



Are Kenya Meteorological Department heavy rainfall advisories useful for forecast-based early action and early preparedness?

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Abstract. Preparedness saves lives. Forecasts can help improve preparedness by triggering early actions as part of a pre-defined protocols under the Forecast-based Action/Finance (FbA) approach, however it is essential to understand the skill of a forecast before using it as a trigger.

In order to support the development of early action protocols over Kenya we evaluate the 33 heavy rainfall advisories (HRA) issued by the Kenya Meteorological Department (KMD) during 2015-2019. The majority of HRA warn counties which go on to receive heavy rainfall. However in general the total area warned is much larger than the extent of significant rainfall.

The three periods of flood impacts during 2018 and 2019 were all preceded by HRA, which warned the counties with recorded losses. By contrast, none of the four flooding periods in 2015-2017 were preceded by HRA. We suggest that access to the UK Met Office Global Hazard Map (GHM) at KMD at the end of 2017 was a key factor in this step-change in skill.

Overall we find that KMD HRA effectively warn of heavy rainfall and flooding and can be a vital source of information for early preparedness. However a lack of spatial detail on flood impacts limits their utility for systematic FbA approaches. We conclude with suggestions for making the HRA more useful for FbA, and outline the developing approach to flood forecasting in Kenya.

1 Introduction

Like many worldwide, the Kenyan population are at significant risk from heavy rainfall-induced flooding. In the last two years alone flood losses and damages have been extensive. Recent examples of this include flooding during the 'Long Rains' season of 2018, impacts of which included the displacement of 300,000 people (OCHA, 2018), shortly followed by the 'Short Rains' flooding of 2019 which induced a landslide in West Pokot, killing 72 (reliefweb, 2019). In response to this kind of climate risk, the Red Cross Red Crescent movement has pioneered Forecast-based Action/Finance approach (FbA/F, see <https://www.forecast-based-financing.org/> for more details).



In the humanitarian action landscape, FbA/F sits within a wider set of approaches to anticipatory risk management which can broadly be termed Early Warning-Early Action, of which there are many examples (see Wilkinson et al., 2018, for a review of FbA/F initiatives). FbA/F specifically has three defining features: A set of objective pre-defined forecast triggers, which when met activate a set of pre-defined preparedness actions, themselves funded by a dedicated finance mechanism. Together
25 these constitute the Early Action Protocols (EAPs) of an FbA/F system. The EAPs facilitate rapid preparedness actions to be implemented before the hazard event occurs, thus moving from disaster response to early preparation and reduction of potential risks posed by the hazard event. Many FbA/F pilots are active worldwide (see Wilkinson et al., 2018, for a review of FbA/F initiatives), and whilst it is not simple to precisely quantify the impact of such programs, evidence suggests programs can significantly reduce individual expenses (Gros et al., 2019) along with unquantifiable benefits to lives and livelihoods.

30 Following the establishment of the IFRC FbA/F by DREF (Disaster Risk Emergency Fund) in December 2017 national Red Cross/Red Crescent societies are working to define their EAPs, for the dominant hazard types. In Kenya, this work is facilitated through the project “Innovative Approaches in Response Preparedness” (IARP) funded by the IKEA Foundation and implemented by the Kenya Red Cross Society (KRCS), with further support from aligned projects notably the the UK-funded NERC/DFID project “Toward Forecast-Based Preparedness Action” (ForPac, www.forpac.org).

35 Setting up a FbA/F EAP for a particular hazard (e.g. flood or drought) begins by identifying priority risks or impacts that can be addressed by anticipatory early action. The next step is to identify the best forecasts to use to trigger early action. In Kenya under the IARP programme, this involved exploring a range of potential forecasts that can support anticipation of the priority risks, and evaluating the accuracy (or skill) of the forecasts. Anticipatory actions are then selected which are consistent with the skill of the forecast. For instance a reliable forecast of extremely high probability of imminent flooding might be an
40 appropriate trigger for a higher-cost intervention such as evacuation, whilst a lower probability level (with a higher chance of action in vain) could still be linked to a lower cost or “no-regret” action, such as repair of river dykes.

Forecast skill assessment is therefore an essential step in designing a system for FbA/F. In order to be used (in this case, by the KRCS and national disaster management agencies), forecasts must show evidence of skill, which should be quantified. In addition, the forecast must be readily available to the actors, from the mandated agency for providing weather forecasts
45 (in this case, the Kenya Meteorological Department, KMD). Finally, the forecast must be provided in such a way to be easily integrated within the EAP.

Through the IARP programme, a ‘menu’ of potential forecasts of flood risk has been developed for the Kenya EAPs. In the absence of a Kenya-wide national flood forecast system (Weingärtner et al., 2018) forecasts of rainfall provide the most appropriate proxy. One key potential forecast for heavy rainfall events that could result in flooding is the KMD heavy rainfall advisories (HRA, described in full in Section 2.1). These text-based advisories are issued on an irregular basis by KMD, when
50 forecasters’ interpretation of conditions and output of dynamical atmospheric models point to risk of heavy rainfall. These advisories are made widely available to the public and risk management agencies in relevant counties. For example, during the exceptionally wet *Long Rains* season of 2018 two heavy rain advisories were issued leading to actions by risk management bodies including KRCS (Kilavi et al., 2018).



55 As these heavy rain advisories are issued from the mandated forecasted agency they have high potential to be used in a more systematic manner as an FbA/F trigger in flood EAPs. However the skill of these advisories is unknown. In addition, they are developed explicitly for heavy rainfall warnings and only implicitly warn of flooding. Here then we assess the accuracy of the historically issued KMD HRAs and evaluate their potential to be used as a trigger in a FbA/F system for flooding. Understanding the level of skill of the advisories supports the development of early action protocols by disaster managers.

60 The verification of the advisories also helps to build confidence in early warnings from subjective forecasts. Many forecasts of natural hazards are produced with some level of expert judgment, but this subjectivity makes verification difficult; a large number of forecasts produced using a consistent method are rarely available for objective evaluation. Without this evaluation, trust in the forecast producer determines confidence in the forecasts. However when a reasonable archive of forecasts is available, forecast verification can help to build confidence in the use of forecast, as well as help increase trust in the forecast
65 producer.

The forecast and verification data are described in the following section, along with an outline of the challenges to verification posed by the format of the advisories and approach to meet this challenge. Results follow and the paper concludes with a discussion of the main findings, limitations to the analysis along with recommendations for design and operation of the Kenya EAPs and further research.

70 **2 Data and verification approach**

2.1 Production of the KMD heavy rainfall advisories

The first HRA was issued at KMD on 2nd June 2015 after being introduced as a forecast product as part of the Severe Weather Forecasting Demonstration Project (SWFDP) for Eastern Africa (<https://www.wmo.int/pages/prog/www/swfdp/SWFDP-EA.html>). This project was implemented with support from the World Meteorological Organisation with the aim of improving
75 the ability of National Meteorological and Hydrological Services (NMHS) to forecast severe weather events, improve the lead time of early warnings and improve the interaction of NMHS with disaster managers before and during the event. The intended audiences for these advisories are national and county risk management agencies, humanitarian organisations, relevant ministries and the media for dissemination to the general public within areas of concern.

The decision to issue a HRA is a subjective one, informed by dynamical model output and forecaster experience. Every
80 day forecasters at KMD's Severe Weather Forecasting section review forecast products from Global Producing Centres (such as ECMWF, NCEP, UK Met Office and Meteo France) using their judgement to produce a five-day running severe weather forecast. The models are deterministic and probabilistic, at a range of spatial resolution from 4km to 28km. A range of meteorological fields are considered, including pressure and wind fields throughout the atmosphere, precipitable water, low level relative humidity, convergence and divergence at the lower and upper levels, and convective available potential energy. Consistency between model fields, observations and satellite imagery is checked to filter out unrealistic model outputs.
85

This five-day severe weather forecast is based on areas expected to receive any of the following: rainfall above 50mm in 24 hours, winds greater than 25 knots or waves above 2m height. The forecasts are presented graphically as polygons, along with



tables showing the level of risk (low, medium or high) over specified areas. At 0900Z representatives from the NMHS of all the contributing countries of the SWFDP participate in a teleconference call to discuss the forecast and develop a consensus.

90 If any models indicate a raised chance of an extreme event occurring over Kenya during the next few days then a high impact weather conference is held at KMD by experts from the forecasting unit and a consensus advisory is drafted. A subjective probability of occurrence is estimated based on the consensus between models, taking into account weighting of the better-performing models (according to forecasters' experience). Once the advisory is drafted it is sent to the Assistant Director of forecasting, then to the Deputy Director, for review and amendments. It is finally examined and signed by the Director and sent
95 to the public weather service section for dissemination to the public and to risk management agencies. The Director has the ultimate authority for the advisory release.

We note that the forecast information used at KMD to produce the HRA has changed over the advisory period under study: in mid-2016, KMD was granted a two year trial license to ECMWF 'eccharts' through the SWFDP and since August 2017 KMD began using the UK Met Office Global Hazard Map (GHM) as part of the ForPac project. The GHM provides an at-a-glance summary of forecast high-impact weather over the coming week (seven days), using global ensemble forecast data.
100 The system visualises forecasts from MOGREPS-G and ECMWF both separately and in a multi-model ensemble forecast. The multi-model informs summary polygons which direct forecasters to attention to potential high-impact weather.

There are no clear objective criteria triggering advisory issuance, which is subjective and depends on forecasters' experience and perception of model skill, consensus within the forecasting section and forecast data available.

105 HRA are the most frequently issued type of advisory by KMD. Advisories for strong winds, marine and temperature are also issued but are not considered in this study. An example of a HRA is shown in figure 1.

