This paper provides an updated analysis of observed changes in extreme precipitation using high quality station data up to 2018. We examine changes in extreme precipitation represented by annual maxima of one day (Rx1day) and five-day (Rx5day) precipitation accumulations at different spatial scales and attempt to address whether the signal in extreme precipitation has strengthened with several years of additional observations. Extreme precipitation has increased at about two thirds of stations and the percentage of stations with significantly increasing trends is significantly larger than that can be expected by chance for the globe, continents including Asia, Europe, and North America, and regions including C. North-America, E. North-America, N. Central-America, N. Europe, Russian-Far-East, E.C. Asia, and E. Asia. The percentage of stations with significantly decreasing trends is not different from that expected by chance. Fitting extreme precipitation to generalized extreme value distributions with global mean surface temperature (GMST) as a co-variate reaffirms the statistically significant connections between extreme precipitation and temperature. The global median sensitivity, percent change in extreme precipitation per Kelvin increase in GMST is 6.6% (5.1 to 8.2%, 5–95% confidence interval) for Rx1day and is slightly smaller at 5.7% (5.0 to 8.0%) for Rx5day. The comparison of results based on observations ending in 2018 with those from data ending in 2000–2009 shows a consistent median rate of increase, but a larger percentage of stations with statistically significant increasing trends, indicating an increase in the detectability of extreme precipitation intensification, likely due to the use of longer records.
A global, continental and regional analysis of changes in extreme precipitation

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Abstract

This paper provides an updated analysis of observed changes in extreme precipitation using high quality station data up to 2018. We examine changes in extreme precipitation represented by annual maxima of one day (Rx1day) and five-day (Rx5day) precipitation accumulations at different spatial scales and attempt to address whether the signal in extreme precipitation has strengthened with several years of additional observations. Extreme precipitation has increased at about two thirds of stations and the percentage of stations with significantly increasing trends is significantly larger than that can be expected by chance for the globe, continents including Asia, Europe, and North America, and regions including C. North-America, E. North-America, N. Central-America, N. Europe, Russian-Far-East, E.C. Asia, and E. Asia. The percentage of stations with significantly decreasing trends is not different from that expected by chance. Fitting extreme precipitation to generalized extreme value distributions with global mean surface temperature (GMST) as a co-variate reaffirms the statistically significant connections between extreme precipitation and temperature. The global median sensitivity, percent change in extreme precipitation per Kelvin increase in GMST is 6.6% (5.1 to 8.2%, 5–95% confidence interval) for Rx1day and is slightly smaller at 5.7% (5.0 to 8.0%) for Rx5day. The comparison of results based on observations ending in 2018 with those from data ending in 2000–2009 shows a consistent median rate of increase, but a larger percentage of stations with statistically significant increasing trends, indicating an increase in the detectability of extreme precipitation intensification, likely due to the use of longer records.
1. Introduction

Long-term change in extreme precipitation has been the subject of extensive investigation based on a range of indices and detection methodologies. The annual maximum amount of precipitation accumulated over one day (Rx1day) or five consecutive days (Rx5day) are two important indices, representing extreme precipitation for moderate duration or more persistent events that often cause severe impacts on society. Long-term changes in these indices have been analyzed in numerous studies and various assessments of the Intergovernmental Panel on Climate Change (IPCC, e.g. IPCC 2012; 2013). These annual extremes have also been used to estimate the probability of rare events such as 100-year return values, which are used in the design of infrastructure. Several previous studies have examined the trends in these annual precipitation statistics over global (Alexander et al. 2006; Asadieh and Krakauer 2015; Donat et al. 2013a, b; Westra et al. 2013) and Northern Hemisphere land areas (Groisman et al. 2005; Min et al. 2011; Zhang et al. 2013), different continents (Min et al. 2011; van den Besselaar et al. 2013), and in some regions (Barbero et al. 2017; Donat et al. 2016; Li et al. 2018). The IPCC 5th Assessment concluded that “it is likely that since about 1950 the number of heavy precipitation events over land has increased in more regions than it has decreased” (Hartmann et al. 2013).

Extreme precipitation over land has intensified on average, with about two-thirds of stations showing increases in Rx1day (Groisman et al. 2005; Alexander et al. 2006; Donat et al. 2013b; Westra et al. 2013). Westra et al. (2013) estimated that the observed increase in Rx1day per degree increase in global mean surface temperature (GMST) ranged from 5.9%/K to 7.7%/K, which is close to the intensification expected from the Clausius-Clapeyron relationship (~7%/K, Boer et al., 1993; Allen and Ingram 2002; O’Gorman 2015).
Most recent global studies of observed changes in extreme precipitation have used the HadEX2 dataset (Donat et al. 2013b) or its earlier version (Alexander et al. 2006), analyzing either station values (e.g. Westra et al. 2013) or gridded values (e.g. Donat et al. 2013b, Asadieh and Krakauer 2015). Some of these studies analyzed only Rx1day (e.g. Westra et al. 2013) while other studies examined more indices (e.g. Donat et al. 2013b). As HadEX2 ends in year 2010, it is important at the time of the IPCC 6th Assessment to ask if the earlier results continue to hold and whether the climate change signal in extreme precipitation has strengthened given the additional precipitation observations and additional warming that has occurred over the past nine years. It is also useful to ask if the changes in extreme precipitation are detectable at the regional scale.

In order to address these questions, here we first update the global analysis of observed changes in daily extreme precipitation of Westra et al. (2013), using the same methodologies but with additional recent observations. This provides a reference for comparison with the earlier study regarding the influence of the additional observations that have accumulated over the past nine years. Building on this, we then substantially expand the earlier study. One extension is to include Rx5day in our analysis as it provides an indication of the extremes of wet conditions persisting over several days that may be linked to widespread regional flooding and landslide disasters. Another important extension is to examine precipitation trends at different spatial scales including global, continental, and regional scales. As an updated version of HadEX2 was not available at the time of this analysis (although HadEX3 now exists (Dunn et al. 2020)), we used a combination of station-based Rx1day and Rx5day data available from various sources that contributed to HadEX2, and Rx1day and Rx5day data from stations that were not available to HadEX2 such as a large collection of Chinese data. This approach is designed to provide as
comprehensive a picture as possible of past changes in extreme precipitation over land areas from global to regional scales. As observations are lacking for many stations prior to the 1950s, we will report results for two periods, 1950-2018 and 1900-2018. The paper is structured as follows: We describe the station data and analysis methods in section 2. The main results are presented in section 3. Conclusions are given in section 4.

