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Calibration and Uncertainty Analysis for modeling Runoff of The Tambo River Basin, Perú, using Sequential Uncertainty Fitting (SUFI-2) algorithm.

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Abstract

Basin scale simulation is fundamental to understand the hydrological cycle, specify essential information for water management, accordingly, the applicability of the Soil and Water Assessment Tool (SWAT) model is evaluated to simulate runoff in the semi-arid Tambo River basin (Peru), due to economic activities are driven by available water. The objective of the study, SWAT model was configured using the basin properties, such as soil type, digital reduction model, land use, meteorological information (precipitation and temperature from Meteorological Stations). The SWAT model was calibrated using the SUFI-2 algorithm for the periods from 1994 to 2001, with 3 years of warming and validated from 2002 to 2016 using daily river discharges. The results during the daily and monthly calibration period had Nash-Sutcliffe Simulation Efficiency (NSE) of 0.69 and 0.86, Determination Coefficient (R2) of 0.70 and 0.87, Percent bias (PBIAS) of -14.4 and Ratio of standard deviation of the observation of the root mean square error (RSR) of the root of 0.55 and 0.37, respectively. For the daily and monthly validation period, they had (NSE) of 0.52 and 0.70, (R2) of 0.67 and 0.87, (PBIAS) of -6.1 and (RSR) of 0.69 and 0.55, respectively. These results show that SWAT model has the ability to predict current flows within the Tambo River basin, in southern Peru. Also, it may serve as guideline for hydrology modellers, being a useful tool to detail change of land use and impact climate in a semi-arid basin.

Keywords: SWAT model, Calibration, Runoff, SUFI-2, NSE, Tambo River Valley, Semi-arid, Peru.

1. Introduction

Accurate analysis of water flow pathways from rain to streams is critical to optimal protection of water resources (Kannan et al., 2007). For this, it is essential to understand the physical phenomena that occur within a basin because they represent the relationships that can be found within the system (Dong et al., 2018). Therefore, the use of hydrological models become an economic and effective tool for the development of almost all water resource management plans. (Suryavanshi et al., 2017).

The great applicability of SWAT model and its versatility, made in different hydrological studies such as climate change impacts, sediment transport, simulation of flows and effects of extreme urbanization (Gassman et al., 2014), the main reason for its implementation and study, finding studies (Aouissi et al, 2016; Duru et al., 2018; Jajarmizadeh et al, 2017; Jodar-Abellan et al., 2018; Mengistu et al, 2019; Niraula et al., 2012; Sellami et al., 2014; Shao et al., 2019) related to similar conditions in basin. SWAT is a continuous, spatially semi-distributed, process-based model capable of simulating water balance (Arnold et al., 1998), developed and supported by the USDA Agricultural Research Service (Arnold et al., 2012; Neitsch et al., 2011).

Hydrological models are generally calibrated against observation variables, to estimate some parameters that cannot be measured directly and to achieve a reliable prediction of the basin response (Sivapalan et al., 2003). The calibration of the model will only be considered successful if the observation period is representative of the hydrological behaviour of basin (Wagener et al., 2003). In calibration process, the parameters were optimized by SUFI-2, it is carried out with SWAT Calibration and Uncertainty Programs (SWAT-CUP) was developed for automatically computing sensitive model parameters (Fakult & Kiel, 2015). Most SWAT-CUP applications are using Sequential Uncertainty Fitting (SUFI-2) algorithms and flow observations to analyze sensitivity, calibration process and uncertainty of model (Wu & Chen, 2015). In SUFI-2 algorithm all uncertainties (parameter, input data, etc.) are mapped onto the parameter ranges as the procedure tries to capture most of the measured data within the 95% prediction uncertaint (K. C. Abbaspour et al., 2004) .

The Tambo River basin, due to its topography, climatic and hydrological factors in the region, produce spatio-temporal variability in the distribution of water resources (Tapley & Waylen, 1990). The thermo-pluviometric interaction with other elements of the climate, has been able to establish that in the lower part of the Tambo River basin there is a water deficit, while in the headwater there is an excess (Alegria, 2007; ANA., 2015), especially in the dry months, due to the diversion of water from a Tambo River basin part to the hydraulic system Pasto grande (ANA., 2005). In the headwater Tambo basin, the annual volume of water available at 75% persistence is sufficient to meet current demand, however, the monthly balance shows that there is an average deficit of 23.65 MMC in the dry season, however there are 10 other sub-basins in the middle and upper part of the Tambo basin, with average annual deficits of less than 1.5 MMC (ANA., 2013). Also droughts, like the one in 1983 that caused estimated losses of USD 200 million in southern Peru (Lavado-Casimiro et al., 2013) and had a critical impact on the success and survival of the region, causing agricultural production in southern Peru to be reduced by up to 75% in 2016 (ANA., 1966; Mortensen et al., 2018).

Finally, the floods in the coastal valleys are recurring problems year after year, generating material and economic damage (ANA., 1966; Mortensen et al., 2018) The complete dependence on water resources is 98.7% of total use, among agricultural, population, industrial and livestock uses, for these reasons the implementation of a hydrological model that is capable of forecasting the amount of available water with a reasonable level of precision. Due to the scarce information and situation of the basin, it is necessary to carry out the hydrological simulation study in the Tambo River basin capable of forecasting surface runoff with a reasonable level of precision.

The main objective of this study is to implement the SWAT model for the hydrological simulation of current flow in the Tambo River basin through the identifiability and sensitivity analysis of fifteen parameters that influence current generation and regime. of basin flow, model calibration defines optimal qualitative performance ratings of the SWAT model using the SUFI-2 algorithm. The results of this study will help to understand the hydrological processes and will provide supporting information regarding the adaptation, planning and management of the water resources of the Tambo River basin.

