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Key Points:
- Methods are developed to estimate temporal trends in rain rates
- These methods are verified against large UK rain gauge studies
- Results of applying the method globally are presented

Supporting Information:
- Captions for Data Set S1
- Data Set S1

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A method to estimate trends in distributions of 1 min rain rates from numerical weather prediction data

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Abstract It is known that the rain rate exceeded 0.01% of the time in the UK has experienced an increasing trend over the last 20 years. It is very likely that rain fade and outage experience a similar trend. This paper presents a globally applicable method to estimate these trends, based on the widely accepted Salonen-Poiares Baptista model. The input data are parameters easily extracted from numerical weather prediction reanalysis data. The method is verified using rain gauge data from the UK, and the predicted trend slopes of 0.01% exceeded rain rate are presented on a global grid.

1. Introduction

Dynamic fading due to rain and wet snow tends to be larger and longer lasting than that due to other mechanisms on terrestrial and Earth-space links at frequencies above approximately 5 GHz. The International Telecommunication Union-Radiocommunication Sector (ITU-R) maintains a set of models for predicting average annual distributions of rain fade, with a 1 min integration time, on individual links. An important parameter in these models of rain fade is the 1 min rain rate exceeded for 0.01% of an average year (R0.01%). At the location of interest, this can be estimated from long-term rain gauge records, sometimes requiring some statistical conversion to allow for different integration periods. If local data are not available, then Rec. ITU-R P.837-6 [*International Telecommunication Union (ITU)*, 2012] provides a method to estimate this parameter at any point globally.

Several recent papers have suggested that temporal trends in climate parameters could be having significant effects on telecommunication systems over their lifetime. A satellite communications system has a typical life cycle of 30 years, from initial conception to decommissioning. Any climate variation, either natural or anthropogenic, with a period of more than 60 years, may be experienced as a monotonic trend in fading over the system lifetime.

Paulson [2010] examines data from 32 rain gauges situated in the Southern UK and operated by the UK Environment Agency. The tipping bucket gauges recorded the time to the nearest second whenever 0.2 mm of rain accumulated. These data showed a strongly increasing trend in the incidence of rain rates at outage levels, consistent with 99.99% and 99.999% availability outage rates, doubling or tripling each decade for the last two decades. A later paper [*Paulson*, 2011] extends the analysis to 100 gauges in the southern and north western England with similar results. More recently, a research study by the UK spectrum regulator Ofcom, using over a thousand gauges, confirmed these results and extended their scope to the whole of the UK [*Bacon*, 2012]. These results are especially significant for the planning of high availability and security critical links. It is likely that other regions, outside the UK, will experience trends in the incidence of rain at outage levels. However, the UK is unusual in having historical data from a relatively dense network of gauges capable of estimating distributions of rain rate with a 1 min integration time. For most of the globe, this is not the case.

A further paper [*Paulson and Al-Mreri*, 2011a] identified global trends in rain height, mostly increasing in altitude over time, derived from NOAA National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis data. The rain height is related to the 0° isotherm and is near the top of the melting layer when the atmosphere is stratified. Increases in 0° isotherm height are correlated with increasing surface temperature. Earth-space links are assumed to experience rain fade up to the rain height, and so increasing rain height is another mechanism that is expected to lead to increasing fade intensity. The situation for terrestrial links is more complicated as increasing rain height can increase or decrease the incidence of wet snow along the link and so can either increase or decrease annual fade levels dramatically [*Paulson and Al-Mreri*, 2011b].

The objective of this work is to develop a method to estimate trends in the R0.01% parameter anywhere on Earth, using readily accessible data. One minute rain gauge data are available in only a very small proportion of the globe. By contrast, numerical weather models, particularly reanalysis data, span the globe and assimilate large amounts of measured data, including rain data from gauges and rain radar networks. The major drawback is that rain data are averaged over very large areas, typically hundreds of kilometers across, and accumulated over long times, typically 6 h or daily. A relationship needs to be found between these very low resolution rain parameters and the 1 min averaged, point rain rates required for radio regulation, spectral efficiency, and performance optimization.

To some extent this relationship has already been developed. Before 1999, Rec. ITU-R P.837-1 provided R0.01% globally by dividing the world into rain zones, over which all regions were assumed to experience the same 1 min rain rate distributions. This was replaced by a new model, Rec. ITU-R P.837-2, where average annual rain distributions were assumed to follow the Salonen-Poiares Baptista (SPB) double exponential model and associated method [*Salonen and Poiares Baptista*, 1997; *Poiares Baptista and Salonen*, 1998; *International Telecommunication Union Radiocommunication Sector* (*ITU-R*), 2014a]. The parameters of this distribution were linked to outputs from ERA-15 reanalysis data, produced by the European Centre for Medium-Range Weather Forecasting (ECMWF). The parameters for later versions of this recommendation were extracted from the ERA-40 database. The Rec. ITU-R P.837-6 model parameters are provided on global maps with a grid spacing of 1.125°. The SPB method is a transformation of the long-term average (many years) of three reanalysis outputs to the average annual distribution of 1 min rain rates. The transformation is applied globally and assumed to be valid for all climates.

