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Assessing the suitability of CFSR data for SWAT model hydrologic simulation of Kunthipuzha river basin, Kerala, India

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सार – जल विज्ञानिक मॉडल के लिए विभिन्न इनपुट के बीच, अच्छी तरह से वितरित और सटीक वर्षा डेटा की जल संभर में विभिन्न प्रक्रियाओं को सटीक रूप से अनुकरण करने में महत्वपूर्ण भूमिका होती है। वर्षा मापकों के खराब वितरण नेटवर्क और सटीक वर्षा डेटा की कमी कई भारतीय जल संभर में शामिल सबसे महत्वपूर्ण समस्याओं में से एक है। यह अध्ययन जल विज्ञानिक मॉडलिंग के लिए डेटा के वैकल्पिक स्रोत का उपयोग करने की क्षमता की जांच करता है। जलवायु पूर्वानुमान प्रणाली पुनर्विश्लेषण (CFSR) डेटा एक वैश्विक, उच्च विभेदन, युग्मित वायुमंडल-महासागर-भूमि सतह-समुद्री बर्फ प्रणाली है। इसे कुछ जल संभरों की डेटा कमी को हल करने के लिए एक वैकल्पिक विकल्प के रूप में बताया गया है। केरल के प्रसिद्ध साइलेंट वैली नेशनल पार्क से होकर बहने वाली कुंथिपुझा नदी के धारा प्रवाह को मॉडल करने के लिए CFSR की उपयुक्तता का आकलन किया गया। जल विज्ञान प्रक्रिया के अनुकरण के लिए मृदा और जल मूल्यांकन उपकरण (SWAT) मॉडल का उपयोग किया गया। मॉडल को अंशांकित प्राचलों का उपयोग करके अनुकरण किया गया जिसमें CN2, ALPHA_BF और ESCO अपवाह को प्रभावित करने वाले प्रमुख कारक हैं। विकसित मॉडल को प्रेक्षितऔर अनुमानित मौसम संबंधी डेटा (CFSR) के साथ चलाया गया और धारा प्रवाह के अनुकरणीय परिणामों की तुलना नैश सटक्लिफ दक्षता (NSI), निर्धारण गुणांक (R^2) और रूट माध्य वर्ग त्रुटि (RMSE) का उपयोग करके की गई। मॉडलिंग के लिए प्रेक्षित किए गए डेटा का उपयोग करने पर प्राप्त NSE, R^2 और RMSE क्रमशः 0.82, 0.85 और 29.25 थे, जबकि CFSR डेटा के साथ, मान क्रमशः 0.70, 0.72 और 37.18 थे। प्रेक्षित मौसम संबंधी डेटा का उपयोग करके SWAT के साथ मॉडलिंग किया गया धारा प्रवाह CFSR डेटा का उपयोग करके मॉडलिंग किए गए धारा प्रवाह के करीब था। CFSR डेटा (0.7 और 0.72) के साथ प्राप्त NSE और R^2 इंगित करता है कि ग्रिडेड डेटा (CFSR डेटा) का उपयोग शायद उचित सटीकता के साथ डेटा की कमी वाले क्षेत्रों में किया जा सकता है।

ABSTRACT. Among the different inputs for the hydrological model, well distributed and precise precipitation datahas a crucial role in accurately simulating the various processes in a watershed. Poor distribution network of rain gauges and lack of precise precipitation data is one of the most important problems involved in many Indian watersheds. This study investigates the potential of using an alternate source of data for hydrologic modelling. The Climate Forecast System Reanalysis (CFSR) data is a global, high resolution, coupled atmosphere-ocean-land surface-sea ice system. Ithas been reported as an alternative option for solving the data deficiency of certain watersheds. The suitability of the CFSR to model the stream flow of Kunthipuzha river, flowing through the famous Silent Valley National Park in Kerala was assessed. The Soil and Water Assessment Tool (SWAT) model was made use of for the simulation of hydrologic process. The model was simulated using calibrated parameters in which CN2, ALPHA_BF and ESCO are the major factors affecting runoff.The developed model was run with observed and predicted meteorological data (CFSR) and the simulated results of stream flow were compared using Nash Sutcliffe Efficiency (NSE), Coefficient of determination (R^2) and Root mean Square Error (RMSE). The NSE, R^2 and RMSE obtained when observed data was usedfor modelling were 0.82, 0.85 and 29.25 respectively, whereas with CFSR data, the values were 0.70, 0.72 and 37.18 respectively. The streamflow modelled with SWAT using observed meteorological data wascloser to the measured streamflow as compared with that using CFSR data. The NSE and R^2 obtained with CFSR data (0.7 & 0.72) indicates that gridded data (CFSR data) can perhaps be utilized in data scare regions with reasonable accuracy.

