on streamflow calibration as compared to impacts of land-based inputs from NCDC weather stations. A framework was developed to aggregate station-based or gridded weather data to subbasins in SWAT using Linux and Windows scripts.

The SWAT model based on PRISM dataset captured daily streamflow more accurately compared to the SWAT model based on NCDC weather. A SWAT model based on conventional weather data from land-based NCDC stations consistently overestimated monthly stream discharges, while NEXRAD and PRISM based models tended to underestimate monthly high flows and overestimate monthly low flows. Regarding the annual hydrologic components, SWAT models with three weather datasets overestimated streamflow in dry years and underestimated it in wet years with PRISM weather generating a smaller bias than NEXRAD and NCDC weather. The models with NEXRAD and PRISM datasets estimated higher BF and RO and lower ET for dry years, and higher ET and lower BF and RO for wet years, compared to NCDC based models. Spatial aggregation of weather data for each subbasin, whether through the distance approach to subbasin centroid by NCDC or area-weighted average scheme for PRISM and NEXRAD, affected the streamflow at USGS sites and hydrologic cycle components differently and need to be accounted in the SWAT model development. Overall, a selection of weather datasets for developing a SWAT model can profoundly impact simulated results for streamflow at daily, monthly and yearly scales. This study was conducted using a SWAT model in an agricultural watershed in the Central Great Plains of the U.S, an area known for highly convective weather systems with a great deal of spatial and temporal variability in precipitation. In other areas with different topography and climate conditions, hydrologic differences between spatially distributed and land-based point weather datasets may force different hydrologic response in a watershed resulting in quantifiable changes of hydrologic regimes. Based on the results of this study, the inclusion of higher spatial resolution of weather datasets may significantly improve SWAT simulated streamflow predictions.

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Table 1. Comparison statistics of NEXRAD and PRISM datasets at eleven NCDC weather stations

NCDC Station		NEXRAD Precipitation				PRISM Precipitation				PRISM Minimum Temperature				PRISM Maximum Temperature			
ID	Name	Slope	R^2	NSE	pBias	Slope	R^2	NSE	pBias	Slope	R^2	NSE	pBias	Slope	R^2	NSE	pBias
USC00143175	Gove	0.8	0.64	0.59	8.39	0.86	0.81	0.78	4.63	-	-	-	-	-	-	-	-
USC00146637	Quinter	0.48	0.25	-0.03	3.12	0.53	0.31	0.07	-1.55	-	-	-	-	-	-	-	-
USC00141699	Colby	0.98	0.75	0.74	18.56	0.95	0.94	0.94	5.17	-	-	-	-	-	-	-	-
USC00141383	Cedar	0.84	0.66	0.63	11.29	0.91	0.89	0.88	3.36	1	0.99	0.99	-0.43	0.99	0.99	0.99	0.39
USC00140135	Alexander	0.68	0.47	0.36	-5.36	0.73	0.66	0.57	0.48	-	-	-	-	-	-	-	-
USC00142452	Ellis	0.76	0.62	0.56	7.31	0.84	0.8	0.77	3.18	-	-	-	-	-	-	-	-
USC00143527	Hays	0.86	0.75	0.73	2.64	0.87	0.91	0.89	-0.36	0.98	0.99	0.99	-3.32	0.99	1	1	-0.38
USC00140865	Bison	0.93	0.76	0.76	0.59	0.93	0.96	0.96	-0.18	0.98	0.99	0.99	2.1	1	1	1	0.11
USC00144893	Luray	0.71	0.6	0.5	3.84	0.73	0.64	0.55	3.04	-	-	-	-	-	-	-	-
USC00142459	Ellsworth	0.88	0.78	0.77	3.14	0.91	0.95	0.94	-1.49	0.99	0.99	0.99	-4.9	0.99	0.99	0.99	0.17
USC00143037	Geneseo	0.66	0.47	0.34	3.56	0.7	0.54	0.45	3.25	-	-	-	-	-	-	-	-
Average		0.78	0.61	0.54	5.19	0.82	0.76	0.71	1.78	0.99	0.99	0.99	-1.64	0.99	1	1	0.07

Table 2. Range and final values of model parameters adjusted during streamflow and crop calibration of the SWAT model in SHRW

