Trends in U. S. Storminess 1949–2009

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ABSTRACT

We use an extensive NOAA database of hourly precipitation data from 5995 stations in the 48 contiguous United States over the period 1949–2009 to investigate possible trends in the frequency and severity of extreme weather events, defined as periods of intense precipitation. The frequency and intensity of these events are quantified by a dimensionless storminess, defined as the variance of the hourly rainfall at a site normalized by the square of the mean rainfall at that site. For 1722 stations with sufficient data, we compute the rate of change of the logarithm of the storminess at each station and set bounds on its mean (over stations) trend; use of the logarithms weights trends at calm stations equally to those at stormy stations and enhances the statistical power of the mean. These results are confirmed by reversing the order of averaging: first computing, for each year, the mean (over stations) logarithm of the storminess, and then fitting to its trend. We set 2σ upper bounds of 0.001/y (doubling or halving time scales > 1000 y) on any trend, increasing or decreasing.

Subject headings: storminess — precipitation — climate change — global warming

1. Introduction

It is generally accepted that atmospheric and surface temperatures in most or all climate zones, temporally averaged over shorter term and decadal oscillations, have warmed since the
19th Century (Jones and Moberg 2003; Menne and Williams 2005; Hansen et al. 2010; Rhode et al. 2013). Although this issue has been settled to the satisfaction of most climatologists, other questions remain open. Many studies (Groisman et al. 2005; Alexander et al. 2006; Peterson et al. 2008; Min et al. 2011; Utsumi et al. 2011; Trenberth 2011; Groisman et al. 2012; Coumou and Rahmstorf 2012; Villarini et al. 2013; Westra et al. 2013; Lehmann et al. 2015; Stott et al. 2016) and the Fifth IPCC consensus report (Hartman et al. 2013) have suggested that warming has been or will be accompanied by an increased frequency of “extreme weather events”. These include periods of unusually high or low precipitation, intense storms or droughts. Although storms and droughts may be considered opposites, one being defined or characterized by intense precipitation and the other by the absence or deficit of precipitation, they both correspond to increased variability of weather. Statistically, they both increase the variance and higher moments of the temporal distribution of precipitation.

Counts and semiquantitative measures of severe storms such as hurricane categories and the Fujita tornado scale have several drawbacks as tools to measure trends in extreme weather events. Detection of storms has improved as technology has improved, biasing their statistics; an obvious example is that satellite observations record hurricanes that never strike land, whose detection in the pre-satellite era required their fortuitous encounter with ships. Quantification of a storm by sampled wind speeds is only a rough approximation to the energy contained in its full three-dimensional velocity field, and is biased by the development of observing systems. Perhaps most important, identified discrete storms are few, limiting the statistical power of their data.

Severe storms are usually accompanied by short periods of intense rainfall. Even tornadoes, not themselves sources of intense rain, are produced by strong thunderstorms accompanied by rapid precipitation. Precipitation data include events over the entire spectrum of intensity, without arbitrary thresholds (such as the distinction between a hurricane and a tropical storm). Most importantly, because precipitation data are available at a large number of stations, at hourly frequency, over several decades, their analysis may have great statistical power.

Previous studies of precipitation statistics (Groisman et al. 2005; Alexander et al. 2006; Min et al. 2011; Utsumi et al. 2011; Balling Jr. and Goodrich 2011; Kunkel et al. 2013; Fischer and Knutti 2014; Anderson et al. 2015; Cavanaugh et al. 2015; Lehmann et al. 2015; Powell and Keim 2015) have mostly been concerned with the largest one-day or few-day (often five-day) precipitation totals found in an annual or longer period. Other studies (Groisman et al. 2012) have similarly studied the frequency of days with precipitation over a high threshold or in a high range. These data are valuable to civil engineers and planners who must design storm water management systems, but do not fully describe the statistics of precipitation. Nor do they have the statistical power and homogeneity of lengthy hourly precipitation records that include the information contained in lesser events and dry periods. The statistics of extreme events (Epstein 1948; Johnson 1964; Doremus 1983; Katz 1998, 1999) do not take advantage of the information present in lesser but more frequent events, nor utilize all the data, and may depend on arbitrary choices of criteria and thresholds. Even studies of hourly data that deal only with their extremes (Lenderink and van
Meijgaard 2008; Wong et al. 2010; Lenderink et al. 2011) suffer from these disadvantages.