2. Data and methods

a. Precipitation data

In this study we first assemble comprehensive up-to-date Rx1day and Rx5day datasets modelled after HadEX2. We started collecting and compiling Rx1day and Rx5day data from some of the main sources on which HadEX2 was based. These include the following: the European Climate Assessment Dataset (ECA&D, https://www.ecad.eu//dailydata/index.php, 1900–2018), Southeast Asian Climate Assessment and Dataset (SACA&D, http://sacad.database.bmkg.go.id/dailydata/index.php, 1900–2017), Latin American Climate Assessment and Dataset (LACA&D, http://lacad.ciifen.org/dailydata/index.php, 1900–2015), and GHCNDEX (Donat et al, 2013b) for the United States and India. Some of these records, notably those for India, end in the 1970s. We extract station data from these sources for the stations included in HadEX2, which represents the latest acquisition of high-quality station data around the globe. For example, in HadEX2, the subset of stations judged to be more likely to be free of discontinuities after 1950 caused by changes in station location were chosen for the U.S. by following the analysis by Peterson et al (2008), who only selected National Weather Service Cooperative and First-Order weather observing sites with reasonably long records. Some HadEX2 data were also obtained from various regional data workshops (Aguilar et al. 2009;
Caesar et al. 2011; Donat et al. 2014). If the station data are not updatable from the above data sources, we retained the data present in the HadEX2 data set. Additionally, there were some data in HadEX2 that were not made publicly available due to data restrictions at the country of origin (e.g. Argentina). We therefore supplemented our data for Argentina by extracting 52 stations from the ETCCDI Climate Extreme Indices dataset (http://etccdi.pacificclimate.org/data.shtml).

Other stations used in this study are from the existing compiled and packaged datasets supplied by the National Meteorological and Hydrological Services of their countries. We include the Adjusted and Homogenized Canadian Climate Data – Daily Temperature and Precipitation (Mekis and Vincent 2011), which includes adjusted daily precipitation for more than 460 Canadian locations. We use 840 Chinese stations available from the China Meteorological Administration, Russian data available from Russian Meteorological Service (http://meteo.ru/english/climate/d_temp.php) and Australian data from the Australian Bureau of Meteorology (http://www.bom.gov.au/climate/change/datasets/datasets.shtml). Data from the China Meteorological Administration have been tested for inhomogeneities and have been assessed for vigorous quality control to eliminate any spurious values. Australian data dataset is based on a historical rainfall dataset first documented in Lavery et al. (1992), that has been quality controlled by identifying and removing problematic records using statistical techniques, visual checks and station history information. Since Rx1day and Rx5day values are not provided directly by these various sources, we used daily precipitation from these sources to calculate the indices, using the same criteria for the completeness of daily records used in the HadEX2 dataset. Thus, (monthly) index values were calculated only if no more than three daily observations were missing in a month and accordingly no more than 15 daily observations per year for the annual indices. If one or more of the monthly index values for a given year was
missing, the corresponding annual index value was set to a missing value flag for that year. When sites from different sources overlapped, we retained those from the compiled and packaged datasets supplied by National Meteorological and Hydrological Services in preference to those from the ECA&D/SACA&D/LACA&D/GHCNDEX datasets since the former have been, at minimum, carefully quality controlled and in some cases, adjusted to improve homogeneity.

Overall, we were able to collect Rx1day and Rx5day data from 14796 land-based observing stations, with each station having at least 30 years of record during 1900–2018. Figure 1 shows a map of station locations classified by sources. The collection includes 5561 stations with data updated to year 2015 or later, which are mostly located in Canada, China, Europe, Russia, southeastern Australia, and the US. Additionally, there are 8040 stations for which data availability stopped in 2009. Compared with Westra et al. (2013) who analyzed 8326 stations with more than 30 years of record over the period of 1900–2009, this represents a 75% increase in the total number of stations, resulting in improved spatial coverage including for Russia and China that were sparsely sampled by the earlier study. There is, however, little improvement over most of Africa, South America, and West Asia, where spatial coverage of stations is still very poor. In addition, prior to 1950 most station records are confined to North America, Europe, South Asia, the Amazon, and Australia. The number of stations increase notably after 1950s (Figure 1b), with 12323 stations having at least 30 years of record during 1950–2018. The Westra et al. (2013) results based on stations with at least 30 years record during 1900–2009 were heavily weighted to changes since the 1950s rather than the whole century, although they found consistent results when using smaller subsets of stations with at least 50 and 70 years of
record over the same time window. For these reasons, we will analyze two periods, one starting from 1950 and another covering the whole period.

We restrict our analyses to stations that have at least 70% of the annual Rx1day/Rx5day data within the corresponding period (at least 48 years and 83 years for the 1950-2018 and 1900-2018 periods, respectively). In practice, this 70% lower bound for temporal completeness results in a collection of stations for which the median level of temporal completeness is about 85%. This is important, because the power of the trend detection test is reduced when records are shorter. A total of 7293 and 1974 stations, respectively, met the 70% completeness criterion for these two periods.

The completeness criterion represents a tradeoff between the power of the trend detection tests we use and spatial coverage. A higher requirement for temporal completeness would result in a substantial reduction of spatial coverage, with the number of complete stations for 1950-2018 dropping to only 855 if we were to require 100% complete records. We have subsampled the 855 complete records in various ways to mimic how data might be missing to evaluate the impact of records with different proportions of missing years, and different placements of those years within the record, on the power of trend detection and our estimates of the sensitivity of extreme precipitation to warming (see details in Figures S1 and S2). We find, not surprisingly, that the rate at which significant intensification is detected is reduced when records contain fewer years. On the other hand, our sensitivity estimates are not largely affected by missing data, but may become more uncertain when records contain few years and all stations have the same missing data profile.

