A risk-based approach to assessing climate impacts

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Abstract

In recent years, the frequency of catastrophic natural disasters worldwide has brought to the fore the possibility that these could be the result of changes in the global climate conditions. It is further anticipated that by the end of this century the occurrence of natural disasters will intensify, rendering regions such as Africa more vulnerable to the impacts of a changing climate. In this paper, we develop a framework for risk assessment associated with the phenomenon of climate change. We delve into what we mean by 'risk', and into statistical techniques that build probabilistic models to capture the behaviour of rare events. These models are aimed at providing reliable and quantifiable estimates of the parameters associated with the occurrence of risk events, which can be used to quantify, in probabilistic terms, their future patterns. Thus, such models provide a means of attaching a value to the risk event of concern, which can be helpful for prioritizing intervention strategies. We discuss risk assessment methods within the context of climate change in five selected southern African domains, namely, coastal infrastructure, west coast fisheries, ground water recharge, wildfires and climate regulation services provided by terrestrial ecosystems. We perform a quantitative risk assessment on the sea-level data from a specific location on the Durban coast as a case study for illustration purposes.

1. Introduction

In recent years, the frequency of catastrophic natural disasters worldwide has brought to the fore the possibility that these could be the result of changes in the global climate conditions (IPCC 2007). It is further anticipated that by the end of this century the occurrence of natural disasters will intensify, rendering regions such as Africa more vulnerable to the impacts of a changing climate (IPCC 2007, IPCC 2008, ICSU ROA 2007). Natural disasters, in addition to having an immediate impact on lives and property, have the consequence of affecting food security, energy demand and supply, health, diminishing natural resources and biodiversity (Amato at al 2005). For instance, agriculture is largely dependent on climate, and as such, prolonged extremes or pattern changes in climate can have negative impacts on product yields. In South Africa, approximately one million people are employed in the agricultural sector, and any reduction in output will have a serious impact on poverty and food security (IPCC 2008). Climate change also has epidemiological consequences. There is mounting evidence that climate change may already be affecting human health in the form of mortality from extreme temperatures, changes in air and water quality as well as changes in the ecology of infectious diseases (McMichael et al. 2004, Sunyer and Grimalt 2006). Southern Africa is particularly vulnerable to water-borne and vector-borne diseases such as cholera and malaria, respectively, as precipitation extremes such as droughts and floods affect the availability of breeding sites for vectors (Githeko 2000). Events that are rare, but catastrophic in nature, are of most concern as often there is little preparedness to combat their effects. The urgency to investigate the mechanisms that drive environmental catastrophic events thus cannot be overstressed. The need is also to be able to find ways to quantify the frequency of future occurrences for the purpose of planning mitigation strategies, and for sustainable adaptability, as a response to climate change.

Rare events are those events which deviate substantially from a routine pattern. Historically, research in understanding the behaviour of rare events has been in flood design studies, which were later adapted to the financial markets and the insurance sector. Not all rare events, however, are of concern. In the environmental context, scientists and stakeholders are concerned with those rare events that are detrimental in nature, and have devastating effects on lives, both human and animal, as well as on property and other infrastructure in the affected region. With the urgency generated from certain climate change scenarios, the need to understand the frequency of future rare events under various climate scenarios has renewed research in this area.

Events that are frequent, or occur at regular intervals, are easier to study as there are often substantial recorded data available for them. This is, however, not the case with rarely occurring events, as by the very nature of being infrequent, there is little accompanying data. As such, the study of rare events is a challenge. In general, the notion of risk is associated with those rare events, that have some detrimental effect. Thus, risk can be partitioned into an identity comprising the product of the likelihood of the occurrence of such an event, with the consequence that their occurrence incurs[1] , i.e. Risk (event) = Likelihood (event) × Consequence (event). When both the components are of small magnitude, the risk is low, while, with any one of them being of high magnitude, the risk increases. In this paper, we focus only on the likelihood part of the above risk identity, and any reference to the term risk will be limited to that.