	Parameters	Definition	Model Range	Calibrated Value
1	CN2	SCS runoff curve number	-10% to 10%	4.78%
2	CANMX	Maximum canopy storage	0 to 10	Forests 8, Agricultural and pasture areas 3, Urban 1.5
3	ESCO	Soil evaporation compensation factor	0 to 1	0.676
4	SURLAG	Surface runoff lag coefficient	0.1 to 12	9.522
5	TIMP	Snow pack temperature lag factor	0 to 1	0.720
6	ALPHA_BF	Base flow alpha factor (days)	0 to 1	0.385
7	GW_DELAY	Groundwater delay (days)	0 to 300	130.0
8	GW_REVAP	Ground water re-evaporation coefficient	0.02 to 0.2	0.080
9	GWQMN	Threshold depth of water in the shallow required for return flow to occur (mm)	0 to 800	789.0
10	RCHRG_DP	Deep aquifer percolation coefficient	0 to 0.1	0.076
11	REVAPMN	Threshold depth of water in the shallow aquifer for re-evaporation to occur (mm)	0 to 800	187.5
12	EPCO	Plant evaporation compensation factor	0.2 to 1	0.585
13	OV_N	Manning's coefficient value for overland flow	0.01 to 0.6	0.559
14	CH_N2	Manning's coefficient for main channels	0.05 to 0.1	0.053
15	SOL_AWC	Available soil water capacity (mm H_2O mm^{-1} in soil)	-30% to 30%	20.30%
16	SOL_K	Saturated hydraulic conductivity (mm/hr)	-30% to 30%	23.41%

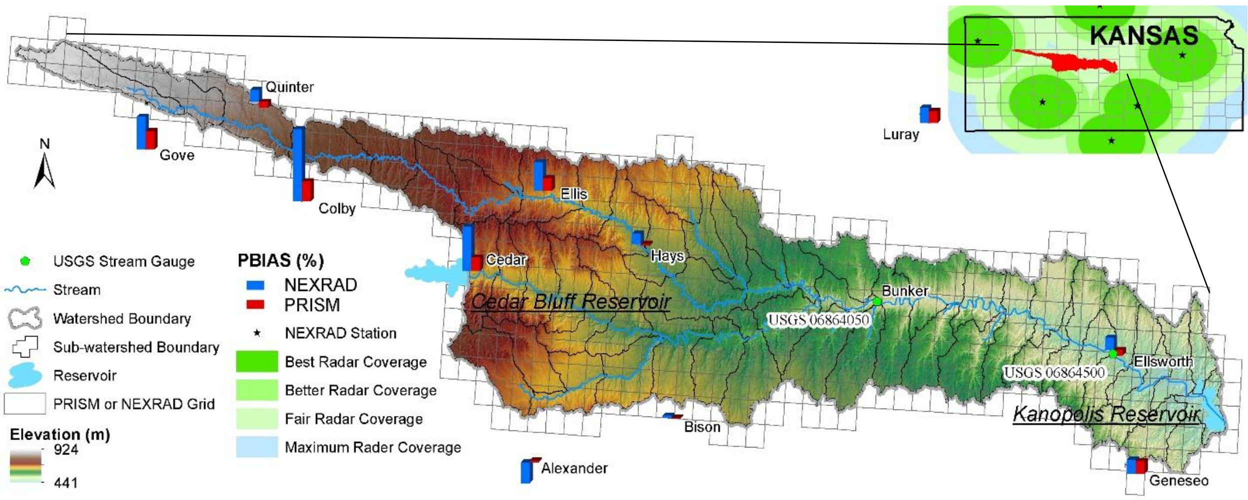

Fig. 1. Map of Smoky Hill River watershed overlaid with a 4×4 km^2 grid of NEXRAD and PRISM coverage. The map shows eleven NCDC stations with bar charts representing pBias of NEXRAD (blue) and PRISM (red) deviations from NCDC, two USGS streamflow gauge sites at Bunker and Ellsworth, and NEXRAD coverage bands (see inset).

