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Abstract

Climate change influences streamflow availability and dependability in watersheds due to its effect on the hydrologic cycle. This study assessed the quantitative impacts of climate change on dependable flow in the Lasang River watershed in southern Philippines using the Soil and Water Assessment Tool (SWAT) model. Three climate change scenarios including the baseline conditions and moderate and extreme conditions were formulated based on CMIP6 climate projections in the Philippines. The SWAT model was adequately calibrated and validated (NSE of 0.54 to 0.56) and was subjected to sensitivity and uncertainty analyses to ensure accurate representation of the watershed's hydrological behavior. Results of model simulation and flow duration analysis showed that moderate increases in precipitation and temperature due to climate change have negligible effects on dependable flow (1.1% increase), while extreme climate change conditions would result in relatively greater impacts on the watershed's dependable flow at a 14% increase. Results suggest that the river system may remain practically normal under a moderate climate change scenario, while greater water availability and dependability could be expected from the watershed under an extreme climate change scenario, particularly during the dry season for irrigation and other purposes. However, increased streamflow may still cause seasonal variability and potential dry-season water availability constraints under future climate conditions. Results obtained in this study could be used for proper irrigation system planning, design, and management and at the same time could serve as a basis for policy formulation geared towards sustainable water resources management under changing climatic conditions in the Lasang River watershed.

Key words: Climate change; CMIP6; dependable flow; SWAT.

Introduction

One of the most pressing global challenges nowadays is the emergence of far-reaching consequences of climate change on both natural and human systems. Issues on water quantity and quality occurred due to the variations in climate affecting watershed conditions (Arceo *et al*., 2018). Rising temperatures, shifts in precipitation patterns, and more frequent extreme weather events heighten the risk of flooding and alter both the total and seasonal availability of water (Parry *et al*., 2007). Managing and planning water resources is becoming more challenging due to the unpredictable nature of climate change (Ficklin *et al*., 2013). These indicate that climate variability poses significant challenges to the reliability of water resources within a watershed.

In the Philippines, manifestations of climate change have become increasingly evident such as the increasing frequency of extreme weather events, occurrences of more intense typhoons, prolonged droughts, and unpredictable rainfall distribution (PAGASA, 2011). These changes threaten not only human lives and infrastructure but also the hydrological stability of river systems and watersheds. The disruption of natural flow regimes may reduce water availability during dry periods while increasing flood risks during extreme rainfall events. Such conditions highlight the need for localized hydrological assessments to better understand how individual watersheds respond to projected climate changes, particularly in areas where water resources play a vital role in agricultural production, domestic supply, and socio-economic development.

The aforementioned manifestations have the potential to adversely influence the hydrology and sustainability of the Lasang River Watershed (LRW) in the Davao Region, Philippines. LRW serves as an important source of water for agriculture, domestic use, and other socio-economic activities in Davao del Norte and nearby areas. The watershed supports irrigation for high-valued crops such as banana, rice, corn/maize, cassava, sweet potato, sugar cane, abaca, ramie, coconut, cacao, coffee, rubber, and fruit trees and vegetables. However, despite its economic and ecological importance, the watershed is increasingly threatened by water degradation caused by climatic and anthropogenic factors. Heavy rainfall events, landslides, soil erosion, and unsustainable land-use practices have contributed to the deterioration of watershed conditions, potentially altering runoff generation, infiltration, and streamflow behavior. In addition, irresponsible quarrying activities near the Lasang River Irrigation System dam have been reported to affect riverbed stability and water retention capacity (Jaron, 2024), thereby increasing the vulnerability of irrigation services during prolonged dry periods.

The vulnerability of LRW became more apparent when the Lasang River Irrigation System sustained severe damage during Typhoon Pablo in 2012. Although rehabilitation and downstream protection works have subsequently been initiated, the watershed remains exposed to both climatic and human-induced disturbances. Furthermore, ongoing government initiatives such as the installation of Small Water Impounding Systems (SWIS) under the Department of Environment and Natural Resources (DENR) program underscore the growing importance of water conservation and watershed resilience in the area. These developments emphasize the need to quantitatively assess how future climate conditions may influence streamflow reliability and water availability within the watershed.

Among the various indicators used in water resources planning, dependable flow is considered one of the most important because it represents the minimum streamflow that can be relied upon for various uses such as irrigation, domestic supply, industrial processes and ecosystem support (Kundzewicz *et al*., 2018). This reliable flow is crucial in developing countries like the Philippines because communities often depend directly on river systems for their livelihoods. Water shortages, agricultural productivity losses, and socio-economic vulnerabilities may result if significant reduction in dependable flow occurs. While increased precipitation under future climate scenarios may potentially increase annual streamflow, such increases do not necessarily imply improved water security. Climate change may also intensify seasonal variability, increase flood occurrence, and reduce streamflow reliability during dry months. Therefore, understanding the impacts of climate change on dependable flow is essential not only for evaluating water availability but also for assessing the long-term reliability and sustainability of irrigation and watershed management systems.

A number of studies have already been conducted on the assessment of the impacts of climate change on hydrological processes in numerous watersheds using different methods (Yan *et al*., 2019; Alibuyog *et al*., 2009; Briones *et al*., 2016; Dapin and Ella, 2020) and they all emphasized that the development of a quantitative prediction model for assessing such can provide the basis for developing policy interventions and formulating sound watershed management schemes that can ensure environmental and economic sustainability. Among the most fundamentally-sound methods is the use of hydrological models since they have comprehensive physical mechanisms and they provide an established framework that thoroughly examines the interrelationships among climate, land use, and hydrologic processes. Among the numerous hydrological models available, the Soil and Water Assessment Tool (SWAT) is the most widely used to analyze such relationships (Yan *et al*., 2019) and for predicting hydrologic responses (Arceo *et al*., 2018; Alibuyog *et al*., 2009). To date, several SWAT-related studies done in some Philippine watersheds have already been published Alibuyog *et al*., 2009; Briones *et al*., 2016; Dapin and Ella, 2020; Alejo and Ella, 2019).

Despite the increasing number of SWAT-based climate change studies, research specifically focusing on dependable flow responses remains limited, particularly in tropical watersheds. Most previous studies primarily evaluated changes in annual runoff, sediment yield, or general streamflow characteristics, while fewer studies examined the reliability of streamflow under future climate conditions. In the Philippine context, only the study of Alejo and Ella (2019) dealt with simulation of climate change impacts on dependable flow using SWAT model. Additionally, no published peer-reviewed study has yet investigated the hydrological impacts of climate change on dependable flow in the Lasang River Watershed using SWAT and CMIP6-based climate projections. This represents a significant research gap considering the watershed's critical role in irrigation and regional water security.

In addition, uncertainties associated with future climate projections and watershed responses remain a continuing challenge in hydrological impact assessments. Variations among climate models, scenario assumptions, and watershed characteristics may influence the magnitude and direction of projected streamflow changes. Consequently, localized watershed-scale studies are necessary to improve understanding of climate-driven hydrological responses and to support more context-specific adaptation planning.

Hence, this study was conducted to assess the impacts of projected moderate and extreme climate change scenarios on the dependable flow of the Lasang River Watershed using the Soil and Water Assessment Tool (SWAT) and CMIP6-based climate projections. Specifically, the study aims to evaluate how future climate variability may influence streamflow reliability and water availability within the watershed. The findings are expected to contribute to the limited literature on dependable flow assessment in tropical watersheds and provide scientific information that may support local governments, water managers, irrigation planners, and other stakeholders in developing sustainable and climate-resilient water resource management strategies.

Materials and Methods

Study area

Lasang River Watershed (LRW), as shown in Figure 1, is one of the major watersheds in Davao Region. It is located in the north-western part of Davao Region, which lies between 7°15' and 7°45' North Latitude and between 125°20' and 125°40' East Longitude covering an area of about 43,507 hectares. The watershed spans portions of Davao City, Panabo City, and Talaingod. The river originates from the Pantaron Mountain Range, a recognized biodiversity hotspot and key hydrological source in Mindanao, and ultimately drains into the Davao Gulf, which serves as a major drainage outlet of Davao City. The watershed is classified by the Department of Environment and Natural Resources (DENR) as one of the country's critical watersheds due to its role in flood control, water supply, and ecosystem preservation.

Climate change scenario development

The climate change scenarios used in this study were derived from the updated climate projections of the Department of Science and Technology-Philippine Atmospheric, Geophysical, and Astronomical Services Administration (DOST-PAGASA, 2024). These projections are based on the Coupled Model Intercomparison Project Phase 6 (CMIP6) and scenarios on Shared Socio-economic Pathways (SSPs). The outputs from 33 global climate models (GCMs) under the (CMIP6) combining with localized climate data were utilized to produce high-resolution projections of temperature and rainfall. The models simulate future climate conditions based on five SSP which represent range of greenhouse gas (GHG) emission scenarios, from low to high emissions for six future time periods. These SSP-based scenarios contain a range of baseline scenarios expanding on RCPs which describe socio-economic characteristics that affect greenhouse gas emissions, providing pathways associated with future levels of climate change.