The advisory is text-based. It generally mentions a rainfall threshold which could be reached: sometimes this is included as a rainfall rate (e.g. 30mm in 24 hours), otherwise an accumulation total without a rate is mentioned. Finer scale details are often mentioned in this description, such as when within the valid period the rainfall can be expected to start for different regions.
110 Following the forecast description, the full list of potentially affected counties is listed, along with general instructions for flood preparedness (e.g. "be on the lookout for potential floods", "avoid driving through or walking in moving water", "people in landslide prone areas...should be on high alert").

The first HRA was issued in 2015 and by the end of 2019 a total of 33 had been produced. Here these HRA are digitized with relevant information extracted: the date of issue and validity, the probability range, the rainfall threshold mentioned, along
115 with all counties mentioned. Details are given in table 1 and descriptive statistics are shown in figure 2. Several aspects of the KMD advisories demand a careful approach to verification, as detailed in the following section.

2.2 Verification approach

There are three characteristics of the HRA forecast data with important implications for the verification approach:

1. The small sample size (33 HRAs) means it is difficult to assess specific aspects of the forecast, such as reliability of
120 probabilities or accuracy of rainfall thresholds, descriptive statistics of which are provided in figure 2., showing for



example that the probability range of “33-66%” is indicated in nearly all advisories (figure 2d, used in 26 advisories) and other probability ranges are rarely used.

2. The forecast window over which advisories are active is variable, from one to six days but most commonly out to three days (figure 2c, 13 advisories) such that the definition of heavy rainfall for verification cannot be consistent.
- 125 3. Ambiguous spatial characteristics of the forecasted heavy rainfall. To illustrate: should we deem an advisory warning of 50mm of rainfall for two named counties to be a ‘hit’ if 50mm accumulated rainfall is observed (a) over single point within at least one of the counties or (b) over the entirety of either or both counties or (c) any areal extent between these extremes? This spatial aspect is further complicated by the wide range of size of Kenyan counties: from just over 200km² (Mombasa) to over 70,000km² (Turkana). The hit rate and false alarm rate would be highly sensitive to these
130 verification criteria.

In order to address these issues, we take a step back and refocus on the question: would these advisories have been worthwhile for flood preparedness? We proceed by considering the advisory from the perspective of a manager responsible for national preparedness at KRCS. First, we assume that every advisory triggers preparedness actions, independent of the rainfall threshold or probability mentioned. Second we define the extent of the preparedness actions according to the counties men-
135 tioned in the advisory. Such actions are unspecified here and could range from a low-regret communication to county-level Red Cross volunteers to a more expensive decision to pre-position supplies. We note that by ‘ignoring’ the forecast probability and the specific rainfall thresholds the decision to trigger action is less flexible, however following discussion in the previous paragraph, carrying out verification based on specific thresholds is unable to provide robust statistics and precludes any meaningful statement. Despite this, the approach followed is still consistent with the FbA/F approach; the action trigger is defined
140 as the probability of heavy rainfall (of any specific threshold) exceeding zero.

After assuming that action was taken within the entire region under advisory for each advisory window, we then consider the question, was this action worthwhile? There is no single answer to this question, as it depends on the specific actions along with the individual and institutional tolerance for false alarms and misses. However following this approach we can identify clear hits and false alarms, and can confront the advisories with ‘what really happened’. As such, our method involves answering
145 the following questions:

1. How well does the total area under advisory warn of the extent of heavy rainfall? (Section 3.1)
2. What is the relative spatial extent of preparedness actions implied by each advisory? (Section 3.2)
3. How many significant flooding events in the period 2015-2019 occurred directly following a HRA? (Section 3.3)
4. How often would an FbA/F system be expected to trigger, if it were based on the advisories? (Section 3.4)

150 By answering these questions we determine the extent to which the KMD HRAs could guide ‘worthy’ preparedness activity. We address question one with a visual comparison of the total area warned under each advisory with the total rainfall accumulation in the subsequent advisory window. Rainfall observations are taken from the Climate Hazards and Infra-Red



Precipitation Data with Stations (CHIRPS) dataset (Funk et al., 2015). With this visual comparison we begin with a subjective assessment of the overall performance of advisories. Following this we calculate the distribution of accumulation totals across all 5km CHIRPS gridpoints inside the polygon associated with the warned counties, quantifying the spatial extent of high rainfall totals for areas under advisory. In addition we show the distribution as the percentage of grid points within the warned region receiving more than a specified rainfall threshold. Throughout the analysis we consider the rainfall accumulation across the window defined separately in each advisory, noting here that the variable window length precludes a standardized verification.

In addition we derive the proportion of the warned area that experienced accumulated rainfall above indicative thresholds. No single rainfall threshold leads to increased flood risk, which depends on many factors, both hydrometeorological and social. Even for a single location the same amount of rainfall may cause a flood in one year but not the next. In the following analysis we show results for 25, 50, 75 and 100mm accumulation over the advisory window and focus the discussion on results for 50mm accumulation. We do not suggest that this threshold has primacy over others; an in-depth analysis would be necessary to determine and quantify the most relevant thresholds for flood risk in a location. Instead we take 50mm as a working definition to keep the discussion concise, whilst including other thresholds in the analysis for reference.

To answer question we estimate the relative scale of preparedness implied by each advisory. In practice preparedness actions would be determined by overlaying the forecast hazard footprint with data on exposure and vulnerability to that hazard. Many different actions are possible, targeting different groups and we do not attempt to evaluate the cost of specific actions. Instead we aim at a broad indication of the relative amount of preparedness appropriate for each advisory. One way of doing this would be to derive the total area of all the counties warned in each advisory as a proxy for the scale of preparedness action required. However population density per county is highly variable (ranging from 12 people/km² in Turkana to over 4,000 people/km² in Mombasa), and so this proxy is likely to overestimate the required intervention where population density is low and underestimate where it is high. Instead then we based this estimate on the total population living in each advisory region.

Population data is taken from the 2015 estimate from the Gridded Population of the World dataset produced by NASA SEDAC dataset at 2.5 arc minute resolution (CIESIN, 2018). We use the total population living in the warned area as a proxy for the number of people likely to benefit from flood preparedness actions in the region, allowing a comparison of the extent of preparedness action required between advisories. For instance an advisory active where 30 million people live is likely to require significantly more preparedness than an advisory relevant for only one million people. We then assess the amount of rainfall falling in the specific areas where people live and estimate the percentage of the 'prepared people' who received above threshold rainfall. From this we can show the relative 'worthiness' of each preparedness action: assuming that when flood preparedness assistance is given in a location and significant rainfall follows the action is considered worthy.

Clearly this estimate of the scale of preparedness is only relative and not absolute, as not everyone living in a region will be seriously affected by heavy rainfall and require flood assistance. In addition this approach carries the relatively strong assumption that the percentage of people exposed to flood risk is relatively constant across counties. If estimates of population at risk from flooding were available they could be used to improve the estimate, however in the absence of this data our approach broadly indicates the relative extent of preparedness associated with each advisory.



This analysis quantifies the extent of rainfall accumulations, and estimates the relative scale of the actions which each advisory may trigger. However heavy rainfall is not the only factor in flooding (Amoako and Frimpong Boamah, 2015), and does not always lead to flooding. Comparing the advisories only to rainfall observations does not therefore fully evaluate their effectiveness for flood preparedness. To do this, we address question 3 and identify flooding events with significant impacts over the period and determine those which were preceded by advisories.

We use the EM-DAT database to extract all significant flood events over Kenya from the date of the first HRA until the end of 2019 (EM-DAT, 2020). EM-DAT collects data on the occurrence and effects of mass disasters globally, and require at least one of the following four conditions for inclusion in the database:

- 10 or more people dead;
- 100 or more people affected;
- The declaration of a state of emergency
- A call for international assistance

Eight significant flood events in Kenya are found in EM-DAT for the period June 2015 to December 2019. We remove the Solai earth dam collapse of May 2018, as the key reasons for collapse were non-meteorological (including lack of maintenance, and an outdated design, NECC, 2018). Accumulated rainfall in the weeks before the event was a factor as it led to saturation of the soil: longer lead time subseasonal and seasonal forecasts (along with close monitoring of rainfall accumulation and soil moisture overlaid with locations of earth dams) may have provided some early warning of the potential for collapse. However the week directly preceding the dam burst did not receive heavy rainfall in the county (Kilavi et al., 2018) and so no HRA directly preceding the event should have been expected. Also we merge the two EM-DAT entries beginning 14th March 2018 as they relate to the same period of heavy rainfall. This leaves six flood events from EM-DAT, to which we add the landslide recorded of November 2019 as this was directly triggered by a period of heavy rainfall.

We note that the EM-DAT inclusion criteria preclude smaller scale events from the database (Gall et al., 2009). For instance a flood leading to fewer than 10 / 100 people dead/affected would not be included, nor would a flood which leads to significant loss of property. This suggests that the lack of an EM-DAT record following an advisory does not necessarily mean that flood impacts were not felt, which advance preparedness may have helped to mitigate. In addition we report EM-DAT mortality statistics as a broad indication of the impact of flooding events, however we note discrepancies with other official sources of information, find that sub-national locations of impact and total numbers do not always agree. However despite these inevitable uncertainties in the details, we take the EM-DAT events to represent the most significant flood impacts in Kenya in recent memory and those which an early warning system should anticipate.

We finish the analysis by addressing question four and determine the number of times a FbA/F system based on HRAs might be expected to trigger in each county, assuming action is triggered by a HRA, but also assuming that an action has a 'lifetime' where the system will not be triggered again if it has not recently been triggered.



