Science of the Total Environment 573 (2016) 66–82

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Evaluation of precipitation input for SWAT modeling in Alpine catchment: A case study in the Adige river basin (Italy)

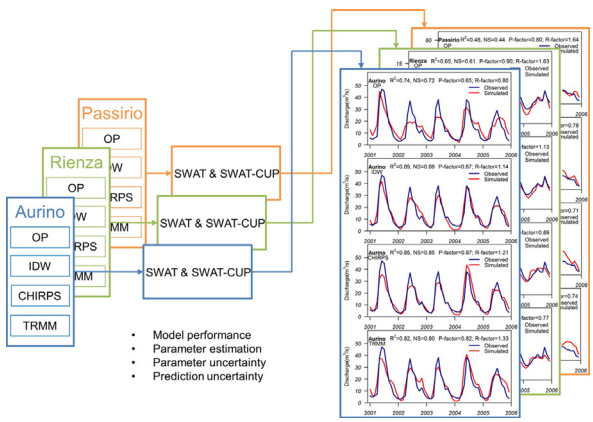
Ye Tuo *, Zheng Duan, Markus Disse, Gabriele Chiogna

Chair of Hydrology and River Basin Management, Technical University of Munich, Arcisstrasse 21, 80333 München, Germany

HIGHLIGHTS

- First assessment of precipitation input for SWAT in headwater of Adige basin, Italy.
- Four precipitation datasets were tested in three Alpine subbasins.
- Elevation band correction was necessary to close the water budget.
- IDW model led to the best NS and R^2 values considering streamflow data.
- The applied precipitation input influenced the estimated model parameters.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 15 June 2016
Received in revised form 5 August 2016
Accepted 5 August 2016
Available online xxxx

Keywords:
TRMM
CHIRPS
IDW
Alpine catchment
SWAT model
Adige

ABSTRACT

Precipitation is often the most important input data in hydrological models when simulating streamflow. The Soil and Water Assessment Tool (SWAT), a widely used hydrological model, only makes use of data from one precipitation gauge station that is nearest to the centroid of each subbasin, which is eventually corrected using the elevation band method. This leads in general to inaccurate representation of subbasin precipitation input data, particularly in catchments with complex topography. To investigate the impact of different precipitation inputs on the SWAT model simulations in Alpine catchments, 13 years (1998–2010) of daily precipitation data from four datasets including OP (Observed precipitation), IDW (Inverse Distance Weighting data), CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) and TRMM (Tropical Rainfall Measuring Mission) has been considered. Both model performances (comparing simulated and measured streamflow data at the catchment outlet) as well as parameter and prediction uncertainties have been quantified. For all three subbasins, the use of elevation bands is fundamental to match the water budget. Streamflow predictions obtained using IDW inputs are better than those obtained using the other datasets in terms of both model performance and prediction uncertainty. Models using the CHIRPS product as input provide satisfactory streamflow estimation, suggesting that this satellite product can be applied to this data-scarce Alpine region. Comparing the performance of SWAT models using different precipitation datasets is therefore important in data-scarce regions. This study has shown that, precipitation is the main source of uncertainty, and different precipitation datasets in SWAT models lead to different best estimate ranges for the calibrated parameters. This has important implications for the interpretation of the simulated hydrological processes.

* Corresponding author.
E-mail address: ye.tuo@tum.de (Y. Tuo).

http://dx.doi.org/10.1016/j.scitotenv.2016.08.034

1. Introduction

Quantitative hydrological models are useful tools to support the development of new water resource management policies and assess water quality issues (Abbaspour et al., 2015; Beven, 2011). Among these models, the Soil and Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005; Arnold et al., 1998) has been widely used for river basins around the world (Guse et al., 2016; Malagò et al., 2016; Nerantzaki et al., 2015; Schmalz et al., 2015; Song et al., 2011). Over the last decades, this open source model has been continuously improved by integrating modules that evaluate the effects of various hydrological and chemical processes (Gassman et al., 2007). SWAT is frequently used by both the global academic community and the practitioners. Over 2500 peer-review papers have been published (Scopus, till 31 July 2016) using modeling results obtained applying SWAT. This model has been proven to be an effective tool for simulating hydrological processes, contaminant transport, soil erosion and for assessing the effects of climate change, land use change, and water management practices in diverse environmental conditions (Abbaspour et al., 2015; Abbaspour et al., 2007; Ayana et al., 2015; Dile et al., 2016; Guo et al., 2008; Rahman et al., 2013; Schuol and Abbaspour, 2006; Woznicki et al., 2016; Yang et al., 2016). It has also been used to support the implementation of environmental directives such as the Clean Water Act in the United States (Gabriel et al., 2014) or the European Water Framework directive (Volk et al., 2009). A new version (SWAT+) that is under development, will implement a landscape unit approach to improve the processes distribution and allocation of management operations in landscapes (Bonumá et al., 2014; Rathjens et al., 2015) and will be more flexible in watershed discretization and configuration so as to represent the physical characteristics of a watershed as realistically as possible (Bieger et al., submitted for publication).

Precipitation is a major driving force of hydrological processes, sediment and chemical fluxes (Cho et al., 2009; Masih et al., 2011; Price et al., 2014), and therefore reliable precipitation data are important inputs for SWAT (Galván et al., 2014; Monteiro et al., 2016; Strauch et al., 2012) and other hydrological models (Andréassian et al., 2001; Bárdossy and Das, 2008; Mei et al., 2016a). Therefore, an accurate representation of the temporal and spatial variability of precipitation is of importance to achieve an accurate river basin model. In other words, physically based hydrological models such as SWAT cannot generate accurate predictions of hydrological processes without adequate representations of the regional precipitation distribution. Subsequently, without an accurate simulation of hydrological processes, reliable predictions of other relevant behaviors such as water quality and erosion cannot be achieved (Chaplot et al., 2005).

The sparse and heterogeneous spatial distribution of rain gauges often results in inaccurate precipitation inputs for SWAT, especially when modeling large river basin or basins with complex heterogeneous terrains like mountainous regions (e.g. Alpine catchments) where the assumption of spatially uniform rainfall is not valid (Cho et al., 2009). Furthermore, the current method of representing precipitation in the SWAT model is simplistic, since it only uses data from one precipitation gauging station that is nearest to the centroid of each subbasin (Galván et al., 2014; Masih et al., 2011). Therefore, improved precipitation inputs which consider regional spatial variations are crucial for achieving reliable modeling results with SWAT (Tobin and Bennett, 2009).

Numerous methods are available for processing precipitation data in order to consider spatial effects. Among these methods, interpolation methods based on ground measurements (e.g., Inverse distance weighting, IDW) and satellites precipitation estimates (e.g., Tropical Rainfall Measuring Mission, TRMM; Climate Hazards Group InfraRed Precipitation with Station data, CHIRPS) have been considered in the present work. IDW-based interpolated precipitation and TRMM have been shown to be useful for obtaining satisfactory model performance in case of spatially varied precipitation patterns (Li et al., 2012; Ly et al., 2011; Shen et al., 2012; Wagner et al., 2012) in particular when used as input data for SWAT models (Galván et al., 2014; Masih et al., 2011; Shen et al., 2012; Strauch et al., 2012; Tobin and Bennett, 2009; Wagner et al., 2012). The CHIRPS dataset has a higher spatial resolution compared to TRMM (0.25°) and is expected to capture more representative precipitation features, because the recently released "satellite-gauge" type CHIRPS product has the finest spatial resolution of 0.05° (Funk et al., 2015).

Comparing with the previous works (Shen et al., 2012; Shope and Maharjan, 2015; Vu et al., 2012; Wagner et al., 2012; Zhang and Srinivasan, 2009), we can state that the choice of the best precipitation input data for the SWAT models is basin-specific. More importantly, few case studies have investigated catchments with high elevation gradients (Shope and Maharjan, 2015; Xu et al., 2010) and none of them refer to SWAT applications in the South-eastern Alps. Therefore, investigations about the optimal precipitation input dataset to model Alpine catchments with SWAT are limited. Furthermore, SWAT utilizes elevation bands to simulate precipitation variability in a subbasin due to orographic effects (Neitsch et al., 2011). Only a few studies have tried to assess the effectiveness of the elevation band approximation and the results may be case-specific (Grusson et al., 2015; Rahman et al., 2013; Strauch et al., 2012). This study aims at comparing different precipitation inputs for SWAT in Alpine headwater catchments belonging to the Adige river basin.

The specific objectives of this study are to: 1) analyze the impact of four different precipitation data sources on SWAT modeling without elevation correction; 2) evaluate the effect of the elevation band method on the performance of SWAT models in alpine catchments; 3) estimate parameter and prediction uncertainties considering the four precipitation inputs in the three study areas; 4) investigate the exportability of the result of this study to other Alpine catchments.

2. Materials and methods

2.1. Study areas

The Adige river basin is located in North-East Italy and has a drainage area of 12,100 km^2 (Fig. 1). It is the second longest river and third largest catchment in Italy and it was selected as one of the research catchments in the FP7 project GLOBAQUA (Navarro-Ortega et al., 2015). Streamflow generation in the catchment is expected to change due to climate change in the area, with important consequences for water management, in particular for its headwaters (Chiogna et al., 2016; Majone et al., 2016). Hence, climate change has been identified as one of the main stressors affecting the Adige river basin. Further environmental stressors in the basin are the occurrence of hydropeaking related to hydropower production, and pollution associated with touristic fluxes especially in mountain areas, and pollutants transported within the river basin due to agricultural activities. The role played by particle-facilitated transport of contaminants is also under investigation (Navarro-Ortega et al., 2015), and therefore erosion could also be listed among the most relevant environmental stressors. To propose adequate management solutions to alleviate the effect of these stressors, it is necessary to have an accurate representation of flow and transport processes at the catchment scale. SWAT can be a useful tool to achieve these goals.

The SWAT model has been set up for the entire Adige basin with 43 subbasins delineated in Fig.1. In this work, we focus on the results of three subbasins representing headwaters of the Adige river basin (Fig.1): Aurino (subbasin 1), Rienza (subbasin 7) and Passirio (subbasin 9). The three subcatchments are part of the larger SWAT model for the Adige river basin. Therefore, the three study areas have not been further subdivided into smaller subcatchments. These three subbasins were selected because they are headwaters of the basin and hydropower production does not exert a significant influence on their streamflow. This allows us to investigate the influence of different precipitation datasets on streamflow generation in mountainous catchments where high elevation gradients are present. The three subbasins are located near each

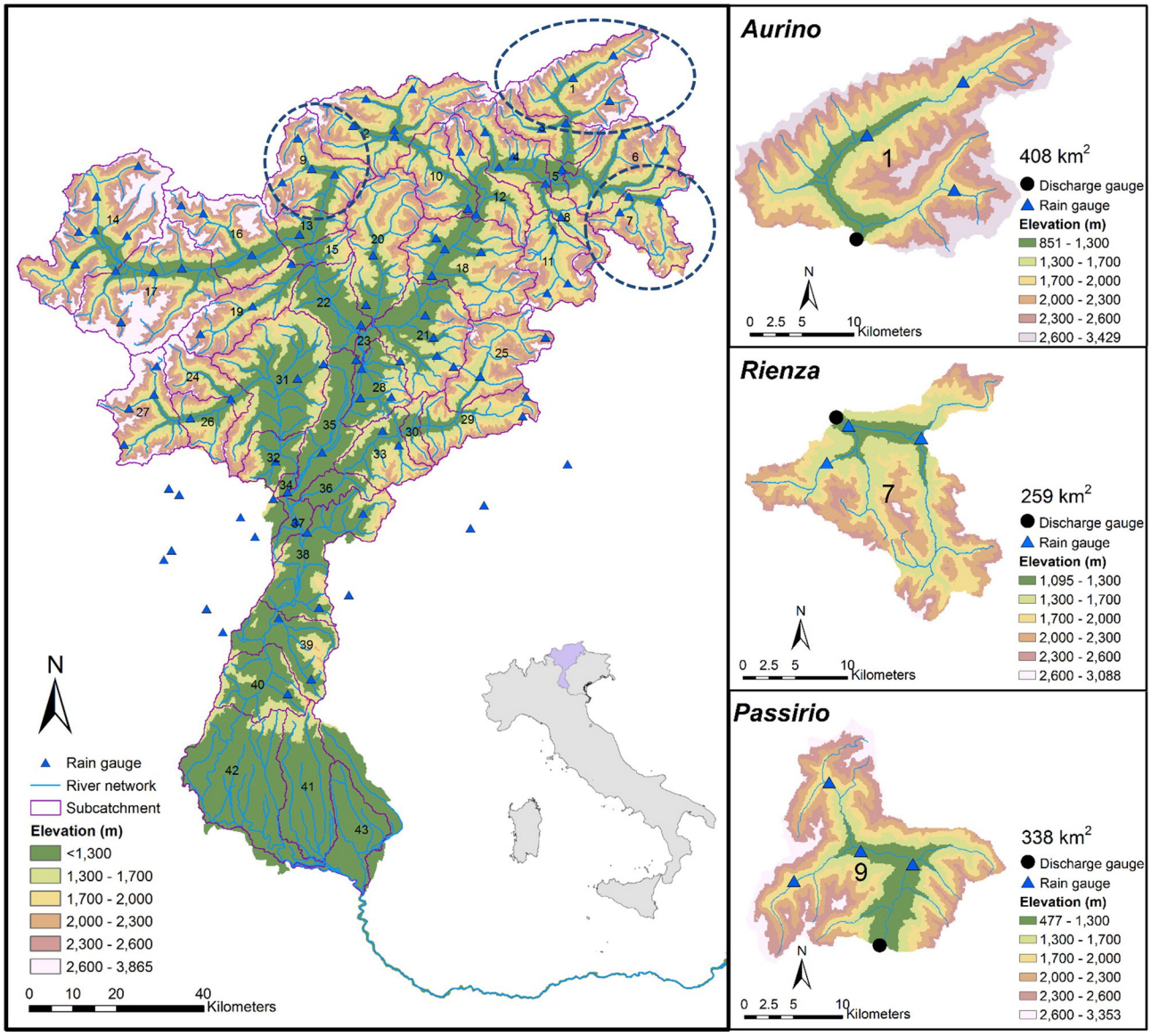


Fig. 1. The Adige river basin and three studied mountainous subbasin (Aurino, Rienza and Passirio).

other and belong to the same Alpine region. The climate of the region is characterized by snowmelt in spring, humid summers and autumns, and dry winters (Chiogna et al., 2016). According to the ground observations of the climate stations, the mean annual precipitation is 909 mm, 767 mm and 1074 mm for the Aurino, Rienza and Passirio subcatchments, respectively; the mean daily average temperature is 3.6 °C, 6.0 °C and 8.5 °C for the Aurino, Rienza and Passirio subcatchments, respectively. According to the local soil investigation (Costantini et al., 2004), the major soils of three subbasins are the same: the main types are Lithic Cryosols, Lithic, Mollic, Eutric, and Rendzic Leptosols, Eutric and Calcaric Cambisols, and Eutric Fluvisols. The main land use types of the three subbasins are forest, grassland, and barren land, which account of 49.2%, 14.6% and 22.2% in the Aurino subbasin, 64.6%, 9.3% and 14.1% in the Rienza subbasin, 49.0%, 23.9% and 12.6% in the Passirio subbasin, respectively. The land use map of the three subbasins is provided in the Supplementary Material (Fig. S1). The mean slope of the region is 51% (Costantini et al., 2004) and the slope map of each subbasin is offered in the Supplementary material (Fig. S2). The elevation for Aurino, Rienza and Passirio ranges between 851 m and 3429 m, 1095 m and 3088 m, and 477 m and 3353 m, respectively (Fig. S3). The area of these three subbasins are 408 km^2, 259 km^2 and 338 km^2, respectively (Fig.1).