This paper explores a logical extension of this method. If a region experiences climate change, then the SPB method should be applicable to intervals both before and after the change, as long as the climates stay within the very wide global range, from desert to rain forest, over which the model has been verified. Quantifying this approach is limited by unanswered questions as to the rate of convergence of distributions of measured rain rates to average annual distributions, and the rate of convergence of averages of reanalysis parameters to long-term averages. Both these questions are further complicated by natural climate cycles of various periods and the possibility of anthropogenic climate change. In a climate change scenario, long-term averages are poor predictors of parameter values in the present or future.

This paper uses the SPB method applied to individual years within a time series to estimate trends over several decades. This is based on the rationale that if the SPB method is reasonable over the long term, it should also be reasonable over the short term; i.e., a wet year, or a year with a greater proportion of convective rain, is likely to have a higher 0.01% rain rate. We use the SPB method only to attempt to quantify the link between changes in rain accumulation and convection to changes in the 0.01% rain rate. As we are only looking at trends, which are defined over the long term (20 years in our case), the method is relatively insensitive to uncertainties in individual years. Even if the yearly results exhibit large random spread around an unbiased estimator, the averaging effects over 20 years can yield a fair estimate of the underlying trend. We have shown that this is the case for the UK in section 6.

This paper summarizes the work presented in the PhD thesis of Channa Ranatunga [*Ranatunga*, 2014]. Section 2 introduces the SPB method and the input parameters. Section 3 describes the ECMWF ERA-40 and the U.S. National Oceanic and Atmospheric Administration (NOAA) NCEP/NCAR reanalysis data sets, and the extraction of the SPB input parameters. Section 4 presents time series of SPB input parameters and the calibration using Global Precipitation Climatology Centre (GPCC) data. Temporal trends are identified in time series of rain parameters from the UK. In section 5 the constants that are part of the SPB model are calculated by optimization of the fit of predicted 0.01% exceeded rain rates with global data from the DBSG3 database. Section 6 uses the SPB model, with optimized constants, to predict time series of R0.01% rain rates for the UK, and these are compared to the results of rain gauge studies. Additionally, a simplified method is tested that does not require the calculation of time series. Section 7 applies the simplified method to produce a global map of predicted temporal trend slopes in the 0.01% exceeded rain rate. Finally, section 8 presents conclusions.

2. Salonen-Poiares Baptista Method

This section summarizes the SPB distribution of 1 min rain rates and the method described in *Salonen and Poiares Baptista* [1997] and *Poiares Baptista and Salonen* [1998], for estimating the distribution parameters from reanalysis data.

The average annual 1 min rain rate complementary cumulative distribution function (CCDF) is assumed to have a distribution well described by the expression

$$P(R) = P_0 \cdot e^{-a R^{\frac{1+bR}{1+cR}}} \tag{1}$$

$P(R)$ is the probability of experiencing a rain rate greater than R, and P_0 is the probability of a 1 min interval experiencing rain. Both probabilities are often expressed as percentages. The four parameters P_0, a, b, and c control the shape of the distribution and match the distribution to the local climate. Rec. ITU-R P.837-6 provides a method to calculate these parameters from three, long-integration time rain parameters. These parameters are M_S = mean annual stratiform rain accumulation (mm), M_C = mean annual convective rain accumulation (mm), and P_{r6} = probability of rainy 6 h periods (%).

The ITU-R model estimates the distribution parameters from these input parameters using

$$\begin{aligned} P_0 &= P_{r6h} \cdot \left(1 - e^{-\alpha_1 \dfrac{M_S}{P_{r6h}}}\right) \\ b &= \frac{M_C + M_S}{\alpha_2 \times P_0} = \frac{M_T}{\alpha_2 \times P_0} \\ c &= \alpha_3 \cdot b \\ a &= \alpha_4 \end{aligned} \tag{2}$$

The constants have changed with revisions of Rec. ITU-R P.837, and the current values are $\{\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4\} = \{0.0079,\ 21797,\ 26.02,\ 1.09\}$. The transformation of reanalysis parameters to 1 min rain rate CCDF parameters has been optimized to provide the best fit to the database of the ITU-R Study Group 3: DBSG3 [*ITU-R*, 2014b]. This contains the 743 experimental CCDF statistics, acquired from over the 139 locations. However, distributions derived from experiments lasting more than 1 year are often included both as individual year and multiyear results. We have selected 415 distributions derived from 1 year experiments.

