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TECHNICAL REPORTS

Environmental Models, Modules, and Datasets

The impact of rainfall distribution methods on streamflow throughout multiple elevations in the Rocky Mountains using the APEX model—Price River watershed, Utah

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Abstract

The hydrology of mountainous watersheds in the western United States is significantly influenced by snow year-round. It is widely known that topography affects precipitation; however, the knowledge of how watershed rainfall designation methods affect streamflow is not well understood for high-relief areas. The objectives of this study were to assess the predictive capability of the Agricultural Policy/Environmental eXtender (APEX) model to simulate streamflow in a snowmelt-dominated watershed with high spatial rainfall variability through (a) allocating weather stations to sub-basins based on a conventional Thiessen polygon method (CM) or a rainfall-elevation–based input (RE) and using an areal average Parameter-Elevation Regression on Independent Slopes Model (PRISM) rainfall designation and (b) improving the snowmelt processes in the Price River watershed, Utah. The updated APEX model with snowmelt parameters significantly improved spring flood simulation. The RE was the most robust method in snowmelt and seasonal streamflow simulations compared with the CM and PRISM rainfall designations. Adapting the APEX model to simulate snow-dominant complex terrains will provide crucial water quantity and quality predictions for reliable environmental and watershed management assessment.

1 | INTRODUCTION

There is a long history of the practical use of distributed watershed models for water resource assessment (Ogden et al., 2001; Perrin et al., 2012; Refsgaard, 1997). Watershed models are used to evaluate the effect of different land management, climate change, and various streamflow scenarios affected by contaminants and amendments (Arnold & Fohrer, 2005; Milly et al., 2005; Saleh & Gallego, 2007; Shen et al., 2009). Distributed models are helpful for environmental decision-makers and planners to better understand the spatial and temporal variability of hydrologic components. These tools can assess environmental issues and natural resource sustainability and simulate mitigation measures (Bahremand & De Smedt, 2010; Chung & Lee, 2009; Refsgaard & Abbott, 1990). Reliable forecasting by hydrologic models relies on accurate spatial and temporal distribution of input variables and consistent and dependable modeling approaches and structures (Chaplot, 2005; Worqlul et al., 2014).

Abbreviations: APEX, Agricultural Policy/Environmental eXtender; CDF, cumulative distribution function; CM, conventional method based on Thiessen polygons; DEM, digital elevation model; NSE, Nash–Sutcliffe efficiency; PU, prediction uncertainty; PRISM, parameter-elevation regression on independent slopes model; PRW, Price River watershed; RE, rainfall-elevation based input.

Precipitation is a primary driver in the hydrologic watershed process, such as streamflow, soil erosion, nutrient dynamics, and crop growth (Arnold et al., 1998; Gassman et al., 2007; Krysanova et al., 1998). An accurate representation of precipitation temporal and spatial distribution is essential. Data scarcity for model input and the hydrologic model's representation of watershed precipitation are significant constraints causing model uncertainty (Abbaspour et al., 2004; Bahremand & De Smedt, 2010; Yaduvanshi et al., 2018). There are multiple rainfall input designation methods applied in hydrological modeling. Among these methods, the most common rainfall designation method in hydrological models is to represent the watershed or subwatershed rainfall by the nearest rainfall station. Hydrologic models, including the Agricultural Policy/Environmental eXtender (APEX) Williams et al., 1998), the Soil and Water Assessment Tool (Arnold et al., 1994), and the Hydrologiska Byråns Vattenbalansavdelning (Lindström et al., 1997), have the option to represent the watershed rainfall by a single proxy station because of data scarcity. A landscape is heterogeneous with different soils, land use, precipitation gradients, and topographies. As data have become increasingly available, additional methods of rainfall designation are necessary to capture precipitation more realistically within watersheds that can reflect their topographies.

Several rainfall designation methods within the APEX model have been tested previously (Sirisena et al., 2018; Tuo et al., 2016). The conventional method based on Thiessen polygons (CM) usage is common to watershed hydrologic models. With the CM, the rainfall station closest to the watershed center is assigned with the representative rainfall for the area. For this study, the APEX model was used to evaluate the effect of the CM and rainfall elevation-based (RE) precipitation allocation on streamflow simulation and output uncertainty. The third designation relies on the average rainfall estimation from the topographically corrected Parameter-Elevation Regressions on Independent Slopes Model (PRISM) (Daly et al., 1994). The PRISM data were developed from gauged data and interpolated by incorporating elevation and landscape position. Even though there are multiple spatial interpolations of precipitation data, such as kriging, these methods require dense gauging stations to develop the variogram model (Ly et al., 2011). The accuracy of these interpolation methods skills relies on the number of stations where data are available. In this study, because there are a limited number of precipitation gauging stations, the conventional method was compared with elevation-based (RE) precipitation allocation (Saleh & Gallego, 2007; Spadavecchia & Williams, 2009) and PRISM data.

The study was applied in the Price River watershed (PRW) located in the mountainous central part of Utah in the western United States. In this part of the United States, seasonal snowpack is a natural water tower (Li et al., 2017). The study was applied to evaluate the effect of rainfall input designation on streamflow simulation using the APEX model. The APEX model has been used as a semi-distributed biophysical model and has proven an effective tool for simulating the hydrologic process in diverse agro-climatic zones (Assefa et al., 2018; Golmohammadi et al., 2014; Medvedev et al., 2015; Tuppad et al., 2010). The specific objectives of this study were (a) to evaluate the current APEX model's precipitation input designation, which uses a CM approach to a rainfall elevation-based (RE) precipitation technique and PRISM to improve precipitation designation in APEX, and (b) to improve the simulation of snowmelt processes by refining conditions to trigger snowmelt in the PRW.