To enable comparison between results presented here and those of Westra et al. (2013), we also analyzed the data for the stations with at least 30 annual maxima, and present the results in
the supplementary material. In addition, we also conduct a comprehensive analysis over different spatial domains including the global land, continents, and regions used in the IPCC WGI 6th assessment report (Iturbide et al. 2020). For this purpose, we select 22 regions with more than 30 stations that have at least 70% of the annual Rx1day and Rx5day values during the 1950–2018 period (Figure 1c).

Figure 1

b. Methods

We use two well-established methodologies that were employed by Westra et al. (2013). These include the estimation of the long-term trend in extreme precipitation and its statistical significance based on non-parametric methods, and quantification of the relationship between extreme precipitation and GMST by fitting generalized extreme value (GEV) distributions to the annual extremes of precipitation with GMST as a covariate. For the latter, we use the GMST of the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS) (Hansen et al. 2010) expressed as temperature anomalies relative to the 1951–1980 mean. These methods are applied to station data separately. Field significance for a region is established using the bootstrap method of Livezey and Chen (1983). These methods are briefly summarized below; more details can be found in Westra et al. (2013).

First, we use the nonparametric Mann–Kendall test (Mann 1945) to identify statistically significant trends in the Rx1day and Rx5day series. The null hypothesis when applying the Mann-Kendall test is that the data are independent and identically distributed (iid). The actual
significance level of the test can differ substantially from the nominal level that is specified when
data are serially dependent, in which case the data can be prewhitened before applying the test
(e.g., Zhang and Zwiers, 2004). Westra et al. (2013), however, showed that serial dependence is
weak in annual maximum precipitation across all global stations, and thus we have not applied a
prewhitening procedure in this study. The test is two-sided, and a trend is considered to be
statistically significant if it is significant at the 5% level. Stations are classified as having
“significant increasing”, “significant decreasing”, or “non-significant” trends depending on the
sign and the absolute value of the test statistic.

Second, the nonstationary GEV distribution is used to quantify the precipitation-
temperature relationship. The cumulative distribution function for a GEV distributed random
variable Z has the form:

\[ G(Z) = \begin{cases} 
\exp \left( - \left[ 1 + \xi \left( \frac{Z - \mu}{\sigma} \right) \right]^{\frac{1}{\xi}} \right) & \text{when } \xi > 0, \ z > \mu - \frac{\sigma}{\xi} \text{ or } \xi < 0, \ z < \mu - \frac{\sigma}{\xi} \\
\exp \left( - \exp \left[ - \frac{z - \mu}{\sigma} \right] \right) & \text{when } \xi = 0, \ z \in \mathbb{R}
\end{cases} \]  

where \( \mu, \sigma, \) and \( \xi \) are the location, scale, and shape parameters, respectively. The distribution can
be made non-stationary, by making one or more of the parameters functions of a covariate. We
would like to examine whether the distributions of the annual maxima are changing with GMST
change. Thus, we fit station Rx1day or Rx5day series to nonstationary GEV distributions
separately, with the location parameter of the distributions \( \mu \) being a linear function of GMST:

\[ \mu = \beta_0 + \beta_1 T \]  

where \( T \) is the GMST anomaly and \( \beta_0 \) and \( \beta_1 \) are the intercept and slope coefficients. Previous
studies have suggested the location-only model is sufficient when considering the precipitation-
temperature relation in observations, with similar results derived from a time-varying scale
parameter model (Westra et al. 2013). The method of the maximum likelihood is used to
estimate the parameters. The statistical significance of this relationship is inferred with the
likelihood ratio test at the 5% level. We classify stations as having “significant positive
association”, “significant negative association”, or “non-significant association” with the
GMST series depending the sign of the slope coefficient and the value of the likelihood ratio
test statistic.

The percentage change in annual extreme precipitation per Kelvin of GMST increase is
estimated with the fitted GEV distributions and interpreted as an estimate of the sensitivity of
extreme precipitation to GMST change. This is achieved by considering how the median of the
fitted distribution, which corresponds to the 2-yr return value, changes conditional on
temperature anomalies of 1 and 0 K from the fitted non-stationary GEV distributions and
interpreting the ratio between the two values as a scaling estimate. Since the \( p \)-th quantile of the
GEV distribution is given by \( \mu + \sigma ((\ln(p))^{-\xi} - 1)/\xi \), where the location parameter \( \mu \) is
given by equation (2), it is easily seen that the sensitivity of the median to 1 K of warming is
given by \( (\frac{\beta_1}{(\beta_0 + \frac{\sigma((\ln(0.5))^{-\xi} - 1))}{\xi}) \times 100\% \).

We estimated the uncertainty of the sensitivity value using a resampling method. We
selected \( n \) years (\( n=69 \) for the 1950–2018 period, \( n=119 \) for the 1900–2018 period) at random
with replacement, and fitted the nonstationary GEV models using the precipitation extremes and
temperatures appropriate to the years selected, which preserves the connection between extremes
and temperature. Then, we estimated the sensitivity from the fitted models. Resampling was
performed 1000 times to develop a sampling distribution for the sensitivity, which was used to
estimate a 5-95% confidence interval for the sensitivity value. Some studies suggested using a
block bootstrapping approach with a block size of two or three, to account for autocorrelation
effects (e.g., Alexander et al. 2006; Kiktev et al. 2003). We compared the outcome of the
conventional spatial bootstrap procedure and the 2-years block bootstrap. The results are similar.
For this reason, we only report results based on the conventional spatial bootstrap procedure. In
addition, we use latitudinal temperature change to adjust local sensitivity values to ensure that
reported sensitivities correspond to latitudinal temperature changes.