2. Materials and Methods

2.1 Study Area

The Tambo River basin is located a South latitude between 16º 00 ’and 17º 15’ and west longitude 70º 30 ’and 72º 00’ in the South of Peru at 3,900 meters above sea level and includes the provinces of Mariscal Nieto y Sánchez Cerro, Islay and San Román; located in the departments of Moquegua, Arequipa and Puno respectively.

The basin has an extension of 13,361 km2, and a maximum length of route, from its source to its mouth, of 289 km, its main tributaries are the rivers: Carurnas, Coralaque, Ichuna and Paltature. The surface water resources of the Tambo River basin are generated in the upper basin, with a total annual volume of 1,077 MMC and an average annual discharge of 31,457 m3 / s. The population of Mollendo is the one with the highest flow with 98.5 l / s, followed by Mejía with 20.6 l / s, Cocachacra with 12.5 l / s, Arenal and La Curva with 8.5 l / s and 6.5 l / s respectively (ANA., 2003), The population of the Rio Tambo basin is concentrated in urban and rural areas, such as the Mollendo and Ubinas district. The productive activities of its population are agricultural, farming and livestock. (Suelos & Ica, 2000).

The basin is characterized by presenting variable thermal conditions, 3 types of climate have been distinguished based on the Köppen criteria: Very dry semi-warm climate (desert or subtropical arid) with average annual rainfall of 150 mm and average annual temperatures of 18º to 19º C, temperate sub-humid climate (Steppe and low inter-Andean valleys) with temperatures exceeding 20º C and annual precipitation is below 200 mm and cold or boreal climate (Meso-Andean Valleys) is characterized by its average annual precipitation of 300 mm and for its annual temperatures of 12º C (ANA., 2003). In the basin the lands without vegetation predominate, you can also find small snow-capped mountains in the upper part, in the south there is the Pasto Grande that contributes 7.4 hm3 annually in the dry seasons from September to December (ANA., 2015).

2.2 The Model—Soil and Water Assessment Tool (SWAT)

The free software Soil and Water Assessment Tool (SWAT) is a rainfall-runoff model, of semi-distributed parameters, capable of simulating various physical processes on a continuous time scale (annual, monthly, daily, and daily). The main objective is to predict the impact of management on water, sediments in hydrographic basins, as well as the impact of agricultural management practices on water quality (nutrients and pesticides). It has reasonable precision in large basins, with a variety of relief, types and uses of the soil. Its high spatial resolution allows it to be implemented at both continental and hydrological basin scales (Arnold et al., 2012, 1998). The hydrological component of SWAT allows calculating the elements of the water balance and, consequently, the water resources (blue, green water, etc.) even at the sub-basin level. The terrestrial phase of the hydrological cycle is simulated based on the following equation of the water balance (Eq. 1).

$$SW_t = SW_0 + \sum_{t=1}^{t} (R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \qquad (1)$$

Where SW_t and SW_0 are the final and initial soil moisture content, R_{day} is the precipitation, Q_{surf} is the is surface runoff, Ea is the evapotranspiration, w_{seep} is the water seepage from the vadose zone into the soil profile, y Q_{gw} is the groundwater volume. The variables are expressed in mm of H_2O to day, i, and time, t, in days. (Neitsch et al., 2011).

2.3 Data Used

Ministry of the Environment of Peru (MINAM) (http://geoservidorperu.minam.gob.pe/) (Figure 1a) was used for topography information; The map of greater land use capacity is available at the geoserver of the Ministry of the Environment of Peru (MINAM) (http://geoservidor.minam.gob.pe/)(Figure 2); The soil map was extracted from the Food and Agriculture Organization of the United Nations (FAO) (http://www.fao.org/) (Figure 3). As input data for the SWAT meteorological generator, such as daily temperature, daily precipitation for periods from 1994 to 2016, they were obtained from the National Service of Meteorology and Hydrology of Peru (SENAMHI) (https://www.senamhi.gob.pe /), while the wind speed, Solar radiation and relative humidity were simulated by the SWAT Model, the flow data with periods from 1994 to 2016 required for the calibration are provided by Autoridad Nacional del Agua (ANA) (https://www.ana.gob.pe/) (Figure 1b). A resume Information is in Table 1.

2.4 SWAT Set-Up

The SWAT model was set up with the help of ArcGIS interface version of SWAT (ArcSWAT 2012). The first step was watershed delineation. The basin and sub-basin were delineated using automatic watershed delineation tool. On the basis of topography, flow direction and flow accumulation, stream networks were generated. The whole basin was divided into 36 sub-basins (Figure 1. c), containing a point source each of them. The delineation was finished by selecting the outlet of the whole watershed and defined a points inlet in the south-east of the basin. Next step was HRU creation. HRUs is the portion of a sub-basin that contains single soil attributes. Depending upon a user defined percentage value of soil type, land use and slope, HRUs of each sub-basin were generated. For this simulation, 598 HRU were generated, threshold values of 2%, 2%, and 5% were used for land use, soil type, and slope value respectively, to maintain an accurate spatial variability as much as possible compared to most articles related to SWAT, where thresholds take values greater than 5%. Moreover, this study used five slope classes, which are the maximum number in SWAT. The watershed's slope classes were defined as 0–5%, 5–10%, 10–15%, 15–25% y > 25% (Figure 4), According to a study conducted by (Niraula et al., 2012) in a semiarid basin. It was considered an inlet point for water from 2001, by a spillway from the Pasto Grande reservoir, which discharge (water) from September to December. The Pasto Grande reservoir is within the basin in the south-east of Peru. The model was built for the period 1994 - 2016.Next step was about writing input tables. In this part, all meteorological data (precipitation, relative humidity, temperature, wind speed and solar radiation) were linked to the existing model. After completing the abovementioned steps, the model was ready to run with the default parameter setting.