2.2. SWAT model

The SWAT model is a comprehensive, time-continuous, semi-distributed, process-based model (Arnold et al., 2012a). It was developed by the Agricultural Research Service of the United States Department of Agriculture (Arnold et al., 1998). SWAT can be used to model changes in hydrological processes, erosion, vegetation growth, and water quality in large river basins and evaluate the effects of climate change and water resources management (Abbaspour et al., 2015; Dile et al., 2016; Yang et al., 2016). It divides the river basin into subbasins and subsequently into Hydrologic Response Units (HRUs), characterized by different combinations of land use, soil characteristic, topography, and management schemes. The hydrological cycle is calculated based on water balance, which is controlled by climate inputs such as daily precipitation and maximum/minimum air temperature. Using daily input time series, SWAT simulates the daily, monthly and yearly fluxes of water and solutes in river basins. Simulations start by calculating the quantity of

water, sediment and contaminants loading from land of each subbasin to the main channel. Then, these loads are transported and routed through the streams and reservoirs within the basin. More information about the model are provided in the literature (Arnold et al., 2012a; Arnold and Fohrer, 2005; Arnold et al., 1998; Gassman et al., 2007) and are available in the official model documentation (Neitsch et al., 2011).

2.3. Model setup

ArcSWAT 2012, with an interface in ArcGIS, was used to setup the model in this work. The datasets used in the model are listed in Table 1. Daily precipitation data come from 101 rain gauges (89 rain gauges inside the basin and 12 rain gauges within 25 km outside the entire Adige Basin boundary, see Fig. 1) for the period 1998–2010. This dataset has been used also for the IDW interpolation to generate an IDW-based precipitation dataset. Regarding the three subbasins of this study (Fig. 1), three rain gauges with elevation of 1080 m, 1450 m and 1562 m are available at Aurino; three gauges with elevation of 1131 m, 1219 m and 1285 m are available at Rienza; four gauges with elevation of 644 m, 1147 m, 1618 m and 1716 m are available at Passirio. In this study, a total of twenty-four models have been set up for three Alpine subcatchments (Aurino, Rienza and Passirio) by inputting four different precipitation datasets into two types of SWAT programs: one with the elevation band method, the other without. The models considered a timeframe of thirteen years, from 1998 to 2010.

2.4. Precipitation datasets

In the present work, four precipitation datasets covering 1998–2010 have been used as SWAT input datasets. They can be classified into three categories: 1) Observed precipitation data from ground rain gauges; 2) IDW-based interpolated data, which were used as one representative of the datasets by interpolation techniques (Ly et al., 2011); 3) two satellite precipitation products: CHIRPS (Funk et al., 2015), which represents one of the latest products from remote sensing community and TRMM 3B42 (Huffman et al., 2007), which represents one of the frequently applied products from the remote sensing community. The two satellite precipitation products have been selected because they performed best in the Adige river basin among eight satellite precipitation products (Duan et al., submitted for publication). The empirical cumulative density function (CDF) of the daily precipitation distribution during 1998–2010 has been computed for the four datasets. The corresponding cumulative frequency has been evaluated based on the rainfall intensity classification of the World Meteorological Organization (WMO) standard (Tan et al., 2015): (1) rain <1 mm (no/tiny rain), (2) 1 mm ≤ rain < 2 mm (light rain), (3) 2 mm ≤ rain <5 mm (low moderate rain), (4) 5 mm ≤ rain < 10 mm (high moderate rain), (5) 10 mm ≤ rain <20 mm (low heavy rain), (6) 20 mm ≤ rain <50 mm (high heavy rain), and (7) rain ≥50 mm (violent rain).

2.4.1. Ground rain gauge dataset

All available precipitation data collected by pointed-based ground rain gauges have been directly used as input to SWAT. This represents the most widely used manner in which the rain gauge data are used in the SWAT model among all existing publications. However, SWAT only uses the data of the rain gauge closest to the centroid of each subbasin, disregarding all other stations (Galván et al., 2014; Masih et al., 2011). Therefore, only data from one single point has been utilized for the entire subbasin without considering any spatial heterogeneity. This precipitation dataset will hereafter be referred to as OP (observed precipitation) and accordingly the model result will be referred to as SWAT model using OP input (OP model).

2.4.2. IDW-based precipitation dataset

A huge variety of methods have been developed in the past to spatially interpolate precipitation datasets (Ly et al., 2011; Wagner et al., 2012; Zhang and Srinivasan, 2009). Babak and Deutsch (2009) state that "Variants of kriging are often proposed as statistical techniques with superior mathematical properties such as minimum error variance; however, the robustness and simplicity of IDW interpolation motivate its continued use in practice." The IDW method is probably one of the simplest interpolation methods and it does not rely on particular statistical assumptions. It is a widely used geometric interpolation method and is considered in most intercomparison studies focusing on the effect of different precipitation inputs on hydrological outputs (Chu et al., 2012; Di Luzio et al., 2008; Ly et al., 2011; Ly et al., 2013; Shen et al., 2012; Shope and Maharjan, 2015; Shope et al., 2014; Tuppad et al., 2010; van der Heijden and Haberlandt, 2010; Wagner et al., 2012; Yang et al., 2015; Zhang and Srinivasan, 2009). IDW estimates values at unknown points by the weighted average of observed data at neighboring points:

$$z(x_o) = \sum_{i=1}^{n} \lambda_i \cdot z(x_i) \tag{1}$$

$$\lambda_i = \frac{|d_{oi}|^{-d}}{\sum_{i=1}^{n} |d_{0i}|^{-d}}, d>0 \tag{2}$$

where $z(x_o)$ represents the rain data of the unknown point, $z(x_i)$ is the rain data of the rain gauge i; λ_i is the weight as defined in Eq. (2), d_{oi} is the distance between the unknown point and the rainfall station i. The parameter d was set to 2, according to the recommendation of Ly et al. (2011).

IDW therefore depends only on the distance between stations and not on their elevation or on direction. This method is based on the assumption that points close to each other are more correlated than points at larger distances (Ly et al., 2011). This interpolation scheme has been chosen for its simplicity, without excluding the possibility that more complex interpolation schemes could improve the results obtained using IDW.

In this work, thirteen years (1998–2010) of daily measured data have been interpolated using the IDW tool in ArcGIS considering the 12 closest stations for each interpolated grid (100 m × 100 m). The number of stations was set as 12 by following the recommendations provided in previous works (Babak and Deutsch, 2009; Ly et al., 2011) and also considering the morphology of the catchments. Averaged IDW daily values for the subcatchment have been calculated and used as precipitation input at the centroid of the subbasin, which, in this way, consider the spatial heterogeneity in precipitation patterns. This

Table 1
Data source and description.

Data type	Scale	Data source
DEM	90 m × 90 m	Shuttle Radar Topography Mission (SRTM) produced by Consortium for Spatial Information (CGIAR-CSI)
Land use	100 m × 100 m	Corine Land Cover 2006(CLC2006) from European Environment Agency
Soil	1:1,500,000	Food and Agriculture Organization (FAO)
River network		EU-DEM product http://www.eea.europa.eu/data-and-maps/data/eu-dem.
Climate		Autonomous Province of Trento (http://www.meteotrentino.it) and Autonomous Province of Bolzano (http://www.provincia.bz.it/meteo/home.as)
River discharge		Autonomous Province of Bolzano

IDW-based precipitation dataset will hereafter be referred to as IDW, and the corresponding SWAT model will be referred to as the IDW model.

2.4.3. CHIRPS dataset

The CHIRPS product provides daily precipitation data at spatial resolution of 0.05° for the quasi-global coverage of 50°N–50°S from 1981 to near present. The latest product is the Version 2.0 dataset that was completed and released in February 2015. The daily precipitation data from CHIRPS were downloaded at: http://chg.geog.ucsb.edu/data/chirps/. The CHIRPS product is based on integration of various datasets: the monthly precipitation climatology (CHPclim) that is created using rain gauge stations collected from FAO and GHCN, the Cold Cloud Duration (CCD) information based on thermal infrared data archived from CPC and NOAA National Climate Data Center (NCDC), the Version 7 TRMM 3B42 data, the Version 2 atmospheric model rainfall field from the NOAA Climate Forecast System (CFS), and the rain gauge stations data from multiple sources. Since rain gauge data are used for bias correction in the product, the CHIRPS product belongs to the "satellite-gauge" category. More detailed information on CHIRPS can be found in Funk et al. (2015). For each subbasin, daily averaged subbasin CHIRPS datasets for the period 1998–2010 have been calculated by averaging all effective 0.05° daily CHIRPS grids within the subbasin boundary, which were then used to force the SWAT model in this study (the CHIRPS model).

2.4.4. TRMM 3B42 dataset

The TRMM 3B42 product is one type of the TMPA (TRMM Multi-satellite Precipitation Analysis) products (Huffman et al., 2007). The TRMM 3B42 product provides 3-hourly precipitation at the spatial resolution of 0.25° for the quasi-global coverage of 50°N-50°S from 1998 to 2015. The latest product version is Version 7 and the applied algorithm is the TMPA algorithm that combines precipitation estimates from microwave and infrared satellites, as well as the GPCC monthly gauge analysis. More details about TMPA algorithms can be found in Huffman et al. (2007). The TRMM 3B42 daily precipitation data were obtained from Goddard Earth Sciences Data and Information Services Center at http://mirador.gsfc.nasa.gov. The mean daily accumulated TRMM 3B42 data during 1998–2010 have been calculated for each subbasin and used as the SWAT inputs in this study. The TRMM 3B42 precipitation data will hereafter be referred to as TRMM, and the corresponding SWAT model will be referred to as the TRMM model.

2.5. Elevation bands

To consider the orographic effects on precipitation and temperature in mountainous areas, SWAT uses the elevation bands method which allows for up to ten elevation bands in each subbasin. In this work, five elevation bands have been applied. As shown in Eqs. (3) and (4), the method modifies the regional precipitation by weighting the elevation difference between the band of the rain gauge and the other bands.

$$R_{band} = R_{day} + \left(EL_{band} - EL_{gauge}\right) \cdot \frac{plaps}{days_{pcp,yr} \cdot 1000}, R_{day} > 0.01 \quad (3)$$

$$\mathrm{R_{day}} = \sum_{\mathrm{bnd}=1}^{\mathrm{b}} \mathrm{R_{band}} \cdot \mathrm{fr_{bnd}} \quad (4)$$

where R_{band} is the precipitation in the elevation band (mm), R_{day} is the precipitation recorded at the rain gauge (mm), EL_{band} is the mean elevation at the elevation band (m), EL_{gauge} is the elevation at the recording gauge (m), *plaps* is the precipitation lapse rate (mm/km) and $days_{pcp,yr}$ is the average number of days of precipitation in the subbasin in a year, fr_{bnd} is the fraction of the subbasin area within the elevation band and *b* is the total number of elevation bands in the subbasin. Notice that in addition to Eqs. (3) and (4) SWAT imposes the following condition: if $\mathrm{R_{band}} < 0$, then $\mathrm{R_{band}} = 0$. This means that if $EL_{gauge} > EL_{band}$ and $abs\left(\left(EL_{band} - EL_{gauge}\right) \cdot \frac{plaps}{days_{pcp,yr} \cdot 1000}\right) > R_{day}$, precipitation of that band is set equal to 0. This condition prevents the elevation band method from being a constant adjustment of the input precipitation data. Galván et al. (2014) has pointed out that this method generally either underestimates or overestimates precipitation due to the difference between the altitude of the subbasin and the elevation of the rain gauge. In addition, they found that *plaps* is erroneously introduced in mm/m instead of mm/km as indicated. Although it has some intrinsic limitations, this method has been proven to be useful in several Alpine catchments (Grusson et al., 2015; Rahman et al., 2013).

