

Hydrological modeling using observed and satellite precipitation datasets for the Ilave River basin, 2011-2015 period, Puno, Peru

Abstract

Precipitation datasets obtained from satellites can be useful in regions where rainfall is very heterogeneous, such as Peruvian Andes, which is usually poorly monitored. The objective of this study is to characterize the main hydrological variables and to understand the potential of precipitation estimates based on satellite datasets for hydrological modeling. This article evaluates the usefulness of estimated precipitation from observed (rain gauges) and satellites datasets (TMPA V7 and TMPA RT products of the TRMM satellite) as input in GR2M hydrological model to simulate monthly streamflows between 2011-2015 for the Ilave River basin located in the Peruvian Altiplano. The results from observational datasets indicate a deficit of streamflows due to decreased rainfall during wet season ($\sim 50\%$), whereas evapotranspiration is greater during dry season ($\sim 24\%$). Our results show that TMPA V7 has a higher similarity with respect to precipitation observed during wet season. Results also indicate that GR2M perform better with observed inputs and when TMPA-V7 precipitation datasets are used, while the opposite occurs with TMPA RT dataset. This poor performance of the hydrological model may be due to inadequate rainfall estimation in the water balance.

Keywords: Precipitation datasets; Hydrological modeling; Andes; TRMM; Satellite.

Introduction

In recent decades, global and quasi-global datasets of satellite-based precipitation, terrestrial observations and general circulation models have been developed at different temporal resolutions (Huffman *et al.*, 2007). Precipitation is an important component of the water cycle and a key input for hydrological modeling applications. The reliable quantification of the spatio-

temporal distribution of rainfall is fundamental to the analysis of extreme hydrological phenomena, such as droughts and floods, in real time or almost real time. However, measurement networks (meteorological and hydrological) in Altiplano regions may be scarce or even non-existent. In addition, the presence of the Andes contributes to the high spatial variability of rainfall (Espinoza *et al.*, 2009), where large amounts of rainfall can precipitate in a few days, increasing the risk of soil instability, landslides and floods (Coscarelli & Caloiero, 2012; Zubieta & Saavedra, 2013; Zubieta, Saavedra, Silva, & Giraldez, 2017a). Satellite-based precipitation products have increasingly facilitated rainfall estimation in much of the world and have become a complementary alternative for hydrometeorological applications and climate studies in unmonitored regions. These include data from the Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) data (Huffman, Adler, Bolvin, & Nelkin, 2010). TRMM was a mission initiated in 1997 by the National Space Development Agency of Japan (JAXA) and the National Aeronautics and Space Administration (NASA) of the United States. It came to an end on April 8, 2015, as part of its deactivation, having exhausted its energy reserves (<https://pmm.nasa.gov/trmm/mission-end>). Recently, the usefulness of these data in Andean-Amazon basins has been evaluated mainly by comparing estimated and observed data for both rainfall and streamflow, noting that precipitation data from satellites can be used as input for modeling flows in watersheds (Zulkafli *et al.*, 2014; Zubieta, Getirana, Espinoza, & Lavado, 2015; Milewski, Elikadri, & Durham, 2015; Zubieta, Getirana, Espinoza, Lavado-Casimiro, & Aragon, 2017b). Zulkafli *et al.* (2014) documents that the performance of hydrological modeling tends mainly to be unsatisfactory for the Andean-Amazonian regions of northern Peru and southern Ecuador. However, better results are obtained for the Andean-Amazonian regions of southern Peru, which are mainly associated with adequate rainfall estimates from satellite (Zubieta *et al.*, 2015).

To assess the usefulness of satellite-based precipitation data, it is necessary to investigate temporal variations in rainfall and its impacts on the hydrological cycle. The variability of the streamflows in Andean basins is consistent with the variability of rainfall on a seasonal and interannual scale. This occurs especially in the Peruvian Andes, which is characterized by different rainfall regimes, due to its latitudinal extension and the presence of the mountain range (Espinoza *et al.*, 2009). For example, rainfall in the basin of the Ramis River in the Peruvian Altiplano shows negative trends of 0.70mm / year, while maximum temperatures show significant positive trends of 0.04°C / year, on average. Likewise, the minimum temperatures at the basin level present an increase of 0.0004°C / year (Belizario, 2015). On the other hand, in recent years, the Altiplano region has suffered serious extreme hydrological events, such as

intense droughts in 2008 and 2010 (ANA, 2010) and floods in 2012 (RPP Noticias, 2012).

The main objective of this study is to evaluate the capacity of TRMM products TMPA V7 and TMPA RT (real time), for satellite-based precipitation, to represent useful precipitation fields for hydrological modeling of the Ilave River basin (IRB). The IRB is located in the Andes of southern Peru, in the northern region of the Altiplano (69.4W-70.38W; 17.14S 15.8S), with drainage area of 7 790 km², altitudes ranging from 3 805 to 5 400 meters and an average altitude of 4 300 masl (Figure 1a-b). The average annual rainfall throughout the IRB is between 494 and 888 mm / year, and it has an average flow of 32 m³ / s. The amplitude of the annual precipitation cycle is relatively large, with maximum values that occur between December and February, and minimum values between June and August.

