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Influence of spatial resolution of radar images on the parameterization and performance of SWAT model

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ABSTRACT

Recent advances in environmental monitoring improve data quality and availability in space and time, but questions about their beneficial use in water resources analysis and modeling still remain. This study assesses the dependency of the parameterization and performance of a watershed-scale simulation model, the Soil and Water Assessment Tool (SWAT), on high-quality (rainfall) data at different spatial resolutions. The SWAT model was applied to the upstream of the Yeongsan River in Korea which remained relatively unexploited, and was calibrated and validated with the observed daily flow and monthly sediment data for the periods of 2012–2013 and 2014, respectively. Results showed that the radar rainfall estimates, derived using bias adjustment factors A_1 and A_2 which allowed the number and magnitude of storm events to be corrected, respectively, fitted excellently with the standard gauging data (R^2 = 0.97–0.98). Interestingly, the recommended parameter sets for steam flow were significantly different among the rainfall data-sets at different resolutions, but not for sediment concentration. The prediction accuracy of the model was, on average, higher not only during the calibration period than for the short-term validation period, but also using all the radar data-sets than using the standard gauging data. These results demonstrate that although we cannot recommend the best input among the new rainfall products in this preliminary study, the optimal parameter sets developed from many local and regional studies using the SWAT model need to be revisited fundamentally.

Keywords: Rainfall radar image; Digital image processing; Soil and Water Assessment Tool; Advanced environmental monitoring; Bias correction; Calibration parameter sets

1. Introduction

Environmental monitoring data in surface waters support scientific analysis and modeling of water resources impairment at different spatial and temporal scales, assisting in developing sustainable watershed management plans [1,2]. Climate and land use changes were found to regulate watershed processes such as stream flow regime, soil erosion, and chemical transport, along with a mix of other human activities [3]. The watershed response, however, significantly differed depending on the intensity, frequency, and duration of these factors as well as environmental settings that had different interactions among physical, chemical, and biological processes [4]. Simulation models for watershed management have been a cornerstone for integrating these complex relationships, no matter how

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the watershed dynamics in terms of the landscape delineation and temporal scheme were handled well in individual models [5,6]. Defining the temporal and spatial boundaries adequately in the simulation models is, therefore, crucial in understanding the chronic and cumulative effects of the environmental factors on surface water resources [1,7]. Further discussion of different representations of the temporal and spatial variability in the watershed simulation models is available elsewhere [1,6,8].

Advanced sensors and computing technologies enhance the simulation models which are adequate for predicting extreme storms and floods, and even debris flow and landslides, as long as fine scale hydrological processes are fully accounted for in those models [9,10]. This is mainly because explaining the variability of the input data (i.e. reducing their uncertainty) contributes to increasing the accuracy and reliability of the simulation model outputs [11,12]. Due to this reason, radar observations, which played an important role in reducing the rainfall heterogeneity (i.e. as high as 1 km for 5 min in the spatial and temporal scales) along with satellite data (i.e. 1–4 km for 5 min), have become favored and acceptable as the input data for common hydrologic studies [13]. The radar-derived rainfall estimates were examined for an inter-model comparison between the lumped and distributed models [14], flash flood prediction through an uncalibrated hydrological model [10], and multiple watersheds of different watershed characteristics and contamination activities using the watershed model [4], just to name a few. The conditional bias of the radar data and their efficient correction remained a major hurdle for operational applications, even though the simulation models accommodated the inherent uncertainty of the input data using calibration in a sophisticated manner [13,15,16]. More information on recent developments and future directions for use of the radar data-sets in hydrologic research is also documented well in literature [13,17].

Accordingly, this study is motivated by an interest in assessing the requirements of the spatial rainfall resolution for the water resources modeling. By applying a semi-distributed watershed model, the SWAT, into a small drainage basin, we specifically (1) investigated the accuracy of the radar rainfall products derived from local bias adjustment factors, (2) identified sensitive parameters and their optimal values for estimates of stream flow and sediment concentration against the rainfall data-sets at different coverage area, and (3) compared the model performance during calibration and validation periods using the parameter sets recommended from each rainfall data-set. It is our hope that the proposed methodology encourages end users to achieve more realistic parameter values that best reflect the watershed response or characteristics in question.

