Downscaling number of events: Hot days and heavy precipitation

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Abstract. We present three statistics-based strategies for downscaling information about extreme climate events such as hot days and heavy precipitation. They are applied to three megacities in India in an attempt to address the question of whether a stronger global warming is likely to disrupt transport systems as a result of more heavy rain events or hot days. We analysed future projections from 108 CMIP5 RCP4.5 simulations to account for uncertainties connected to the range of natural variability and inter-model differences. A consequence of further global warming is a clear increase in the number of hot days, but the results were more ambiguous for precipitation. This analysis made use of interpolated gridded daily precipitation, but bi-linear interpolation distorts the statistics of the rain intensity. Gridded data may nevertheless provide credible information about the frequency of rainy days. Projections for future wet-day frequency were unsuccessful, however, due to GCM misrepresentation of the mean monsoon sea-level pressure anomalies over the Indian sub-continent.

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1. Introduction

Severe weather events have disruptive effects on society, and climate change will influence weather-associated risks [1]. Climate can be defined as weather statistics resulting from various geophysical processes on earth [2], and its variables may be quantified in terms of a *probability distribution function* (pdf) that describes the expected frequency for a magnitude to materialise [3, 4]. The character of the pdf provides a "fingerprint" of a complex system of phenomena, with an imprint of the effects of processes, phenomena, and conditions. Climate change is equivalent to a change in the parameters of the pdf (e.g. shape and location), and can be expressed in terms of differences, trends, and the recurrence of record-breaking events [5]. Severe weather events are often referred to as "climate extremes" and involve rare recurrence (low probability) and are associated with the lower or upper parts of the pdf [6].

There is a long history of studies on climate extremes (or severe weather events), and a recent account is provided in the Intergovernmental Panel on Climate Change (IPCC) "SREX" report [1]. Part of our understanding of extreme events is derived from empirical information based on historical observational records, and part is due to insight from physics, meteorology, and statistical theory [7, 8, 6]. Potential foresights about climate extremes for the future rely on numerical model simulations of relevant physics such as dynamics and thermodynamics, carried out with global climate models (GCMs) [9, 10]. One objective in climate research is to provide information about the likely effects that a continued global warming has on local scales and climate extremes. The local response ζ to the large-scale condition X can be expressed mathematically as $\zeta = n + f(X)$, where n is the local noise and $f(X)$ is a function of the large scales. A global warming may or may not influence some local aspect ζ, which can involve temperature, precipitation, or the number of severe weather events (e.g. storms, heatwaves, days with heavy rains, droughts, lightening strokes).

1.1. Motivation

A common approach for studying extremes in climate research has involved the use of extreme value theory (EVT) and return-values applied to time series for variables like daily temperature or precipitation [1, 11, 12, 13, 14]. This strategy provides useful information for e.g construction (design values) if the statistics is stationary ($\zeta = n$) or the future shape of the pdf can be predicted. It is also possible to make use of a pdf for estimating the frequency of events that exceed a given threshold x_0 ($Pr(X > x_0)$) and use it together with the binomial distribution to generate the likely range for the number of events [15]. Both assume that the shape of the pdf is known for parametric distributions [3] or constant empirical distributions. For instance, the likelihood of hot days will be influenced by systematic changes in the variance in daily temperature as well as the mean [16, Fig 1.8], but the probabilities of occurrence may be difficult to estimate if the statistical distribution deviates from the well-behaved parametric distributions.

A less common approach in climate research is to study the *number of events* and

their dependency to large-scale conditions, rather than the magnitude. For instance, the number of days with the temperature exceeding 30°C or days with precipitation exceeding 50mm. This approach has the advantage of not having to rely on a certain type of distribution, such as the normal distribution. The number of events, however, will in theory follow a Poisson distribution for a random process. There are well-established statistical methods for analysing and modelling Poisson distributions; one example is the projection of the number of rain-on-snow (ROS) events over Svalbard, as the probability of a ROS event is sensitive to the winter mean temperature [17].

Here, our objective was to make practical use of the modelled statistics for the number of severe weather events in India, where transport in megacities is affected by extreme weather conditions such as extreme rainfall (flooding) and hot days.

2. Data & Method

2.1. Data

Daily maximum temperature and rainfall from three Indian megacities (Delhi, Mumbai/Bombay, and Bangalore) were extracted from gridded IMD data set (provided by M.S. Madhusoodanan). The daily precipitation covered the period 1901–2004 whereas there was daily maximum temperature for the period 1969–2005. Surface temperature (T_{2m}) and mean sea-level pressure (SLP) from the NCEP/NCAR reanalysis 1 [18] were used as predictors during the calibration of the downscaling model for Indian hot days and precipitation events, and GCM results from the CMIP5 RCP 4.5 experiments [19] were used for making projections. For downscaling of wet-day mean precipitation μ, large-scale saturation vapour pressure e_s was used as predictor, estimated from the maritime T_{2m} by applying a land mask and then using the Clausius-Clapeyron equation to estimate monthly mean e_s from monthly mean 2-m surface temperature [15]. These were then aggregated to June-September mean values. The choice of reanalysis depended on availability of data and the length of data record, and in this study included the period 1948–2016.