2.6. Model calibration, evaluation and uncertainty analysis

The first three years (1998–2000) have been used as the warm up period to mitigate the effect of initial conditions. For each SWAT model, monthly simulated stream flow of the three alpine subbasins have been calibrated separately using the time period 2001–2005 and then validated in the period 2006–2010, based on the measured discharge records of stations Aurino-Caminata, Rienza-Monguelfo and Passirio-Saltusio for Aurino, Rienza and Passirio, respectively (Fig. 1). The automatic calibration and validation were performed by using the Sequential Uncertainty Fitting algorithm version 2 (SUFI-2) (Abbaspour et al., 2004; Abbaspour et al., 2007) in the SWAT-CUP tool package (Abbaspour, 2015). Snow parameters can be very influential in SWAT (Grusson et al., 2015). Before calibration, we therefore applied snow parameters available in the literature for neighboring regions

Table 2
Hydrological parameters considered for sensitivity analysis ("a_", "v_" and "r_" means an absolute increase, a replacement, and a relative change to the initial parameter values, respectively).

Parameters	Description	Range	Default
a_SOL_AWC().sol	Available water capacity of the soil layer [mm H_2O/mm soil]	0/0.9	Soil layer specific
a_SOL_K().sol	Saturated hydraulic conductivity [mm/h]	−10/10	Soil layer specific
r_SOL_BD().sol	Moist bulk density [g/cm^3]	−0.5/0.5	Soil layer specific
a_CN2.mgt	SCS runoff curve number	−20/20	HRU specific
v_ESCO.hru	Soil evaporation compensation factor	0/1	0.95
v_EPCO.hru	Plant uptake compensation factor	0/1	1
a_HRU_SLP.hru	Average slope steepness [m/m]	−0.2/0.4	HRU specific
a_SLSUBBSN.hru	Average slope length [m]	−9/130	HRU specific
a_OV_N.hru	Manning's "n" value for overland flow	0.01/29	0.1
v_CH_K2.rte	Effective hydraulic conductivity [mm/h]	0/400	0
v_CH_N2.rte	Manning's n value for main channel	0/0.3	0.014
a_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur [mm]	−500/500	1000
a_REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur [mm]	−500/500	750
v_GW_REVAP.gw	Groundwater "revap" coefficient	0.02/0.2	0.02
v_GW_DELAY.gw	Groundwater delay [days]	0/300	31
v_ALPHA_BF.gw	Baseflow alpha factor [days]	0/1	0.048

Table 3
Initial parameter ranges for calibration. Final calibrated ranges for the different precipitation products are available in the Supplementary material (Fig. S4–S6).

Parameters	Default	Calibration range
Aurino		
v_PLAPS.sub	0	0/0.15
a_SOL_AWC().sol	0.01–0.06	0/0.9
a_CN2.mgt	55–94	−20/4
v_ESCO.hru	0.95	0/1
a_SLSUBBSN.hru	9.146–15.244	−9/130
a_GWQMN.gw	1000	−300/300
a_REVAPMN.gw	750	−300/300
v_GW_REVAP.gw	0.02	0.02/0.2
v_GW_DELAY.gw	31	0/300
v_ALPHA_BF.gw	0.048	0/1
v_CH_K2.rte	0	0/400
Rienza		
v_PLAPS.sub	0	0/0.15
a_SOL_AWC().sol	0.06	0/0.9
a_CN2.mgt	55–60	−20/38
v_ESCO.hru	0.95	0/1
a_SLSUBBSN.hru	9.146–18.293	−9/130
a_HRU_SLP.hru	0.183–0.719	−0.2/0.4
a_GWQMN.gw	1000	−300/300
v_GW_REVAP.gw	0.02	0.02/0.2
v_GW_DELAY.gw	31	0/300
v_CH_K2.rte	0	0/400
Passirio		
v_PLAPS.sub	0	0/1
a_SOL_AWC().sol	0.01–0.06	0/0.9
a_CN2.mgt	55–84	−20/14
v_ESCO.hru	0.95	0/1
a_SLSUBBSN.hru	9.146–18.293	−9/130
a_GWQMN.gw	1000	−300/300
v_GW_REVAP.gw	0.02	0.02/0.2
v_GW_DELAY.gw	31	0/300
v_CH_K2.rte	0	0/400

(Adler et al., 2015; Rahman et al., 2013; Zanotti et al., 2004) to avoid the potential interference of snow processes on the interpretation of the results obtained using different precipitation inputs. The sensitivity analysis has been performed by the one-at-a-time procedure of SWAT-CUP (Abbaspour, 2015) for several common sensitive hydrological parameters (Table 2) to select the sensitive hydrological parameters for each subbasin. This procedure tests the model sensitivity by changing one parameter while keeping all other parameters constant. Furthermore, starting with the initial ranges of parameters shown in Table 3, the models were calibrated with four iterations. The initial parameter ranges are qualified to physically reasonable intervals according to the literature (Grusson et al., 2015; Vu et al., 2012) and SWAT official documentation (Arnold et al., 2012b). For each iteration, 1500 simulations were run. After each iteration, the ranges of the parameters have been modified (normally narrowed down) according to both the new parameters suggested by the program (Abbaspour et al., 2004; Abbaspour et al., 2007) and their reasonable physical limitations. More details about the protocol to calibrate the model can be found in Abbaspour (2015) and Abbaspour et al. (2015).

Several metrics are available in the literature to evaluate model performance (e.g., Bennett et al., 2013). In this work, we follow the approach suggested in Abbaspour et al. (2015) where model performance was evaluated taking into account the parameter uncertainties and 95% prediction uncertainty (95PPU) of the outputs by using SUFI-2 (Yang et al., 2008). The Nash–Sutcliffe coefficient (NS) (Nash and Sutcliffe, 1970) and the coefficient of determination (R^2) have been used as the goodness of fit indicators for the best simulation. NS measures the quantity difference between the predictions and the observed data, with NS = 1 being the optimal value. R^2 ranges from 0 to 1 and represents the trend similarity between the observed data and the simulated ones, with higher R^2 values indicating better model performance. The model performance has been classified using the NS value according to the work of Moriasi et al. (2007): unsatisfactory performance (NS ≤ 0.50), satisfactory performance (0.50 < NS ≤ 0.65), good performance (0.65 < NS ≤ 0.75) and very good performance (0.75 < NS ≤ 1.00).

As described by Abbaspour (2015) and Abbaspour et al. (2007), uncertainty in parameters are expressed as the final ranges of the parameter sets with which the model reached the satisfactory result. Hence, these parameter uncertainties lead to the output uncertainty 95PPU which is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable generated through the propagation of the parameter uncertainties using Latin hypercube sampling. The uncertainty analysis of SUFI-2 is based on the theory that the model

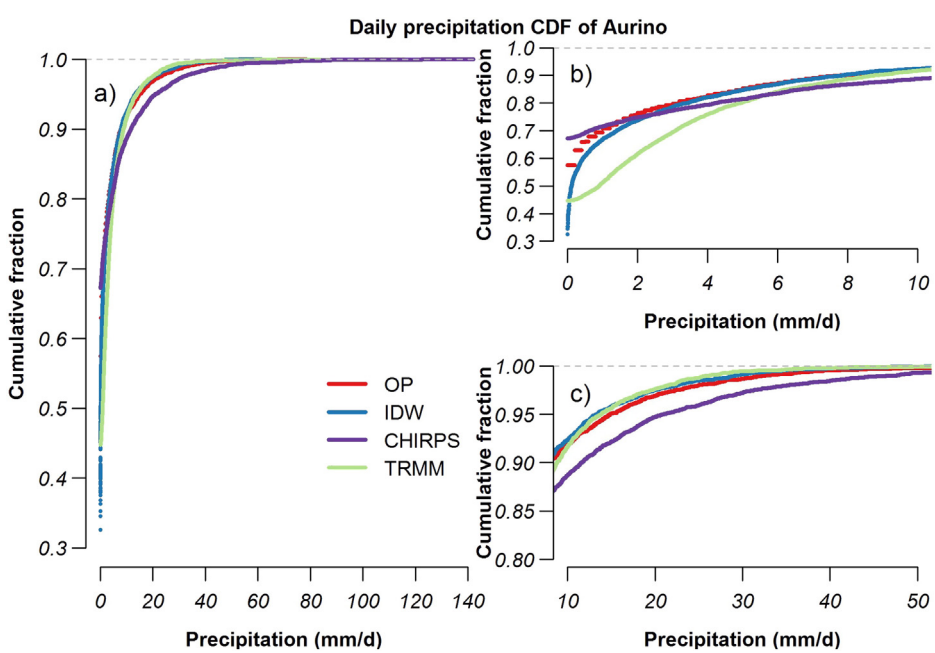


Fig. 2. Distribution of daily precipitation values of the four precipitation inputs (OP, IDW, CHIRPS, TRMM) at Aurino: a) distribution of all precipitation values; b) distribution of precipitation < 10 mm; c) distribution of 10 mm ≤ precipitation < 50 mm.

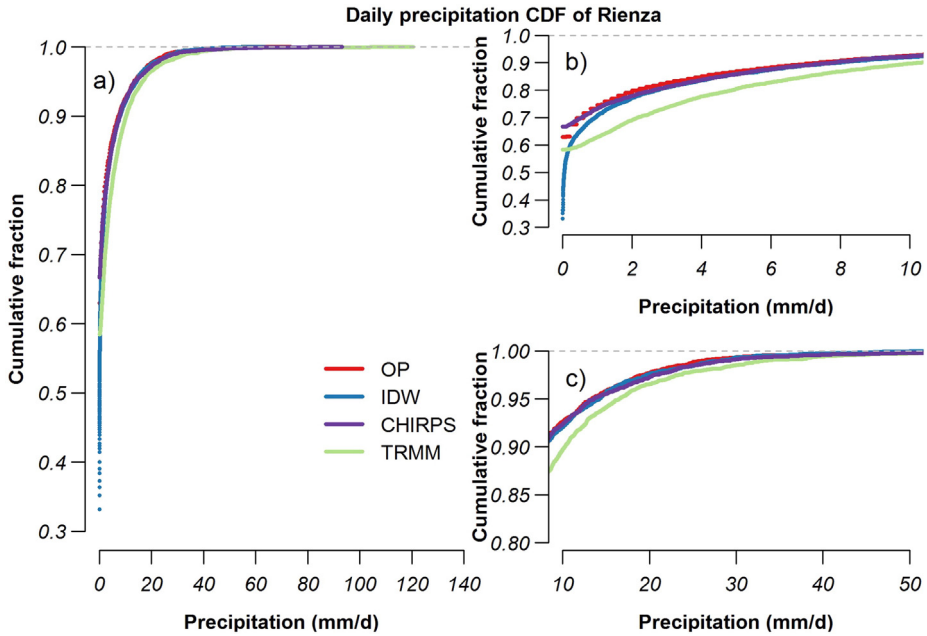


Fig. 3. Distribution of daily precipitation values of the four precipitation inputs (OP, IDW, CHIRPS, TRMM) at Rienza: a) distribution of all precipitation values; b) distribution of precipitation <10 mm; c) distribution of 10 mm ≤ precipitation <50 mm.

performance is represented by an envelope of good solutions expressed by the 95PPU, generated by certain parameter ranges, rather than a single signal.

To quantify the prediction uncertainties, two indices were introduced (Abbaspour et al., 2004): P-factor and R-factor. The P-factor is the fraction of measured data enveloped by the 95PPU band. It ranges from 0 to 1, in which 1 is optimal and indicates 100% bracketing of the observed data within model prediction uncertainty. The R-factor is the thickness of the 95PPU envelop, which means the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. For discharge, P-factor > 0.7 and R-factor < 1.5 are considered acceptable in terms of prediction uncertainty (Abbaspour, 2015).

3. Results and discussion

3.1. Comparison of the four different precipitation datasets

Considering the Aurino subbasin (Fig. 2), the four products display different probability of occurrence of dry days (rain = 0 mm/d), which are 57%, 31%, 67% and 45% for OP, IDW, CHIRPS and TRMM, respectively. The largest difference in the CDFs of the four products occurs for precipitation events smaller than moderate rain (<2 mm/d): particularly, for the occurrence of tiny rain, the probabilities are 12%, 35%, 4% and 5% for OP, IDW, CHIRPS and TRMM, respectively. OP, IDW and CHIRPS show great similarity for low moderate rain (8%, 9%, and 7%,

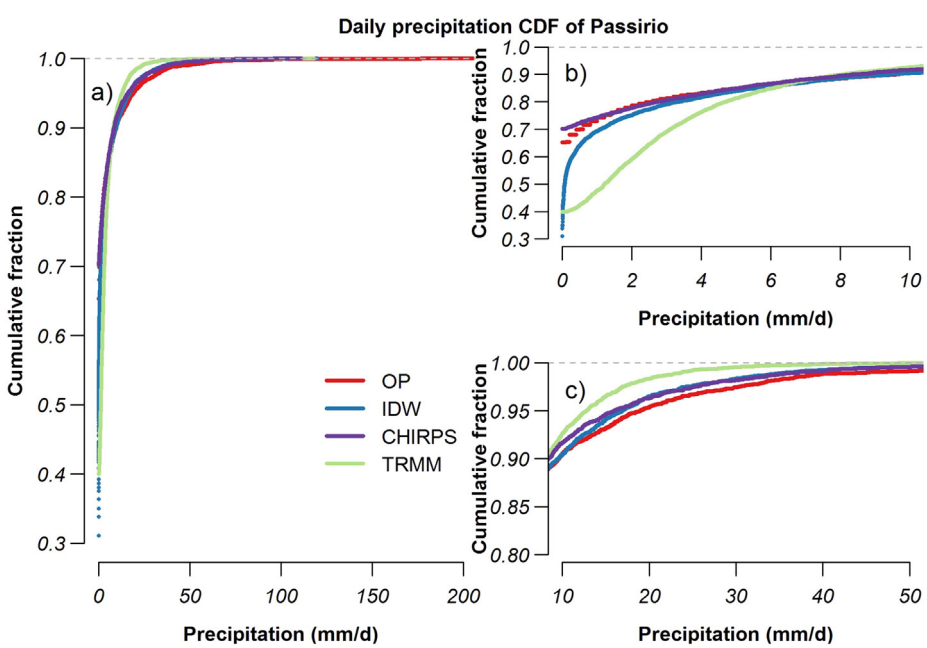


Fig. 4. Distribution of daily precipitation values of the four precipitation inputs (OP, IDW, CHIRPS, TRMM) at Passirio: a) distribution of all precipitation values; b) distribution of precipitation <10 mm; c) distribution of 10 mm ≤ precipitation <50 mm.

respectively), while TRMM displays a larger probability (18%). Results show negligible differences (<2%) of occurrence rates for rainfall larger than 5 mm/d between the four precipitation datasets. At Rienza (Fig. 3), the occurrence of dry days shows the largest variability among the four datasets (62% for OP, 31% for IDW, 67% for CHIRPS, and 58% for TRMM). The occurrence of tiny rain presents the largest discrepancy and the probabilities are 10%, 31%, 4% and 3% for OP, IDW, CHIRPS and TRMM, respectively. For other precipitation events including light, moderate, heavy and violent rain, OP, IDW and CHIRPS datasets are quite similar, while TRMM has relative higher CDF values than the other three products for values up to 40 mm/d. In the Passirio subcatchment (Fig. 4), the probabilities of dry day are 65%, 30%, 70% and 40% for OP, IDW, CHIRPS and TRMM, respectively. The largest difference of the four datasets occurs for the tiny rain (7% for OP, 38% for IDW, 4% for CHIRPS and 5% for TRMM). As shown in Fig.4, the CDF of the TRMM dataset evidently deviates from the others: higher cumulative rates in light, low moderate, and heavy rains.