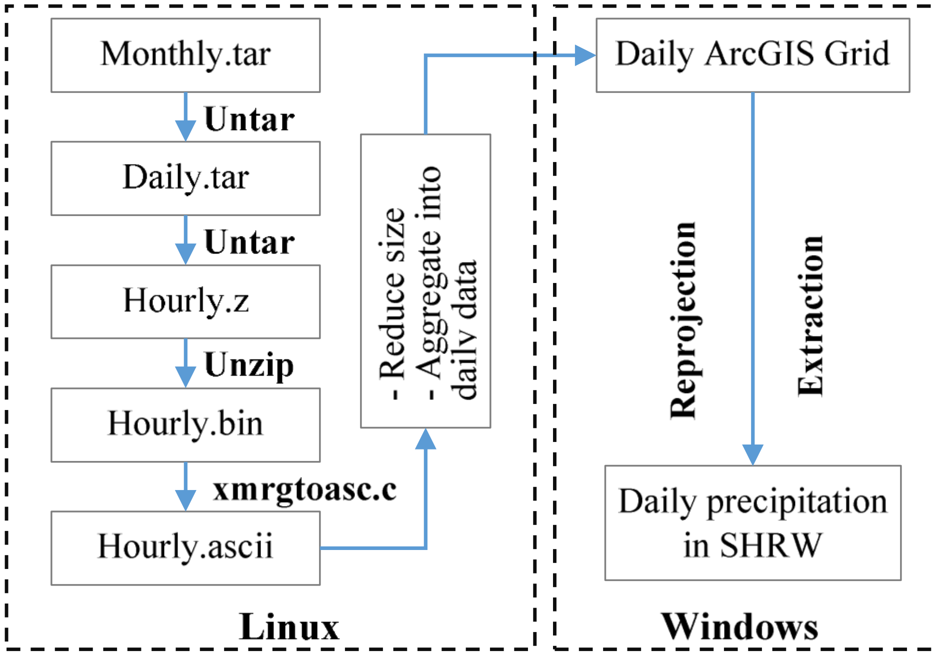

Fig. 2. Work flow chart of PRISM data extraction using Perl and C/ C++ languages in Linux and subbasin aggregation with Python language in Windows.

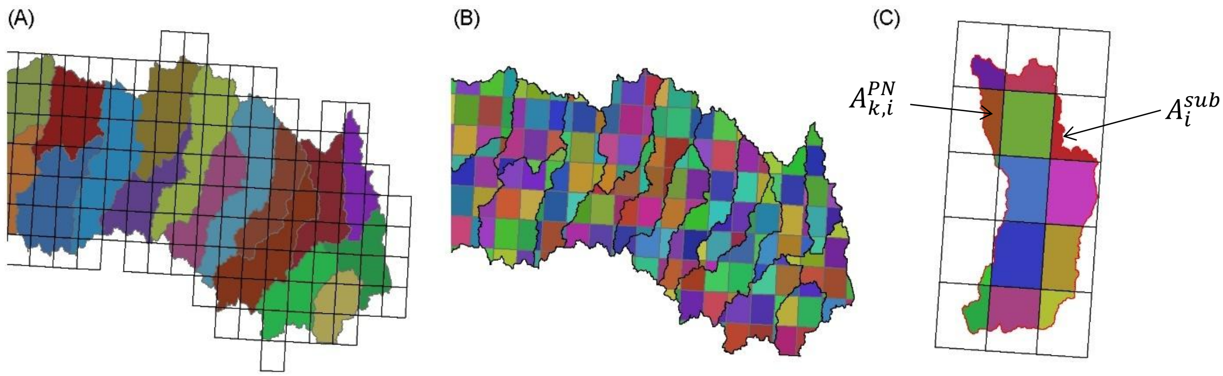

Fig. 3. (a) A PRISM and/or NEXRAD original grid, (b) grid-cells intersected with SWAT subbasins, and (c) a schematic of calculating precipitation and temperature at subbasin level.