2.2. Method

2.2.1. Downscaling Three different strategies were explored for downscaling information about climate extremes: henceforth referred to as the "parameter downscaling" (for precipitation statistics), "number-of-events" approach (heavy precipitation events), and a hybrid of the two (temperature and number of hot days). We used a Poisson regression model similar to types which have been applied to mortality connected to heat waves [20]. There have also been some studies where the hot days themselves or number of tropical cyclones have been modelled as Poisson processes [21, 22]. The downscaling model procedure consisted of a step-wise screening multiple regression with common EOFs used as predictors [23]. For the "parameter downscaling",

the predictand was the principal components from a *principal component analysis* (PCA) applied to the seasonal mean μ or f_w at the three stations [24, 25].

2.2.2. Precipitation Two different approaches were explored for deriving large-scale dependent information about heavy precipitation events, i.e. the consequence $f(X)$ of a global warming for extreme rains. The "number-of-events" approach was used to downscale the number of days with daily precipitation amounts greater 100mm in Mumbai and 50mm for Delhi and Bangalore. The parameter downscaling strategy, on the other hand, assumed that precipitation can be approximated by an exponential distribution if only wet days are considered [15]. The wet-day frequency f_w and the wet-day mean precipitation μ were aggregated on an annual basis over the monsoon season (May–October) on par with earlier studies [25, 15].

2.2.3. Temperature The strategy for downscaling the number of hot days can be described as a hybrid between the number-of-event and changed-pdf approaches. The daily maximum temperature T_x exhibits statistical characteristics that somewhat resembles the normal distribution, and the mean local summer mean daily maximum temperature T_x (June-August) can be used as a proxy for the number of hot days n_h, assuming that the variance is stationary. The number of hot days was modelled according to $g(n_h) = \beta_0 + \beta T_x$, making use of a general linear model (GLM) with a logarithmic link function $g(.)$ to accommodate for the character of Poisson processes.

2.2.4. Projections Ensemble results for large-scale mean sea-level pressure (SLP) and temperature (T_{2m}) from global climate models (108 RCP4.5 runs) were used to downscale f_w, μ and the summer mean temperature T_x. The predictor choice was the same as in [25]: SLP for f_w, the saturated vapour pressure e_s for μ, and large-scale T_{2m} for the summer mean daily maximum temperature T_x. More details and source code listing are provided in the supporting material (SM).

3. Results

3.1. Heavy precipitation events

3.1.1. Parametric downscaling Most of the precipitation over the three Indian megacities fall during the monsoon season (May–October) and the mean seasonal peak is mainly due to more rainy days during the monsoon season than the rest of the year, as the mean seasonal variation in the precipitation intensity is of secondary importance (SM). Mumbai receives on average about 2000 mm rain during May–October, while Delhi and Bangalore have drier climates (675 mm and 800 mm respectively). The mean number of rainy days (Mumbai 97 wet days, Delhi 45 wet days, and Bangalore 60 wet days) and mean intensity (Mumbai: 20.7 mm/day, Delhi: 13.4 mm/day, Bangalore: 10.8 mm/day) also vary geographically. Analysis of long-term trends in the wet-day

frequency f_w from the observations hinted to slight changes, but only the trend in New Delhi appeared to be statistically significant at the 5% level. For μ, only the record for Mumbai suggested a significant long-term trend at the 5%-level. There were a couple of years during the 1950s which stood out as unique seasons with particularly intense rainfall in Mumbai due to high values in μ.

An evaluation was carried out to test how closely the exponential distribution described the observed wet-day precipitation statistics, and a comparison between the wet-day 95th percentile and the derived equivalent for an exponential distribution $q_p = -\ln(1-p)\mu$ exhibited a scatter along the diagonal. The results verified that the daily wet-day precipitation is approximately exponential [26] (SM) so that the wet-day mean precipitation μ could be used as an indicator for intense precipitation events.

A PCA was applied to the records of monsoon season μ estimates and the results were dominated by the Mumbai precipitation, and in particular two years in the 1950s with exceptionally high estimates for μ (SM). The PCA was used in the parameter downscaling strategy, but the model failed to capture peak values in μ, possibly because they were due to very local effects (mesoscale convection or super cells) and not closely connected to large-scale conditions (Figure 1). These features were not present in the data for Bangalore and Delhi, however, which is consistent with being a local feature rather than related to a large-scale condition. The residuals from the regression were checked for any structure left in the data such as co-variance and auto-correlation. This evaluation suggested that not all factors influencing precipitation have been accounted for in the downscaling. The statistical model for μ was nevertheless used to downscale projections for the future, keeping in mind this limitation, because we were unable to find further suitable predictors. The downscaling of ensembles of GCM projections indicated little future changes in μ, and the evaluation of the results suggested that the downscaling underestimated the inter-annual variability (SM).