Core Ideas

- Rainfall designation methods were evaluated for streamflow simulation in a mountain watershed.
- Snowmelt simulation in APEX was revised to adjust the timing of snowmelt.
- APEX performed better with the elevation-based rainfall designation method than other methods.

2 | MATERIALS AND METHODS

2.1 | Watershed description

The PRW is located in the central part of Utah, spanning between Carbon, Emery, Utah, Wasatch, Sanpete, and Duchesne counties within the Wasatch Range, a south-central segment of the Rocky Mountains. The watershed covers ~4,540 km^2 as extracted from a 30-m resolution digital elevation model (DEM). The watershed has a complex topography, with elevation ranging from 1,409 to 3,182 m above mean sea level and an average slope of 19%. Figure 1a–d shows the watershed location, rainfall gauging stations distribution, and elevation profile from northwest to southeast and southwest to northeast cross-sections.

2.2 | Climate and streamflow data

The gauged climate data were obtained from a national database developed from ground station–based climate data for the 12-digit watersheds (White et al., 2017). The data were processed from 40,000 weather stations across the United States in which missing data were filled using Shepard's inverse distance weighting (Shepard, 1968). Inverse distance weights were applied to the nearest five stations on a daily

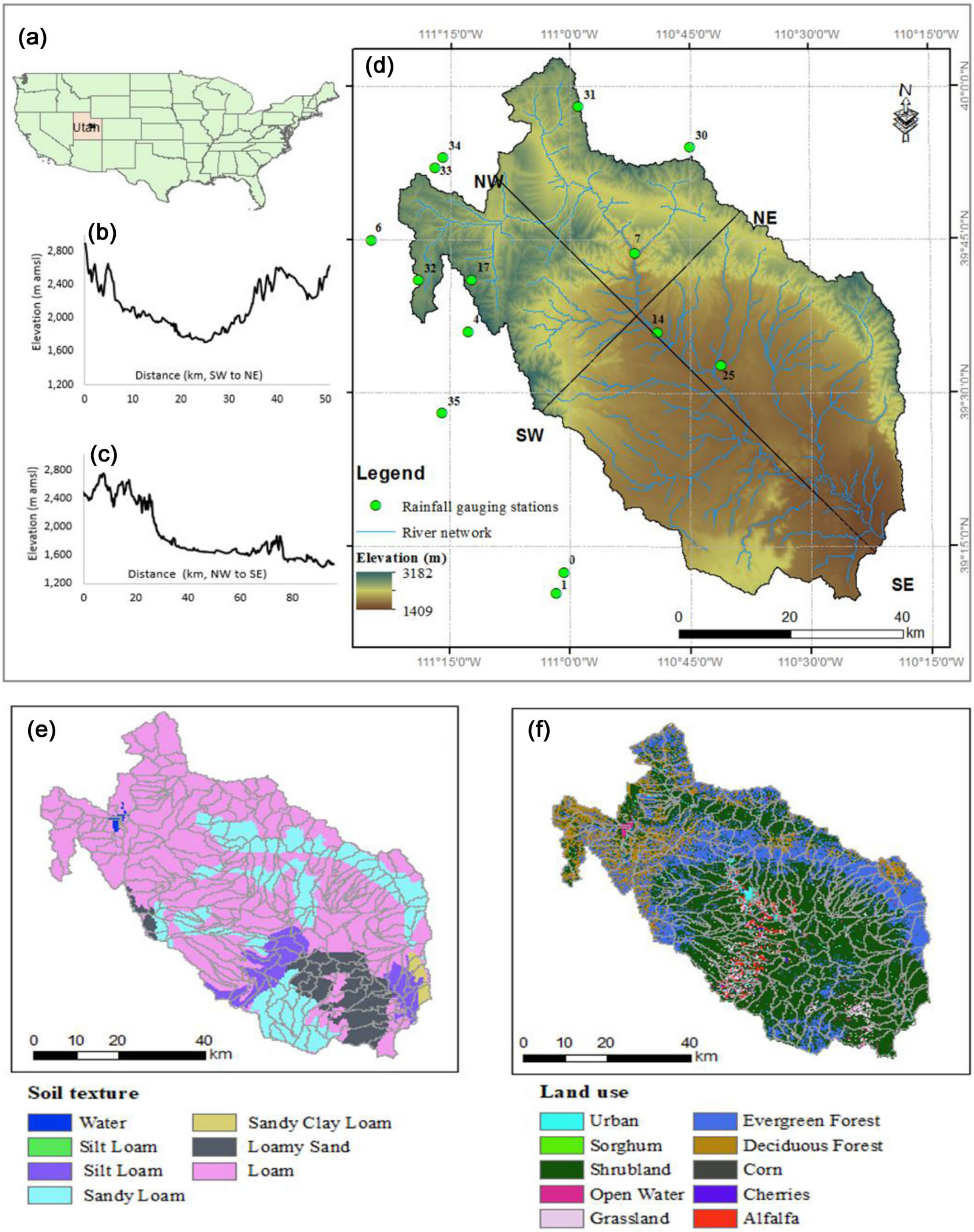

FIGURE 1 The Price River watershed (PRW). (a) The United States and Utah, where the PRW is located. (b) Elevation profile of cross-section from northwest to southeast. (c) Cross-section from southwest to northeast. (d) Price watershed river network with 30-m digital elevation model as background and rainfall gauging stations distribution, (e) soil map, and (f) land use map

basis because there are missing data among the surrounding stations as well. The climate data come from a standard network of stations equipped with Alter shields (windshields) for reducing wind-induced under-catch. There are 38 ground rainfall observation stations inside or within proximity of the watershed (Figure 1d). Fourteen stations have continuous daily-recorded data for ≥75% of the time during the study period (2000–2015). The annual average rainfall exceeds 800 mm at high elevations but drops to 300 mm in the downstream lowland area (Figure 1).