3. Reanalysis and Gauge Data

The original work by SPB used ERA-15 and later ERA-40 reanalysis data provided by the ECMWF. ERA-40 data span the interval 1957 to 2001 [*Uppala et al.*, 2005]. Similar data are also provided by NOAA NCEP/NCAR: reanalysis 1 spanning 1958 to 2011. The motivation for the NOAA NCEP/NCAR reanalysis project was to remove the apparent climate change artifacts introduced by the occasional changes made to numerical weather models [*Kalnay et al.*, 1996]. Kalnay et al. further state: "The basic idea of the Reanalysis Project is to use a frozen state-of-the-art analysis/forecast system and perform data assimilation using past data." Although the numerical weather prediction algorithm does not change, the data available for assimilation do. For ERA-40 between 1973 and 1988, the amount of satellite data that was assimilated increases with time. After 1988 the amount of satellite data is large and the system can be considered stable [*Poiares Baptista and Salonen*, 1998].

Precipitation data from reanalysis products require calibration to surface measurements. For example, ERA-40 has known problems with the humidity scheme of the ECMWF assimilation system [*Poiares Baptista and Salonen*, 1998]. Rain parameters over land used in Rec. ITU-R P.837-6 uses calibration factors derived from the GPCC rain gauge data set maintained by the Global Precipitation Climatology Centre of the Germany's National Weather Service. Rain parameters over sea use a calibration factor derived from the "satellite-gauge precipitation product" produced by the Global Precipitation Climatology Project of the NASA Goddard Space Flight Center (USA). For this project the Variability Analyses of Surface Climate Observations (VASClimO) data set version 1.1 is used [*Schneider et al.*, 2011; *Beck et al.*, 2005]. This data set provides daily precipitation accumulation derived from rain gauge measurements, integrated over regions of diameter 1°, over land. The data set is based on time series from more than 9300 gauge stations and covers more than 90% of the period between 1951 and 2000.

Table 1. Centers of NOAA Grid Regions Spanning the UK

Name	Latitude	Longitude
North	54.3°	−0.9°
Midlands	52.4°	−0.9°
South	50.5°	−0.9°

This project also refers to UK rain rate trends derived from rain gauge data acquired by the UK Environment Agency [*Paulson*, 2010, 2011; *Bacon*, 2012]. Each tipping bucket gauge records the time of each 0.2 mm accumulation to the nearest second. Most gauges started recording to this resolution in the mid-1990s although the earliest data started in 1989. The published trends are compared to those produced by the methods developed in this paper.

4. Time Series of Precipitation Parameters

Although the original work by SPB that led to the current global ITU-R rain models was based on ERA-40 data; we have chosen to use NOAA NCEP/NCAR reanalysis data due to the temporal span of data up to 2011. For statistically significant trend identification, the length of interval is important. Furthermore, as underlying climate trends appear to be accelerating, i.e., surface temperatures [*Solomon et al.*, 2007], it is important to include the most recent data. Two precipitation parameters have been extracted from the NOAA reanalysis databases: total precipitation and convective precipitation, over 1.875° integration regions, over 6 h periods. The three parameters M_T, M_C, and P_{r6} are estimated over each integration region and for each 365 day interval starting at midnight UTC. M_T and M_C are calculated as running sums of 4×365 consecutive values (4 per day times 365 days), while P_{r6} is the percentage of 4×365 consecutive values for which the total precipitation is greater than 0.1 mm/6 h.

Three NOAA grid regions have been explored in detail. Each has a diameter of 1.875° and centered on the points listed in Table 1.

The accumulations need to be calibrated to VASClimO surface rain gauge measurements. Figure 1 provides a scatterplot of M_T derived from NOAA and VASClimO, for the NOAA grid region covering the Southern UK, for the period 1981 to 2000. The corresponding VASClimO estimates are produced by forming weighted sums of the smaller 1° VASClimO regions where the weights are proportional to the region overlap areas.

These plots show high correlation between the accumulation estimates, with regressions lines with slope very close to 1 but a significant offset as large as 30% of the annual accumulation. This result is in marked contrast with that of *Poiares Baptista and Salonen* [1998] where a multiplicative calibration factor was required to match ERA-40 accumulations with GPCC data. The correlations in the range 0.92 to 0.94 provide the confidence to use GPCC data to calibrate NOAA accumulations. Table 2 lists the slope a, intercept b, and Pearson correlation coefficient r, for the three NOAA regions.