These factors also complicate combining information from multiple stations that may be in different climatic regimes in which different definitions of “extreme weather events” might be appropriate; for example, thunderstorms that occur nearly daily on the U. S. Gulf Coast would be extraordinary in the maritime climate of the Pacific Northwest. Utilization of all available data has been a powerful tool for extracting global warming from temperature trends that may be inconsistent among stations that show stochastic local and correlated regional variations (Hartman et al. 2013; Rhode et al. 2013). Therefore, we define metrics that combine information distributed throughout entire time series, and that are weighted so that trends at calm and stormy stations contribute comparably to the overall averages. Our metrics utilize information from periods of lower intensity precipitation as well as from intense storms because trends in either may be manifestations of changing climate.

For quantification of the “storminess” of climate, hourly data offer information and insights lost when precipitation is averaged over 24 hour periods. A day of steady rain is not the same as a day during which an intense storm produces the same amount of rain but concentrates it in one or a few hours. In order to take advantage of the full statistical power of the extensive NOAA database containing (allowing for missing hours) about a billion hourly data, this study uses information from more than a thousand stations over the 61 years 1949–2009 to determine continent-wide trends.

The increase of water saturation vapor pressure with increasing temperature (according to the Clausius-Clapeyron equation) as the climate warms has been predicted to increase the mean precipitation, the frequency of periods (typically one or a few days) with precipitation above thresholds, and record values of precipitation. There is evidence of such effects (Pall et al. 2007; Berg et al. 2013; Kunkel et al. 2013b,c; Allan et al. 2014; Berg et al. 2014; Lehmann et al. 2015). However, we distinguish trends in storminess (a measure of the concentration of precipitation into extreme events) from trends in mean precipitation.

2. Methods

The NOAA database (U. S. National Oceanographic and Atmospheric Administration 2011) contains records of hourly precipitation at 5995 stations in the 48 contiguous United States from 1948 to 2009. There are few data from 1948, so we exclude that year. A master (“COOP”) file lists the intervals (typically of many years duration) during which each station was nominally collecting data. Individual station files contain information for each day during which there was at least one hour with measured precipitation and flag hours with missing data. An individual station file and the COOP file must be used together to determine the hours when the station was actually collecting data. We ignore three stations for which no information is included in the COOP file.

Over the time period considered, almost all stations had at least some months or years without
data. Indeed, according to the COOP file, only 1051 stations (of those for which there are hourly precipitation data) were collecting data without extended interruption (these stations were still subject to transient interruptions, typically of a few hours duration, indicated in the individual station files but not in the COOP file). Even stations without extended interruptions generally do not have a complete 1949–2009 data series. Many stations also moved small distances (typically a few km) during the period analyzed. We ignore these small moves.

We first addressed the problem of missing data. The individual data files have a code for isolated hours when the station was “down”, and some files used the same code for whole months when that station was not recording data. Hours and days so indicated were removed from the data. More problematic were entries indicated as holding the cumulative precipitation for an unspecified number of hours ending in the hour of the entry. In such cases the individual hourly values cannot be determined, so we ignored any day with such an indicated hour.

It is also necessary to ensure that accurate counts of hours of data collection in order to compute valid averages. The absence of an entry in a station data file may be due to either the station being down or the absence of precipitation. Unfortunately, the station data collection times obtained from the COOP file are sometimes inconsistent with the precipitation data in the individual station data files. This can be in either direction: a) precipitation data shown when the COOP file indicates that the station was down that day, or b) no data in the station files for months and in places where it is very implausible that there was no precipitation although the COOP file indicates the station was up. We

a) ignore any months for which the COOP file indicates the station was down during a period (within that month) but during which the data file indicates data were collected;

b) ignore data for complete years during which the individual station file lists no precipitation (this is very unlikely to be true for any location in the 48 states). We cannot distinguish individual months for which the COOP file indicates data were collected, but that might be missing data, from months that actually had zero precipitation. We do not exclude such months because many stations, particularly in the Southwest and California, have months without any precipitation, so that the complete absence of recorded precipitation in a month is not an indication that a station was down.

A second set of cuts was made to reduce bias introduced by some types of missing data:

a) We ignore data from a station for a calendar year during which the station was not up at least 80% of the days; the absence of data for some seasons would introduce bias.

b) In order to study the variation of precipitation statistics as the climate warms, we further restrict consideration to stations which have a long duration of data collection. We require that there be at least 30 years of data spread over at least four eleven year Solar cycles (to minimize any spurious trends resulting from possible Solar cycle effects on weather), with at
least 6 valid years (with the station up at least 80% of the days) of data in each cycle after earlier cuts have been made.

After subjecting the data in [U. S. National Oceanographic and Atmospheric Administration (2011)] to these cuts, 1722 stations remain. This gives our results statistical power not found in a preliminary study (Muschinski and Katz 2013) of 13 stations that were considered individually. That earlier study found a nominally very significant (5σ) trend in storminess at one station, a significance that depends on the assumption of a normal distribution of annual storminess at each station about its mean trend.