2. Materials and methods

2.1. Study area

Fig. 1 shows the geographical location of study area, the upper section of the Yeongsan (YS) River in Korea. We specifically selected the YS River as an example case study of the SWAT model run because this river had homogeneous land use characteristics while retaining its near-pristine condition in terms of the hydrological regime. Note also that the YS River holds the record for the shortest river in Korea as compared to other principal river systems such as Han, Geum, and Nakdong Rivers, and thus, is much simpler to accurately represent and simulate through the model (see Fig. 1). All these ideal conditions will reduce additional complexity involved in the model parameterization and performance assessment. The selected basin mainly consisted of agricultural and forest lands with a drainage area of 498.6 km^2. The rainfall and other weather variables in the selected basin were regularly monitored by two standard gauges, Damyang and Gwangju Institute of Science and Technology (GIST), which were located in the cities of

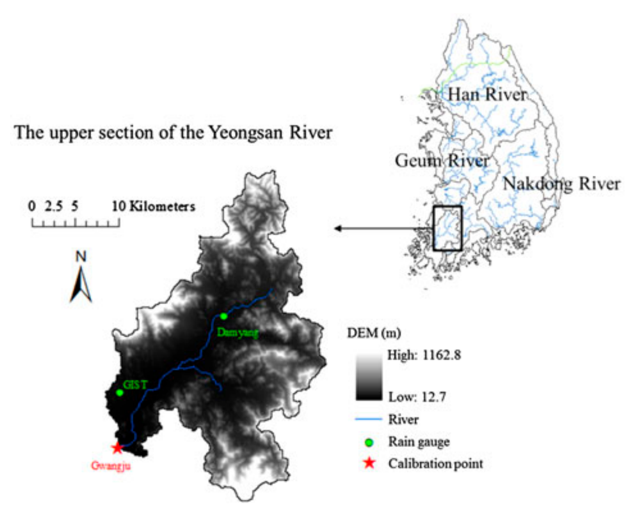

Fig. 1. Map of the study area located in the upper section of the Yeongsan River (Basin), Korea. Solid circles shown in green color indicate two rain gauges installed at the Damyang City and the Gwangju Institute of Science and Technology (GIST) which is located in the Gwangju City. The Gwangju station represents the final outlet of the basin which is used for calibration.

Damyang and Gwangju, respectively. The Gwangju station was one of the monitoring locations along the river measuring stream discharge and sediment concentration, which was used later as a calibration point that compared observed with predicted ones. The weather, discharge, and sediment data were obtained through online information websites which were supervised by the Korea Meteorological Administration (KMA, http://www.kma.go.kr/), Ministry of Land, Infrastructure, and Transport (http://www.wamis.go.kr/), and Ministry of Environment (http://water.nier.go.kr/), respectively.

2.2. SWAT simulation

We used the SWAT model as a prototype to investigate the effect of spatial rainfall resolution on the water resources modeling. The SWAT model is a popular simulation tool that allows watershed-scale analysis for water quantity and quality regimes, supporting water management activities at various spatial (for field to continental analysis) and temporal scales (on daily to decadal basis). The input data for the model are divided into two categories: mandatory (e.g. digital elevation, land cover/land use, and soil data) and optional data-sets (e.g. external point discharge and reservoir outflow data) [9]. Specifically, the weather data (e.g. rainfall, solar radiation, relative humidity, etc.), which are also classified as the necessary inputs, are used to account for the spatial variability of hydrological processes in different drainage units (i.e. sub-basins) based on changes in atmospheric boundary conditions [16]. After all digital data-sets required were submitted to the model, the entire basin was initially divided into a series of sub-basins, which were then discretized further into multiple hydrological response units (HRUs). The number of sub-basins and HRUs delineated finally varied depending on the threshold size (in units of km^2, hectares, or number of cells) and definition of land use, soil, and slope (in units of percentage or area), respectively. As will be discussed in more detail later, we increased the number of (virtual) weather stations derived from the radar images correspondingly with increasing numbers of sub-basins, from the default 3 to 34 sub-basins (see Table 1), to assess the relationship between the spatial rainfall resolution and model parameterization or accuracy. A total of four different sets of sub-basins (i.e. 3, 11, 21, and 34) were prepared for this purpose. In each set of sub-basins, the parameters that were highly sensitive to the model outputs were determined using the Latin Hypercube One-factor-At-a-Time (LH-OAT), which was found to more efficiently retrieve samples (or values) within the full parameter ranges than random or full factorial sampling [18]. The SWAT model was calibrated to the (observed) daily flow and monthly sediment data for two years (2012–2013), and run for validation in the following one year (2014). More detailed information is available elsewhere, specifically for the model operation [19] and the LH-OAT [18].

