



Regionalized Design Rainfall Estimation: an Appraisal of Inundation Mapping for Flood Management Under Data-Scarce Situations

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Abstract

Availability of regionalized design rainfall is crucial for flood modeling, particularly over the regions with sparse raingauge networks. This study proposes a new comprehensive framework for generating regionalized design rainfall time series for data-poor catchments involving non-linear and non-parametric optimization approaches. A large set of parametric and non-parametric families of distribution were considered for multivariate rainfall frequency analysis using at-site station data, while a unique design temporal pattern over the region was derived by quantifying the flood causing potential of design hyetographs. The regionalized design rainfall time series was used as one of the inputs to a two-dimensional (2D) flood model. The accuracy and performance of the derived regionalized design rainfall for flood inundation modeling were evaluated by comparing with those derived from different spatial interpolation methods. There was a high consensus of the former with those of widely used kriging and spline interpolation methods. A severely flood-prone and data-poor (no raingauge available within study area) large coastal catchment lying along the coast of the Bay of Bengal, India, was chosen for a demonstration of the proposed framework. The study showed that the framework can be used for extreme events arising due to floods, even under changing climatic scenarios. It further invokes the necessity for incorporating the proposed framework into various commercially and freely available flood models along with other existing interpolation techniques to support improved flood management.

Keywords Flood management · Multivariate rainfall frequency analysis · Regionalized design rainfall time series · Spatial interpolation methods · Two-dimensional flood model

1 Introduction

Spatial analysis of flood risk assessment can guide efficient and effective mitigation options (Karmakar et al. 2010; Wang et al. 2015). However, a major hindrance is the lack of availability of rainfall data at high spatial and temporal resolution for partially gauged or ungauged regions. This is where regionalized design rainfall becomes necessary. The method of regionalization can be accomplished in two ways: (i) spatial interpolation of rainfall using available rainfall data from other locations and (ii) estimation of a single

design curve from available rainfall data for an area located within a climatologically homogeneous region using methods such as maximum likelihood method, station averaging (Buishand 1991) or regional averaging (Overeem et al. 2009), index variable and growth curve (Svensson and Jones 2010).

In the past, a wide range of spatial interpolation schemes have been used for generating continuous rainfall patterns; these schemes range from simple methods to complex methods. They can be categorised into four classes: deterministic methods, global methods, geostatistical methods, and others which involve a combination of these. In rainfall analysis, the deterministic methods include mainly Inverse Distance Weighting (IDW) and Thiessen polygons, whereas spline and kriging fall under geostatistical methods (Vicente-serrano et al. 2003).

The second approach of regionalization derives design rainfall through depth-duration-frequency (DDF) curves or intensity-duration-frequency (IDF) curves. Here, frequency analysis is implemented either through: (i) univariate probability distribution where rainfall depth is the sole parameter and (ii) bivariate joint probability distribution between rainfall depth and duration, or intensity and duration (Vandenberghe et al. 2010). Although the former is simple and easy to implement, bivariate analysis is a more realistic and comprehensive approach as it describes an association among these variables, which is an important parameter in understanding extreme events such as floods. For simplicity, an assumption that “the marginals from bivariate distributions are identical” is frequently considered. In practice, however, this may not always be the case. In such situations, a bivariate copula provides flexibility in choosing the marginal distributions and reveals the dependence between the two variables (Grimaldi and Serinaldi 2006). The other important parameter is the temporal pattern of rainfall which is essentially a non-dimensionalized hyetograph plotted using rainfall depth versus elapsed time (Prodanovic and Simonovic 2004). Thus, regionalized design rainfall time series can be obtained by utilising the bivariate model of DDF curves along with the design rainfall temporal pattern under an optimization framework. Sarkar et al. (2010) used a combination of the L-moment approach and Thiessen polygon interpolation to derive a regionalised IDF curve for the Tehri-Garwal Himalaya region, India using four rain gauging stations data. Haddad et al. (2011) demonstrated rainfall frequency analysis for 203 rainfall stations in Australia by coupling regression (generalised least squares) and L-moment-based index method. Design rainfall depths were estimated and compared with the already available records from five stations for a set of return periods.

In another study, Al Mamoon et al. (2014) used a similar approach to generate IDF curves for Qatar using L-moment approach combined with regional frequency analysis. Recently, self-organizing map clustering (SOM), that belongs to the group of Artificial Neural Networks (ANN), has been used to analyse complex data through a series of feature and density maps and to group them into clusters (Kohonen 2001). This methodology has been used in deriving design hyetographs for ungauged sites in the form of percentage of total rainfall depth (%) versus time (dimensionless) by assigning them to clusters of gauged sites (Kalteh and Berndtsson 2007; Lin and Wu 2007; Lin et al. 2010). However, such a method may be applicable only under the presence of dense raingauge network.

It is well known that India is severely affected by floods, and faces around 20% of the global deaths due to floods (Guhathakurta et al. 2011). In such a context, the quantification of parameters that indicate the damage potential, such as flood extent, maximum depth and velocity and duration require the use of robust flood simulation tools and good quality data set. The simulation-based flood inundation mapping is essentially a planning tool and it can

be used across a wide spectrum for effective reduction of flood damage. Since a few years, there has been increasing use of 2D models, mostly due to reduction in computational cost (Horritt and Bates 2002).

In spite of multiple past attempts of estimating regionalised design rainfall, numerous complexities are involved in the existing methodologies. Several studies have tried to formulate regional DDFs, based on numerous empirical equations, regression analyses (Alila 2000; Madsen et al. 2002; Brath et al. 2003), weighted averaging of hyetographs at gauged sites (Lin et al. 2005; Chen et al. 2011; Yeh et al. 2013), and reciprocal-distance-squared method (Lin et al. 2010). While the empirical formulations are site specific, rest of the approaches have been found to be computationally rigorous as several parameters need to be estimated (Borga et al. 2005). While it might be argued that spatial interpolation schemes may solve the purpose, the sole dependence on them might not always be a good idea, as they suffer from large uncertainties due to random nature of rainfall variability (Diaconis and Efron 1983). At the same time, there are very scanty studies which have tried to quantify the flood causing potential of temporal pattern of regionalised design hyetograph. Alfieri et al. (2008) compared a few of commonly used methods for deriving synthetic temporal patterns such as the rational method, the variational method, the Chicago hyetograph, and the best linear unbiased estimation (BLUE). In their analysis they found, that in most of the cases BLUE hyetograph produces better results than other methods, however producing biased flood peak estimates in most of the climatic and hydrologic conditions considered.

It is imperative to mention that non-availability of fine resolution long-term rainfall data is a serious issue for many underdeveloped and developing regions, such as India, that are prone to frequent floods. Under such circumstances, it is critical to formulate reliable methods to estimate regionalized design rainfall for data poor regions to support in a better understanding and modeling such incidences. Unfortunately, the studies on regionalized design rainfall hyetographs for hydrologic events, especially for flood inundation is limited in the literature. The generation of flood inundation maps for various durations and return periods can serve as a vital tool for flood modellers and practitioners by demarcating areas of data poor regions with different levels of risk.

Considering the limitations and future research directions as envisaged previously, this research is twofold (I) a comprehensive framework for regionalization of design rainfall using a non-linear optimization approach, which is first of its new kind in regionalization approach of design rainfall and, (II) its appraisal to modelling flood inundation. In phase I, the proposed framework uses a multivariate analysis of rainfall by considering both depth and duration together with the design temporal pattern. A set of parametric and non-parametric models and extreme value distributions were used to derive at-site DDF curves for three raingauge stations. The regionalization of the design rainfall was obtained by using the parameters obtained from the extreme value distribution and the best fitting parametric/non-parametric model under a non-linear optimization framework. In phase 2, a comparative study of the flood inundation statistics, derived by using regionalized design rainfall and spatially interpolated areal rainfall from geostatistical and deterministic spatial interpolation techniques, is presented. The regionalised flood inundation maps were derived using the regionalized design rainfall together with other geospatial data sets such as fine resolution topography, distributed Manning's roughness coefficients and built-up land in the MIKE 21 2D hydrodynamic model. The proposed framework was applied to Jagatsinghpur District, a large catchment situated in the lower deltaic part of the Mahanadi

River basin in Odisha, India. This region frequently experiences severe flooding, and there is an absence of a well-maintained raingauge network.