220 3 Results

3.1 How much rain fell in counties under HRA?

We begin by identifying the total area of all counties named in each HRA, and comparing this with the accumulated rainfall over Kenya during the advisory valid window. For convenience, advisories are labelled (A-Z, followed by A' to G') in table 1 and these labels are used from this point.

225 Figure 3 shows all the advisories and the resultant accumulation. From a visual comparison, we see that eighteen advisories provide a good forecast of all areas going on to receive at least 50mm rainfall accumulation (A, F, H, J, K, L, P, R, S, Y, Z, A', B', C', D', E', F' and G'). For these advisories preparedness is most likely to have been considered worthy, and local actions based on these advisories are likely to be hits.

230 Nine advisories do successfully warn of heavy rainfall in some areas, whilst failing to warn other counties which received similar amounts (G, I, M, N, O and T, V, W, X). In these cases preparedness may have been considered worthy, although preparedness would not have reached all those potentially affected by flooding, with risk of missed events and therefore failing to act.

235 Five advisories warned the “wrong” counties, where more accumulation was seen in unwarned counties than those receiving warnings (C, D, E, Q and U). One advisory (B) warned coastal counties of heavy rain yet 20mm fell in during a two-day window, a relatively normal amount for the region. For these six advisories it is unlikely that preparedness triggered by the advisories would be considered worthwhile, instead would possibly be seen as false alarms and misses.

240 Next, we consider the rainfall distribution across these regions under advisory. Figure 4(a) shows the rainfall accumulation across the warned region for each advisory, presented as the distribution over the sample of $25km^2$ CHIRPS gridpoints. Figure 4(b) shows the percentage of the warned area which receives rainfall accumulation above thresholds 25, 50, 75 and 100mm. We see that for the vast majority of advisories (29 out of 33), less than 50% of the warned area received over 50mm. This implies that for any point location falling in an area under advisory there is quite a reasonable chance that no ‘significant’ accumulation will be seen. This is inevitable for rainfall early warnings, particularly in a region with a large contribution from small-scale convection, leading to high spatial variability in rainfall totals. As the advisories associate each warning with a probability, these findings are quite consistent.

245 From a meteorological perspective then we find the advisories to be relatively good indications of heavy rainfall: 18 successfully warned those regions which did receive heavy rainfall, nine provide warning for some regions but miss other regions, whilst only six of 33 are unlikely to be useful for early preparedness actions. However at the same time, nearly all ‘good’ advisories warn significantly larger areas compared to the areas which go on to receive heavy rainfall.

250 We next turn to potential actions triggered by the advisories; estimating the relative extent of preparedness action implied by advisories along with the potential public perception of the actions based on locally experienced rainfall.



3.2 What is the extent of preparedness action implied by advisories?

We use gridded population estimates from NASA SEDAC to estimate the extent of preparedness implied by each advisory. Population density is shown in figure 5 for reference. This is integrated across the warned region for each advisory to estimate the total number of people warned by the advisory, shown as the black stars in figure 6(a). This calculation represents an
255 extreme upper bound on the number of people requiring assistance, since vulnerability to heavy rainfall is not felt equitably. However the numbers do allow an order-of-magnitude comparison of the extent of action required between advisories.

Significant variability in the extent of the warning is apparent: eight advisories cover nearly the entire country and warn at least 24 million people and six warn around 15 million. The rest warn fewer than 10 million people and of these, the warning from 14 advisories is ‘only’ targeted at fewer than 5 million people (these smallest scale warnings are generally when
260 only warnings for coastal counties are active). This demonstrates that if flood preparedness based on advisories is undertaken nationally then the extent and cost of preparedness action taken based on advisories will vary significantly.

To evaluate the extent to which this preparedness would have been perceived as worthwhile, we also show the number of people living in a warned area which then went on to receive accumulation of 25, 50, 75 or 100mm. These results are also shown in figure 6(a), whilst figure 6(b) presents these values as a percentage of the population warned which received rainfall
265 above each threshold. Since these scores are conditioned on population, they are highly sensitive to the underlying population density. They will only be improved if heavy rain falls on a populated area, and this improvement will be higher if the area is more densely populated. In this way we move beyond purely meteorological verification and take into account real-world implications of acting on a forecast. This also considers the potential response of beneficiaries of flood preparedness: if flood preparedness is carried out in a region that subsequently receives significant rainfall, most people will see the preparedness as
270 worthwhile. Conversely, people are more likely to see the action as a false alarm if no significant rainfall falls where they live.

Focusing again on 50mm accumulation as a nominal threshold for increased flood risk, we see several advisories for which most people receiving early preparedness would not have seen significant rainfall. For eight advisories (A-E, P, Q and U) less than 10% of those receiving assistance would have seen more than 50mm; these are unlikely to be seen by most as worthy actions. A further seven (G, K, N, R, V, Z and G’) fare a little better, with between 20-30% of those receiving assistance
275 perceiving it to be worthwhile. The remaining 18 would have seen significant rainfall for at least 40% of those receiving assistance, with five of these advisories (M, T, X, C’ and E’) seeing significant accumulation for at least 70% of those assisted. Notably by this metric the first five advisories (covering mid 2015 to mid 2017) are among the worst-performing.

3.3 Did advisories precede significant impacts of heavy rainfall?

We now turn to observed impacts of heavy rainfall and compare the seven events selected from the EM-DAT database with any
280 relevant advisories. We consider an advisory to be relevant if it was issued in the seven days preceding the indicated start date of the impact, since early preparation triggered by that advisory would have been in place for the onset of the event. We do not require the heavy rainfall window to explicitly overlap with the recorded period of impact, allowing for some lag between



heavy rain and flooding. The locations and details of the events are plotted in figure 7, which also shows the counties mentioned in any relevant advisories as defined above (if any). These seven events are now discussed in turn.

285 Figure 7a shows the significant flooding which occurred across Kenya in December 2015 during the large 2015 El Niño event, which peaked in December. This event led to the most number of deaths recorded in the sample (112). No HRA was issued at any point before or during this event, or during the season as a whole. Notably seasonal forecasts did indicate an increased risk of a particularly wet season; although as a whole, the seasonal rainfall anomalies were smaller than previous comparable El Niño events (Siderius et al., 2018; MacLeod and Caminade, 2019).

290 Figure 7b represents a smaller event in Turkana county, caused by intense rainfall on a single afternoon (10th March 2016). This rainfall led to river overflow, three deaths, displacement of 1,000 people and loss of livestock. No HRA was issued for this event.

The third event (figure 7c), occurred at the end of April 2016. This flooding impacted over 10,000 people across semi-arid counties in the north (Turkana, Marsabit and Wajir) along with Nairobi. In Nairobi the rainfall triggered the collapse of a building in the Huruma estate (a building which was not constructed to safe standards), ultimately leading to 52 deaths. In advance of this period, a HRA was issued by KMD (advisory C here), however warnings were given for coastal and parts of Western Kenya and not for those counties most seriously impacted. KRCS did trigger an early response based on this advisory, activating response teams and sending out warnings via SMS to communities living in lowland areas. Although no heavy rainfall was directly experienced in those regions for which the response was triggered, the action was felt to be worthwhile at
300 KRCS, as some flooding was experienced later due to Tana River bursting its banks after heavy rainfall in the central highlands.

The next EM-DAT event occurred in May 2017 (figure 7d). This involved coastal counties along with some in the central highlands and some in the west. 26 deaths were recorded with over 25,000 affected for this event, during which a reported 235mm of rain fell on Mombasa in a 24 hour period between 8-9 May. Although an advisory for coastal counties was issued in late April (advisory E), the valid period was a single day which saw little accumulation in the warned counties. This advisory
305 also predated the beginning of observed flood impacts by over a week and so we do not consider it to have provided adequate warning of the impacts.

Figure 7e shows the impacts of heavy rainfall during the 2018 long rains season, which has been evaluated in depth elsewhere (Kilavi et al., 2018; Finney et al., 2019). Widespread flood impacts were seen across the country, beginning on 14 March and extending throughout the month. Two advisories were issued during March (advisories K and L). The first was issued on the
310 9th and covered the period 13-15th and a follow-up was issued on the 15th, covering the period 16-19th. Both of these periods saw significant rainfall accumulation (see figure 3, and Kilavi et al., 2018). Every county noted in EM-DAT as experiencing flood impacts was mentioned in these advisories, except for Mandera in the extreme northeast of Kenya.

Figure 7f shows impacts occurred from 17-24 October during the short rains 2019. Flash floods, landslides and riverine floods were reported in Turkana, Wajir and Elgeyo-Marakwet counties. Two advisories were issued preceding this event (advisories Z and A'). The first was issued on the 10th, covering the period 10-14th and a second was issued on the 14th, covering the period
315 16-20th. Counties with reported flood impacts were all mentioned in these HRAs.



The final event in the sample also occurred during the 2019 short rains: a landslide in West Pokot on the 23rd November (figure 7g). This occurred following heavy rainfall across many counties, for which a warning was issued several days ahead of the event 18th November, covering the 19-24th of the month (advisory C').