The five SSP include SSP1-1.9 (low emissions, sustainable pathway), SSP1-2.6 (sustainability-focused, very low emissions), SSP2-4.5 (middle-of-the-road emissions), SSP3-7.0 (high emissions due to regional rivalry and fragmentation), and SSP5-8.5 (very high emissions driven by fossil fuel development) and the future time periods are 2021-2050, 2031-2060, 2041-2070, 2051-2080, 2061-2090, and 2071-2100. This framework enables analysis of short-term impacts, mid-century transitions, and long-term risks under various SSPs. The methodology involves bias correction and downscaling of GCM outputs using the Delta-Change method calculating changes relative to a historical baseline period from 1981–2010. The baseline data was sourced from PAGASA's ClimGridPh dataset which is a high-resolution (1 km x 1 km) gridded dataset combining in-situ observations, satellite rainfall estimates, and ERA5 reanalysis data to ensure accuracy and consistency. The projections were presented as multi-model ensembles, providing percentile ranges of 25th (lower bound), 50th (median), and 75th (upper bound) percentiles to account for uncertainties. This ensemble approach allows representation of uncertainty bounds in projected climate changes rather than relying on a single deterministic projection. In this study, the climate projections considered were specifically guided by the revised Climate Information Risk Analysis Matrix (CLIRAM) tool. This provides localized, province-wide level monthly projections of rainfall and temperature. The future time period 2031-2060 with 50th percentile (moderate) and 75th percentile (extreme) climate projections was selected to represent mid-century climate conditions critical for near- to medium-term adaptation planning. The 50th percentile projection represents the moderate or most likely future climate condition based on the median response of the climate model ensemble, providing a balanced estimate of future rainfall and temperature changes. In contrast, the 75th percentile projection represents a more extreme but plausible future condition, reflecting stronger climate forcing and greater hydroclimatic variability. Using both percentiles allows assessment of watershed response under both moderate and intensified climate change conditions. The final monthly projected changes in rainfall and temperature were calculated by weighing the provincial projections of Davao del Norte and Davao del Sur based on the watershed's coverage in each province. Three (3) scenarios were established to predict the potential impacts on the dependable flow considering climate change as presented in Table 1. Scenario 1 is the baseline condition used to serve as basis for comparing the results of changing climate in the watershed. This baseline scenario utilizes the historical meteorological data from 2006-2014 as climatic input for simulating the streamflow using SWAT model. Scenarios 2 and 3 represent the condition of changing the climatic data under the medium and extreme settings under future period 2031-2060, respectively. That is, the historical data were changed considering the projected variation in precipitation and temperature leaving other climatic variables constant.

SWAT model inputs

The Digital Elevation Model with 5m x 5m resolution from National Mapping and Resource Information Authority (NAMRIA) was utilized to properly delineate the watershed boundaries, stream networks, and slope data of the study area. The land use and land cover data used was also gathered from the aforementioned agency as additional input for the hydrologic impact analysis. The map showed the arrangement of various land resource cover types in the area and served as the foundation for characterizing the landscape and comprehending land management practices. The model also utilizes a soil map which describes the range of soil types and/or properties within the study areas. This was gathered and clipped from the Digital Soil Map of the World which is anchored from the Food and Agriculture Organization. The user soil table from the SWAT database was utilized to interpret the soil data effectively. Furthermore, weather data are a fundamental component of the SWAT Model setup, serving as the driving force behind the simulation of hydrological processes within a watershed. The daily weather data were collected from the remotely sensed rainfall from Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) for precipitation and National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resource (POWER) Data Access for maximum and minimum temperature, solar radiation, relative humidity, and wind speed. CHIRPS is a satellite rainfall product that provides free online rainfall estimates in different parts of the world. Based on the study of Alejo *et al*. (2021), this can be accessed through Google Earth Engine using codes and proved that this satellite is an adequate rainfall source for watershed modeling and can be used as an alternative or supplementary SWAT input in small and large watersheds. In this study, the rainfall data was separately extracted using the table assets created in Google Earth Engine by uploading the validated shapefile boundary of the watershed. On the other hand, NASA POWER Data Access provides solar and meteorological data sets from NASA research for support of renewable energy, building energy efficiency and agricultural needs. These satellite and model-based products have been shown to be sufficiently accurate to provide reliable solar and meteorological resource data over regions where surface measurements are sparse or nonexistent. The study of Dapin and Ella (2020) had utilized data from this access. The meteorological data used for calibrating and validating the SWAT model was similar to the historical data period of the streamflow with an additional year for the warmup period. As for the final SWAT model simulation, the data used for the calibration period only (2006-2014) were utilized for better results.

The historical streamflow data from 2010-2017 were downloaded from the Department of Public Works and Highways (DPWH)-Streamflow Management System and utilized to calibrate and validate the model. Missing streamflow data were determined using simple linear regression since for 5% missing data, this method practically results to good prediction performance (Bleidorn *et al*., 2022). For this small missing data proportion, statistical efficiency is therefore not compromised. Daily streamflow records were gathered and utilized first to enhance the study's accuracy given the limited availability of historical streamflow data. However, the model shows poor performance when simulating using shorter time step (Moriasi *et al*., 2007). The alternative was to use the monthly time step for practical modeling purposes. Most related studies have also utilized monthly time steps to calibrate and validate the SWAT model. The streamflow data was divided into two periods for the calibration (2010-2014) and validation (2015-2017) of the SWAT model.

In this study, a 20% expected measurement error was also assumed for model calibration. This means considering the observed streamflow data to have an uncertainty of up to 20% due to measurement errors, data collection inconsistencies, or inherent variability in hydrological processes. This assumption is justified based on the studies of Moriasi *et al*. (2007; Harmel *et al*. (2009). The former authors suggest that streamflow measurement uncertainty typically ranges between 6% and 19% which means that even under normal conditions, actual measured values may deviate from the true streamflow within this range. The latter authors also indicated that a hydrological model’s streamflow prediction is considered "good" if its simulated values are within 10% to 15% of measured streamflow data of standard quality. This implies that models are generally expected to have some level of discrepancy, and a deviation within this range is still acceptable. Given these factors, assuming a 20% expected measurement error accounts for potential sources of uncertainty in both observed and modeled streamflow data. It provides a reasonable margin to accommodate real-world measurement challenges while ensuring that model calibration remains robust and realistic.

SWAT model development

The QSWAT extension for QGIS is the graphical user interface utilized for the SWAT model simulation. SWAT divides the sub-watersheds into smaller hydrologic response units (HRUs) based on the homogeneous biophysical properties of land cover, soil, and slope classes within the watershed. The model incorporates meteorological data and modifies soil and land use databases to obtain the necessary information for the study area. Hydrologic response units are distinct sections within a subbasin that pose unique attributes related to land use, management, and soil properties. By employing HRUs, SWAT effectively addresses the diversity present in the watershed. This approach simplifies model runs by grouping similar soil and land use areas into a single response unit, as simulating individual fields is often impractical. The concept of HRUs assumes no interaction between HRUs within a subbasin. In this study, a total of 702 full HRU counts were initially generated from the 15 subbasins in Lasang River

Watershed. Filtering was eventually done with threshold values of 8% land use, 5% soil type and 5% slope on area percentage. This means that any land use that covers less than 8% of the subbasin is ignored in HRU creation. A soil type covering less than 5% of the subbasin and slope category covering less than 5% of the subbasin is excluded and not considered. Filtering aims to reduce the number of HRU making the model more computationally efficient. It will also eliminate minor land use-soil-slope combinations thereby focusing only on dominant hydrological processes. This setting of threshold to ignore the minor land use/land cover, slope and soil types was based on the study of Narsimlu *et al.* (2015) wherein a threshold of 10% on HRU creation was set to avoid unnecessary large number of HRUs in the analysis. However, validation was done first before accepting the final actual HRU count by comparing the streamflow simulation result from the full HRU versus the filtered one. This is to ensure that no small but hydrologically significant areas are omitted and loss of potential detail in the watershed is avoided. Thus, the final actual HRU count in the watershed used for the simulation is 252 after generating an acceptable R^2 of 0.98 simulation result.

In the SWAT model simulation, a warm-up period of four (4) years was employed since a longer period of meteorological data was available. This is to establish the initial values for model state variables and ensure the hydrologic cycle is fully operational. In this study, the 2006-2009 weather data was used as the warm-up period.

SWAT model calibration and validation

The SWAT model involves numerous parameters that describe the different hydrological conditions and characteristics across the study basin. SWAT-CUP Sequential Uncertainty Fitting version 2 (SUFI2) algorithm was used in this process because it integrates various calibration, sensitivity, and uncertainty analysis procedures for SWAT (Dapin and Ella, 2020) and is widely used and recommended by many researchers. The available monitoring data was divided into two distinct time periods: one for calibration and one for validation as discussed previously. As an initial step in the model calibration process, the most influential model parameters that enable a good match between the simulated model and observed streamflow data were first identified. Calibration is an iterative process that involves adjusting model parameters to improve the agreement between simulated and observed data. After completing the initial model setup, refinement of the parameter values was done through multiple model runs, comparing the simulation results with the observed data until a satisfactory calibration is achieved. Model validation was consequently performed after calibration. This aims to ensure that the model accurately represents the hydrological processes in the watershed subject. This was done by testing the resulting output using another time series of data without changing any parameter that had been adjusted during calibration. The calibration period used was from 2010-2014 and validation covered the period 2015-2017. The model is considered validated when the simulation results closely match the observed data and reveal satisfactory performance. The evaluation of model performance during calibration and validation was based on statistical measures that indicate an adequate goodness of fit, such as the coefficient of determination (R^2), Nash-Sutcliffe model efficiency (NSE), Ratio of Root Mean Square Error to the standard deviation of the observation (RSR), and Percent Bias (PBIAS) as summarized in Table 2.