Key words – CFSR, SWAT, Kunthipuzha, Hydrology, Modelling.

1. Introduction

To understand the hydrologic response of watersheds and to find solutions to water resource management problems, most effective tools available are hydrological models (Prasad *et al*., 2020). For any hydrologic model, precipitation data is the primary and most important input for the accurate simulation of the watershed (Liu *et al*., 2017; Sirisena *et al*., 2018). Classification of such models is based on the physical process, spatial representation and randomness. Based on the spatial representation, distributed hydrological models need more input data in comparison with the lumped models (Singh *et al*., 2002). There is large data complexity and more computational requirements needed for the distributed hydrological models. To overcome these issues, semi-distributed hydrological models are usually adopted. SWAT is a semi-distributed hydrologic model used worldwide (Stehr *et al*., 2010; Swain *et al*., 2022).

In developing countries, data on observed spatial rainfall is subject to uncertainties because of poor distribution of the gauges (Strauch *et al*., 2012). The weather data obtained may not actually represent the characteristics of a watershed and can also have gaps when taken for a period of time. Numerous methods, including interpolation techniques, radar data, and remote sensing data, have been used to get beyond data scarcity issues and lack of quality observations (Auerbach *et al*., 2016). Later, with the advent of high-end computation facilities, gridded rainfall data was developed by certain international institutes. Various databases developed includeTropical Rainfall Measuring Mission (TRMM) (Huffman *et al*., 2007), CFSR, National Centre for Environmental Prediction (NCEP) (Saha *et al*., 2010) and Precipitation Estimation from the Remote Sensing information using the Artificial Neural Network (PERSIANN) (Ashouri *et al*., 2015).

Research attempts have been made to understand the applicability of such climate databases for use in hydrological models. Among the different climatic databases, CFSR data was used in the present study because of its data flexibility and input file compatibility with the SWAT model interface (Cuceloglu and Ozturk, 2019). The CFSR dataset includes all the climate parameters required for the study is available at a spatial resolution of the 0.3°. In order to overcome the problems of data deficiency in the watersheds, CFSR data may be considered as an alternate option when rain gauge stations are limited.

Several research studies have been done to evaluate the climate databases and observed meteorological data using SWAT model. According to Dile and Srinivasan (2014), the simulated results using conventional weather data were satisfactory when compared with the CFSR data, and in data scarce regions, CFSR can be a beneficial option. Tomy and Sumam (2016) has recommended CFSR data for the ungauged stations and watersheds with a smaller number of rain gauges (3 or below). Fuka *et al*., (2014) reported that watershed simulations using CFSR data gave promising stream discharge values which were comparable with that using the traditional weather gauging stations, especially when the stations were at a distance greater than 10 km from the watershed. Jajarmizadeh *et al*. (2016) has suggested CFSR data for hydrologic modelling in arid climates with inaccessible areas and situations of data scarcity. Hence, the study focuses on evaluating the option of using NCEP's CFSR data as input for the SWAT model for the data scarce region of Kunthipuzha.

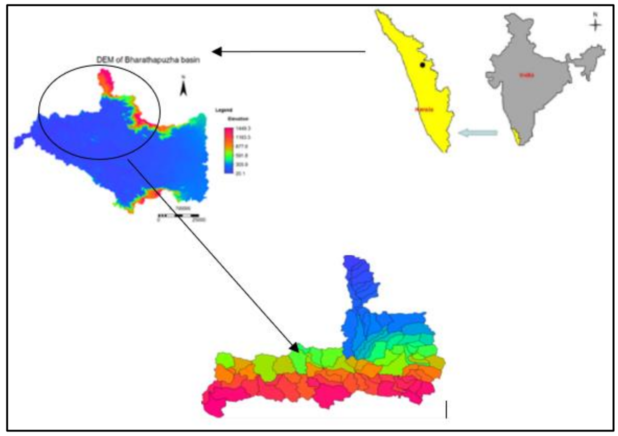

Fig. 1. Location of Kunthipuzha watershed

Fig. 2. Location where Kunthipuzha joins the main river

The study area (Kunthipuzha) is a major tributary of the river Bharathapuzha in Kerala, India, and flows through the Silent Valley National Park. The