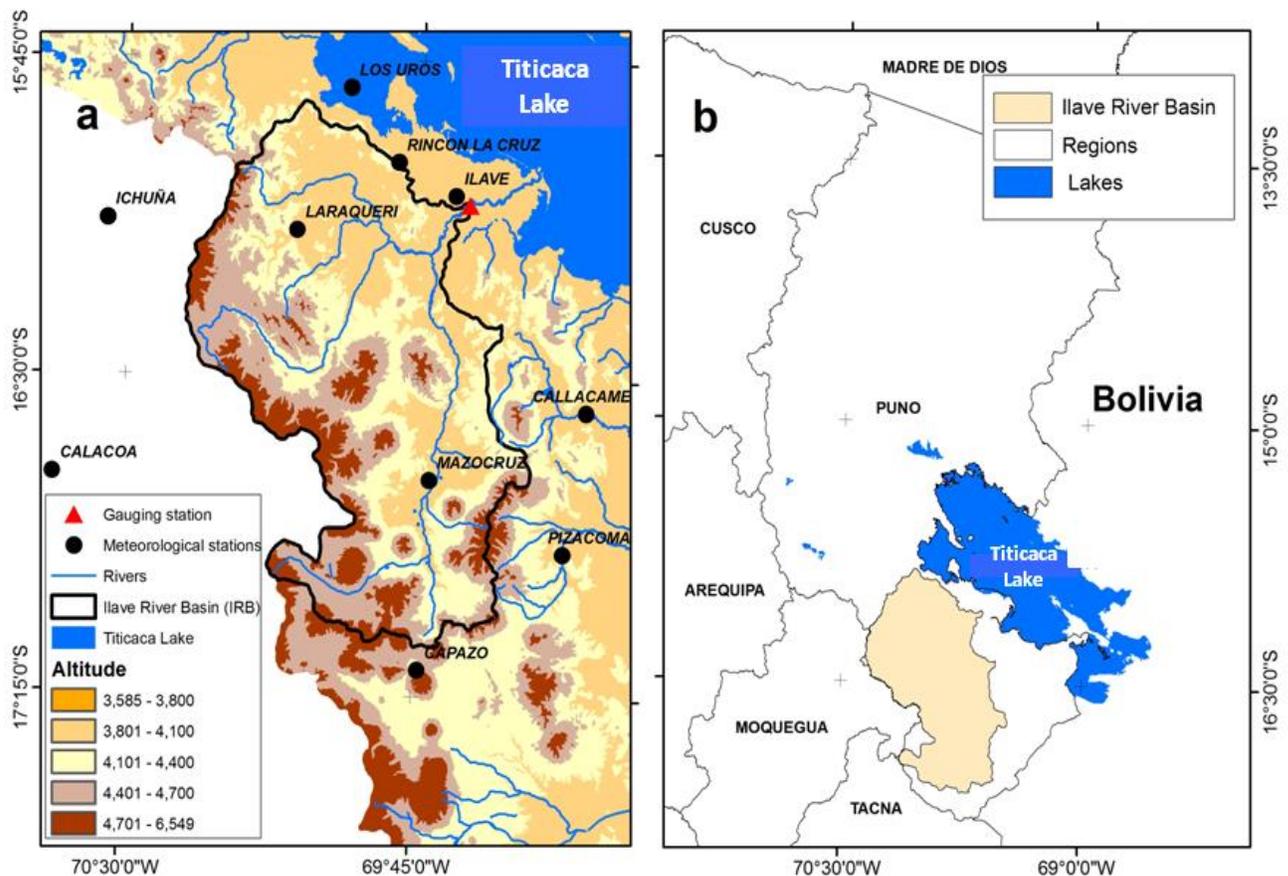


Figure 1. a) Location of weather stations; b) location of the Ilave River basin, IRB.

A ground-based precipitation dataset was used for comparison with the satellite estimates. Each precipitation dataset (observed and satellite) was

used as input for the GR2M model (Niel, Paturel, & Servat, 2003), which is based on the GR2M model (Edijatno & Michel, 1989; Kabouya, 1990), and adapted by Makhlouf & Michel (1994). Streamflow simulations were compared to observed flows. GR2M has been used to simulate the hydrological behavior of numerous Andean-Amazon basins in Peru (Lavado, Labat, Guyot, Ronchail, & Ordoñez 2009; Lavado, Labat, Guyot, & Ardoin-Bardin, 2011; Vera & Felipe, 2011). Recently, Lujano, Felipe, Lujano and Quispe (2015) showed that TMPA data are feasible to use as input for the GR2M model for the Ramis River basin, which is located northwest of the IRB.