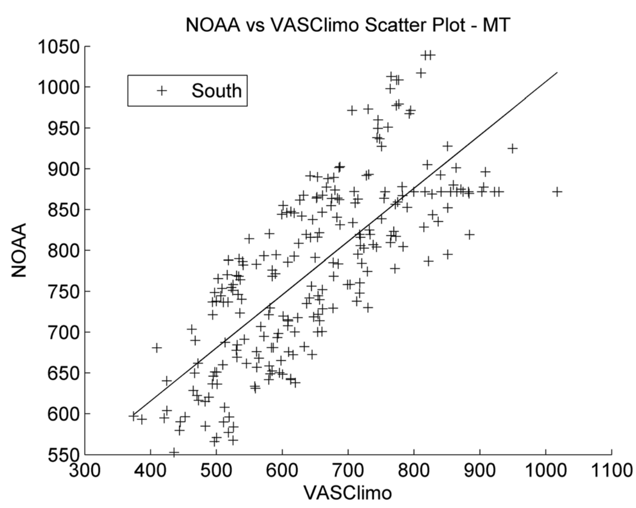

Figure 1. Scatterplot of annual accumulation in millimeter (M_T) derived from NOAA and from VASClimO for the Southern UK.

Constant linear calibrations, such as those listed in Table 2, have been applied to all average annual NOAA accumulations to make them consistent with the VASClimO database of gauge measurements. Assuming that the NOAA convective fraction

$$\beta \equiv \frac{\text{annual convective accumulation}}{\text{total annual accumulation}} \tag{3}$$

remains unchanged, then the same linear calibration can be applied to the annual convective accumulation, M_C. We assume that the calibration does not change over time.

Figures 2a and 2b illustrate the time series of the three parameters M_T, M_C, and P_{r6}, for the three UK NOAA grid cells. All parameters exhibit increasing temporal trends.

Table 2. Regression Slope, Intercept, and Correlation Coefficient for Three NOAA Grid Regions Spanning the UK

Name	*a*	*b* (mm)	*r*
North	1.02	250	0.92
Center	1.03	300	0.94
South	1.04	200	0.93

5. Estimation of the Rain Rate Distribution

SPB proposed a link between the three parameters M_T, M_C, and P_{r6} and the average annual distribution of 1 min rain rates. The four distribution parameters P_0, a, b, and c from (1) need to be determined from the three meteorological parameters, as in (2). The transformation defined by (2) is specific to ERA-40 1° reanalysis data. The form of the transformation is expected to remain, but the constants with numerical values in (2) are likely to be different when using NOAA 1.875° data.