In general, IDW datasets have the largest occurrence probability of days with tiny rain (35%, 31% and 38% for the Aurino, Rienza and Passirio subcatchments, respectively), which is ascribed to the effect of the interpolation method. In fact, the precipitation value at a given point of the interpolated dataset is influenced by the nearest 12 observation stations (Fig. 1). Hence, the IDW dataset of each subbasin is influenced also by stations outside the subbasin which may have recorded local precipitation events. The results of a set of two-sample Kolmogorov-Smirnov tests at the 5% significance level show that the four precipitation inputs have different statistical distributions in the three subcatchments. In particular, as shown in Fig. 5, their monthly precipitation patterns throughout the period 2001–2010 are not identical, and hence they represent four different input datasets for the hydrological model. The mean standard deviation (i.e., standard deviation of the four precipitation datasets computed at the monthly time scale and averaged over the 10 years considered) is 31 mm, 27 mm and 30 mm for the Aurino, Rienza and Passirio subcatchments, respectively.

3.2. Model performance without elevation band

As shown in Fig. 6, it is evident that the four precipitation inputs fail in promoting the model to reproduce the discharge records at all three subbasin. In particular, the peak flow in summer is underestimated by >50%. According to the model performance classification of Moriasi et al. (2007), the only model which achieves satisfactory performance

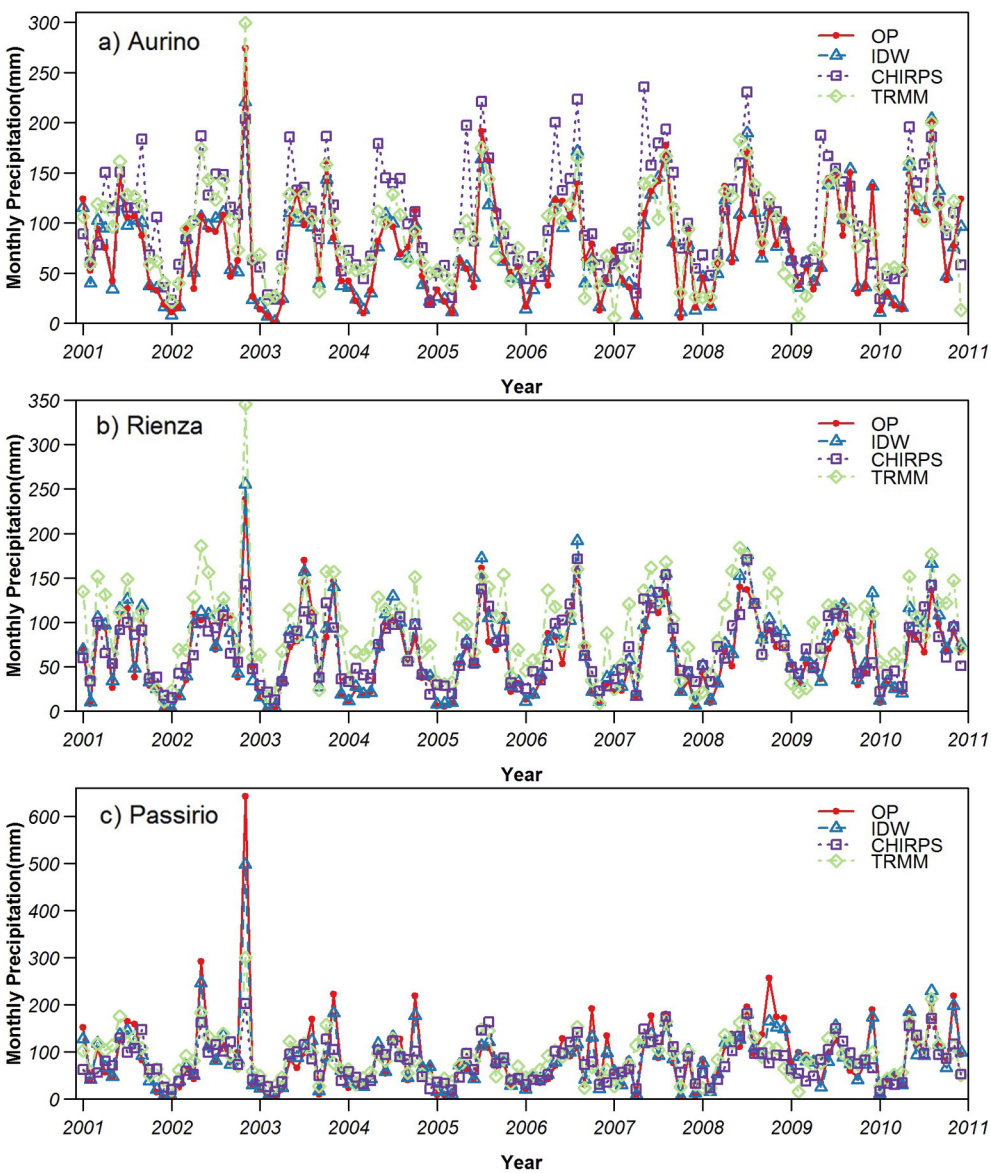


Fig. 5. Monthly precipitation of the four precipitation datasets in the three Alpine catchments: a) Aurino, b) Rienza, and c) Passirio.

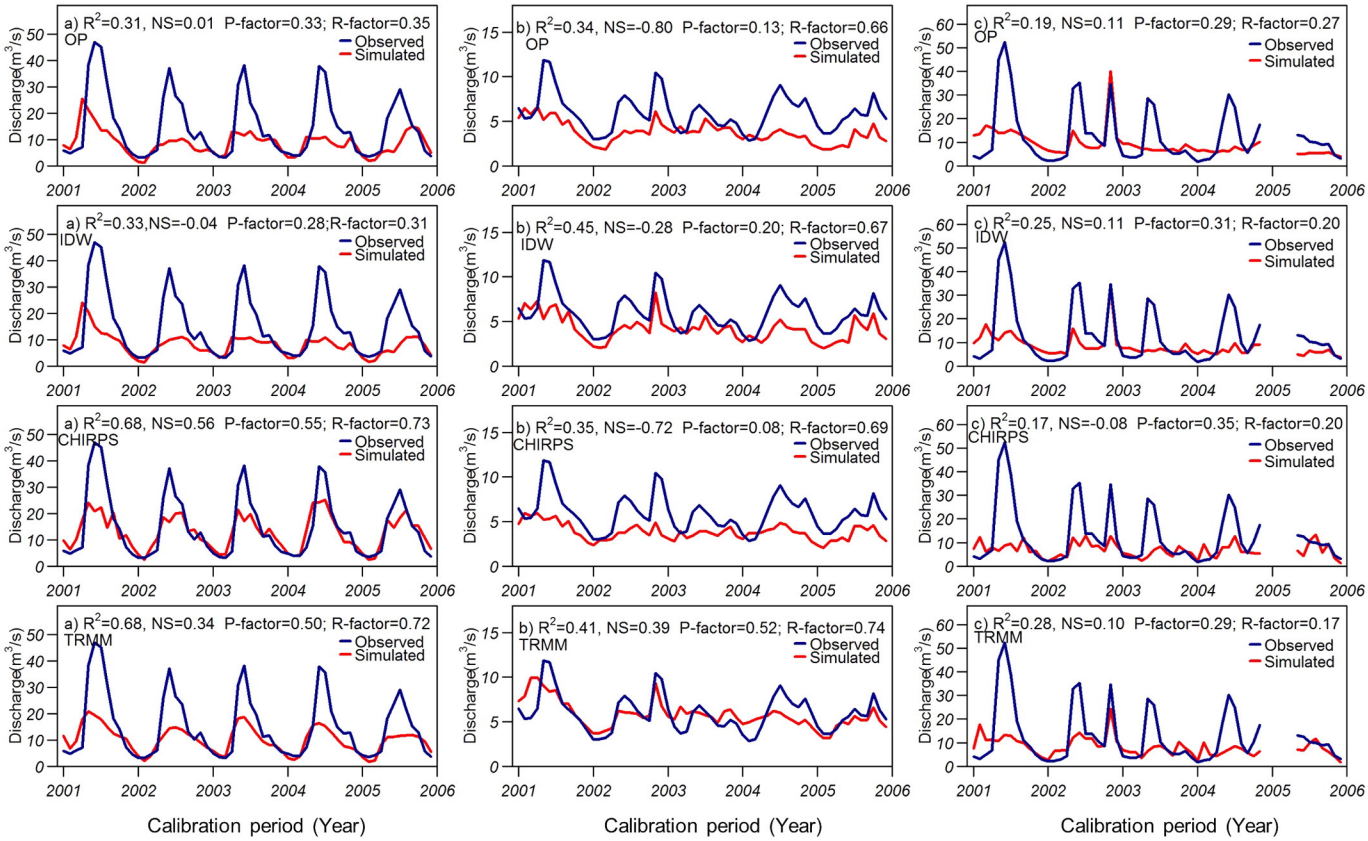


Fig. 6. Calibration results of the three subbasin without elevation band correction: a) Aurino, b) Rienza, c) Passirio. The results represent monthly stream flow data of the best simulation, i.e., highest NS and R^2 values obtained in a set of 1500 simulations (red lines), and observed stream flow data (blue lines), along with the prediction uncertainty (P-factor and R-factor). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

($0.50 < NS \leq 0.65$) is the one for the Aurino subcatchment using the CHIRPS precipitation input. All the other models achieve unsatisfactory results ($NS \leq 0.50$).

A rough calculation of the ratio of annual observed streamflow to annual precipitation leads to anomalously large values: mean values computed for the period 2001–2010 using OP dataset are 1.24 ± 0.20 for Aurino, 0.91 ± 0.16 for Rienza, and 1.02 ± 0.26 for Passirio; mean values using IDW based dataset are 1.29 ± 0.21 for Aurino, 0.84 ± 0.14 for Rienza, and 1.07 ± 0.25 for Passirio; mean values using CHIRPS dataset are 0.89 ± 0.13 for Aurino, 0.84 ± 0.15 for Rienza, and 1.11 ± 0.26 for Passirio; mean values using TRMM dataset are 1.04 ± 0.14 for Aurino, 0.62 ± 0.15 for Rienza, and 1.00 ± 0.20 for Passirio. All four datasets often underestimate the total precipitation of the studied subbasins. The underestimation is most likely due to the poor representation of the spatial variability of precipitation patterns in the region, thereby leading to the high ratio of streamflow-to-precipitation and results shown in Fig. 6. Since the IDW model is driven by interpolated data, its results depend on the ground observations. Therefore, since the ground observations systematically underestimate the total precipitation in the study area, the interpolated data will also underestimate it. Moreover, the underestimation of precipitation in the two remote sensing datasets CHIRPS and TRMM could be attributed to the fact that the topographic effects have not been considered in the bias correction using rain gauge analysis. Additionally, satellite precipitation estimates have their own uncertainties (Duan et al., submitted for publication). Therefore, as a consequence of the underestimation of precipitation, it is not possible to close the water balance for the three subbasins considering the available products. We conclude that the four tested precipitation products considerably underestimate the amount of precipitation over a large part of the Adige headwaters. Such underestimation is common in Alpine catchments (Isotta et al., 2014). Indeed, the high variability in the morphology and orography of Alpine catchments, leads to a high heterogeneity in precipitation patterns and intensity (Panziera et al., 2015). Ground observations, used also for the validation of satellite products, are normally located at low elevations (below 2000 m a.s.l.) and are not representative for the entire catchment (Duan and Bastiaanssen, 2013; Javanmard et al., 2010). Only 3% of the rain gauges are located at elevations higher than 2000 m a.s.l. in the upper part of the Adige river basin, while >30% of the Adige river basin closed at Bronzolo is above 2000 m a.s.l. (Adler et al., 2015). Mei et al. (2016a) also found streamflow/precipitation ratios larger than 1 in several subbasins (Aurino, Passirio, Isarco, Rienza) of the Adige river basin. Furthermore, Mei et al. (2014, 2016b) also identified the critical role of precipitation input for this region in case of flood protection and assessed the quality of some available satellite products for this region. Our work therefore complements the current knowledge about these catchments involving different precipitation inputs, different spatial scales and different hydrological models.