Data used

A daily rainfall dataset was collected from 11 rain stations belonging to the National Meteorology and Hydrology Service of PERÚ (SENAMHI). The data period selected for the hydrological analysis was between 2010 and 2015. However, to ensure the maximum availability of rainfall and hydrometric data, a common period (2011-2015) was selected (Figure 1b, Table 1). To evaluate its quality, this database was composed of a total of 10 rainfall stations on a monthly basis, the regional vector method (RVM) was applied, which uses the concept of extended precipitation averaged over the study period (Hiez, 1977; Brunet-Moret, 1979; Vauchel, 2006).

Table 1. General characteristics of weather stations: latitude (Lat), longitude (Long), altitude (Alt), annual rainfall (rain), maximum temperature (T max), minimum temperature (T min) and the percentage of data availability for the period 2011-2015.

Sation Name	Lat	Long	Alt	Rain	T max	T min	Availability of data (%)
Capazo	-17.19	-69.74	4 530	464	13.6	-6.3	99.8
Mazo Cruz	-16.74	-69.72	4 003	564	17.5	-5.0	99.9
Laraqueri	-16.15	-70.07	3 900	788	16.7	-1.6	99.8
Los Uros	-15.82	-69.94	3 808	810	15.8	3.9	99.9
Rincón La Cruz	-15.99	-69.81	3 935	872	15.3	2.7	99.
Ilave	-16.07	-69.66	3 871	647	15.3	1.5	99.9

Callacame	-16.57	-69.32	3 951	413	14.0	1.0	99.8
Pizacoma	-16.91	-69.37	3 930	583	17.0	-0.9	99.9
Ichuña	-16.13	-70.55	3 800	595	20.1	2.5	99.9
Calacoa	-16.74	-70.68	3 260	386	25.0	4	99.8

The least squares method was applied to determine an annual regional rainfall index, Z_i , and extended average precipitation. For this purpose, this calculation can be made by minimizing the sum of Equation (1), where P_{ij} stands for the annual rainfall in the station j , P_j is the average precipitation extended i is the year index, j is the index of the station, N the number of years, and M the number of stations. Finally, the Z_i data series is called the annual regional vector of rainfall indices.

$$\sum_{i=1}^N \sum_{j=1}^M \left(\frac{P_{ij}}{P_j} - Z_i \right)^2 \quad (1)$$

Thus, the climate zone was considered the same as the IRB with the same rainfall regime. It is assumed that the annual rainfall in the basin's stations shows the proportionality between the stations. TRMM provides data derived from its products, which were evaluated in this study. One product used was the TMPA 3B42 version 7 was used, obtained both in real time and near real time from a set of data from many sensors on precipitation satellites (TMPA 3B42 data is available at <https://pmm.nasa.gov/data-access/downloads/trmm>).

TMPA shows the most successful experience, since its processing has been improved by using data having a better scale than other data sources, which is essential to creating spatial-temporal averages that are appropriate for the user's application (Huffman *et al.*, 2010). The other set of data was taken from TMPA-RT precipitation estimates. Unlike TMPA V7, these data do not include calibration measurements of rain stations, which are incorporated more than one month after the satellite data.

Both TMPA V7 and TMPA RT provide precipitation data with spatial resolution a of $0.25^\circ * 0.25^\circ$ and a temporal resolution of 3 hours. Daily rainfall data was collected from 11 rain stations belonging to the National Meteorology and Hydrology Service (SENAMHI). The data period selected for the hydrological analysis was between 2010 and 2015. However, to ensure the maximum

availability of rainfall and hydrometric data, we selected a common period (2011-2015) (Figure 1b, Table 1).

To evaluate its quality, this database was composed of a total of 10 rainfall stations on a monthly basis. The regional vector method (RVM) was applied, which uses the concept of average precipitation extended to the study period (Hiez, 1977; Brunet-Moret, 1979; Vauchel, 2006).

Methodology

The GR2M model (Niel *et al.*, 2003) is a lumped hydrological model that requires monthly average information related to climatic variables for a drainage area (Figure 1a). Due to the reduced number of rainfall stations (10) and some unmonitored regions in the basin, precipitation data was interpolated, at the same resolution of the TMPA (0.25 ° * 0.25 °) by means of the kriging method, considering the relationship between the stations located inside and outside the basin. The method selected in this study is the ordinary Kriging, which consists of quantifying the assumption that nearby measurements tend to be more similar than those that are located further away. Detailed information about the Kriging interpolation method can be found in Lichtenstern (2013). Finally, the average precipitation values for each month and for the entire basin in the 2010-2015 period were determined. Due to the availability of maximum and minimum temperature data, the evapotranspiration variable (ETP) was estimated with the Hargreaves & Samani model (1985). This calculation is shown in Equation (2):

$$ETP = 0.0023 (T_m + 17.8)(T_{max} - T_{min})^{0.5} * Ra \quad (2)$$

where *ETP* is evapotranspiration (mm / day), T_m is mean temperature (° C), T_{max} is maximum temperature (° C), T_{min} is minimum temperature (° C) and *Ra* is extraterrestrial radiation (mm / day). This method provides a suitable approximation with respect to data obtained by lysimeters in the northern Altiplano regions (higher humidity), similar to those obtained by the FAO Penman-Monteith equation (García, Raes, Allen, & Herbas, 2004). In fact, studies carried out in the Bolivian Altiplano using pasture varieties (above 3

000 masl) as a reference crop suggest that the Penman-Monteith and Hargreaves-Samani methods sufficiently agree with data from lysimeters (García, Raes, & Jacobsen, 2003; García *et al.*, 2004; Vacher, Imana, & Canqui, 1994). However, Hargreaves-Samani (1985) tends to slightly underestimate data observed in the southern region of the Altiplano, where the aerodynamic factors that affect evapotranspiration are more important than in the northern Altiplano, due to the plains and greater aridity (García *et al.*, 2004).

