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The Life and Times of the Weather Risk Attribution Forecast

### Permalink

<https://escholarship.org/uc/item/7r03s6h7>

### Journal

Bulletin of the American Meteorological Society, 103(3)

### ISSN

0003-0007

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### Publication Date

2022-03-01

### DOI

10.1175/bams-d-21-0263.1

Peer reviewed

# The Life and Times of the Weather Risk Attribution Forecast

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The Weather Risk Attribution Forecast (WRAF) provided a testbed for proactive estimation of the human role in extreme monthly events. This paper looks back on issues that the WRAF highlighted.

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**DOI:** 10.1175/BAMS-D-21-0263.1

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In the 2000s, a few studies had demonstrated the potential for evaluating the role of anthropogenic emissions in specific observed weather and climate events (Stott et al. 2004; Hoerling et al. 2007; Yiou et al. 2007; Jones et al. 2008; Perlwitz et al. 2009). Researchers involved in such studies were wondering if these methods could be developed into operational services that would provide an assessment in close to real time (Stott and Trenberth 2009; Stott and Walton 2013). However, research focused on further tests and development of the analysis methods because they were still poorly understood (Otto et al. 2012), leaving creation of operational services until a later date.

We identified a drawback of this approach. While at some time in the future event attribution researchers would supposedly become confident in their attribution methods for evaluating the anthropogenic role, they would have to further their understanding and capabilities to deploy these methods in an operational process (National Academies of Sciences Engineering and Medicine 2016). As a research institute without operational responsibility, the University of Cape Town did nevertheless have expertise in regular provision of climate services, in particular a seasonal climate fore-

cast (Browne Klutse et al. 2016). This provided a suitable environment for developing and testing a prototype operational event attribution service: expertise in climate service provision, no official liability for trying things out, a seasonal climate forecast system to serve as the engine, and expertise in event attribution research (Angélil et al. 2014; Wolski et al. 2014). Hence there was an opportunity to gain experience with quasi-operational production of event attribution information that could be shared with other institutions throughout the world that were considering to develop operational services at a later date. An additional motivation was a possibility that event attribution services would be particularly useful in the African context in terms of monitoring losses and damages to climate change.

With these motivations in mind, we developed the Weather Risk Attribution Forecast (WRAF) system to provide information about the human role in extreme events at the monthly scale (Lawal et al. 2015). The WRAF was designed as a proactive system that would calculate event attribution metrics before the occurrence of the events, with the realization that most analyzed events would never materialize. There were four main objectives:

- 1) to demonstrate the feasibility of a global proactive event attribution system;
- 2) to gain experience with the usage of a proactive event attribution service;
- 3) to share lessons from that experience with other institutions; and
- 4) to provide a preliminary attribution information service.

In this paper we will discuss how these objectives shaped the development of the WRAF, and how successfully it responded to each.

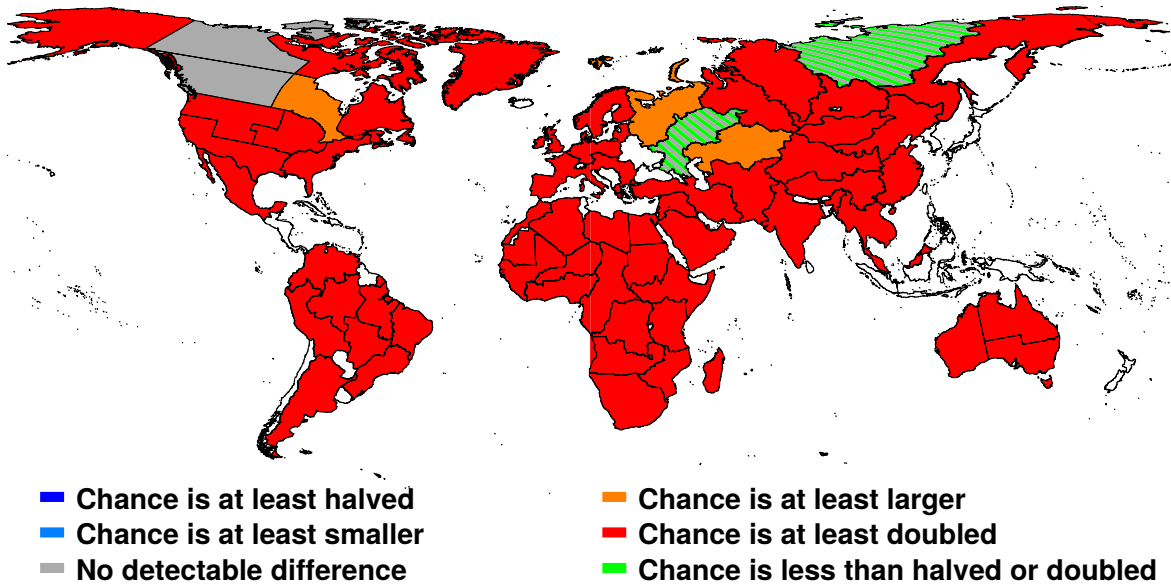
## Design.