2.5 SUFI-2 algorithm description of SWAT-CUP

The algorithm SUFI-2 calibration is performed with a series of iterations including numerous simulations. Each iteration is fed with the results of the previous one. This achieves approximate (optimize) the simulated variable. The results of the iterations are a set of values (ranges) assigned to the parameters that represent the hydrological processes, the physical characteristics and the dynamics of each hydrographic basin. Each new iteration presents intervals (ranges) of the parameters recursively closest to their real value. This aims to limit the uncertainty existing in the initial ranges of the parameters, since measurements of these are often not available. (Karim C. Abbaspour et al., 2017; Karim C. Abbaspour et al., 2007) . Thus, based on flow measurements, introduced in SUFI-2, it provides iteration after iteration greater accuracy in the ranges of the parameters of each study area. This procedure is called Reverse Hydrological Modeling (K. C. Abbaspour et al., 2004; Karim C. Abbaspour et al., 2007; Beven & Binley, 1992). an objective function must define to calculate the sensitivities of the response parameters, with the method specified by the user (Yang, Reichert et al., 2008). Different methods defining an objective function may lead to different results (Legates & McCabe, 1999). Several objective functions have been used to estimate model performance, including (R2) and Nash-Sutcliffe (NSE) efficiency to reduce the problem of non-uniqueness in model characterization (Duan et al., 2006).

2.6 Sensitivity Analysis

The sensitivity analysis is performed by the average changes in the objective functions, they are estimated based on the consequent changes of each parameter, called here the relative sensitivities. It provides partial information on the sensitivity of the objective function and It´s based on the linear approximation of the model parameters. Furthermore, to estimate the level of significance between the data sets, a t-test is applied to identify the relative significance of each parameter. The t-test and p-values were used to provide a measure and significance of sensitivity, respectively. Larger absolute values of t are more sensitive than lower ones, while a p value closer to zero are of more importance (Narsimlu et al., 2015), all these procedures are developed in SWAT-CUP.

2.7 Calibration and Validation

The calibration process consists of adjusting the values of the model parameters so that the simulated values approach those observed, which best represents the simulated process. It is important to emphasize the hydrological model does not know the initial simulation conditions, the conditions that can have great difficulties in the simulated process, therefore, it needs heating (Li et al., 2015).

The degree of measurement of the calibrated model explains the uncertainties, it was evaluated by factor P and factor R, with factor P being the percentage of observations in square brackets for the 95% prediction uncertainty (95PPU). The R factor, which is the average thickness of the 95PPU band divided by the standard deviation of the data. The suggested values are> 0.7 and <1.5 respectively (K. C. Abbaspour et al., 2004, 2007, 2015).

Validation is based on the use of the model with parameters calibrated in a mass of independent data for the application of the model to the event can be evaluated through various tests (Daggupati et al., 2015; Pereira et al., 2014). After the validation phases, if the model achieves satisfactory performance, it is possible to perform model simulations according to different movements (Marek et al., 2016).

SWAT calibration and validation was processed with the SUFI-2 algorithm (Sequential Uncertainty Fitting version-2) included in the SWAT-CUP (K. C. Abbaspour et al., 2015). A divided sample procedure will be used that uses runoff data from the Puente Santa Rosa bridge station for the period 1994-2001 and 2002-2016. The objective function was NSE since it is suggested in several studies related to SWAT for example (Asadzadeh et al., 2016; Brighenti et al., 2019) or as the study by (Kouchi et al., 2017). indicates that It has the most common parameters with other objective functions, this results in a reduction of uncertainty compared to other objective functions. Throughout the Calibration and Validation process, 3 years of heating (1994-1996) were carried out to have a better performance, since the initial conditions of the system are not known, executing multiple simulation iterations with a minimum of 250 and 500 simulations in every execution.

2.8 Model Performance Evaluation

El R2, NSE For scientifically sound model calibration and validation, a combination of different efficiency criteria is suggested (Krause et al., 2005) and (D. N. Moriasi et al., 2007) three quantitative statistics be used in model performance evaluation in watershed simulations: The Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS) and ratio of the root mean square error to the standard deviation of measured data (RSR). In this study, NSE, R2, RSR and PBIAS are the four parameters that are used to evaluate the performance of the results of the Hydrological model. The Nash-Sutcliffe Efficiency Criteria (NSE) is one of the most often used performance criteria in hydrology, focuses on determining the relative magnitude of the residual variance compared to the measured data variance (Nash & Sutcliffe, 1970) and its value. varies from $-\infty$ to 1, with a high value indicating an accurate model. NSE is calculated using the following define by (Eq. 2):

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_m - Q_s)_i^{\,2}}{\sum_{i=1}^{n} \left(Q_{m,i} - \bar{Q}_m\right)^2} \qquad (2)$$

where, Qm is mean of observed discharges, and Qs is simulated discharge and n is the total number of observations.

The degree of collinearity between the simulated and measured flow rate can be obtained using the coefficient of determination (R2) and the range of R2 is 0 to 1, with a higher value signifying better performance. It can be calculated as following (Eq. 3):

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Q_{m,i} - \bar{Q}_m\right)\left(Q_{s,i} - \bar{Q}_s\right)\right]^2}{\sum_{i=1}^{n}\left(Q_{m,i} - \bar{Q}_m\right)^2 \sum_{i=1}^{n}\left(Q_{s,i} - \bar{Q}_s\right)^2} \qquad (3)$$

PBIAS (Percent Bias) measures the average tendency of the simulated data to be larger or smaller than the observed equivalents (Gupta et al., 1999). Small magnitude PBIAS values are preferred. The optimal value of PBIAS is zero, where low magnitude values indicate better simulations. Positive values indicate an underestimation of the model and negative values indicate an overestimation of the model (Gupta et al., 1999), It can be calculated as following (Eq. 4):

$$PBIAS = 100 \times \frac{\sum_{i=1}^{n}(Q_m - Q_s)_i}{\sum_{i=1}^{n} Q_{m,i}} \qquad (4)$$

where, Q is a variable (e.g. discharge), and m and s stand for measured and simulated, respectively.