The conceptual layout of the GR2M model is shown in Figure 2, where the parameters of the model are noted as $X1$ (maximum storage capacity of the reservoir in mm) and $X2$ (groundwater exchange coefficient, dimensionless). The GR2M model's parameters are described as follows (Niel *et al.*, 2003): $X1$ parameter is adjusted in order to multiply, in the same proportion, rainfall and evapotranspiration rates ranging from 0 to 1; α is a parameter multiplied by effective rainfall, (Pe) corresponds to direct flow while $(1 - \alpha)$, Pe flow discharges into the gravity drainage tank; finally, the discharge of the second tank is defined with parameter $X2$ with ranges from 0 to 1.

The model is based on the transformation of precipitation-runoff through two functions: production and transfer. The GR2M model is a model with two reservoirs, where the production function is organized around a reservoir called reservoir-soil, and the transfer function is governed by the second reservoir called gravitational water reservoir, where the contribution is instantaneous at the beginning of the time step, then the reservoir empties gradually. The level of this reservoir determines the flow rate that can be released (Figure 2).

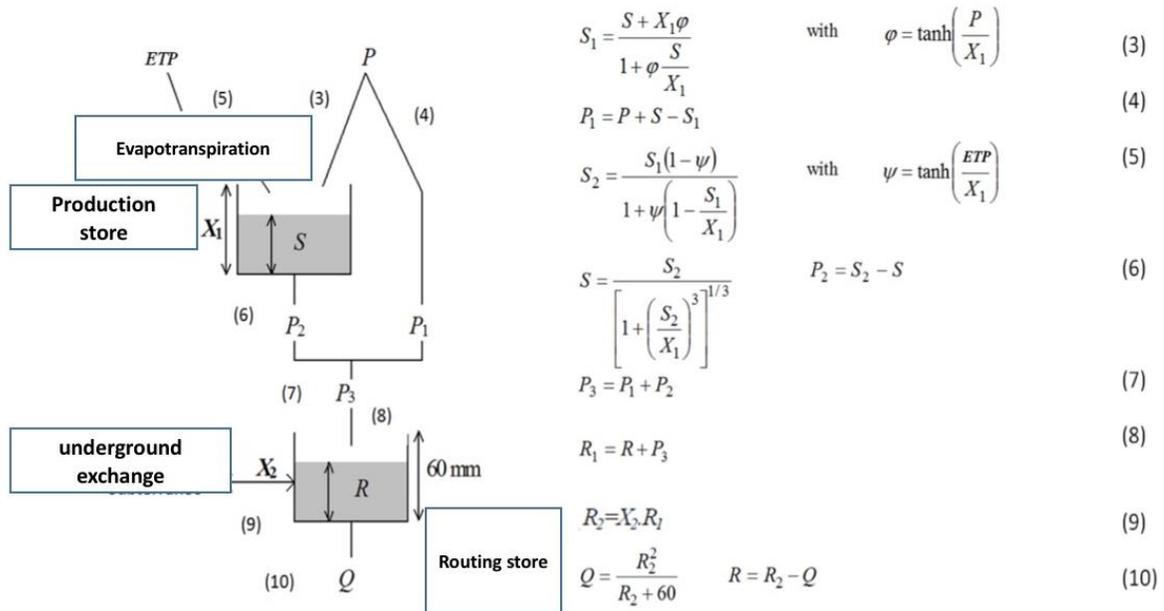


Figure 2. GR2M Model (Mouelhi, 2003).

Source: Cemagref (www.cemagref.fr).

The input (P) and output (ETP) variables of the reservoir-soil (production stored-maximum capacity X_1) are calculated based on the storage of the production reservoir (S). A portion of precipitation P_1 refers to the difference between P and the precipitation that enters the soil, and another portion, P_2 , refers to the amount of water that contributes to underground exchange. The sum of P_1 and P_2 corresponds to the effective precipitation, P_3 , that enters the gravitational water reservoir (R) (maximum capacity set at 60 mm). The underground exchange (R_2) is included in the X_2 model (Figure 2). Finally as a result for the output flow, the gravitational water reservoir is released according to a quadratic function. The optimization of the model responds mainly to two parameters: X_1 , capacity of the reservoir-soil in millimeters, and X_2 , coefficient of underground exchange (dimensionless). For this, a previous manual calibration was carried out, to finally use the Excel SOLVER tool.