The wet-day frequency f_w had comparable magnitude between the three cities, unlike μ, and the PCA placed more even weights on the three locations. The leading PCA for f_w was also well-captured by the downscaling with a cross-validation correlation of 0.71 (Figure 2), and the accompanying large-scale SLP predictor pattern had a typical monsoon finger print. Nevertheless, the downscaling of the RCP 4.5 ensemble of climate change projections indicated little change in f_w, as the climate model simulations did not suggest that the large-scale SLP conditions will change in such a way as to introduce a shift in the frequency of rainy days. The downscaled GCM ensemble under-estimated the inter-annual variability, in spite of the good results obtained when using only reanalysis as predictor. The reduced variability was a result of differences in the simulated large-scale SLP variability over the Indian sub-continent. We tested the GCMs' ability to reproduce the spatio-temporal structure of variance in the mean monsoon SLP through diagnosis based on common EOFs (SM) and found substantial differences between models and reanalysis data.

A comparison with raw precipitation totals ($p_{tot} = nf_w\mu$) from the GCMs averaged over the Indian sub-continent indicated a slight increase in the annual mean large-scale

precipitation (SM). This increase implies more extreme events either as a result of more rainy days (SM) or higher values for μ [27].

3.1.2. Downscaled number of events The number-of-event approach involved modelling the number of days with heavy precipitation. The results for Mumbai indicated little connection with large-scale e_s or T_{2m} anomalies (Figure 3). Although the pdf for n_h had some resemblance to the Poisson distribution, it appeared to be over-dispersed with too many years with a small number of events and $\sigma^2 > \overline{x}$. These results also underlined the difficulty in finding a link between the precipitation intensity and large-scale conditions. The analysis was repeated for Delhi and Bangalore and days with more than 50 mm of precipitation, however, the number-of-event approach did not result in a good capture of the range of possibilities (SM). There may be several plausible reasons for that: weak dependency to large-scale conditions or issues with data quality (SM).

3.2. Hot days

The 1969–2005 mean temperature was 31.6°C (min: 11.6°C; max 47.0°C) in Delhi, 30.9°C in Mumbai (min: 23.9°C; max 38.1°C) and 30.9 in Bangalore (min: 20.9°C; max 38.9°C). Trend analysis for T_x over 1969–2005 indicated slight warming except for in Delhi with practically a zero trend. The summer season standard deviation exhibited small trends and the summer T_x was close to being normal distribution (SM). The results from the downscaling of the summer mean daily maximum temperature for the three megacities are shown in Figure 4. There was a close association between the large-scale surface temperature in the reanalysis and the temperature from the stations, with a cross-validation correlation of 0.75. The predictor pattern associated with the leading PCA (upper left panel), however, exhibited a complex structure, which may suggest somewhat less than perfect account. GLM calibration results for $g(n_h) = \beta_0 + \beta T_x$ indicated that the number of hot days can be reproduced to a reasonable degree (SM), however, T_x deviated from being normally distributed, and the number of hot days was not quite Poisson-distributed. The strategy of a direct prediction of the number of events nevertheless gave a reasonable account of the number of hot days, as the observed range of n_h was comparable to the range derived from the downscaling (Figure 5). Typical "warm", "cold", and "normal" years were represented in terms of using the 95th, 5th percentiles as well as the mean of the RCP 4.5 ensemble. The downscaled GCM ensemble projections indicated an increase in all cases, but a much stronger increase in the number of hot days in warm years.

4. Discussion

Our results for temperature were in accordance with previous conclusions that a global warming gives more intense, frequent and longer lasting hot days [28, 29]. We used ESD to quantify the number of hot summer days associated with a typical 'cold', 'normal'

and 'warm' summer respectively, and found that most of the summer days ($n_h > 90$) may exceed 40°C in Delhi for an anomalously warm season by 2050.

The estimates for number of hot days assumed a constant variance for daily temperature, and there have been some studies indicating that the internal variability (standard deviation) may change in the future, such as the annual mean temperature [30]. Such indications were not found in these projections for the annual mean nor has there been trends in the annual standard deviation from daily data derived from historical record (SM).

The downscaling analysis of temperature and f_w also showed a clear link to large-scale conditions as cross-validation studies suggested that the models were able to capture a large portion of the variability in both cases. It was difficult to find good predictors for μ, however, possibly because it is more strongly affected by small-scale and local factors. The lack of clear connection to large-scale predictors for μ has been noted in in earlier studies from different parts of the earth [15, 25]. The exact reason why needs to be explored.