The article has been organised into six sections. The Section 1 “Introduction” considers the past literature used for estimation of regionalized design rainfall for flood inundation and establishes the “objectives of the study”, by defining the specific tasks addressed in this study. The Section 2 on “Site description and data scarcity” explains the study area and its relevance for the demonstration of the proposed framework. The Section 3 on “Proposed framework for regionalization of design rainfall” addresses briefly the various steps involved in the study. It is followed by Section 4, “Demonstration of the proposed framework” with a detailed description of the methodology used for regionalized design rainfall and flood inundation assessment. The Section 5, “Results and Discussion” discusses the representative findings of rainfall analysis and flood inundation. The article ends with “Concluding remarks” regarding the proposed framework, its application to flood modelling, along with future research prospects.

2 Site Description and Data Scarcity

Jagatsinghpur District (geographical area: 1759 km²) is situated in Odisha, an eastern Indian state, between 19° 58' N to 20° 23' N latitude and 86° 3' E to 86° 45' E longitude. The region falls in the downstream reaches of Mahanadi river basin within the deltaic zones of two major rivers, namely, River Mahanadi and Devi, as given in Fig. 1. The district comprises of 8 blocks, 2 municipalities, 8 tehsils and 1320 villages. Ghosh et al. (2016)

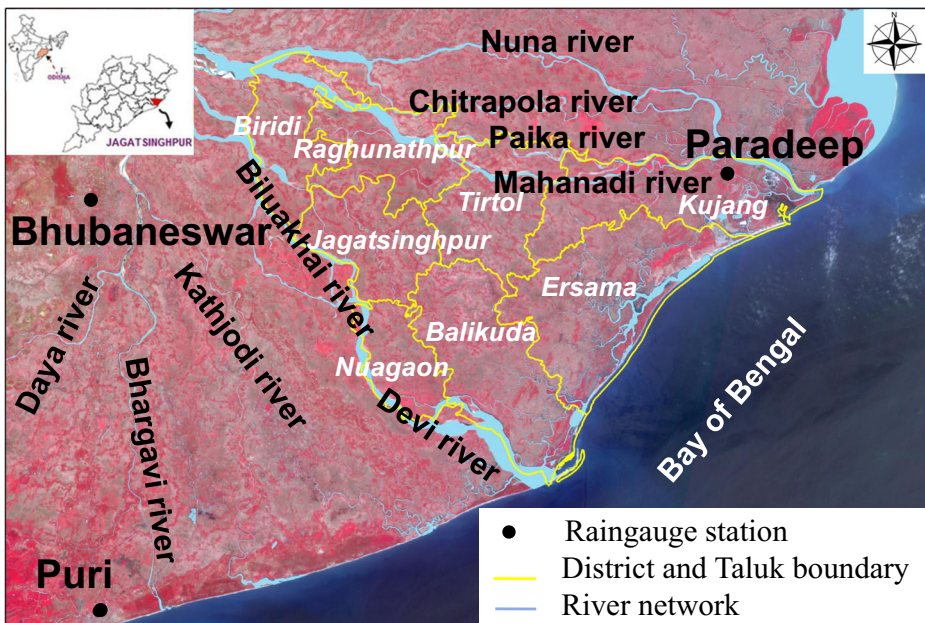


Fig. 1 Geographical location of Jagatsinghpur District in the lower Mahanadi River Basin, Odisha, showing IMD operated raingauge stations installed at Paradeep, Bhubaneswar and Puri (The base map is an FCC composite image derived from the Resourcesat2-AwiFS on 22 February 2015)

observed that there is a positive trend in the extreme rainfall over the Mahanadi region during monsoon season (June, July, August and September), which can result in frequent disastrous floods. During the monsoon season, the heavy rainfall in the upper and lower reaches of the study area, along with heavy discharge cause floods in the region. Blocks such as Ersama, Kujanga and Balikuda are highly prone to floods on an almost annual basis (District Emergency Operation Center 2016). The severity of floods is further aggravated by the tidal disturbances along the Bay of Bengal. During the last four decades, multiple major flood disasters have occurred in the region. The major floods in 1982, 1999, 2001, 2008 and 2011 are some of the events that incurred huge socio-economic and agricultural losses for the region. The demonstration of the regionalized design rainfall framework in this region is highly relevant because the district does not have a raingauge station that can provide hourly rainfall data to aid in flood management. The next section explains the proposed framework of the regional design rainfall and its application.

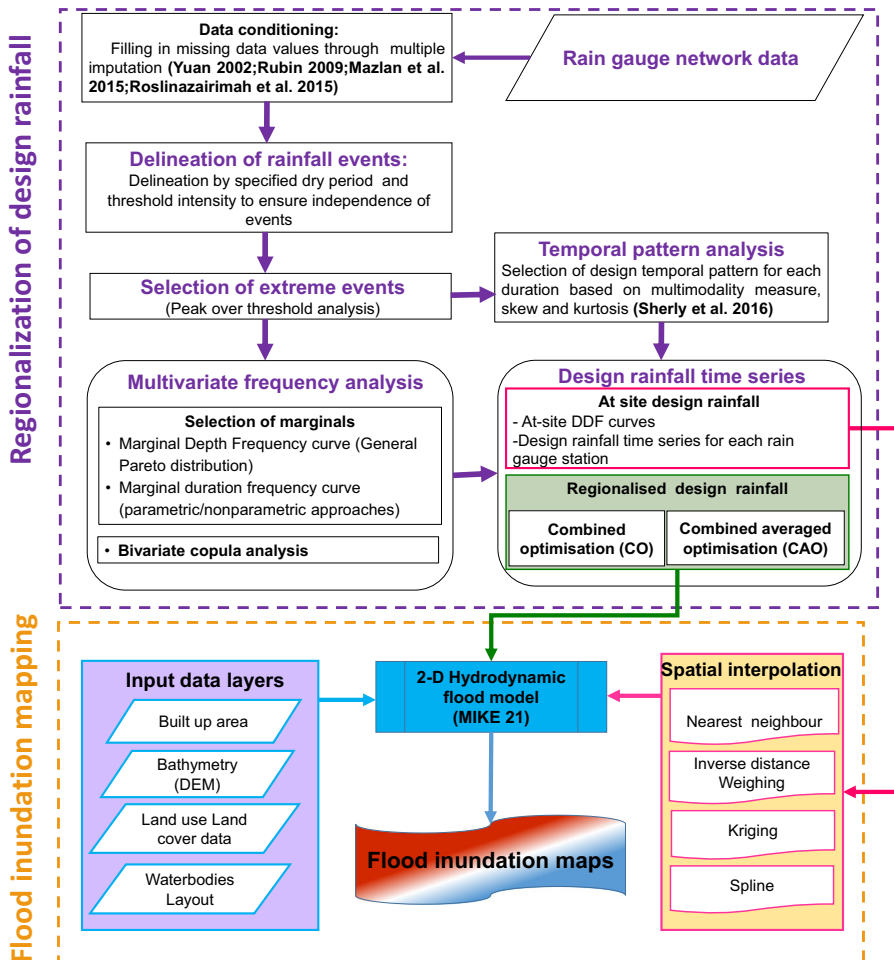


Fig. 2 Proposed framework of the regionalization of design rainfall and flood inundation mapping

3 Proposed Framework for Regionalization of Design Rainfall

The proposed framework is illustrated in Fig. 2. The outline of the procedure is given here: To estimate the design rainfall, hourly information was obtained from India Meteorological Department (IMD) for 3 neighbouring rain gauge stations located at Paradeep (1969–2013), Bhubaneswar (1969–2013) and Puri (1970–2013). Firstly, to ensure consistency and continuity of the data, data conditioning was performed. The Multiple imputation technique through fully conditional specification (FCS) method implemented through the Markov Chain Monte Carlo (MCMC) was used to replace the missing values in the continuous rainfall time series. Using this technique, rainfall time series was obtained for each raingauge station.

