

Impact of Land-Use Changes on the Runoff of Nandigama, Andhra Pradesh, India

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ABSTRACT

Present study investigated the effect of land-use variations on the excess flow for a Nandigama, Andhra Pradesh, India by using HEC-HMS model. The model was calibrated and validated using observed rainfall and runoff data. The R^2 and NSE values were both greater than 0.65 after calibration, indicating a reasonable fit of the model. An analysis was conducted to understand how the land-use changes in a basin have affected the runoff. The analysis revealed that the stream flow increased due to variations in land use, and a reduction in the timing of peak flow at the outlet was observed. Additionally, the study analysed the trend of maximum rainfall time series and found that the months of June, July, and August show a decreasing trend in maximum rainfall over the study period, while other months show an increasing trend. The results of the analysis can be used to implement informed policies and management practices aimed at mitigating the negative impact of land-use changes and climate changes in Nandigama.

Keywords: climate change; land-use and land cover; Nandigama; rainfall runoff.

INTRODUCTION

The life on the Earth is primarily based on the presence of water. The cycle deals with the event, circulation and circulation of water resources on the Earth. Environment is prone to major changes with altered meteorological conditions and people impacting the hydrologic cycle. The effects may include excessive floods, huge variations in temperatures (Global Warming), disturbances in surrounding ecological systems, variation in rainfall patterns. The frequent occurrence of floods has direct impacts on socio-economic aspects as well as ecological balance. The information regarding flood intensities and extent of area likely to be flooded will be helpful in attractive essential actions to excluding budget and lives of people [Amarasinghe et al., 2020]. Soil is a vital natural resource which directly affects the yield of agriculture production and prosperity of any country. By understanding the hydrological processes one can possibly deal with the proper operation and management of reservoirs and watersheds. The development of concept of a

“Model” is an outstanding approach to analyses water. Response of basin to an individual storm is defined by event-based hydrologic modelling while continuous hydrologic modelling accounts for a number of rainfall events and its response on the basin outlet by considering dry and wet period both [Yarrakula et al., 2016]. The parameters that are to be defined in order to understand the catchment response are meteorological as well as catchment physical characteristics. To simulate rainfall-runoff processes, hydrologic models have been successfully developed [Chen et al., 2021]. Bertilsson et al. (2019) compared WEEP model (Water erosion prediction project) and HEC HMS model and originate that the HEC -HMS model predicted and simulated runoff more accurately. Several researchers have carried out hydrological modelling using HEC-HMS [He et al., 2021]. In event-based rainfall runoff simulation, SCS curve number and Green Ampt method are used for calculating runoff volume, the Muskingum method is employed for routing [Dasallas et al., 2019]. The results of event-based model were found to give satisfactory

performance for forecast of inflows at the outlet of the watershed that can be used for forecasting the flood. Pallavi et al., (2022) reported that soil moisture accounting method can be used for event-based as well as continuous modelling.

Flood risk assessment is a vital non-structural flood management strategy that needs to be treated with utmost gravity and commands global attention; it has proven essential not only to civic bodies and decision makers but to general public as well. Flood risk essentially comprises of two major components, flood hazard and flood vulnerability, and is represented as a combination of both factors. However, very less importance has been given to socio-economic vulnerability in the previous studies in terms of flood risk mapping. It has become essential to recognise the significance of socioeconomic aspects of vulnerability, since floods bring considerable losses in society, like death of a family member, loss of temporary or permanent jobs, destruction of property, while simultaneously quantifying the flood damage in terms of hazard. Flooding in urban areas is now commonly seen due to illegal encroachments causing heavy damage to the storm drains, settlements, roads and other properties. Many studies were carried out on the flood caused by rivers that mainly affect the coastal and remote areas. Recent scenarios show that there is a high potential for damage due to overflow of storm water even for a small intensity of rainfall and for a minor

concentration. Urbanisation due to encroachments of highly prone flood plains leads to an increase in perviousness of the land causing the excess amount of rainfall volume to overflow [Prakash et al., 2020]. However, considering the hydrologic modelling in understanding the characteristics of flood in the urban area allow combating the extreme effect of flooding. GIS and remote sensing integrated with models make it likely to study water elevation profile of the storm water drainage network of the highly inundated areas. By understanding the hydrological processes one can possibly deal with the proper operation and management of reservoirs and watersheds. A substantial resides in the coastal cities, hence are immensely by normal flooding. The urban population is at a greater risk to damages caused by flood [Rangari et al., 2019].