Here, the results for μ were strongly influenced by two summers with exceptionally high precipitation intensity, and we hypothesise that those were a consequence of convective activity. However, the peaks were only seen for Mumbai. The quality of the results for μ hinges on how representative these features were for the region and how closely they were associated with large-scale conditions. We can expect substantial sampling fluctuations from rain gauges with a small cross-section (cm^2) compared to the scales of the clouds (km^2), as they only provide a tiny sample of the system. Inhomogeneities and errors in the observed series may result in a degraded analysis or incorrect results when the numbers do not reflect the actual weather conditions. Typical issues include instrumental change, site removal, or changes to the surroundings. For instance, wind around the rain gauges affects capture and may be strongly affected by changes in the surroundings [31, 32]. There was a lack of information and meta-data for the data used, precluding an assessment of the data quality. Data from station records in India are difficult to access, but the Indian Meteorological Department (IMD) gridded product is more readily available [33, 34]. The format of the original station files with raw data was cryptic and difficult to read, increasing the risk of the introduction of errors when writing, reading, and deciphering the files (see the supporting material, SM). Using gridded precipitation, where the interpolated value is a weighted sum, is not a preferred solution for daily precipitation§. Potential shortcomings should be kept in mind regarding how well the results represent the actual conditions. The interpolated results tend to exhibit different statistical characteristics compared to the original station data (see the SM for a demonstration). Hence, it is likely that the estimates for μ have large errors which may explain the poor results for the intensity and the number of heavy precipitation events.

Finding zero change does not rule out the possibility of change, possibly due to a

§ http://www.icrc-cordex2016.org/images/pdf/Programme/presentations/parallel_D/D3_Chandler_CORDEX2016.pdf

missing dependency to large scales. It is unclear exactly what consequences a global warming has on small-scale convective precipitation intensity, however, higher cloud tops [35], deeper convection [36], and more moisture may result in more intense rainfall amounts. More precipitation on monthly scales may be expected over parts of the Tropics according to GCM simulations [37], which may be due to an increase in f_w, μ or both if the probabilities of heavy rainfall follows $Pr(X > x) = f_w \exp(-x/\mu)$ [15]. It is also easy to demonstrate that the wet-day frequency has an effect on the number of observed heavy precipitation days (SM).

The proposed number-of-events strategy can provide a successful means for deriving information about extreme events given a strong dependency, and it has been used to downscale bird population in a habitat and the number of events with excessive run-off in small catchments (see SM for examples applied to dipper population and hydrological studies). The problem with downscaling in India appears to be linked with data availability, quality, or a weak connection between local and large scales.

5. Conclusions

Empirical-statistical downscaling can provide some information about local climate extremes such as the number of hot days. The results for India suggests more pronounced interannual variations may be expected for the number of hot days in India in the future, with a dramatic increase for the warmest summers. The analysis did not provide clear indications for future heavy precipitation events, and the ensemble of GCMs did not suggest that a warmer world will result in a change in the number of rainy days. Raw GCM results averaged over the sub-Indian continent suggest a slight increasing trend in the total precipitation, but the regression analysis did not capture well any dependency of the local precipitation intensity to large-scale conditions. It is possible that the precipitation amounts used in this study were not really representative for the past, as they were obtained from interpolation of gridded daily data. It is difficult to make a firm assessment in the lack of proper metadata.

5.1. Acknowledgments

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6. References.