320 In summary, the first three recorded events in the study period were not well warned by advisories. The fourth event in May 2017 was preceded by a warning, but it did not target the counties with significant flood impacts. The final three events in 2018 and 2019 were all preceded by advisories correctly targeting the counties which saw major impacts from heavy rainfall; the lead time between the first advisory and the recorded start of the impacts for these three events was five, seven and five days respectively. Advisories issued in 2018-2019 therefore gave effective warning to areas experiencing significant flooding
325 impacts, whilst the earlier advisories did not. This suggests that in recent years advisories have the potential to act as a trigger for an FbA/F system. However it should be recalled that the warned area is often much larger than the area experiencing heavy rainfall (see figures 4, 6, 7). Even those advisories leading to worthy action where impacts are felt will also simultaneously trigger in many places which do not require early preparedness, and these 'actions in vain' may be quite expensive in highly populated regions such as West Kenya. In the next and final section, we turn to a practical consideration of basing such a system
330 on advisories and estimate how often such a system might be expected to trigger.

3.4 How often would an FbA/F system based on advisories trigger?

An important consideration in setting up an FbA/F system is how frequently it can be expected to be activated. It is desirable to prepare for all significant events, however more frequent triggering limits the cost of actions if the system is to remain financially sustainable. Here we estimate how often such a system might trigger.

335 Naturally the number of advisories will fluctuate year to year, depending on climate variability. However 2018 and 2019 could reasonably indicate the potential number of activations of a FbA/F system, given that they both experienced significant rainy seasons (with 11 advisories issued in 2018 and 13 in 2019, figure 2a). For low-cost actions such as targeted communication of the warning to vulnerable communities this may be an acceptable number of triggers, and results from section 3.3 suggest that these would successfully warn against all significant flood events. A key requirement of the advisories is to warn
340 the vulnerable public of significant hazards and so for this purpose the frequency of issuance is appropriate to the cost of the warning.

In the FbA/F context, the advisories could be used to instigate actions from response organizations and disaster management. Several actions have already been identified as potentially forming part of an EAP (Maurine Ambani, personal communication):

- Enforcement of barriers for people not to cross rivers or places where there is usually fast flowing water
- 345 – Provision of water containers and water treatment
- Provision of vouchers to affected populations to access water treatment tablets, containers and treated mosquitoes nets

These kinds of actions would have significant costs, and so more than ten triggers in a year may not be realistic. However on the other hand, for such actions triggering on every advisory may not be necessary. Frequently an advisory is issued which



follows on from another, describing a continuing rainfall event (e.g. J-L, M-O, C'-G'). Significant flood preparedness may not
350 need to be carried out for each individual one of the advisories in sequence as actions of this nature will have a "lifetime"
that may span the interval between several consecutive issued warnings (Coughlan de Perez et al., 2016). For example, river
defenses will still be effective several weeks after action is taken to repair or reinforce them.

The impact of action lifetime on trigger frequency is illustrated for each county in 2019 in figure 8. Here we assume that
the action will not be repeated if another advisory follows closely after the action is triggered. The number of total actions is
355 shown, assuming an action lifetime of one, two, three or four weeks. Note that we consider multiple chained advisories such as
C'-G' as triggering a single preparedness action, since after the first days of heavy rain activity will have already moved from
preparedness to response mode.

With an action lifetime of one week most counties would have triggered four times in 2019. With a longer lifetime the system
activates less often and in the longest case of four weeks no county would have activated in 2019 more than twice (on average,
360 once for each of the rainy seasons).

4 Discussion and recommendations

Here we have evaluated the KMD HRAs. This has been done from the perspective of a humanitarian agency such as KRCS, as
if the advisories were used to initiate a preparedness protocol such as FbA/F in order to reduce risks related to heavy rainfall.
Such EAPs for a national flood FbA/F system are currently being developed. Our assessment of the advisories has considered:

- 365
- the relationship between area warned and the subsequent rainfall received
 - the scale of preparedness triggered by the advisories, and the perception of the actions based on locally experienced rainfall
 - whether the most significant recent flood events followed HRAs
 - how frequently an FbA/F system could be expected to trigger

370 We now draw some general conclusions and provide some recommendations for improvement of the HRAs and outline the
development of flood risk forecasting in Kenya.

4.1 Conclusions

Advisories issued in the 'early period' (from the first in 2015 through to 2017 inclusive) do not appear to be particularly
effective for preparedness for flood or heavy rain impacts. For each of the nine advisories that were issued in this early period
375 the counties which were warned did not generally receive significant amounts of rainfall. Furthermore, four significant flood
events were reported in this period and none were anticipated by any advisory. We conclude then that it is unlikely that
conducting preparedness actions based on advisories between 2015-2017 would have effectively reduced flood or heavy rain
impacts.



380 However we note evidence of an improvement in the potential utility of advisories in the more recent period 2018-2019,
where they were more frequently issued. Notably these years had particularly wet seasons, March-May 2018 and October-
December 2019. More than half of the advisories led to at least 40% of all people warned receiving more than 50mm accumu-
lation. In addition, all three of the periods in these years which saw significant mortality directly associated with heavy rainfall
which were well-warned by advisories. We conclude then that advisories issued across 2018-19 were particularly skillful at
anticipating heavy rainfall, and that preparedness actions based on these could have led to reductions in the impacts of the
385 worst floods in this period. If the performance of advisories over this period is indicative of future performance, then they have
the potential to effectively warn of all significant flooding impacts in Kenya.

One factor in the poor performance in the early period may be the novelty of the system. The first advisories were issued in
2015 and it may have taken some time to develop the systems and expertise and gain confidence in issuing advisories. Another
explanation for the change in skill is the evolving access to forecast information from global models at KMD.

390 In mid-2016, KMD was granted a two year trial license to ECMWF 'eccharts' through the SWFDP which is reported to have
been crucial in informing the advisories released during that period (Mary Kilavi, personal communication), and particularly so
during the long rains 2018 (advisories J-Q). In addition the GHM in use since August 2017 has provided a multi-model easy-
to-interpret visualization of potential severe weather. Evaluation has shown that multi-model forecasts outperform individual
models for extreme precipitation (Robbins and Titley, 2018). The availability of a higher skill multi-model forecast at KMD
395 in an easy-to-interpret format may then be a factor in the significant improvement in skill of advisories during 2018 and 2019.
Indeed, it is reported that the GHM was a key source of information for the advisories which were issued in advance of all
three significant heavy rainfall impacts reported during 2018 and 2019 (figure 7e-g). See also Kilavi et al. (2018) for analysis
of the GHM forecasts use during the 2018 'Long rains'.

Overall we demonstrate here in the first systematic verification conducted of the HRA that they have skill. We find that an
400 increase in skill over time, and that they have anticipated the most significant flood events during 2018 and 2019. However, we
also find they lack spatial precision on the precise location of heavy rainfall impacts, which may limit their use as a trigger in
KRCS EAPs.

4.2 Recommendations

Though the HRA have skill, their likely utility will clearly depend on the specific context of use. Their intended purpose is to
405 alert county governments, other agencies and the general public of the possibility of heavy rainfall. For this purpose they are
effective: they are widely disseminated, the text identification of counties under advisory requires no technical knowledge to
understand, and most importantly, they have skill. Indeed, Kilavi et al. (2018) note dissemination and use of HRA during the
Long Rains 2018.

As a source of information for a systematic FbA/F system for flooding, the advisories have several useful characteristics
410 for KRCS: they are produced by the national mandated agency for weather forecasting, they are readily available at no cost,
and being text-based, they require no specific knowledge for interpretation. However it is likely that they are not suitable for
triggering a KRCS EAP for flood. The county-scale warning limits the spatial precision of interventions and the frequency of



the triggering per county is likely to be too high for FbA/F, which is intended to target extreme events with a return period of one in five years or greater. In addition, the HRA only provides a general picture of potential flood impacts, without taking into account any local hydrological conditions. However given the clear skill of HRA found here, there is clear scope of KMD to develop these in the context of Impact-based Forecasting (WMO, 2015): here we make some recommendations for improving the HRAs and the flood forecasting from the perspective of stakeholders such as KRCS.

4.2.1 Developing the HRAs

The probabilistic information in the HRA should be improved. A single category 33-66% is issued in nearly all advisories which limits options for preparedness actions. More diverse and precise probabilities would allow a range of increasing levels of preparedness activities, where high-cost actions are only triggered for the highest probabilities. Of course it is essential that these probabilities are reliable, and a relatively low frequency of subjectively developed forecasts makes this aspect of the forecast difficult to evaluate. However the use of historical forecasts and hindcasts from ensemble forecasting systems used in the GHM (Robbins and Titley, 2018), currently in use at KMD, would help to establish the reliability of probabilities and provide a scientific basis for issuing more specific heavy rainfall probability forecasts. Analysis of these dynamical models should also evaluate their performance for the four flooding events in the early period of the KMD advisories (figures 7a-d) to see if these systems did capture these events.

The heavy rain warning area could also be more precise, by providing it as a free-shape rather than administrative county boundaries. Whilst naming counties in the advisory is essential for communication to the public and to county government disaster risk management structures, the precise area of heavy rainfall areas will not align with administrative boundaries and so warning whole counties will tend to overestimate the total area expected to experience rainfall. Such warning polygons are generated by the GHM, already in use at KMD and forecasts could be based upon this. KRCS could then overlay these with maps of population exposure and vulnerability to flood risk, in order to further narrow down targets for intervention. This would then provide the building blocks of an Impact-based Forecasting system, following WMO guidelines WMO (2015).

Finally many preparedness actions are limited by the lead-time of the HRA. They are often issued in the morning of or the day before the expected start to the rainfall, leaving a small window to coordinate and implement preparedness. A longer lead heavy rainfall forecast would extend the scope of preparedness actions. Currently the time afforded by existing 7- and 5-day forecasts from KMD could be used by KRCS to prepare higher-cost actions, which are finally triggered upon the issuance of a HRA for the next few days. This approach would be analogous to the ready-set-go approach of the Red Cross designed to integrate seasonal forecasts into decision making, adapted to a much shorter overall anticipation window (Bazo et al., 2019).