3.3. Model performance with elevation band method

SWAT is designed to cope with the aforementioned underestimation problems related to precipitation input using elevation bands (Eqs. (3) and (4)) which modulates the amount of precipitation depending on the orography of the catchment. Fig. 7, Fig. 8 and Fig. 9 show evident improvements in the performances of the model for all three subbasins.

For the Aurino subbasin (Fig. 7), all models driven by the four different precipitation input datasets well reproduce the measured streamflow. Using the performance classification of Moriasi et al. (2007), the model using OP as precipitation data achieves good

performance in the calibration period and very good performance in the validation one, while the models utilizing IDW, CHIRPS and TRMM data attain very good performance. The IDW model reaches the highest NS (0.91) and R^2 (0.91) values in the validation period. For the Rienza subcatchment (Fig. 8), during the calibration period, the use of OP and CHIRPS data lead to satisfactory model performance. The IDW model attains the level of good model performance, while TRMM model does not achieve satisfactory model performance. During the validation period (Fig. 8), NS and R^2 increase for all precipitation datasets. The IDW and OP model achieve very good model performance, while CHIRPS model does not exceed satisfactory performance. The best simulation obtained using the TRMM dataset improves to the level of good performance. In the Rienza subcatchment, considering both calibration and validation periods, the IDW model reaches the best performance; OP and CHIRPS model show a consistent satisfactory performance in reproducing streamflow. For the Passirio subcatchment (Fig. 9), during the calibration period, the IDW model attains good model performance, the CHIRPS model obtains satisfactory performance, while the performances of OP model and TRMM model are unsatisfactory. During the validation period, all models obtain higher NS and R^2 values: the IDW model reaches very good performance, the CHIRPS model improves to good performance, while the OP model achieves satisfactory performance. The performance of TRMM model is still unsatisfactory.

In summary, the introduction of elevation bands, despite the limitations discussed in the method section, greatly improves model performance regardless of which precipitation input is used. We can see in Table 4 that elevation bands have a large effect (increase in precipitation between 10% and 103% by the elevation band method) on all precipitation products, although CHIRPS and TRMM consistently show the need for a lower correction in comparison to OP and IDW. However, we can observe differences in the effect of elevation bands among different subcatchments, which prevents the generalization of the conclusions obtained for a specific catchment to other Alpine catchments. Despite the model performance improvements, clear differences are still present in the model results depending on the precipitation dataset applied for the different case studies. Models utilizing IDW data have the best

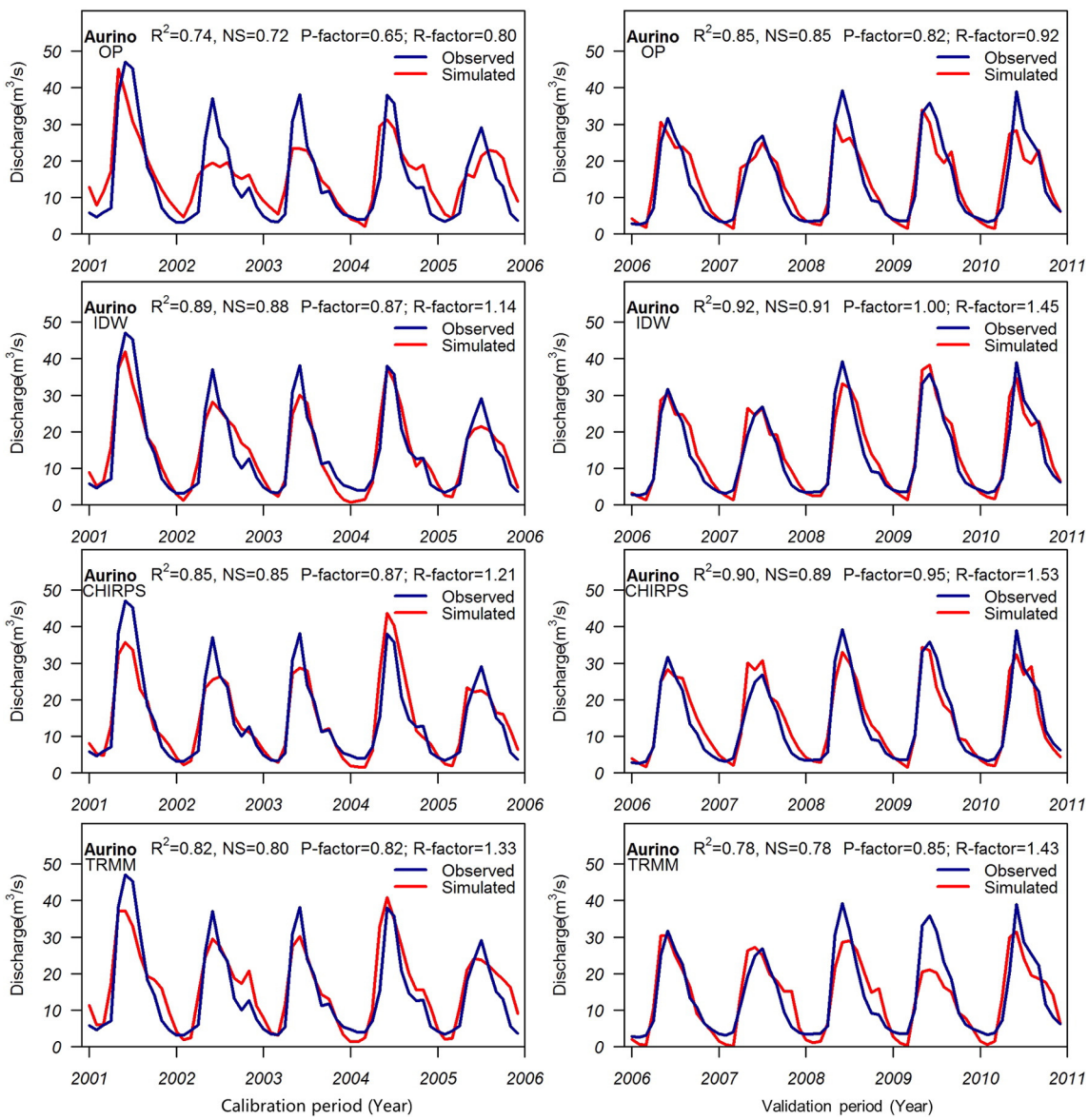


Fig. 7. Calibration (2001–2005) and validation (2006–2010) results of subbasin Aurino with elevation band method. The results represent monthly stream flow data of the best simulation, i.e., highest NS and R^2 values obtained in a set of 1500 simulations (red lines), and observed stream flow data (blue lines), along with the prediction uncertainty (P-factor and R-factor). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

performance in terms of NS and R^2. Concerning satellite products, the CHIRPS dataset is a feasible choice with at least satisfactory model performances at all subbasins.

The best performance of models with IDW is probably caused by the distinct behavior of the IDW datasets that have a larger occurrence probability of rainfall days (Fig. 2–5). As a result of interpolation, IDW precipitation time series have more rainfall days than the other datasets in form of tiny rain and >80% of them have intensity larger than 0.01 mm/d (Fig. 2–5). According to the equation of the elevation band method (Eqs. (3) and (4)), daily precipitation data will be modified only when they are larger than 0.01 mm/d. A larger amount of days corrected with the elevation band method increases the probability of obtaining a better model result for IDW models (Fig. 10) as discussed in the following section in details. Besides, the similarities in the CDF of OP, IDW and CHIRPS products lead to the at least satisfactory performance of the best model simulations obtained using these three input datasets. The differences in the daily rainfall distribution of TRMM data in comparison to the other three datasets lead to unsatisfactory model performance (Fig. 8–9). However, it is not possible to unequivocally identify the direct impact of rainfall distribution on the model performance of simulating discharge in the above study areas. In fact, the relation between streamflow and rainfall is strongly nonlinear and a change in the precipitation input leads to the definition of different best parameter sets involved in streamflow generation.

3.4. Evaluation of model performance

Beside the evaluation of the best simulation achieved with each precipitation dataset, as described above, we have also evaluated the ensemble of all available simulations. We have calculated the frequency of NS values obtained for both final calibration (1500 simulations) and validation (1500 simulations) model results. In total, 3000 simulation results are available for each precipitation dataset. Fig. 10 shows the NS distribution for the three subbasins. The performance classification of Moriasi et al. (2007) has been used as the reference for evaluation of the results.

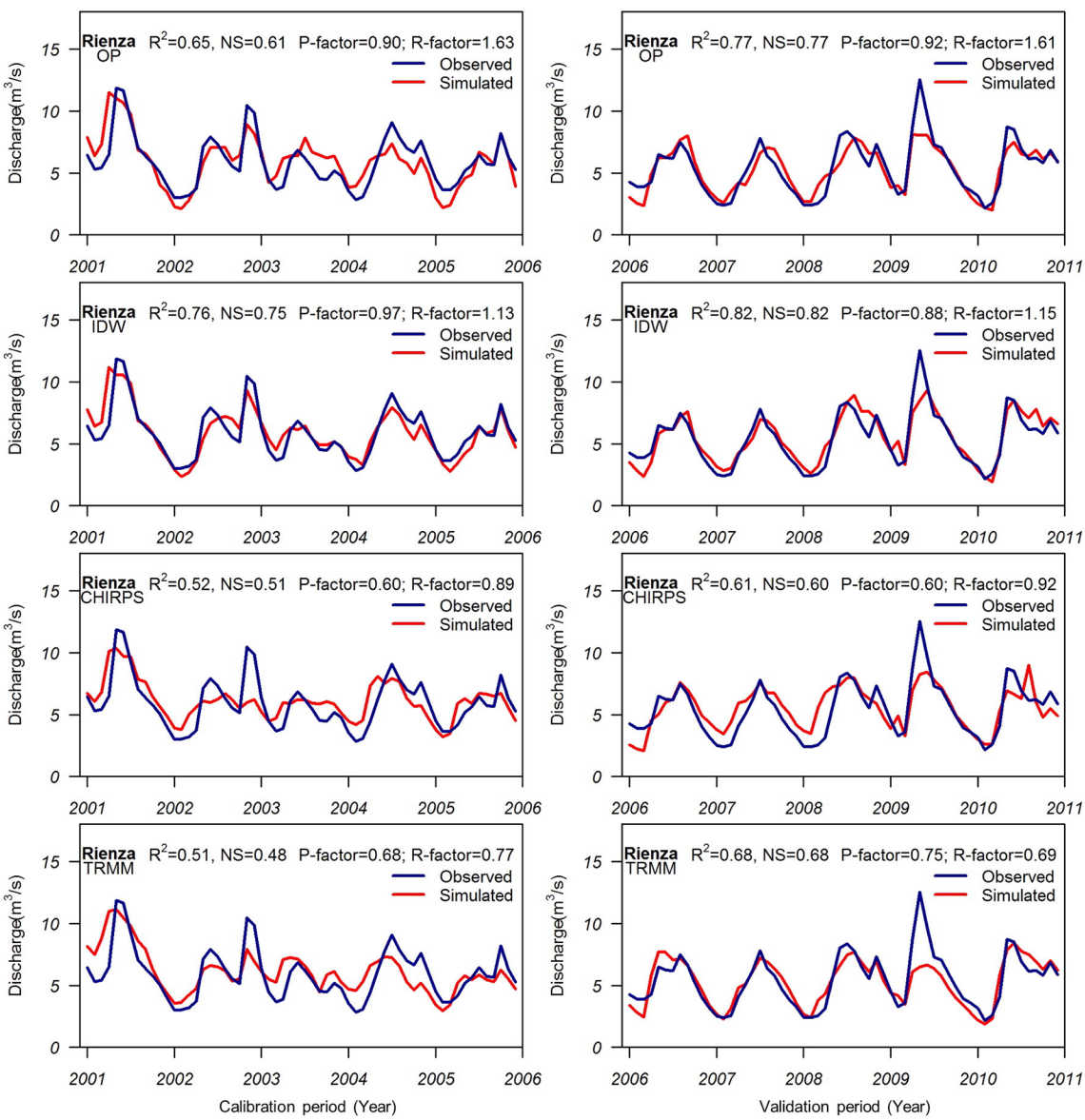


Fig. 8. Calibration (2001–2005) and validation (2006–2010) results of subbasin Rienza with elevation band method. The results represent monthly stream flow data of the best simulation, i.e., highest NS and R^2 values obtained in a set of 1500 simulations (red lines), and observed stream flow data (blue lines), along with the prediction uncertainty (P-factor and R-factor). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In the Aurino subbasin, all four models have good performance and most of model results reach at least a satisfactory level. Using IDW-based dataset, 77% of the model results reach at least a good level, while lower fractions are obtained using OP, CHIRPS, and TRMM (41%, 61% and 38%, respectively). Moreover, the IDW model displays the largest fraction of simulations having NS > 0.75, which represents very good model performance. In the Rienza subbasin, the distribution of NS values is different in comparison to those of Aurino subbasin. The percentage of simulations with NS > 0.5 are 75%, 49%, 44% and 5% for the IDW, OP, TRMM and CHIRPS models, respectively. Besides, the IDW model gets the highest percentage of NS larger than 0.75, which achieves very good model performance. In the Passirio subbasin, the IDW model consistently ranks first in occurrence rate of NS > 0.5 (70%) in comparison to OP (9%), CHIRPS (47%) and TRMM (0.1%) models. It also has the highest frequency of NS > 0.75.

Therefore, IDW is not only the precipitation dataset which leads to the best model run in terms of NS and R^2 values, but it is the dataset that generally leads to the best set of model simulations. As described above, this better performance of the IDW model in NS distribution can be ascribed to the most frequent application of an elevation correction factor in the case of the IDW-based dataset. Regarding the other products, it is not possible to identify a consistent ranking among the three subbasins. This could be caused by the joint effects of multiple calibrated parameters (Guse et al., 2016).