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7. Figures

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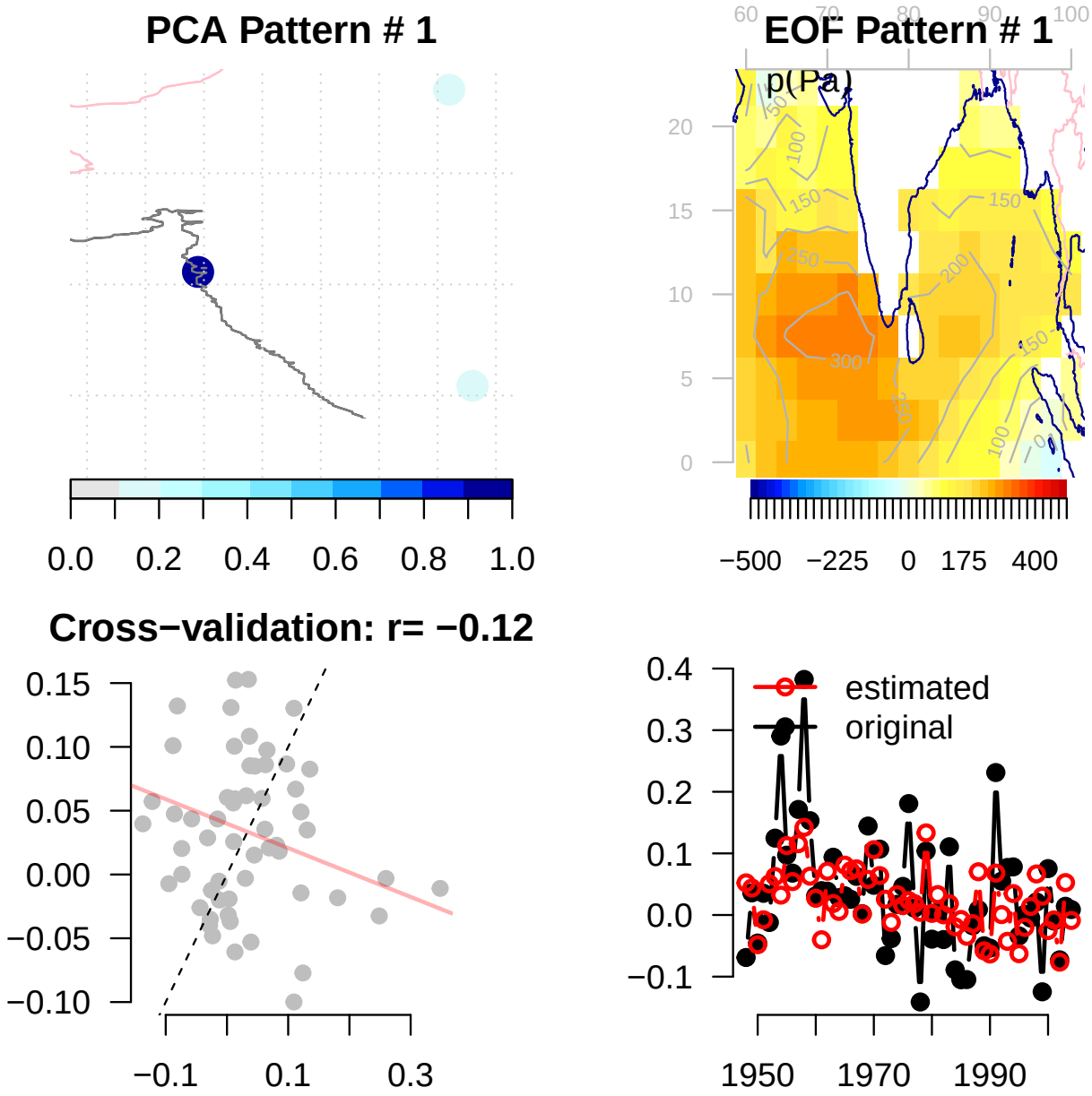

Figure 1. Evaluation of the parameter downscaling of the leading PCA for μ showing the weights applied to the location (upper left), predictor pattern (upper right), correlation from cross-validation (lower left), and a comparison between the best-fit calibration (red) and observations (black).