The standard deviation index (RSR) of observations is the mean squared error index (RMSE) divided by the standard deviation of the measured data. RSR varies from the optimal value of 0 to ∞ (Moriasi et al., 2015), where zero indicates zero RMSE or residual variation and, therefore, perfect simulation of the model, to a large positive value. The lower the RSR, the lower the RMSE and the better the performance of the model simulation (D. N. Moriasi et al., 2007; Kumar wet al., 2017) .It can be calculated as following (Eq. 5):

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}(Q_m - Q_s)_i^{\,2}}}{\sqrt{\sum_{i=1}^{n}\left(Q_{m,i} - \bar{Q}_{m,i}\right)^2}} \qquad (5)$$

where, Qm is mean of observed discharges, and Qs is simulated discharge and n is the total number of observations. The optimal ranges of the parameters can be observed using Table 2.

3. Results

3.1 Parameter sensitivity analysis

The results of the sensitivity analysis of 15 parameters (CN2, ALPHA_BF, GW_DELAY, GWQMN, GW_REVAP, REVAPMN, RCHRG_DP, ESCO, EPCO, SLSUBBSN, OV_N, SOL_BD, CH_K2, CH_N2, TRNSRCH) with respect to model output. Table 3 summarizes the parameter sensitivity with respect to surface flow, base flow, and stream flow and the initial values and the best ranges of model parameters. In this study, the result of the global sensitivity analysis with the t-test indicates that the most sensitive parameters ($0.05 < p$) , the fraction of transmission losses from main channel that enter deep aquifer (TRNSRCH, p= 0.00, t= -18.51) was found to be the most sensitive parameter followed by effective hydraulic conductivity of the soil layer (CH_K2 (p=0.00, t= -11.84) and Groundwater delay (days) (GW_DELAY , p=0.026, t= -2.218), Deep aquifer percolation fraction (RCHRG_DP, p=0.0312, t= -2.159) and Manning's n value for overland flow (OV_N, p=0.043, t= 2.024) in calibration process.

Groundwater studies should be carried out to provide more information, according to the sensitivity analysis indicated by sensitive parameters, as well as the improvement of channels to avoid loss water.

Dotty plot (Figure. 5) is the plot of parameters versus objective function; indicating distribution of the sampling points which explain the parameter sensitivity (K. C. Abbaspour et al., 2015).The parameters are related to the configuration of the lateral flow between the root zone and the connection of the shallow aquifer to the river bed, pointing out the importance of the shallow aquifer and the main channel relationship in Semi-Arid zones. This situation is also reported in other countries basins Mediterranean and France (Sellami et al., 2014; Zhang et al., 2019).

3.2 Calibration and uncertainty analysis

Before calibration, the model was incapable of simulating stream flow value and shows indices poor R2 0.48, NSE -0.98, RSR 1.41 and PBIAS -162 values, necessitating the calibration process and automated analysis of flow uncertainty to improve such indices.

The sensitive parameters were continuously modified for daily and monthly time period of time of 1994 - 2001 using SUFI-2 algorithms for 500 simulations. In the selection of parameters, it was carried out according to the study of (Lévesque et al., 2008). The measured and predicted results were correlated at the same time with the output end, FLOW_OUT_34 (sub-basin 34). During the calibration, the P-factor and R-factor obtained were 0.98 and 1.18 respectively, the final results turned out to be good as expected, the ratio of P-factor and R-factor is high enough (greater than 1 for SUFI-2) for a typical uncertainty analysis (Rostamian et al., 2008; Xue et al., 2014; Yang, Reichert et al.2008) indicating the acceptable performance of uncertainty analysis in this study. the results of daily simulation have a different value in the daily and monthly simulation. For calibration in daily time series simulation, the value of NSE, R2, PBIAS, RSR are 0.69, 0.70, -14.4 and 0.55 respectively. Those values describe that the SWAT model could be simulated well in this area. According to Table 2, those results categorize as satisfactory due to the results is more than 0.5 for NSE, R2, RSR values. The hydrograph of daily simulation is presented in Figure 6. The output of calibration in monthly simulation has better value than daily simulation. the value of NSE, R2, PBIAS, RSR in monthly simulation are 0.86, 0.87, -14.4, 0.37 respectively. According to Table 2, those results categorize as very good. It indicated that the model could describe hydrological processes very good for monthly simulation. Although, the model simulated low streamflow in the catchment particularly during may - december than what were observed. This should be attributed to land-use largely changed in this period. The hydrograph of monthly simulation is presented in Figure 7, and the scatter plot of the monthly simulation is presented in Figure 8. The calibrated parameter ranges were later used to validate. The adjusted values and the best final distribution of parameters are represented in Table 3.