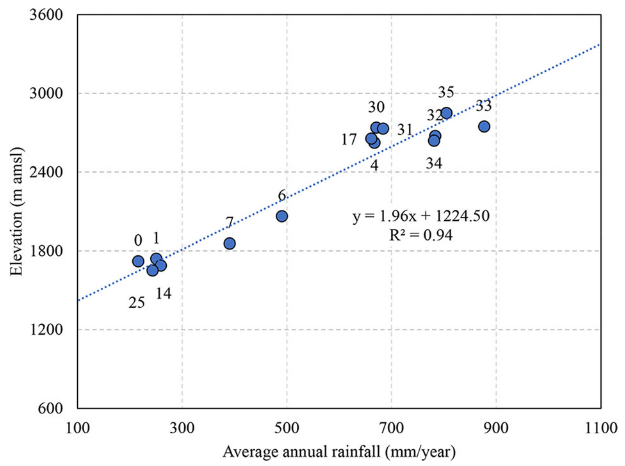

FIGURE 2 Rainfall-elevation–based (RE) relationship in the Price River watershed (USGS gauge ID 09314500)

A rainfall–elevation relationship was developed using data from all weather stations. Figure 2 presents a robust linear relationship between annual rainfall and elevation, where the elevation regimes captured 94% of the observed rainfall variability. The linear function indicates a nearly 2:1 relationship that describes a precipitation lapse rate of 500 mm km^{-1}. The climate data are available at https://ars-usda.box.com/s/5xljg6386n3gth4y035m3d2pwah61qtn (White et al., 2017).

The PRISM rainfall dataset is available on the daily time step and can be obtained from https://prism.oregonstate.edu/explorer/. The data were produced using the gauged climate variables, DEM, and other spatial datasets (i.e., coastal proximity, topographic orientation) to generate gridded precipitation estimates at 4-km spatial resolution (Daly et al., 1997; Radcliffe & Mukundan, 2017). The PRISM data may not be accurate in regions where weather stations are sparse (Raleigh & Lundquist, 2012), though the PRISM incorporated terrain characteristics for improved accuracy.

The streamflow data from 2000 to 2015 were collected from the USGS stream gauge (ID 09314500) located at the outlet of the PRW (Figure 1d). The long-term average monthly streamflow indicated that 65% of the runoff is generated between January and June.

2.3 | Description of the APEX model

The APEX model is a semi-distributed process-based agro-hydrological model. In the APEX model, a watershed is divided into sub-basins based on topography. Then each sub-basin conceptually represents a unique combination of soil, land use, and slope. The APEX model can simulate a detailed landscape process on a daily time step, and the output can be reported on a daily, monthly, or annual basis (Baffaut et al., 2013). The model evaluates the effect of various field and watershed management practices (e.g., streamflow, evapotranspiration, soil loss, water, quality, etc.) at multiple temporal and spatial scales, including field or watershed scales. Input data for the APEX model encompasses soil spatial data; land management practices; landscape information; observed streamflow; digital elevation modeling; and daily climate time series data, including rainfall, temperature, wind speed, relative humidity, and solar radiation.

The current snowmelt routine in the APEX model is based on the soil layer temperature threshold. The melted snow is treated the same as rainfall for estimating runoff and hydrology with rainfall energy set to zero (Williams et al., 2008). The APEX model triggers the snowmelt subroutine when the average air temperature is above 0 °C. In mountainous watersheds where a significant slope gradient on hillslopes exists, air temperature at high elevations may not be well represented by weather stations in lower elevations. The warmer daily average temperature measured at a weather station in the lower elevation can trigger early snowmelts at high elevation subareas where snow accumulates during the winter.

2.4 | Spatial data

The soil map of the watershed was generated by combining the two soil databases: the State Soil Geographic (16%) and Soil Survey Geographic (84%). The soil map indicates that the watershed consists of loamy soil (65.4%), sandy loam (19%), and loamy sand (9%) (Figure 1e). The land use map collected from the USGS National Land Cover Database (NLCD2011; Homer et al., 2015) indicates the primary land use types in the watershed are shrubland, 59%; evergreen forest, 24%; and deciduous forest, 11%. The remaining watershed comprises grassland, urban, open water, and alfalfa (*Medicago sativa* L.) (Figure 1f).

2.5 | Rainfall input designation

In APEX, rainfall volume in each subarea is represented by the nearest single rainfall station to the centroid of the subarea (Galván et al., 2014; Tuo et al., 2016). In a complex topography with high topographic gradients and limited ground rainfall observation stations, the current method of assigning subarea rainfall using a single proxy rainfall station may not be accurate if the rainfall station network is relatively more sparse than subarea sizes.

Fourteen rainfall stations having missing data <25% of the time during the study period were selected in the model. With the CM, the model can only utilize five rainfall stations closest to individual subareas. In the RE interpolation, the linear regression model that characterizes how rainfall volume varies along different elevations (Figure 2) was used to

TABLE 1 The average rainfall of the different rainfall designation methods across the five rainfall regimes

Elevation regime	Conventional method	PRISM	Rainfall elevation–based interpolation	Rain gauges
m amsl	mm			
1,400–1,760	244	236	244	242
1,761–2,120	260	292	355	440
2,121–2,480	464	423	554	–
2,481–2,840	595	552	704	732
2,841–3,200	616	630	837	805

Note. amsl, above mean sea level; PRISM, Parameter-Elevation Regression on Independent Slopes Model.

predict the annual rainfall using the DEM. Next, the predicted annual rainfall was classified into multiple rainfall regimes. The classification applied natural breaks (Jenks) (De Smith et al., 2007; Jenks, 1989). This technique is based on natural grouping (i.e., creating groups of similar values with the least within-class sum of squared differences while maximizing the difference between groups). Finally, a representative nearby rainfall station was designated per subarea in each rainfall regime to represent the spatial rainfall heterogeneity. The grided PRISM rainfall data were aggregated to area-weighted averages at the subarea level and then used as input to APEX. In Table 1, the most notable information is that the distribution of rainfall across elevation regimes is similar between the CM and PRISM methods. At the same time, the RE interpolation differs the most from the CM and PRISM rainfall input designations in high-elevation regimes.