Bharathapuzha river (second longest in Kerala) originates in the Western Ghats and has four major tributaries. The boundaries of this watershed are Silent valley in the north, Nellipuzha watershed in the east, Ottappalam taluk in the south and Perinthalmanna taluk in the west, with the location as shown in Figs. 1&2. The area lies within 10°48′47.36″ N latitude to 11°13′01.08″ N latitude and 76°05′00.70″ E longitude to 76°38′02.89″ E longitude. The elevation of the watershed area ranges from 4 m near the outlet point of the watershed to 2367 m (which is situated near the silent valley) from mean sea level. The area receives rainfall from both the south west (June to September) and north east monsoons (October to December). Maximum rainfall is received from the south west monsoon. The catchment receives an annual rainfall of 2300 mm and has an average temperature of 27.3 °C.

2. Data and methodology

ArcGIS software developed by Environmental System Research Institute (ESRI), New York was used for the preparation of maps. It was used as a platform for the simulation of the hydrological processes using SWAT model.

The SWAT model divides the watershed into sub watersheds and helps to analyse the spatial variability within a watershed. The use of sub watersheds in simulation is very beneficial when there is a substantial difference in land use and soil which may impact the hydrology. Hydrologic response units are areas in the sub basin that comprise of distinctive land cover, soil and management classes.

The model simulation is divided into two major phases. The first division models the processes occurring over land which calculates the amount of water, sediment, nutrients *etc*. to the major channel. The second phase is the routing phase (water phase) of the hydrologic cycle, which can be defined as the movement of water and sediments through the channels.

The details of the input datasets are given in Table 1. Different morphological characteristics of the soils were also collected along with the soil map. Weather data used for the study were: (*i*) Observed meteorological data and (*ii*) CFSR data. The observed data represents the actual climate of the particular place measured from the meteorological observatories in the area. The CFSR data represents the high-resolution coupled atmosphere-ocean-land surface-sea ice system satellite-based rainfall products. The discharge (river flow) data of Pulamanthole gauging station was used for the calibration of the model. Other soil properties needed were calculated using the software Soil Plant Air Water (SPAW).

TABLE 1

Details of data used for developing SWAT model

Data	Data Source
DEM (30m × 30m resolution)	Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM)https://earthexplorer.usgs.gov.
Land se map	Kerala State Remote Sensing and Environment Centre (KSREC), Trivandrum
Soil map	Directorate of Soil Survey and Soil Conservation, Trivandrum
Meteorological data (1989-2016)	Regional Agricultural Research Station, Pattambi, Kerala Agricultural University; Indian Meteorological Department (IMD) and Water Resources Department, Government of Kerala
CFSR data (1989-2014)	https://swat.tamu.edu/data/cfsr
Discharge Data	Central Water Commission (CWC), India

The major steps involved in the SWAT model set up are watershed delineation, HRU analysis, preparation of input tables and SWAT input editing. SWAT simulation was done for a period of 23 years ranging from 1st January 1989 to 31st December 2013 with two years of warm up period using observed meteorological data. Sensitivity analysis is a crucial step in model development. It is carried out to find out the most sensitive parameters before doing the calibration and validation of the model. Later model simulation was also carried out using the CFSR data.

The model performance was evaluated by Nash-Sutcliffe Efficiency (NSE), Coefficient of determination and Root Mean Square Error. The Nash-Sutcliffe efficiency coefficient (Nash and Sutcliffe, 1970) was used to evaluate the predictive power of the hydrological model. These parameters were used because of its sensitivity to the peak flows (Krause *et al*., 2005). The value of the NSE ranges from 1.0 to -∞. The NSE value of 1 indicates the perfect fitting. The coefficient of determination (R^2) is the squared value of the coefficient of correlation. The value of R^2 varies from 0 to 1, where avalue close to 1 represents a good result, whereas the value close to 0 represents a poor model. The major drawback of R^2 is that it only quantifies dispersion. The Root Mean Square Error (RMSE) was used to measure the differences in the observed and predicted values.