The coefficient of determination (R^2) measures the ability of a model to predict or explain an outcome in the linear regression setting (Getu *et al*., 2021). Da Silva *et al*. (2015) mentioned that NSE quantifies how the scatter plot of observed data against simulated values aligns with the 1:1 line. The model is more accurate when the model efficiency is closer to 1. When the NSE value falls from 0 to 1, it signifies deviations between the measured and predicted values. A negative NSE indicates poor predictions, where the average value of the output serves as a more reliable estimate than the model prediction. On the other hand, percentage bias (PBIAS) calculates the mean discrepancy between the simulated and measured values of a specific quantity over a defined time period, typically encompassing the entire calibration or validation period. The root mean square error (RMSE) metric quantifies the average difference between the measured and simulated values, and it can have both positive and negative values. A value close to 0.0 indicates a perfect fit, while values smaller than half the observed values' standard deviation (SD) is considered low. Another useful metric is the RSR (RMSE to the standard deviation ratio), which provides additional information and can be applied to various constituents. It is important to note that no established standards define the acceptable range of values for these statistical parameters that would indicate satisfactory performance of the model. The criteria used in this study were determined based on a literature review.

Sensitivity and uncertainty analysis

The Sequential Uncertainty Fitting version 2 (SUFI2) algorithm in SWAT-Calibration and Uncertainty Programs (SWAT-CUP) was used to perform sensitivity and uncertainty analysis of the model. The results of sensitivity and uncertainty analysis were acquired after calibrating and validating the model. The simulation period used for the sensitivity and uncertainty analysis was the same period used during the calibration and validation. The global sensitivity analysis technique incorporated in SUFI2 was employed in the study to identify highly sensitive SWAT parameters for streamflow in LRW. The two global sensitivity indices that determine the parameter sensitivity rank include t-stat and p-value. The larger the absolute value of the t-stat and the smaller the p-value indicates a more sensitive parameter (Abbaspour *et al*., 2015). The t-stat provides a measure of sensitivity, while the p-value determines the significance of sensitivity. In this study, the sensitivity of the parameters was ranked based on the highest absolute value of t-stat and the p-value of less than 0.05. Final sensitivity rank was identified after finalizing the uncertainty factors of the model. Uncertainty analysis was performed to evaluate the strength of the calibrated model. SUFI2 maps all uncertainty from all possible sources and attempts to contain most of the measured data within the 95 percent prediction uncertainty (95PPU) of the model through iteration. The strength of calibration and uncertainty analysis can be quantified by two statistics: p-factor and r-factor. The values of the p-factor refer to the fraction of measured data within the 95PPU band, whose values are between 0 and 1 (100%), while the r-factor is the average width of the 95PPU band divided by the standard deviation of the measured data, whose value could be within 0 to infinity. A p-factor close to 1 combined with an r-factor close to 0 indicates that the simulated result lies within the line of the observed data. The calibrated values of the SWAT parameters were considered as the initial values during the model sensitivity and uncertainty analysis. The initial range of the parameters after each iteration is substituted using a new range of parameters obtained from the model, and a limited uncertainty domain of the parameters is calculated. This procedure continues until the two quantifying sensitivity indices and the r-factor and p -factor reaches a proper limit (Abbaspour *et al*., 2015; Goudarzi *et al*., 2021). The parameter ranges were narrowed down to represent the condition of the watershed appropriately.

Dependable flow analysis

The water balance analysis was conducted first, which includes the collection of SWAT model inputs such as the digital elevation model (DEM), LULC data, soil data, slope data, climatic data, and streamflow data. The first five data were used to set up and run the SWAT Model, while the latter served as the data for calibration and validation of the model. After model calibration and validation, the sensitive SWAT parameters on the corresponding hydrologic processes involved were identified as the basis for the final simulation. The calibrated model was then used to generate streamflow values under various climate change scenarios.

Dependable flow was determined based on the streamflow data generated from the main outlet of the Lasang River Watershed. This represents the downstream portion of the watershed where accumulated runoff and flow dynamics are most noticeable. Streamflow was simulated by calculating the water balance at the HRU level, where surface runoff was estimated using the SCS Curve Number method, lateral flow and percolation were modeled based on soil and slope characteristics, and baseflow was simulated using shallow aquifer approach governed by groundwater parameters. These components were then routed through the watershed's channel network using Muskingum Routing method and combined at the subbasin outlets to represent total streamflow under various climate scenarios.

The dependable flow value under each climate change scenario was determined using flow duration analysis at 80% probability of exceedance, which is the commonly used level in assessing flow dependability for irrigation purposes. This analysis essentially involves a systematic evaluation of streamflow variability by determining how often specific flow rates are equaled or exceeded over a given period. The simulated mean monthly mean streamflow data were arranged in descending order from the highest to the lowest values, and were assigned a rank used to calculate the exceedance probability using the formula $P=m/(n+1)$, where P is the exceedance probability, m is the rank of the flow, and n is the total number of observations. These values are then plotted to create a Flow Duration Curve (FDC), which visually represents the relationship between flow magnitude and the percentage of time it is exceeded. From this curve, the flow that corresponds to 80% exceedance probability was then taken to represent the dependable flow for the given climate change scenario. To address concerns regarding robustness of a single threshold, the FDC approach provides a full distributional context of streamflow variability, allowing interpretation of both high-flow and low-flow behavior under climate change scenarios.

Results

Projected Monthly Rainfall and Mean Temperature Increase

The projected changes in monthly rainfall and mean temperature for the Lasang River Watershed under CMIP6 climate scenarios are shown in Figure 2. Results indicate general increase in both temperature and precipitation under most months, particularly under the upper-bound (75th percentile) scenario, which represents more extreme climate conditions. Under the median range projection, rainfall changes exhibit mixed patterns, with slight decreases observed during months of March, April, and September. In contrast, most months show modest increases in rainfall and temperature. The upper-bound scenario demonstrates more pronounced increases in both variables, reflecting higher climate variability and intensified hydroclimatic conditions. Overall, the projected climate signal suggests a warming environment combined with increased rainfall variability, indicating potential intensification of both wet and dry seasonal conditions within the watershed.

Climate change scenarios

Three (3) simulation scenarios were used to predict the potential impacts of precipitation and temperature variations in the watershed hydrology. One (1) scenario was used as the baseline data (Scenario 1) and two (2) scenarios for change in climate (Scenarios 2 and 3). The development of the scenario was anchored on the calculated climate projections specific to the Lasang River watershed. The historical meteorological data from the watershed were selected as baseline data for the impact analysis to determine the changes of watershed hydrology given the variations of climate. The climate change scenario was represented by the median and upper range monthly variations of rainfall from -5.20% to 4.8% and 2.3% to 18% with temperature increase of 1.2°C to 1.3°C and 1.3°C to 1.6°C, respectively, as shown in Table 3. These changes were inputted into the SWAT model.

SWAT model calibration and validation

Twenty (20) parameters were selected to undergo initial and further simulations as presented in Table 4. The selected parameters were tailored fit from the research conducted by Dapin and Ella (2020); Alejo and Ella (2019); Arceo *et al.* (2018) and many others as they are considered highly sensitive in estimating streamflow. The calibration was set to 2000 simulations on the first few iterations and decreases as the resulting best simulation was generated. Several iterations were conducted to calibrate the model. Initially, the SWAT default values for some of the parameters were used for calibration.

The SWAT model simulation of streamflow in LRW, as presented in Figure 3, achieved an R^2 and NSE values of 0.57 and 0.54 for calibration indicating acceptable model strength and satisfactory efficiency.

The RSR value of 0.68 shows a satisfactory value range and the PBIAS of 4.2% indicates a mild underestimation of streamflow. On the other hand, during validation (Figure 4), the performance improved slightly in terms of NSE (0.56) further indicating model acceptability. The RSR of 0.66 implies improved model accuracy and the PBIAS was -2.4%, still denoting highly accurate flow volume predictions. While the statistical measures of goodness of fit proved to be highly acceptable during both calibration and validation, results showed that the model slightly underestimated the streamflow during high flow periods, suggesting limited model sensitivity to extreme hydrological events. Despite this limitation, the model is considered suitable for scenario-based analysis, particularly for evaluating relative changes in streamflow and dependable flow under future climate conditions rather than for exact flow prediction purposes.

Sensitivity and uncertainty analysis

The sensitivity was conducted by employing Global Sensitivity Analysis techniques incorporated in SWAT CUP-SUFI2. Final sensitive parameters were determined after calibration and validation of the SWAT parameters by examining the statistical indices t-stat and p-value. The higher the absolute value of t-stat and p-value of less than 0.05 were considered sensitive. A total of twenty (20) parameters were optimized and findings revealed that RCHRG_DP.gw, SOL_K(..).sol, GWQMN.gw, and REVAPMN.gw were the most sensitive in simulating the streamflow for LRW as shown in Table 5. This indicates that groundwater recharge, soil hydraulic conductivity, and baseflow processes are dominant controls of the watershed hydrology. These results highlight the strong influence of subsurface hydrological processes on streamflow generation in the study area.