2.6 | Snowmelt module in APEX

Snowmelt is an important subcomponent of watershed hydrology (Hock, 2003). During the winter season in the PRW, the river freezes, and snowpack accumulates on the ground. The accumulated snowpack melts in the spring months, providing a higher runoff that can result in spring floods. The snowmelt-driven flow is a dominant hydrologic process that contributes 37% of the annual streamflow to the Price River. In comparison, excess rainfall contributes to 19–25% of the annual flow; the rest is contributed by groundwater return flow.

The most commonly applied snowmelt processes in a watershed include the temperature index or the degree-day models (Debele et al., 2010; Hock, 1998, 2003). The temperature index or the degree-day model is based on the empirical relationship between air temperatures and melting rates (Braithwaite, 1995; Hock, 2003). This procedure is already incorporated into the APEX model. In APEX, precipitation is partitioned between rainfall and snowfall. If the average daily air temperature and soil surface temperature are above 0 °C, the precipitation is considered as rainfall; otherwise, the precipitation is considered snowfall and deposited on the land (Williams et al., 2006). If snow is present for the day, the APEX model estimates the actual snowmelt amount based on topsoil temperature and solar radiation rate:

$$\begin{aligned} \text{Snowmelt} &= \sqrt{T_{mx} \times \text{SRAD}} \times \left(1.52 + 0.54 \times f \times \frac{2T_{soil2} + T_{avg}}{3}\right) \\ \text{where } f &= \frac{A_{sno}}{A_{sno} + \exp(\alpha \times A_{sno} + \beta)} \end{aligned} \tag{1}$$

where the snowmelt amount is expressed in mm d^{-1}, which is limited by the amount of snow present in mm of water; T_{mx} is the daily maximum temperature in °C; SRAD is daily solar radiation in MJ m^{-2} d^{-1}; T_{soil2} is the daily temperature of Soil Layer 2 in °C; T_{avg} is the daily average temperature in °C; and A_{sno} is the age of snowpack in days. The exponents α and β are the slope and intercept, respectively, that characterize the timing of snowmelt in the spring season. Default values for these parameters are α = −2.395 and β = 5.34. Data on snowpack accumulation and snowmelt volume were unavailable in the study watershed. Thus, the exponential coefficients were refined using streamflow data to characterize snowmelt process. Based on spring flood data at the watershed outlet, these parameters were refined to α = −0.0017 and β = 5.26 to simulate optimum timing and magnitude of spring floods. (Figure 3). As a result, the snowpack's maximum number of days to melt by 99% because the number of snow days was increased from 20 to 96 d. During 2010–2015, the average monthly maximum snow accumulation increased from 18.5 mm in January to 41.2 mm in February, and the snowpack lasted ≥2 mo. In APEX, the increased volume of snowpack and extended duration of the snow-cover period led to a significant volume of streamflow during March and May.

2.7 | APEX model construction and evaluation

The APEX model was evaluated multiple times with a predefined watershed and river network to calibrate the model for the different rainfall input scenarios (CM, RE, and PRISM). The entire watershed was divided into 169 subareas to

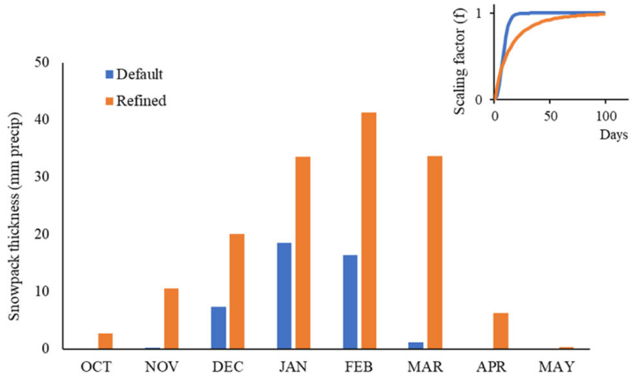

FIGURE 3 The refinement of the snowmelt scaling factor Snow accumulation during winter months is sensitive to the scaling factor in the polymerase chain reaction. The refined scaling factor extends the duration of snowpack until 99% loss of snow from 20 to 96 d in the Agricultural Policy/Environmental eXtender simulation

capture the heterogeneity of soil type, land use, weather, and topographic features. The calibration model parameters controlling the simulated variables were selected from the literature (Wang et al., 2014). Before model calibration, the minimum and maximum model parameters were determined based on our understanding of watershed hydrology (Table 2). The study period was divided into parameter estimation warm-up period (2000–2004), calibration period (2005–2010), and validation period (2011–2015).

The parameter sensitivity analysis and model calibration were achieved using the APEX Calibration and UncerTainty Estimator (Wang & Jeong, 2015), which uses a Dynamically Dimensioned Search (DDS) algorithm to find the optimal parameter combination within the specified model parameter space. The model's parameter sensitivity analysis was achieved by allowing the parameters to change simultaneously, followed by estimating the standardized regression coefficient of the simulated variable (Alfano et al., 2015), and was simulated 3,000 times for parameter optimization. The sensitivity analysis provided insights into the contribution of the model parameter's influence on the output variable (streamflow). The sensitivity index shows the relative strength of the parameters that influence the simulated variable (streamflow). The performance of the different rainfall input methods in the APEX model was evaluated based on streamflow prediction accuracy, parameter uncertainty, and output (simulated streamflow) uncertainty. In all simulations, the current APEX model's snowmelt routine was revised to capture the snowmelt contributions to the runoff.