2.1. *Comparison of SWAT outputs*

The main SWAT output taken for the comparison is stream flow. The model was first simulated with observed

TABLE 2

Sensitive parameters and their rankings for Kunthipuzha river basin

Sensitivity Rank	Parameter	Parameter Description
1	CN2	SCS curve number for AMC II
2	ALPHA_BF	Base flow alpha factor (1/days)
3	ESCO	Soil evaporation compensation factor
4	CH_K2	Effective hydraulic conductivity (mm/hr)
5	RCHRG_DP	Deep aquifer percolation fraction
6	SOL_Z	Depth from soil surface to layer bottom (mm)
7	SURLAG	Surface runoff lag coefficient

weather data from 1st January 1991 and 31st December 2013. For comparison, the model was again simulated with CFSR data by keeping the spatial inputs constant. The simulation was done on a monthly basis and the SWAT outputs were obtained on a monthly basis using the observed meteorological data and CFSR data.

Stream flow was considered as the main SWAT output for comparison. The comparison and evaluation were done using statistical measures such as NSE, R^2 and RMSE. Graphical comparison was carried out with graphs plotted between the simulated discharge using observed meteorological data, simulated discharge using predicted meteorological data (CFSR data) and observed discharge.

3. Results and discussion

Sensitivity analysis was performed to get the most sensitive parameters. CN2 (SCS curve number for AMC II), followed by ALPHA_BF (Base flow alpha factor) and ESCO (Soil evaporation compensation factor) were identified as the most sensitive parameters. The most important influencing factor was the CN2, is a function of soil characteristics, land classes and AMC conditions. ALPHA_BF, the most dominating factor of river flow, represents the base flow for the Kunthipuzha river basin. George and Sathian (2016) reported similar results, with ALPHA_BF and CN2 as the most sensitive parameters of the Kunthipuzha watershed of central Kerala. Tejaswini and Sathian (2018) also reported similar results in which ALPHA_BF and CN2 were obtained as the most sensitive parameters for the Kunthipuzha basin. The results of sensitivity analysis are presented in Table 2.

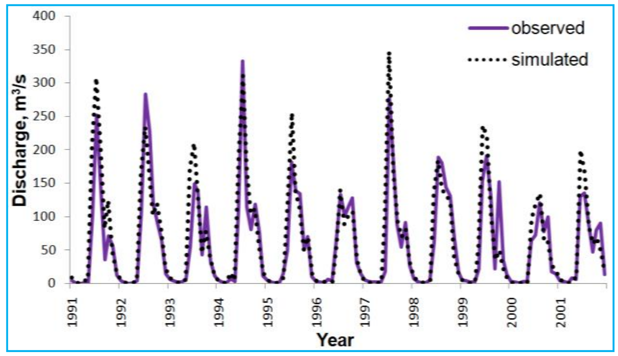

Fig. 3(a). Average monthly discharge for the period from 1991 to 2001 after calibration

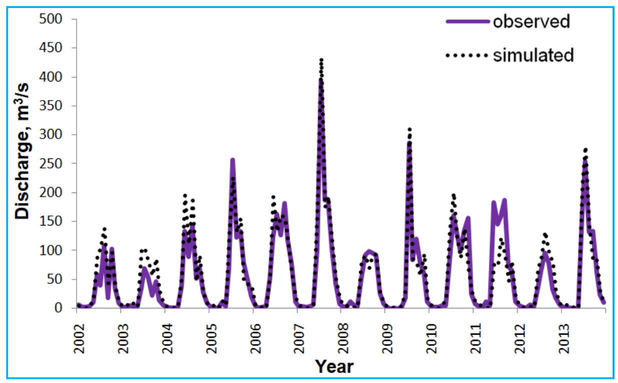

Fig. 3(b) Average monthly discharge for the period from 2002 to 2013 after calibration

3.1. *Model simulation with observed meteorological data after calibration*

Curve Number (CN2), ALPHA_BF and ESCO parameters influence the run off while using the model for hydrologic simulation. The calibrated model was simulated with observed meteorological data as input, and the output of the model (simulated monthly streamflow) was compared with the observed monthly streamflow. The graphs of simulated and observed monthly stream flow are shown in Figs. 3(a&b). The simulated peak flows were slightly underestimated during 1992, 1994, 1998, 2005 and 2011 in calibration and vice-versa for the remaining years. Basically, the main cause of these errors is the lack of precise information regarding input data. Abraham *et al.*, (2007) got similar results and Tejaswini and Sathian (2018), reported that the peak runoff of simulated flow was under estimated and overestimated.