To evaluate the performance of the model, the following objective functions were used: Nash Sutcliffe Coefficient (NS), difference between calculated and observed volumes by the volume error (ΔV) and coefficient of determination shown as $(\rho_{Q_{obs}, Q_{cal}})$ in Equations 11, 12 and 13:

$$NS = 1 - \frac{\sum_{t=1}^{nt} (Q_{obs}(t) - Q_{cal}(t))^2}{\sum_{t=1}^{nt} (Q_{obs}(t) - \overline{Q_{obs}})^2} \quad (11)$$

$$\Delta V = \frac{\sum(Q_{obs}(t)) - \sum(Q_{cal}(t))}{\sum(Q_{obs}(t))} \quad (12)$$

$$\rho_{Q_{obs}, Q_{cal}} = \frac{\sigma_{Q_{obs}, Q_{cal}}}{\sigma_{Q_{obs}} \cdot \sigma_{Q_{cal}}} \quad (13)$$

Where Q_{obs} is the observed flow, Q_{cal} is the estimated flow, $\sigma_{Q_{obs}, Q_{cal}}$ is the covariance between Q_{obs} and Q_{cal} , and, finally $\sigma_{Q_{obs}}$ and $\sigma_{Q_{cal}}$ represent the standard deviation of the variables, respectively.

Results and discussion

In average terms, the visual analysis of the estimated evapotranspiration regime for the period 2011-2015 did not show significant variations during the wet season (~ 166 mm, December-February), however, there was an approximate increase from 64 mm to 80 mm during the dry season. As a result of the water balance, this increase is associated with the reduction in precipitation identified throughout the study period ($\sim 50\%$) (see Figure 3a). The average annual precipitation in the IRB indicates that TMPA V7 (836.4 mm) and TMPA RT (1022.5 mm) overestimated observed data (688.0 mm) by 21.6% and 48.6%, respectively.

The analysis of monthly precipitation in the IRB shows that the TMPA V7 data were more realistic in relation to observed data when a high coefficient of determination between them was identified ($r^2 = 0.86$) and lower standard error ($EME = 25$ mm) (Figure 3b). However, TMPA V7 shows differences with respect to observed data for rainfall estimates above 50 mm / month. Likewise, TMPA RT dataset shows greater differences than TMPA V7 for estimates above 50mm / month, despite having an acceptable coefficient of determination ($r^2 = 0.76$) and a higher error ($EME = 33.1$ mm) (Figure 3c).

For a temporal analysis of rainfall, average monthly rainfall was calculated for each data set (PLU, TMPA V7, TMPA RT). The analysis corroborates that the TMPA V7 estimates best approximate data observed during the wet season (December-March) (Figure 3d). However, TMPA V7 shows a tendency to overestimate rainfall observed during the dry season by ~ 22 mm (May-September). On the other hand, TMPA RT data show a tendency to overestimate data observed predominantly throughout the year.