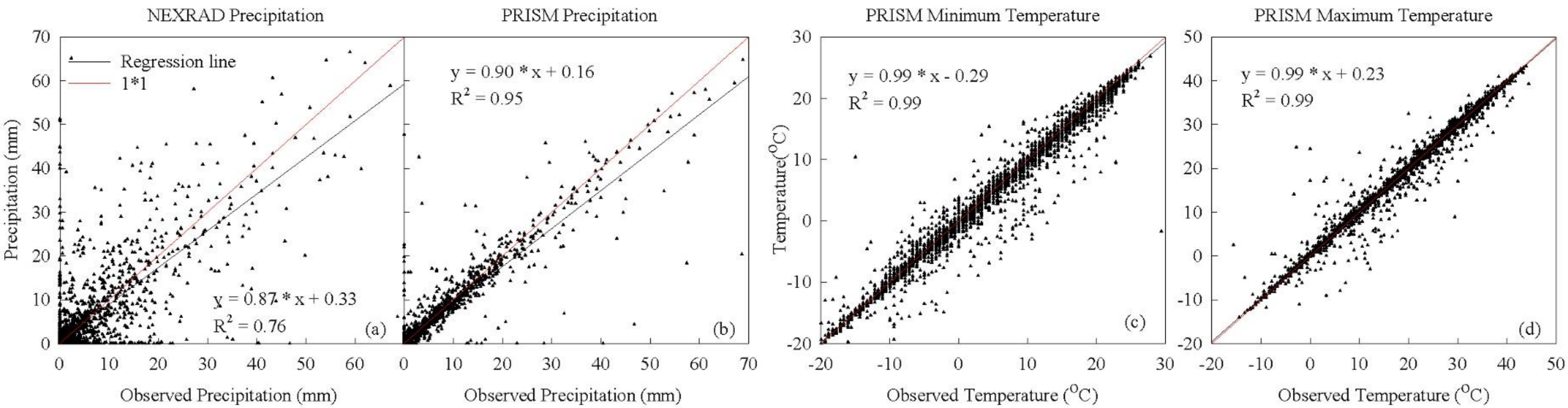

Fig. 4. Scatter plots of daily precipitation (a,b) and minimum (c) and maximum (d) temperature for PRISM and NEXRAD data at Ellsworth, KS (USC 00142459).