The performance indices NSE and R^2 after calibration were 0.82 and 0.85 respectively. The results of the statistical analysiss how that the simulated flow has a 'very good; correlation with the observed stream flow (Moriasi *et al.*, 2007). The definition of NSE statistics implies that it put more emphasis on the peak values

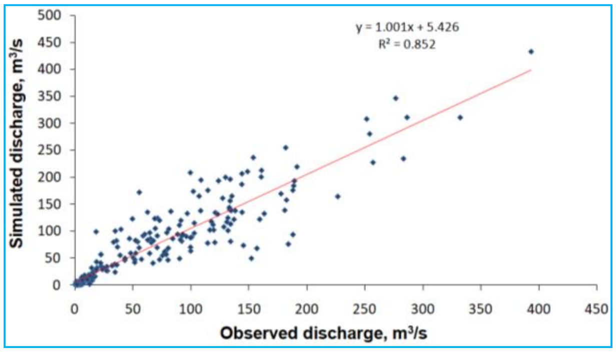

Fig. 4. Scatter plot of observed and simulated monthly discharge at Pulamanthole gauging station after calibration

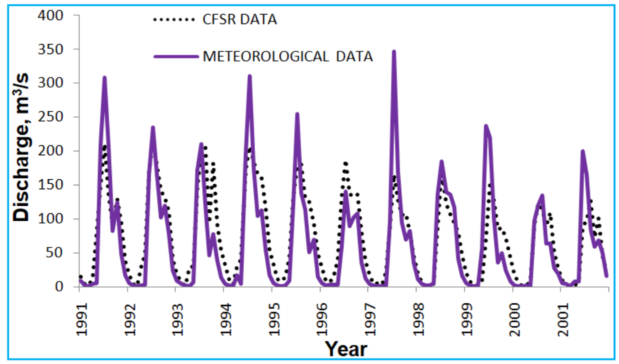

Fig. 5(a). Average monthly simulated discharge of observed meteorological data and CFSR data for the period 1991 to 2001

(extreme events) than on the average flows (Malago *et al*., 2015). Also, the timing of simulation influences the statistic (MacLean, 2005) and since the simulation here was done on a monthly basis, the improvement in the statistics is less.

Another graphical form for evaluating the model is based on a scatter plot. The scatter plot of monthly stream flow after calibration is shown in Fig. 4. It mainly represents the relationship between observed and simulated values with the statistical measure of coefficient of determination.

3.2. *Model simulation with CFSR data*

The calibrated model was run with CFSR data and the simulated streamflow was compared with the observed monthly streamflow. The simulated CFSR data and the observed meteorological data were evaluated with the following statistical measures.

The statistical measures adopted for assessing the performance of the model on a monthly basis (comparing the observed dischargeand model outputdischarge) are NSE and coefficient of determination (R^2). The performance indices NSE and R^2 while using the CFSR data were 0.7 and 0.72 respectively. The results show that the simulated discharge has a good correlation with the observed discharge.

3.3. *Comparison of SWAT outputs using CFSR data and observed meteorological data*

Surface runoff/out flow was taken as a major component for comparing the CFSR data and observed meteorological data. The outflow is simulated using the calibrated SWAT model with observed meteorological data. Simulation was also done with input as CFSR data to compare the performance of the data. The model was

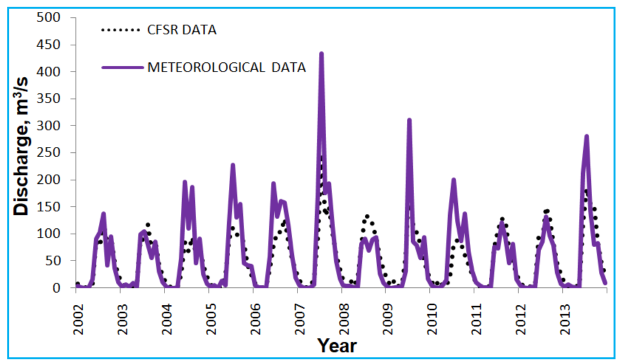

Fig. 5(b). Average monthly simulated discharge of observed meteorological data and CFSR data for the period 2002 to 2013

simulated for the period 1st January 1991 and 31st December 2013. The SWAT outputs using both data are compared with the observed data. The comparison of SWAT outputs for the different climate data can be evaluated using different statistical measures like Nash Sutcliffe efficiency, coefficient of determination and Root Mean Square Error. The observed meteorological data has given a better performance when compared with the CFSR data.