3.3 Model Validation

The model validation is to check accuracy of the output representation towards the real stream flow data. Model validation was conducted for a different period of the calibration using comparison observed data and simulated data. The model validation process both daily and monthly simulation was conducted from 2002 to 2016. The result of daily flow validation was the less than calibration periods. NSE, R2, PBIAS, RSR values were 0.52, 0.67, -6.1 and 0.69, respectively. According to Table 2, Those results can be categorized as satisfied simulation. The hydrograph of daily simulation is presented in Figure 9. For monthly simulation, NSE, R2, PBIAS, RSR values were less than calibration periods. NSE, R2, PBIAS and RSR values were 0.70, 0.87, -6.1 and 0.55 respectively. According to Table 2, Those results can be categorized as good simulation. The hydrograph of monthly simulation (Figure 10) and the scatter plot of the month simulation is presented in (Figure 11).

4. Conclusions and discussion

The purpose of this study was to evaluate the performance of the SWAT model using SUFI-2 algorithm. The SWAT model presented a good performance in the calibration stage and in the validation stage it was satisfactory. The SWAT-CUP module was an important tool for sensitivity analysis, calibration and validation of the model. Monthly simulation has better results than daily simulation in basin with the categorize of monthly simulation as very good for calibration ($R2$ = 0.87, NSE = 0.86, PBIAS = -14.4, RSR = 0.37) and good for validation ($R2$ = 0.87, NSE = 0.70, PBIAS = -6.1, RSR= 0.55) periods in other hand classification of daily simulation categorize as good for calibration ($R2$ = 0.70, NSE = 0.69, PBIAS = -14.4, RSR = 0.55) and satisfactory for validation ($R2$ = 0.67, NSE = 0.52, PBIAS = -6.1, RSR = 0.69) periods. The process of modelling streamflow becomes even more difficult in catchments where irregular rainfall distribution occurs. Even more so, the lack of continuous high quality data especially in Peru, is a challenge that hydrologists face when modelling streamflow. Land use and soils are the most important data for the HRUs definition step; any effort to achieve more accurate data and maps will reduce the model uncertainty. A hydrological station for calibration increases the uncertainty model since it simplifies parameters and phenomena. All impediments have not been able to influence the performance indices.

The sensitivity results showed that TRNSRCH, RCHRG_DP, GW_DELAY, CH_K2, and OV_N were more sensitive ($p<0.05$) to the simulation of flow, compared to others (ESCO, CN2, ALPHA_BF, ...) in basin. This result confirms similar studies done by (Thavhana et al., 2018) and (Jajarmizadeh et al., 2017) where these parameters were shown to be most sensitive to streamflow. the relative processes to groundwater and high precipitation at the head of the Basin, makes water transport one of the most important processes. This may be seen in parameters related to transport efficiency processes in channels.

Finally, The generality of suchfindingsis may help with select parameters for calibration processes and more applications in other semi-arid areas. The calibrated model may be used to guide water management decisions by stakeholders who have water provision targets to meet, especially in the assigning of more realistic agricultural water demands. Furthermore, the modelling can be applied for planning of dam construction in the future, climate change studies and flood disaster risk management, which will contribute to the water resources management in the Tambo River basin.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Abbaspour, K. C., Johnson, C. A., & van Genuchten, M. T. (2004). Estimating Uncertain Flow and Transport Parameters Using a Sequential Uncertainty Fitting Procedure. *Vadose Zone Journal*, *3*(4), 1340–1352. https://doi.org/10.2113/3.4.1340

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. *Journal of Hydrology*, *524*, 733–752. https://doi.org/10.1016/j.jhydrol.2015.03.027

Abbaspour, Karim C., Vaghefi, S. A., & Srinivasan, R. (2017). A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. *Water (Switzerland)*, *10*(1). https://doi.org/10.3390/w10010006

Abbaspour, Karim C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., … Srinivasan, R. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology*, *333*(2–4), 413–430. https://doi.org/10.1016/j.jhydrol.2006.09.014

Alegria, J. F. (2007). The Challenges of Water Resouces Management in Peru. In *International*

Water Management Workshop (Vol. 18). https://doi.org/10.5751/ES-04629-180114

ANA. (1966). PROYECTO DE IRRIGACIÓN DE MOQUEGUA. In *Repositorio Institucional - ANA*. Retrieved from MKE website: http://repositorio.ana.gob.pe/handle/20.500.12543/4113

ANA. (2003). FICHA-MANANTIALES ADMINISTRACION TECNICA DE DISTRITO DE RIEGO MOQUEGUA. In *Autoridad Nacional del Agua*. INRENA.

ANA. (2005). MINISTERIO DE AGRICULTURA INSTITUTO NACIONAL DE RECURSOS NATURALES INTENDENCIA DE RECURSOS HIDRICOS AFIANZAMIENTO HIDRICO DEL VALLE DE TAMBO TOMO II INFORME PRINCIPAL. In *Autoridad Nacional del Agua*. INRENA.

ANA. (2013). Estudio hidrológico para la determinación del potencial hídrico de las cuencas de los ríos Tambo y Moquegua, mediante la elaboración de un modelo de soporte de decisiones con la aplicación del Software WEAP: informe final. *Autoridad Nacional Del Agua*.

ANA. (2015). PLAN de GESTIÓN de los RECURSOS HÍDRICOS de la CUENCA CAPLINA-LOCUMBA. In *Autoridad Nacional del Agua*. Autoridad Nacional del Agua.