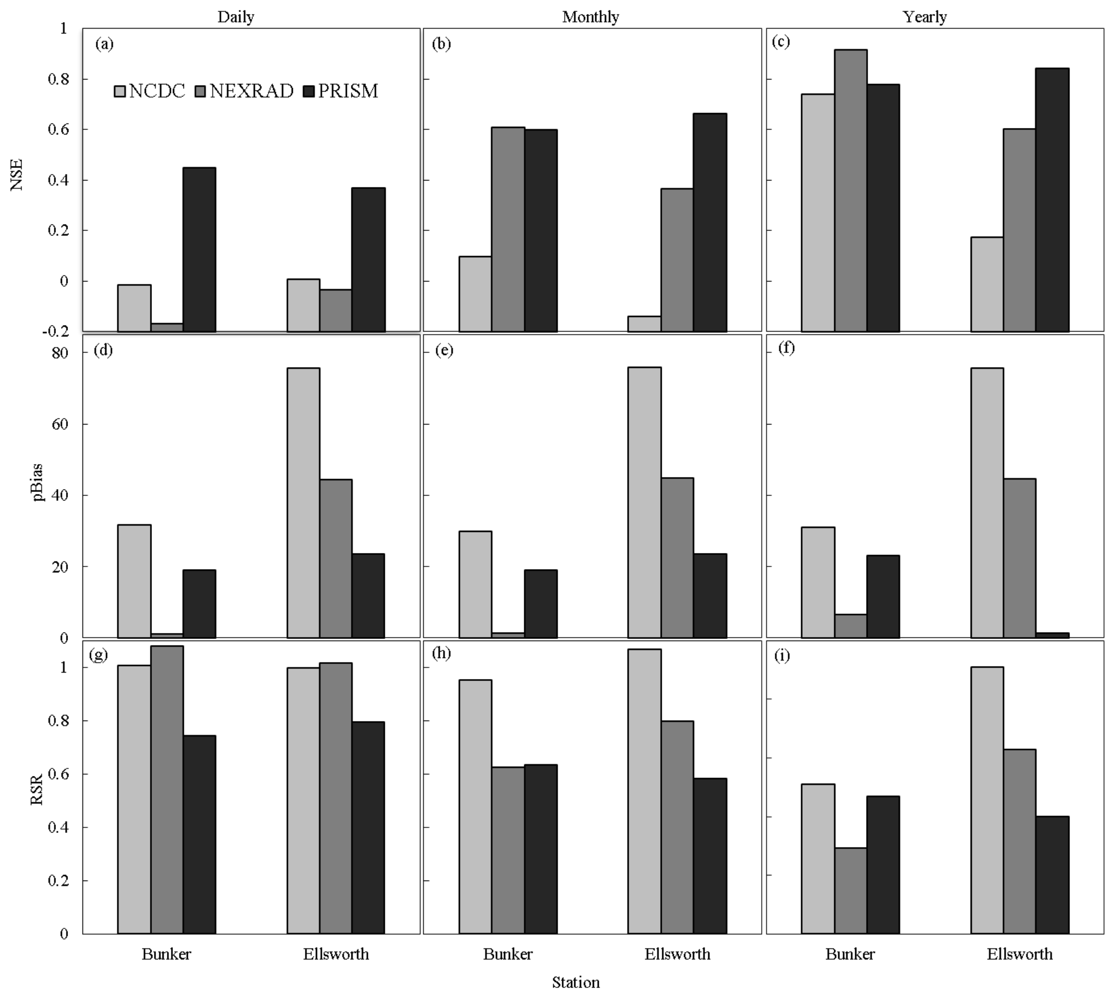

Fig. 5. Daily, monthly, and yearly performance statistics of SWAT models with three weather datasets (NCDC, NEXRAD and PRISM) at two streamflow gauge stations (Bunker and Ellsworth): NSE (a-Daily, b-Monthly, and c-Yearly), pBias (d, e, f), and RSR (g, h, i).

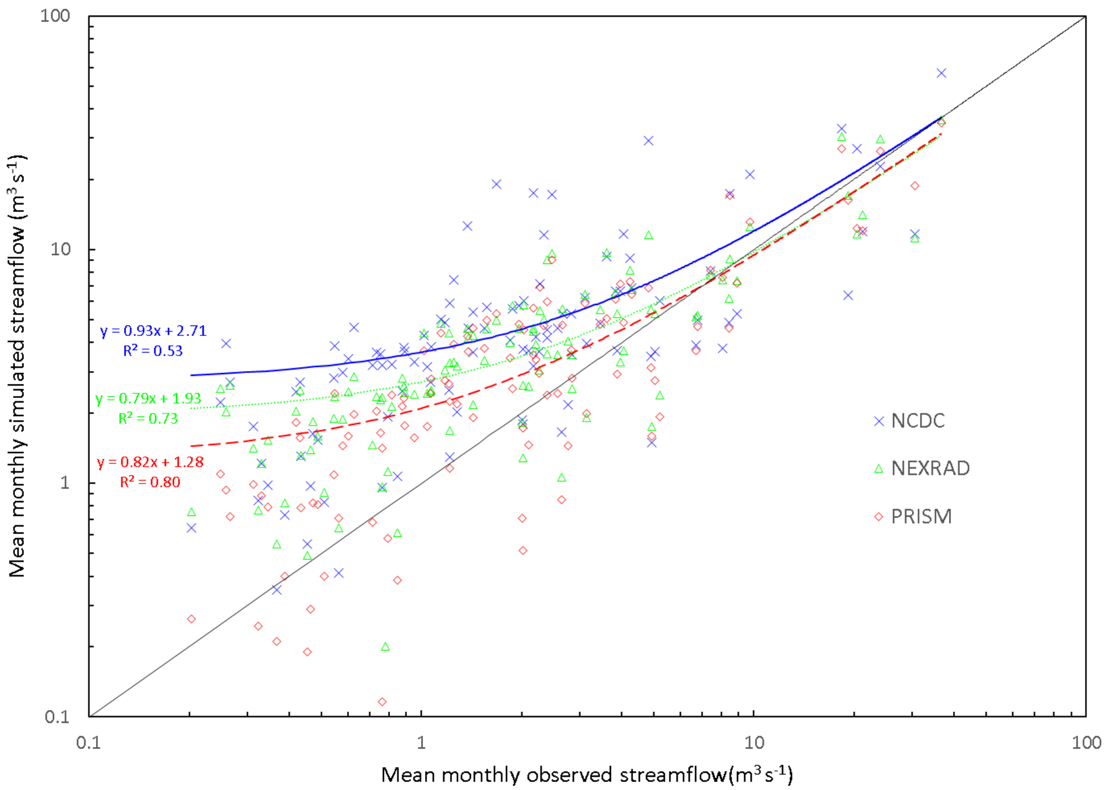

Fig. 6. Monthly simulated versus measured streamflow (m^3 s^{-1}) for three SWAT models with NCDC, NEXRAD, and PRISM weather datasets at Ellsworth, KS station.