In the next step, using the criterion of minimum threshold, events series were generated from the rainfall events. Marginal depth frequency analysis was performed using a series of extreme value distributions while, marginal duration frequency analysis involved various parametric and nonparametric distributions. An optimal threshold depth was selected by plotting the various parameters from the series of extreme value distribution with varying thresholds. Bivariate joint probability was calculated using copula from marginal distributions of depth and duration. Following this, inverse of the conditional probabilities was used to estimate the design rainfall depths to plot at-site DDF curves. The other important component, i.e. design rainfall temporal pattern was obtained for all selected durations from the observed ones by identifying the pattern showing the highest flood causing potential. For each station, at-site design rainfall time series was generated by combining design rainfall depth corresponding to a design return period and duration obtained from the DDF curves, along with design temporal pattern.

For regionalization of design rainfall, a new concept of non-linear optimization technique using two approaches, namely (i) Complete Optimization (CO), and (ii) Combined Averaging Optimization (CAO) were used. Regionalized DDF curves were generated for different durations and return periods. The regionalized design rainfall time series was obtained for different combinations of return periods and durations. In the second phase, flood inundation modelling using 2D MIKE 21 model is demonstrated. In this model, a 10 m grid resolution LiDAR DEM and land use land class (LULC) map obtained from National Remote Sensing Centre (NRSC), Hyderabad was used. Following this, a series of spatial interpolation techniques were chosen for areal estimation of rainfall using the at-site design rainfall. Then, the regionalized and the spatially interpolated design rainfall time series were given as inputs to 2D flood model. A comparison of the inundation statistics for all cases was performed for a critical evaluation of their performance.

4 Demonstration of the Proposed Framework

This section elucidates the proposed framework, given in Section 3. The details of the various steps involved is described in the following subsections.

4.1 Multivariate Frequency Analysis

To explore the relationship between rainfall depth and the duration, insight into the two components, namely, marginal depth frequency and marginal duration frequency, is

necessary. Various extreme value-type models such as the general extreme value (GEV), Pearson type-III, and log Pearson type-III, normal and log normal models have been used for rainfall-depth frequency analysis. Although there are no general guidelines, the General Pareto distribution (GPD) is widely used (Van de Vyver and Demarée 2010; Meylan et al. 2012; Esteves 2013; Li et al. 2014). For duration frequency analysis, durations shorter than the time of concentration of the catchment play a major role in flood causing potential. Hence, both families of parametric and non-parametric distributions should be used to model rainfall duration. In this study, a multivariate rainfall frequency analysis using a copula-based method (Karmakar and Simonovic 2009; Vittal et al. 2015) has been adopted. The proposed methodology is summarized using the pseudo-code format in Algorithm 1.

Algorithm 1 Steps followed for multivariate frequency distribution in pseudo-code format

1: Marginal Frequency Analysis

- i. Marginal depth frequency curve (using GPD)

$$F_X(x) = 1 - \left\{ 1 + \left[\frac{\kappa(x-\mu)}{\alpha} \right]^{-1/\kappa} \right\}, \quad x = \mu + (\alpha/\kappa)\{1 - [1 - F_X(x)]^\kappa$$

($\mu > 0$, $\alpha > 0$ and $-1/2 < \kappa < 1/2$ are the location, scale, and shape parameters respectively)

- ii. Marginal duration frequency curve, $F_D(d)$

- a. Parametric family (out of 17 models tested): Gamma, lognormal, Loglogistic
 b. Nonparametric family (out of 4 models tested): Gaussian, Triangle, Epanechnikov

- iii. Goodness of fit for (i) and (ii) using RMSE, AIC and BIC

2: Bivariate Copula Analysis

- i. Joint return period of rainfall depth (H) and duration (D), $T_{H,D} = \frac{m}{N(1-F_{H,D})}$

$$F_{H,D}(h,d) = C[F_H(h), F_D(d)] = C_{v_1, v_2}(v_1, v_2)$$

(m : rainfall time series (years), N : sampled extremes, and $F_{H,D}$ is the bivariate joint probability of 'H' and 'D', $v_1 = F_H(h)$, $v_2 = F_D(d)$).

- ii. Gumbel-Hougaard copula, $C(v_1, v_2) = \exp\{-[(-\ln v_1)^\theta + (-\ln v_2)^\theta]^{1/\theta}\}$,

$$C(v_1|v_2) = v_2^{-1} \times [(-\ln v_1)^{\theta-1} \times (-\ln v_1)^\theta] \times (-\ln v_2)^\theta]^{(1/\theta)-1} (\theta \in [1, \infty], \phi(t) = \ln(t^\theta))$$

- iii. Goodness of fit for (ii) using RMSE, AIC and BIC
-

4.2 Design Rainfall Temporal Pattern

Unique design temporal pattern of rainfall indicates that pattern, which can cause the most disastrous flood event among all the observed patterns for a particular duration. Such a pattern can be quantified using various statistical measures such as skew, kurtosis and multimodality measure. It is chosen as the one which shows the highest skew and kurtosis along with the lowest bimodality (Sherly et al. 2015). A unimodal pattern will have more flood causing potential than a bimodal pattern as it continuously peaks up intensity unlike the latter. Similarly, kurtosis identified by the peakedness along with a thick and heavy tail, has a higher flood causing potential as a higher intensity of rainfall contributes to a more severe flood event. As such a leptokurtic pattern (highest kurtosis) shall lead to more severe event than compared to mesokurtic and platykurtic patterns (lower kurtosis). Lastly,

skewness which describes the shape of the hyetograph, constitutes a more severe flood event if the hyetograph is positively skewed in the initial time periods, as there is chance of flash flooding with limited response time to effectively drain the flood water. By combining the design temporal pattern of a specified duration with its corresponding design rainfall depths, design rainfall time series can be generated for various return periods. The Algorithm 2 in pseudo-code format shows the methodology for design rainfall temporal pattern analysis.

Algorithm 2 Steps followed for design rainfall temporal pattern in pseudo-code format

1: Calculation of skew (m_3) and excess kurtosis (m_4)

$$m_3 = \frac{\mu_3}{\sigma_3} = \frac{\frac{1}{n} \sum_{i=1}^n (t_i - \bar{t})^3}{\left[\frac{1}{n} \sum_{i=1}^n (t_i - \bar{t})^2 \right]^{3/2}}, \quad m_4 = \frac{\mu_4}{\sigma_4} = \frac{\frac{1}{n} \sum_{i=1}^n (t_i - \bar{t})^4}{\left[\frac{1}{n} \sum_{i=1}^n (t_i - \bar{t})^2 \right]^2} - 3$$

2: Calculation of Hartigan’s dip statistic (HDS)

Null hypothesis logic p -statistic, $p < 0.05$ indicates bimodal or multimodal

3: Calculation of bimodality coefficient (BC)

$$BC = \frac{m_3^2 + 1}{m_4} \quad (0 \leq BC \leq 0.555)$$

4: Selection of design temporal pattern as $\{(Max\ m_3) \cap (Max\ m_4) \cap (Max\ p) \cap (Min\ BC)\}_d$

4.3 Regionalization of Design Rainfall

The pre-requisite for regionalization of design rainfall is climatological homogeneity of the raingauge stations. This will facilitate the construction of regionalized DDF curves by averaging the parameters of the at-site DDF curves (Overeem et al. 2009). In this study, a non-linear optimization based framework was used to derive the regional bandwidth of the non-parametric kernel function, based on Sherly et al. (2013). This study adopts two approaches of optimization as follows: (i) CO, wherein all parameters of GPD and marginal duration frequency are obtained using optimization; and (ii) CAO, in which a non-linear optimization is used to calculate the regional bandwidth (w) of non-parametric kernel and the remaining three GPD parameters are averaged. The proposed methodology is given in the pseudo-code format in Algorithm 3.