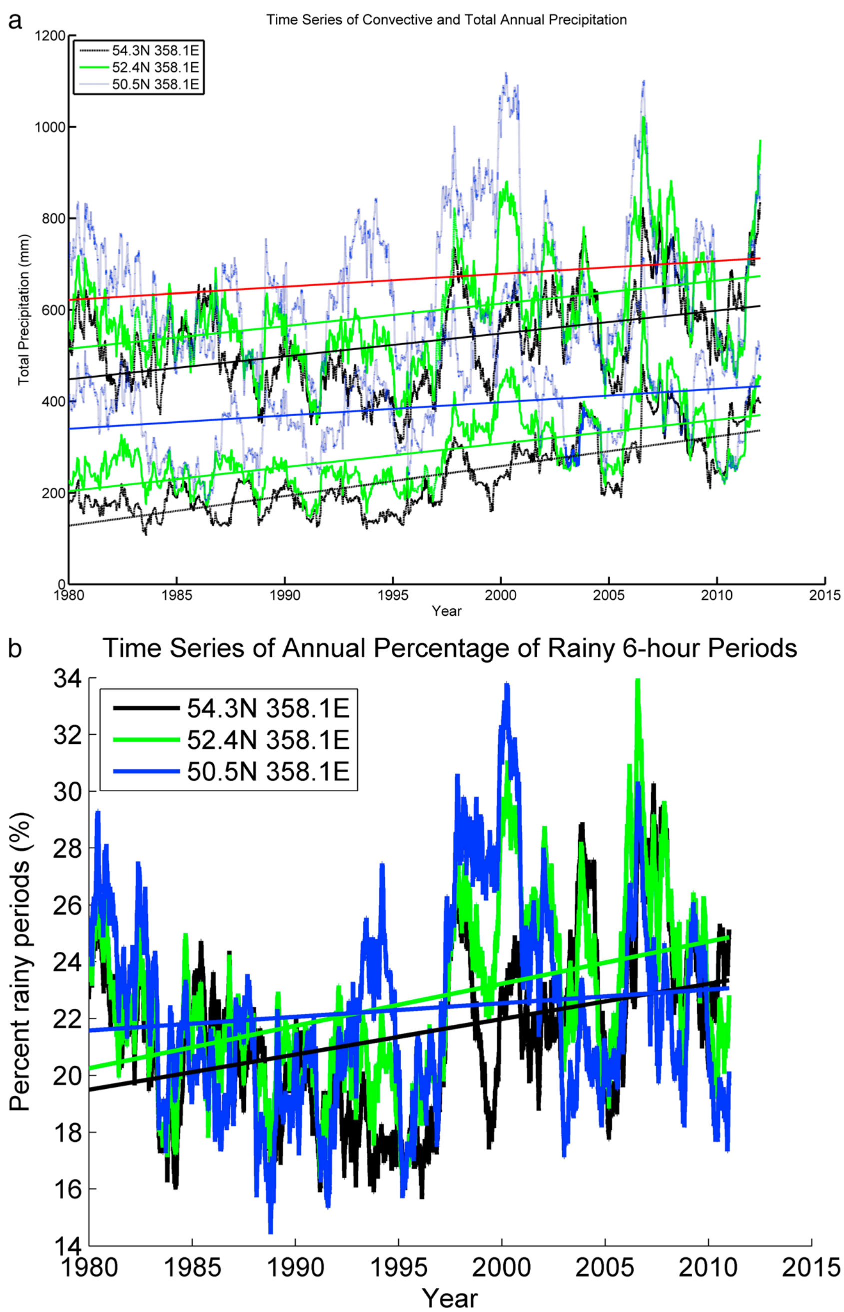

Figure 2. (a) Time series of annual convective (top) and total (bottom) precipitation accumulation for three grid areas covering the UK. (b) Time series of the percentage of annual 6 h periods that experience rain for three grid areas covering the UK.

Table 3. Experiment Results With Optimal Values and the Minimum Error

	Optimal Solution				
	$\alpha_1 \times 10^2$	$\alpha_2 \times 10^{-5}$	$\alpha_3 \times 10^{-1}$	α_4	Error
Case 1	48.15	0.635	0.838	0.4603	0.2976
Case 2	19.50	0.609	1.391	0.7791	0.2418
Case 3	8.79	0.921	1.151	0.5866	0.3167
Case 4	10.47	0.961	1.078	0.5392	0.2789

These four numerical values have been recalculated to provide the best fit to the four experimental CCDF statistics derived from single years of observation, archived in DBSG3.

The data in the DBSG3 database can be used in different ways. SPB assumed stationarity and so used values of meteorological parameters, averaged over all ERA-40 data from 1957 to 2001. We are looking for nonstationary trends in precipitation, and so, in some cases, we used the meteorological parameters from the time interval (1 year) over which the exceeded rain rates were measured. We expect this to yield a better fit as in wet years, with a larger M_T; we would also expect a higher R0.01%.

We have defined a number of cases using combinations of average annual and specific annual reanalysis parameters. The four constants α_j in the SPB method (2) are allowed to vary to optimize the fit between DBSG3-measured R0.01% values, and the prediction using equations (2) with inputs being either average or specific annual meteorological parameters. Two sets of annual accumulation data are available: NOAA and VASClimO. We either use VASClimO calibrated NOAA data or the VASClimO data directly. The data in the DBSG3 database are not from sites evenly distributed around the world. To partially address this bias, site data are assigned a weight which is inversely proportional to the number of sites in a specific country.

The four cases considered are the following: Case 1: Specific annual M_T, M_C, and P_{r6} from VASClimO calibrated NOAA data; case 2: Average annual M_T, M_C and P_{r6}; from VASClimO calibrated NOAA data; case 3: Specific annual VASClimO, mean annual total precipitation M_T, and specific annual M_C and P_{r6} from NOAA; and case 4: Average annual VASClimO, mean annual total precipitation M_T, and average annual M_C and P_{r6} from NOAA.

The error functional is defined in a way analogous to the definition in Rec. ITU-R P.311-14 [*ITU*, 2013], but with a weighted sum to compensate for the distribution of sites:

$$\text{Error} \equiv \frac{1}{n\text{Country}} \sum_{i=1}^{415} \mathrm{W_i} \left| \log\left(\frac{R_i^{\text{DBSG3}}}{R_i^{S-B}} \right) \right| \tag{4}$$

In (4), W_i is the weight for the *i*th site, and R_i^{DBSG3} and R_i^{S-B} are the exceeded rain rates from DBSG3 and from the model with the test parameters, respectively. In this paper, only the 0.01% exceeded rain rate was used. The constant *n*Country is the number of countries with sites used in the DBSG3 database. This normalization allows the error value to be interpreted as the average relative error per site. This functional has been minimized using the Nelder-Mead simplex method [*Nelder and Mead*, 1965], starting from the current Rec. P.837 values. Numerical experiments showed that doubling any initial parameter yielded the same minimum. The optimum parameters are listed in Table 3.

The numerical experiment results show that case 2, which uses the stationary parameters, yields the minimum error value of 0.2418 compare to the other results. This result can be directly comparable with *Castanet et al*. [2007] study which yielded average relative errors around 0.3. Figure 3 illustrates the DBSG3 R0.01% values for the 415 DBSG3 site years with annual data, and the best fit predicted R0.01% values using the optimal parameters from cases 1, 2, and 4. The data are in latitude order, and the decreasing trend in the rain rates is due to the increasing latitude. The majority of the sites are equatorial, within 20° of the equator; or around 40°N in Europe or USA and Canada. A temporal trend also exists where data acquired before 1990 are typically from temperate climates while later data are more often tropical. The best fit follows gross trends well, but there is still considerable deviation for specific site years.