Table 4
Average increase ratio (i.e., relative amount of precipitation added to the original value using elevation band method) of precipitation with elevation band method in order to obtain the best simulations over the calibration period for each subbasin shown in Fig. 7–9.

	OP	IDW	CHIRPS	TRMM
Aurino	0.78 ± 0.12	0.91 ± 0.11	0.32 ± 0.02	0.47 ± 0.11
Rienza	0.49 ± 0.07	0.45 ± 0.05	0.39 ± 0.03	0.10 ± 0.02
Passirio	1.03 ± 0.24	0.89 ± 0.20	0.87 ± 0.16	0.70 ± 0.20

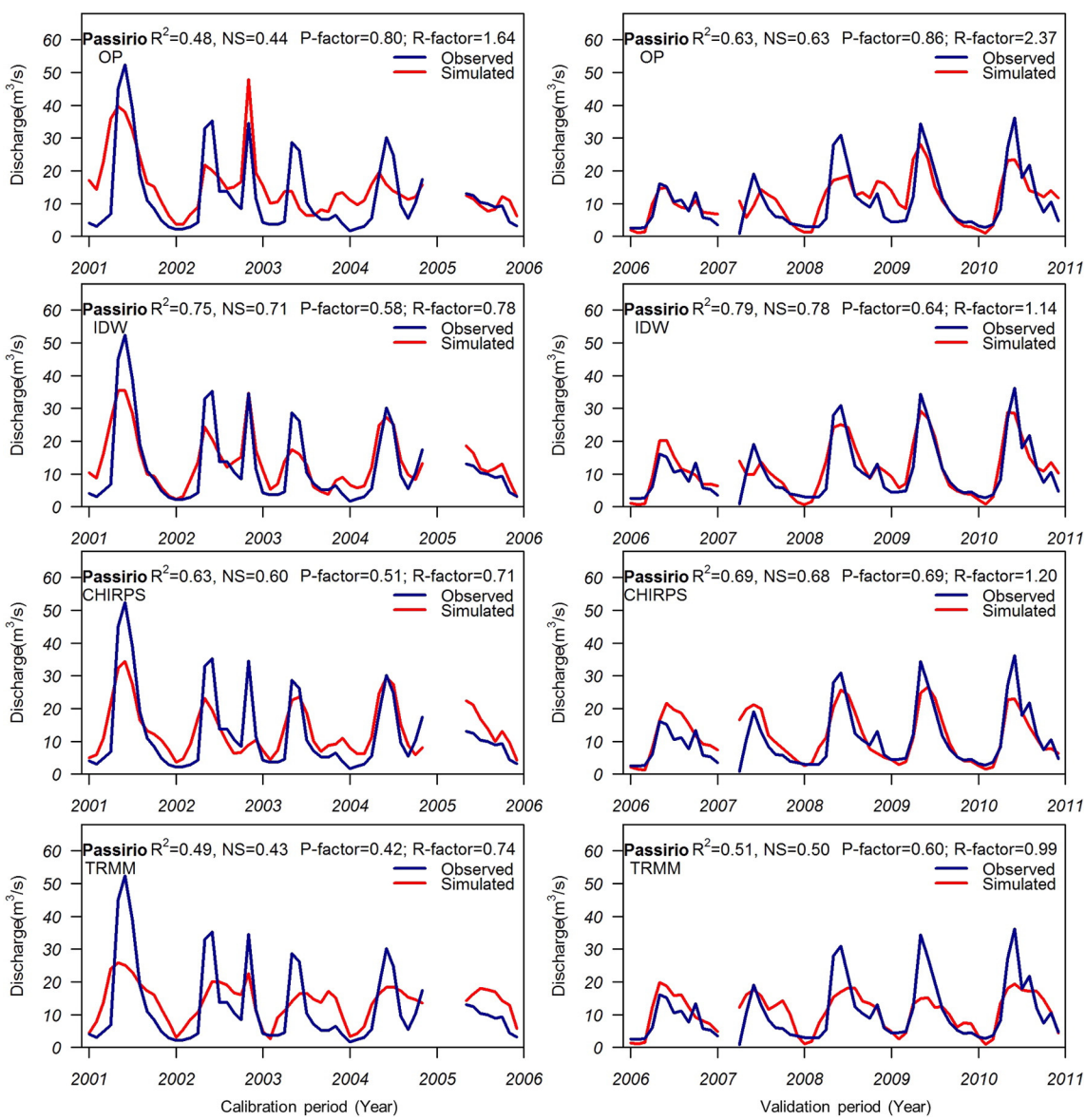


Fig. 9. Calibration (2001–2005) and validation (2006–2010) results of subbasin Passirio with elevation band method. The results represent monthly stream flow data of the best simulation, i.e., highest NS and R^2 values obtained in a set of 1500 simulations (red lines), and observed stream flow data (blue lines), along with the prediction uncertainty (P-factor and R-factor). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

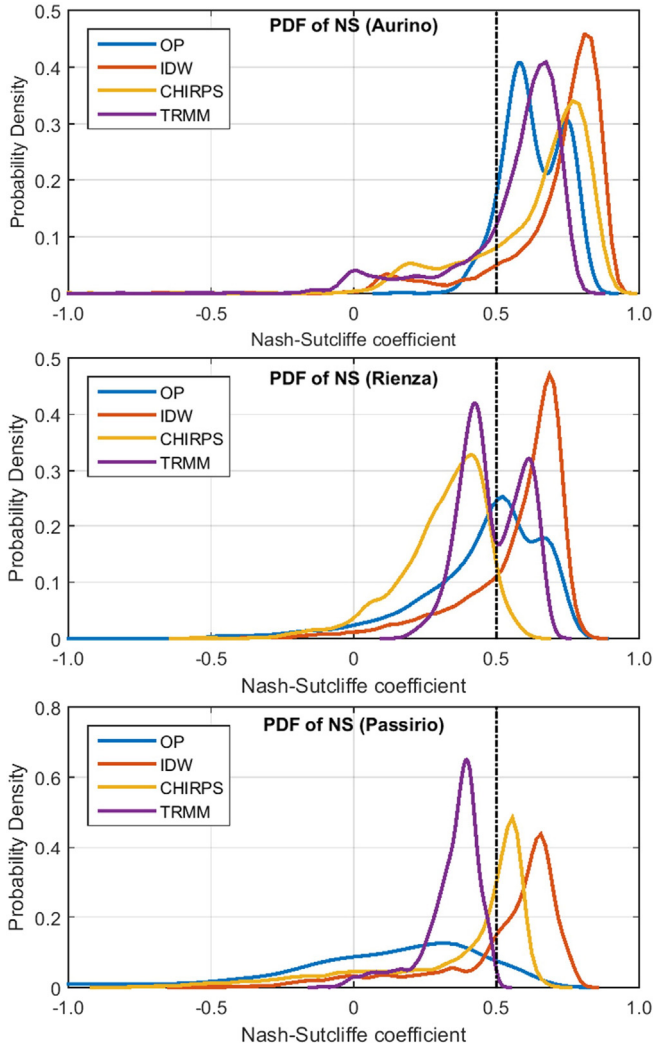


Fig. 10. Nash-Sutcliffe coefficient distribution of the simulation results with elevation band method for three study catchments.

3.5. Parameter uncertainty

The application of the elevation band method to correct the precipitation inputs improves the fitting between model results and observed streamflow data. However, the models have been able to reproduce the streamflow by adjusting other relevant hydrological parameters and converging to different optimum intervals of calibrated parameters.

Among the selected parameters shown in Fig. 11, CN2 is normally one of the most sensitive hydrological parameters and it indicates an influence of reducing the surface runoff caused by the precipitation (Strauch et al., 2012; Vu et al., 2012; Xu et al., 2010). Different precipitation inputs lead to different best CN2 values and ranges, among which the most apparent differences can be observed in the Passirio subbasin (the best fit values for a_CN2 range between −5.5 and 6.3). However, it is not possible to identify a common pattern for all basins and hence a correlation between the estimated CN2 range with a specific precipitation input cannot be derived. SOL_AWC, responsible for available water capacity of the soil layer, displays a smaller variability compared to CN2 (the coefficient of variation of the parameter range for a_SOL_AWC is 0.16 while for a_CN2 is 0.33) in both best values and ranges for different subbasins and for considering different precipitation inputs. Therefore, in these three subcatchments, SOL_AWC is less affected by a change in the precipitation input than CN2. ESCO is an important parameter related to soil evaporation. The values of ESCO span over the entire physical range (0–1) not only for different precipitation inputs but also for different subbasins (Fig. 11). GWQMN is responsible for base flow. Different precipitation inputs result in different best GWQMN values and ranges at each subbasin. The variability in the estimated parameter is again basin-specific (the coefficient of variation of the best fit value is 6.4, 2.0 and 32.1 for Aurino, Rienza and Passirio, respectively).

In summary, no clear pattern emerges to correlate the ranges of the estimated parameters and their uncertainties with the precipitation products considered in this study. The results show that different precipitation inputs affect both the best estimate of a parameter as well as its uncertainty range. It is not possible to identify which precipitation datasets would generally have smaller or larger parameter uncertainties. Additionally, the sensitivity of a parameter towards a change in the precipitation input is catchment specific. Calibrated SWAT models with different precipitation datasets corrected using the elevation band method are able to reproduce the measured discharge. However, in order to fit the measured river discharge, SWAT-CUP adjusts the water volume of different hydrological components (e.g., surface runoff and groundwater contribution) by calibrating the parameters distinctly to cope with the different rainfall features of the four precipitation products (Fig. 2–5). As shown in Table 5, despite the significant range of variability among the different fitted values and the different datasets, similar water volumes are assigned to the main hydrological compartments (evapotranspiration, percolation and base flow). Soil water and runoff display the largest variability depending on the applied precipitation input. This has a direct influence on erosion rates and contaminant transport (Neitsch et al., 2011). Hence, it is important to constrain the model using streamflow data, and to validate it using other datasets such as soil moisture, evapotranspiration and snow coverage measurements (Grusson et al., 2015).

As a result, even though all the models might fit streamflow data well (e.g. the model performances in of Aurino subbasin shown in Fig. 7), the redistribution of the single discharge components across different hydrological compartments is different. For example, at Passirio, the model calibrated using IDW-based dataset has higher optimal CN2 ranges than the other three models calibrated with OP, CHIRPS and TRMM data. This suggests that facing similar rainfall, the IDW model tends to produce more surface runoff than the other models. As a consequence, the IDW model might predict different soil erosion rates in comparison to the other models (Neitsch et al., 2011). At Aurino, the TRMM calibrated model has higher GWQMN values than the other three models. Hence, the TRMM model reflects a different groundwater processes in comparison to the other models, which subsequently would affect groundwater management practice. In the Rienza subcatchment, the model calibrated using CHIRPS data converges towards a range of ESCO values much lower than the models calibrated using the other three datasets. Consequently, the CHIRPS model would probably present higher soil evaporation, which could result in a different implication for water resources management plans in comparison to the other models. The parameter uncertainty caused by the use of different precipitation input therefore propagates to the uncertainties of predicted hydrological processes (Table 5) and then further propagates to subsequent processes controlled by hydrological drivers (Neitsch et al., 2011) and impact decision making processes (e.g., groundwater management and integrated water resources management).

3.6. Prediction uncertainties

Parameter uncertainties also contribute to the prediction uncertainties of the models (Abbaspour, 2015). The prediction uncertainties discussed here only refer to the prediction uncertainties of streamflow, which are reflected by the values of P-factor and R-factor of each model (Fig. 7-9).

In the Aurino subbasin (Fig. 7), in the calibration phase, all the other models except OP obtain acceptable uncertainties, capturing >70% of the observations and having an acceptable 95PPU envelope narrower

than 1.5 (Abbaspour et al., 2015). Among the models, the IDW model presents the smallest prediction uncertainties with the highest P-factor and smallest R-factor. Considering the validation period, the values of the P-factor of the four models are all within the satisfactory range (Fig. 7). The values of the R-factor are satisfactory for all products, except CHIRPS (unacceptable). As suggested by a rough balance between P and R, all the models generally present good prediction uncertainty in the Aurino subbasin.