Third, the field significance for the ensemble of test results obtained from all stations was
assessed using the method of Livezey and Chen (1983) in order to avoid “false discovery”. All
statistical tests are designed to have a specified false discovery rate (i.e., type I error rate) when
the null hypothesis is true, which is given by the stated significance level. When a 5%
significance level is set, we should expect rejection of the null hypothesis to occur, on average, at
5% of locations when the null hypothesis is true. The Livezey and Chen procedure is used to
determine whether there is evidence that the null hypothesis is being rejected at more locations
than would be consistent with the specified false discovery rate. The procedure does this taking
the effects of the spatial correlation between test results into account. Field significance can be
evaluated for the whole global land area, or a continent or a region. This procedure involves
shuffling the spatial fields of extreme precipitation by year such that data for the same year in the
observation for all stations are kept in the same year in the shuffled series to retain the spatial
dependence. Temperature, however, is not reshuffled, thereby breaking any connection between
extreme precipitation and temperature. After each reshuffling, trends are computed and tested for
statistical significance for both the non-parametric and GEV-based approaches. The bootstrap
sampling is conducted 1000 times. The statistics such as the percentage of stations with
significant trends are used to construct the probability distribution for those statistics. A
particular statistic computed from the original unshuffled data that lies above the 95th percentile
of statistics from the bootstrap sample is considered to be field significant at the 5% significance level.

3. Results and discussion

a. Changes in extreme precipitation since 1950s

1) GLOBAL SCALE

Figure 2 shows the maps of Rx1day and Rx5day trends along with the proportion of stations with a significant positive or negative trend for 1950–2018 and the bootstrap distribution of this proportion when the link between time and the observed sequence of annual maxima is broken. Overall, trends over the space are very noisy with widely scattered increasing and decreasing trends. This is consistent with the Li et al. (2019) finding that a well-constrained estimate of changes in extreme precipitation is difficult to obtain with individual records of limited length and a relatively weak signal compared to background year-to-year variability. There are important patterns, however. There are many more stations showing increasing than decreasing trends, with about two thirds (66%) of stations showing increasing trends and close to one third (34%) showing decreasing trends in Rx1day. This result is very close to the findings in previous studies using HadEX2 station data (Westra et al. 2013) or gridded values (Min et al. 2011). Furthermore, 9.1% of stations show a statistically significant increasing trend, which is much higher than could be expected from random chance alone, as it is far outside of the simulated bootstrap distribution when the link between time and extreme precipitation is broken (indicated by the blue bars in Figure 2b). In contrast, the percentage of stations showing a statistically significant decreasing trend is only about 2.1%, comparable with what one would expect from
random chance (Figure 2c). This means that at the global scale, there is indeed a detectable
increase in Rx1day. Although the spatial distribution of stations with significant increasing trend
is largely random, there is slightly higher concentration in eastern North America, Europe and
South Africa. It is also noted that even though stations with significantly decreasing trends are
largely randomly distributed over space, there are a few relatively well organized areas where the
intensity of extreme precipitation seems to be weakening, such as the Canadian Prairies, some
parts of the western US, Australia, and north China.

Results for Rx5day are very similar to those for Rx1day, with a larger percentage of stations
(10.9%) showing statistically significant increasing trends, which is again highly field
significant. Of all the stations, about 5% show statistically significant increasing trends for both
Rx1day and Rx5day. About 2.3% of stations have statistically significant negative trends in
Rx5day, consistent with what one would expect from random chance.

**Figure 2**

2) RELATIONSHIP WITH GLOBAL MEAN SURFACE TEMPERATURE

Figure 3 provides maps of local extreme precipitation sensitivity to global warming along
with global median sensitivity based on the GEV fitting. About two thirds (68%) of stations
show an increase in Rx1day with warming while the remaining stations show a decrease. The
percentage of stations showing a significant positive relation, at 11.6%, is significantly higher
than what would be expected from random chance alone, while the percentage of stations
showing a significant negative relation is only about 2.4%, consistent with expectations from
random chance. Taking all stations together, the median percentage Rx1day increase is about 6.6% per Kelvin of GMST increase (5.1 to 8.2%/K, 5-95% confidence interval). This value is comparable to that of Westra et al. (2013). Results for Rx5day are similar to Rx1day except the precipitation sensitivity is slightly smaller at 5.7%/K (5.0 to 8.0%/K). As global land warms faster than GMST, precipitation sensitivity is thus smaller than what may be expected from the C-C relation when scaled with land temperature change, although a detailed comparison between global sensitivity and local sensitivity is outside of the scope of this analysis.

To reduce the influence of the uneven geographic distribution of stations, we adopted the area-weighted average method suggested in Westra et al. (2013) to calculate a revised estimate of the sensitivity of Rx1day and Rx5day to GMST. The global land area is divided into 1° × 1° latitude longitude grid boxes. Within each grid box, the mean of the sensitivity values obtained at all stations within that grid box is calculated. An area weighted global average sensitivity is then calculated from the grid box averages. The revised global land sensitivity values, which are slightly lower than their unweighted counterparts, are 6.1%/K and 5.4%/K for Rx1day and Rx5day, respectively. Evidence from climate models suggests that these numbers (either weighted or unweighted) should be roughly representative of global land areas despite incomplete land coverage. In particular, Kharin et al (2013) calculated sensitivities of 20-year return levels of extreme precipitation to warming from CMIP5 (see Figures 5 and 6 their paper), and obtained sensitivities that are relatively uniform over land. Overlaying the locations of the stations used in this study on their map of estimated sensitivities suggests that the available observing network configuration roughly samples land areas where sensitivities are representative of typical values for global land areas.
Figure 3

3) CONTINENTAL SCALE

Figure 4 shows the percentage of station with significant positive or negative trends during the 1950–2018 period over six continents. The percentage of stations with significant negative trends is not field significant for both Rx1day and Rx5day in all continents. The evidence for intensification is field significant in the well gauged continental domains (Asia, Europe, and North America) but not in Africa, South America, and Australasia (including Australia and New Zealand). As also detailed in the following paragraphs, increasing trends in Rx1day and Rx5day can be detected in all continents except Australasia.