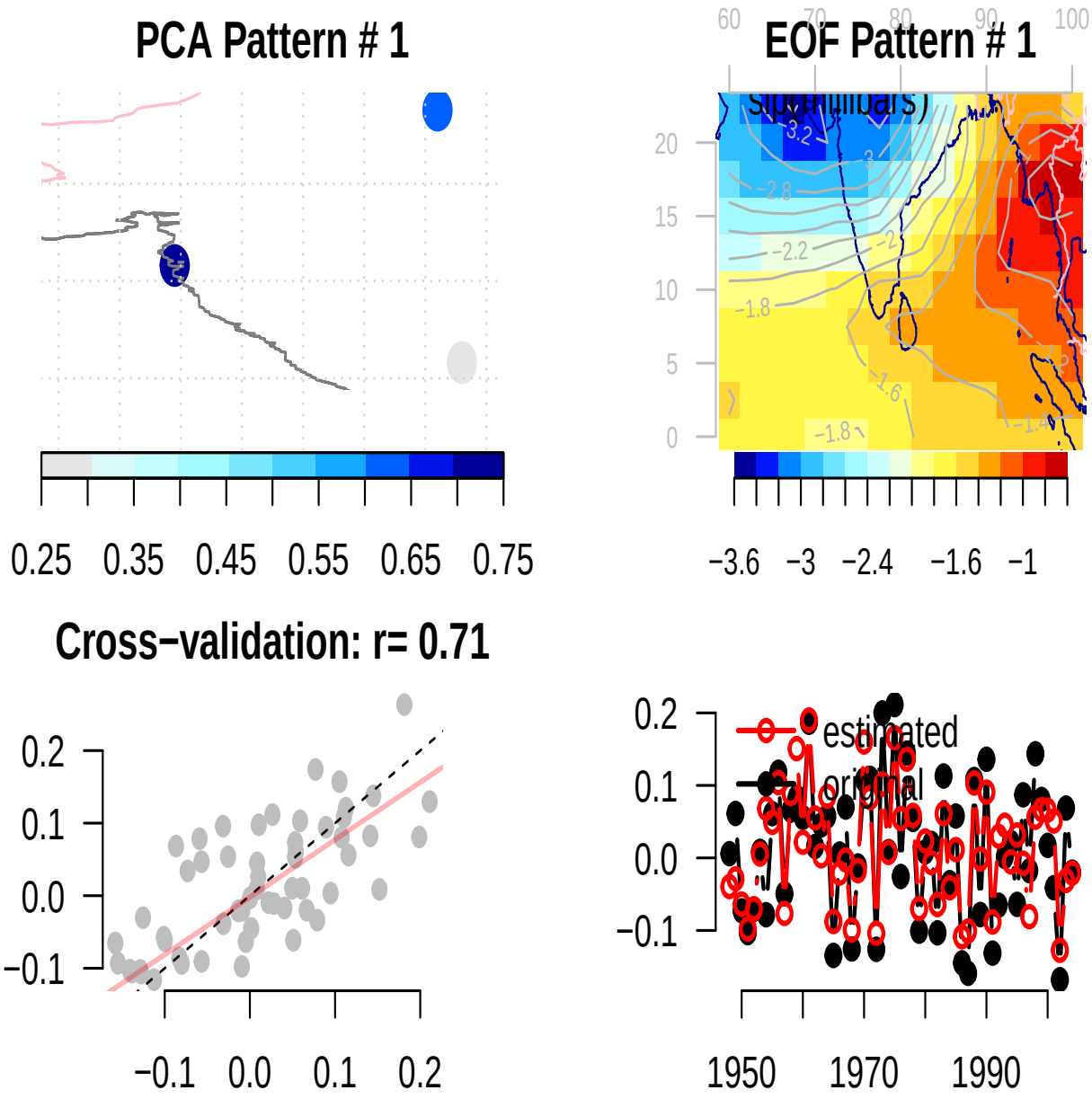

Figure 2. Same as Figure 1 but for f_w. The evaluation of the downscaling for the wet-day mean suggest high skill and a close dependency of the local rain frequency on the large-scale conditions.