The dimensionless normalized n-th moment for station \( j \) is defined:

\[
M_{j,n,T} = \frac{\sum_{i \in T} (p_{j,i} - \langle p_{j,i} \rangle_{i \in J})^n}{N_T \langle p_{j,i} \rangle_{i \in J}^n},
\]

where the \( p_{j,i} \) are the measured hourly data, including hours when there was no precipitation, \( i \) denotes the date and hour of measurement, \( T \) denotes the temporal interval (the year) over which the moment is averaged, \( N_T \) is the number of valid data included in the sum in the numerator (missing data are ignored), \( J \) is the set of all valid data (over the entire period 1949–2009), containing \( N_J \) elements, for station \( j \). \( N_T \) is generally less than the number of hours in \( T \) and \( N_J \) is less than the number of hours in \( J \) because some data are missing and some months or years of data are rejected because of inconsistency with the COOP file or to minimize bias from incompletely sampled years. The mean precipitation

\[
\langle p_{j,i} \rangle_{i \in J} \equiv \frac{1}{N_J} \sum_{i \in J} p_{j,i}.
\]

We define the “storminess” as the normalized second moment \( M_{j,2,T} \) for the station \( j \) and year \( T \). Normalization distinguishes storminess from wetness or dryness, and permits comparison of storminess at wet and dry stations. Wet stations may be either stormy (on the Gulf Coast) or calm (in the Pacific Northwest), while dry stations are generally stormy (in the desert Southwest) because what precipitation they do receive comes in infrequent storms.

Normalization by the mean over the entire record minimizes any artefacts resulting from shorter time scale variations of the mean precipitation. Such phenomena may be aliased into long term trends if folded into bins such as calendrical decades. By fitting a linear trend to the entire record of annual storminess at each station we minimize effects of phenomena on decadal or shorter time scales. It is still, with only 61 years of data, not possible to distinguish the effects of phenomena on that, or longer, time scales (e.g., the Little Ice Age) from “genuine” secular trends. This is a well-known problem in all, necessarily finite, geophysical time series (Mandelbrot and Wallis 1969) because they are characterized by noise with a “pink” spectrum.

In averaging over the 1722 surviving stations we have not attempted to allow for the spatial density with which they sample climatic information, in contrast to the work of [Rhode et al. (2013)] with temperature data. We question the utility of doing so because the spatial scale on which
climate varies is very nonuniform. Large areas (such as the U. S. Midwest) may have similar climate, but in mountainous areas and near coasts, especially the U. S. Pacific Coast, sites separated by one km may have different, and perhaps independently varying, climate, as is familiar to residents of San Francisco. It is not straightforward to define an unbiased algorithm to account for this. In our earlier study of drought [Finkel et al. 2016], the site-averaged and area-averaged results agreed to about 10% despite a non-uniform distribution of stations.

3. Results and Discussion

Fig. 1 shows the mean values of the natural logarithms of the storminess at our 1722 stations. Storminess is high in regions (the Southwestern desert, Californian coast and western Great Plains) where precipitation is concentrated both seasonally and into intense storms. Storminess is low in regions, such as the Appalachian Mountains and the Northeast, where precipitation is frequent, and especially in the maritime climate of the Pacific Northwest where precipitation occurs as omnipresent drizzle. There is also a strong east-west gradient of storminess in the Great Plains, dividing humid regions from drier but occasionally stormier regions requiring dry farming.

![Fig. 1](image-url)

Fig. 1.— Natural logarithms of mean (1949–2009) storminess at 1722 stations. Symbols indicate the percentile ranks of the storminess, divided into vigintiles (0–5%, 5–10%, 90–95%, 95–100%) and deciles (10–20%, ..., 80–90%).
For each station we make a linear fit to the logarithm of the storminess as a function of time; the slope is the time derivative of ln(storminess). Logarithms are used, in part, because we are interested in the percentage (or fractional) rate of change in storminess. This permits comparison of trends at stations whose storminesses may differ by large factors (as much as 50); a significant trend would be scientifically interesting (and might be practically important) whether it occurred at a stormy or a calm station.

Logarithms are used also because their mean slope is not dominated by those of a few very stormy stations; a 10% change (for example) at a calm station contributes as much to the mean slope (and to our understanding of climate change) as a 10% change at a stormy station. The uncertainty in the mean slope is about $1/\sqrt{1722}$ of the standard deviation of the individual (logarithmic) slopes, not $1/\sqrt{N_{\text{stormy}}}$ where $N_{\text{stormy}}$, a few dozen, is the number of stormy stations that would contribute most of the variance in the slopes of the raw storminess. The results are shown in Fig. 2.