Aouissi, J., Benabdallah, S., Lili Chabaâne, Z., & Cudennec, C. (2016). Evaluation of potential evapotranspiration assessment methods for hydrological modelling with SWAT—Application in data-scarce rural Tunisia. *Agricultural Water Management*, *174*, 39–51. https://doi.org/10.1016/j.agwat.2016.03.004

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., & Neitsch, S. L. (2012). *Input/Output Documentation Soil & Water Assessment Tool*.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). LARGE AREA HYDROLOGIC MODELING AND ASSESSMENT PART I: MODEL DEVELOPMENT. *Journal of the American Water Resources Association*, *34*(1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x

Asadzadeh, M., Leon, L., Yang, W., & Bosch, D. (2016). One-day offset in daily hydrologic modeling: An exploration of the issue in automatic model calibration. *Journal of Hydrology*, *534*, 164–177. https://doi.org/10.1016/j.jhydrol.2015.12.056

Beven, K., & Binley, A. (1992). The future of distributed models: Model calibration and uncertainty prediction. *Hydrological Processes*, *6*(3), 279–298.

https://doi.org/10.1002/hyp.3360060305

Brighenti, T. M., Bonumá, N. B., Grison, F., Mota, A. de A., Kobiyama, M., & Chaffe, P. L. B. (2019). Two calibration methods for modeling streamflow and suspended sediment with the swat model. *Ecological Engineering*, *127*(November 2018), 103–113. https://doi.org/10.1016/j.ecoleng.2018.11.007

D. N. Moriasi, J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, & T. L. Veith. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *Transactions of the ASABE*, *50*(3), 885–900. https://doi.org/10.13031/2013.23153

Daggupati, P., Yen, H., White, M. J., Srinivasan, R., Arnold, J. G., Keitzer, C. S., & Sowa, S. P. (2015). Impact of model development, calibration and validation decisions on hydrological simulations in West Lake Erie Basin. *Hydrological Processes*, *29*(26), 5307–5320. https://doi.org/10.1002/hyp.10536

Dong, W., Lian, Y., & Zhang, Y. (2018). *Sustainable Development of Water Resources and Hydraulic Engineering in China Proceedings for the 2016 International Conference on Water Resource and Hydraulic Engineering*. https://doi.org/10.1007/978-3-319-61630-8

Duan, Q., Schaake, J., Andréassian, V., Franks, S., Goteti, G., Gupta, H. V., … Wood, E. F. (2006). Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops. *Journal of Hydrology*, *320*(1–2), 3–17. https://doi.org/10.1016/j.jhydrol.2005.07.031

Duru, U., Arabi, M., & Wohl, E. E. (2018). Modeling stream flow and sediment yield using the SWAT model: a case study of Ankara River basin, Turkey. *Physical Geography*, *39*(3), 264–289. https://doi.org/10.1080/02723646.2017.1342199

Fakult, M., & Kiel, M. P. (2015). *A guideline for hydrologically consistent models*.

Fernandez, G. P., Chescheir, G. M., Skaggs, R. W., & Amatya, D. M. (2005). Development and testing of watershed-scale models for poorly drained soils. *Transactions of the American Society of Agricultural Engineers*, *48*(2), 639–652. https://doi.org/10.13031/2013.18323

Gassman, P. W., Sadeghi, A. M., & Srinivasan, R. (2014). Applications of the SWAT Model Special Section: Overview and Insights. *Journal of Environment Quality*, *43*(1), 1. https://doi.org/10.2134/jeq2013.11.0466

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of Automatic Calibration for

Hydrologic Models: Comparison with Multilevel Expert Calibration. *Journal of Hydrologic Engineering*, *4*(2), 135–143. https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135)

Jajarmizadeh, M., Sidek, L. M., Harun, S., & Salarpour, M. (2017). Optimal Calibration and Uncertainty Analysis of SWAT for an Arid Climate. *Air, Soil and Water Research*, *10*. https://doi.org/10.1177/1178622117731792

Jodar-Abellan, A., Ruiz, M., & Melgarejo, J. (2018). Evaluación del impacto del cambio climático sobre una cuenca hidrológica en régimen natural (SE, España) usando un modelo SWAT. *Revista Mexicana de Ciencias Geologicas*, *35*(3), 240–253. https://doi.org/10.22201/cgeo.20072902e.2018.3.564

Kannan, N., White, S. M., Worrall, F., & Whelan, M. J. (2007). Hydrological modelling of a small catchment using SWAT-2000 - Ensuring correct flow partitioning for contaminant modelling. *Journal of Hydrology*, *334*(1–2), 64–72. https://doi.org/10.1016/j.jhydrol.2006.09.030

Kouchi, D. H., Esmaili, K., Faridhosseini, A., Sanaeinejad, S. H., Khalili, D., & Abbaspour, K. C. (2017). Sensitivity of Calibrated Parameters and Water Resource Estimates on Different Objective Functions and Optimization Algorithms. *Water*, *9*(6), 384. https://doi.org/10.3390/w9060384

Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences*, *5*, 89–97. https://doi.org/10.5194/adgeo-5-89-2005

Kumar, N., Singh, S. K., Srivastava, P. K., & Narsimlu, B. (2017). SWAT Model calibration and uncertainty analysis for streamflow prediction of the Tons River Basin, India, using Sequential Uncertainty Fitting (SUFI-2) algorithm. *Modeling Earth Systems and Environment*, *3*(1), 0. https://doi.org/10.1007/s40808-017-0306-z

Lavado-Casimiro, W. S., Felipe, O., Silvestre, E., & Bourrel, L. (2013). ENSO impact on hydrology in Peru. *Advances in Geosciences*, *33*, 33–39. https://doi.org/10.5194/adgeo-33-33-2013

Legates, D. R., & McCabe, G. J. (1999). Evaluating the use of “goodness-of-fit” Measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, *35*(1), 233–241. https://doi.org/10.1029/1998WR900018

Lévesque, É., Anctil, F., Van Griensven, A., & Beauchamp, N. (2008). Evaluation of streamflow simulation by SWAT model for two small watersheds under snowmelt and rainfall. *Hydrological Sciences Journal*, *53*(5), 961–976. https://doi.org/10.1623/hysj.53.5.961