2.3. Radar image processing

In addition to the precipitation data obtained from (two) standard rain gauges, the rainfall estimates from the radar images were provided as alternative weather inputs to the SWAT model. Fig. 2(a) and (b) shows examples of raw and processed radar data-sets, respectively, which is initially obtained on a 10-min basis for most parts of the Koran Peninsula from the KMA (http://kma.go.kr/weather/images/rader_composite_cappi.jsp) and then converted to red, green, and blue (RGB) color space for selected areas using the image processing toolbox in MATLAB. Note that the raw data-set integrated from multiple sites over the peninsula is provided from the KMA after bias correction due to signal attenuation by clouds, smog, fog, etc. The processed data-set that contained the RGB color code between 0 and 255 for each cell was transformed to rainfall rates (in unit of mm/h) using color indices provided along with the raw radar image (see color legend in Fig. 2(a)). In other words, the same image processing applied to the color indices to match the color code of the processed data-set and that of the color indices. The raw radar image contained a total of 527 × 576 grids (see Fig. 2(a)), each of which had a resolution of 2 km by 2 km (see Fig. 2(b)). The converted rainfall estimates were corrected with the number (A_1) and magnitude of storm events (A_2) observed in the standard rain gauges, such that:

$$A_1 = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{RIS}_i}{\mathrm{RIR}_i} \quad (1)$$

$$A_2 = \frac{\mathrm{RIS}_{\max} - \mathrm{RIS}_{\min}}{\mathrm{RIR}_{\max} - \mathrm{RIR}_{\min}} \quad (2)$$

where RIS and RIR indicate the rainfall intensities of the standard rain gauges and radar images, respectively. Also, n refers to the number of the rain gauges used in this estimation, whereas subscripts min and max represent the minimum and maximum values for a specific storm event, respectively. The mean of

Table 1
Characteristics of various weather data used for the SWAT simulation

Names	Data sources	Sub-basins	Weather stations	Average coverage area (km^2)[a]
Gauge 2	Rain gauges	3	2	249.32
Radar 3	Radar images	3	3	166.21
Radar 11	Radar images	11	11	45.33
Radar 21	Radar images	21	21	23.74
Radar 34	Radar images	34	34	14.67

[a]The average coverage area is estimated by dividing the total area of basin by the number of weather stations.

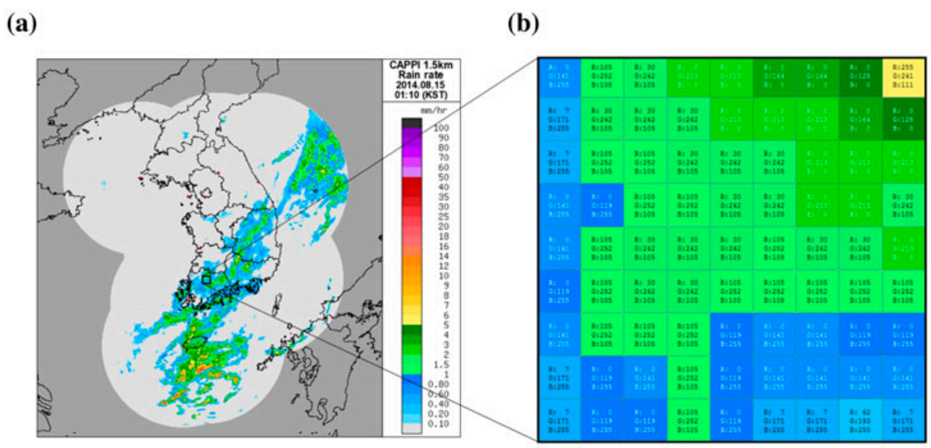

Fig. 2. A snapshot for image processing operation: (a) an example radar image which is obtained from the Korea Meteorological Administration (http://kma.go.kr/weather/images/rader_composite_cappi.jsp) and (b) the converted red, green, and blue (RGB) color image.

several estimated values for A_1 and A_2 in the selected basin was finally used to adjust the rainfall estimates, which were converted through the image processing operation, all at once. Note that there is no difference in the temporal resolution between the radar and rain gauge data-sets when comparing them to each other: in fact, both are accumulated on a daily basis.