Figure 5 presents the uncertainty analysis using SWAT-CUP.. Results of calibration were p-factor = 0.62, r-factor = 0.76 and validation (p-factor = 0.56, p-factor = 0.78). The p-factor represents the observed data that is within the 95PPU bracket, while r-factor indicates the thickness of the band. The results indicate that a moderate proportion of observed streamflow data is captured within the 95% prediction uncertainty band, although some observations particularly peak flows fall outside the uncertainty range. This suggests that while the model is generally reliable, uncertainties related to model structure, input data, and hydrological variability remain present and should be considered when interpreting simulation outputs. Generally, the model still shows an acceptable uncertainty analysis performance. It showed satisfactory model performance showing strong reliability for streamflow simulation. With the desirable results of goodness of fit and uncertainty analysis, the model was used to simulate effects of climate change on hydrologic responses of the watershed.

Model simulation of streamflow under climate change scenarios

The calibrated and validated SWAT model was used in simulating mean monthly and annual streamflow values in Lasang River watershed. The fitted parameter settings derived from model calibration were used to re-write the model inputs and re-run the SWAT model to determine the impacts of moderate and extreme climate change on the dependable flow in LRW. Simulation results revealed that streamflow response in LRW varies depending on the magnitude of climate forcing. On an annual scale, the upper bound projection of climate change significantly increases the mean streamflow to 330.03 m^3/s from baseline value of 281.16 m^3/s, corresponding to an increase of approximately 17.38%.. In contrast, the median scenario showed negligible change with slight decrease of 0.31% relative to baseline conditions. These results suggest that streamflow response is highly sensitive to higher-end climate projections, where increased precipitation becomes the dominant driver of hydrological change.

At the monthly scale, as presented in Figure 6 and 7, results show that streamflow increases are unevenly distributed throughout the year. The extreme scenario produces pronounced increases during the early wet season, particularly in January and February, with increases of 26.41% and 30.13%, respectively, corresponding to higher projected rainfall during these months. However, during transitional and dry-season months such as April and May, increases are lower, and slight reductions in streamflow are observed in some cases. This indicates that while total annual streamflow may increase, seasonal variability becomes more pronounced, with stronger wet-season flows and relatively constrained dry-season flows. The median scenario shows minimal changes throughout most months, with slight increases limited to wetter periods and negligible changes during the rest of the year, indicating limited hydrological sensitivity under moderate climate forcing.

Overall, the simulations indicate that extreme climate change considerably results to significant increase in streamflow, particularly during the rainy months. However, results also showed that during the dry season, the dependable flow may be reduced since the projected rainfall is appreciably lower. These findings suggest the need for incorporating adaptation measures to enhance climate resilience in watershed planning and management, including infrastructure and water conservation strategies to sustain dependable flow for agriculture, ecosystems and human use.

Climate change impacts on dependable flow in LRW

The flow duration curves generated from the simulated streamflow under all scenarios are presented in Figure 8. The figure clearly depicts the streamflow values corresponding to probability of exceedance in LRW under the baseline condition and the specified climate change scenarios. The differences of the dependable flow values due to climate change relative to the baseline condition are depicted in Figure 9. The extreme projection displayed higher streamflow response (21.81 m^3/s) compared to the moderate projection (19.41m^3/s) and baseline condition (19.21m^3/s). Findings revealed that median climate projections generate small increase (1.1%) in dependable flow due to relatively lower increase in rainfall despite temperature increase. Extreme climate change increases the dependable flow in the watershed which implies that an increase in precipitation of up to 18% and temperature by up to 1.6 degrees Celsius, leads to almost 14% increase in dependable river flow in LRW.

While these results indicate an increase in statistically reliable low flow under future climate scenarios, they should be interpreted with caution. An increase in Q80 does not necessarily imply improved overall water security, as seasonal variability and dry-season flow constraints may still persist. In particular, shifts in rainfall distribution may lead to stronger wet-season flows but do not guarantee stable or sufficient dry-season availability. Overall, the results suggest that climate change may increase both total and dependable streamflow under extreme conditions, but may also intensify seasonal variability, highlighting the importance of considering both magnitude and temporal distribution of flow in water resources planning and management.

Discussion

The multi-model multi-scenario ensemble for the projected changes in rainfall in the Philippines is related to the baseline period as highlighted in the climate projection report by PAGASA. Due to seasonal rainfall, knowledge of the different trends that can be observed across months is essential. Based on data analysis, the observed rainfall has an increasing trend from December to January, coinciding with the northeast monsoon season. From July to October, the increasing rainfall trend corresponds to the southwest monsoon season where the western areas in the Philippines are typically affected. The months of March and May demonstrate a drying trend across the country, but a noticeable drying trend in Mindanao was observed in most months. The models used in the report provide a broad range of future changes in the amount of rainfall in the Philippines. The projected rainfall in the median range (50th percentile) shows that the study area may experience a slight increase in precipitation to about 5.8% in the mid-21st century (2021–2050) which is projected to decrease into 4.8% in 2031-2060 as revealed in the report. For the upper bound (75th percentile), the projection indicates that it may increase to about 15% in the mid-21st century (2021–2050) which may rise up to 18% given an extreme condition.

Rainfall projections for the study area indicate overall rainfall increases, particularly from December to February due to the influence of the Northeast Monsoon (locally known as *Amihan*) and the Intertropical Convergence Zone (ITCZ), which enhance cloud formation and precipitation. Despite this general increase, a slight decrease in rainfall is expected during March to April and in September, due to the weakening of Amihan, the transition to the dry season, and the retreat of the Southwest Monsoon (locally known as *Habagat*). Rainfall stabilizes from June to August under the full establishment of Habagat and active ITCZ conditions. Overall, rainfall variability in the area is largely governed by monsoonal shifts and ITCZ movement.

Meanwhile, temperature projections show a consistent warming trend driven by increased greenhouse gas emissions under future SSP scenarios, regional climate dynamics, and land use changes (Seto *et al*., 2012), such as deforestation and urbanization. The Davao Region has already experienced a historical warming rate of about 0.2 °C per year, and future temperature increases are expected to intensify due to weaker monsoonal cooling and rising sea surface temperatures. These combined changes highlight the need for comprehensive and adaptive water resource management strategies to safeguard watershed functions and sustain human livelihoods amid a warmer and more variable climate.

Results of the sensitivity analysis of the SWAT model parameters in this study are consistent with those obtained from other watershed studies conducted in the country. For example, Reyes (2017) obtained that GWQMN.gw was one of most sensitive parameters in his study of predicting streamflow in Wahig, Inabanga Watershed, Bohol. Similar outcomes were also reported from the studies conducted in other countries like the SUFI2 parameter sensitivity results achieved by Zhao *et al*. (2018) in Jingchuan River Basin, China and Das *et al*. (2013) in Yarra River Australia wherein SOL_K, RCHRG_DP, and GWQMN were found to be more sensitive to streamflow. Tilahun (2022) also highlighted the sensitivity of the mentioned parameters in reviewing the most sensitive SWAT parameters. Moreover, the findings of Xiang *et al*. (2022) also identified the three parameters of the previous authors as the most sensitive ones in simulating streamflow at Upper Heihe River Basin, Mongolia while Liu *et al*. (2020) and Huerta *et al*. (2024) determined SOL_K, and GWQMN.gw and REVAPMIN.gw as one of the most sensitive parameters in their studies conducted in Upper Weihe River, China and Pativilca Basin, Peru, respectively.

The sensitivity analysis output in this study demonstrated that streamflow in the watershed is more intricately regulated by soil-water dynamics, groundwater thresholds, and evaporative losses. This indicates that LRW is more responsive to short-term hydrologic processes like rainfall events and evapotranspiration due to shallower soils and aquifers. RCHRG_DP.gw is important in groundwater recharge dynamics. The saturated hydraulic conductivity of soil layer (SOL_K(..).sol) controls infiltration rate through soil layers. The high sensitivity of this parameter reflects that surface infiltration and subsurface water movement through the soil are fundamental due to highly variable soils or shallow groundwater. GWQMN.gw or the threshold water depth in shallow aquifer for baseflow influences the start of streamflow since baseflow will only begin when the water table reaches this threshold. This affects the initiation of baseflow implying that small changes in groundwater storage greatly alter streamflow. Furthermore, threshold depth for re-evaporation from shallow aquifer (REVAPMN.gw) triggers the minimum water depth in shallow aquifer for water to move upward to the unsaturated zone and be lost to evapotranspiration. High sensitivity of this parameter indicates that the evaporation losses from the shallow aquifer are significant, which can reduce streamflow, especially during dry periods. Overall, the key SWAT model parameters that greatly influence streamflow in LRW are governed by surface and subsurface interactions and evapotranspiration processes that controls soil water movement, shallow aquifer thresholds and ET losses induced flow progressions. The mismatch between simulated and observed peak flows can be explained by the strong sensitivity of the SWAT model to four key parameters. Because SWAT simplifies subsurface processes, uncertainties in deep recharge, soil hydraulic conductivity, and aquifer thresholds cause noticeable deviations in the magnitude and timing of simulated flows. This leads to slight underestimation during calibration and slight overestimation during validation, explaining why the simulated hydrographs do not perfectly match the observed streamflow despite acceptable overall performance.