Statistical modelling of rare events entails the study of the probability distributions of the events, based on the data available. With the paucity of data in the case of rare events, a prediction based on little historical data requires sophisticated techniques to capture their behaviour. In Section 2, we discuss statistical models, beginning with naïve techniques and moving to the more sophisticated, albeit complicated, models and also discuss the non-trivial issues associated with the behaviour of rare events. In Section 3 we discuss application of these methods in five selected domains of interest in the context of climate change in the southern African regions, namely, sea-level rise, the west coast Benguela upwelling fisheries, ground-water recharge, wildfires, and carbon regulation. In Section 4, we focus on a specific case study from the domain of sea-level rise, and consider the wave heights data of the Durban coast, motivated by the occurrence of the 2007 floods there, as well as the availability of relevant data. We will conclude the paper in Section 5 with a short discussion.

2. Methods and issues

In classical data analysis, extreme values, as those associated with rarely occurring events, are often labelled as outliers, and ignored in the analysis to facilitate the fitting of a model. However, when the question is about rare events, one needs to investigate the behaviour of the tail values of the distribution of the phenomenon. Here-in lies the application of the Extreme Value Theory (EVT). Risk assessment of rare events based on EVT methods can be dated back to the early 1920s with the celebrated work of Fisher and Tippet's (1928) three type theorem, which was later given a more mathematical rigour by Gnedenko (1943). Risk assessment based on the EVT has evolved over the years as their applications have evolved. Extreme value behaviour can either be quantified in terms of investigating observations by modelling the optima (maxima or minima)[2] of the process, or by modelling values that are above (or below) a certain threshold (Coles 2001). In what follows, we present some of the methods that are based on these two approaches, and discuss issues associated with them when applied in practice. We also discuss methods that incorporate the spatial analysis of extreme events, as well as methods involving the inclusion of prior knowledge about the process generating the values, in conjunction with observed data, via the Bayesian techniques.

2.1. The block maxima approach

The advantage of the EVT methods stems from the fact that even if the distribution of the underlying process is unknown, under some conditions, by the Fisher-Tippet theorem, block-maximas converge to the Generalized Extreme Value (GEV) distribution. More specifically, if $X_1, X_2, \ldots$ are independent and

[1] Another extension of this identity can include the availability of means to control for the consequence of the occurrence of the rare event, i.e., defining risk as likelihood × consequence × (1 – system effectiveness)

[2] For the remainder of the document we shall discuss the EVT methods for maximas. The methods for minimas are analogous.

identically distributed random variables generated from some unknown underlying distribution F, and if $M_n = \max\{X_1, \cdots X_n\}$ is the maximum of a block of size n, then by the Fisher-Tippet theorem, for some suitable sequence $a_n > 0$ (a scale parameter), and b_n (a location parameter), the probability of a standardized value of M_n, $P\left\{\frac{M_n - b_n}{a_n} \leq x\right\}$, converges to the GEV distribution $H(x; \mu, \psi, \xi)$, where μ is the location parameter, ψ is the scale parameter, and ξ is the shape parameter of the distribution (Jenkinson 1955, Prescott and Walden 1980, Hosking et al. 1985, Smith 1985).

In the block maxima method, the primary issue is in the definition of the block. For instance, if we are investigating extreme annual rainfall, then we would need to define whether a block of a year matches a calendar year, or otherwise. Also, larger block size results in fewer block-maxima to work with, thereby affecting the precision of the estimates, while smaller blocks result in too many maxima, not all of which can be regarded as extreme, as well as affecting the asymptotic assumption for the application of EVT methods (Coles 2001).

For practitioners, useful information on assessing the risk associated with extreme events is the quantification of the return period of such events. Suppose from the data we have k blocks of size n. A return level corresponds to that value at which just one of the k block maxima will exceed the level. Longer return periods relate to more rare events. However, if the process is affected, by say, changes in climate scenarios, the return periods may become shorter, indicating an increase in the frequency of their occurrence.

2.2. Methods based on threshold exceedances

One of the concerns in the block maxima approach is that eventually one only works with the k observations, which correspond to the maxima values from the k blocks, discarding all the other values during the analysis. An alternative to the block maxima approach is to work with all values that are above a certain threshold value of concern, thereby including more data from the phenomenon being observed.