In the present study, an attempt was made to simulate the rainfall-runoff processes of the Nandigama catchment, Andhra Pradesh, India using HEC-HMS. The calibration of the model parameters was undertaken using the data of years 2009 and 2010, and validation was carried out for the years 2011, 2012 and 2013.

STUDY AREA

The most prevalent natural disaster worldwide is flooding, impacting a significant number of

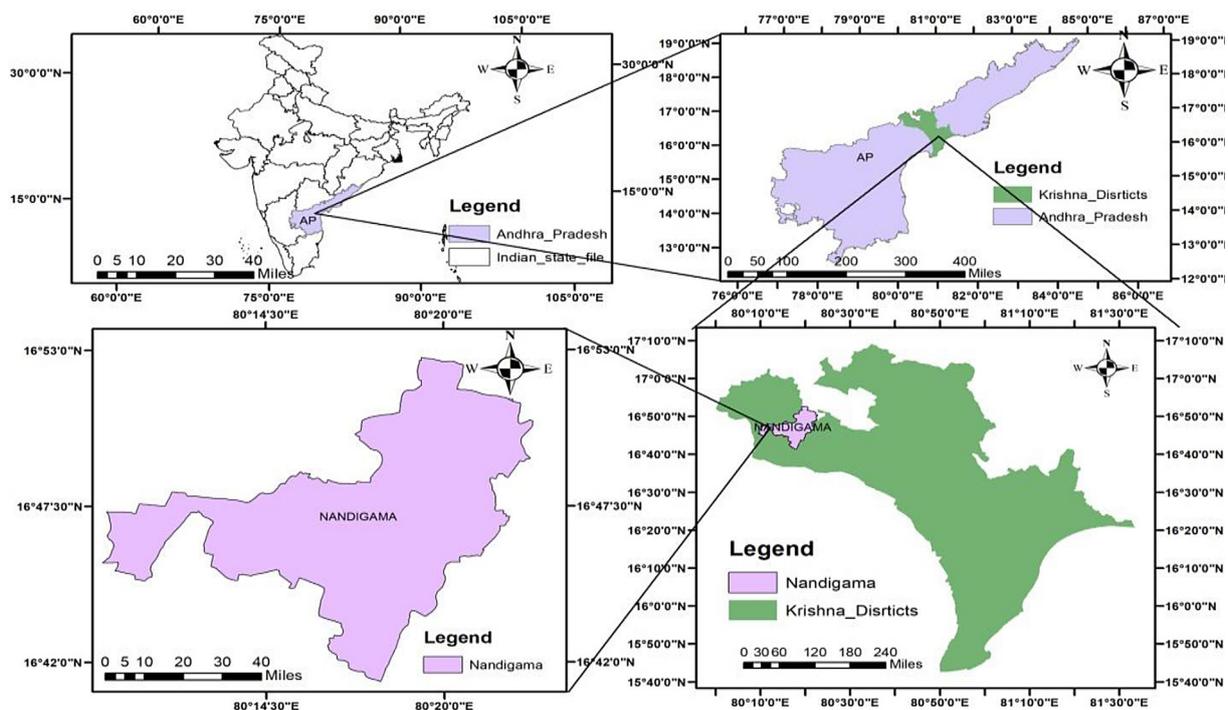


Figure 1. Study area of Nandigama

Table 1. Data and their source

Input data	Data source
Topography	SRTM DEM 30 m data (https://earthexplorer.usgs.gov/)
Precipitation	High spatial resolution daily gridded rainfall data set for the Indian region (Grid data) (IMD)
Land use / Land cover (LULC)	LandSat 2008 (https://earthexplorer.usgs.gov/)
Soil types	FAO – UNESCO soil map of the world