Although the SWAT model shows satisfactory performance (NSE = 0.54–0.56), it is important to emphasize that this level of performance reflects acceptable basin-scale representation rather than precise predictive accuracy. The moderate NSE values indicate that while the model captures general hydrological trends, it has limitations in reproducing peak flow dynamics and extreme hydrological variability. Uncertainty analysis further highlights this limitation. The two factors fully describe the performance of the calibrated model as p-factor closer to 1 and r-factor to 0 indicate a better model that could represent the measurements (Abbaspour, 2022). That study stated that based on experience and only as a reference, the bracket about 70% of the measured data in the 95PPU band (P-factor ≥ 0.7, R-factor ≤ 1.5) for river discharge is suggested. With calibration and validation findings, the bracketing of the two indices for the uncertainty analysis were narrower, enveloping only 62% and 56% of the observed data within the uncertainty band. This is attributed to input uncertainty. Some of the observed peak flows and low flows were outside the 95PPU bracket. Data points that were not captured by the 95PPU were considered as error which is the difference between 1 and the value of p-factor. As stated in Abbaspour (2007), a narrow parameter ranges results to a narrower 95PPU envelop creating a smaller p-factor and r-factor. A larger p-factor can be achieved at the expense of a larger r-factor. The uncertainty of the model results may be attributed also by the quality of measured streamflow data used for calibration and validation. Despite these uncertainties, however, the model still captured the general pattern of temporal variability of streamflow in the watershed.

The simulation results indicate that streamflow in LRW generally increases under future climate scenarios, particularly under extreme conditions. This response is primarily attributed to the projected intensification of rainfall during wet months, which increases surface runoff generation and channel discharge. The hydrological response of LRW suggests that precipitation exerts a stronger influence on streamflow generation than temperature-induced evapotranspiration losses, especially during periods of high rainfall. Similar findings were reported by Khadka *et al*. (2023), who observed a 10–14% increase in streamflow in the Mun River Basin in Thailand under warmer and wetter CMIP6 climate conditions. Likewise, Mollel *et al*. (2023) noted that intensified precipitation events increase overland flow and peak discharge, thereby elevating wet-season streamflow reliability. ..

The hydrological response observed in LRW can also be explained by the watershed's physical and land surface characteristics. The watershed contains areas with highly variable soil properties, steep slopes, and portions of degraded land cover, which promote rapid runoff generation during intense rainfall events. The sensitivity analysis further showed that streamflow is strongly controlled by groundwater recharge, soil hydraulic conductivity, and shallow aquifer processes, indicating that subsurface water movement plays a major role in regulating flow behavior in the watershed. Because of these characteristics, LRW responds rapidly to rainfall inputs, producing higher wet-season discharge but relatively limited groundwater storage that could sustain dry-season flows. In addition, land use changes and anthropogenic disturbances such as deforestation, agricultural expansion, and quarrying activities near river systems may further reduce infiltration capacity and increase runoff sensitivity under future climate conditions.

Regional climate dynamics also contribute to the observed streamflow behavior. The projected increases in rainfall during December to February are associated with stronger Northeast Monsoon (*Amihan*) influence and enhanced Intertropical Convergence Zone (ITCZ) activity, both of which contribute to increased precipitation over Mindanao. Meanwhile, the relatively lower rainfall changes during some dry-season months reflect transitional monsoon periods, resulting in uneven seasonal water distribution. This indicates that future climate change in LRW is likely to intensify seasonal hydrological variability rather than uniformly increase water availability throughout the year.

The findings of this study are further supported by other international studies. Getachew *et al.* (2021) projected increased streamflow in the Lake Tana Basin in Ethiopia due to higher precipitation and temperature, while Chen *et al.* (2020) reported increased runoff in the Jinsha River Basin associated with intensified rainfall. Similar hydrological responses were also observed by Shi and Shiraiwa (2023) in Japan. Furthermore, studies by Teuling *et al.* (2019) and Yang and Liu (2011) emphasized the strong sensitivity of streamflow to precipitation variability, supporting the results obtained in LRW. Nevertheless, contrasting findings from some Philippine watersheds suggest that climate change impacts are highly watershed-specific due to differences in rainfall patterns, topography, land use, soil characteristics, and groundwater dynamics. Therefore, the response of LRW should not be used to generalize the hydrologic behavior of other watersheds in the country. Overall, the results of this study indicate that climate change may increase streamflow in LRW, particularly during wet periods, but may also intensify seasonal variability and uncertainty in dependable dry-season flows. These findings emphasize the importance of adaptive and integrated watershed management approaches that consider both increasing wet-season runoff and potential dry-season water constraints under future climate conditions.

In the Philippine context, the findings of this study both align with and differ from previous dependable flow assessments conducted in other watersheds. For instance, Alejo and Ella (2019) reported reduced dependable flow in the Maasin River Basin under extreme climate scenarios due to declining rainfall and increased evapotranspiration, which resulted in lower irrigation water availability. In contrast, the present study showed an increase in dependable flow under the extreme climate scenario in LRW, primarily driven by projected increases in rainfall during wet months. However, under moderate or median-range climate projections, both studies showed relatively small changes in dependable flow, suggesting that watershed response under moderate climate forcing may remain comparatively stable. These contrasting results highlight that climate change impacts on dependable flow in the Philippines are highly watershed-specific and strongly influenced by local watershed characteristics, regional rainfall patterns, land use conditions, soil properties, and groundwater dynamics. Since PAGASA climate projections indicate substantial spatial and temporal variability in rainfall distribution across the country, hydrological responses cannot be generalized uniformly among Philippine watersheds.

The Flow Duration Curve (FDC) analysis used in this study provides important insight into streamflow reliability and hydrological variability under changing climate conditions. The dependable flow at 80%

exceedance probability (Q80) was selected because it is widely used in irrigation and water resources planning to represent the streamflow that can be relied upon most of the time during the year. This threshold is commonly applied in the Philippines for estimating potential irrigable areas, allocating water supply, and evaluating watershed sustainability under low-flow conditions. The results indicate that Q80 increases under future climate scenarios, particularly under the extreme scenario, suggesting a potential increase in statistically reliable flow availability.

However, the interpretation of dependable flow should be approached cautiously. Although Q80 is a useful indicator of flow reliability, it represents only one point along the flow duration curve and does not fully capture the complete range of hydrologic variability. Changes in other portions of the FDC may indicate different hydrological responses, such as increased high-flow events or greater seasonal variability, which are not fully reflected by the Q80 metric alone. For example, increased wet-season flows may elevate the dependable flow value statistically, while dry-season baseflows may still remain vulnerable due to higher evapotranspiration and reduced groundwater recharge. Thus, an increase in Q80 does not necessarily imply uniform improvement in year-round water security.

Moreover, dependable flow sensitivity may vary depending on the selected exceedance threshold. Lower exceedance probabilities like Q50 generally represent average flow conditions, while higher exceedance probabilities such as Q90 or Q95 are more representative of severe low-flow or drought conditions. The use of Q80 in this study provides a practical representation of streamflow reliability for irrigation purposes; however, evaluating additional thresholds could provide a more comprehensive understanding of climate change impacts on both average and extreme low-flow conditions. Future studies may therefore incorporate multiple exceedance probabilities and additional indicators such as seasonal low-flow indices, ecological flow requirements, and water demand scenarios to improve assessment of water resource reliability under future climate conditions. Overall, the FDC analysis demonstrates that climate change may alter not only the magnitude of streamflow but also its temporal distribution and reliability characteristics. This highlights the importance of integrating dependable flow analysis with broader hydrological assessments to support climate-resilient watershed and irrigation management strategies in LRW.

Conclusions

This study assessed the impacts of climate change on streamflow and dependable flow in Lasang River Watershed in the Philippines using the SWAT model and CMIP6-based climate projections for the mid-21st century. The SWAT model demonstrated acceptable performance during calibration and validation, with NSE values ranging from 0.54 to 0.56, indicating that the model is adequate for watershed-scale hydrological simulation under the specified climate scenarios. Sensitivity and uncertainty analyses further showed that streamflow in the watershed is strongly influenced by groundwater recharge, soil-water interactions, and evapotranspiration processes, emphasizing the importance of subsurface hydrological dynamics in regulating streamflow behavior in LRW.

Climate projections indicated increases in both rainfall and temperature under the moderate and extreme climate scenarios. Simulation results showed that these projected changes generally increased streamflow and dependable flow in the watershed, although the magnitude of response varied between scenarios. Under the moderate climate scenario, dependable flow increased only slightly by about 1.1%, indicating relatively limited changes in overall water availability. In contrast, the extreme climate scenario resulted in a larger increase in dependable flow of approximately 14%, mainly due to substantially higher projected rainfall and runoff generation.

However, the results also indicate that increased annual streamflow does not necessarily imply uniformly improved water availability throughout the year. Despite the projected increases in dependable flow, some dry-season months exhibited relatively smaller flow increases and potential low-flow vulnerability due to increased evapotranspiration and uneven seasonal rainfall distribution. These findings suggest that climate change may intensify seasonal hydrological variability in the watershed, with wetter wet-season conditions but continued uncertainty in dry-season water reliability.

Overall, the study highlights the importance of incorporating climate variability, streamflow reliability, and seasonal hydrological responses into watershed and irrigation planning in Lasang River Watershed. The findings may support the development of adaptive water management strategies such as water conservation measures, improved irrigation scheduling, and appropriate water storage infrastructure to enhance resilience under future climate conditions. Future studies may further improve the assessment by evaluating additional exceedance probability thresholds, alternative SSP pathways, land use changes, and future water demand scenarios to better characterize uncertainty and long-term watershed response to climate change.