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**Fig. 2.** Rates of change, per century, of the natural logarithms of the storminess at 1722 stations. Symbols indicate the percentile ranks of the slopes, divided into vigintiles (0–5%, 5–10%, 90–95%, 95–100%) and deciles (10–20%, ..., 80–90%). There is much more spatial heterogeneity than for the mean storminess (Fig. 1), with less correlation among neighboring stations. There are hints of decreasing trends in the Pacific Northwest and around Lake Superior and of increasing trends in the Intermountain Basin and the southern Great Plains. More rapidly increasing storminess is found in the Los Angeles area.

**Fig. 3** shows a histogram of the distribution of slopes (time derivatives) of the logarithms of the
storminess. The mean slope is \((-2.8 \pm 1.7) \times 10^{-4}/y\), where the nominal standard deviation assumes independent random variables, and the median slope is \(1.5 \times 10^{-4}/y\). The mean slope nominally differs from zero by \(-1.6\sigma\), which is not significant. The nominal \(2\sigma\) range is \((-6.2, 0.6) \times 10^{-4}/y\), corresponding to a nominal range from exponential decrease of storminess with a halving time of 1000 y to exponential increase of storminess with a doubling time of 10,000 y (this extremely long \(2\sigma\) bound is an artefact of the fact that the mean is nearly \(-2\sigma\); the \(3\sigma\) bound is about 3000 y). Qualitatively, this may be described by saying that the characteristic (\(e\)-folding) time of variation of the mean (across the 48 states) storminess is no less than a millenium. It is not possible to exclude more rapid local trends.

Most of the logarithmic slopes are small, with characteristic time scales of variation (defined as the reciprocal of the slope of the logarithm) of centuries. Negative and positive slopes are nearly balanced in number and magnitude, and the mean slope is much less than the magnitudes of the slopes at the stations with the most rapid change. Although it cannot be proven, the large differences among neighboring sites, even in the same climate regimes, are consistent with the hypothesis that the observed slopes are mostly the consequence of stochastic local events rather than systematic trends. However, by averaging over a large number of stations we can set tight bounds on the mean trend. In the period 1949–2009, during which global warming was comparatively rapid, the mean storminess in the 48 contiguous states changed comparatively slowly, if at all.

Fig. 4 plots the logarithmic slope of the storminess at each station against its mean value. There is a weak correlation (Pearson’s correlation coefficient is 0.25) that is nominally significant, but the random scatter is greater than any trend related to the mean storminess, and the fitted trend only accounts for a small part of the scatter.

Fig. 2 shows a striking concentration of positive storminess slopes in the greater Los Angeles area. This is shown in more detail in Fig. 5. The boundaries of this region are necessarily arbitrary, but of the 38 stations inside it, 9 have slopes in the highest vigintile (5%) of slopes of the 1722 stations, 13 in the highest decile and 10 in the second decile. The \(a\ priori\) probability of 9 in the highest vigintile is \(7 \times 10^{-5}\), of 13 in the highest decile is \(4 \times 10^{-5}\) and of 23 in the highest quintile is \(5 \times 10^{-8}\). There are roughly 150 independent regions of similar size in the 48 contiguous states, so the probability of finding such an anomaly \(somewhere\) is 150 times as great, but still \(\ll 1\%\). This geographical concentration of large positive slopes may be described as no more than a correlation among nearby stations, but the fact of such a correlation indicates it is a real regional effect, and not an accidental fluctuation. It invites speculation about its cause.

It may also be useful to look for trends in the mean storminess by first averaging over stations, and then fitting a slope to those averages. This inverts the order of analysis shown in Figs. 2–4 in which the slopes are first fitted at each station. In Fig. 6 the mean (over stations with sufficient data to be valid) natural logarithm of the storminess is computed for each year. The logarithms of storminess are used, rather than the storminesses themselves, so that the mean trend is not dominated by the stormy stations. The best linear fit is indicated, with a slope of
Fig. 3.— Distribution of slopes of logarithms of storminess at 1722 stations in the 48 contiguous United States. The mean is \((-2.8 \pm 1.7) \times 10^{-4}/y\), consistent with zero, and indicating the storminess in the period 1949–2009 for which we have data is varying on an e-folding time scale of no less than \(\sim 1000\) years. The skewness of the distribution is \(-0.67 \pm 0.06\) and its excess (compared to a Gaussian) kurtosis is \(2.79 \pm 0.12\), both of which are, at least nominally, very statistically significant. They suggest strong local or regional trends, which are consistent with the existence of a variety of correlated (in space and time) weather variations on all temporal and spatial scales.
Fig. 4.— Logarithmic slopes of storminess vs. mean storminess at 1722 stations in the 48 contiguous United States. The red line is a linear fit. The Pearson’s correlation coefficient is 0.25; the correlation only accounts for a small fraction of the station-to-station variation in slopes.