people on the planet. Over recent years, unregulated urbanisation and climate change have led to an increase in severe floods in urban areas, and this trend is anticipated to persist in the future. In major Indian cities, such events cannot be avoided, but with technological advancements, flood-vulnerable areas can be identified by modelling critical rainfall events. The challenge associated with urban floods lies in the uncertain flow conditions that result from swift variations in topography and insufficient raw data sets in urban settings. Nandigama, a city located in southern India’s Andhra Pradesh State, has experienced a surge in population and urbanisation in recent years. To analyze extreme rainfall events in a specific area of Nandigama, a simple approach was utilised. The four seasons are distinct, the surface vegetation dries in winter and flourishes in summer, and the seasonal changes are obvious. The average annual rainfall is 830 mm. The total area of Nandigama is 18466 ha. Nandigama urban catchment is divided into three storm-water zones based on drainage areas and their outlets.

MATERIAL AND METHODS

Taking into account the large losses because of flood events, application and mitigation of appropriate ways to reduce the areal extent of inundation and probable drainage risk is forefront for the decision makers. In hydrologic modelling, the input data plays a vital role in defining the accuracy of the effects. For this study, the gridded rainfall data set of $0.25 \times 0.25^\circ$ spatial resolution of Nandigama was used, obtained from the India Meteorological Department (IMD) for the years 2009 to 2013. The data sources used in this study are presented in Table 1. Wet, dry, and normal years were categorised as suggested. The characteristics of wet and dry years were investigated using mean and standard deviation (SD) of the annual precipitation. If rainfall is more than $P_{\text{mean}} + 0.75 \cdot \text{SD}$, it can be classified as wet year, if it is less than $P_{\text{mean}} - 0.75 \cdot \text{SD}$, it can be classified as dry year and the one which lies in between $(P_{\text{mean}} + 0.75)$ and $(P_{\text{mean}} - 0.75)$

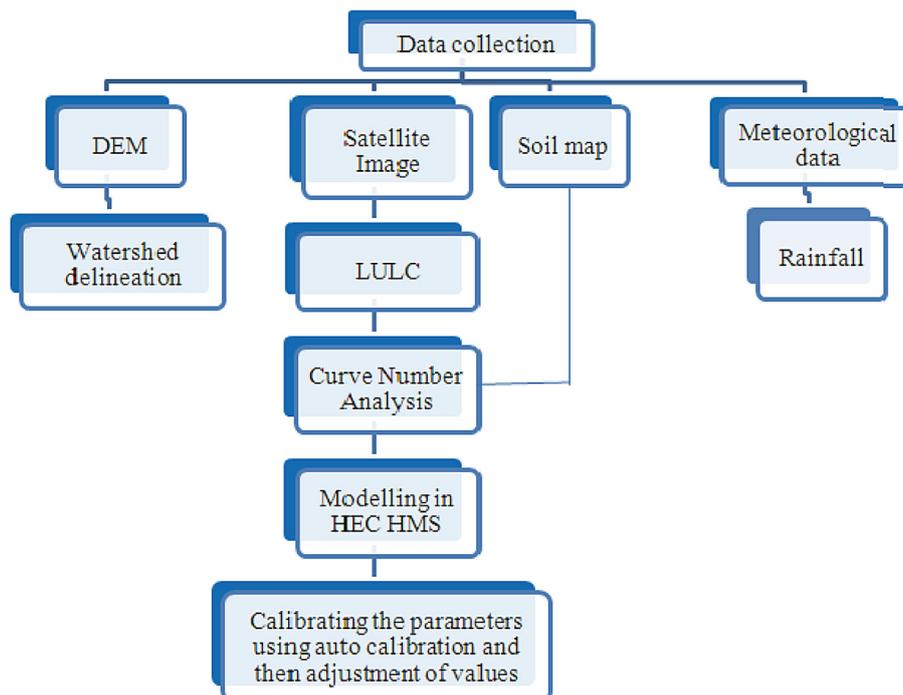


Figure 2. Methodology adopted for the present study

can be considered as normal year (Guan et al., 2021). Daily discharge data at the Keesara gauging station for the years 2009 to 2023 were collected from stations. The time series of outflow from Nandigama were collected from the IWRS website. The software used for the present study was HEC-HMS (v4.2.1) downloaded from USACE website <http://www.hec.usace.army.mil/software/hec-hms>.