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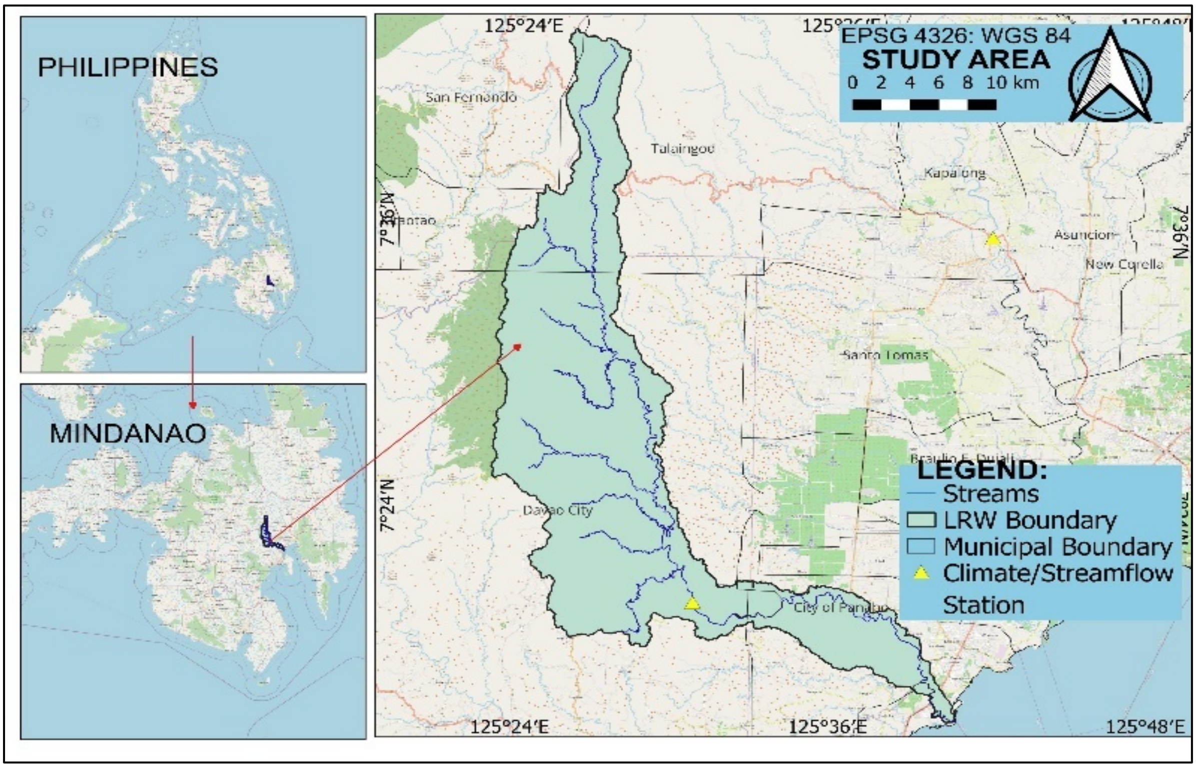

Figure 1. Location map of Lasang River Watershed.

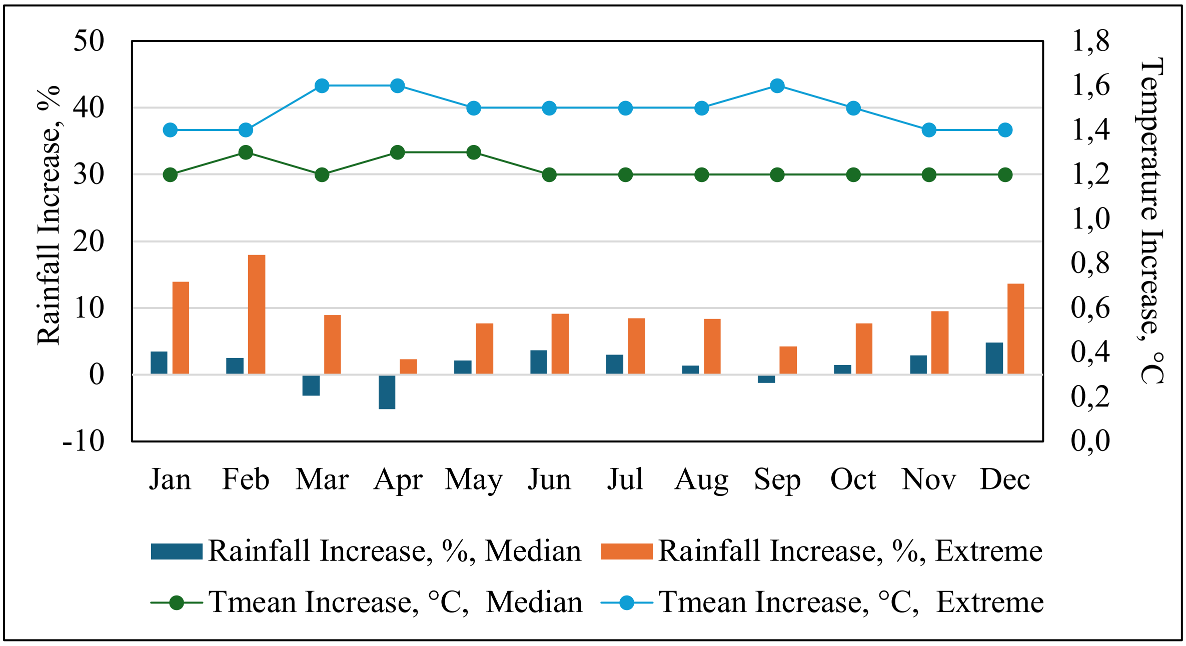

Figure 2. CMIP6 rainfall and temperature increase projections in LRW.

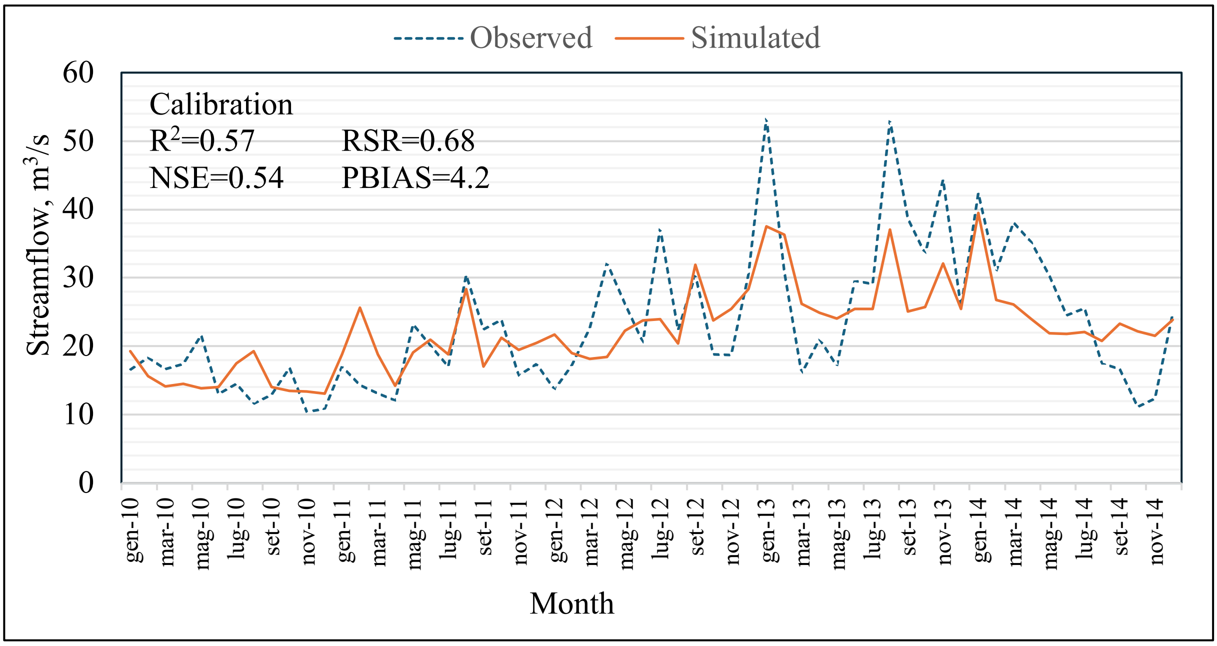

Figure 3. Monthly observed and simulated streamflow during model calibration in LRW.