A proactive event attribution system, one that performs calculations before any event, could be formed by tying it to an existing seasonal forecast system. The WRAF followed from a then-new method for using simulations of an atmospheric model for event attribution evaluation (Pall et al. 2011) and applied it to the University of Cape Town (UCT) seasonal forecast system. This seasonal forecast comprised a 10-member initial condition ensemble of the HadAM3P-N96 atmosphere–land model (Jones et al. 2004) run at  $1.875^\circ \times 1.25^\circ$  horizontal resolution with observed greenhouse gas concentrations and other radiative forcings. The first month (which we refer to as the hindcast) was driven with observed sea surface temperatures (SSTs; Reynolds et al. 2002), with subsequent months driven by a continuation of the seasonal anomaly from that first month added to the seasonal climatological SSTs; although the simulations extended out an additional three months, we used only the first month with fully forecast SSTs (2 months after the first month) as our forecast period. This persistent-anomaly forecast of SSTs was skillful for the primary oceanic influences on southern African climate, in particular El Niño–Southern Oscillation (ENSO) and the Indian Ocean dipole (Jury et al. 2004), because they tend to vary slowly on monthly to seasonal time scales (Ratnam et al. 2020; Ren et al. 2019). We found no systematic difference between results using the forecast month (with fully forecast SSTs) or hindcast month (with observed SSTs). Attribution estimates for the chance of an unusually hot, cold, wet, or dry month based on the forecast period were posted immediately after completion of the forecast simulations, and updated with replacement estimates three months later based on the hindcast month of the new simulations. In this paper we present sample results produced under the hindcast (observed SST) conditions covering January 2009 through 2011 because we produced additional simulations (a total of 60 per scenario) for this period and hindcast setup. The forecasts were compared to a set of naturalized counterfactual forecast simulations, inspired by previous factual–counterfactual comparisons. Following Pall et al. (2011), we surmised that interest would tend to be in the effect of anthropogenic greenhouse gas (GHG) emissions rather than of all anthropogenic interference. A parallel “non-GHG” forecast explored this effect by rerunning the seasonal