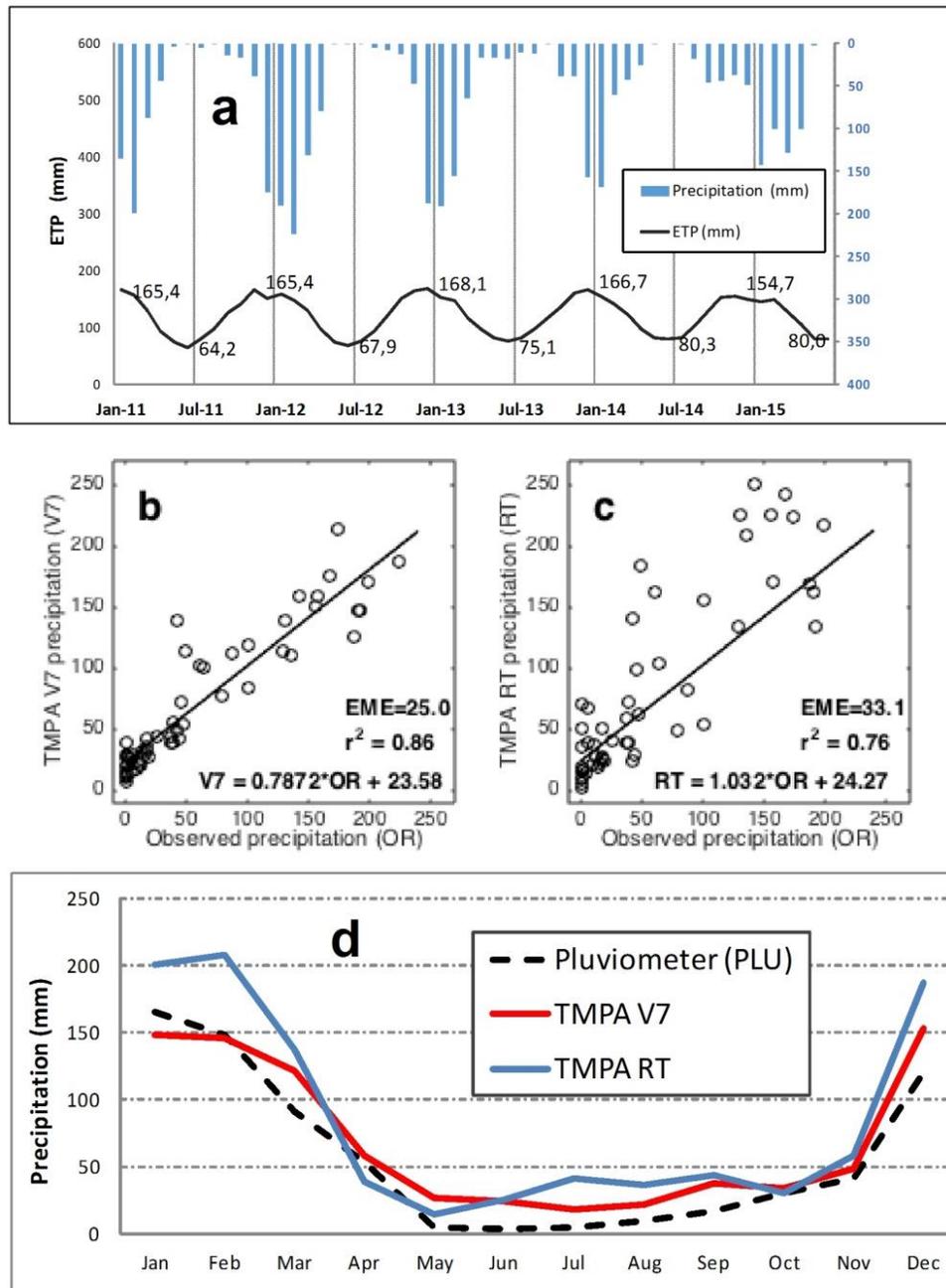


Figure 3. a) Comparison between evapotranspiration and observed rainfall; b-c) dispersion diagrams based on the rainfall products TMPA V7 and TMPA RT in relation to observed rainfall (*PO*); d) average monthly rainfall for each rain product.

The differences identified between the satellite estimates and observed rainfall data may be associated with observational variations and/or data from sensors providing data input to the algorithm used to estimate satellite precipitation (Huffman *et al.*, 2007). In fact, similar results were found in the Ramis River basin in the Peruvian Altiplano (Lujano *et al.*, 2015) and other regions in the Andes of Peru and Ecuador (Zulkafli *et al.*, 2014; Zubieta *et al.*, 2015).

For the calibration process of the model, the selection of the number of years of the calibration and validation periods was evaluated previously. On average conditions, for a one-year calibration period (validation period of 4 years) the model performance tended to be better than when selecting 2 or 3 years (validation period of 3 and 2 years), which were 30% and 45% lower in performance, respectively.

The calibration of both the observed rainfall and satellite model only included 2011, while the validation included the 2012-2015 period.

The model's input variables were average monthly values for precipitation, potential evapotranspiration and streamflows. The optimization process was based mainly on obtaining suitable model parameters ($X1$ and $X2$) according to Equation 10, using observed rainfall data and satellite data (TMPA V7, TMPA RT) as input. The optimized $X1$ and $X2$ values for each set of precipitation data are shown in Table 2, where the values found for the Nash coefficient, water balance and correlation coefficients are also presented for evaluating flow data modeled with respect to observed flows.

Table 2. Calibration parameters, Nash-Sutcliffe performance coefficients, differences between volumes, and coefficient of determination between calculated and observed flows.

Parameter	Observed Rainfall	TMPA V7	TMPA RT
X1: Production reservoir (mm)	5.76	5.57	6.35
X2: Exchange parameter (mm)	1.00	0.96	0.74
Nash Sutcliffe (NS) coefficient	0.95	0.74	0.54
% difference between observed and calculated volume (ΔV)	-5	-23	-41
Coefficient of determination (R^2)	0.85	0.64	0.45

Similar to the rainfall regime, the streamflow regime observed also showed a clear decrease from 2011 to 2015, both in the wet and dry seasons, with

similar patterns in each series of streamflows estimated from satellite data (TMPA V7 and TMPA RT). Given the water balance and the high performance of the GR2M model in the estimation of streamflows using observed data, this deficit is due to the predominant decrease in rainfall, which was also identified in the streamflows series obtained from satellite. It is also affected by the increase in evapotranspiration estimated during the dry period between 2011-2015 (Figures 4a and 3a).