3. Results and discussion

3.1. Coverage area and accuracy of rainfall estimates

Fig. 3 illustrates different sets of sub-basins and their corresponding weather stations in the selected basin. Here, the standard rain gauges and (virtual) weather stations that are generated from the radar images are indicated by solid circles (see Fig. 3(a)) and squares (see Fig. 3(b)–(e)), respectively. In Fig. 3(a), there is a sub-basin to which the rain gauge is not assigned. In such a case, the weather data obtained from the closest gauge are typically provided. In contrast, there are no sub-basins that do not include the weather stations for the radar data-sets. This is because we intentionally allocate them (mainly) in the center of individual sub-basins to assess their effect on the model parameterization and accuracy while increasing the number of both sub-basins and weather stations, simultaneously. Table 1 shows detailed information of various weather data used for the SWAT simulation and their average service area per either rain gauge or weather station. As shown in the table, the average coverage area decreased considerably with increasing number of weather stations. This indicated that we provided sufficiently high resolution rainfall products to the model, which was around 17 times greater than the original rain gauges. However, note that the resolution of each grid in the radar data-set is 4 km^2, so it is still lower than the highest resolution rainfall product that is provided to the model. This implies that we provide as much accurate information as possible for each sub-basin rather than simply averaging or interpolating the adjacent values in individual grids. Fig. 4(a) and (b) presents the accuracy of the rainfall estimates derived from the radar data-set against the observed ones in the GIST and Damyang,

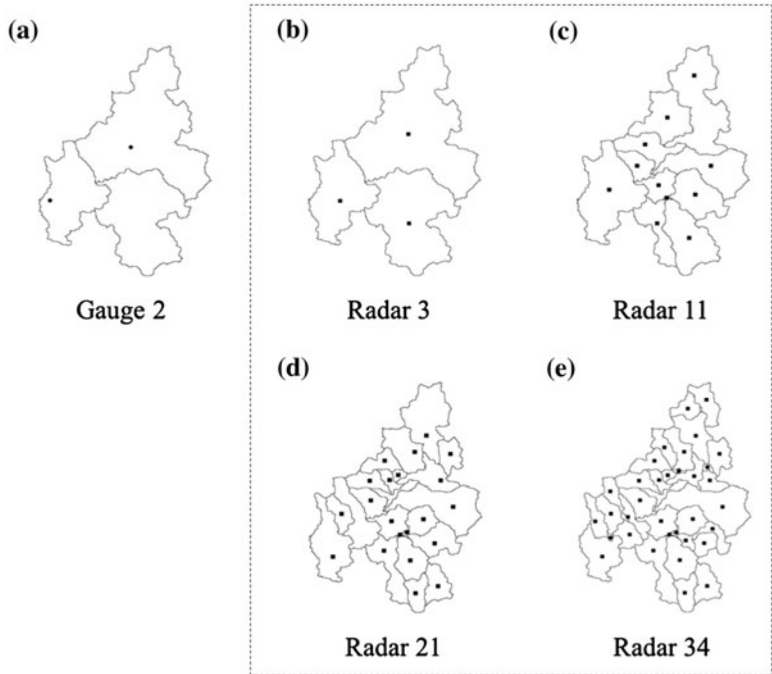

Fig. 3. The location of weather stations in the upper section of the Yeongsan River (Basin), Korea. Shown as solid circles in (a) are the original rain gauges, whereas solid squares in (b) through (e) indicate the stations that are newly created from the radar images according to the number of sub-basins.

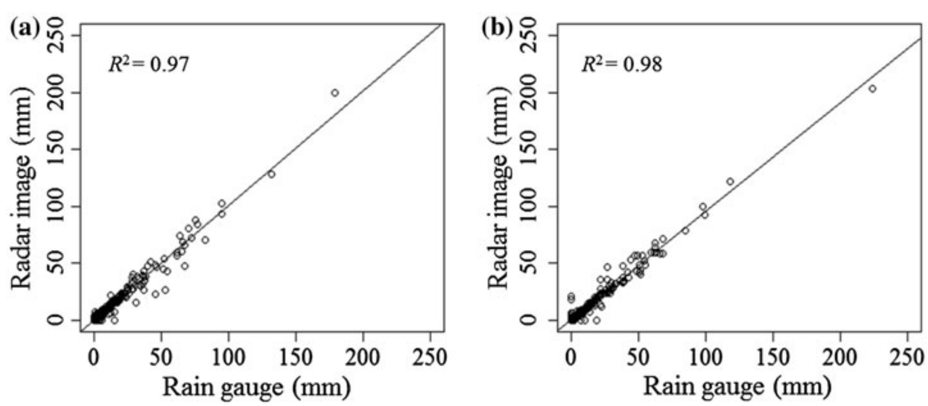

Fig. 4. A comparison between the observed data and rainfall estimates which are computed from the radar images after adjustment to the rain gauge data: (a) GIST and (b) Damyang.

respectively, using the adjustment factors A_1 and A_2 averaged for the selected basin. As shown in both figures, the radar-derived precipitation estimates were in good agreement with the measured data ($R^2 = 0.97$–0.98), indicating that the adjustment factors developed locally were useful for bias correction of the radar data-sets.