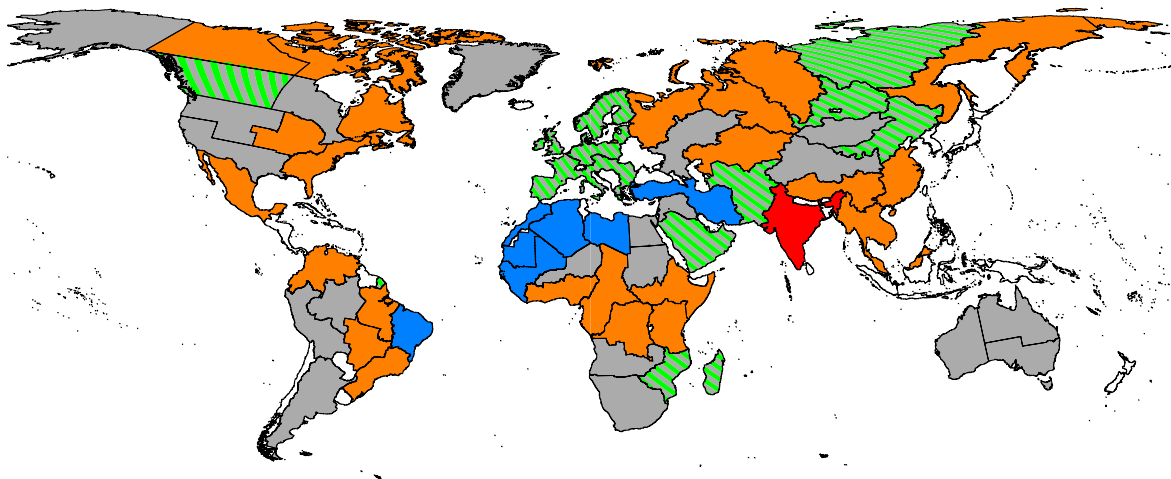
forecast but with greenhouse gas concentrations reduced to preindustrial levels and the SSTs cooled according to a spatially and seasonally varying estimate of the historical warming attributable to anthropogenic emissions based on the HadCM3 atmosphere–ocean model (Pall et al. 2011).

Results were issued monthly online (now available at <http://climate.web.runbox.net/wraf/>), with calculations for unusually hot, cold, wet, and dry monthly averages across 58 terrestrial regions of about 2 million km<sup>2</sup> size (Stone 2019). We only considered monthly averages because of existing support for HadAM3P-N96’s general performance at monthly time scales and to keep assessments to a manageable number of cases. Figure 1 shows how changes in greenhouse gas concentrations altered the chance of an unusually hot and an unusually wet June 2011 in each of the 58 regions (unusually cold maps and dry maps not shown). The question was how have emissions altered the chance of exceedance of the 90th percentile for Junes in historical simulations for all prior years starting in 1960. Calculations were based on Gaussian fits to the 10 (or 60) member ensembles with results categorized according to what could be said with confidence.

### Greenhouse gas role in unusually hot June 2011



### Greenhouse gas role in unusually wet June 2011



**Fig. 1.** The attribution hindcast (i.e., using observed SSTs) issued for June 2011 for the effect of anthropogenic greenhouse gases on the chance of (top) an unusually hot month and (bottom) an unusually wet month in each of 58 regions, using 60 simulations per scenario (issued in August 2011).