Europe has the highest station density used in our analysis with 3510 stations. The fraction of stations exhibiting positive trends is also largest among all continents at about 73% in Rx1day. Among them, there are about 10.7% of stations showing significant positive trends, mostly located in the northern and central Europe where a higher station density can be found. Only 1.1% of stations have significant negative trends, and these are distributed quite randomly over Europe. These results are in general agreement with previous European-wide studies (e.g., Zolina 2012; van den Besselaar et al. 2013) and some national studies (e.g., Blöschl et al. 2012, Zolina 2012, Jones et al. 2013) of changes is daily precipitation in which an increase in extreme winter precipitation over Europe and an increase in extreme autumn, winter and spring precipitation in northern Europe were found. Results for Rx5day are similar to those for Rx1day, except the percentages of stations with increases and with significant trends are both slightly higher.
Asia has a second highest number of gauges, being represented by 1684 stations in our study. The fractions of stations showing increasing trends and statistically significant increasing trends are 62% and 8.1%, respectively, with increases mainly located in southern China and Russia. About 38% stations show a downward trend, mostly in northern China. The percentage of stations showing significant positive trends in Rx5day is slightly higher than that for Rx1day. The percentage of stations with significantly increasing trends lies outside the 95% uncertainty range determined with the 1000 bootstrap realizations under the no-trend hypothesis for both Rx1day and Rx5day (Figure 4), implying that an overall increasing trend in extreme precipitation can be detected. Note that it is more difficult to detect significant increases (or decreases) at smaller spatial scales. For instance, Li et al. (2018) found that fractions of significant increase or decrease in Rx1day in Chinese stations are both within the 95% uncertainty range when a similar method was used. It should be noted that Indian data in GHCN-Daily mostly ends in the early 1970s; thus trends for India can’t be updated this point.

The results for North America are similar to those for Asia and Europe, again showing extreme precipitation has increased in many more locations than where it has decreased in both Rx1day and Rx5day. These results are also consistent with earlier studies (e.g., Barbero et al. 2017), which analyzed changes in extreme precipitation at 733 North American stations for the period from 1950 to 2011. The similarity of our results with those of Barbero et al. (2017) indicates intensification of daily precipitation extremes is robust to differences in sample size.

The spatial coverage of stations over Africa and South America is poor and uneven, making it difficult to infer whether there is an overall significant increasing trend in extreme precipitation in these two continents. Nevertheless, more than 72% of stations available in these continents show positive trends.
Australasia is distinct from other continents in that, amongst available stations, more stations show negative trends than positive trends for both Rx1day and Rx5day. Stations with decreasing trends are mainly located in southwestern and southeastern Australia (Figure 1a, c). The fraction of stations with significant decreases are 4.8% for Rx1day and 7.3% for Rx5day. This is consistent with previous studies that suggested a decrease in extreme precipitation in southwest Western Australia, Southeast Australia and southeast Queensland (Dey et al. 2019). Some of the causes of the observed decrease in the intensity of precipitation extremes in these regions have been linked to changes in circulation, including the southward shift in the subtropical ridge due to Hadley cell expansion (Timbal and Drosdowsky 2013; Whan et al. 2014), external forcing induced reduction in the number of synoptic systems (Hope 2006; Raut et al. 2014; Dey et al. 2019), or changes in the Southern Annular Mode due to ozone depletion over Antarctica and increasing GHGs (Cai et al., 2011; Thompson et al. 2011). However, note that other parts of Australia (e.g. the northwest) have seen observed increases in extreme rainfall including Rx1day (e.g. Alexander and Arblaster 2017). Also, Alexander and Arblaster (2017) and Contractor et al. (2018) found evidence of an overall intensification of Rx1day for Australia as a whole. For example, Alexander and Arblaster (2017) looked into trends in Rx1day and Rx5day averaged over Australia (their Table 3 and Fig 4 for time series) and found increasing Rx1day trends over the period 1911-2010. This somewhat contradicts the findings here but it should be noted that the stations included in this study are primarily located in the regions (southern Australia) where most of the declines in extreme precipitation have been detected. Results for Australia are sensitive to the choice of indices, time period, and dataset used and are heavily affected low frequency modes of variability such as ENSO/IPO (e.g. King et al. 2013),
which makes trend estimation substantially more uncertain. Therefore, some care is required when interpreting the results from this study as ‘Australia-wide’.

Figure 4

Figure 5 displays continental summaries of changes in Rx1day and Rx5day, expressed as percent change per Kelvin GMST increase, as estimated by fitting GEV distribution to precipitation data with GMST as a co-variate. Results indicate significant intensification of extreme precipitation with warming over continents where sufficient data are available to make confident assessments i.e. Europe, Asia, North America. The median sensitivities over these continents for both Rx1day and Rx5day are significantly greater than zero, with median values close to ~7% per Kelvin warming in GMST in Europe and North America, and values that are somewhat smaller in Asia. The sensitivity has a wider spread from bootstrap samples over regions with poor spatial coverage including Africa, South America, and Australasia. Based on available data, sensitivities to warming appear to be positive in Africa and South America, and negative in Australasia.

Figure 5

4) REGIONAL SCALE

Table 1 summarizes trend analysis results for Rx1day and Rx5day over 22 of 45 land regions used in the IPCC WGI 6th Assessment Report that contain at least 30 stations that satisfy
our data completeness criteria. Almost all regions have a higher fraction of stations with positive trends than that with negative trends for Rx1 day, except for N.W. North-America, Russian-Arctic, and S. Australia. Further, statistically significant intensification in Rx1 day is found in seven regions, comprising C. North-America, E. North-America, N. Central-America, N. Europe, Russian-Far-East, E.C. Asia, and E. Asia, with the percentages of stations with significant increases being higher than would be expected in a stationary climate. It should be noted that the percentages of stations with significantly increasing and significantly decreasing trends are both higher than would be expected in a stationary climate in the Russian-Arctic. The results for Rx5 day are similar except night regions (two more than Rx1 day) showed statistically significant intensification. These results indicate again that the intensification of extreme precipitation is widespread since the 1950s, occurring over almost all observed regions based on the data used in this study.