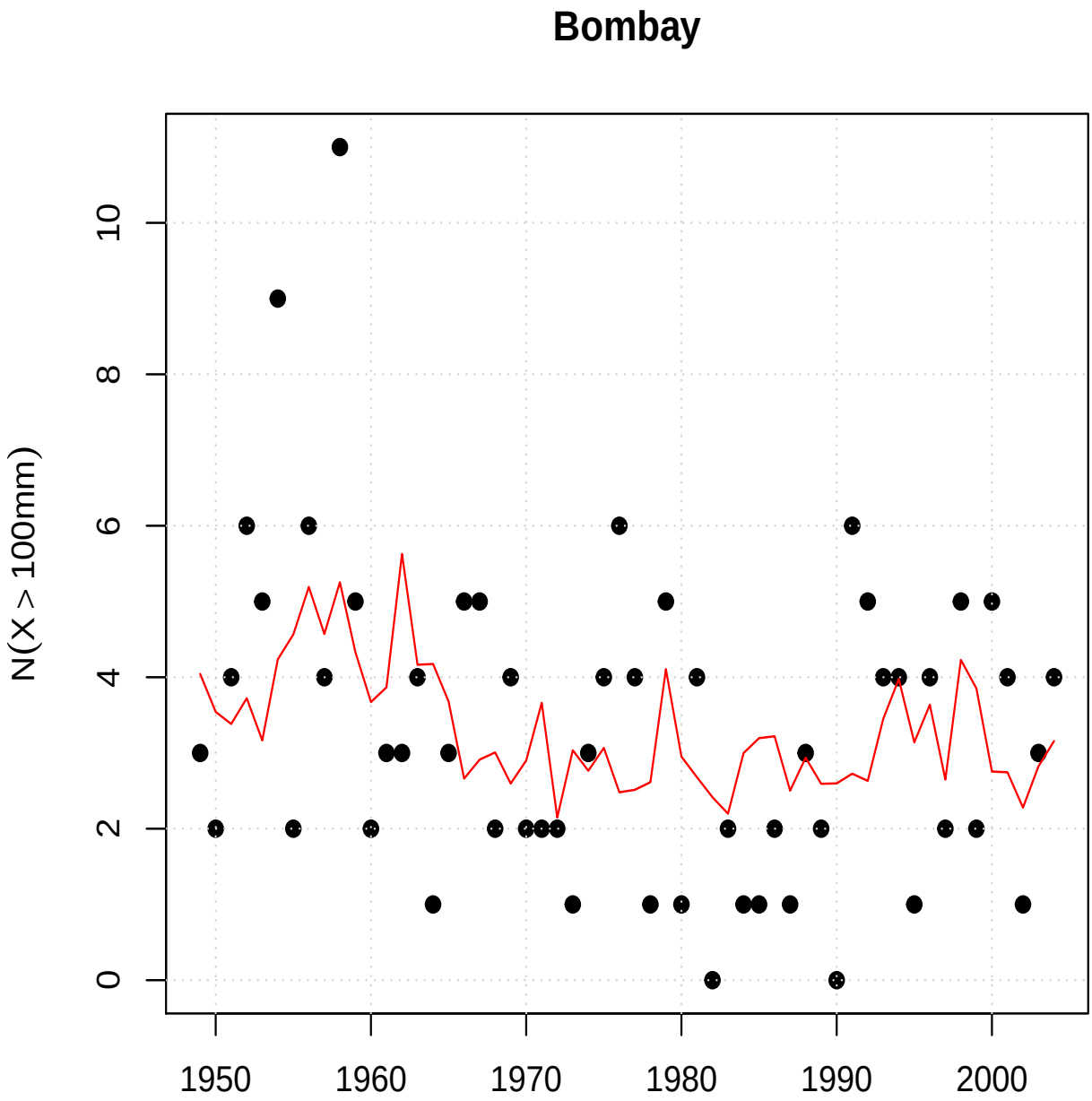

Figure 3. The observed (symbols) and downscaled number of heavy rain events in Mumbai, defined as number of days with more than 100mm/day. The results were derived through the number-of-event approach. They only hint to a weak link between the large-scale e_s or maritime T_{2m} and the number of days with heavy precipitation.

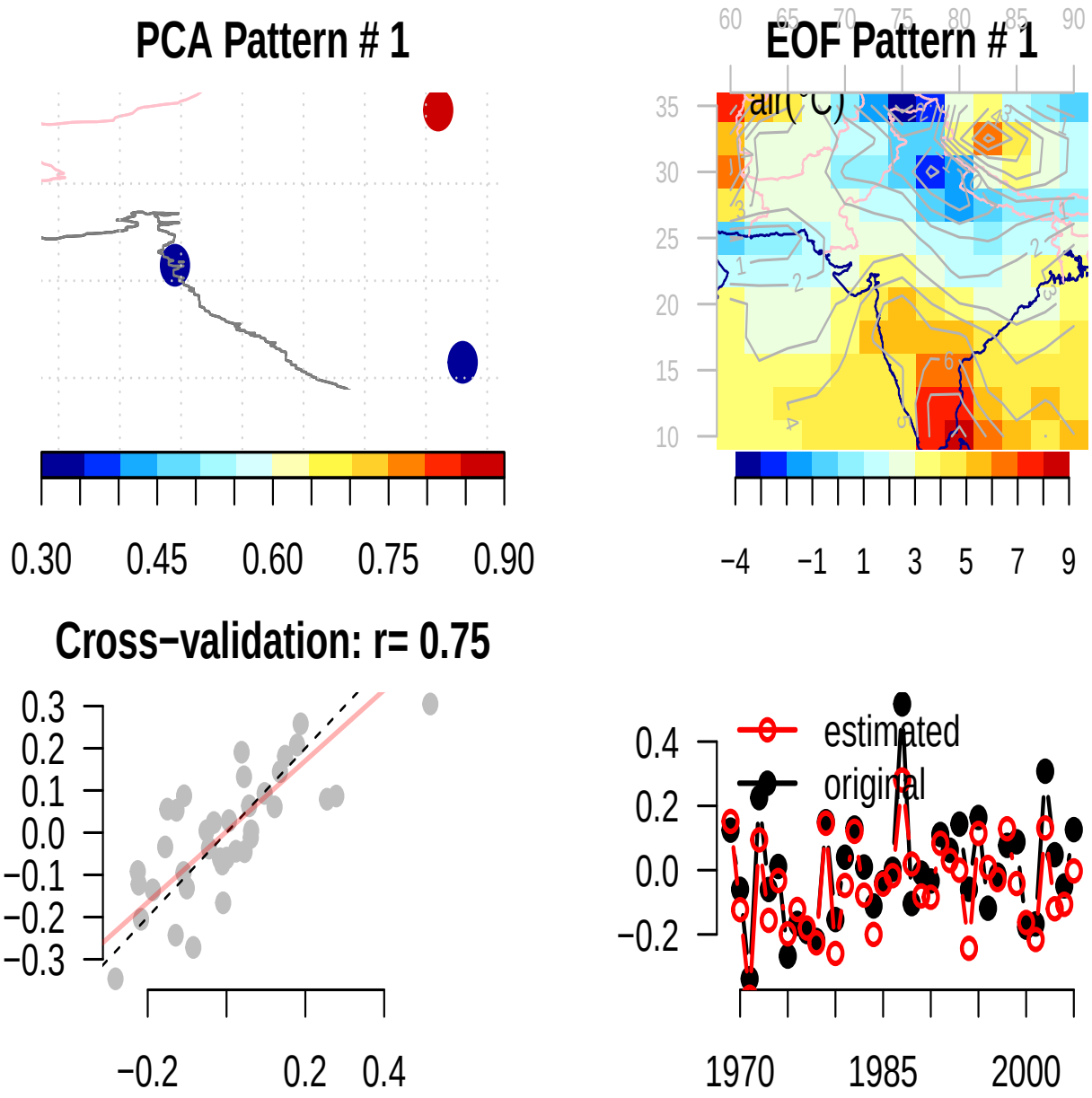

Figure 4. Same as Figure 1 but for T_{2m}. The results for temperature show a good correspondence between local measurements and the large-scale reanalyses.