In the Rienza subbasin, the four models perform distinctly for what concerns prediction uncertainties. The P-factor and R-factor also vary

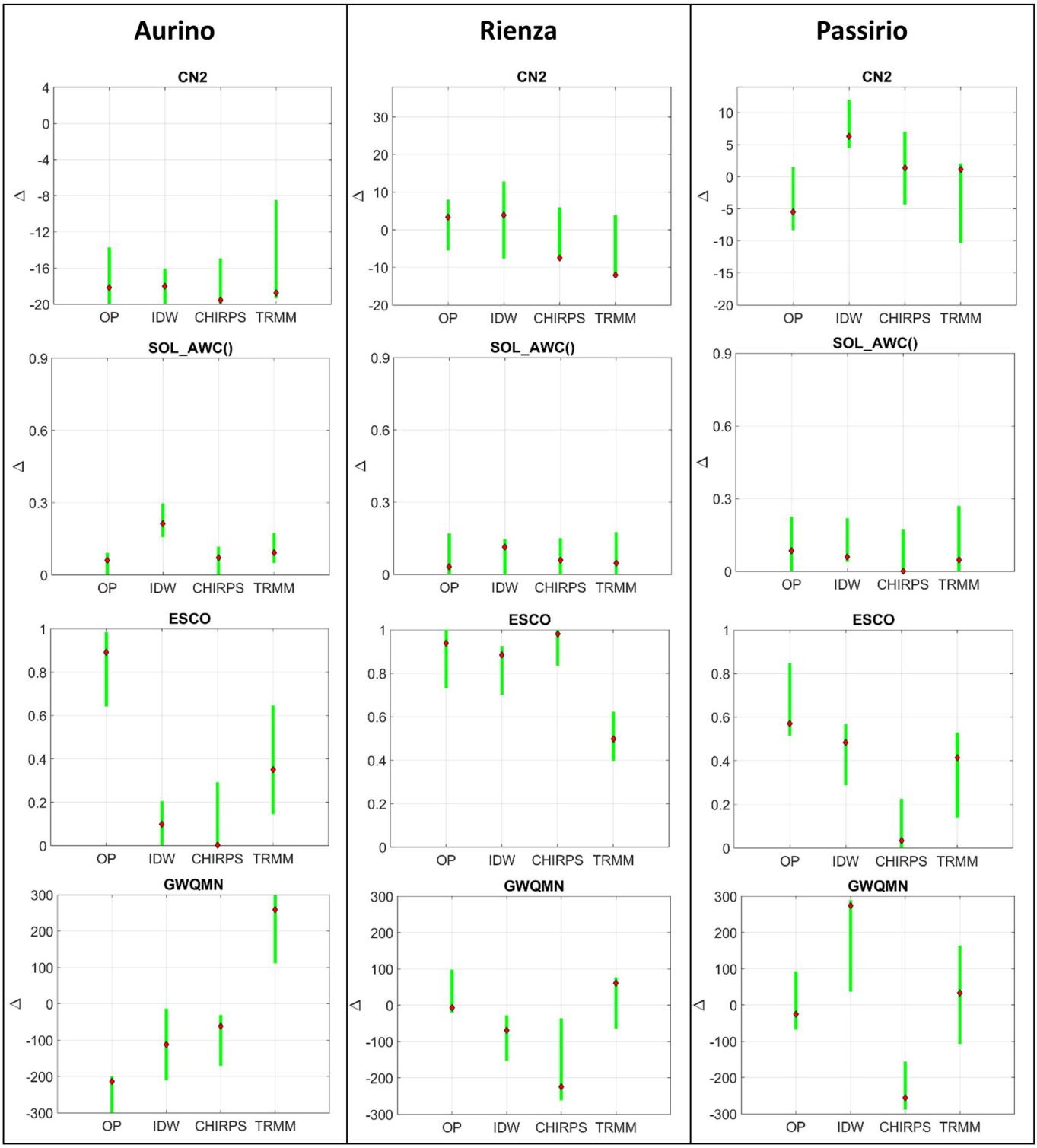


Fig. 11. Calibrated parameter distributions of four global sensitive hydrological parameters for the four precipitation inputs within the initial parameter range (y-axis domain): green bars show the final parameter ranges; red points represent the values of "best parameter". "Δ" means an absolute increase, without "Δ" means absolute value. The analysis of the other calibrated parameters is provided in the Supplementary material (Fig. S4–S6). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Water volume of major hydrological processes simulated by the best simulation. Mean annual data for calibration period.

	Evapotranspiration (mm)	Soil water (mm)	Percolation (mm)	Runoff (mm)	Baseflow (mm)
Aurino					
OP	320	96	872	137	827
IDW	367	201	707	83	611
CHIRPS	451	106	806	170	702
TRMM	333	134	927	96	851
Rienza					
OP	406	82	645	31	601
IDW	437	162	634	28	589
CHIRPS	387	112	633	10	631
TRMM	533	95	639	10	642
Passirio					
OP	621	137	991	234	833
IDW	506	105	896	258	748
CHIRPS	502	38	884	182	784
TRMM	422	91	730	78	602

between the validation and the calibration periods (Fig. 8). The IDW model performs consistently well in reaching desirable uncertainties with acceptable values of P-factor and R-factor (Fig. 8). On the contrary, the other models have at least one factor with an unsatisfactory value either in the calibration or in the validation phase (Fig. 8). Considering the entire period, a good prediction uncertainty is hence achieved by the SWAT model calibrated using the IDW datasets.

In the Passirio subbasin, only the model calibrated utilizing the OP dataset achieves an acceptable P-factor in both the calibration (0.80) and validation (0.86) periods. Considering the R-factor, only the model calibrated with the OP has a value above 1.5. It is evident that all models fail to achieve at a good balance between the P-factor and the R-factor, and therefore none of the models reach an acceptable prediction uncertainty (Fig. 9).

Only IDW models obtain consistently acceptable or non-acceptable P-factors and R-factors in both calibration and validation periods; this is not the case for the models using other three precipitation datasets. Therefore, IDW based precipitation dataset leads to more consistent prediction uncertainties than the other three precipitation datasets. Different precipitation inputs generate distinct prediction uncertainties in modeling streamflow. Also in this case, the results are heterogeneous and it is not possible to generalize the outcomes obtained in one subcatchment to another one, i.e., the prediction uncertainty of each precipitation product is basin-specific.

3.7. Influence of the precipitation input on a model with fixed parameters

In the previous sections, we showed the impact of different precipitation inputs on the calibrated parameters of the SWAT model. We showed that, despite the catchment similarities in terms of land use, major soil types, and slopes (see also Figs. S1–S2 in the supplementary material), calibrating the model using different precipitation inputs leads to significantly different model parameters (i.e., the optimal parameter ranges identified using different precipitation inputs may not overlap). We have also shown that the best four simulations for each subbasin (i.e., the simulation that achieves a maximum NS value for a specific precipitation input) have NS values that may vary by >40%. This means that the crucial input parameter is the precipitation dataset used.

In this section, we define a fix set of parameters for each of the three subcatchments. The three sets of hydrological parameters have been defined for each subcatchment by averaging the parameter values obtained for the simulations that maximized NS using each precipitation dataset. This test is performed in order to focus on the effect of the precipitation input in a situation that is not biased by the auto-calibration effect. The hydrological parameters used in this section have been provided in the Supplementary material (Table S1). The elevation band parameters for each subbasin and each precipitation input have been reported in Table 6.

Table 6
The elevation band parameters (PLAPS in Fig. S4–S6 that maximized NS during calibration period) for each subbasin and each precipitation input.

	OP	IDW	CHIRPS	TRMM
Aurino	0.042	0.142	0.150	0.103
Rienza	0.041	0.103	0.141	0.042
Passirio	0.134	0.375	0.672	0.285

The results obtained using IDW-based precipitation data have the best performance in terms of NS and R^2 (the only exception being the NS value computed for Rienza subcatchment) (Table 7). In the three case studies considered in this work, a simple interpolation algorithm coupled with the elevation band correction provides the best model results in terms of NS and R^2 values. The result of the IDW model is particularly good for the Passirio subcatchment, where only the IDW model reaches NS and R^2 values larger than 0.75, while the other models do not reach NS and R^2 values larger than 0.55. CHIRPS models rank second in terms of NS and R^2 values in the Aurino and in the Passirio subcatchments, while the performance is poor in the Rienza subcatchment.

Comparing the results presented in Table 7 with those shown in Figs. 7 to 9, we can see that the Aurino subcatchment is the least sensitive to the applied parameters. In fact, NS and R^2 values obtained using parameter sets specifically calibrated for a particular precipitation dataset are comparable with the one obtained using the computed mean parameter set. Results obtained using the IDW model show less variability in terms of NS and R^2 values in comparison to the other precipitation input models. In fact, comparing the IDW results shown in Table 7 with those shown in Figs. 7 to 9, we observe NS and R^2 values that vary by <25%.

4. Conclusions

This study investigates the impact of four different precipitation inputs on streamflow predicted using SWAT in three Alpine catchments. We have analyzed the rainfall features, model performances, parameter uncertainty, prediction uncertainty and the potential relationships among the above components. High elevation Alpine catchments are generally data-scarce regions. In particular, the problem for hydrological modeling is that precipitation data are poorly resolved in space and do not capture heterogeneous orographic effects (e.g., Le Moine et al., 2015). Most available meteorological stations are located at low elevations, which often leads to an underestimation of precipitation input (Adler et al., 2015; Isotta et al., 2014).

SWAT uses the elevation band methods to consider the orographic effects on precipitation in mountainous areas. The elevation band method implemented in SWAT currently has some known limitations (Galván et al., 2014) and it is simplistic in comparison to other more

Table 7
NS and R^2 coefficients for the four precipitation datasets considering fixed hydrological parameters for each subbasin.

	OP		IDW		CHIRPS		TRMM	
	R^2	NS	R^2	NS	R^2	NS	R^2	NS
Aurino	0.81	0.80	0.84	0.83	0.84	0.81	0.75	0.73
Rienza	0.66	0.64	0.70	0.61	0.46	0.35	0.60	0.49
Passirio	0.51	0.38	0.79	0.78	0.55	0.48	0.40	0.36

physically based corrections (Bárdossy and Pegram, 2013). However, comparing the results obtained without any correction (Fig. 6) with the results obtained using the elevation band method (Fig. 7–9), there is an evident improvement in model performance (NS increases by at least 9%). In this study, the application of this method to four different precipitation datasets (OP, IDW, TRMM and CHIRPS) has been found to greatly improve the match between simulated streamflow and measurements in three high-elevation Alpine subcatchments of the Adige river basin (Aurino, Rienza and Passirio).

We have investigated the influence of the different datasets on model performance and on the calibrated range of the estimated parameters. The four different precipitation inputs are different in terms of the amount and the temporal distribution of precipitation. The models with the IDW dataset coupled with elevation band method reach the best NS and R^2 values in all three investigated catchments. This dataset is characterized by a greater number of rainy days in form of tiny rain (average 1646 days) resulting from the interpolation of 12 nearest rain gauges. The model with the CHIRPS dataset performs satisfactorily in simulating streamflow, and thus this satellite precipitation product can be a favorable choice for this Alpine region facing data scarcity. The TRMM dataset generally leads to unsatisfactory results when used as SWAT precipitation input for streamflow modeling in these Alpine catchments.

The uncertainty affecting the estimated parameters and their calibrated range of variability changes when applying different precipitation inputs and it is catchment specific, which prevents the generalization of the outcomes achieved for a single case study. This has important consequences on the hydrological interpretation of the results, on the computation of processes driven by hydrological forcing such as erosion and solute transport, and on water management.

We have also investigated the influence of the precipitation input on models with fixed parameters. The use of a precipitation input computed using a simple interpolation algorithm (IDW) allows us to obtain results which are less sensitive to the calibrated model parameters and have higher NS and R^2 values than results obtained using satellite products or single ground observations. This conclusion is only valid for the study areas investigated in this work and should be verified in other Alpine catchments to be generalized.

In summary, selection of precipitation products has a crucial effect on model performance, model uncertainties and parameter uncertainties in streamflow simulations. Model simulations driven using different datasets can lead to different conclusions about the most relevant hydrological processes in a catchment. Moreover, this cascade of uncertainty then propagates towards processes such as erosion and contaminant transport, and in the end it would likely result in different water management strategies or policies. Nowadays, several precipitation datasets can be available for a single catchment. The uncertainty generated by the use of different precipitation inputs has then to be taken into consideration since it is at the base of the previously described cascade of uncertainty.

Acknowledgments

This research has been partially supported by the European Communities 7th Framework Program under grant agreement no. 603629-ENV-2013-6.2.1-Globaqua. The authors acknowledge the Autonomous Province of Bolzano, Dr. Bruno Majone and Ing. Francesca Villa for providing the data. The first author gratefully acknowledges China Scholarship Council (CSC) for the financial support. The authors are grateful for FAO offering the soil map. Heartfelt thanks go to the Goddard Earth Sciences Data and Information Services Center for providing TRMM 3B42 product and Climate Hazards Group for CHIRPS product. The authors wish to thank Pascal Polonik and Punit Kumar Bhola for proofreading the manuscript. The authors would like to thank the anonymous reviewers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.scitotenv.2016.08.034.

References

Abbaspour, K., 2015. SWAT-CUP 2012: SWAT Calibration and Uncertainty Programs: A User Manual. Department of Systems Analysis. Integrated Assessment and Modelling (SIAM), Eawag, Swiss Federal Institute of Aquatic Science and Technology, Duebendorf, Switzerland.

Abbaspour, K., Johnson, C., Van Genuchten, M.T., 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone J. 3, 1340–1352.

Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., et al., 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J. Hydrol. 333, 413–430.

Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J. Hydrol. 524, 733–752.

Adler, S., Chimani, B., Drechsel, S., Haslinger, K., Hiebl, J., Meyer, V., et al., 2015. Il clima del Tirolo-Alto Adige-Bellunese. Zentralanstalt für Meteorologie und Geodynamik (ZAMG), Ripartizione Protezione antincendi e civile – Provincia Autonoma di Bolzano. Agenzia Regionale per la Prevenzione e Protezione Ambientale del Veneto (ARPAV).

Andréassian, V., Perrin, C., Michel, C., Usart-Sanchez, I., Lavabre, J., 2001. Impact of imperfect rainfall knowledge on the efficiency and the parameters of watershed models. J. Hydrol. 250, 206–223.

Arnold, J.G., Fohrer, N., 2005. SWAT2000: current capabilities and research opportunities in applied watershed modelling. Hydrol. Process. 19, 563–572.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment part I: model development. J. Am. Water Resour. Assoc. 34, 73–89.

Arnold, J., Moriasi, D., Gassman, P., Abbaspour, K., White, M., Srinivasan, R., et al., 2012a. SWAT: model use, calibration, and validation. Trans. ASABE 55, 1491–1508.

Arnold, J.G., Kiniry, J.R., Srinivasan, R., William, J.R., Haney, E.B., Neitsch, S.L., 2012b. Soil and Water Assessment Tool Input/Output Documentation: Version 2012. Texas Water Resources Institute.

Ayana, E.K., Worqlul, A.W., Steenhuis, T.S., 2015. Evaluation of stream water quality data generated from MODIS images in modeling total suspended solid emission to a freshwater lake. Sci. Total Environ. 523, 170–177.

Babak, O., Deutsch, C.V., 2009. Statistical approach to inverse distance interpolation. Stoch. Env. Res. Risk A. 23, 543–553.

Bárdossy, A., Das, T., 2008. Influence of rainfall observation network on model calibration and application. Hydrol. Earth Syst. Sci. 12, 77–89.