Figure 3 illustrates some features of the problem. All the optimized fits follow the gross pattern of higher rain rates in tropical climates than in temperate. The prediction methods based on average annual parameters, cases 2 and 3, yield one predicted distribution for each site. Measured 0.01% exceeded rain rates from a single

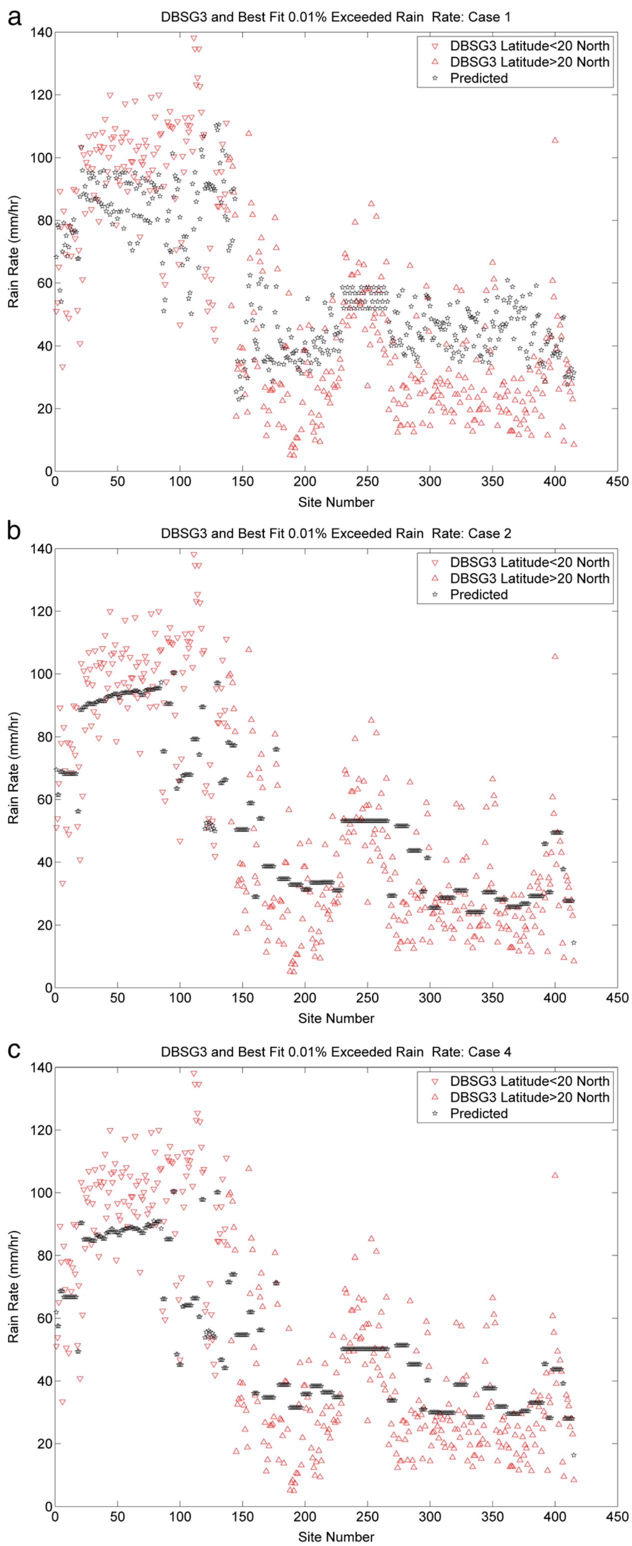

Figure 3. Time series of measured annual 0.01% exceeded rain rates compared to the best fit prediction using (a) case 1, (b) case 2, and (c) case 4.

site can show factors of 4 variation due to year-to-year variability. The use of specific annual input parameters yields some correlation between predicted and measured R0.01% in Europe but does not perform better due to general overestimation in Europe and underestimation in Asia and South America. These biases are also present in the other cases and reflect an underlying problem with the transformation (2). In particular, the difference in convective fractions between temperate and tropical climates does not affect the distribution parameters *a*, *b*, and *c*.

6. Time Series of Predicted Rain Rates

The calibrated NOAA data illustrated in Figures 1 and 2 allow the calculation of time series of 0.01% exceeded rain rates using the distribution (1) and the transformation (2) using case 2 optimized constants. This is speculative as the input and output parameters to the SPB distribution and transformation are average annual values, as discussed in section 1. However, even if the method is a poor predictor of individual yearly rain rate distributions, it is possible that long-term trends will be reproduced. Figure 4 illustrates these 0.01% exceeded rain rate time series for the three NOAA grid regions spanning the UK. All three time series not only show large year-to-year variation but also exhibit increasing trends of approximately 0.2, 0.4, and 0.1 mm/h/yr for the regions south, midlands, and north, respectively.