The graphs of average monthly simulated discharge of CFSR and observed meteorological data for the Pulamanthole gauging station are shown in Figs. 5(a&b). The simulated discharge of CFSR data was underestimated during 10 years of the 23 years for which simulation was done. In the graphs, it is clearly noticed that the simulated discharge of observed meteorological data was underestimated during 1996, 2003, 2008, 2011 and 2012. These results show that there is clear dominance of observed meteorological data for the simulated stream flows except in some years. According

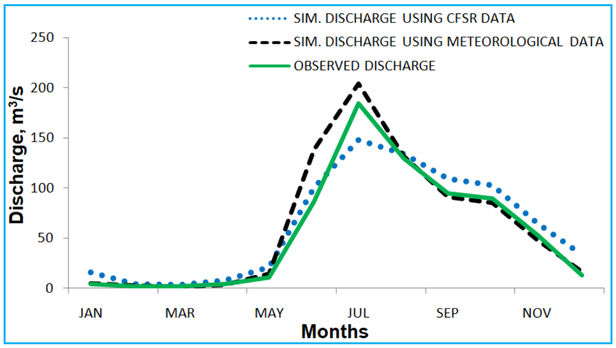

Fig. 6. Comparison of average monthly discharge of SWAT outputs and observed discharge for the period between 1991 and 2013

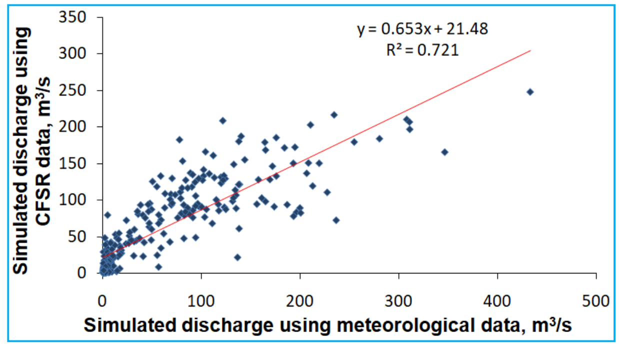

Fig. 7. Scatter plot of simulated monthly discharge using meteorological data and CFSR data at Pulamanthole gauging station

TABLE 3

Performance indices for CFSR data and observed meteorological data

Statistical criteria	Observed meteorological data	CFSR data
NSE	0.82	0.70
R^2	0.85	0.72
RMSE	29.25	37.18

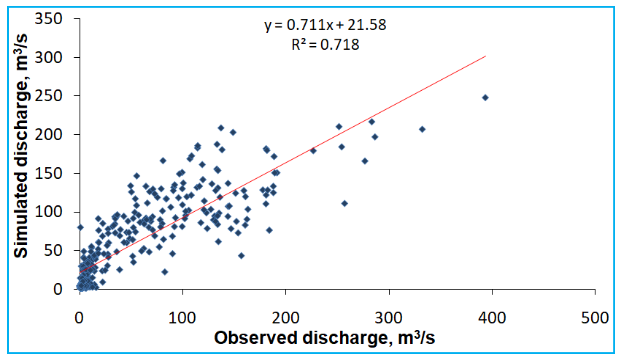

Fig. 8. Scatter plot of observed *vs* simulated monthly discharge at Pulamanthole gauging station for CFSR data

to Roth and Lemann (2016), simulationswith conventional data resulted in more accurate prediction than the simulations with the CFSR data. The results indicate that the monthly simulated discharge of forecasted data shows a high correlation except at peaks. Hence, the forecasted data can be kept as a reliable data source in situations or areas of data scarcity. According to Tomy and Sumam (2016), this forecasted data gives comparable results when available rain gauge stations are 3 or less in an area.