Li, Q., Chen, X., Luo, Y., Lu, Z. H., & Wang, Y. G. (2015). A new parallel framework of distributed SWAT calibration. *Journal of Arid Land*, *7*(1), 122–131. https://doi.org/10.1007/s40333-014-0041-5

Marek, G. W., Gowda, P. H., Evett, S. R., Baumhardt, R. L., Brauer, D. K., Howell, T. A., … Srinivasan, R. (2016). Calibration and validation of the SWAT model for predicting daily ET over irrigated crops in the Texas High Plains using lysimetric data. *Transactions of the ASABE*, *59*(2), 611–622. https://doi.org/10.13031/trans.59.10926

Mengistu, A. G., van Rensburg, L. D., & Woyessa, Y. E. (2019). Techniques for calibration and validation of SWAT model in data scarce arid and semi-arid catchments in South Africa. *Journal of Hydrology: Regional Studies*, *25*(August), 100621. https://doi.org/10.1016/j.ejrh.2019.100621

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and water quality models: Performance measures and evaluation criteria. *Transactions of the ASABE*, *58*(6), 1763–1785. https://doi.org/10.13031/trans.58.10715

Mortensen, E., Wu, S., Notaro, M., Vavrus, S., Montgomery, R., De Piérola, J., … Block, P. (2018). Regression-based season-ahead drought prediction for southern Peru conditioned on large-scale climate variables. *Hydrology and Earth System Sciences*, *22*(1), 287–303. https://doi.org/10.5194/hess-22-287-2018

Narsimlu, B., Gosain, A. K., Chahar, B. R., Singh, S. K., & Srivastava, P. K. (2015). SWAT Model Calibration and Uncertainty Analysis for Streamflow Prediction in the Kunwari River Basin, India, Using Sequential Uncertainty Fitting. *Environmental Processes*, *2*(1), 79–95. https://doi.org/10.1007/s40710-015-0064-8

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011). *COLLEGE OF AGRICULTURE AND LIFE SCIENCES Soil and Water Assessment Tool Theoretical Documentation Version 2009*.

Niraula, R., Norman, L. M., Meixner, T., & Callegary, J. B. (2012). Multi-gauge Calibration for modeling the Semi-Arid Santa Cruz watershed in Arizona-Mexico border area using SWAT. *Air, Soil and Water Research*, *5*, 41–57. https://doi.org/10.4137/ASWR.S9410

Pereira, D. D. R., Martinez, M. A., de Almeida, A. Q., Pruski, F. F., da Silva, D. D., & Zonta, J. H. (2014). Hydrological simulation using SWAT model in headwater basin in Southeast Brazil. *Engenharia Agricola*, *34*(4), 789–799. https://doi.org/10.1590/S0100-69162014000400018

Rostamian, R., Jaleh, A., Afyuni, M., Mousavi, S. F., Heidarpour, M., Jalalian, A., & Abbaspour, K. C. (2008). Application of a SWAT model for estimating runoff and sediment in two mountainous basins in central Iran. *Hydrological Sciences Journal*, *53*(5), 977–988. https://doi.org/10.1623/hysj.53.5.977

Sellami, H., La Jeunesse, I., Benabdallah, S., Baghdadi, N., & Vanclooster, M. (2014). Uncertainty analysis in model parameters regionalization: a case study involving the SWAT model in Mediterranean catchments (Southern France). *Hydrology and Earth System Sciences*, *18*(6), 2393–2413. https://doi.org/10.5194/hess-18-2393-2014

Shao, G., Zhang, D., Guan, Y., Xie, Y., & Huang, F. (2019). Application of SWAT Model with a Modified Groundwater Module to the Semi-Arid Hailiutu River Catchment, Northwest China. *Sustainability*, *11*(7), 2031. https://doi.org/10.3390/su11072031

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., … Zehe, E. (2003). IAHS Decade on Predictions in Ungauged Basins (PUB), 2003-2012: Shaping an exciting future for the hydrological sciences. *Hydrological Sciences Journal*, *48*(6), 857–880. https://doi.org/10.1623/hysj.48.6.857.51421

Suelos, I. N. de R. N. D. G. de A. y, & Ica, A. T. del D. de R. (2000). ANA. *Autoridad Nacional Del Agua*.

Suryavanshi, S., Pandey, A., & Chaube, U. C. (2017). Hydrological simulation of the Betwa River basin (India) using the SWAT model. *Hydrological Sciences Journal*, *62*(6), 960–978. https://doi.org/10.1080/02626667.2016.1271420

Tapley, T. D., & Waylen, P. R. (1990). Variabilité spatiale des précipitations annuelles et caractère variable de enso dans l’ouest du pérou. *Hydrological Sciences Journal*, *35*(4), 429–446. https://doi.org/10.1080/02626669009492444

Thavhana, M. P., Savage, M. J., & Moeletsi, M. E. (2018). SWAT model uncertainty analysis, calibration and validation for runoff simulation in the Luvuvhu River catchment, South

Africa. *Physics and Chemistry of the Earth*, *105*, 115–124. https://doi.org/10.1016/j.pce.2018.03.012

Van Liew, M. W., Arnold, J. G., & Garbrecht, J. D. (2003). Hydrologic simulation on agricultural watersheds: Choosing between two models. *Transactions of the American Society of Agricultural Engineers*, *46*(6), 1539–1551. https://doi.org/10.13031/2013.15643

Wagener, T., McIntyre, N., Lees, M. J., Wheater, H. S., & Gupta, H. V. (2003). Towards reduced uncertainty in conceptual rainfall-runoff modelling: Dynamic identifiability analysis. *Hydrological Processes*, *17*(2), 455–476. https://doi.org/10.1002/hyp.1135