The performance of the simulated streamflow with the different rainfall inputs was evaluated with performance statistics metrics, including percentage bias, which measures the

TABLE 2 Agricultural Policy/Environmental eXtender model parameters used in model calibration and parameter estimation sensitivity analyses for the three rainfall input designations

Rainfall input designation, parameter description (range)[a]	Conventional		Rainfall-elevation based		PRISM[c]	
	SI[b]	Rank	SI	Rank	SI	Rank
PARM92: Runoff volume adjustment (0.1–2.0)	2.76E-04	1	2.76E-04	1	4.05E-01	1
PARM49: Max. canopy rainfall interception (0.0–15.0)	8.75E-03	2	8.75E-03	2	2.69E-01	2
PARM20: Runoff CN initial abstraction (0.05–0.40)	1.07E-01	3	9.42E-02	3	8.40E-02	4
PARM23: Hargreaves PET equation coeff (0.0023–0.0032)	8.14E-02	4	8.51E-02	4	9.53E-02	3
PARM40: Groundwater storage threshold (0.001–1.0)	2.93E-01	5	2.93E-01	5	5.25E-02	5
PARM15 Runoff CN residue adjustment (0.0–0.3)	3.62E-02	6	3.82E-02	6	3.15E-02	6
PARM17: Soil evaporation-plant cover factor (0.0–0.5)	2.99E-02	7	2.30E-02	8	2.77E-02	7
PARM91: Flood evaporation limit (0.001–1.0)	5.74E-01	8	5.74E-01	7	2.32E-02	8
PARM50: Rainfall interception coefficient (0.05–0.3)	1.36E-03	9	1.36E-03	10	1.03E-02	10
PARM90: Subsurface flow factor (1.0–10.0)	2.36E-02	10	2.36E-02	9	1.13E-02	9
PARM25: Rainfall intensity effect on Curve Number (0.0–2.0)	3.29E-03	11	3.72E-03	11	2.79E-03	11
PARM16: Extends CN retention parameter (1.0–1.5)	1.78E-03	12	2.00E-03	12	1.05E-03	12
PARM61: Soil water upward flow limit (0.05–0.95)	9.46E-03	13	9.46E-03	13	1.00E-03	13
PARM5: Soil water lower limit top 0.5 m (0.0–1.0)	4.29E-04	14	2.76E-04	14	4.92E-04	14
PARM12: Soil evaporation coefficient (1.5–2.5)	2.79E-04	15	1.60E-04	15	2.26E-04	15

[a]The model parameter range represents the possible minimum and maximum value of the parameter adopted from the APEX User Manual (Steglich & Williams, 2008). CN, curve number. [b]Sensitivity index. [c]Parameter-Elevation Regression on Independent Slopes Model.

average tendency of the simulated values to be larger or smaller than those observed; R^2; and the Nash–Sutcliffe efficiency (NSE). The NSE is a normalized statistic that determines the relative magnitude of the residual variance compared with the measured data variance (Nash & Sutcliffe, 1970). The NSE indicates how well the simulated data capture the pattern of the observed data. The value of NSE = 1 indicates a 1:1 match of the model simulation to the observed data; NSE < 0 demonstrates that the observed data mean is a better predictor of the measured variance than the model.

2.8 | Output and parameter estimation uncertainty

The optimal model parameter estimation distribution sets and their respective simulated streamflow estimated values were used to evaluate their parameter values and output uncertainty levels. The behavioral parameter sets of the CM, RE, and PRISM rainfall inputs were identified by applying a threshold value of 15% from the optimal NSE values. The different rainfall input model parameter estimates were used to generate cumulative distribution functions (CDFs) to evaluate the uncertainty of the optimal model parameter values. The understanding of model parameter value uncertainty ranges was used to narrow the parameter calibration ranges and reduce the model output uncertainty.

The model output uncertainty was compared (Her & Chaubey, 2015) per method of rainfall input designation. The uncertainty of the output values was measured by the percentage of data bracketed by 95% predicted uncertainty (PU) and the average thickness of the 95% PU over dry and wet periods. The 95% PU was calculated as the 2.5 and 97.5% level of the behavioral parameter's cumulative distribution, which is 15% of the optimal solution.

3 | RESULTS AND DISCUSSION

3.1 | Effects of rainfall designations on model performance

The strong association between annual rainfall and elevation relationship reveals the significant effect of topographic relief affecting the watershed's rainfall pattern with an R^2 of .94 (Figure 2). This demonstrates that the topographic relief affects the rainfall pattern by obstructing the moist airstreams and can create a combination of orographic and convective rainfall (Spreen, 1947).

The performance of the PRISM data was compared with the gauged-ground rainfall data stationed within the PRISM grid (point-to-grid comparison) (Worqlul et al., 2014). Figure 4 illustrates the comparison of the monthly average gauged and PRISM rainfall (2000–2015). The PRISM data captured the measured precipitation well, with a R^2 ranging from .75 to .96, which indicated that the PRISM rainfall captured 75–96% of the gauged rainfall variability with an average of 91% and a median of 93%. Similar performance of PRISM data was reported in mountainous areas, including Kandal, Cambodia (Lee et al., 2014); South Korea (Jeong et al., 2020); and the northwestern corner of Washington State, United States (Currier et al., 2017). Overall, the PRISM data are well situated in mountainous terrains because the data incorporate a conceptual framework that considers orographic precipitation (Daly et al., 1994).