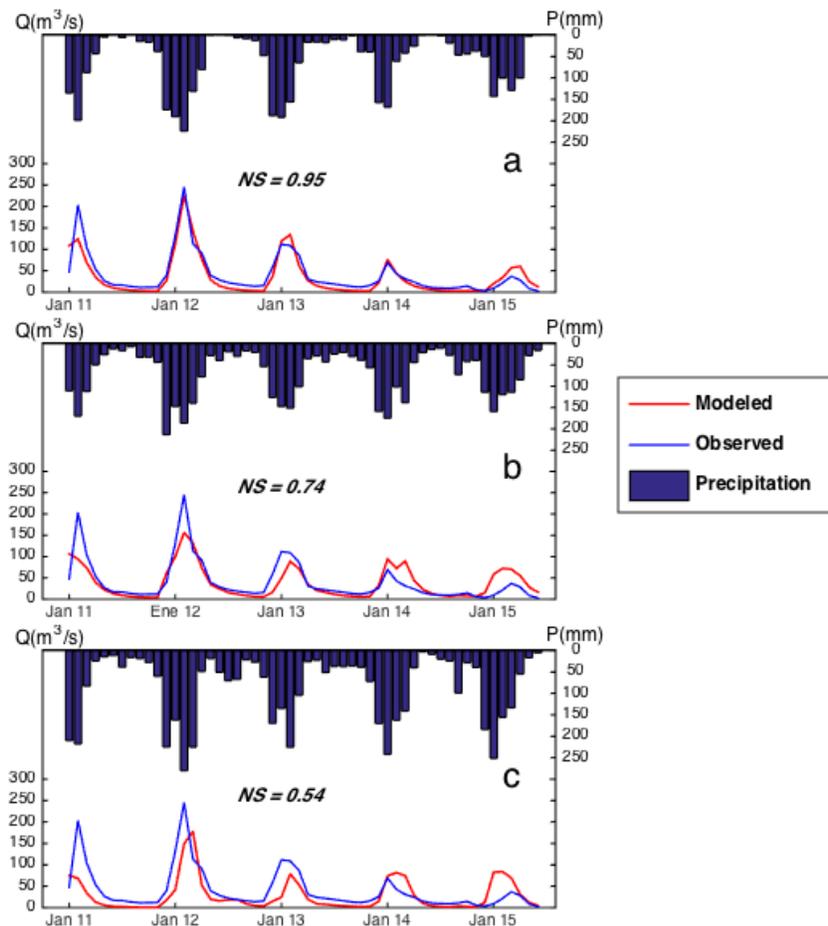


Figure 4. Observed and modeled streamflows at the Puente Carretera Ilave station from January 2011 to June 2015. Modeled streamflows were calculated using precipitation data obtained from (a) rain gauges, (b) TMPA V7 and c) TMPA RT at the Ilave River basin (IRB).

The decrease in rainfall may be associated with the substantial increase in the occurrence of warm fronts in the Altiplano, which may increase atmospheric evaporation, in addition to reducing vegetation (Thibeault, Seth, & Garcia,

2010). The visual analysis of the hydrographs shows that the streamflows obtained from observed rainfall (rain gauges) are more similar to observed streamflows in the Puente Carretera Ilave gauging station ($NS = 0.95$ and $\Delta V = -5\%$), which are shown in Figure 4a. The rainfall regime is consistent in relation to the streamflows obtained in the water balance (see Figure 4a). Seasonal fluctuations in the flow regime are very well represented by the GR2M model when using observed data, mainly during the validation period, such as those recorded in the 2012, 2014 and 2015 flows.

However, the performance of the GR2M model when using TMPA V7 data in the IRB is minimally acceptable ($NS = 0.74$, $\Delta V = -23\%$) despite presenting a relatively high NS (Figure 4b). It was not possible to adequately represent all the peak flows, which could be due to the overestimation of the rain during wet season (December-January).

However, it can better reproduce seasonal streamflows, mainly during dry periods. Lower performance was found with TMPA RT ($NS = 0.52$, $\Delta V = -41\%$) (Figure 4c). Results from TMPA RT data were due to an inadequate rainfall estimate by the TRMM satellite, This is characterized in average values by a very marked overestimation with respect to the observed dataset (rain gauge) (31%) and the TMPA V7 dataset (35%) during the wet period (Figure 3d). This overestimation was also observed during dry season, which resulted in 81% more than observed rain (rain gauges) and 16% more than rainfall based on TMPA V7.

Monthly streamflows between 2011 and 2015 obtained from satellite were also compared to observed streamflows (Puente Carretera Ilave station) using dispersion diagrams (Figure 5a-c). Flows show that the series generated by the model using observed data (rain gauges) and TMPA V7 better represent the observed streamflow, presenting acceptable coefficients of determination (0.85 and 0.64, respectively). However, the streamflows ($Q > 75 \text{ m}^3 / \text{s}$) present predominantly during the wet period (January-March) presented a greater dispersion of the data, unlike other periods (dry season during Junio-Julio or precipitation start period between September and December). In general, this suggests a better approximation by the TMPA V7 dataset, whose data was most similar to observed streamflows. However, the streamflows simulated using TMPA RT presented greater differences with respect to the observed streamflows (low coefficient of determination ($r^2 = 0.45$)).