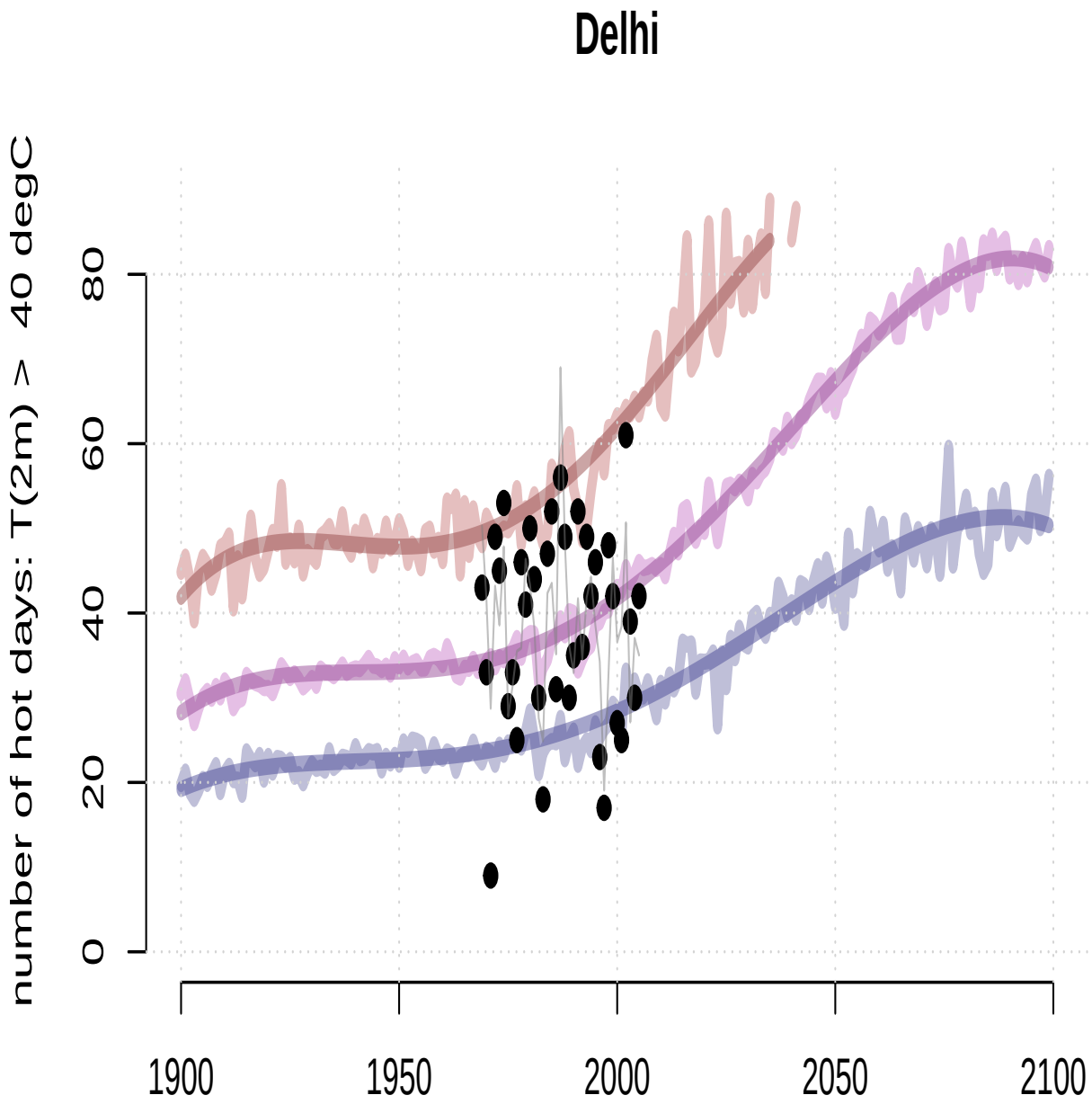

Figure 5. Downscaled projections of the number from the hybrid approach of hot days for a typically hot year (red), an avarage year (purple) and cold year (blue). These correspond to the 95th and 5th percentiles of the downscaled RCP4.5 ensemble as well as the ensemble mean [25]. Black symbols show past statistics based on observations.