3.2. Sensitivity and parameterization of the SWAT model

Table 2 presents sensitivity test results for important input parameters that have large effects on output variables (i.e. stream flow and sediment concentration) at the Gwangju station, in response to different weather data from Gauge 2 to Radar 34. In the table, the string in columns of the input parameters

Table 2
Sensitivity analysis of flow and sediment parameters in the SWAT model using the weather inputs with different coverage areas

		Input parameters[a]				
Output variables	Rank	Gauge 2	Radar 3	Radar 11	Radar 21	Radar 34
Flow	1	Surlag	Surlag	Cn2	Ch_K(2)	Ch_K(2)
	2	Cn2	Cn2	Surlag	Surlag	Cn2
	3	Alpha_Bf	Alpha_Bf	Ch_K(2)	Cn2	Surlag
	4	Ch_K(2)	Ch_K(2)	Alpha_Bf	Alpha_Bf	Alpha_Bf
	5	Ch_N(2)	Ch_N(2)	Ch_N(2)	Ch_N(2)	Ch_N(2)
	6	Gwqmn	Gwqmn	Gwqmn	Gwqmn	Gwqmn
Sediment	1	Spcon	Spcon	Spcon	Spcon	Spcon
	2	Prf	Prf	Prf	Prf	Prf
	3	Spexp	Spexp	Spexp	Spexp	Spexp

[a]Definitions: Surlag = the surface runoff lag coefficient, Cn2 = the moisture condition II curve number, Alpha_Bf = the baseflow alpha factor, Ch_K(2) = the effective hydraulic conductivity in main channel alluvium, Ch_N(2) = the Manning's n value for the main channel, Gwqmn = the threshold water level in shallow aquifer for baseflow, Spcon = the linear parameter for channel sediment routing, Prf = the peak rate adjustment factor for sediment routing, and Spexp = the exponent parameter for channel sediment routing. For more detailed information on the parameters, refer to the SWAT input/output file documentation for version 2012 (http://swat.tamu.edu/documentation/).

indicates the data sources of weather data, whereas the integer refers to the total number of gauges or weather stations provided to the model (see also Table 1). From the table, it was found that the input parameters related to sediment concentration were not sensitive to both the type of weather data and the number of weather stations. However, the ranking of sensitive model parameters for stream flow highly varied depending on the number of weather stations, except for the parameters Ch_N(2) and Gwqmn. For example, while the effective hydraulic conductivity in main channel alluvium Ch_K(2) was ranked as the most sensitive parameter for Radar 21 and 34, this was ranked the third for Radar 11 and the fourth for Gauge 2 and Radar 3. Note that there is no difference in parameter sensitivity between Gauge 2 and Radar 3 due to a small difference in the rainfall products between them (see Fig. 4(a) and (b)). These results clearly implied that the number of weather stations above certain threshold played an important role in predicting stream flow, although this statement was not always true for basins with other environmental conditions. Table 3 shows the optimal parameter values obtained from calibration of stream flow and sediment concentration in the final outlet of the selected basin for various weather data. As discussed above, the calibrated parameters for sediment concentration had similar values regardless of weather data-sets, whereas there was a significant difference between the parameter sets for stream flow. Most of the parameters related to stream flow were still in their recommended range, except for Cn2 and Ch_N(2), in all weather data-sets as well as only Surlag in Gauge 2. This revealed that not only should those parameter values be carefully refined in future local studies, but also there was a need for a trade-off between the number of weather stations and multiple Pareto-optimal (or near-optimal) solutions.

3.3. Model performance during calibration and validation

Based on the optimum parameter sets for each weather data-set, the simulated data appeared to correspond well with the observed ones in terms of R^2 and E_{NS} (see Table 4). The SWAT model achieved higher prediction accuracy for stream flow and sediment concentration during the calibration period than for the validation period probably due to the best calibration setup and short length of the one-year validation period. Although the prediction accuracy of stream flow in Gauge 2 was higher than in other radar data-sets for the calibration period, the model appeared to make more accurate prediction in Radar 3 and 11 than in the remaining data-sets with respect to both R^2 and E_{NS} during both calibration and validation phases. In contrast, the best model prediction for sediment concentration was made when increasing the number of weather stations, such as Radar 21 and 34 during both periods. This implied that the optimum parameter solution should be carefully evaluated and