Pikands (1975) showed that for high threshold value u, threshold excesses can be approximated by a Generalized Pareto distribution (GPD) $G(x; \sigma_u, \xi)$, where σ_u is a scale parameter depending on u, while ξ is the shape parameter. Davison (1984) looked at the basic properties of the GPD, as well as investigated their behaviour in the presence of covariates. A natural extension of the GPD approach is to combine the information on the excess with the number of times these occur, which is called the Poisson-GPD distribution.

An issue with the application of threshold methods is that contiguous values above a threshold are likely to have dependence between them. The development of statistical techniques, such as the GPD (as also the GEV distribution), are built on the assumption that the observations are independent. However, it has been shown that under some general conditions, for stationary processes, the excesses over a threshold are asymptotically independent (Leadbetter et al. 1983). However, if the underlying process has strong dependence, and may also have an underlying trend, and one has reason to believe that exceedances occur in clusters, it can still be assumed that peaks within clusters are independent across clusters, and one can still apply the Poisson-GDP method (Davison and Smith 1990, Smith and Weissman 1994). This is also known as the Peaks-over-Threshold approach.

As with the block maxima approach where the choice of block size is crucial, in the threshold method there has been, and still is, considerable debate regarding the appropriate choice of the threshold value u. Low threshold values violate the asymptotic basis of the model, while too high a value will leave very few observations to work with. A way to avoid arbitrariness, often, in the case of high threshold excesses, is to take, say, the 90th or the 95th percentile values. A more objective way is to use what is called the mean-residual-life-plot in which the mean of the excess above a threshold are plotted against corresponding threshold values. The threshold value below which the plot is approximately linear is selected (Coles 2001).

2.3. Multivariate extreme values

So far we have assessed risk related to a single process. For two or more processes, one needs to incorporate the interrelationships, if any, between the extremes from the different series. The probability theory for multivariate extremes is analogous to the univariate cases (Coles 2001, Galambos 1987, Resnick 1987). Barnett (1976) has critically reviewed several concepts surrounding multivariate extreme value (MEV) theory that can be used for risk assessment in multivariate data setup.

2.4. Spatial extreme values

In climate data, observations are often scattered in space. Although considerable research is available for investigating the mean behaviour of spatially located observations, the theory of spatially located extreme values is still developing, since the dependence structure between observations in space for extreme observations may differ considerably from that of their mean behaviour (Coles 1993, Coles and Walshaw 1994).

2.5. Bayesian methods in extreme value analysis

The methods enumerated above for quantification of risk involve models that are solved using the maximum likelihood techniques (Prescott and Walden 2001, Smith 1980). Another alternative is offered by the application of Bayesian methods, where a belief regarding the model parameter can be incorporated, without reference to the data. This belief can often include expert knowledge. Bayesian methods assume that the parameters have a distribution, instead of being constants as in the more classical approach. There are a number of reasons to adopt Bayesian methods in climate research, the main being the scarcity of data, which can be complemented by incorporating appropriate prior information. Another reason for using Bayesian methods is that by associating a distribution with parameters, quantification of risk, say in terms of return times, can also reflect the uncertainty associated with that estimate (Coles and Tawn 1996).

3. Domains of application

Climate change impact studies undertaken in southern Africa have not had an explicit risk assessment component. IPCC identifies Africa as being especially vulnerable to climate change. Below we present some of the focus areas where such risk assessment in the southern African context is not only applicable, but urgent.

3.1. Ground water recharge

In sub-Saharan Africa, hydro-meteorological events account for the highest proportion of natural disasters, with 59% of them having occurred in the period 1975-2002. It is expected that tropical regions will experience an increase in mean precipitation by the end of the 21st century, whilst in arid and semi-arid regions, mean precipitation is expected to decrease (Contributors to the Technical Paper of the IPCC on Climate Change VI 2008). Most regions in southern Africa are projected to experience water stress by 2025. With most farmers in the region dependent on ground water for their personal as well as agricultural needs, access to potable water is a key indicator of the quality of life in the region. Ground water can only be sustained when the abstraction rate from the aquifers is lower than the recharge rate. In the context of climate change, it is anticipated that both the amount and frequency of rainfall will affect the recharge of aquifers. Application of risk assessment methods in the context of aquifer levels could involve the estimation of the return period of certain low aquifer levels and how these will change with projected changes in precipitation patterns.