The present study focuses on loss method, transformation method and the routing method. Figure 2 presents the methodology used in the study. The Hydrologic Modelling System (HEC-HMS), which has been used, is next generation software for rainfall-runoff simulation. The output of the rainfall-runoff simulation processes is the stream flow at the outlet of the catchment. Basin model in HEC-HMS consist of their processes. It simulates surface runoff response of the catchment by understanding each hydrologic and hydraulic component. It can be used in lumped parameter-based modelling and semi-distributed parameter-based modelling. It also helps in the analysis of urban flooding, flood frequency, flood warning system, reservoir spillway capacity, stream re rotation etc.

Non-parametric Mann–Kendall test

The Mann-Kendall test is a non-parametric statistical test used to detect trends in time series data. The test is based on the ranks of the data and assesses whether there is a monotonic trend (either increasing or decreasing) over time. This method was used for detecting trends in hydrological data, such as precipitation and temperature. Climate variability was studied using various statistical analyses such as linear along with climate change models to identify its characteristics (Rafiq et al., 2016; Puno et al., 2022), this test emerges out to be the most commonly used techniques for detecting the changes in the climate. To conduct this test, it is necessary to arrange the monthly observations in chronological sequence and then compare the differences between the observed and simulated readings. The computation of the difference between the number of positive and negative differences, S , is also performed along with Eqn. 1, which is utilised to determine the Mann-Kendall (MK) test statistics.

$$S = \text{Sum of sign}(\text{rank}_j - \text{rank}_i), \text{ for } i < j \quad (1)$$

where: rank_i and rank_j are the ranks of the i th and j th observations, respectively, and the sum is taken over all pairs of observations where $i < j$.

The variance of S is given by:

$$\text{Var}(S) = (n*(n-1)*(2*n+5) - \sum (t_i*(t_i-1)*(2*t_i+5)), \quad (2)$$

for $i = 1$ to m)/18

where: n is the number of observations, m is the number of tied groups, and t_i is the number of tied observations in the i th group.

The test statistic Z is calculated as:

$$Z = (S - 1)/\text{sqrt}(\text{Var}(S)) \quad (3)$$

where: S is the Mann-Kendall test statistic and $\text{Var}(S)$ is its variance.

If the absolute value of Z is greater than the critical value for a given significance level (e.g., 0.05), then the null hypothesis of no trend is rejected in favor of the alternative hypothesis of a trend.

The variance of S is calculated using Eqn. 2, after which the standard normal variant Z can be calculated using Eqn. 3. These equations use x_j and x_i as the data values of rainfall for the j th and i th year, and n as the total number of years. This test involves two hypotheses– the null hypothesis (H_0) and the alternative hypothesis (H_1). The null hypothesis assumes that there is no trend in the time series, meaning that the values used for analysis. The alternate suggestion accepts a tendency in the time sequence. To analyse the trend using XLSTAT 2016, the Mann Kendall statistic (p) is used. The test is performed at a 95% confidence interval for the time series. During the Mann-Kendall test using XLSTAT, Kendall's tau is obtained as another parameter in the time series. This parameter specifies the correlation between two variables, with the values of Kendall's tau ranging from -1 to +1. Positive correlation values indicate that the ranks of both variables increase together, while negative correlation values imply that the rank of one variable increases while the other decreases.

Prior to conducting trend analysis in time series, it is crucial to account for autocorrelation, which is the correlation of a variable with itself over time intervals. Autocorrelation can lead to false positives or negatives in trend detection. To map the climate change conditions, the rainfall

Mann Kendall Z values were calculated and the degree of significance was used to generate a diagram of the entire Nandigama.

Sen's slope estimator test

Sen's slope estimator is a statistical technique used to estimate the slope of a linear relationship between two variables over time. It is particularly useful in the situations where the data is not normally distributed or when there are outliers present. The estimator is based on a non-parametric method that involves calculating the median of the slopes between all pairs of points in the data set. This provides a robust estimate of the slope that is less sensitive to outliers than other methods. The Sen's slope estimator test is used to determine whether there is a significant trend in the data over time.

$$S = \text{median}(y_j - y_i)/(x_j - x_i) \quad (4)$$

where: S is the Sen's slope estimator, y_i and y_j are the values of the dependent variable at times i and j , respectively, and x_i and x_j are the values of the independent variable at times i and j , respectively.