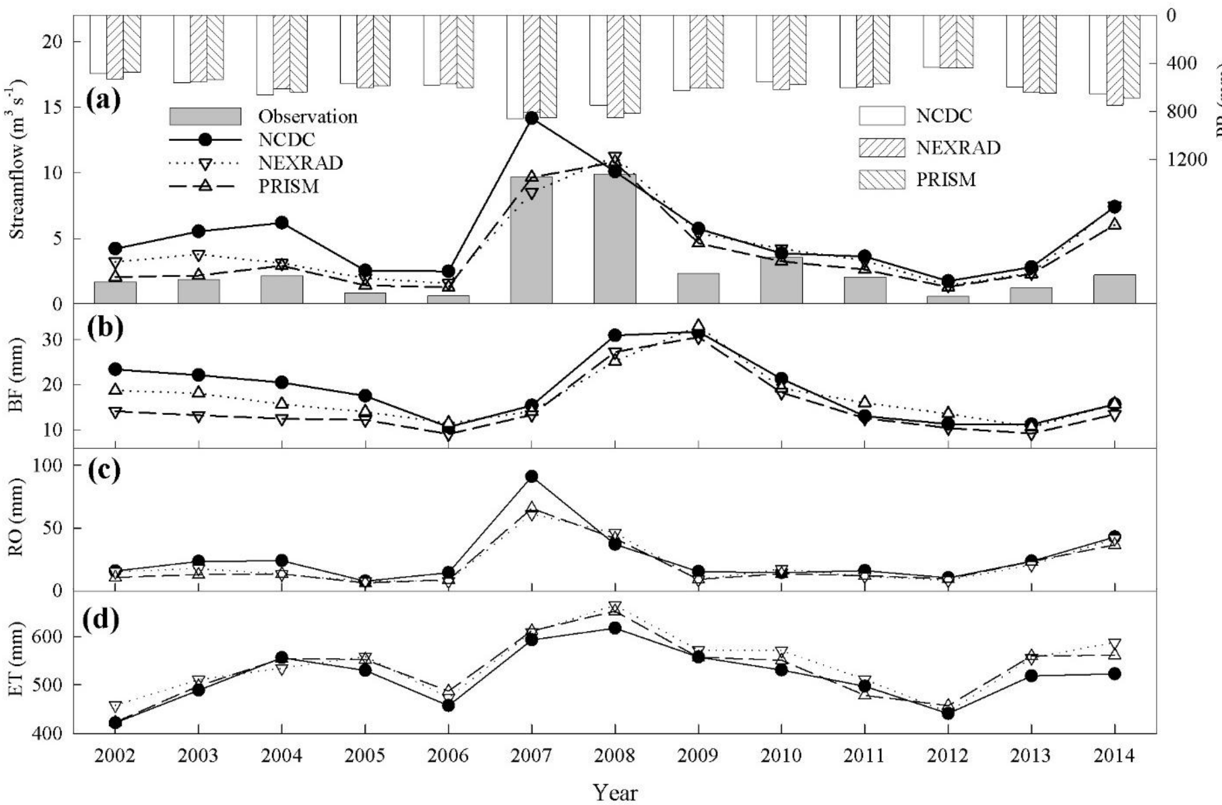

Fig. 7. Annual hydrologic balance components for three SWAT models from 2002 to 2014 for SHRW: (a) mean simulated streamflow at Ellsworth, KS ($m^3\ s^{-1}$), (b) baseflow (BF), (c) surface runoff (RO), and (d) evapotranspiration (ET). Annual precipitation (PR) of three weather datasets are shown in (a) as bars.