## **Selection bias.**

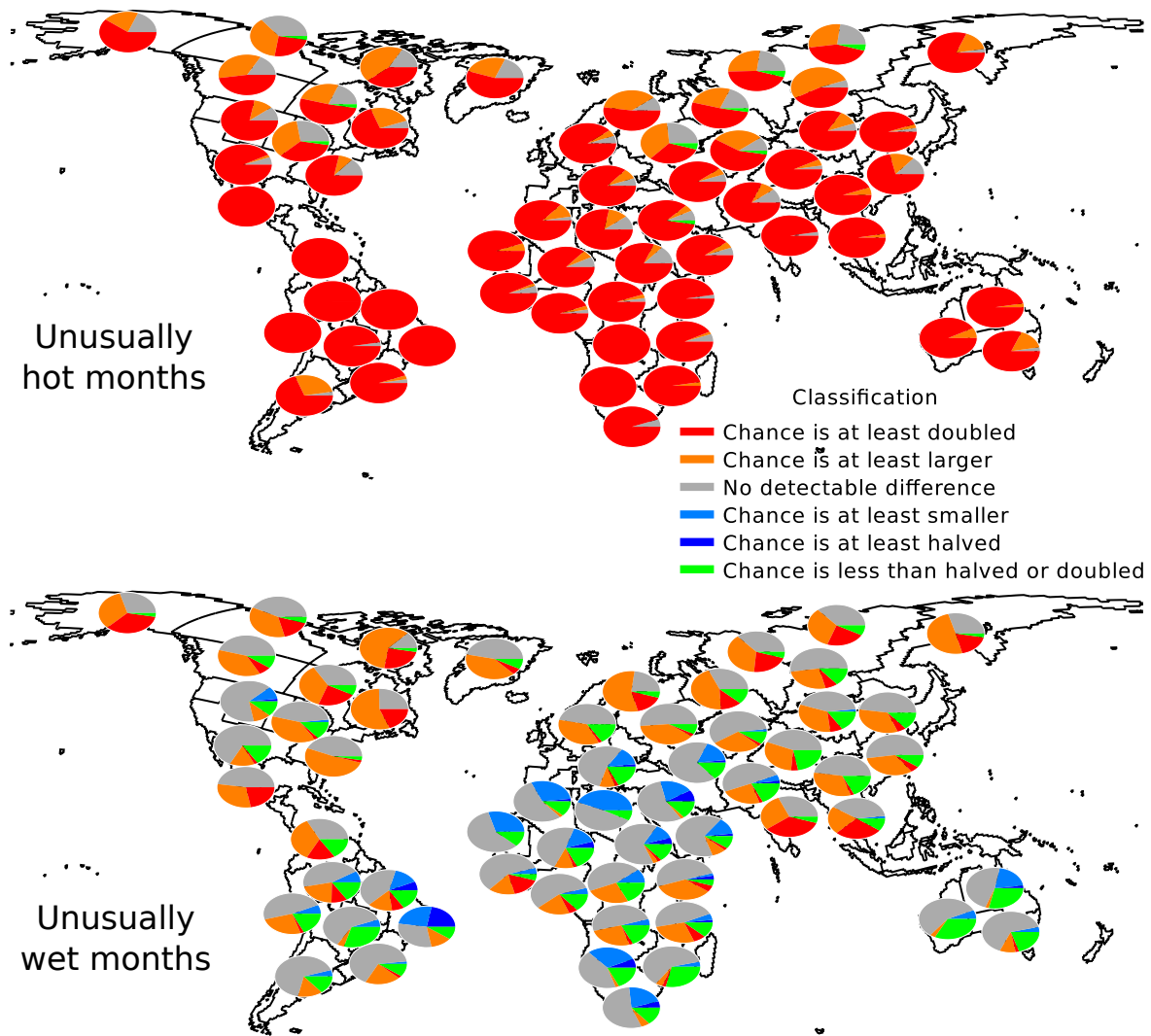
Selection bias poses a major challenge for event attribution analysis (Chase et al. 2006; Christiansen 2015): conclusions can be influenced by selection or definition of extreme events based on event occurrence or by assumptions about causes of their occurrence. For instance, in a synthesis setting it may be relevant if attribution of the cold events that did not occur is not considered, simply because these events hardly ever occur now. The WRAF's proactive operation was specifically designed to minimize post hoc selection bias, by ignoring whether events had occurred. However, in the end we have concluded that selection bias is an innate feature of any operational event attribution service. Anecdotally, we and others (e.g., conference attendees) found that we could still justify consideration of neighboring regions (when trialing with smaller regions), neighboring months, or the same month from other years. Attempts to circumvent this only made the analysis less relevant, for instance outputting to enormous 10 million km<sup>2</sup> regions did not capture colloquial extreme events (Stone 2019). More importantly, selection inevitably occurred through the public communication of conclusions: no one was interested in assessment of events that had not occurred. Nevertheless, we did conclude that proactive services have an application in synthesis monitoring of changing climatic hazard (Risser et al. 2017).