Table 1

Regional results for GEV modelling analysis are listed in Table 2. Overall, Rx1 day and Rx5 day has intensified significantly with warming over ten and eight regions, respectively, though extreme precipitation decreases with warming in the S. Australia region. Donat et al. (2016) showed that Rx1 day averaged over both dry and wet regimes increases with global surface temperature change in both observations and climate models. The dominate increasing trends over dry regions do not change since other arid/semi-arid regions, such as E. Siberia, W. Siberia, W.C. Asia, E.C. Asia, and Tibetan-Plateau, show positive sensitivity value. Overall, results are generally similar to those for long-term trends as summarized in Table 1, the magnitude of sensitivity varies widely. Different factors may have contributed to the wide
sensitivity range, especially for large sensitivity values. These include possible regional forcing
differences, circulation changes that may or may not be due to an anthropogenic influence, and
likely most importantly, differences between the regional and global warming rates. In addition,
sampling variability is expected to be much higher at the regional scale, and this is also likely to
contribute to the wider sensitivity range. The sensitivity in the northern high latitudes becomes
much smaller if changes in precipitation are scaled with latitudinal temperature change since
temperature changes in the high northern latitudes are larger than global mean temperature
changes. This does raise a question regarding which temperature—global, regional, or local
temperature—to use when discussing extreme precipitation sensitivity at the regional scale.
Exactly what temperature to use to satisfactorily approximate the change in saturation vapour
pressure with temperature under non-ideal conditions is far from clear. Several previous studies
summarizing and assessing observed or projected changes in extreme precipitation at a global
scale have used GMST, and thus for comparability as well as its policy relevance (IPCC, 2018),
we do so here as well.

Table 2

b. Changes in extreme precipitation in longer records

Figure 6 displays the percentage of land-based stations globally with significant trends in
relation to sample size. Figure 6a and Table 3 shows results for the 1900–2018 period using 1974
stations that have at least 70% of the annual Rx1day and Rx5day data. These long-term stations
are located mainly in the Northern Hemisphere mid-latitudes and parts of Australia and South
It is clear that extreme precipitation has increased over the region with data coverage. Overall, extreme precipitation has increased in many more regions than where it has decreased, for both Rx1day and Rx5day. The fraction of stations showing an increasing trend is greater than 70% for both Rx1day and Rx5day, and the fraction of stations with significant increasing trends is 17.1% and 23.0% for Rx1day and Rx5day, respectively. These fractions are roughly double the corresponding fractions of the same collection of stations when only data for 1950-2018 is used (Figure 6a). The fractions are also larger when at regional scales (Table 3, Table S1). These large differences in the proportion of stations with significant increase between the two periods is unlikely due to the difference in spatial coverage of the stations. Over the regions where long-term observations exist, stations with significant trends are also quite evenly distributed.

The percentage of stations with significant increases is also much larger than that obtained from analysis using stations with more than 30 years of data (Figure S4, S5) as was done in Westra et al. (2013). The station selection criterion allowing stations with records as short as 30 years would have resulted in a predominance of information from trend tests based on shorter records with a shorter median length of record; such tests are inherently less powerful than tests based on longer records. On the other hand, the percentage of stations with significant negative trends is unchanged, remaining consistent with that which would be expected from the null hypothesis of no trend.

For the 1900–2018 period using 1974 stations, the estimated precipitation sensitivities of Rx1day and Rx5day to GMST increase are 5.5%/K (4.8–7.5%/K) and 6.3%/K (4.9–7.5%/K), respectively. They are comparable with that for the 1950–2018 period and Westra et al. (2013),
indicating that analysis period does not have a substantial effect on the scaling relationship between annual maximum precipitation and GMST on a global scale.

The addition of nine years of data since 2010 increases the fraction of stations with significant positive trends while the percentage of stations with significant negative trends remains unchanged and consistent with what would be expected under the null hypothesis of no trend. This is the case for long-term stations that have sufficient data for trend analysis over 1900–2018 but have relatively confined spatial distribution and for the shorter time period 1950–2018 when spatial coverage of data is much improved. It is clear that the signal of extreme precipitation intensification is more detectable with additional records, which may due to the higher power of detection that results from using longer records (Zhang et al. 2004).

To help interpret these findings we produced 1000 Monte Carlo simulations of annual extremes for the period 1950–2018 by sampling from the nonstationary GEV distributions described in Section 2 that were fitted at each station. Mann-Kendall trend analysis was conducted on the simulated time series of annual extremes. The percentage of stations with significantly increasing trends during 1950–2018 is always larger than that over 1950–2009, indicating a larger power of detection when the data since 2010 is added. The observed difference in fraction of stations with significant trends in Rx1day between the 1950–2009 and 1950-2018 is also consistent with that due to the sample size increases by nine years. Thus while low frequency climate variability could have contributed to higher rates of detection when recent data are included, it seems more likely that this is the result of the enhancement statistical power of trend detection for longer records.

Table 3
4. Conclusions and discussion

We have analyzed trends in the annual maximum amount of precipitation accumulated in a day (Rx1day) and in 5-consecutive days (Rx5day) over global land areas for which we have access to station observations. We have also analyzed the relation between annual maximum precipitation and GMST.

Our analyses are conducted for two time periods, over 1950–2018 when we have the best spatial coverage and over 1900–2018 when we have longer station records (i.e. better temporal coverage) but much more limited spatial coverage. Rx1day and Rx5day have both intensified significantly at the global and continental scales, as well as in many large regions. For the period 1950–2018, close to two-thirds of stations show increasing trends, with about 9.1% and 10.9% of stations showing statistically significant increasing trends for Rx1day and Rx5day, respectively, based on a nonparametric trend test that is expected to falsely detect increasing trends 2.5% of the time. These percentages are significantly greater than 2.5%, indicating evidence for broad and systematic change in the intensity of extreme precipitation. This same test shows significant decreasing trends at rates that are consistent with the 2.5% false detection rate, indicating that the test performs as expected in the absence of processes that would be expected to weaken extreme precipitation over time in land areas with observations. This latter result also indicates that any departures from the assumption of serial independence that is made when applying the test do not produce spurious significant trends. For the period 1900–2018, more than two-thirds of stations show increasing trends with the percentage of stations showing significant increasing
trends double that in 1950-2018. On the other hand, the percentages of stations with significant decreasing trends are again small and consistent with the expected false detection rate.