RESULTS

In modelling a flood event, the most important factor of the hydrograph is the peak flow, because the peak flow is the deciding factor for assessing the inundation downstream. In this study, the Kessara discharge gauge located in lower stretch was taken as outlet point and project area

was generated with respect to that point. In order to predict the runoff from a basin with varying LULC surroundings, the HEC-HMS model was developed. To achieve this, the stream flow from the routing model was utilised for validation and calibration purposes. The model was validation using two sets of rainfall events, while validation was carried out using another set of observed rainfall and runoff data. The modelling process was done using the SRTM 90 m resolution DEM, which was used to identify the location of channels within the watershed. The channel network, which had a total length of around 14.67 km, not only helped in identifying the location of channels but also aided in understanding the hydrology of the watershed and the flow of water through the landscape. To achieve the desired simulation results during the calibration process, changes were made in parameters. The manual calibration was done by maximizing the R^2 and NSE value. After calibration, the R^2 and NSE values were both greater than 0.65, which is considered reasonable. To validate the model, rainfall and stream flow data from June 3, 2017, collected by field observation, were used. A comparison of observed runoff with simulated runoff using the HEC-HMS model is presented in Figure 3. The simulated peak runoff rate using the HEC-HMS model was found to be close to the observed peak runoff. All of these findings and results contribute significantly to the understanding of the hydrological behaviour of the watershed and the flow of water through the landscape under different land-use scenarios.

An analysis was conducted to understand how land-use changes in a basin have affected the