3.2. Wildfires

Africa accounts for about half of the area burned by wildfires throughout the world (FAO 2008). Fires are the inevitable consequence of a combination of fuel, weather and a source of ignition, and are an important process that shapes and often rejuvenates vegetation. While some fires can be beneficial, in most cases vegetation fires pose a threat to crops, livestock, infrastructure and human life. In southern Africa, close to 200 million tonnes of plant material burn each year (van Rooney 2008). Fires can occur at different frequencies and in different seasons, and they can burn at different

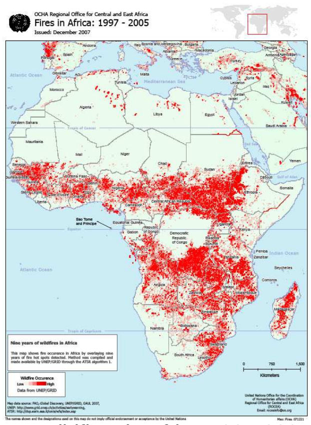

Figure 1: Wildfires in Africa 1997-2005
Source: OCHA

intensities depending on the fuel and weather conditions at the time. Preliminary analysis of fire data from the South African Cape region has revealed that the mean return period of such fires has decreased from 31.6 years in the 1970s to as small as 13.5 years in this decade (Forsyth and van Wilgen 2008). Also, over the past 40 years over 2000 fires have been recorded in 10 conservation areas in the Western Cape, of which about only 20 were responsible for 25% of the area burnt. Similarly, 14 out of 212 fires in the Kruger National Park accounted for 81% of the area that burnt in the park in a single year. It is the conditions that lead to these large, rare fires that are of interest.

Risks associated with wildfires are restricted to those which are damaging in nature, which make up a subset of all wildfires. Such wildfires are relatively rare, and they tend to occur during periods of exceptionally high, and prolonged, presence of factors contributing to fire danger, as measured by risk indices (such as the McArthur Forest Fire Danger Index and the Keech-Byram drought index). Thus risk assessments could involve statistical analysis of trends in daily fire danger indices leading to the identification of threshold values for a fire danger index associated with large wildfires. Risk assessment could also involve the statistical modelling of the occurrence of two or more consecutive days in which the fire danger index is above a certain threshold. A further step in this process could involve the inclusion of estimates of future human population density, on the assumption that ignition densities (and therefore the probability of igniting a fire under dangerous conditions) would increase in proportion to human population density. The climate change risk assessment will entail an analysis of the change in the probability of exceeding the components of fire danger indices thresholds, and their return times, under the scenario of climate change.

3.3. Upwelling fisheries

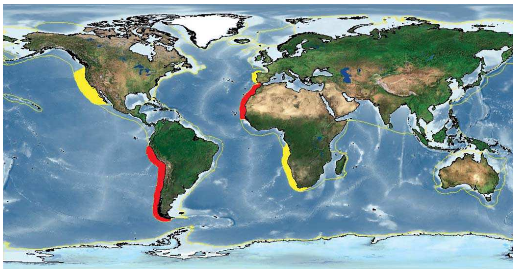

Figure 2: Large Marine Ecosystems associated with upwelling systems
Source: NOAA (www.lme.noaa.gov)

Globally, upwelling systems appear as cold water anomalies from equatorial to subtropical ocean systems. The upwelling regimes are highly productive, and account for a large fraction of global fisheries production, and similar to other marine systems, they are becoming increasingly susceptible to the proliferation and detrimental effects of harmful algae blooms (HABs). The upwelling circulation overrides both the nutrient limitation of stratified waters and the light limitation of well-mixed waters (Hood et al. 1992, Kudela et al. 2005). HABs in upwelling systems have been closely linked to wind, which is the main driving force in upwelling systems (Pitcher et al. 1998).