However the provision of forecasts at even longer lead-time could further enlarge the window for preparedness. For instance, subseasonal forecasts have been shown to have skill out to several weeks ahead (Vitart et al., 2017) and there is clear potential for warnings on this timescale to inform humanitarian preparedness (White et al., 2017), Evaluation of these timescales is being carried out as part of the ForPac project which has identified potential utility over Kenya and these subseasonal forecasts are currently being trialed at KMD after being made available in real-time as part of phase two of the S2S project (Kilavi et



al. 2019, MacLeod et al. in preparation). The longer lead time of these rainfall forecasts can afford KRCS more flexibility and potential for early preparedness.

4.2.2 Improving flood forecasting

Explicit modelling of local hydrology is necessary to provide accurate forecasts of flood risk, rather than reliance on rainfall forecasts alone. Although here we do find that HRAs warn of the most significant flooding events (consistent with the analysis of Robbins and Titley (2018), who also find a good relationship between precipitation forecasts and heavy impacts across the globe), it is unlikely that flood impacts will always be felt after heavy rainfall. Or indeed it is not the case that heavy rainfall is always necessary to trigger flood impacts, which can occur with ‘normal’ rainfall if the soil is already saturated (MacLeod et al., in preparation). Accurate characterisation of flood impacts requires consideration of non-meteorological and non-hydrological factors.

A unified national flood modelling and forecasting system would provide KRCS with a standardized view of flood risk across the country, however KMD do not yet have such a system and different approaches are being followed in different basins. Flood forecasting is most developed for the Nzoia basin of western Kenya, where a three-day forecast produced by a basin-scale hydrological model based on monitoring of basin rainfall and soil moisture along with a short range rainfall forecast. Substantial new investment is being made in flood forecasting in Kenya, notably under the World Bank-supported Water Security and Climate Resilience project, which will both upgrade the Nzoia flood forecasting system with a new hydrological model software and will support an extension of river flood early warning systems to other main river basins of Kenya, including upgraded hydro-meteorological observation networks supporting hydrological flood forecast models. This will help to provide more targeted relevant flood forecasts, and as the hydrological monitoring network is expanded this will help to evaluate the background level of flood risk, supported by new hydrological model simulations. Other parallel related activities include: the SHEAR HiPac project, which for the Nzoia river basin will map inundation risk in high resolution and link this to forecasts from the existing system; the EU-supported ECHO project for the Tana River.

In the absence of readily available flood forecast information from the NMHS covering the entire country, some national Red Cross societies are now considering the use of ECMWF GloFAS flood forecasts (see Alfieri et al., 2013, and www.globalfloods.eu) to trigger flood EAPs. In Kenya, GloFAS may be an appropriate product whilst the basin scale flood forecasting remains under development in Kenya and there remains no unified national flood forecasting system. Whilst GloFAS is advantageous as it is freely available with national coverage, the GloFAS forecasts are unable to take advantage of real-time local hydrological observations to initialise the model, limiting the forecast skill. A locally-calibrated model which assimilates initial hydrological states would likely provide the optimal basin-scale flood risk forecast. In addition the need for GloFAS forecast verification remains outstanding for most basins. KRCS should work with relevant organisations to undertake this analysis. Further, use of GloFAS should be sensitive to issues of national ownership of warnings systems.

Ultimately the evaluation of HRA presented here should be put in the context of flood preparedness systems such as the KRCS flood hazard EAPs. It points to the need, now widely recognised, for strengthened co-production of forecast information and products which support the effective uptake of forecasts into risk management systems. In Kenya, recent projects



480 exemplify this approach including ForPac, WISER SCIPEA and W2SIP, whilst the national Early Warning-Early Action plat-
form convened by KRCS in September 2019 brought together relevant national actors. Co-ordinated verification of existing
forecast products such as the HRA presented here will help to integrate these into systematic preparedness activities. Whilst in
this case the current form of the HRA may preclude their use as a trigger for the KRCS EAPs, they are able to effectively warn
of heavy rainfall and should therefore take a key role in a seamless approach toward mitigating the risk from risks associated
485 with heavy rainfall across Kenya.

Author contributions. All authors collaborated on the development of the verification strategy and contributed to the manuscript. MK, EM and DM digitized the advisories whilst PR advised on the use of EM-DAT database and extracted flood impact data. DM co-ordinated the study and wrote the text.

Competing interests. The authors declare no competing interests.

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References

- Alfieri, L., Burek, P., Dutra, E., Krzeminski, B., Muraro, D., Thielen, J., and Pappenberger, F.: GloFAS-global ensemble streamflow forecasting and flood early warning, *Hydrology and Earth System Sciences*, 17, 1161, 2013.
- Amoako, C. and Frimpong Boamah, E.: The three-dimensional causes of flooding in Accra, Ghana, *International Journal of Urban Sustainable Development*, 7, 109–129, 2015.
- 500 Bazo, J., Singh, R., Destrooper, M., and de Perez, E. C.: Pilot Experiences in Using Seamless Forecasts for Early Action: The “Ready-Set-Go!” Approach in the Red Cross, in: *Sub-Seasonal to Seasonal Prediction*, pp. 387–398, Elsevier, 2019.
- CIESIN: Gridded Population of the World, Version 4 (GPWv4): Population Count Adjusted to Match 2015 Revision of UN WPP Country Totals, Revision 11., <https://doi.org/10.7927/H4PN93PB>, 2018.
- 505 Coughlan de Perez, E. R., Van den Hurk, B., Van Aalst, M. K., Amuron, I., Bamanya, D., Hauser, T., Jongma, B., Lopez, A., Mason, S. J., Mendler de Suarez, J., et al.: Action-based flood forecasting for triggering humanitarian action, *Hydrology and Earth System Sciences*, 20, 3549–3560, 2016.
- EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, www.emdat.be, 2020.
- Finney, D. L., Marsham, J. H., Walker, D. P., Birch, C. E., Woodhams, B. J., Jackson, L. S., and Hardy, S.: The effect of westerlies on east african rainfall and the associated role of tropical cyclones and the madden–julian oscillation, *Quarterly Journal of the Royal Meteorological Society*, 2019.
- 510 Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al.: The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes, *Scientific data*, 2, 1–21, 2015.
- Gall, M., Borden, K. A., and Cutter, S. L.: When do losses count? Six fallacies of natural hazards loss data, *Bulletin of the American Meteorological Society*, 90, 799–810, 2009.
- 515 Gros, C., Bailey, M., Schwager, S., Hassan, A., Zingg, R., Uddin, M. M., Shahjahan, M., Islam, H., Lux, S., Jaime, C., et al.: Household-level effects of providing forecast-based cash in anticipation of extreme weather events: Quasi-experimental evidence from humanitarian interventions in the 2017 floods in Bangladesh, *International Journal of Disaster Risk Reduction*, 41, 101 275, 2019.
- Kilavi, M., MacLeod, D., Ambani, M., Robbins, J., Dankers, R., Graham, R., Titley, H., Salih, A. A., and Todd, M. C.: Extreme rainfall and flooding over central Kenya including Nairobi city during the long-rains season 2018: causes, predictability, and potential for early warning and actions, *Atmosphere*, 9, 472, 2018.
- 520 MacLeod, D. and Caminade, C.: The moderate impact of the 2015 El Niño over East Africa and its representation in seasonal reforecasts, *Journal of Climate*, 32, 7989–8001, 2019.
- NECC: Solai Dam Report, November 12th 2018, Tech. rep., National Environmental Complaints Committee, <https://perma.cc/66E4-R9L2>, 2018.
- 525 OCHA: Flash Update 6: Floods in Kenya 7th June 2018, Tech. rep., UN Office for the Coordination of Humanitarian Affairs, <https://perma.cc/B47A-HSYF>, 2018.
- reliefweb: Kenya: Floods and Landslides - Oct 2019, Tech. rep., reliefweb, <https://perma.cc/8C4Q-HTQQ>, 2019.
- Robbins, J. and Titley, H.: Evaluating high-impact precipitation forecasts from the Met Office Global Hazard Map (GHM) using a global impact database, *Meteorological Applications*, 25, 548–560, 2018.
- 530 Siderius, C., Gannon, K., Ndiyoi, M., Opere, A., Batisani, N., Olago, D., Pardoe, J., and Conway, D.: Hydrological response and complex impact pathways of the 2015/2016 El Niño in Eastern and Southern Africa, *Earth’s Future*, 6, 2–22, 2018.



- Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., Déqué, M., Ferranti, L., Fucile, E., Fuentes, M., et al.: The subseasonal to seasonal (S2S) prediction project database, *Bulletin of the American Meteorological Society*, 98, 163–173, 2017.
- 535 Weingärtner, L., C. J., M. T., S. L., S. M., and D. M.: Reducing flood impacts through forecast-based action: Entry points for social protection systems in Kenya, Tech. rep., ODI (Overseas Development Institute), <https://www.odi.org/sites/odi.org.uk/files/resource-documents/12645.pdf>, 2018.
- White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J., Lazo, J. K., Kumar, A., Vitart, F., Coughlan de Perez, E., Ray, A. J., Murray, V., et al.: Potential applications of subseasonal-to-seasonal (S2S) predictions, *Meteorological applications*, 24, 315–325, 2017.
- 540 Wilkinson, E., Weingärtner, L., Choularton, R., Bailey, M., Todd, M., Kniveton, D., and Cabot Venton, C.: Forecasting hazards, averting disasters: implementing forecast-based early action at scale, Tech. rep., Overseas Development Institute (ODI), 2018.
- WMO: WMO Guidelines on Multi-Hazard Impact-Based Forecast and Warning Services, 2015.