Wu, H., & Chen, B. (2015). Evaluating uncertainty estimates in distributed hydrological modeling for the Wenjing River watershed in China by GLUE, SUFI-2, and ParaSol methods. *Ecological Engineering*, *76*, 110–121. https://doi.org/10.1016/j.ecoleng.2014.05.014

Xue, C., Chen, B., & Wu, H. (2014). Parameter Uncertainty Analysis of Surface Flow and Sediment Yield in the Huolin Basin, China. *Journal of Hydrologic Engineering*, *19*(6), 1224–1236. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000909

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. *Journal of Hydrology*, *358*(1–2), 1–23. https://doi.org/10.1016/j.jhydrol.2008.05.012

Zhang, L., Xue, B., Yan, Y., Wang, G., Sun, W., Li, Z., … Shi, H. (2019). Model uncertainty analysis methods for semi-arid watersheds with different characteristics: A comparative SWAT case study. *Water (Switzerland)*, *11*(6). https://doi.org/10.3390/w11061177

Tabla 1 Input Variables Used For SWAT modeling

Input Data	Description	Source
Extreme Temperatura	Minimum and maximum daily Temperatura. Period (1994-2016). 19 Station.	The National Service of Meteorology and Hydrology of Peru (SENAMHI) https://www.senamhi.gob.pe /
Precipitation	Daily Precipitation. Period (1994-2016). 19 Station.	
DEM	Digital elevation model (30 m resolution)	GeoServidor Ministry of the Environment of Peru (MINAM) http://geoservidorperu.minam.gob.pe/
Land use	resolution 30 m	
Soil Type	resolution 10 km	The Food and Agriculture Organization of the United Nations (FAO) http://www.fao.org/
River discharge and Point Inlet	Daily river discharge. Period (2001-2016).	Autoridad Nacionaldel Agua (ANA) https://www.ana.gob.pe/

Table 2. Classification of statistical indices.

E_{NS}	P_{BIAS}	R^2	RSR	Classification
$0.75 < E_{NS} \leq 1.00$	$P_{BIAS} \leq \pm 10$	$0.75 < R^2 \leq 1.00$	$0.00 \leq RSR \leq 0.50$	Very good
$0.60 < E_{NS} \leq 0.75$	$\pm 10 < P_{BIAS} \leq \pm 15$	$0.60 < R^2 \leq 0.75$	$0.50 \leq RSR \leq 0.60$	Good
$0.36 < E_{NS} \leq 0.60$	$\pm 15 < P_{BIAS} \leq \pm 25$	$0.50 < R^2 \leq 0.60$	$0.60 \leq RSR \leq 0.70$	Satisfactory
$0.00 < E_{NS} \leq 0.36$	$\pm 25 < P_{BIAS} \leq \pm 50$	$0.25 < R^2 \leq 0.50$	$RSR > 0.7$	Bad
$E_{NS} \leq 0.00$	$\pm 50 \leq P_{BIAS}$	$R^2 \leq 0.25$		Inappropriate

Source: (D. N. Moriasi et al., 2007; Fernandez et al., 2005; Van Liew et al., 2003)

Table 3. Sensitivity ranking of SWAT model parameters in the Tambo River Basin catchment

Rank	Parameter Name	Description	Initial range	Final range	t-Stat	P-Value
1	v__TRNSRCH.bsn	Fraction of transmission losses from main channel that enter deep aquifer	0 - 1	-0.204633 - 0.598633	-18.5109484	0.0000000
2	v__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/h)	0 - 100	18.539167 - 72.860832	-11.8464087	0.0000000
3	v__GW_DELAY.gw	Groundwater delay (days)	5 - 50	-17.031847 - 27.661848	-2.21875986	0.0269661
4	v__RCHRG_DP.gw	Deep aquifer percolation fraction	0.4 - 1	0.24304 - 0.74776	-2.15961564	0.0312928
5	r__OV_N.hru	Manning's n value for overland flow	-0.1 - 0.1	-0.14152 - 0.01952	2.02458484	0.0434586
6	r__CN2.mgt	Curve number II	-0.3 - 0.1	-0.313439 - -0.037761	-1.49212675	0.1363174
7	r__SOL_BD().sol	Baseline flow recession constant (days)	-0.2 - 0.2	-0.03064 - 0.30824	-1.27785105	0.2019144
8	v__GW_REVAP.gw	Ground water re-evaporation coefficient	0.01 - 0.3	0.097406 - 0.272334	-1.21252521	0.2259029
9	v__CH_N2.rte	Manning's ''n'' value for the channel	0 - 1	0.338401 - 1.015599	0.9599710	0.3375490
10	v__REVAPMN.gw	Threshold depth of water in the shallow aquifer for re-evaporation to occur (mm)	15 - 60	15.107997 - 45.042004	0.6500594	0.5159622
11	v__ESCO.bsn	Soil evaporation compensation factor	0.5 - 0.9	0.608161 - 0.824639	0.4283419	0.6685927
12	v__ALPHA_BF.gw	Base flow recession constant	0.5 - 0.85	0.656239 - 0.968861	0.4061440	0.6848162
13	r__SLSUBBSN.hru	Average slope length (m)	-0.2 - 0.2	-0.340641 - 0.019841	-0.3696609	0.7117968
14	v__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	500 - 1600	621.441467 - 1273.958496	0.2568921	0.7973711
15	v__EPCO.bsn	Plant uptake compensation factor	0.4 - 0.8	0.546961 - 0.841039	0.1728068	0.8628754

* r_ refers to a relative change in the parameters were their current values are multiplied by (1 plus a factor in the given range)

** v_ refers to the substitution of a parameter value by another value in the given range (Karim C. Abbaspour et al., 2007)

List of Figure