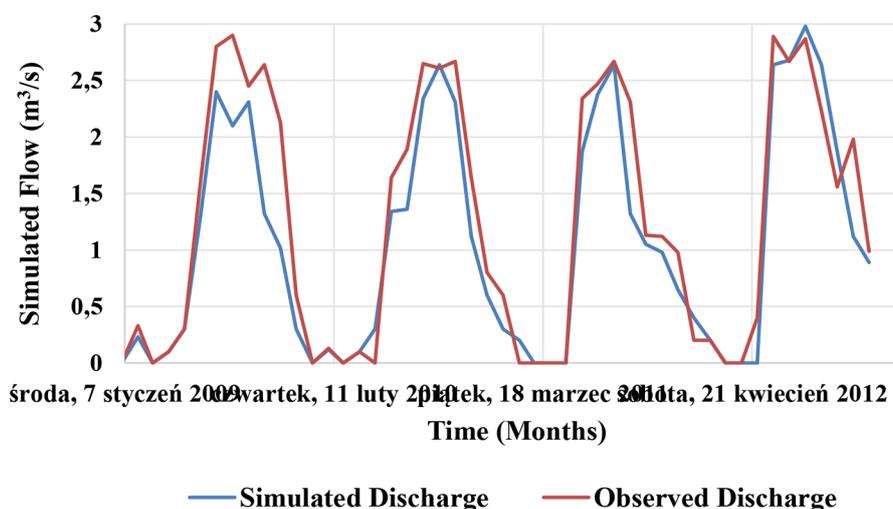


Figure 3. Simulated and observed runoff of Nandigama

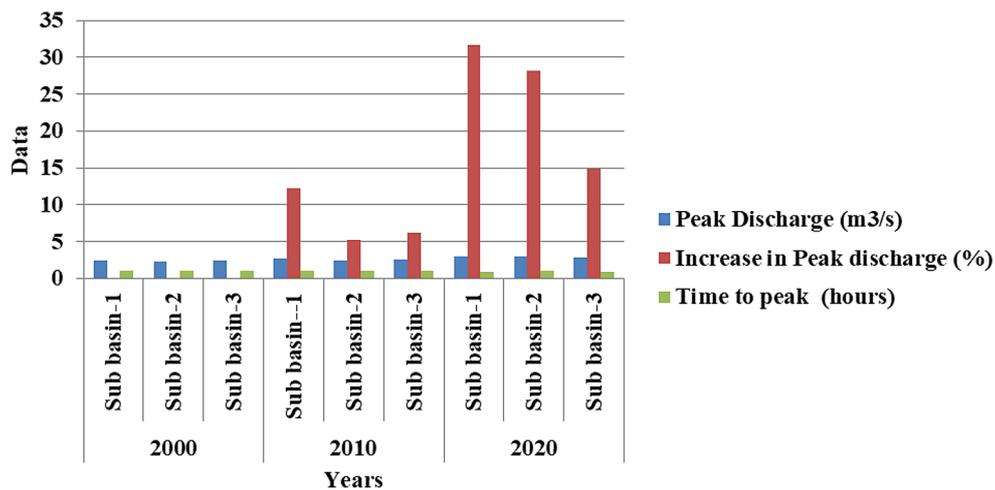


Figure 4. Different years peak discharge data for three basins

runoff from the area. The land-use data from the years 2000, 2010, and 2020 were used in conjunction with rainfall events to compare the variations in the generated excess flow. To assess the impact of LULC over the last three decades on the runoff from the Nandigama different LULC date was used in the model. Simulations were conducted using the available rainfall events to compute stream flows. Figure 4 shows the results of simulations using different land-use data. The analysis revealed that 12.19% from the year 2000 to 2010, and by 31.70% from the year 2000 to 2020. This indicates that the stream flow increased due to the changes in land-use. Furthermore, a noteworthy observation revealed a reduction in the timing of peak flow at the outlet, transitioning from duration of 1 hour in the year 2000 to a slightly shorter span of 0.94 hours by the year 2020. The analysis provides valuable insights into the impact of land-use changes on the runoff generated in a basin. The results can be used to inform policies and management practices aimed at mitigating the negative on the environment.

Trend analysis of rainfall

Long-Term rainfall Trends

In the present research, Mann-Kendall (non-parametric rank) two-tailed assessment and Sen's Slope Estimator (SS) were performed to identify the trends in the rainfall time series of Nandigama. Trend analysis is done for maximum rainfall because flooding or runoff leads only maximum rainfall.

Maximum rainfall trend over Nandigama

An analysis of the maximum precipitation time series was conducted on a monthly, seasonal, and yearly basis for trend identification. Maximum rainfall time series plots on annual and seasonal scales are presented in Figure 5. Table 2 presents the results of testing the trend analysis for a specific month using the two-tailed Mann-Kendall test and Sen's estimator of slope at a significance level of 95%. The table presents the values of a meteorological parameter for each month of the year. The parameter can be any meteorological variable, such as temperature, precipitation, or humidity. The table also includes the statistical parameters found from the test, Sen's slope, Kendall's Tau, and their respective p-values. The Sen's Slope (S) having a positive value; it indicates an upward trend, while a negative value of S indicates a downward trend.

By performing Mann-Kendall test on annual scale results shows that June, July and August months show a decreasing trend over the study period with value of p is 0.778, 0.043 and 0.728 respectively. The value of Sen's Estimator of Slope shows a decreasing trend of June, July and August month. Months other than these show an increasing trend during the study period with maximum value of Sen's Slope 0.013. Long term trend test was also performed on seasonal and annual scale, which shows an increasing trend during the annual maximum rainfall. Southwest monsoon season shows a decrease trend of annual minimum rainfall during the entire period. Winter, Pre monsoon and Post monsoon season also shows a significant increase trend during the study period.