\((-2.5 \pm 7.7) \times 10^{-4}/y\), consistent with zero. The nominal 2σ range of slopes is \((-1.8, 1.3) \times 10^{-3}/y\), corresponding to characteristic e-folding times of the storminess of greater than 500 years. This result is fully consistent with the upper bounds found by first fitting slopes at each station, as illustrated in Figs. 3, 4.

There is a long history of searching for effects of the eleven year Solar cycle on climate, with controversial results. We folded the mean (over stations with sufficient data to be valid) natural logarithms of storminess shown in Fig. 6 by year of an assumed exact eleven year Solar cycle (actual times between sunspot maxima or minima have varied by a year or more from their nominal 11.0 year period). The results are shown in Fig. 7. The amplitude of the best fit sine wave is 0.039, but
the null hypothesis of constant log storminess (equal to 4.362, 10 degrees of freedom) cannot be rejected at the 75% confidence level ($\chi^2 = 11.4$ with 10 degrees of freedom).

4. Conclusions

The data shown here set upper bounds on any long term trend in the mean storminess, defined as the normalized second moment, averaged over the 48 contiguous United States during the span of our data 1949–2009. During that period the mean storminess had a characteristic (e-folding) time scale of variation of not less than about 1000 years at the 2σ level of significance, or a corresponding mean rate of change of not more than 0.1% per year. There is no evidence for a rapid increase in storminess, and the mean over stations decreased, though the rate of decrease was not significantly different from zero.

Extrapolation of these conclusions to the long term future climate depends on the assumption (necessarily uncertain) that the 60 year period 1949–2009 will be representative of long term secular
Fig. 6.— Mean (over stations with sufficient data to be valid) natural logarithms of storminess vs. year. No significant trend is found, setting a lower bound on the characteristic $e$-folding time scale of $> 500$ years. This result may be subject to bias if stations with greater or lesser storminess preferentially have sufficient data to be included in our analyses. However, the resulting mean trend is consistent with that found by first fitting trends to data from each station, and then averaging.

trends, and was not affected by shorter term fluctuations analogous to the Little Ice Age. The mean global warming rate over the period 1950–2010 was $0.010^\circ C/yr$ (NASA Goddard Institute for Space Studies, 2012). If the natural logarithm of the normalized second moment of storminess varies in proportion to the warming, the nominal $2\sigma$ range of their ratio, the sensitivity of $\ln$ (storminess) to global warming, is in the range $-0.06^\circ C$ to $+0.006^\circ C$ and is consistent with zero. It is not known if this can be extrapolated to the future, for which climate models predict significant additional warming.

We normalized storminess to the mean precipitation (at each station) over the entire period 1949–2009, making no allowance for the mean increase of precipitation of about $7 \times 10^{-4}/y$ predicted from the mean warming rate and the Clausius-Clapeyron equation. If this assumed mean increase is applied to the normalizing denominator in Eq. 1 (where it is included to equalize the weighting of trends from stations in different climate regimes, not to allow for long-term trends in mean precipitation), the resulting predicted trend in this modified mean storminess would be $-17 \times 10^{-4}/y$, with an uncertainty that depends chiefly on the uncertainty in the rate of increase of mean precipitation that is difficult to estimate. Unlike the storminess defined in Eq. 1, this would not be a measure of the absolute size of extreme weather events.
Fig. 7.— Mean natural logarithm of storminess, averaged over stations, folded with an assumed 11.0 year Solar cycle (phase is arbitrary). Error bars are $\pm 1\sigma$, based on the distributions of averaged (over stations) log-storminesses in the five or six calendar years corresponding to each year of the Solar cycle. There is no significant evidence for an eleven year periodicity.

We can only speculate as to the cause of the comparatively rapid and statistically significant increase in storminess in the Los Angeles basin shown in Fig. 5. During the period covered by our data, 1949–2009, air pollution in that basin was dramatically reduced. Particulate smog may serve as condensation nuclei for water vapor; if they are numerous the supersaturated water vapor content of the atmosphere is divided among many small droplets, producing a gentle drizzle. Cleaning the air reduces the number of condensation nuclei, so that the supersaturated water vapor condenses as fewer but larger droplets, producing more intense rain and increased storminess.

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