The performance indices with the use of forecasted data and observed meteorological data are shown in Table 3. The NSE, R^2 and RMSE for monthly simulated discharge of observed meteorological data and CFSR data ranges from 0.82 & 0.70, 0.85 & 0.72 and 29.25 & 37.18 respectively. When the results are analysed, it is seen that the simulated discharge of observed meteorological data and CFSR data performed "very good" and "good" for NSE and R^2. For the RMSE, monthly simulated discharge of observed meteorological data gave better comparison than CFSR data.

The graph of mean monthly discharge incorporating simulated discharge using observed meteorological data, simulated discharge using predicted meteorological data (CFSR) and observed discharge is shown in the Fig. 6.

The graph depiction shows that the simulated discharge using observed meteorological data was higherthan the observed discharge at the peaks, whereas the simulated discharge using predicted meteorological data was lowerthan observed dischargeat peaks.This variation of predicted flow from the observed values is more predominant in the month of July. The simulated discharge using predicted meteorological data (CFSR) was clearly dominating in the months of September to December, and overlapping otherwise, expect at the peaks.So, CFSR data is hereby thought of as a reliable data source for usein data scarce regions.

Another method for comparing the observed meteorological and CFSR data is using scatter plots. The comparative assessment of monthly simulated discharge of observed meteorological data and CFSR data is shown in Fig.7. It mainly represents the relationship between respective values with the statistical measure of coefficient of determination. The scatter plot of observed *vs* modelled monthly discharge at Pulamanthole gauging station for CFSR data was shown in Fig. 8. It mainly represents the relationship between measured and model output values using a statistical measure of coefficient of determination.

4. Conclusion

To overcome the data deficiency problem, one of the best reanalysis datasets available, NCEP's CFSR data was used in the present study. The calibrated and validated SWAT model was simulated with the predicted meteorological data (CFSR) and observed meteorological data. Comparison of the model simulations was done on the basis of statistical measures such as NSE, R^2 and RMSE. The NSE, R^2 and RMSE for model simulation with observed meteorological data were 0.82, 0.85 and 29.25, whereas for the predicted meteorological data the values were 0.70, 0.72 and 37.18 respectively. From the analysis, it is seen that the variation between the simulated discharge obtained from the observed meteorological data and the observed discharge is mainly because of the variation between the values at the peaks. Even though the simulations with the predicted meteorological data (CFSR) had slightly less correlation than the observed meteorological data, the statistical indicators suggest that it can be well utilized for areas where the availability of accurate observed meteorological data is a hindrance for hydrologic studies.

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References

Abraham, L. Z., Jackson, R., and Chekol, D. A., 2007, "Calibration and validation of SWAT hydrologic model for Meki watershed, Ethiopia [abstract]", In: Abstracts, Conference on International agricultural research for development, 9-11, October, 2007, WItzenhausen, Germany.

Ashouri, H., Hsu, K. L., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., Nelson, B. R. and Prat, O. P., 2015, "PERSIANN-CDR: Daily precipitation climate data recorded from multisatellite observations for hydrological and climate studies", *Bulletin of the American Meteorological Society*, **96**, 69-83.

Auerbach, D. A., Easton, Z. M., Walter, M. T., Flecker, A. S. and Fuka, D. R., 2016, "Evaluating weather observations andthe Climate Forecast System Reanalysis as inputs for hydrologic modelling in the tropics", *Hydrological Processes*, **30**, 3466-3477.

Cuceloglu, G., and Ozturk, I., 2019, "Assessing the Impact of CFSR and Local Climate Datasets on Hydrological Modelling Performance in the Mountainous Black Sea Catchment", *Water*, **11**, 2277. doi : https://doi.org/10.3390/w11112277.

Dile, Y. T. and Srinivasan, R., 2014, "Evaluation of CFSR climate data for hydrologic prediction in data scarce watersheds: An application in the Blue Nile River basin", *J. of the American Water Resources Association.* doi : 10.1111/jawr.12182.

Fuka, D. R., Walter, M. T., MacAlister, C., Degaetano, A. T., Steenhuis, T. S. and Easton, Z. M., 2014, "Using the CFSR as weather input data for watershed models, *Hydrol. Process*, doi : 10.1002/hyp.10073.

George, S. and Sathian, K. K., 2016, "Assessment of water balance of a watershed using the SWAT model for water resources management", *Int. J. of Eng. Sci. & Res. Technol.*, **5**, 4, 177-184.

Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wol, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P. and Stocker, E. F., 2007, "The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-SensorPrecipitation Estimates at Fine Scales", *J. Hydrometeorol.*, **8**, 38-55.

Jajarmizadeh, M., Sidek, L. M., Mirzai, M., Alaghmand, S., Harun, S. and Majid, M. R., 2016, "Prediction of surface flow by forcing of CFSR data", *Water Resour. Manag.*, **30**, 2627-2640.

Krause, P., Boyle, D. P. and Base, F., 2005, "Comparison of different efficiency criteria for hydrological model assessment", *Adv. Geosci*., **5**, 89-97.

Liu, Z., Wang, Y., Xu, Z., Duan, Q., 2017, "Conceptual Hydrological Models. In: Duan, Q., Pappenberger, F., Thielen, J., Wood, A., Cloke, H., Schaake", *J. (eds) Handbook of Hydrometeorological Ensemble Forecasting*. Springer, Berlin, Heidelberg. doi : https://doi.org/10.1007/978-3-642-40457-3_22-1.

MacLean, A., 2005. Statistical evaluation of WATFLOOD. [on-line]. Available: http://www.civil.uwaterloo.ca/watflood/downloads/statsusersmanual.pdf.

Malago, A., Liliana, P., Faycal, B. and Marco, F., 2015, "Comparing calibrated sets of the SWAT model for the Scandinavian and Iberian peninsulas", *Hydrol. Sci. J.*, **60**, 5, 949-967.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. and Veith, T. L., 2007, "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations", *Trans. ASAE.*,**50**, 3, 885-900.

Prasad, V., Yousuf, A. and Sharma, N., 2020, "Hydrological modeling for watershed management", *J. Natural Resource Conservation and Management*, **1**, 29-34. 10.51396/ANRCM.1.1.2020.29-34.

Roth, V. and Lemann, T., 2016, "Comparing CFSR and conventional weather data for discharge and soil loss modelling with SWAT in small catchments in the Ethiopian highlands", *Hydrol. Earth Syst. Sci.*, **20**,921-934.

Saha, S., Moorthi, S., Pan, H. L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R., Woollen, J. and Behringer, D., 2010, "The NCEP Climate Forecast System Reanalysis",*Bull. Am. Meteorol. Soc.*, **91**, 1015-1058.

Singh, V. P. and Woolhiser, D. A., 2002, "Mathematical Modelling of Watershed Hydrology", *J. Hydrol. Engg.*, **7**, 270-292.

Sirisena, T. A. J. G., Maskey, S., Ranasinghe, R. and Babel, M. S., 2018, "Effects of different precipitation inputs on streamflow simulation in the Irrawaddy River Basin, Myanmar", *J. Hydrol. Regional Studies*, **19**, 265-278. doi : https://doi.org/10.1016/j.ejrh.2018.10.005.

Stehr, A., Debels, P., Romero, F. and Alcayaga, H., 2010, "Hydrological modelling with SWAT under conditions of limited data availability: evaluation of results from a Chilean case study", *Hydrological Sciences J.*, **53**,3, 588-601, doi: 10.1623/hysj.53.3.588.

Strauch, M., Bernhofer, C., Koide, S., Volk, M., Lorz, C. and Makeschin, F., 2012, "Using precipitation data ensemble foruncertainty analysis in SWAT streamflow simulation, *J. Hydrol*. 414-415, 413-424.

Swain, S., Mishra, S. K., Pandey, A., Pandey, A. C., Jain, A., Chauhan, S. K. and Badoni, A.K.,2022, "Hydrological modelling through SWAT over a Himalayan catchment using high-resolution geospatial inputs", *Environmental Challenges*, **8**, 100579. doi : https://doi.org/10.1016/j.envc.2022.100579.

Tejaswini, V. and Sathian, K. K., 2018, "Calibration and validation of the SWAT model for Kunthipuzha basin using the SUFI2 algorithm", *Int. J. of Curr. Microbiol. and Appl. Sci.*, **7**, 1, 2162-2172.

Tomy, T. and Sumam, K. S., 2016, "Determining the adequacy of CFSR data for rainfall-runoff modelling using SWAT", *Procedia Technol.*, **24**, 309-316.