Table 3
The final values of flow and sediment parameters in the SWAT model calibrated for the weather inputs with different coverage areas

Output variables	Input parameters[a]	Units	Range	Calibrated values				
				Gauge 2	Radar 3	Radar 11	Radar 21	Radar 34
Flow	Surlag	d	1–24	0.827	1.213	1.227	1.479	1.457
	Cn2	–	35–98	13.216	15.136	14.158	3.884	3.838
	Alpha_Bf	d	0–1	0.039	0.042	0.059	0,983	0.993
	Ch_K(2)	mm/h	−0.01 to 500	19.556	18.772	17.105	95.596	108.79
	Ch_N(2)	–	−0.01 to 0.3	0.983	0.879	0.939	0.881	0.908
	Gwqmn	mm	0–5,000	1,000.000	994.790	14.158	330.300	347.920
Sediment	Spcon	–	0.0001–0.01	0.001	0.001	0.001	0.001	0.001
	Prf	–	0–2.0 (or N/A)[b]	0.273	0.303	0.316	0.236	0.315
	Spexp	–	1.0–2.0	1.000	1.000	1.006	1.000	1.082

[a]Refer to Table 2 for definitions of individual input parameters.
[b]There is a difference in the recommended values between the reference source [9] and SWAT user manual for version 2000 (http://swat.tamu.edu/documentation/). N/A is short for not available.

Table 4
The performance of the SWAT model during calibration (2012–2013) and validation periods (2014) for stream flow and sediment yield at the Gwangju station in the upper section of the Yeongsan River (Basin), Korea

Weather inputs	Evaluation statistics[a]	Flow (m^3/s)		Sediment (metric tons/month)	
		Calibration	Validation	Calibration	Validation
Gauge 2	R^2	0.84	0.31	0.83	0.16
	E_{NS}	0.82	−0.66	0.80	−0.32
Radar 3	R^2	0.83	0.45	0.84	0.25
	E_{NS}	0.80	0.10	0.81	0.07
Radar 11	R^2	0.80	0.47	0.84	0.27
	E_{NS}	0.77	0.07	0.81	0.10
Radar 21	R^2	0.81	0.42	0.87	0.26
	E_{NS}	0.79	−0.05	0.85	0.21
Radar 34	R^2	0.81	0.42	0.86	0.27
	E_{NS}	0.79	−0.08	0.83	0.19

[a]Definitions: R^2 = the coefficient of determination and E_{NS} = the Nash–Sutcliffe efficiency.

determined with the input data-sets of different spatial resolutions to improve the prediction accuracy of more than two output variables simultaneously. Considering all these points together, the performance of SWAT model using all radar data-sets was at least equivalent or superior to that of the rain gauge data, even though we did not recommend the best one out of them at this moment. However, the radar data-sets with smaller number of (virtual) weather stations may be preferred as too fine discretization of sub-basins neither ensure the improvement of prediction accuracy in the simulation model nor reduce the data complexity.

4. Conclusions

In this study, we attempt to identify the high resolution rainfall data will be helpful in improving the parameterization and performance of a semi-distributed river basin model, the SWAT. The upper part of the YS River which had no apparent contamination activities and large hydraulic structures was selected as a target study area to simplify such an assessment. The SWAT model was calibrated and validated with respect to daily stream flow and monthly sediment concentration for two periods of 2012–2013 and 2014, respectively. The following are the main findings in this study:

(1) During the image processing operation, the resolutions of the rainfall products were increased up to approximately 17 times larger than the original map. The areal average adjustment factors A_1 and A_2 in the selected basin allowed a good estimate of the rainfall rates to be obtained from the radar data-sets.
(2) The SWAT model responded differently to the weather data-sets at various resolutions. The top four parameters related to stream flow showed the greatest change in rank when forcing different weather data, whereas no significant differences were observed in the sensitivity and optimal values for those associated with sediment concentration. However, this will likely differ among basins with different environmental settings as well as output variables such as total nitrogen and phosphorus.
(3) The SWAT model predicted stream flow and sediment concentration well during the calibration period than for the validation period performed in a short period of time, even using different sets of the optimal parameter values. Although the radar data-sets are more favorable for water quantity and quality simulation in the selected basin than the rain gauge data, further research is still warranted to fully explore the relationship between the data quality of various inputs and output accuracy of different types of the simulation models, from the lumped through semi-distributed to fully distributed models.

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