Intensification of extreme precipitation is evident throughout global land areas for which station data is available; stations with significant increasing trends are not limited to specific geographic locations but are widespread. At the continental scale, a significant intensification of extreme precipitation has been observed in well gauged continental areas including Europe, Asia and North America. Uncertainty in the characterization of changes in precipitation extremes is higher in continents where data coverage is poor including Africa, South America, and Australasia due to sparse station coverage and non-representative spatial sampling. It appears that increases in extreme precipitation dominate in both Africa and South America over areas with data coverage. At the regional scale, detection of significant trends becomes more difficult as the signal to noise ratio decreases. Nevertheless, statistically significant intensification in extreme precipitation is still observed in many regions, including C. North-America, E. North-America, N. Central-America, N. Europe, Russian-Far-East, E.C Asia, and E. Asia, whereas an obvious decreasing trend in Rx5day is observed in the region S. Australia.

Fitting Rx1day and Rx5day to GEV distributions with GMST as a co-variate reveals a significant association between changes in extreme precipitation and temperature. The connection is again statistically significant at the global scale, as it is in three continents and many regions where precipitation data are more abundant. The median estimated sensitivity of extreme precipitation to warming over the global land areas with station data is 6.6% (5.1 to 8.2%, 5-95% confidence interval) and 5.7% (5.0 to 8.0%) per Kelvin temperature increase for Rx1day and Rx5day, respectively. These scaling rates are broadly consistent with the expected increase in the water holding capacity of the atmosphere governed by the C-C relation. Estimated
scaling rates are more uncertain for records that are less complete, but do not seem to be greatly
influenced by the timing of the missing years in the indices records. Nevertheless, the sensitivity
of extreme precipitation to warming can differ substantially from these median values regionally,
both because circulation change may be an important factor in some regions and because GMST
change may not be a good indicator of regional changes in atmospheric water holding capacity.
Warming over global land is typically larger than that of GMST due to differences in sensible
heat production over land and ocean surfaces. As a result, extreme precipitation sensitivity is
generally smaller over land than predicted by the CC-relation if local or regional temperature
change is used in the estimation, except in some tropical convergence regions. Yet, it is unclear
what is the most appropriate temperature for the purpose of estimating the sensitivity (Trenberth
et al. 2015).

While our results are generally consistent with those of Westra et al. (2013), the extent to
which direct comparison can be made is limited because of different selections of stations in the
two analyses and also because we have used more stringent criteria for retaining stations for
analysis in our study. We compared our analyses with data ending in year 2018 with analyses
using data ending 2009 and found that, with the additional nine years of data, a larger percentage
of stations show significant increases in extreme precipitation but that there is effectively no
change in the number of stations showing significant decreases. We showed that this increase is
consistent with the expected increase in detection power that should result from the availability
of records that are nine years longer in the context of a warming climate. Based on the results
presented here, the findings of extreme precipitation intensification over land by Westra et al.
Although the distribution of trends across space is very noisy, our results do exhibit some spatial structure at the regional scale, such as a weakening of extreme precipitation in the Canadian Prairies, some parts of the western US, Australia, and in northern China. This suggests that other factors, such as changes in atmospheric circulation, oceanic oscillations, and aerosols may also have influenced regional trends in extreme precipitation to some extent. For instance, the decline of the Asian monsoonal circulation strength that has been related to aerosols may have contributed to the regionally coherent pattern of decreasing trends in extreme precipitation in north China (Wang and Zhou 2005; You et al. 2011). Decreasing extreme precipitation over the Canadian Prairies may be connected with low-frequency atmospheric, oceanic oscillations and snowfall decreases (Vincent et al. 2015; Yang et al. 2019). Atmospheric circulation change and low frequency modes of variability have also been implicated in changes in southern Australian precipitation (Li et al. 2012; Dey et al. 2019). Changes in the subtropical ridge (Timbal and Drosdowsky 2013; Whan et al. 2014) and the Southern Annular Mode (Cai et al. 2011; Thompson et al. 2011) were shown as potential drivers for the decline in extreme precipitation in parts of Australia. Despite the considerable research in this area, the causes of these variations are not fully understood. The association between large-scale circulation anomalies, aerosols and changes in non-well-mixed GHGs such as ozone and changes in extreme precipitation events therefore requires further investigation.

We conclude by pointing out some caveats to our analysis. While we have used an area weighting scheme that should ensure that statistics are representative of the global land area that is sampled by the available observing networks, their uneven and incomplete spatial coverage means that our results may not be fully representative of the global land surface average of extreme changes. In particular, we note that the vast majority of stations are in the mid-latitudes
of the northern hemisphere. Tropical, subtropical and mid-latitude southern hemispheric areas are much less well sampled, and there is a dearth of observations in regions where projections (e.g., Kharin et al., 2013) suggest declines in future precipitation extremes. There remains an urgent need to improve data collection in regions in which the stations records are limited, especially sub-tropical and tropical regions, Africa, and South America, to better constrain changes in extreme precipitation.

Another caveat is that while we have attempted to use data that have been systematically quality controlled, the data quality remains a concern. Precipitation measurements are difficult to homogenize due to their high spatial and temporal variability. Thus the data we use are likely not free of inhomogeneities from, for example, changes in the type of instrumentation used to measure precipitation since different rain gauges have different wind under-catch, wetting losses, and evaporation losses (Metcalf et al. 1997). Automatic gauges, which have different recording characteristics than the gauges that they have replaced (WMO. 2017) have been widely adopted owing to the cost of manual or mechanically recorded gauges together with the development of electronic recording gauges (Kidd et al. 2017). The adoption of these gauges has no doubt induced inhomogeneities in the precipitation data we analyze, that for the moment, are unavoidable since the exclusion of data from automated stations would result in extremely limited global coverage in recent decades (Kidd et al. 2017). However, we were careful to focus on data that has previously been assessed to be of high quality and in some cases, has been adjusted to improve homogeneity. As inhomogeneities are unlikely to be systematic globally, our results should hold.