	Kenya Meteorological Department	P.O. Box 30259-00100, Ngong Road, Dagoretti-Corner, Nairobi. Tel: +2542038567880-5, +254724255153-4 Email: director@meteo.go.ke
	Heavy Rain & Storm Advisory	
Message Type:	Heavy rain /storm	
Message Update No.:	One	
Date of Origin:	13 th January 2016, 1200 UTC	
Validity:	15 th to 17 th January 2016	
Severity:	Mild to Moderate	
Certainty:	Probability of occurrence (33%)	
Message Description:	Rainfall of more than 30 millimeters is likely to occur over some areas of Mount Kenya and South Rift Regions on 15 th and 16 th , including Nairobi and Kiambu on 17 th January 2016.	
Area(s) of Concern:	These areas include Narok, Bomet, Kericho, Nakuru, Nyahururu, Nyeri, Muranga, Embu, Meru, Kiambu and Nairobi.	
Instructions:	Residents in these areas are advised to be on the lookout for sudden downpours which may cause flash floods. They are advised to exercise caution especially if these rains persist for a long time in one place. Further advisories will be issued as we follow up on the progress of this weather event.	
Message Addressed to:	Media, County Directors of Meteorological services in affected areas and other emergency response institutions.	
Originator:	Director, Kenya Meteorological Department-Headquarters Nairobi	

Figure 1. An example of a heavy rainfall advisory issued by KMD.

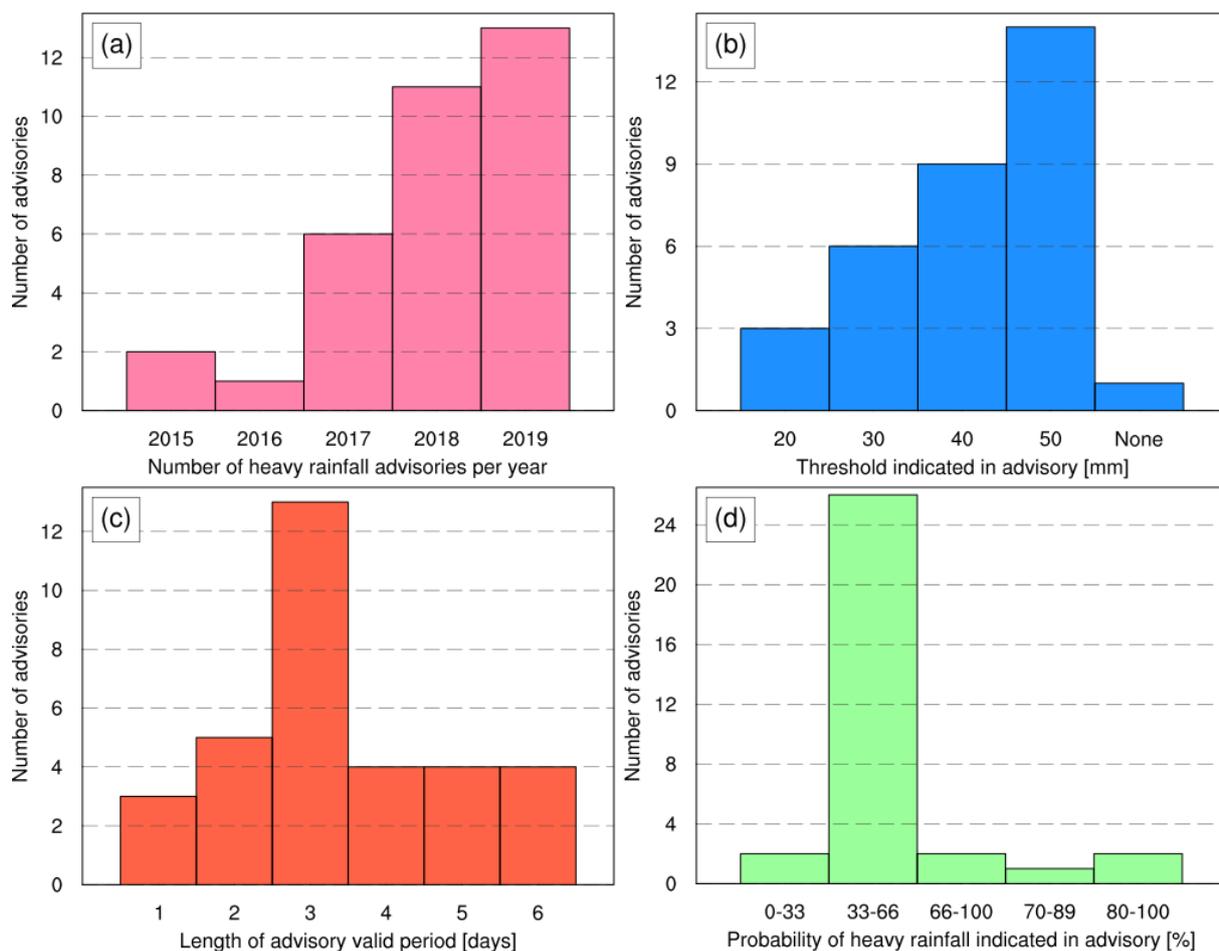
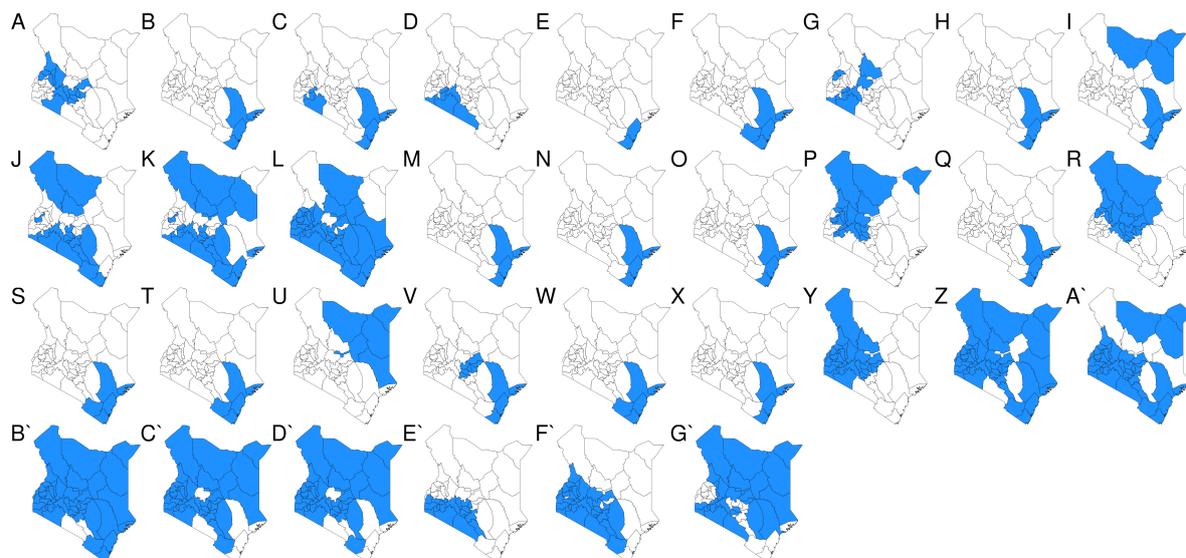


Figure 2. Summary statistics of advisories issued over 2015-2018. Showing (a) the number of advisories issued per year, (b) the rainfall threshold mentioned, (c) the length of the valid period and (d) the probability mentioned.



