Journal of Environmental Management 115 (2013) 98–105

Contents lists available at SciVerse ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Consequences to flood management of using different probability distributions to estimate extreme rainfall

Luciana S. Esteves*

Cities Institute, London Metropolitan Business School, London Metropolitan University, Stapleton House, 277-281 Holloway Road, London N7 8HN, UK

ARTICLE INFO

Article history:
Received 26 September 2011
Received in revised form
19 October 2012
Accepted 5 November 2012
Available online 12 December 2012

Keywords:
Extreme rainfall
Probability distribution
Return period
Flood defence
Risk management

ABSTRACT

The design of flood defences, such as pumping stations, takes into consideration the predicted return periods of extreme precipitation depths. Most commonly these are estimated by fitting the Generalised Extreme Value (GEV) or the Generalised Pareto (GP) probability distributions to the annual maxima series or to the partial duration series. In this paper, annual maxima series of precipitation depths obtained from daily rainfall data measured at three selected stations in southeast UK are analysed using a range of probability distributions. These analyses demonstrate that GEV or GP distributions do not always provide the best fit to the data, and that extreme rainfall estimates for long return periods (e.g. 1 in 100 years) can differ by more than 40% depending on the distribution model used. Since a large number of properties in the UK and elsewhere currently benefit from flood defences designed using the GEV or GP probability distributions, the results from this study question whether the level of protection they offer are appropriate in locations where data demonstrate clearly that alternative probability distributions may have a better fit to the local rainfall data. This work: (a) raises awareness of the limitations of common practices in extreme rainfall analysis; (b) suggests a simple way forward to incorporate uncertainties that is easily applicable to local rainfall data worldwide; and thus (c) contributes to improve flood risk management.

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1. Introduction

Flooding is the most frequent and damaging natural hazard worldwide, which affected 178 million people and caused losses that exceeded US$ 40 billion (about £25.32 billion) in 2010 (Jha et al., 2012). The mortality risk associated with major floods and storms has declined globally in the last two decades; however, the exposure of people and economic assets to natural hazards is rapidly increasing, especially in developed countries (UNISDR, 2011). In the UK, for example, about 2.05 million properties were estimated to be at risk from flooding in 2004 (Evans et al., 2004). More recently the Environment Agency (EA, 2009) estimated that 5.2 million properties were at risk from flooding in England alone. Of these, 3.8 million properties are at risk from flooding from surface runoff (EA, 2011). Despite differences in the methodology used in the two assessments, it is clear that flood risk in England (and worldwide) is becoming a much larger threat than previously anticipated. Climate change and poor urban planning are likely to increase flood risk in the future; the first by affecting local rainfall patterns and enhancing storminess; and the latter for placing people and critical infrastructure in flood-prone areas. Despite the implementation of policies regulating occupation of flood risk areas, planning systems often favour development needs above the need to reduce flood risk (e.g. White and Howe, 2002; Wheater and Evans, 2009; Jha et al., 2012). In the last two years, extreme rainfall caused devastating floods in developing and developed countries across all continents (e.g. Australia, Pakistan, Philippines, Thailand, South Africa, Brazil, France, the UK and the USA).

Uncertainties are inherent in the prediction of the frequency and extent of all types of flood. However, flooding from some sources can be better predicted than others. Coastal flooding is a serious threat at many locations, and a network of flood defences is usually in place to provide protection from water levels of specific return periods. The cyclic nature of tides facilitates the prediction of extreme water levels, which occur when storm surges coincide with high spring tides. Despite some uncertainties related to the prediction of storm surges, extreme water levels can be modelled with reasonable results (e.g. Pugh, 1996; Flather et al., 1998; Verlaan et al., 2005; Brown et al., 2010). Additional uncertainties arise when the impacts of climate change are included in the predictions of

* Current address: School of Applied Sciences, Bournemouth University. Tel.: +44 (0) 1202 962446.
E-mail address: lesteves@bournemouth.ac.uk.

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http://dx.doi.org/10.1016/j.jenvman.2012.11.013

Table 1
Summary of the Met Office MIDAS datasets of daily rainfall used in this study.

Station name (code)	Coordinates[a] (m)	Period	n	Observations
Southsea (src_id 861)	463,700; 99,100 (Hampshire)	01/01/1916 to 30/06/1997	29,299 days 966 months 81 years	Elevation: 2 m Drainage: coastal
Southend (src_id 492)	587,600; 185,200;	24/01/1961 to 01/01/1971	12,721 days	Elevation: 27 m
Southend Southchurch Park (src_id 496)	589,986; 184,998 (Essex)	01/01/1971 to 01/10/2010 (major data gaps 01/1977–02/1986, 09/2005–08/2008)	419 months 39 years	Elevation: 4 m Drainage: coastal
Deptford P Sta (src_id 6704)	537,600; 177,000 (Greater London)	24/01/1961 to 31/12/2010 (data gap 02/1999–02/2000)	11,969 days 580 months 49 years	Elevation: 5 m Drainage: Ravensbourne

[a] Coordinates are provided in the British National Grid system.

return periods of extreme sea levels (e.g. Lowe and Gregory, 2005; Wang et al., 2008).