Algorithm 3 Steps followed for regional design rainfall analysis in pseudo-code format

Two different optimization approaches to minimise the combined RMSE of all N stations

1: Complete Optimization or CO

$$Min\ Z(x) = \sum_{i=1}^N (RMSE)_i$$

$$x = (x_i | i \in N)$$

subjected to:

$$x_i > 0,$$

$$x_i = [\mu, \alpha, \kappa, w]_i, \forall i \in N$$

(w : nonparametric kernel bandwidth)

2: Combined Averaging Optimization or CAO

$$Min\ Z(x) = \sum_{i=1}^N (RMSE)_i$$

subjected to:

$$x_i > 0,$$

$$x_i = [w]_i, \forall i \in N$$

4.4 Flood Inundation Mapping Using the MIKE 21 Model

MIKE 21 model is a widely used robust flood simulation tool for fluvial, pluvial and coastal flood modeling (Kadam and Sen 2012; DHI 2014; Timbadiya et al. 2014). The model in this study utilizes a finite difference method (FDM) and solves the fully dynamic shallow water equations as presented in Eqs. (1), (2) and (3), with a constant grid spacing.

$$\frac{\partial z}{\partial t} + \frac{\partial p}{\partial x} + \frac{\partial q}{\partial y} = \frac{\partial d}{\partial t} \quad (1)$$

$$\frac{\partial p}{\partial y} + \frac{\partial}{\partial x} \left(\frac{p^2}{h} \right) + \frac{\partial}{\partial y} \left(\frac{pq}{h} \right) + gh \frac{\partial z}{\partial x} + \frac{gp\sqrt{p^2 + q^2}}{C^2 h^2} - \frac{1}{\varphi_w} \left[\frac{\partial}{\partial x} (h\tau_{xx}) + \frac{\partial}{\partial y} (h\tau_{xy}) \right] = 0 \quad (2)$$

$$\begin{aligned} & \frac{\partial q}{\partial x} + \frac{\partial}{\partial y} \left(\frac{q^2}{h} \right) + \frac{\partial}{\partial x} \left(\frac{pq}{h} \right) + gh \frac{\partial z}{\partial y} + \frac{gp\sqrt{p^2 + q^2}}{C^2 h^2} - \frac{1}{\varphi_w} \left[\frac{\partial}{\partial y} (h\tau_{yy}) + \frac{\partial}{\partial x} (h\tau_{xy}) \right] \\ & = 0 \end{aligned} \quad (3)$$

where, z is surface elevation (m); p is flux density in the x direction ($\text{m}^3/\text{s}/\text{m}$); q is the lateral inflow (m^3/s); h is water depth (m); t is time (sec); x and y are space coordinates (m); C is the Chezy resistance; φ_w is the density of water (kg/m^3); τ_{xx} , τ_{xy} and τ_{yy} are the components of effective shear stress (N/m^2); and g is acceleration due to gravity (m/s^2).

The advance and recession of a flood wave can be predicted through flood simulation, and outputs include maximum flood extent, flood velocity, and flood duration. In this study, simulations were performed to define flood inundation zones by inputting rainfall from the proposed regionalized design rainfall analysis followed by various spatial interpolation methods (SIM).

4.4.1 Hydrodynamic Model Setup

In this study, the parent LiDAR DEM of 2 m resolution for the entire study area was resampled to 10 m using the nearest neighbouring technique in Arc GIS 10.1, to compromise with the complexity in simulation time and cost. The DEM was pre-processed to include the built-up area residing in the study area. The raster DEM was later converted to ASCII format and imported into MIKE 21 domain (*.dfs2 MIKE 21 format) using the Grid to MIKE toolbox. A model resolution of 10 m \times 10 m grid size consisting of 2.64×10^9 [$67,250$ (j) \times $39,375$ (k)] grid cells was created as shown in Fig. 3. The values at the end rows and columns of the model domain were closed by providing a land value of 60. This ensured that any grid having elevation more than 60 m in the model domain was not utilised in the simulation. The resistance from various land use classes to the flood water flow were compiled using the Manning's N values as represented in Table 1. A smaller time step of 1 s was chosen to run the model, as it is well known that lower time step enhances model stability. The courant number, which is given by $c_r = U_{\max} \frac{\Delta t}{\Delta x}$, where, U_{\max} is the wave celerity, Δt is the time step and Δx is the grid size was fixed at a value of 0.7. The flooding depth and drying depth were fixed at 0.2 and 0.1 m respectively.

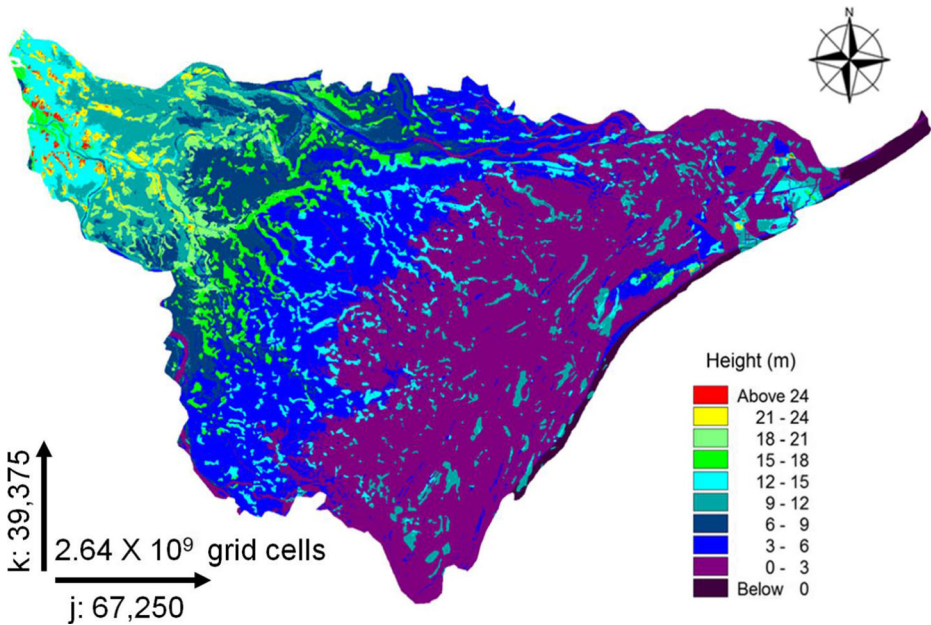


Fig. 3 DEM used as input to the MIKE 21 model

Table 1 Description of different land use classes with Manning's resistance number

Land Use class	Mannings n (s/m ^{1/3})	Manning's Resistance number ($N = 1/n$)
Agricultural land		
Agricultural land: aquaculture	0.037	27.03
Agricultural land: crop land kharif	0.12	8.33
Agricultural land: crop land rabi	0.11	9.09
Agricultural land: crop land: two crop area	0.1	10.00
Agricultural land: crop land: zaid crop	0.037	27.03
Agricultural land: fallow land: current fallow	0.025	40.00
Crop Land: Summer crop	0.048	20.83
Agricultural land: plantation	0.07	14.29
Built up		
Built up: rural	0.05	20.00
Built up: Urban	0.1	10.00
Built up: Mining	0.08	12.50
Forest		
Forest: Deciduous: dense	0.1	10.00
Forest: Deciduous: open	0.15	6.67
Forest: forest plantation	0.07	14.29
Forest: Littoral Mangrove	0.1	10.00
Forest: Scrub Forest	0.05	20.00
Tree		
Tree clade area	0.06	16.67
Wastelands		
Wastelands: sandy area: coastal	0.025	40.00
Waterbodies		
Waterbodies: river stream	0.02	50.00
Wetlands		
Wetlands: coastal natural	0.06	16.67
Wetlands: Inland natural	0.05	20.00

4.4.2 Rainfall Data

In this study, the performance of the regionalized design rainfall was compared with rainfall obtained from various SIMs through flood inundation analysis. Some of the commonly used deterministic and geostatistical methods: Inverse Distance Weighting (IDW), nearest neighbor (NN), kriging (KR) and spline (SP) interpolation (available within the spatial analyst toolbox of Arc GIS 10.1) were considered. The at-site design rainfall for 3 stations of 24 h duration and various return periods were interpolated to form a single representative time series (*.dfs0 MIKE format). The 24 h rainfall time series of 50, 100 and 200-year derived from regionalisation and interpolation were used as the rainfall inputs into the MIKE 21 model.