(a) Counties warned in each advisory



(b) Accumulated rainfall during each advisory window

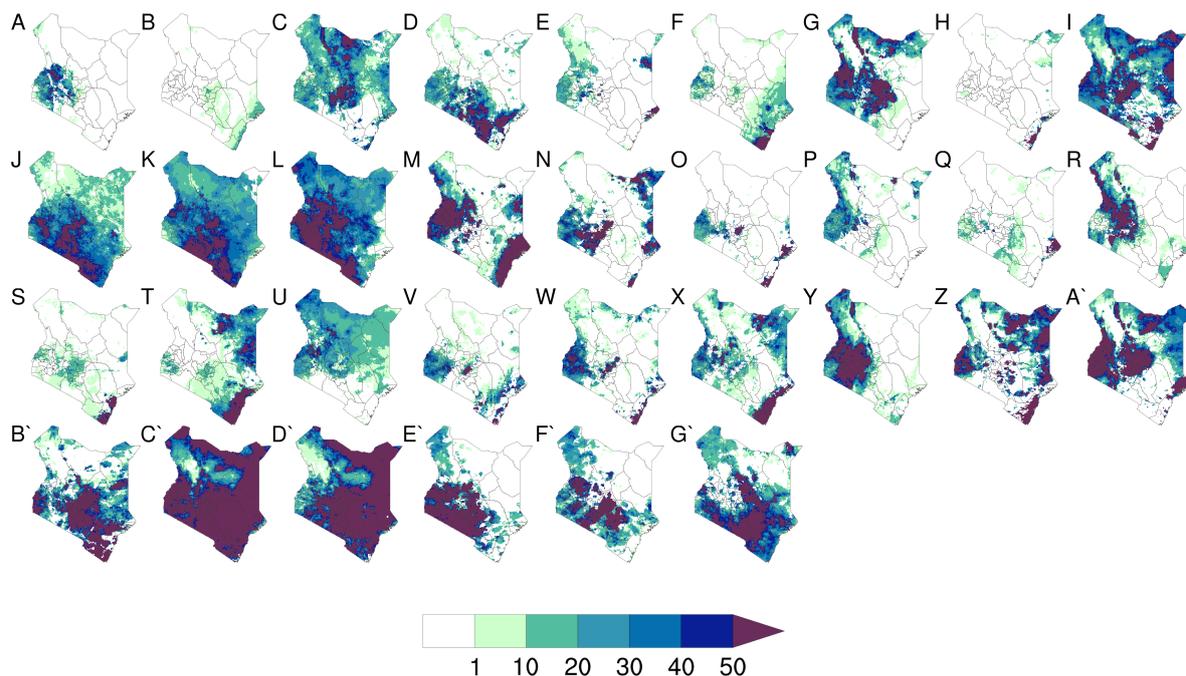
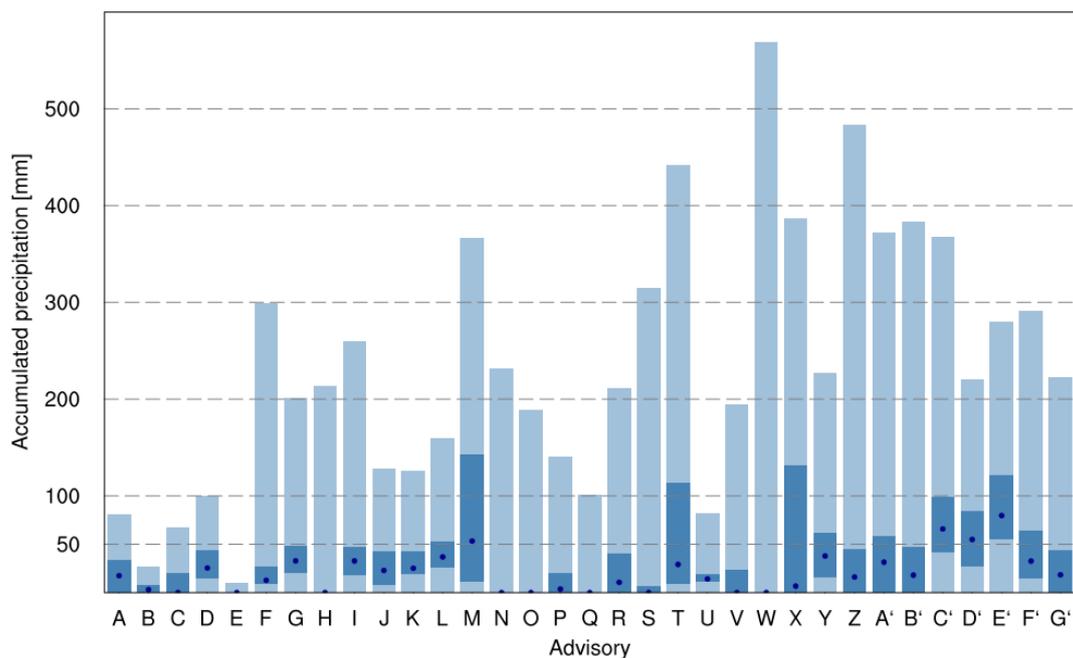


Figure 3. (a) Counties with active warnings for each of the 33 heavy rainfall advisories issued by KMD during 2015-2018 (advisory details are given in table 1). (b) Rainfall accumulations (mm) during each advisory window, based on CHIRPS.



(a) Distribution of accumulation across the area under advisory



(b) Percentage of advisory area receiving threshold accumulation

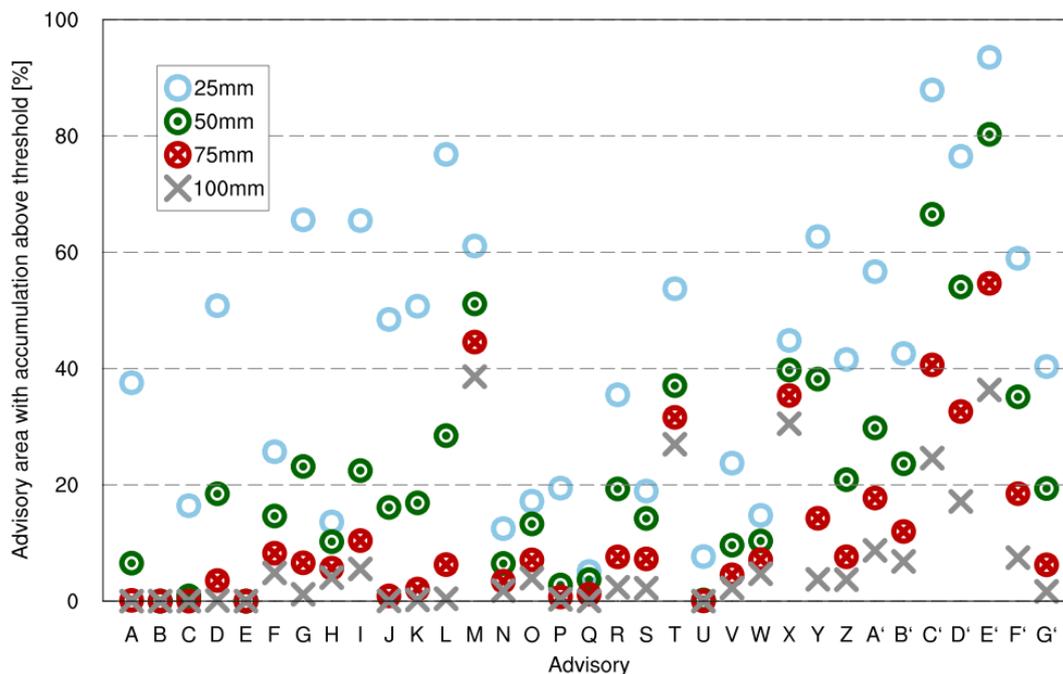


Figure 4. How much rain fell in counties under advisory? (a) Rainfall accumulation during advisory window, showing distribution over all 5km gridpoints within counties mentioned in advisory (dark/light shading shows inner/outer quartiles and dot indicates the median). (b) Percentage of each advisory region where rainfall accumulation was above 25, 50, 75 or 100mm.

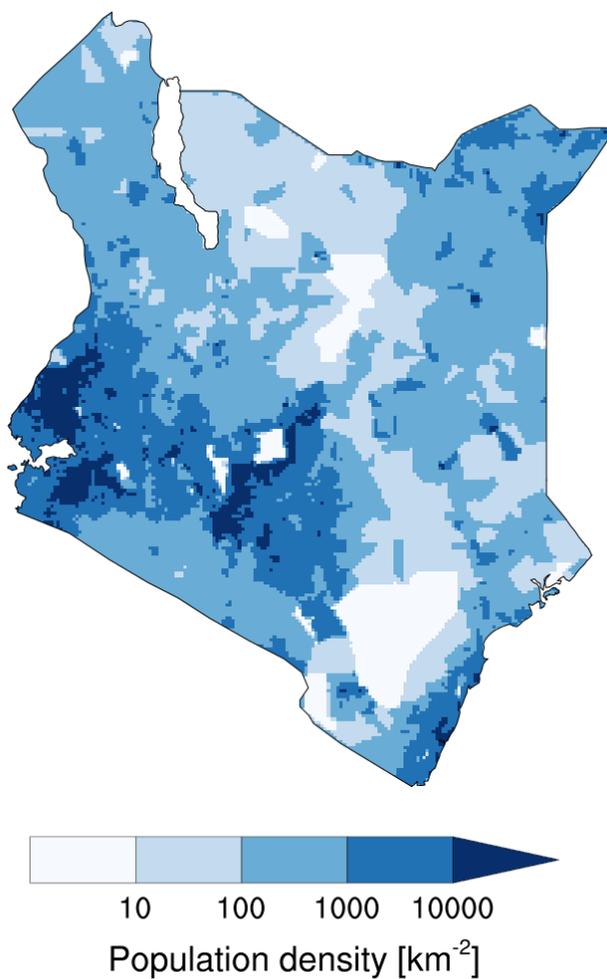
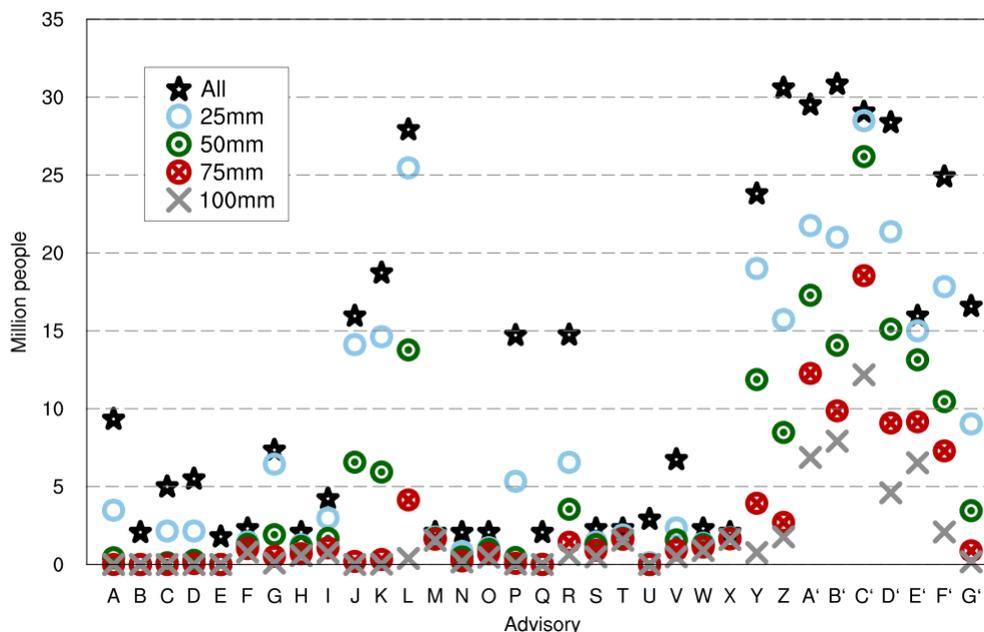