Flooding caused by other processes is more difficult to predict (and mitigate) due to the number of influencing variables and their complex relationships. For example, extreme rainfall can lead to flooding from overwhelmed rivers and sewers. This is very difficult to predict (Wheater and Evans, 2009), especially at meaningful time-scales for adequate response. Further complexity is added by urbanisation, particularly by the increase in impervious surfaces and obsolete combined sewer/stormwater drain systems (Thurston et al., 2010). Many locations have systems of pumps and water storage to prevent floods from surface runoff and/or overwhelmed drains (Wheater and Evans, 2009). However, the efficiency of these systems depends on their (flow/volume) capacity, which is designed to deal with rainfall of specific return period (e.g. 1 in 100 years). To provide the desired level of protection, it is imperative that the precipitation depths used to design flood defences are estimated taking into consideration uncertainties related to the method and to the potential changes in rainfall patterns and trends caused by climate change.

At many locations worldwide, flood defences at the coast and in urban areas are in urgent need of upgrading to cope with the effects of urban development and predicted impacts of climate change (e.g. higher sea levels and more frequent and intense extreme rainfall). Return periods of extreme rainfall are usually estimated by fitting a probability distribution (PD) to annual maxima series (i.e. datasets comprised by the highest rainfall depth in each year) or partial duration series (i.e. datasets formed by rainfall depths exceeding a selected threshold) (e.g. Cunnane, 1973; Rosbjerg, 1977; Davidson and Smith, 1990; Adamowski, 2000). The most common PD used in the analysis of extreme rainfall are the Generalised Extreme Value (GEV) or the Generalised Pareto (e.g. Davidson and Smith, 1990; Coles, 2001; Bodini and Cossu, 2010; Toretti et al., 2010). However, other PDs might show a better fit to some datasets and the difference in the precipitation depths for the resulting return periods can be significant. Adequate selection of the PD is one of the "*more important issues in flood frequency analysis*" (Adamowski, 2000, p. 220).

This article draws attention to the limitations of the common approach used in extreme rainfall analyses and discusses the potential consequences for the design of flood defences and the level of protection they offer. The influence of using different PDs in estimating extreme rainfall is demonstrated using, as examples, three selected locations in southeast England. A simple way forward to incorporate uncertainties in the estimates of rainfall depths of return periods relevant to flood risk management is then suggested. The findings of this study will assist local authorities responsible for flood management in improving decision-making concerning mitigation of flood risk.

2. Methods

Time-series of daily rainfall measurements were obtained from the Met Office MIDAS Land Surface Stations.[1] The data analysis was conducted as part of the EU-funded project *Solutions for Environmental Contrasts in Coastal Areas* (SECOA). The stations analysed here were selected to assess the magnitude and frequency of extreme rainfall in Portsmouth and the Thames Gateway, the project's study areas in the UK. For the area of Portsmouth, the Southsea station was selected due to the length of the daily rainfall record. Two locations were selected in the Thames Gateway: Southend in the eastern sector of the study area and Deptford in the western sector. Table 1 shows the characteristics of the datasets used here in the analysis of extreme rainfall. Data from two closely located stations were used to extend the time-series at Southend.

Annual maxima series (AMS) for 1-day, 2-day and 3-day durations were produced from the daily rainfall time-series at the three locations. Maxima series for winter (WMS) and summer (SMS) precipitation were also produced for 1-day, 2-day and 3-day durations. The WMS were based on records from December, January and February months and the SMS were based on data recorded in June, July and August. The precipitation depths for selected return periods were estimated by fitting PDs to the AMS, WMS and SMS datasets for the three durations. Six PDs were tested: Generalised Extreme Value (GEV), lognormal (LN), Gumbell Maximum (EV1), Log-Pearson III (LP3), Weibull and Burr. Description of these distributions can be found on a wide range of publications on statistical distributions (e.g. Johnson et al., 1994; Forbes et al., 2011) or in focused articles (e.g. Burr, 1942; Tadikamalla, 1980). The goodness-of-fit was measured using the Kolmogorov–Smirnov (K–S) and the Anderson–Darling (A–D) tests. Additionally, the software EasyFit[2] was used to find the best-fit distribution to the datasets. Precipitation depths for selected return periods were then estimated based on the best-fit probability distributions.

2.1. Kolmogorov–Smirnov test (K–S)

This test is used to decide if a sample comes from a population with a specific distribution (NIST/SEMATECH, 2010). For a detailed description of the test see Chakravarti et al. (1967). It is based on the empirical cumulative distribution function denoted by

$$\mathrm{Fn}(x) = \frac{1}{n}[\text{Number of observations} \le x] \tag{1}$$

[1] http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas.

[2] http://www.mathwave.com/products/easyfit.html.

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