Table 2. Trend and correlation for monthly precipitation data

Month	Kendall's Tau	Trend	Mann-Kendall p-value	Sen's Slope	Sen's Slope p-value	Trend Interpretation
Jan	0.085	Rising	0.006	0.04	0.005	Insignificant increasing
Feb	0.088	Rising	0.008	0.036	0.008	Significant increasing
Mar	0.095	Rising	0.008	0.026	0.008	Significant increasing
Apr	0.115	Rising	0.009	0.009	0.009	Significant increasing
May	0.021	Rising	0.003	0.285	0.003	Insignificant increasing
June	-0.069	Falling	0.778	-0.0057	0.778	Insignificant decreasing
July	-0.186	Falling	0.043	-0.011	0.043	Significant decreasing
Aug	-0.073	Falling	0.728	-0.00584	0.728	Insignificant decreasing
Sep	0.022	Rising	0.002	0.282	0.002	Insignificant increasing
Oct	0.037	Rising	0.003	0.19	0.003	Insignificant increasing
Nov	0.178	Rising	0	-0.004	0.011	Significant increasing
Dec	0.305	Rising	<0.0001	0.013	<0.0001	Significant increasing
Winter	0.105	Rising	0.02	0.009	0.02	Significant increasing
Pre-Monsoon	0.138	Rising	0.004	0.021	0.004	Significant increasing
South-West Monsoon	-0.103	Falling	0.431	-0.011	0.431	Insignificant decreasing
Post Monsoon	0.231	Rising	<0.0001	0.03	<0.0001	Significant increasing
Annual	0.21	Rising	0	0.062	0	Significant increasing

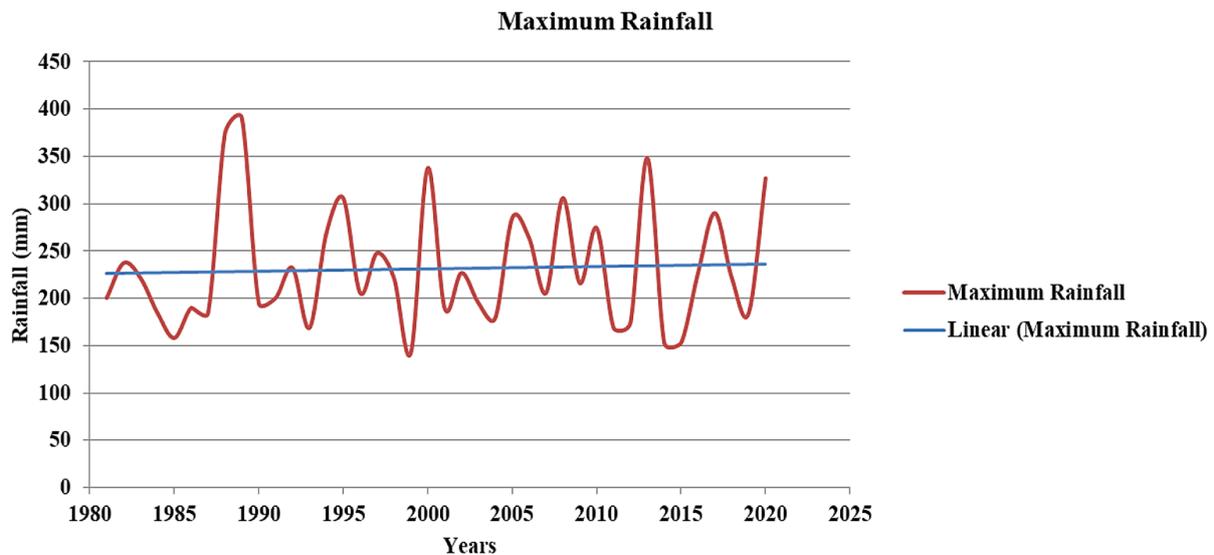


Figure 5. Maximum rainfall trend

Statistically significant results were obtained when the null hypothesis was rejected. The analysis of Mann-Kendall revealed an increasing annual trend of maximum temperature in West Nandigama, with Mann Kendall tau co-efficient showing a rising trend of 0.216 with Sen's slope of 0, as well as in winter, Pre-Monsoon, and Post-Monsoon, respectively. However, a decreasing trend was observed in South West Monsoon, with Mann Kendall tau co-efficient of -0.103 and Sen's slope of 0.431.