4.4.3 Flood Inundation Modelling

The flood inundation was quantified based on the flood depth, which were decided based on the experimental results of studies on instability criteria under flooding as reported earlier by Jonkman and Penning-Rowsell (2008). Generally, flood depths upto 0.6 m, is identified as hazardous to children although it is in the moderate self-help range for adults, however the depths beyond 1.5 m can be treated as life threatening. Likewise, 4 different classes of flood inundation representing different degrees of hazard based on flood depth (h) from low to very high were quantified in the flood simulation outputs (Table 2).

5 Results and Discussion

Figure 4 shows the results of the graphical method of POT analysis, in which the modified scale (α') and shape (κ) parameters of GPD have been plotted against the location parameter (threshold), μ . Accordingly, the optimal thresholds for the three stations were found to be 29 mm.

To generate marginal duration frequency, a set of parametric and non-parametric distributions were tested. Among these, Gaussian, triangle and Epanechnikov kernels from the nonparametric family of kernels, and Gamma, log-logistic, and lognormal models from the parametric family showed the best fit based on the RMSE values, as shown in Fig. 5.

The three sites exhibit a similar temporal pattern which indicates the climatological homogeneity of the region. This result also supports the fact that Paradeep, Bhubaneswar and Puri fall under homogeneous monsoon regions, as per the classification by IITM (2005). Moreover, there are other studies which consider the three sites under a homogeneous region (Shashikanth et al. 2014; Subash and Sikka 2014; Patwardhan et al. 2016). To ensure the approach was generic, four distributions (three best fitting among non-parametric methods and one best fitting among parametric models) were considered to obtain the DDF curves.

Table 2 Description of hazard indices based on flood depth (h)

Hazard category	Depth of flooding (m)
Low	0 to 0.6
Medium	0.6 to 1.25
High	1.25 to 3.5
Very high	>3.5

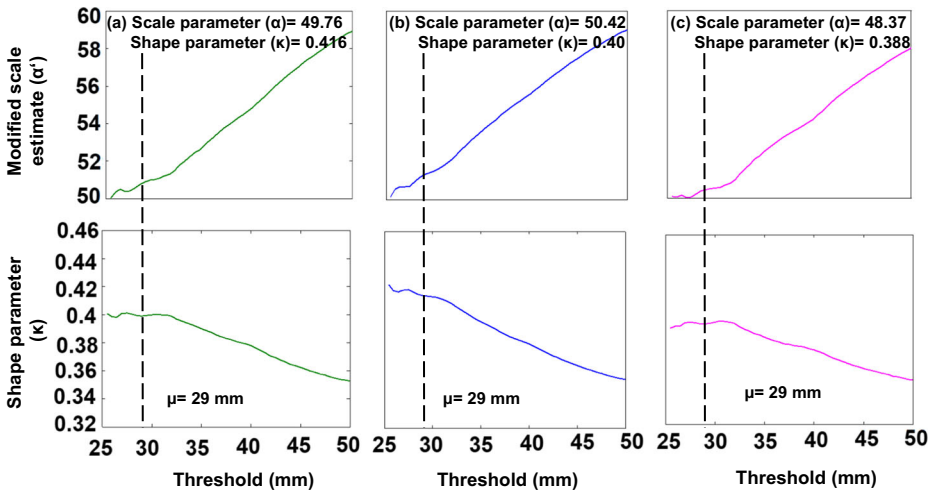


Fig. 4 Optimal thresholds of GPD for (a) Paradeep (b) Bhubaneswar (c) Puri

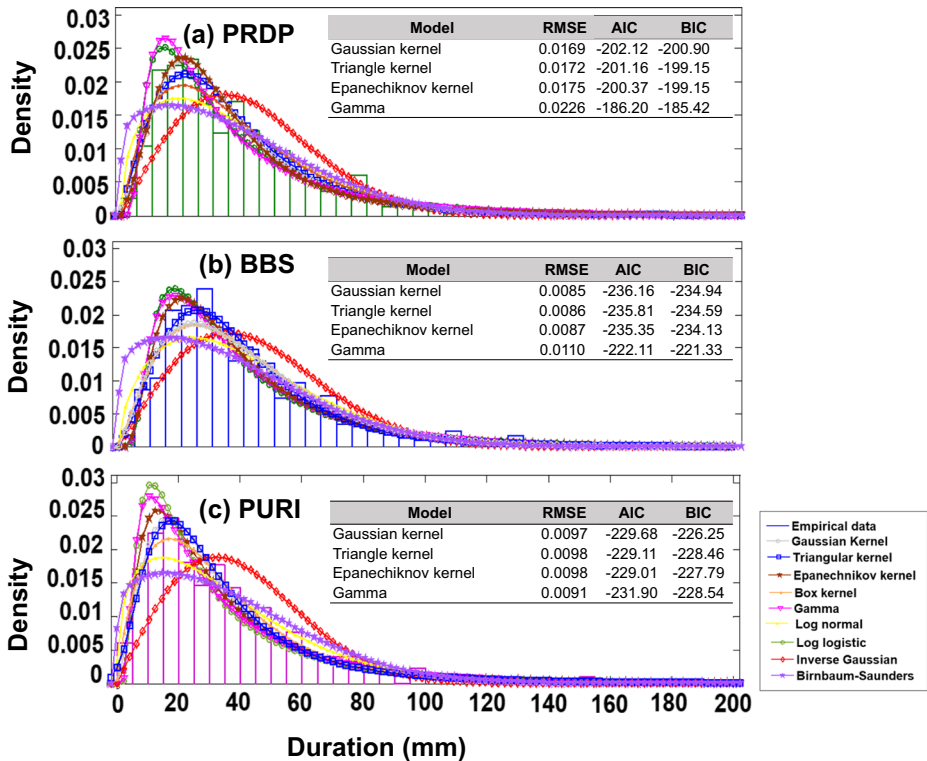


Fig. 5 Marginal duration-frequency curves for (a) Paradeep (PRDP) (b) Bhubaneswar (BBS) and (c) Puri (PURI)

5.1 At-Site Design Rainfall

Figure 6 shows the bivariate joint probability distributions for all the best fit models. It can be noticed that all models resembled to their corresponding empirical models.

The DDF curves obtained from the 4 best fit models for return periods of 5, 10, 25, 50, 100, 200 and 300-year return periods for durations 1–72 h are represented in Fig. 7. The extreme events for individual stations characterised by 1-day rainfall depth > 244.5 mm (as mentioned by IMD in <http://imd.gov.in/section/nhac/termglossary.pdf>), are represented as separate scatter plots inside the DDF curves. In all the DDF curves, a smooth representation of the curves from 5 to 300-year return periods proves the numerical consistency of the models for extrapolation to longer durations. A unique observation showed that Paradeep station recorded a higher amount of rainfall depth (for all periods in all the best fit models), followed by Bhubaneswar and Puri. This observation is evident in all the copula models as well.

Following the generation of DDF curves, the next step was performing design rainfall temporal pattern analysis for selective durations of 6, 12, 18, and 24 h. From the analysis of HDS and BC, it was found that only few of the events were unimodal at a 95 percentile confidence interval. It was observed that the skew values ranged from -5 to +5. Among the temporal patterns, most of them showed a higher kurtosis (leptokurtic), which implies severe flood-causing potential. Based on these statistical measures, the unique temporal pattern having the least bimodality, and the highest skew and kurtosis was selected as the unique design temporal pattern for the chosen durations of 6, 12, 18 and 24-h respectively. By combining the design rainfall depths obtained from the DDF curves with the unique design rainfall temporal pattern for each specified duration, the at-site design rainfall time series were generated. Thus, a set of design rainfall depths for three stations were estimated corresponding to return periods of