3.2 | Sensitivity analysis

The results of the sensitivity analysis are listed in Table 2, with the sensitivity index and their respective ranking. The most sensitive parameters within the three rainfall input designations were runoff volume adjustment factor (PARM92), maximum canopy rainfall interception (PARM49), and runoff curve number initial abstraction (PARM20). It is evident from the sensitivity ranking that surface runoff processes significantly influence streamflow in the main channel. The model parameters ranking 10–15 were excluded from further calibrations due to their negligible influence over the simulated variable.

3.3 | Impact of improved snowmelt simulation

The simulated streamflow performance, with the original and revised snowmelt routines, is presented in Table 3. In all cases of rainfall input designation, the model's performance statistics indicate improvement with the revised snowmelt routine. The simulated streamflow without snowmelt improvement exhibited higher spring flood peaks that occurred in earlier months when compared with the snowmelt improved output. These shifts in spring floods influenced both central tendencies and variances negatively. Among the three cases of rainfall designation, the RE interpolation yielded the most robust correlation coefficients (R^2: calibration, .83; validation, .64) in streamflow.

3.4 | Streamflow simulations with different rainfall input designations

The simulated streamflow performances for the calibration and the validation periods under the CM, RE, and PRISM rainfall input designations are presented in Table 3. The simulated performances of the three rainfall input designation

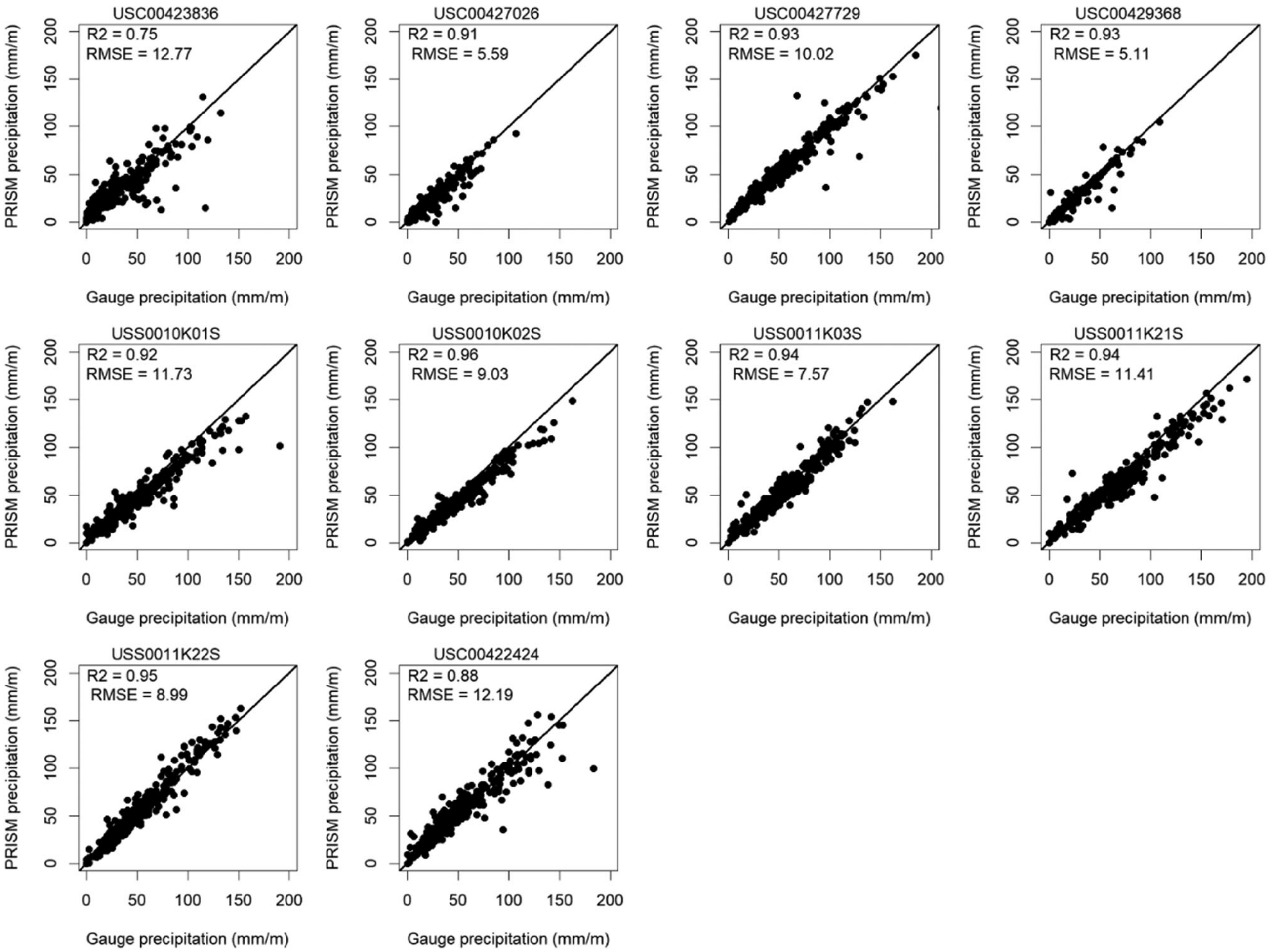

FIGURE 4 Correlation between gauged rainfall and Parameter-Elevation Regression on Independent Slopes Model (PRISM) rainfall data in the Price River watershed (2000–2015)

TABLE 3 Performance of the original and revised Agricultural Policy/Environmental eXtender (APEX) model snowmelt routine for the three-rainfall input designations

Rainfall input designation			Conventional method	Rainfall elevation-based	PRISM
Original APEX snowmelt routine	Calibration (2005–2010)	PBIAS	–17.91	21.85	–5.76
		R^2	.23	.41	.19
		NSE	.01	.37	–12
Revised APEX snowmelt routine	Calibration (2005–2010)	PBIAS	2.56	15.60	21.50
		R^2	.58	.83	.57
		NSE	.54	.70	.55
	Validation (2011–2015)	PBIAS	6.15	16.14	19.60
		R^2	.40	.64	.55
		NSE	.36	.46	.32

Note. NSE, Nash–Sutcliffe efficiency; PBIAS, percentage bias (a negative value means that the model overestimated streamflow); PRISM, Parameter-Elevation Regression on Independent Slopes Model.