Spatial distribution of rainfall

By observing Figure 6, it is clear that Nandigama experiences an average annual rainfall between 585 and 670 mm. In the southern part of Nandigama, the precipitation tends to be slightly higher, ranging from 670 to 700 mm. Notably; both watershed areas receive considerable rainfall, with the first area getting slightly less compared to the other two. After a detailed examination of the rainfall patterns, it was observed that

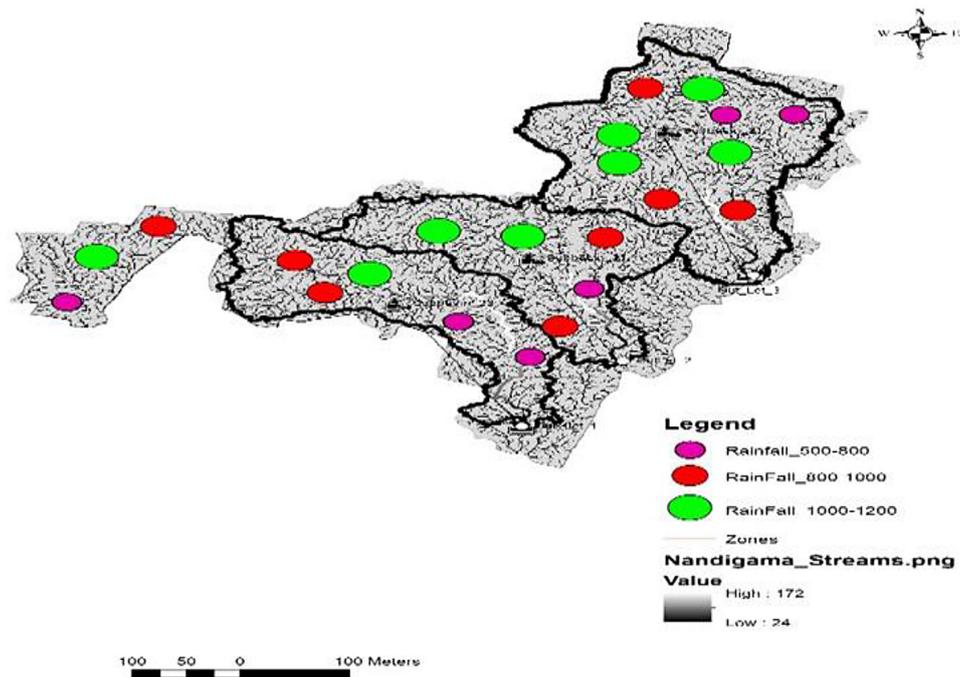


Figure 6. Spatial distribution of annual rainfall in the Nandigama

the first, second, and third watersheds recorded 864 mm, 913 mm, and 1013 mm of rainfall, respectively. These specific values were chosen for the runoff analysis in the TREX model based on how rainfall is distributed across each watershed area. The volume of rainfall received over an area determines the amount of water available to meet the various societal needs. Hence, time-based annual precipitation affects the socio-economic wellbeing. Therefore, the spreading of precipitation in time is a very important factor in the national economy. The long-term average annual rainfall for the country is 823 mm, which is the highest. Such a heavy concentration of rainfall results in a scarcity of water in many parts of the study area during the non-monsoon period. The distribution of rainfall across the area displays significant spatial differences, influenced by the local topography and the uneven occurrence of rain-producing weather systems in specific regions.

CONCLUSIONS

The hydraulic model was used aimed at predicting excess flow from a basin with varying land-use conditions. The model was calibrated and validated using observed rainfall and runoff data, and the SRTM 90 meter DEM was used to

identify the location of channels within the watershed. The direct use of HEC-HMS as a flood model is not divisible in the case of the present basin under consideration due to its inefficiency in predicts value. The calibrated model achieved reasonable fit with both R^2 and NSE values greater than 0.65. Validation was done by relating the detected runoff with virtual runoff, and the virtual peak excess runoff was close to the detected peak excess runoff. Analysis revealed that the changes in land use have increased the stream flow and reduced the timing of peak flow at the outlet. The results can be used to implement informed policies and management practices aimed at mitigating the negative impact of land-use changes on the environment. The study revealed that maximum rainfall trends are decreasing during June, July, and August months, as well as in the Southwest monsoon season. However, there is an increasing trend in other months, and winter, Pre monsoon, and Post monsoon seasons show a significant increasing trend during the study period. This study demonstrated that a combination of HEC-HMS and Muskingum hydrological routing method incorporating proper computation hydrological lag time can provide better results than a combination of HEC-HMS and HECRAS where the direct filed measured cross sectional details are not available.

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