Paulson [2011] calculated the 1 min rain rates exceeded at annual time percentages of 0.005%, 0.01%, 0.03%, 0.05%, and 0.1%, for the 80 rain gauges in Southern England, over a 20 year period. Slopes were derived using a maximum likelihood (MLE) method, applied to the best fit Weibull distribution to all the available exceeded rain rates for each annual period. The gradient of the maximum likelihood (MLE) line fitted to the 0.01% exceedance data has a slope on 0.44 mm/h/yr.

The slope of the 0.01% exceeded rain rate can also be compared to that found in the

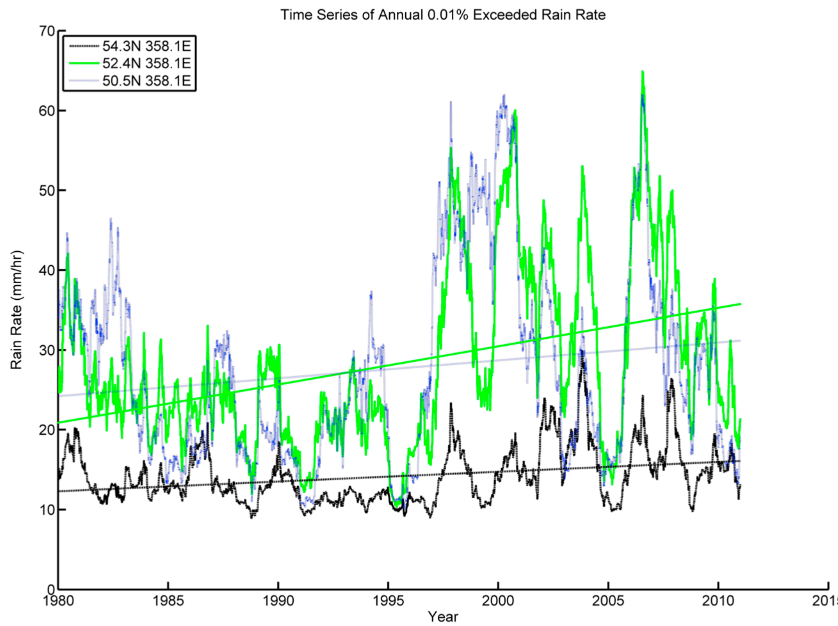

Figure 4. Time series of 0.01% exceeded rain rates derived from NOAA reanalysis data using distribution (1) and the transformation (2).

Ofcom study, based on 1350 high-resolution rain gauges across the UK [*Bacon*, 2012]. This found increasing trends in 0.01% exceeded rain rates around 0.4 mm/h/yr in the north and 0.8 mm/h/yr in the south. Given the different time periods considered and the standard errors in the slopes, these results are roughly consistent.

We have considered a simpler method where the transformation from rain parameters to 0.01% exceeded rain rate is linearized; i.e.,

$$\frac{\mathrm{d}R_{0.01\%}}{\mathrm{d}t} = \frac{\mathrm{d}R_{0.01\%}}{\mathrm{d}M_T}\frac{\mathrm{d}M_T}{\mathrm{d}t} + \frac{\mathrm{d}R_{0.01\%}}{\mathrm{d}M_C}\frac{\mathrm{d}M_C}{\mathrm{d}t} + \frac{\mathrm{d}R_{0.01\%}}{\mathrm{d}P_{r6h}}\frac{\mathrm{d}P_{r6h}}{\mathrm{d}t} \tag{5}$$

The derivatives of M_T, M_C, and P_{r6} were estimated by fitting linear regression lines to 21 year time series, 1980 to 2001, of calibrated NOAA parameters. The derivatives of the transformation between rain parameters and the 0.01% exceeded rain rate were evaluated numerically around the 21 year average parameter value. From the chain rule (5), trend slopes in Figures 2, the 0.01% rain rate was estimated for the three regions spanning the UK and results are compared with those from the Ofcom study in Table 4. The values predicted by this method are marginally higher than those derived from gauge studies but exhibit the same geographic trend.

7. Global Trends in 0.01% Rain Rates

Given the yearly variation in R0.01%, trends calculated over different decadal time intervals yield results that can vary 100% but are generally positive in the UK. The method (5) yields plausible results that agree within expected tolerances with large rain gauge studies in the UK. It is likely that the method will also be applicable in temperate climates similar to the UK, and possibly into tropical regions, but this needs to be tested. This extrapolation is reasonable as the SPB method is applied globally in Rec. ITU-R P.837-6 and so is applicable to a very wide range of climates.