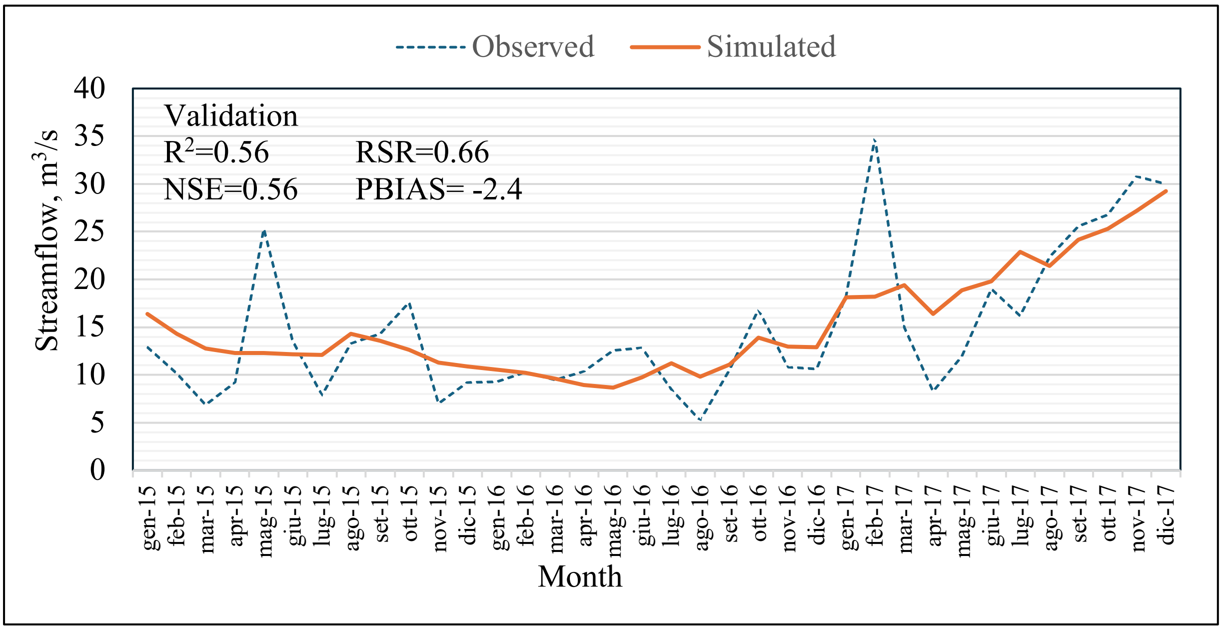

Figure 4. Monthly observed and simulated streamflow during model validation in LRW.

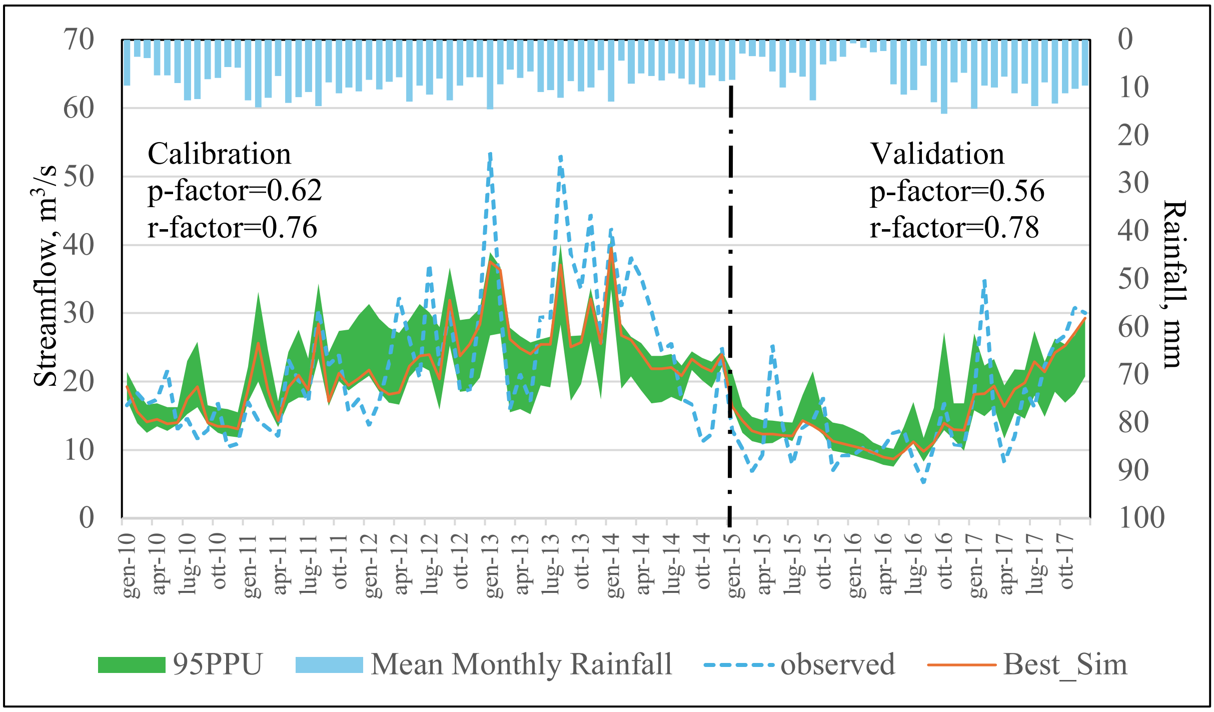

Figure 5. Uncertainty analysis in modeling Lasang River Watershed using SWAT CUP.

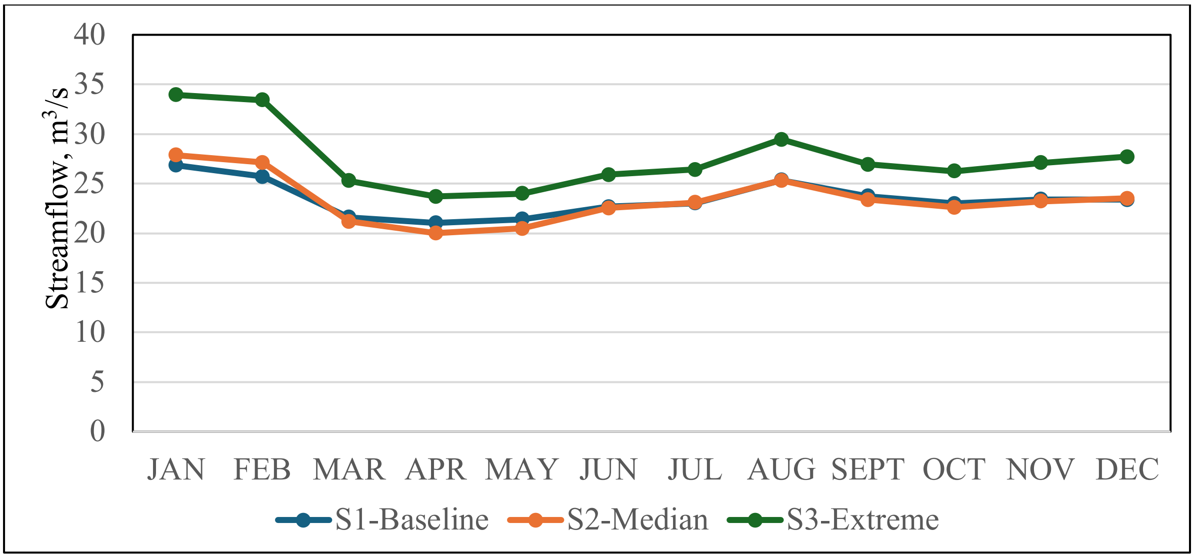

Figure 6. Mean monthly streamflow in LRW under climate change scenarios.

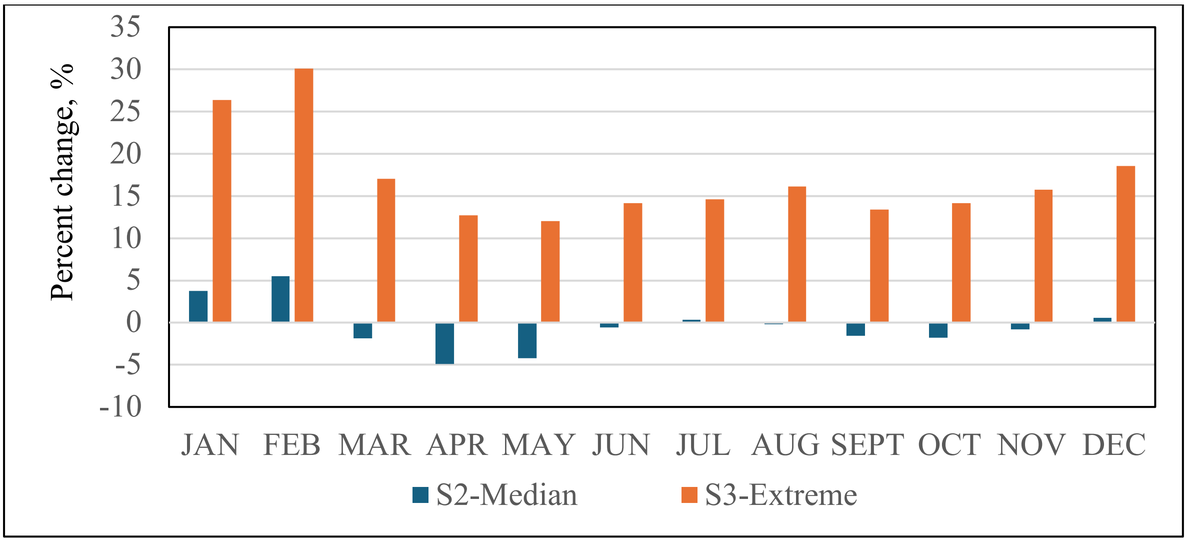

Figure 7. Percentage change in the mean monthly streamflow relative to baseline conditions in LRW due to climate change.