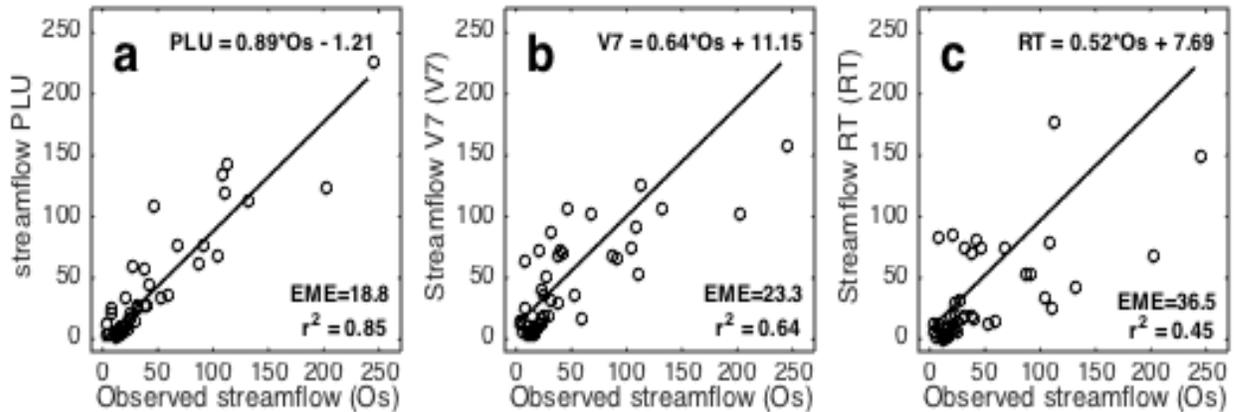


Figure 5. Observed and modeled streamflows using rain gauges: **a)** PLU; **b)** TMPA V7 and **c)** TMPA RT.

The greater similarity between TMPA V7 and observed rainfall dataset, as well as overestimation of TMPA RT with respect to observed data (Figure 4b-c), are congruent with the observed affect on the maximum storage capacity parameter of the reservoir, $X1$, since these parameters obtained in the optimization process ($X1$) are more similar when they are obtained from TMPA V7 and observed data (PLU). In addition to $X1$ tends to be higher when it is provided by TMPA RT (see Table 2).

On the other hand, the streamflows modeled with GR2M using satellite rain (TMPA V7, TMPA RT) tend to underestimate observed flows. This is mainly associated with the optimization process of the model. Therefore, a lower underground exchange ($X2$) is effective when using TMPA V7 ($X2 = 0.96$) and TMPA RT ($X2 = 0.74$) (see Table 2). This suggests a negative impact on the final production of streamflows ($X2$ is low), which implies that although satellite precipitation tends to overestimate rainfall observed in the wet season, the results of the model of this rainfall tend to underestimate observed flows.

Conclusions

A clear deficit was identified in the streamflow regime of the Ilave River in the Peruvian Altiplano for the period 2011-2015. According to the hydrologic balance, the water deficit was due to the decrease in precipitation in the rainy period ($\sim 50\%$) and increased evapotranspiration in the dry period ($\sim 24\%$).

Two monthly rainfall datasets from the TRMM satellite (TMPA V7, TMPA RT) were compared with a ground-based precipitation dataset (PLU) on the Ilave River basin.

With average conditions and based on statistical analyses, TMPAV7 was highly associated with observed precipitation, especially during the wet season (January-March). However, TMPA V7 tended to overestimate observed rainfall during the dry period (May-September). On the other hand, data based on TMPA RT predominantly showed overestimations throughout the year.

To investigate the advantage of satellite data in hydrology, an observed rainfall dataset (PLU) and a satellite-based rainfall dataset (TMPA V7, TMPA RT) were used as input variables to the GR2M hydrological model.

The analysis of the hydrographs showed that the flow rates obtained from observed rain (rain gauges) were more similar to flow rates observed in the Puente Carretera Ilave gauging station ($NS = 0.95$). It should be noted that when using TMPA V7, the performance of the GR2M model data can adequately represent the seasonal flow cycle ($NS = 0.74$). However, it does not have the ability to adequately represent peak flows. This mainly suggests an inadequate estimate of rainfall during the month of February, characterized by an underestimation of rainfall.

It was found that TMPA RT ($NS = 0.54$) performed poorer than TMPA V7. This poorer performance with the TMPA RT dataset was due to inadequate satellite estimates, characterized by a marked overestimation of observed rainfall data. Indeed, the streamflows showed that the series generated by the model using observed data (rain gauges) and TMPA V7 better represented observed flows during the wet period.

Errors in the streamflow simulations by the GR2M model may be associated mainly with rainfall or evapotranspiration input data, in addition to the model's limited representation of physical processes. However, the results show that it is possible to use data from satellites for hydrological modeling of small basins in the Altiplano of the Peruvian, in order to adequately simulate flow rates.

It is of great interest in hydrology to evaluate the data from the new generation of rainfall estimates provided by the GPM (Global Precipitation Measurement) satellite (Schwaller & Morris, 2011). This type of data provides the possibility of taking advantage of sub-daily data or precipitation sub-

schedules to estimate flows of the same temporal resolution using hydrological models.

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