## **Categorization.**

WRAF conclusions were expressed in terms of categories describing what we could say with confidence, for instance that greenhouse gas emissions had “at least doubled” the chance of the event. In our experience this was a successful communication format in the sense that the conclusion seemed to be accurately interpreted by audiences we interacted with. However it did have some quirks. Figure 2 shows the frequency at which each category was assigned to each region over a 36-month period, for unusually hot and unusually wet months. While tropical regions were classified as red (“chance is at least doubled”) in almost all of the 36 months, the northern high-latitude regions were only classified as such about half of the time. In fact the estimated most likely risk ratios tended to be similar (considerably greater than 2) for the tropical and high-latitude regions, but the higher endogenous month-to-month variability in northern high-latitude regions during winter produced a broader confidence interval and hence less frequent allocation of the confidently “at least doubled” category (and even of the “at least increased” category) (Risser et al. 2017).

## **Question of demand.**

A number of possible users of event attribution information had been identified by the research community around the time of the start of the WRAF project, including a test bed for improving our understanding of the climate system, a response to public demand during the occurrence of events, evidence for litigation, insight into adaptive capacity and adaptive needs, monitoring of geoengineering efforts, and support for more adaptive insurance (Stott et al. 2013). Two of these could be particularly relevant for Africa: event attribution information could inform international loss and damage claims, by demonstrating whether “dangerous anthropogenic interference with the climate system” had occurred within African territories; event attribution information might be used to monitor the actual degree of climate resilience achieved, supporting the strong interest that African economic development should be resilient to plausible future climate change. We did not actively engage with potential non-research audiences, but interest in African-specific applications seemed limited during the course of the project, in part because the concept of reparation for attributable losses and damages runs counter to a policy of supporting general sustainable development in Africa (Huggel et al. 2016; Parker et al. 2017). We also had some anecdotal experiences that suggested that evidence produced by African institutions would not be considered as credible.



**Fig. 2. Maps showing the frequency of categorization for unusually hot months and unusually wet months during the January 2009 through December 2011 period. These particular plots are based on the hindcast (observed SSTs) simulations, during three years with 60 simulations per scenario.**

### Legacy.

After seven years, the WRAF ceased operation with the March 2017 attribution forecast. Most pressingly, UCT was ceasing its seasonal forecasting product, meaning the WRAF would have to be a stand-alone activity. More generally, the WRAF had achieved its original objectives, through demonstration and experience of a proactive event attribution system, and sharing that experience in such venues as the international Attribution of Climate Events (ACE) series of workshops (Stott and Walton 2013; Stott et al. 2013) and a major report on the status of event attribution science (National Academies of Sciences, Engineering, and Medicine 2016). These contributions helped inform the first generation of event attribution services at mandated institutions around the world, and thus reducing the requirements for further testbeds.

Perhaps ironically, one of the main contributions of the WRAF was in highlighting how event attribution research was hindered by the lack of data products designed specifically in support of that research. This led to the International CLIVAR C20C+ Detection and Attribution project (Stone et al. 2019), a multi-institution, multimodel effort to produce petabytes of climate model data for event attribution research, which is based on many of the protocols developed and tested on the WRAF test bed. Although it is no longer running, the legacy of the WRAF is visible in a number of research and service activities around the world.

**Acknowledgments.** Development and operation of the WRAF was supported by Microsoft Research, the South African Water Research Commission under contract K5-2067, and the Director, Office of Science, Office of Biological and Environmental Research of the U.S. Department of Energy under Contract DE340AC02-05CH11231. Knowledge transfer was also supported by the U.S. National Oceanic and Atmospheric Administration's Climate Program Office; the International Meetings on Statistical Climatology; the U.K. Foreign and Commonwealth Office; and the World Climate Research Programme. This paper was written with support from the Endeavour Whakahura project of the Ministry of Business, Innovation and Employment of Aotearoa New Zealand. We thank two reviewers for their help in improving the manuscript.

**Data availability statement.** Data from the WRAF are available from the C20C+ D&A project's archive at <https://portal.nersc.gov/c20c/data.html>, under the UCT-CSAG/HadAM3P-N96/All-Hist/est1/v1-0 (forecast/hindcast) and UCT-CSAG/HadAM3P-N96/NonGHG-Hist/HadCM3-p50-est1/v1-0 (naturalized forecast/hindcast) labels.

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