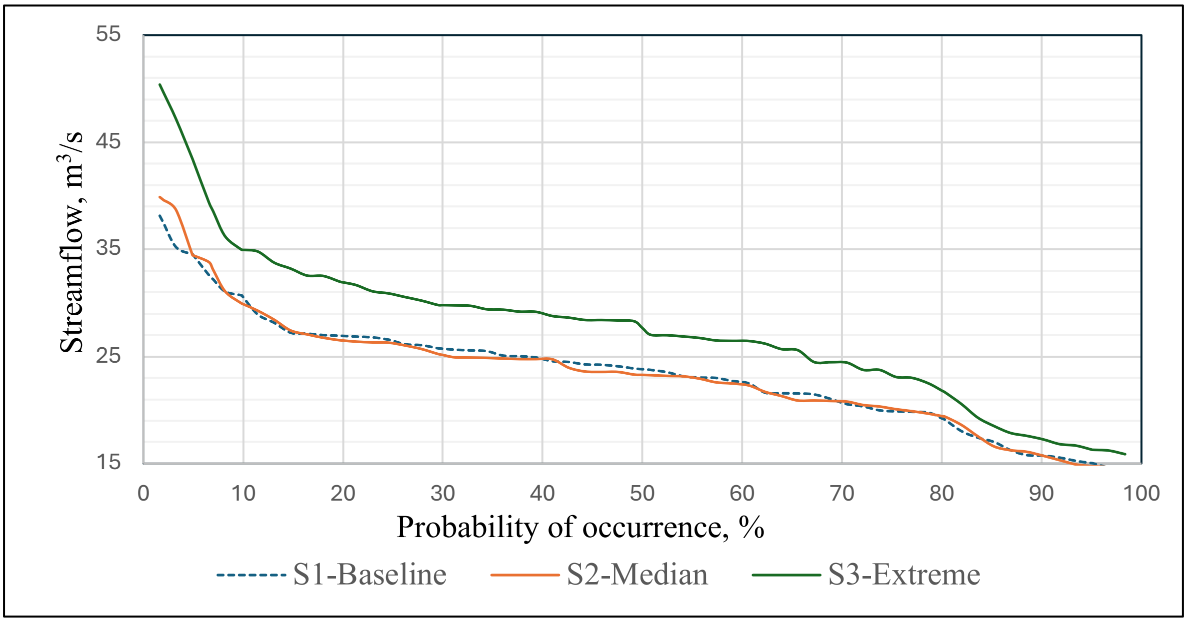

Figure 8. Flow duration curve of LRW.

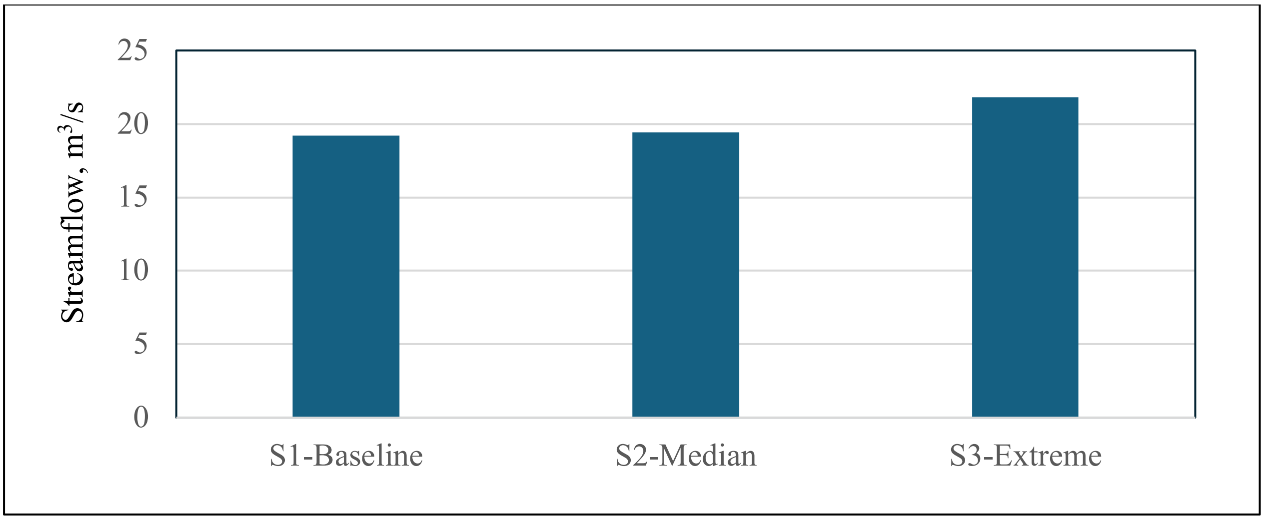

Figure 9. Dependable flow in LRW under climate change scenarios.

Table 1. Climate change scenario.

Scenario	Climate change
1	Baseline
2	2031-2060 (50th percentile) climate projection
3	2031-2060 (75th percentile) climate projection

Table 2. Criteria for assessing the performance of the hydrological model and their respective classifications.

Statistical criterion	Value	Performance classification	References
Coefficient of determination $R^2 = \frac{\Sigma (X_i - X_{av}) (Y_i - Y_{av})}{\sqrt{\Sigma (X_i - X_{av})^2} \sqrt{\Sigma (Y_i - Y_{av})^2}}$	0-1	Higher values indicate less error variance. Values greater than 0.5 are considered acceptable	Getu et al. (2021)
Nash-Sutcliffe coefficient $NSE = 1 - \frac{\Sigma\,(Oi\ - Si){}^\wedge 2}{\Sigma\,(Oi\ - O){}^\wedge 2}$	0.75<NSE≤1.00	Very good	Da Silva et al. (2015)
	0.65<NSE≤0.75	Good	
	0.50<NSE≤0.65	Satisfactory	
	0.40<NSE≤0.50	Acceptable	
	NSE≤0.40	Unsatisfactory	
	0.40<NSE≤0.70	Acceptable	
Percent bias $PBIAS = \frac{\Sigma\,(Oi\ - Si) * 100}{\Sigma\,(Oi)}$	PBIAS<±10	Very good	Da Silva et al. (2015)
	±10≤PBIAS< ±15	Good	
	±15≤PBIAS≤ ±25	Satisfactory	
	PBIAS ≥ ±25	Unsatisfactory	
Ratio of the Root Mean Square Error to the standard deviation of the observations $RSR = \frac{[\Sigma\,(Oi\ - Si)^2]{}^\wedge 0.5}{[\Sigma\,(Oi\ - O){}^\wedge 2]{}^\wedge 0.5}$	0.00 ≤RSR≤ 0.50	Very good	Da Silva et al. (2015)
	0.50 ≤RSR≤ 0.60	Good	
	0.60 ≤RSR≤ 0.70	Satisfactory	
	RSR > 0.70	Unsatisfactory	

Table 3. Description of climate change scenario.

Scenario	Climate change	
	Rainfall increase (%)	Temperature increase (°C)
1	0.0	0.0
2	-5.20 to 4.8	+1.2 to 1.3
3	+2.3 to 18	+1.3 to 1.6

Table 4. Calibrated SWAT parameters for LRW.

Parameter name	Description	Min value	Max value	LRW fitted values
V__ALPHA_BF.gw	Baseflow alpha factor (days)	0	1	0.946734
V__RCHRG_DP.gw	Deep aquifer percolation fraction	0	1	0.557665
R__ESCO.hru	Soil evaporation compensation factor	-0.6	0.1	-0.490043
V__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium.	0	200	40.545387
V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	5000	4287.279297
R__SOL_AWC(..).sol	Available water capacity of the soil layer	0	2	0.500717
V__SURLAG.bsn	Surface runoff lag time.	1	24	8.602828
V__CH_N2.rte	Manning's "n" value for the main channel.	0	0.2	0.141122
V__OV_N.hru	Manning's "n" value for overland flow.	0	0.5	0.037492
V__CANMX.hru	Maximum canopy storage.	0	100	65.083221
V__GW_DELAY.gw	Groundwater delay (days)	30	450	325.595154
R__HRU_SLP.hru	Average slope steepness	-0.5	0.25	-0.513064
V__GW_REVAP.gw	Groundwater "revap" coefficient.	0.02	0.25	0.19245
V__REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	0	1500	475.2589
V__LAT_TTIME.hru	Lateral flow travel time.	0	180	12.645679
R__SLSUBBSN.hru	Average slope length	-0.2	0.2	-0.09001
R__CN2.mgt	SCS runoff curve number	-0.6	0.25	-0.517205
V__EPCO.hru	Plant uptake compensation factor	0	1	0.243869
V__SOL_BD(..).sol	Moist bulk density	1	1.5	0.980299
V__SOL_K(..).sol	Saturated hydraulic conductivity	0	100	0.981323

Table 5. Results of sensitivity analysis.

Parameter name	LRW		Rank
	t-stat	*p*-value	LRW
V__ALPHA_BF.gw	-1.49	0.14	7
V__RCHRG_DP.gw	-9.06	0.00	1
R__ESCO.hru	-1.61	0.11	6
V__CH_K2.rte	1.10	0.27	8
V__GWQMN.gw	-3.34	0.00	3
R__SOL_AWC(..).sol	-0.94	0.35	9
V__SURLAG.bsn	-0.75	0.45	10
V__CH_N2.rte	-0.21	0.83	14
V__OV_N.hru	-0.55	0.58	13
V__CANMX.hru	-0.01	0.99	18
V__GW_DELAY.gw	-0.58	0.56	12
R__HRU_SLP.hru	0.00	1.00	20
V__GW_REVAP.gw	-0.09	0.93	19
V__REVAPMN.gw	-2.62	0.01	4
V__LAT_TTIME.hru	0.39	0.70	16
R__SLSUBBSN.hru	0.13	0.90	17
R__CN2.mgt	-0.74	0.46	15
V__EPCO.hru	-0.68	0.50	11
V__SOL_BD(..).sol	-1.61	0.11	5
V__SOL_K(..).sol	9.04	0.00	2