Among the many pressing questions to understand the behaviour of the HABs, is one to discern 'Whether climate indicators are predictive of HAB events in upwelling systems?' (Kudela et al. 2005). The Benguela system in the south-eastern coast of Africa (Figure 2), is one of five Large Marine Ecosystems (LMEs) associated with eastern boundary upwelling regimes. The Benguela system, with its relatively good data coverage and process understanding, offers an opportunity to address a question of global interest, analysis of which may provide important clues to the rates of changes in southern African ecosystems as a whole. HABs-related risk assessment of the upwelling system could include investigating risks of wind conditions using appropriate risk models, and extending them to include variations under different climate change scenarios.

3.4. Climate regulation services

Climate regulation services remains perhaps one of the least studied and understood areas in South Africa (Mills and Cowling 2006). The service of climate regulation is provided through the direct (biophysical) and indirect (biogeochemical) regulation of both the macro and microclimate. A mechanism in this regard is the buffering of the carbon cycle. It is now feared that the present carbon sink activity will become a future carbon source as a result of climate change, especially when combined with future changes to land use. An emerging research area is the physical effect of land cover on the climate, largely driven by changes in albedo. Vegetation cover has profound effects on the microclimate, ranging from wind shelter, to temperature and humidity. All these climate regulating services are likely to change as a result of the combination of climate and management changes. Currently there is no basis in South Africa for predicting the magnitude (or in some cases, even the sign) of the change. Considering the potential impacts of climate change on South African biodiversity, ecosystem services and human wellbeing (van Jaarsveld and Chown 2001) this is a key gap in the current management and planning frameworks.

A risk assessment framework related to climate regulation can involve a detailed case study, such as of the Little Karoo region, which can be extended to the rest of South Africa's biomes. The Little Karoo is the site of much research into biodiversity and ecosystem services in planning frameworks.

3.5 Sea level rise

The Fourth Assessment Report of the IPCC projects sea-level rise of 0.2-0.6m by 2100. It mentions that since 1961 the average temperature of the global ocean has increased, which causes seawater to expand, contributing to sea-level rise. Although the recorded average rise in sea level has been relatively modest (Church et al. 2006), the interaction with changing storm intensities and wind fields can produce changes in sea conditions that can flood existing infrastructure. With South Africa's Coast: Perimeter ratio being 37%, rise in sea level is an important risk to the country's coastline and the shipping infrastructure, especially for the ports and coastal cities and towns. In March 2007, a cut-off low-pressure system induced a sea storm, which wreaked havoc along the entire KwaZulu-Natal (KZN) coastline. Maximum run-up levels on the open KZN coast near Durban on the SA east coast during this storm, reached up to about 8.5m above mean spring tide. Direct infrastructure damages alone resulting from this storm is estimated to be over R400 million. Thus, this event represents a suitable case study for investigating the impact of coastal events resulting from climate change, and is even more useful in that some of the causes (equivalent to future SLR and increased storms) and effects have been measured.

Sea-level rise appears as a classic situation for applying extreme event analysis. Coastal infrastructures are designed for ‘expected’ sea states. If sea states change, for example, as a result of climate change, coastal infrastructure design may no longer be adequate, and undesirable events may become more frequent. The return levels of various sea level run-ups would be useful to coastal planners and these can be extracted from appropriately fitted extreme value distributions.

4. The Durban sea-level case study

As mentioned in the previous section, on 19th March, 2007, a storm along the eastern coast of South Africa inflicted serious damage to coastal infrastructure, with significant wave height (HMO) reaching as high as 8.5 meters. At the peak of the storm, the water level was almost 40 cm above the predicted tide. To analyse the pattern of such extreme events along the eastern coast of South Africa, we focus on Durban as it is a centre of high economic activity in the region and was in particular negatively affected by the 2007 storms. We analyse 11 years of 8-hourly HMO data from 1997 to 2008 obtained from the National Oceanic and Atmospheric Administration (NOAA). The threshold selection plots for GPD application suggest 3.8m to be the HMO beyond which wave heights can be considered rare (Figure 3).