Bárdossy, A., Pegram, G., 2013. Interpolation of precipitation under topographic influence at different time scales. Water Resour. Res. 49, 4545–4565.

Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., et al., 2013. Characterising performance of environmental models. Environ. Model. Softw. 40, 1–20.

Beven, K.J., 2011. Rainfall-Runoff Modelling: The Primer. second ed. John Wiley & Sons.

Bieger, K., Arnold, J.G., Rathjens, H., White, M.J., Bosch, D.D., Allen, P.M., et al., 2016. Introduction to SWAT+ and its application to the Little River Experimental Watershed in Georgia, USA. J. Am. Water Resour. Assoc. (submitted for publication).

Bonumá, N.B., Rossi, C.G., Arnold, J.G., Reichert, J.M., Minella, J.P., Allen, P.M., et al., 2014. Simulating landscape sediment transport capacity by using a modified SWAT model. J. Environ. Qual. 43, 55–66.

Chaplot, V., Saleh, A., Jaynes, D.B., 2005. Effect of the accuracy of spatial rainfall information on the modeling of water, sediment, and NO3–N loads at the watershed level. J. Hydrol. 312, 223–234.

Chiogna, G., Majone, B., Cano Paoli, K., Diamantini, E., Stella, E., Mallucci, S., et al., 2016. A review of hydrological and chemical stressors in the Adige catchment and its ecological status. Sci. Total Environ. 540, 429–443.

Cho, J., Bosch, D., Lowrance, R., Strickland, T., Vellidis, G., 2009. Effect of spatial distribution of rainfall on temporal and spatial uncertainty of SWAT output. Trans. ASABE 52, 1545–1555.

Chu, J., Zhang, C., Wang, Y., Zhou, H., Shoemaker, C.A., 2012. A watershed rainfall data recovery approach with application to distributed hydrological models. Hydrol. Process. 26, 1937–1948.

Costantini, E., L'Abate, G., Urbano, F., 2004. Soil Regions of Italy. CRA-ISSDS, Firenze.

Di Luzio, M., Johnson, G.L., Daly, C., Eischeid, J.K., Arnold, J.G., 2008. Constructing retrospective gridded daily precipitation and temperature datasets for the conterminous United States. J. Appl. Meteorol. Climatol. 47, 475–497.

Dile, Y.T., Karlberg, L., Daggupati, P., Srinivasan, R., Wiberg, D., Rockström, J., 2016. Assessing the implications of water harvesting intensification on upstream–downstream ecosystem services: a case study in the Lake Tana basin. Sci. Total Environ. 542 (Part A), 22–35.

Duan, Z., Bastiaanssen, W.G.M., 2013. First results from version 7 TRMM 3B43 precipitation product in combination with a new downscaling–calibration procedure. Remote Sens. Environ. 131, 1–13.

Duan, Z., Liu, J.Z., Tuo, Y., Chiogna, G., Disse, M., 2016. Evaluation of eight high spatial resolution gridded precipitation products in Adige Basin (Italy) at multiple temporal and spatial scales. Sci. Total Environ. (submitted for publication).

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2.
Gabriel, M., Knightes, C., Dennis, R., Cooter, E., 2014. Potential impact of clean air act regulations on nitrogen fate and transport in the Neuse River basin: a modeling investigation using CMAQ and SWAT. Environ. Model. Assess. 19, 451–465.
Galván, L., Olías, M., Izquierdo, T., Cerón, J.C., Fernández de Villarán, R., 2014. Rainfall estimation in SWAT: an alternative method to simulate orographic precipitation. J. Hydrol. 509, 257–265.
Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. Trans. ASABE 50, 1211–1250.
Grusson, Y., Sun, X., Gascoin, S., Sauvage, S., Raghavan, S., Anctil, F., et al., 2015. Assessing the capability of the SWAT model to simulate snow, snow melt and streamflow dynamics over an alpine watershed. J. Hydrol. 531 (Part 3), 574–588.
Guo, H., Hu, Q., Jiang, T., 2008. Annual and seasonal streamflow responses to climate and land-cover changes in the Poyang Lake basin, China. J. Hydrol. 355, 106–122.
Guse, B., Pfannerstill, M., Strauch, M., Reusser, D.E., Lüdtke, S., Volk, M., et al., 2016. On characterizing the temporal dominance patterns of model parameters and processes. Hydrol. Process. 30, 2255–2270.
Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., et al., 2007. The TRMM Multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. J. Hydrometeorol. 8, 38–55.
Isotta, F.A., Frei, C., Weilguni, V., Perčec Tadić, M., Lassègues, P., Rudolf, B., et al., 2014. The climate of daily precipitation in the alps: development and analysis of a high-resolution grid dataset from pan-alpine rain-gauge data. Int. J. Climatol. 34, 1657–1675.
Javanmard, S., Yatagai, A., Nodzu, M.I., BodaghJamali, J., Kawamoto, H., 2010. Comparing high-resolution gridded precipitation data with satellite rainfall estimates of TRMM_3B42 over Iran. Adv. Geosci. 25, 119–125.
Le Moine, N., Hendrickx, F., Gailhard, J., Garçon, R., Gottardi, F., 2015. Hydrologically aided interpolation of daily precipitation and temperature fields in a mesoscale alpine catchment. J. Hydrometeorol. 16, 2595–2618.
Li, X.H., Zhang, Q., Xu, C.Y., 2012. Suitability of the TRMM satellite rainfalls in driving a distributed hydrological model for water balance computations in Xinjiang catchment, Poyang lake basin. J. Hydrol. 426–427, 28–38.
Ly, S., Charles, C., Degré, A., 2011. Geostatistical interpolation of daily rainfall at catchment scale: the use of several variogram models in the Ourthe and Ambleve catchments, Belgium. Hydrol. Earth Syst. Sci. 15, 2259–2274.
Ly, S., Charles, C., Degré, A., 2013. Different methods for spatial interpolation of rainfall data for operational hydrology and hydrological modeling at watershed scale. A review. Biotechnol. Agron. Soc. Environ. 17, 392.
Majone, B., Villa, F., Deidda, R., Bellin, A., 2016. Impact of climate change and water use policies on hydropower potential in the south-eastern Alpine region. Sci. Total Environ. 543 (Part B), 965–980.
Malagò, A., Efstathiou, D., Bouraoui, F., Nikolaidis, N.P., Franchini, M., Bidoglio, G., et al., 2016. Regional scale hydrologic modeling of a karst-dominant geomorphology: the case study of the Island of Crete. J. Hydrol. http://dx.doi.org/10.1016/j.jhydrol.2016.05.061.
Masih, I., Maskey, S., Uhlenbrook, S., Smakhtin, V., 2011. Assessing the impact of areal precipitation input on streamflow simulations using the SWAT model. J. Am. Water Resour. Assoc. 47, 179–195.
Mei, Y., Anagnostou, E.N., Nikolopoulos, E.I., Borga, M., 2014. Error analysis of satellite precipitation products in mountainous basins. J. Hydrometeorol. 15, 1778–1793.
Mei, Y., Nikolopoulos, E.I., Anagnostou, E.N., Borga, M., 2016a. Evaluating satellite precipitation error propagation in runoff simulations of mountainous basins. J. Hydrometeorol. 17, 1407–1423.
Mei, Y., Nikolopoulos, E.I., Anagnostou, E.N., Zoccatelli, D., Borga, M., 2016b. Error analysis of satellite precipitation-driven modeling of flood events in complex alpine terrain. Remote Sens. 8, 293.
Monteiro, J.A.F., Strauch, M., Srinivasan, R., Abbaspour, K., Gücker, B., 2016. Accuracy of grid precipitation data for Brazil: application in river discharge modelling of the Tocantins catchment. Hydrol. Process. 30, 1419–1430.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — a discussion of principles. J. Hydrol. 10, 282–290.
Navarro-Ortega, A., Acuña, V., Bellin, A., Burek, P., Cassiani, G., Choukr-Allah, R., et al., 2015. Managing the effects of multiple stressors on aquatic ecosystems under water scarcity. The GLOBAQUA project. Sci. Total Environ. 503–504, 3–9.
Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and Water Assessment Tool Theoretical Documentation Version 2009. Texas Water Resources Institute.
Nerantzaki, S.D., Giannakis, G.V., Efstathiou, D., Nikolaidis, N.P., Sibetheros, I.A., Karatzas, G.P., et al., 2015. Modeling suspended sediment transport and assessing the impacts of climate change in a karstic Mediterranean watershed. Sci. Total Environ. 538, 288–297.
Panziera, L., Giovannini, L., Laiti, L., Zardi, D., 2015. The relation between circulation types and regional alpine climate. Part I: synoptic climatology of Trentino. Int. J. Climatol. 35, 4655–4672.
Price, K., Purucker, S.T., Kraemer, S.R., Babendreier, J.E., Knightes, C.D., 2014. Comparison of radar and gauge precipitation data in watershed models across varying spatial and temporal scales. Hydrol. Process. 28, 3505–3520.
Rahman, K., Maringanti, C., Beniston, M., Widmer, F., Abbaspour, K., Lehmann, A., 2013. Streamflow modeling in a highly managed mountainous glacier watershed using SWAT: the upper Rhone river watershed case in Switzerland. Water Resour. Manag. 27, 323–339.
Rathjens, H., Oppelt, N., Bosch, D.D., Arnold, J.G., Volk, M., 2015. Development of a grid-based version of the SWAT landscape model. Hydrol. Process. 29, 900–914.
Schmalz, B., Kuemmerlen, M., Kiesel, J., Cai, Q., Jähnig, S.C., Fohrer, N., 2015. Impacts of land use changes on hydrological components and macroinvertebrate distributions in the Poyang lake area. Ecohydrology 8, 1119–1136.
Schuol, J., Abbaspour, K., 2006. Calibration and uncertainty issues of a hydrological model (SWAT) applied to West Africa. Adv. Geosci. 9.
Shen, Z., Chen, L., Liao, Q., Liu, R., Hong, Q., 2012. Impact of spatial rainfall variability on hydrology and nonpoint source pollution modeling. J. Hydrol. 472–473, 205–215.
Shope, C.L., Maharjan, G.R., 2015. Modeling spatiotemporal precipitation: effects of density, interpolation, and land use distribution. Adv. Meteorol. 2015, 16.
Shope, C.L., Maharjan, G.R., Tenhunen, J., Seo, B., Kim, K., Riley, J., et al., 2014. Using the SWAT model to improve process descriptions and define hydrologic partitioning in South Korea. Hydrol. Earth Syst. Sci. 18, 539–557.
Song, X., Duan, Z., Kono, Y., Wang, M., 2011. Integration of remotely sensed C factor into SWAT for modelling sediment yield. Hydrol. Process. 25, 3387–3398.
Strauch, M., Bernhofer, C., Koide, S., Volk, M., Lorz, C., Makeschin, F., 2012. Using precipitation data ensemble for uncertainty analysis in SWAT streamflow simulation. J. Hydrol. 414–415, 413–424.
Tan, M., Ibrahim, A., Duan, Z., Cracknell, A., Chaplot, V., 2015. Evaluation of six high-resolution satellite and ground-based precipitation products over Malaysia. Remote Sens. 7, 1504.
Tobin, K.J., Bennett, M.E., 2009. Using SWAT to model streamflow in two river basins with ground and satellite precipitation data. J. Am. Water Resour. Assoc. 45, 253–271.
Tuppad, P., Douglas-Mankin, K.R., Koelliker, J.K., Hutchinson, J.S., 2010. SWAT discharge response to spatial rainfall variability in a Kansas watershed. Trans. ASABE 53, 65–74.
van der Heijden, S., Haberlandt, U., 2010. Influence of spatial interpolation methods for climate variables on the simulation of discharge and nitrate fate with SWAT. Adv. Geosci. 27, 91–98.
Volk, M., Liersch, S., Schmidt, G., 2009. Towards the implementation of the European water framework directive?: lessons learned from water quality simulations in an agricultural watershed. Land Use Policy 26, 580–588.
Vu, M.T., Raghavan, S.V., Liong, S.Y., 2012. SWAT use of gridded observations for simulating runoff – a Vietnam river basin study. Hydrol. Earth Syst. Sci. 16, 2801–2811.
Wagner, P.D., Fiener, P., Wilken, F., Kumar, S., Schneider, K., 2012. Comparison and evaluation of spatial interpolation schemes for daily rainfall in data scarce regions. J. Hydrol. 464–465, 388–400.
Woznicki, S.A., Nejadhashemi, A.P., Abouali, M., Herman, M.R., Esfahanian, E., Hamaamin, Y.A., et al., 2016. Ecohydrological modeling for large-scale environmental impact assessment. Sci. Total Environ. 543 (Part A), 274–286.
Xu, H., Taylor, R.G., Kingston, D.G., Jiang, T., Thompson, J.R., Todd, M.C., 2010. Hydrological modeling of River Xiangxi using SWAT2005: a comparison of model parameterizations using station and gridded meteorological observations. Quat. Int. 226, 54–59.
Yang, J., Reichert, P., Abbaspour, K.C., Xia, J., Yang, H., 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. J. Hydrol. 358, 1–23.
Yang, Y., Onishi, T., Hiramatsu, K., 2015. Impacts of different spatial temperature interpolation methods on snowmelt simulations. Hydrological Research Letters 9, 27–34.
Yang, X., Liu, Q., Fu, G., He, Y., Luo, X., Zheng, Z., 2016. Spatiotemporal patterns and source attribution of nitrogen load in a river basin with complex pollution sources. Water Res. 94, 187–199.
Zanotti, F., Endrizzi, S., Bertoldi, G., Rigon, R., 2004. The GEOTOP snow module. Hydrol. Process. 18, 3667–3679.
Zhang, X., Srinivasan, R., 2009. GIS-based spatial precipitation estimation: a comparison of geostatistical approaches. J. Am. Water Resour. Assoc. 45, 894–906.