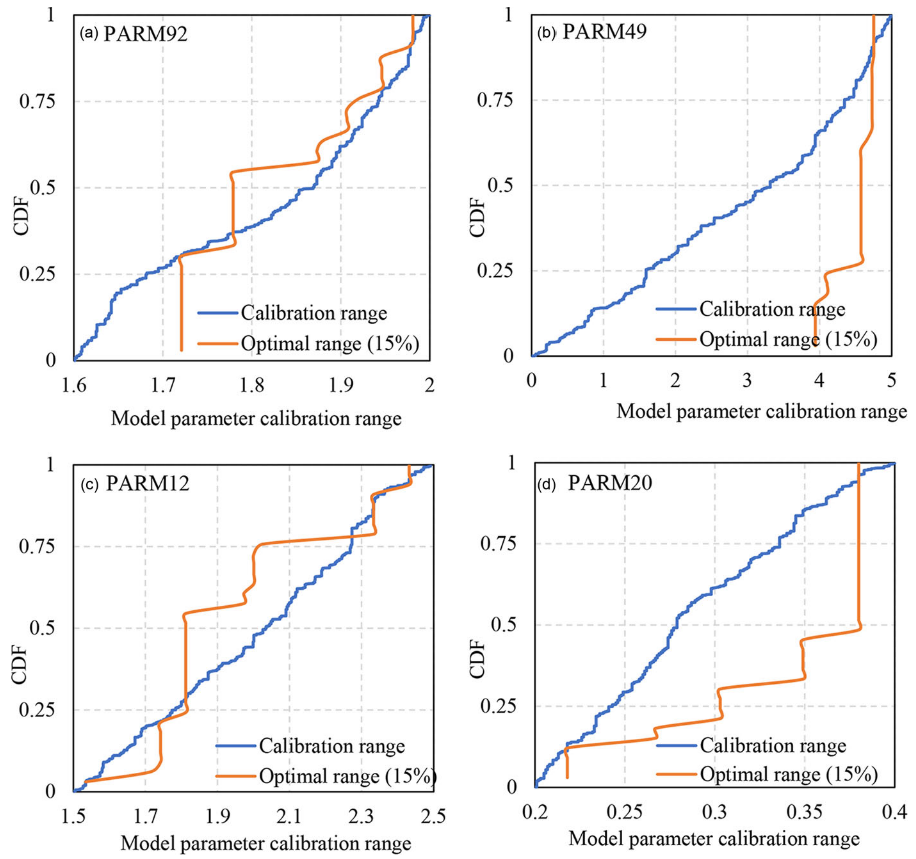

FIGURE 5 Cumulative distribution functions (CDFs) of the most (a, b) and least (c, d) sensitive parameter estimate value ranges for the behavioral solutions for the conventional Thiessen polygon method, Parameter-Elevation Regression on Independent Slopes Model, and rainfall-elevation–based rainfall input designations

methods were compared among each other's results to discern their significant variability in rainfall distribution due to topography. The result indicated that the simulations are statistically significantly different from each other ($\alpha = .05$), with the RE and PRISM simulated streamflow being the most significantly different. The CM rainfall designation to a subarea by proximity performed similarly to the PRISM rainfall data. The RE interpolation was the most accurate in capturing seasonal streamflow trends (high flow or low flow). The CM was the most robust interpolation for estimating the mean streamflow rate.

3.5 | Uncertainty analysis

For each rainfall input designation, parameterization uncertainty was evaluated by constructing the CDF for the parameter's complete and behavioral solutions. The behavioral model parameters were extracted within the 15% threshold of the optimal NSE. The analyses indicated 10, 32, and 151 behavioral solutions for the CM, PRISM, and RE rainfall input designations, respectively. The CDF of the most sensitive and least sensitive parameters were constructed for the complete and behavioral solutions in Figure 5. The most sensitive model parameters, including PARM92 and PARM49, indicated a narrow range of optimal solutions. However, the least sensitive model parameters, such as PARM12 and PARM20, showed a more comprehensive range of optimal solutions; this indicates that nearly 100% of the model parameters' calibration ranges could provide an optimal solution (Green & Van Griensven, 2008). Regardless of rainfall input designation, the CDFs provided considerable uncertainty of optimal solutions of the least sensitive model parameters providing suitable fitting model parameter estimates throughout the model parameter value ranges. In comparison, the most sensitive model parameters indicated lower estimated uncertainty value ranges by providing a narrow range of solutions for the three rainfall designations.