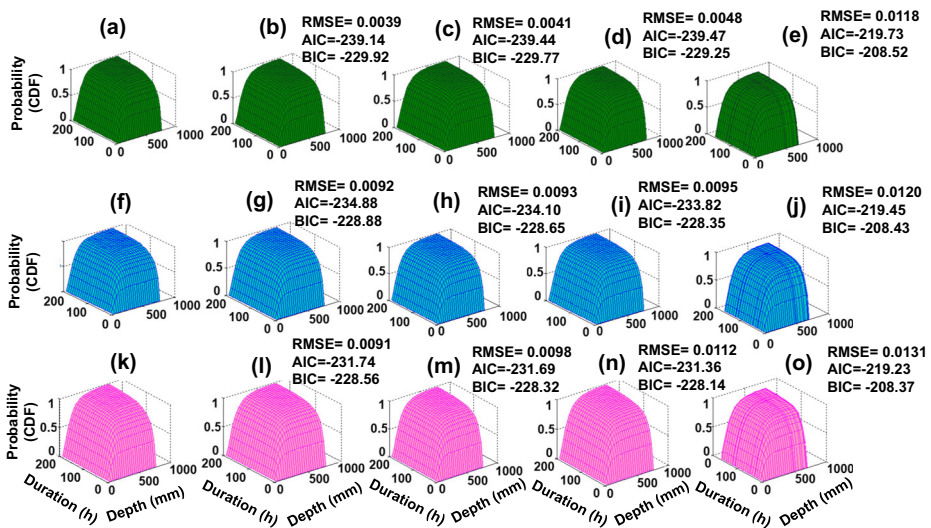


Fig. 6 Bivariate joint probability distribution of the best-fit models for (i) Paradeep (row 1: **b, c, d** and **e**); (ii) Bhubaneswar (row 2: **g, h, i** and **j**) and (iii) Puri (row 3: **l, m, n** and **o**), along with their empirical models (column 1: **a, f**, and **k**) respectively. The columns II, III, IV and V represent Gaussian, triangle and Epanechnikov kernels, and Gamma distribution respectively

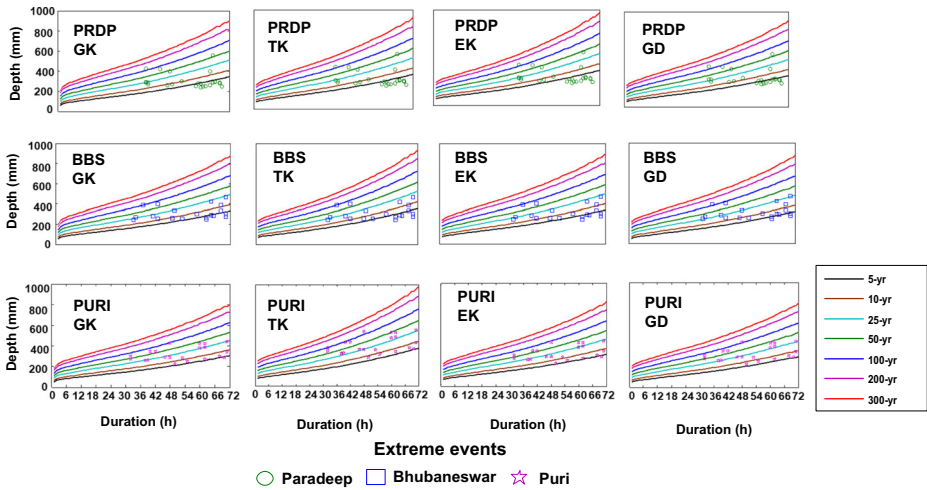


Fig. 7 At-site depth-duration-frequency (DDF) curves derived from the best-fit models: Gaussian kernel (GK), triangle kernel (TK), Epanechnikov kernel (EK) and Gamma distribution (GD) for Paradeep, Bhubaneswar and Puri for various return periods (scatter plot shows the extreme rainfall events occurred at each station)

100, 200 and 300-year for the selective durations, as shown in Table 3. Figure 8 shows a representative set of at-site design rainfall time series generated from the Gaussian kernel based copula for 24 h duration with return periods of 100, 200 and 300-year.

A comparison of the at-site design rainfall of the 3 stations for various durations and return periods as obtained from the four models is shown in Fig. 9. The highest at-site design rainfall depth is observed for Paradeep, followed by Bhubaneswar and Puri. Paradeep station, located at the coast line near the Bay of Bengal, consistently showed the highest rainfall depth among all three stations. This station has consistently received higher rainfall due to monsoons and depressions arising in the Bay of Bengal. Additionally, the copula with the Gaussian kernel exhibited a higher rainfall depth compared to the three other kernels and the Gamma distribution. This observation remains consistent for all scenarios with different return periods and durations.

Table 3 Estimated at-site design rainfall depths for a representative set using the four best-fitting copula-based models

Representative models	Return period (years)	Design rainfall depth (mm)								
		Paradeep			Bhubaneswar			Puri		
		6 h	12 h	24 h	6 h	12 h	24 h	6 h	12 h	24 h
Gaussian kernel	100	220.6	258.68	328.51	213.52	250.33	317.91	195.73	229.47	299.42
	200	264.3	308.66	389.97	255.76	298.7	377.39	234.44	273.81	345.94
	300	293.2	340.89	430.69	283.69	329.9	416.79	260.05	302.41	382.06
Triangle kernel	100	220.6	254.59	323.59	213.52	246.37	313.15	192.94	225.31	300.96
	200	264.3	303.89	383.15	255.76	294.08	370.78	233.13	275.07	348.99
	300	293.2	336.31	423.29	283.69	325.46	409.63	256.41	301.22	385.36
Epanechnikov kernel	100	227.1	264.73	334.53	219.73	256.19	323.73	198.42	225.9	301.72
	200	271.7	315.86	395.7	262.92	305.68	382.93	238.01	280.2	351.03
	300	301.3	348.63	436.5	291.54	337.38	422.42	267.24	309.27	387.22
Gamma distribution	100	212.00	246.00	278.00	205.77	231.88	262.00	190.67	212.80	238.30
	200	232.20	295.45	320.65	226.58	275.65	312.55	212.70	258.54	284.72
	300	315.44	375.80	412.86	300.47	360.88	397.55	285.81	335.42	368.55

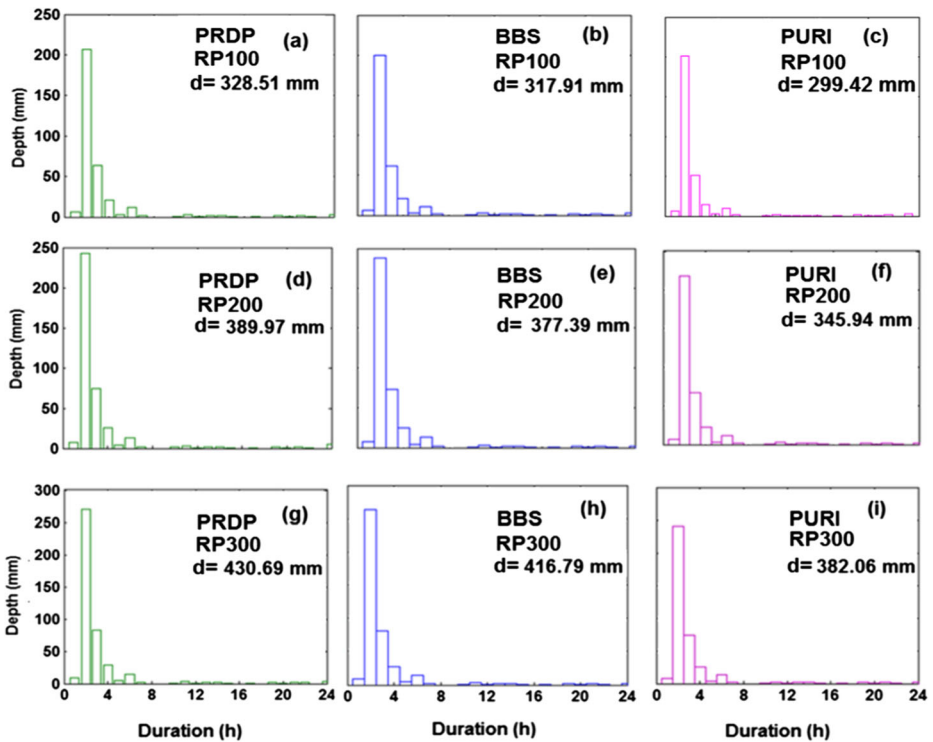


Fig. 8 At-site 24-h design rainfall time series generated using Gaussian kernel (GK) based copula for three stations corresponding to return periods of 100, 200 and 300-year

5.2 Regionalized Design Rainfall

The regional copula parameter for Jagatsinghpur District was obtained by applying weights to each station based on the record length. Figure 10 shows the regional bivariate distribution derived for Jagatsinghpur District using both optimization approaches. It was found that CAO method is more reliable and accurate than the CO method based on the various goodness-of-fit measures used in the study. The regionalized DDF curves for Jagatsinghpur District are shown in Fig. 11.