While these are important caveats, we reiterate that the preponderance of evidence from the available global collection of well-studied long records of observed daily precipitation amounts
indicates that precipitation extremes are intensifying in most observed regions and on a global scale, and that these changes appear to be consistent with the warming that has been observed over the same period. Moreover, this evidence, which is also supported by formal detection and attribution analyses (Min et al. 2011; Zhang et al. 2013; Li et al., 2017; Dong et al. 2020, Kirchmeier-Young and Zhang, 2020; Paik et al. 2020), has strengthened somewhat with the additional observations that have accumulated over the past 9 years.

Acknowledgement

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References


Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.


TABLE 1. Percentage of stations with increasing, decreasing, statistically significant increasing, and statistically significant decreasing trends in Rx1day and Rx5day based on the Mann–Kendall test over the IPCC AR6 reference regions (Iturbide et al. 2020) during the 1950–2018 period. Values higher than the upper 97.5\textsuperscript{th} percentile from the 1000 bootstrap realizations under the no-trend null hypothesis are shown in bold. There are not regions in which the percentage values lie below the lower 2.5\textsuperscript{th} percentile of these bootstrap distributions.

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<td>Decrease (%)</td>
<td>Significant increase (%)</td>
<td>Significant decrease (%)</td>
<td>Increase (%)</td>
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TABLE 2. Percentage (%) of stations with statistically significant positive, or negative association between extreme precipitation (Rx1day and Rx5day) and global mean surface temperature (GMST), and the median sensitivity of extreme precipitation to a 1 K increase in GMST for IPCC AR6 reference regions during the 1950–2018 period. Values significant at 5% level are shown in bold.

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TABLE 3. Percentage of stations with increasing, decreasing, statistically significant increasing, and statistically significant decreasing trends in Rx1day and Rx5day based on the Mann–Kendall test over the IPCC AR6 reference regions during the 1900–2018 period. Values higher than the upper 97.5th percentile from the 1000 bootstrap realizations under the no-trend null hypothesis are shown in bold. There are not regions in which the percentage values lie below the lower 2.5th percentile of these bootstrap distributions.

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Figure Caption List

FIG. 1. Locations of stations available for this study and IPCC6 regions. (a) Sources of station observations. The colored dots represent the different data sources that are described in the main text. (b) Number of stations that have less than 30% missing Rx1day and Rx5day values for each period and each IPCC AR6 reference region. (c) IPCC AR6 reference regions with more than 30 stations that have less than 30% missing Rx1day and Rx5day values during the 1950–2018 period. There are 22 such regions.

FIG. 2. Summary of Mann-Kendal trend analyses for the period 1950–2018 for 8354 stations. (a) and (d), maps of locations of stations with trends for Rx1day and Rx5day, respectively. Light blue open dots indicate non-significant increasing trends and light red open dots mark non-significant decreasing trends. Dark blue and red filled dots indicate statistically significant trends as determined by a two-sided test conducted at the 5% level. (b), (c), (e) and (f), percentage of stations with statistically significant increasing and decreasing trends. The histogram represents the distribution of percentage of stations with significant trends from 1000 bootstrap realizations when the connection between time and the occurrence of annual extremes is broken. The red dots represent the values from the observational data.

FIG. 3. Estimated local sensitivity of precipitation extremes to temperature change (percent change per 1 K increase in global mean surface temperature) during the period 1950–2018 for Rx1day (a and b) and Rx5day (c and d). The red dots in (b) and (d) represent median sensitivity amongst global land based observing stations while the box-and-whisker plots summarizes the
breadth of the estimated distribution of the sensitivity from 1000 bootstrap realizations under conditions when the null hypothesis that the sensitivity is zero is true (i.e., the resampling process has broken the link between temperature and precipitation). In these plots, the 25th/75th percentiles are shown as upper and lower edges of the boxes while the median is marked by the center line; The upper and lower whiskers show the 97.5th and the 2.5th percentiles. The observed median sensitivity estimate is evidently significantly larger than zero.

FIG. 4. Continental summaries of the percentage of stations with statistically significant trends (according to the Mann-Kendall trend test) in extreme precipitation for 1950–2018. The blue and color colors indicate significant positive and negative trends, respectively. Dots indicate percentages estimated from the observations. Box-and-whisker plots summarize the breadth of the distribution from 1000 bootstrap realizations under the no-trend null hypothesis. In the plots, the 25th/75th percentiles are shown as upper and lower edges of the boxes while the median is marked by the center red line. The upper and lower whiskers show the 97.5th and the 2.5th percentiles respectively.

FIG 5. Continental summaries of sensitivity of extreme precipitation per Kelvin increase in global mean surface temperature for 1950–2018. The red dots indicate the media of local sensitivities estimated at stations within each continent. The box-and-whisker plots summarizes the breadth of the distribution from 1000 bootstrap realizations under the zero sensitivity hypothesis. In these plots, the 25th/75th percentiles are shown as upper and lower edges of the boxes while the median is marked by the center red line; The upper and lower whiskers show the
97.5th and the 2.5th percentiles. The horizontal dashed line shows the nominal CC-rate of 7%K^{-1} for reference.

FIG. 6. Summaries of the percentage of stations with statistically significant trends in extreme precipitation for different datasets and different periods. (a) to (c) display results for subsets of stations that have less than 30% missing values during 1900–2018, 1900–2009, and 1950–2009 respectively. Blue and red dots indicate the percentage of significant positive and negative trends, respectively. The box-and-whisker plots summarize the breadth of the distribution from 1000 bootstrap realizations under the no trend null hypothesis. These plots show the 25th/75th percentiles as the upper and lower edges of the boxes while the median is marked by the center red line; The upper and lower whiskers show the 97.5th and the 2.5th percentiles.
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