The output uncertainty was evaluated using the simulated streamflow within 15% of the best fit for the optimal solution. It was measured with the percentage of simulated flow bracketed by 95% PU and by the average thickness of the 95% PU over dry and wet periods (Figure 6). The result indicated that RE rainfall designation had a higher output uncertainty. On average, the thickness of the 95% PU was ~1.36, compared with 0.77 for the CM and 0.99 for the PRISM data. The

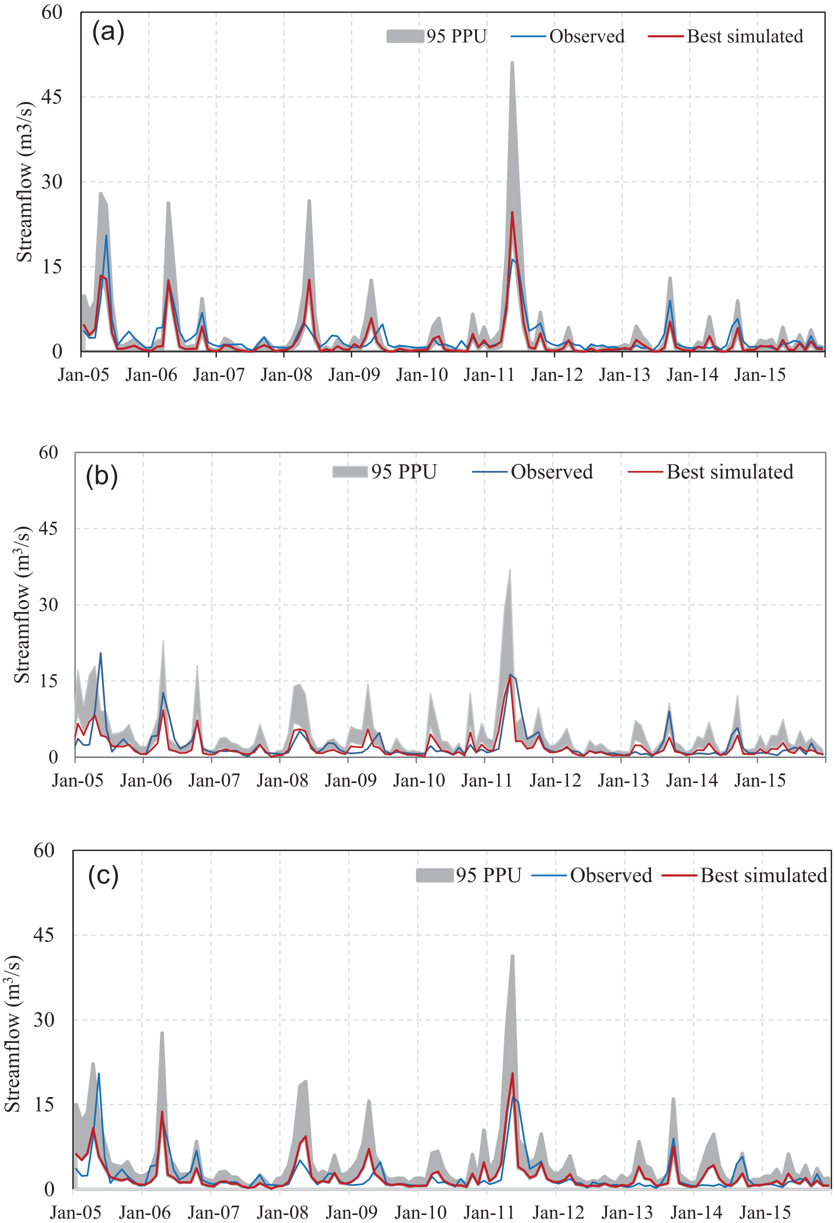

FIGURE 6 Output uncertainty of the behavioral solution within 15% of the optimal solution for the (a) conventional Thiessen polygon method (CM), (b) rainfall-elevation based (RE) method, and (c) the Parameter-Elevation Regression on Independent Slopes Model method. 95 PPU, 95 percent prediction uncertainty

output uncertainty evaluated on dry and wet seasons indicated that RE rainfall input designation has a higher output uncertainty for both seasons.

A simplistic rainfall representation accommodates small watershed–scale and field-scale models; however, to capture elevation gradients with heterogeneous rainfall distributions, a more rigorous method must be used for an accurate representation of precipitation distribution. According to Masih et al. (2011) and Tuo et al. (2016), a correct watershed representation with realistic subarea development, including rainfall with the proxy rainfall station(s), needs the optimal tools and understanding of the method of rainfall input with elevation; otherwise, an ill-posed model structure and insufficient parameter valuation present further problems. Therefore, improved prescription of rainfall inputs that consider spatial variation is crucial.

4 | CONCLUSION

The study evaluated the effect of precipitation input data designation in a high-elevation-gradient watershed on reproducing observed streamflow using the APEX model. Three sets of precipitation datasets (i.e., gauge, elevation-corrected gauge, and PRISM) were tested in the APEX model. Unlike the conventional approach, whereby each sub-basin is assigned with the nearest gauging station data to a sub-basin centroid, both the elevation-corrected and PRISM precipitation data were prescribed to each sub-basin. The model's performance was evaluated by comparing the simulated streamflow with the observed streamflow using multiple performance statistics. Additionally, the output and behavioral model parameter uncertainty was estimated for each input rainfall data source.

Traditional rainfall representation in the APEX model is simplistic, which could work reasonably at a field or watershed scale. For a large watershed with a significant elevation gradient with a heterogeneous rainfall distribution, representing subarea rainfall with the proxy rainfall station will lead to overparameterizing the model. Therefore, improved rainfall inputs, such as elevation-based rainfall designation and elevation-corrected rainfall data like PRISM, are crucial. The study indicated that the model parameter uncertainty is not highly correlated with the rainfall input; however, the simulated outflow indicated a significant variation based on the rainfall designation because they provide different rainfall data at spatial and temporal scales.

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AUTHOR CONTRIBUTIONS

Abeyou W. Worqlul: Conceptualization; Formal analysis; Investigation; Visualization; Writing-original draft. Jaehak Jeong: Conceptualization; Formal analysis; Funding acquisition; Writing-original draft; Writing-review & editing. Colleen H.M. Green: Project administration; Writing-review & editing. Tadesse A. Abitew: Data curation; Formal analysis.

CONFLICT OF INTEREST

The authors declare the following financial interests/personal relationships, which may be considered as potential competing interests: Colleen Green is an employee of the Bureau of Land Management, which is the funding source for this project.

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