Regional Flood Frequency Analysis

Subjects: Engineering, Environmental
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Regional flood frequency analysis (RFFA) consists of two principal steps: identification of homogeneous regions and development of regional flood estimation equations.

floods regional floods regional frequency analysis regionalization

1. Introduction

Flooding is a natural disaster that often causes extensive economic damage and loss of life [1]. Flooding is becoming more intense and frequent due to climate change [2]. To reduce flood damage at a given location, a flood risk assessment is often carried out. It involves estimation of a design flood, which is defined as a flood discharge associated with an annual exceedance probability. Design floods are used in the design of hydraulic structures and many other flood management tasks. At a gauged location, at-site flood frequency analysis is carried out to estimate design floods. However, many locations where a design flood estimate is needed are ungauged or have little recorded streamflow data. For these ungauged sites, a regional flood frequency analysis (RFFA) is adopted to estimate design floods [3][4][5]. RFFA may focus on peak, volume, frequency, depth and duration of flood events [6][7].

RFFA consists of two principal steps: identification of homogeneous regions and development of regional flood estimation equations [8][9]. Homogeneous regions can be formed based on a geographical boundary where all the sites in an assumed region form a fixed region [10][11][12][13]. Alternatively, a region-of-influence (ROI) approach can be adopted where each of the selected sites forms its own region [14][15]. Regional homogeneity is a vital assumption of RFFA, which may affect relative accuracy of flood quantile estimates [16][17][18][19]. To assess the degree of homogeneity in a proposed region, various statistical tests are proposed [20][21][22][23]. Regions can be formed on a geographical space or in a catchment attribute space. Various multivariate statistical techniques such as principal component analysis [24][25], cluster analysis [25][26][27] and canonical correlation analysis [28][29][30] are used to derive homogeneous regions. More recently, Han et al. [9] applied network theory in identification of homogeneous regions in RFFA.

2. Homogeneity Testing in RFFA

Dalrymple [31] proposed a homogeneity test based on the ratio of 10-year flood to mean annual flood. This test was widely used in the context of the index flood method. Wiltshire [20] mentioned that this test is not very powerful as in most of the applications the proposed region appeared to be homogeneous when the test was applied. Fill and

Stedinger [17] stated that the Dalrymple [31] test should not be applied in practice as L-moments-based tests [21] are more powerful. Wiltshire [20] proposed a CV-based test, which is based on the coefficient of variation (CV) in annual maximum (AM) flood series of the gauged sites in a proposed region. The power of this test increases with the number of sites and streamflow record length of sites in a region, which is indeed true for any homogeneity test. Fill and Stedinger [17] stated that this CV-based test is not preferable to an L-moments-based test. Lu and Stedinger [32] proposed a homogeneity test, which depends on the variability of at-site normalized flood quantiles estimated by fitting a generalized extreme value (GEV) distribution to AM flood data of each of the sites in a proposed region.

The L-moments-based test proposed by Hosking and Wallis [21] has become a standard in RFFA as noted by Ouarda [3]. However, this test does not work well for highly skewed data as reported by Viglione et al. [23]. The application of Hosking and Wallis [21] test could not deliver a homogeneous region for Australia [33][34]. Chebana and Ouarda [22] extended the Hosking and Wallis [21] test to a multivariate case which can consider the correlations among the variables. To apply this test to the bivariate case, Chebana and Ouarda [22] considered peaks and volumes of flood events with the Gumbel logistic model and Gumbel marginal distributions. It was noted that for regions with a smaller number of sites and short record length, the multivariate test does not perform well, which is the case for any homogeneity test. Although the Hosking and Wallis test [21] has good power, it depends on the subjective choice of a distribution for the data and a poorly justified rejection threshold [18]. To overcome some of these limitations, Masselot et al. [18] integrated a nonparametric method with the L-moments-based homogeneity test. Further research is needed in this area as the proposed homogeneous regions lack of physical significance; there is also a paucity of guidance on how these tests should be conducted under nonstationary conditions.

3. Development of Regional Estimation Equations

Dalrymple [31] proposed the index flood method in 1960. In this method, AM flood data at each site in the region are normalized by dividing the at-site mean (index flood). These normalized data are then used to develop a regional growth factor. A regional prediction equation is developed for the index flood as a function of climatic and physical characteristics. The index flood method was once favoured by the US Geological Survey, but it was discarded since it was found that the CVs of AM flood data vary with catchment area and other catchment characteristics [35]. However, since the introduction of the L-moments-based index flood method by Hosking and Wallis [21], the index flood method has become popular in RFFA. As noted by Kjeldsen and Jones [36], the index flood method is widely used in RFFA in the UK. In Australia, the index flood method is not adopted as homogeneous regions cannot be identified in the country [37].

The United States Geological Survey (USGS) proposed the quantile regression technique (QRT) where a flood peak of T-year return period is estimated from selected catchment characteristics [38][39][40][41]. Ordinary least squares or generalized least squares regression techniques are generally used to estimate the coefficients of the regression equations [42][43][44][45][46]. The US Interagency Working Group on Flood Frequency Estimation at Ungauged Sites found that regression-based methods in RFFA are the most consistent [47]. The parameter regression technique (PRT) develops regression equations of the parameters of a probability distribution [44][48]. In a comparative study in Australia, Haddad and Rahman [44] found that QRT and PRT provide very similar performance in flood quantile estimation; however, PRT is more consistent. Based on their findings, the Australian Rainfall and Runoff (national guideline) has recommended PRT for general use in Australia except in the arid regions [37][49].

There are other approaches to develop estimation equations in RFFA. For example, Chebana et al. [50] applied a generalized additive model to Quebec province in Canada and noted that this allows incorporating non-linear effects of explanatory variables in RFFA. Similarly, Rahman et al. [51] and Noor et al. [52] applied a generalized additive model to an Australian data set and reported positive outcomes. Dawson et al. [53] applied artificial neural networks (ANN) to 850 catchments in the UK to develop an RFFA model and noted that ANN provides improved flood estimates when compared to multiple regression models. Shu and Ouarda [54] applied adaptive neuro-fuzzy inference systems (ANFIS) in RFFA in Quebec province, Canada based on data from 151 catchments for design flood estimation at ungauged sites. They noted that ANFIS has much better generalization capability than the non-linear regression approach. Aziz et al. [55] applied ANN to 452 Australian catchments and found that an ANN-based RFFA model outperforms the QRT. Kumar et al. [56] applied ANN and a fuzzy inference system to 17 Indian catchments and noted that ANN outperforms the L-moments-based index flood approach. Further research is needed in these types of artificial intelligence (AI)-based RFFA techniques as there is a lack of user-friendly tools to apply AI-based techniques in practice.

4. Impacts of Climate Change on RFFA

Leclerc and Ouarda [57] presented a nonstationary RFFA using data from southeastern Canada and the northeastern United States. They noted that not considering trends can lead to serious under- or overestimation of flood quantile estimates. Kalai et al. [47] compared nonstationary RFFA methods for real-world and synthetically generated data. Han et al. [58] presented a nonstationary RFFA technique using 105 Australian catchments which can capture the differing behaviour of flood quantiles in frequent and rare ranges under a warming climate. Guo et al. [59] developed a nonstationary Bayesian RFFA method for Dongting Lake Basin in China. They noted that the nonstationary model reduces the uncertainty in flood quantile estimates. Further research is needed in this area as there is a dearth of guidance on how to consider the effects of non-stationarity in regional flood quantile estimation: for example, Australian Rainfall and Runoff does not include any recommendation on this.

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