Table 4. Trend Slopes of 0.01% Exceeded Rain Rates Over Three UK Regions

Region	Slope (This Work)	Slope (Ofcom Study)
North	0.6 mm/h/yr	0.4 mm/h/yr
Midlands	0.8 mm/h/yr	0.6 mm/h/yr
South	1 mm/h/yr	0.8 mm/h/yr

The chain rule method (5) method has been applied to the estimation of 0.01% rain rate trends over the rest of the world. The GPCC data are only available for land areas, and so the predictions are similarly constrained. From the calibrated NOAA/GPCC meteorological parameters, the time series of M_T, M_C, and P_{r6} can then

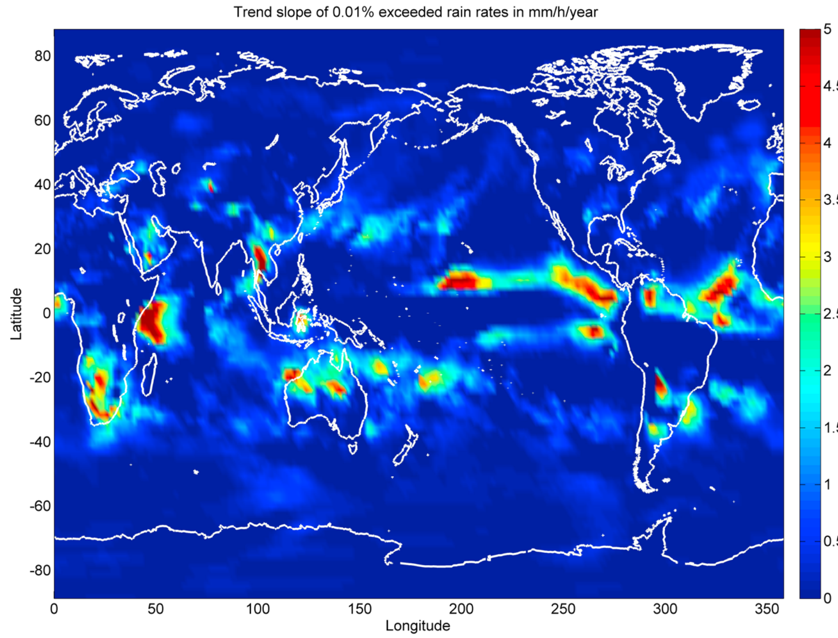

Figure 5. Trend slope of 0.01% exceeded rain rates, in mm/h/yr, derived using the SPB distribution and transformation from NOAA/GPCC time series of precipitation parameters.

be calculated for each NOAA grid region. The case 2 parameters have been used to calculate the SPB derivatives in (5), and the slope of the trend line for R0.01% can be calculated for each grid cell. Figure 5 illustrates this trend slope. The data in this figure are associated with this paper on the Radio Science website.

For some regions the trend slopes are not reliable due to the low incidence of rain, particularly Saharan Africa and mountainous regions such as the Himalayas, Andes, and Rockies. Of all the NOAA grid cells, 90% yielded trends that are statistically significant with a probability of occurring by chance of less than 1%. Of the trend slopes greater than 0.2 mm/h/yr, 40% is statistically significant. The results presented in Figure 5 suggest that many parts of the world are experiencing rapid increases in 0.01% rain rate. The most rapid increases are particularly tropical areas within 30° of the equator, where the proposed method has not been tested.

8. Conclusions

Methods have been developed for predicting the evolution of 1 min rain rate distributions, over land areas, globally. The methods are based on the widely accepted Salonen – Poiares Baptista method that is integral to Rec. ITU-R P.837. We have extended the SPB method by removing the implicit assumption of climate stationarity and using GPCC-calibrated NOAA reanalysis data rather than the ECMWF ERA-40 data. The trend slope in 0.01% exceeded rain rates in three NOAA grid regions spanning the UK have been estimated with the new method and are consistent with results produced by two independent researchers analyzing a large database of high-resolution rain gauge data.

When climate trends lead to large changes in the underlying fade distributions, over the lifetime of a radio system, then these can have serious effects on system performance. Such changes can undermine the business model or make the system not fit for purpose. These considerations are particularly important for expensive space-based systems where hardware adaptation is difficult or impossible. Such systems are designed with wide margins to allow for climate variability. Introducing climate trends into the margin calculation may lead to more realistic estimates of the range of climates a system will encounter over its lifetime.

The assumption of climate stationarity is deeply embedded in the ITU-R recommendations and the processes controlling their evolution. Refinements of recommendations are tested against the DBSG3 database of measurements, collected over the last 50 years. Removing the assumption of stationarity changes the way this database is used, as we have in the work described in this paper. When predicting the performance of systems several decades into the future, nonstationary recommendations are likely to produce more reliable results.

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