Both approaches show a similar trend and smoothness of fit. It was noticed that CO yielded higher rainfall depths for the lower tail (80 to 250 mm) than the CAO (10 to 200 mm) for all return periods. In the at-site DDF curves of Paradeep, Bhubaneswar and Puri (Fig. 6), the rainfall depth for the lower tail exhibited a similar range to that of CAO. Design rainfall depths obtained from the regionalized DDF curves were combined with the design rainfall temporal pattern to generate the regionalized design rainfall time series. Figure 12 shows the regionalized 24 h design rainfall time series corresponding to return periods of 100, 200, and 300-year, obtained using the best fit Gaussian kernel for Jagatsinghpur District.

5.3 Flood Inundation Mapping Using MIKE 21 Model

A comparison of the distribution of flood depth statistics corresponding to return periods of 50, 100 and 200-year, from both spatial interpolation and regionalization approach, is presented in Fig. 13. As clearly observed, all of the interpolation techniques performed in a similar manner.

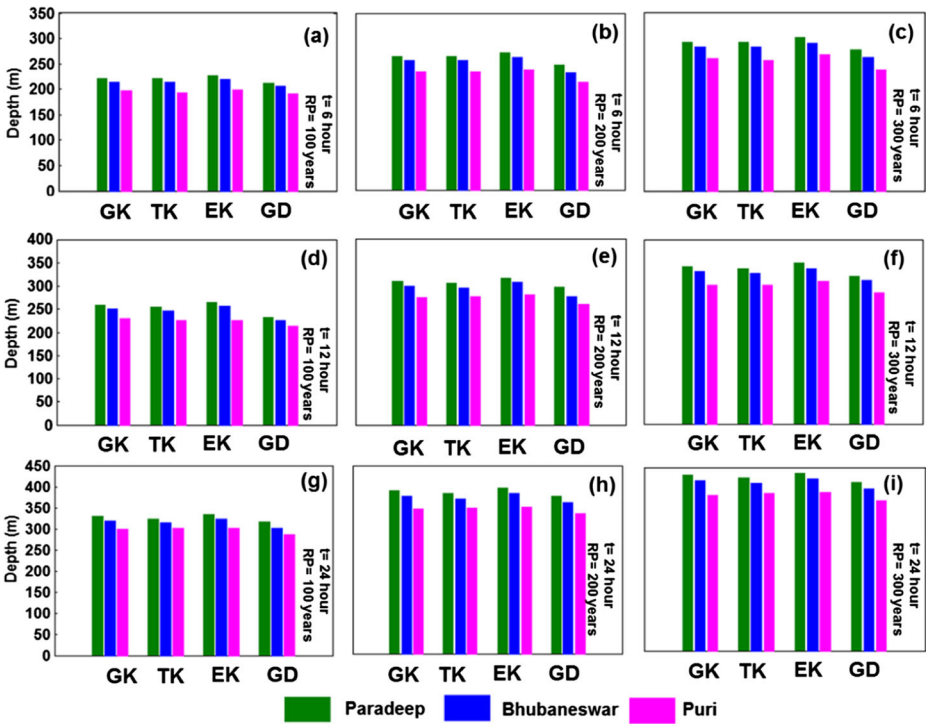


Fig. 9 Design rainfall time series derived using a copula-based Gaussian kernel (GK), triangle kernel (TK), Epanechnikov kernel (EK) and Gamma distribution (GD) for Paradeep, Bhubaneswar and Puri

Also, simulated flood depth was directly proportional to the rainfall depth applied as input. For example, SP showed a higher flood depth (>3.5 m, 6.81%) for a return period of 200-year, which was about a fourfold increase compared to that a return period of 50-year scenario. However, a comparison of the percentage flood depth under each class for different return periods indicated a significant difference among these methods. Spatial variations, such as

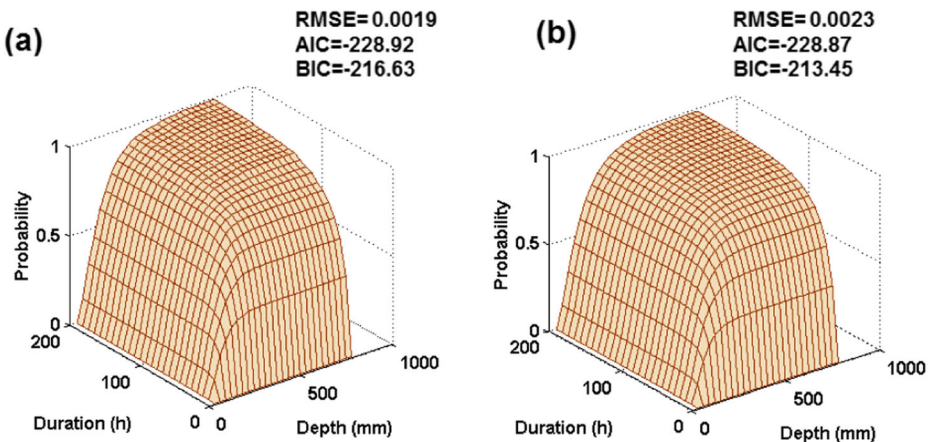


Fig. 10 Regional bivariate distribution derived for Jagatsinghpur District using (a) CAO and (b) CO

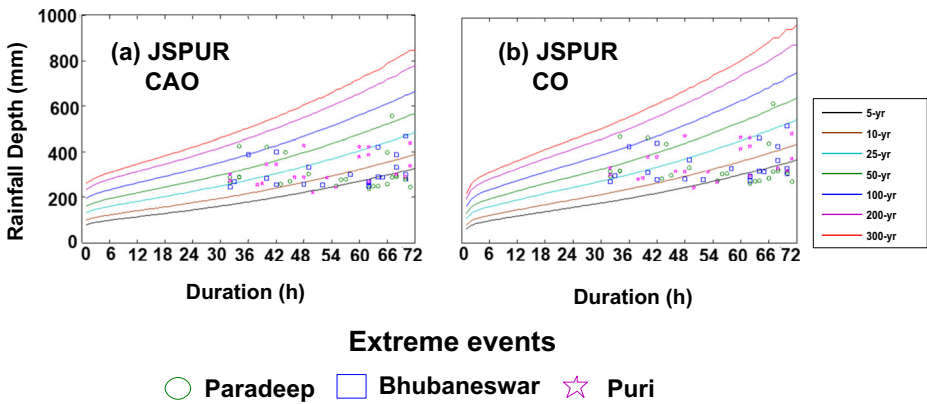


Fig. 11 Regionalized DDF curves for Jagatsinghpur district (JSPUR) using (a) CAO and (b) CO

different soil types across a region, physical barriers, and landscape changes may also affect the accuracy of interpolation (Jensen et al. 2006; Little et al. 1997; Zhu and Lin 2010).

A comparison of the inundation statistics of SIMs with the regionalized design rainfall showed that the SP and KR interpolation methods exhibited similar pattern. Several studies in the past concluded that geostatistical methods were more suited to rainfall analysis than conventional techniques (Tabios and Salas 1985; Phillips et al. 1992). As noted by Isaaks and Srivastava (1989), sparse data density affects the performance of IDW and NN techniques, which was evident in this study. However, KR and SP showed better accuracy as the former uses the best linear unbiased estimate (BLUE), while the latter retains small-scale features, leading to better accuracy. Figure 14 shows the MIKE 21 model produced flood inundation maps for the Jagatsinghpur District for the selected return periods considering the regionalized design rainfall.

There is a direct relationship between rainfall depth and flood inundation, as evident from the proportion of the areas affected by high (>3.5 m) and medium (0.6–1.5 m) flood depths. In particular, the deltaic region near the coastline can be observed to be the worst affected due to flooding. Major flood events occurred in this region during 1969, 1980, 1982, 1994, 1999, 2001, 2003, 2006, 2007, 2008, 2011 and 2014 (District Emergency Operation Center 2016). Some of the chronic flooding spots identified by the local authorities in the region are namely, Nuagaon, Kujanga and Ersama blocks. Similarly, it was found that the simulated flood maps also reflected higher flood depths in these localities. The study also finds that, the flood plains along the banks of River Mahanadi and Devi exhibit higher flood depths.