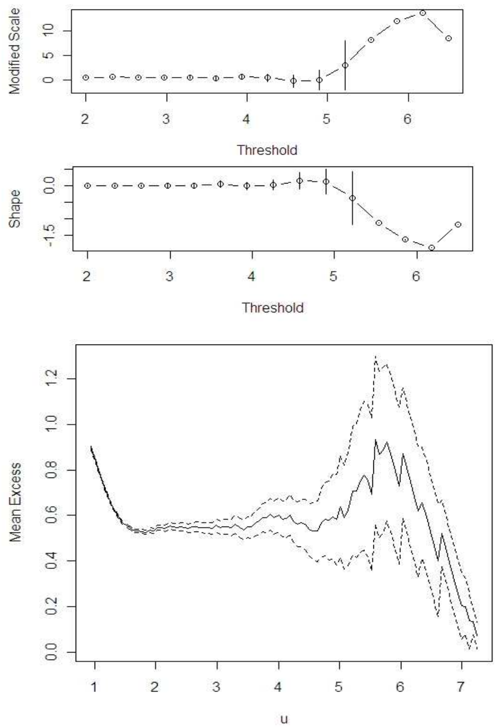

Figure 3: Diagnostic plots for selection of the threshold from the NOAA Durban HMO data

We evaluate the return periods for a storm as severe as the 19 March 2007 event (8.5m), as well as events slightly more, as well as slightly less severe, with the threshold value kept at 3.8m. We repeat the same analysis, this time incorporating an increase in sea level by 0.4m (the mean of the IPCC projected increase in sea level between 0.2-0.6m by 2100). We compare the GPD results with the GEV block maxima method. All analyses were carried out using the extRemes package in R, an open source statistical package.

Table 1: Return period using GPD for the NOAA data (I) and under projected climate scenario (II)

	Mean return periods (years)				
	7.5	8	8.5*	9	9.5
I	18.97	45.85	111.66	273.96	677.39
II	6.55	12.93	24.90	46.85	86.25

*: 19th March 2007 waves in Durban reached 8.5m

From Table 1, using the GPD approach with threshold value of 3.8m, we observe that the return period for a wave height as high as the 19 March 2007 event is about once in 111 years. However, slightly lower wave height of 8m can occur once in about 45 years. Under the projections of climate change, these values drop dramatically.

In Table 2, we present the results of the GEV application to the original data and the original data boosted with the addition of 0.4m respectively. We consider a calendar month to be a block. The estimates of the GEV parameters were $\mu = 3.17, \sigma = 0.57, \xi = 0.047$.

	Mean return periods (years)				
	7.5	8	8.5*	9	9.5
III	30.75	42.76	58.96	80.64	109.39
IV	23.48	32.87	45.63	62.81	85.76

Table 2: Return period using GEV for the NOAA data (III) and under projected climate scenario (IV)

*: 19th March 2007 waves in Durban reached 8.5m

From Table 2, using the GEV approach we observe that a storm as severe as the one on March 19, 2007 can occur about once in 59 years. Under the projected climate change, all the return periods become shorter.

Comparison of the return periods of the two models reveals much disparity. This is primarily because the data above the threshold of 3.8m is quite different from the data used for the GEV approach with month as block size. In fact, in the GPD with threshold of 3.8m, there were 319 observations, while in the GEV there were only 131 block maxima values. Recall that in the GEV approach, once a block is defined, the behaviour of only one value from each block, in this case the maximum value, is of interest. However, in sea-level data, high values occur in clusters, and values close to the block maxima can also be as severe as the maxima. Thus, where data is available, it is more appropriate to include values above a threshold, to capture the behaviour of the extreme observations better.

5. Concluding remarks

Probabilistic risk assessment of rare events is a challenge because by their very definition, there is a paucity of their observed instances. In the environmental context in southern Africa, data are often sparse, rendering their analysis difficult.

Such challenges have led researchers to devise novel methods to evaluate appropriate models, to make future probabilistic predictions of the occurrence of rare events for the purpose of devising mitigation strategies. However, a caveat to risk assessment of extreme events lies in the fact that different extreme value analysis methods can give different predictions for return times of rare events, as has been demonstrated in the case study. It is thus imperative to understand the scope and limitations of each method in the context of application. An extension to this work can be to perform a Poisson-GPD analysis on the data, and use the results to derive the appropriate GEV parameters, since under certain conditions, above a certain threshold, the GEV and the Poisson-GPD are consistent with each other (Coles 2001).

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7. Endnote

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