Figure 5. Population density over Kenya, from the Gridded Population of the World Database produced by NASA SEDAC CIESIN (2018))



(a) Population under advisory receiving threshold accumulation



(b) Percentage of warned population receiving threshold accumulation

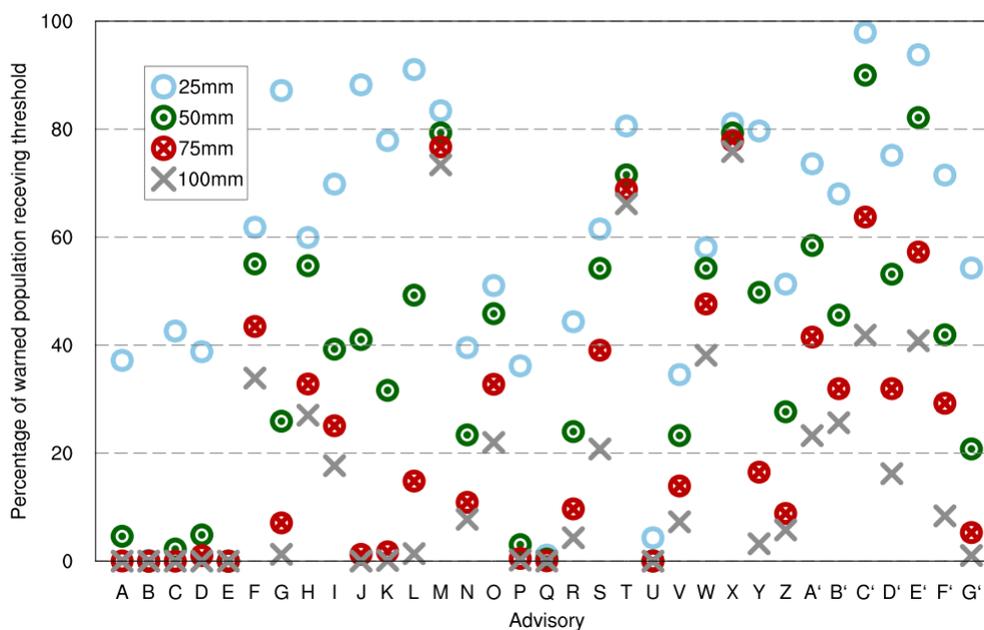


Figure 6. What is the extent of preparedness action implied by advisories? (a) The total population living in the warning region (black star) and the number living in that region also receiving at least 25, 50, 75 or 100mm rainfall over the advisory window. (b) Percentage of the population living in the advisory region and also receiving above-threshold rainfall.

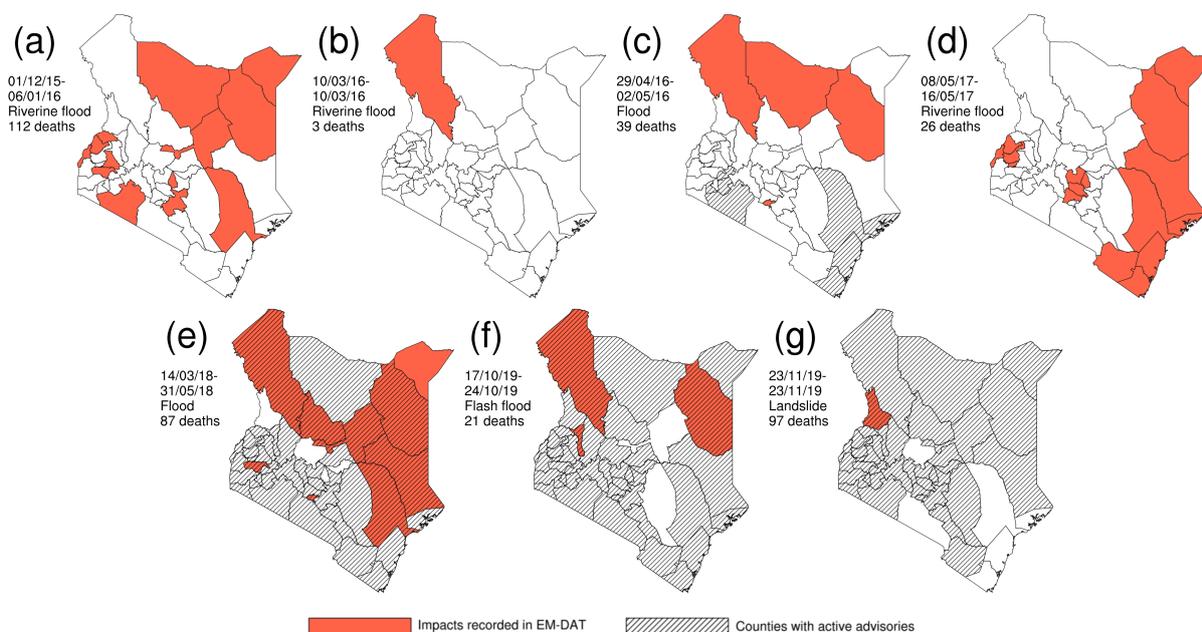


Figure 7. Were the most significant impacts of heavy rainfall preceded by advisories? Showing all seven relevant events extracted from EM-DAT across the advisory period (see section 2.3 for details of event selection). Counties reporting impacts are shown in orange, whilst hatching indicates counties for which warnings were active when the impact was recorded to have begun.

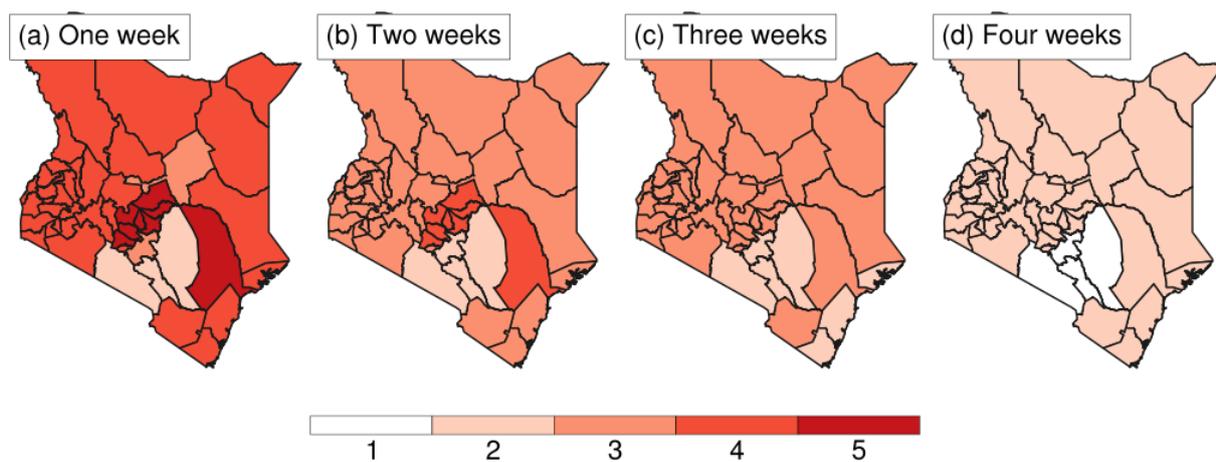


Figure 8. How many times per year might an FbA/F system based on advisories trigger? Showing the number of potential triggers per county during 2019: here we assume that an action is triggered if an advisory is issued, as long as no action had already been triggered in the preceding one, two, three or four weeks (a-d).



Table 1. Summary of all advisories 2015-2019 evaluated in this study

Label	Issue date	Period length	Largest rainfall threshold mentioned	Probability indicated
A	2nd June 2015	2	50mm	33-66%
B	2nd July 2015	2	50mm	0-33%
C	25th April 2016	2	50mm	80-100%
D	18th April 2017	2	50mm	33-66%
E	28th April 2017	1	50mm	70-89%
F	18th September 2017	3	50mm	80-100%
G	11th October 2017	3	50mm	33-66%
H	30th October 2017	2	50mm	33-66%
I	2nd November 2017	4	30mm	66-100%
J	27th February 2018	3	50mm	33-66%
K	9th March 2018	4	40mm	0-33%
L	15th March 2018	4	50mm	66-100%
M	27th April 2018	5	40mm	33-66%
N	2nd May 2018	3	50mm	33-66%
O	7th May 2018	3	50mm	33-66%
P	20th May 2018	1	50mm	33-66%
Q	30th May 2018	1	30mm	33-66%
R	4th June 2018	3	40mm	33-66%
S	24th September 2018	3	50mm	33-66%
T	23rd October 2018	3	40mm	33-66%
U	25th March 2019	3	30mm	33-66%
V	3rd May 2019	4	40mm	33-66%
W	7th May 2019	5	30mm	33-66%
X	22nd May 2019	3	40mm	33-66%
Y	31st May 2019	6	40mm	33-66%
Z	10th October 2019	5	20mm	33-66%
A'	14th October 2019	5	40mm	33-66%
B'	23rd October 2019	6	20mm	33-66%
C'	18th November 2019	6	40mm	33-66%
D'	23rd November 2019	3	30mm	33-66%
E'	28th November 2019	6	30mm	33-66%
F'	3rd December 2019	3	None	33-66%
G'	6th December 2019	3	20mm	33-66%