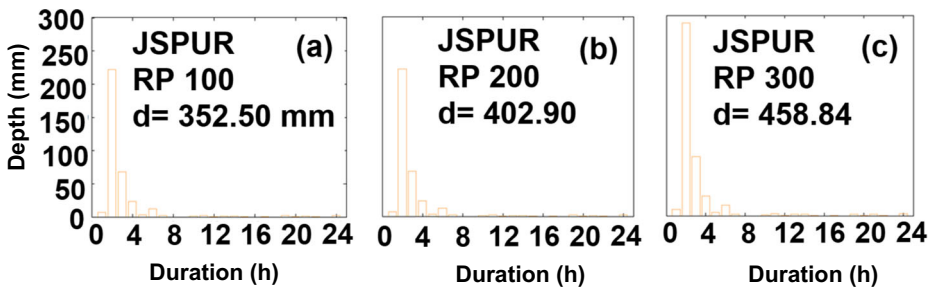


Fig. 12 Regionalized 24 h design rainfall time series of Jagatsinghpur District corresponding to return periods of: a 100-year b 200-year and c 300-year

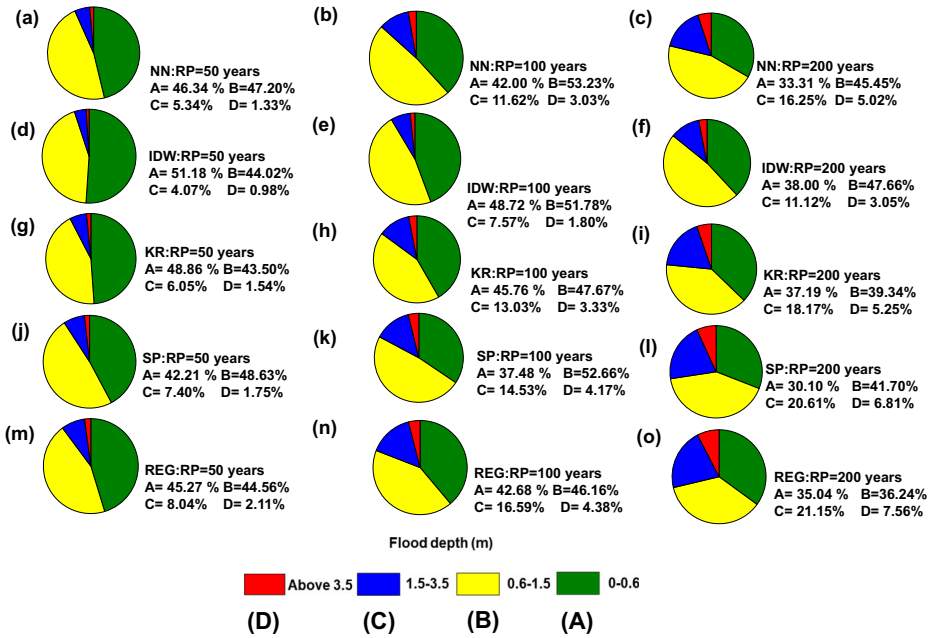


Fig. 13 Flood depth distribution for Jagatsinghpur District using interpolation techniques: NN, IDW, KR, SP, and a regionalization method (REG) for return periods of 50, 100 and 200-year

6 Concluding Remarks

This study focused on the issue of the lack of rainfall data and how to address this situation during extreme hydro-climatic events such as floods. For such situations, regionalization of design rainfall, which provides rainfall for a desired location for different durations and return periods, forms an integral component. A comprehensive framework to perform regionalized design rainfall analysis was proposed here. To perform this analysis, a region with sparse raingauge network was selected in the severely flood-affected regions of the lower Mahanadi River basin (India). Here, design rainfall time series is generated using multivariate frequency and design temporal pattern analyses. The two important aspects of multivariate rainfall frequency analysis, i.e., marginal distributions of depth and duration, were analysed. This study considered a flexible copula based approach, wherein both parametric and non-parametric families of distributions were included. A unique pattern among a set of observed rainfall temporal patterns was chosen for each design duration, based on various statistical measures namely skew, kurtosis and multimodality measure. A new method of regionalization of the design rainfall through non-linear optimization based approach was proposed for generation of design hyetographs over the region. The next part of the study was dedicated to demonstrating the efficacy of the regionalized design rainfall through flood modeling. For this purpose, the MIKE 21 model was set up considering a grid size of 10 m for an area of 1759 km². A comparison of the flood inundation statistics obtained with spatially interpolated rainfall and regionalized design rainfall was conducted. We concluded that the interpolation by geostatistical methods (spline and kriging) matched closely with the regionalized rainfall-derived flood maps. A set of flood inundation maps using regionalized design rainfall was also

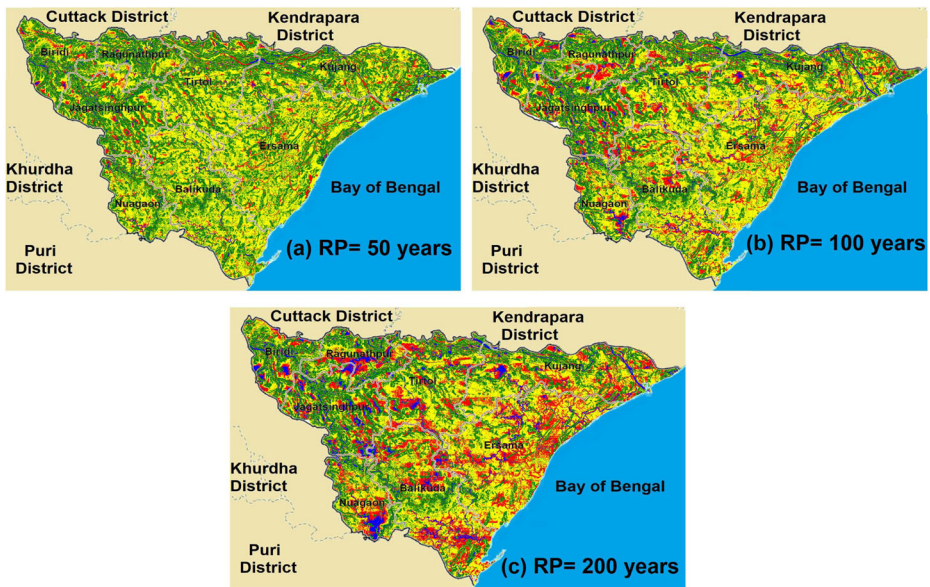


Fig. 14 Comparison of flood inundation depth obtained using regionalized design rainfall for return periods of: (a) 50-yr (b) 100-yr and (c) 200-yr using MIKE 21 model

derived for a set of return periods. It can be inferred from the foregoing analysis that the proposed framework can provide at-site and regionalized design rainfall time series for regions with sparse raingauge network. The flood model developed in the study is simple, yet detailed enough to capture the physical feature in larger catchments ($> 1000 \text{ km}^2$). Such studies can help in estimating regionalized design rainfall for ungagged or partially gaged catchments that can be extended to simulate flood events to support efficient flood risk management.

It is important to mention that the proposed framework can help in better estimation of rainfall data, especially for ungauged/partially gauged catchments in developing and underdeveloped countries. It is a known fact there is an increase in flood risk across the globe, mainly due to climate change and urbanisation, thus proving that the lack of rainfall data makes flood management a daunting task. In the future, additional effort may be made to capture rainfall information with the assumption of non-stationarity, for flood prone catchments through the inclusion of statistical models. Hence, any flood risk management effort should start with collection and analysis of reliable rainfall data, followed by various flood modeling options. This will ensure efficient and economical mitigation and adaptation options, rather than dealing with flood damages. In this study, we showed that the framework can be used for extreme events arising due to floods that can support in improved flood management. In future, the concept of regionalization can be incorporated into flood simulation tools along with other existing set of interpolation techniques.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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