

Response to Report #1

S. Parey (Referee #2)

sylvie.parey@edf.fr

The authors would like to thank again Sylvie Parey for the comments that helped us to improve our manuscript. Our responses to the comments are as follows.

1. p9 l39: "When looking at the wet-bulb temperature ... show some overlap with the those derived from station observations" "the" seems useless before "those" ?

Ans: "the" is removed on page10, lines 364-365.

2. p10 l33: "Although the ERA Interim ... magnitude of the extremes, but it provides" I did not expect a "but" here.

Ans: "But" is replaced with "still", page11, line 429.

3. p10 l38: "Although the bias corrected ERA Interim ... with the meteorological station data, statistically differences remain" something seems to be missing between "statistically" and "differences" (like significant for example)

Ans: word "yet" is added to complete the sentence, page12, line 442

4. Table 4 legend: "and standard error $\Delta\xi$ " I would have mentioned both "and standard errors $\Delta\xi$ and $\Delta\sigma$ " as both are in the table

Ans: $\Delta\sigma$ is added in the caption of table 3, page18.

Response to Report #2

Pingping Luo (Referee# 4)

robertluoping@126.com

The authors would like to thank Pingping Luo for the constructive comments and suggestions that helped us to improve our manuscript. Our point-by-point responses to the comments are given below.

1. Please use the continuous line number.

Ans: The continuous line number is provided.

2. Introduction section, I think it need restructure the order and paragraph in this section. Some small paragraph should connected with another paragraph.

Ans: The introduction section is modified.

3. Page3-4, from Page 3 Line 22 to Page 4, line 5, It need make it shortly. It is difficult to identify your objectives.

Ans: The objectives are modified and revised, page 3, between lines 92-110.

4. Table 3, The first part of “Observed Tmax”, the format of line should be same with the others.

Ans: It has been formatted. Please see page 17.

5. Figure 4, the figure is not clear because there are some background in the figure. Please try to delete the background and make the figure clearly.

Ans: Background is removed.

6. Figure 5, the figure is not clear because there are some background in the figure. Please try to delete the background and make the figure clearly.

Ans: Background is removed.

7. I suggest the author should add some discussion on how your work connected with the extreme storm or dry. What your result can be contribute for? Such as flood management and so on. What is your research limitation.

Ans: Thank you for the suggestion. In this manuscript we focus on high temperature extremes, but we are well aware that other extremes of potentially huge impact exist in the region. Your reference to flood risk is most relevant, indeed. We have already prepared another manuscript on the precipitation extremes for flood management authorities, where we have linked the temperature and precipitation extremes. Besides temperature, an increase in transport of moisture flux from the Arabian Sea is also considered responsible for the intense precipitation in southern Pakistan (Kalim and Shouting, 2012, Freychet et al. 2015). We have added few lines 384-385 and 417 -

419 on page 10 & 11 to give our readers an idea about the impacts of temperature extremes.

The current paper is only focusing on two types of temperature extremes due to their direct impact on crops, livestock and society. The main aim of this publication is to guide the local administrations for preparation of baseline contingency plans to deal with strong heat waves based on the current climatology. Such measures are not yet present in the territory and lead to many casualties each year. This is already mentioned in the paper between lines 453 – 454 on page 12.

The sparse network of weather stations and lack of long-term data are the main limitations of this study. This is more explicitly mentioned in the manuscript now.

References:

Kalim, U. and Shouting, G. A. O., 2012: Moisture Transport over the Arabian Sea Associated with Summer Rainfall over Pakistan in 1994 and 2002. *Advances in Atmospheric Sciences*, 29(3): 501–508.

Freychet, N., Hsu, H. H., Chia, C., and Wu, C.-H., 2015: Asian Summer Monsoon in CMIP5 Projections : A Link between the Change in Extreme Precipitation and Monsoon Dynamics. *Journal of Climate*, pages 1477–1493.

7. Reference is a little old, please try to add some recent references.

8. Suggested references:

1) Weili Duan, Bin He, Kaoru Takara, Pingping LUO, M. Hu, Nor Eliza ALIAS, and Daniel Nover, Changes of precipitation amounts and extremes over Japan between 1901 and 2012 and their connection to climate indices, *Climate dynamics*, Published online, DOI 10.1007/s00382-015-2778-8.

2) Pingping LUO, APIP, Bin He, Weili Duan, Kaoru Takara, and Daniel Nover: Impact assessment of rainfall scenarios and land-use change on hydrologic response using synthetic Area IDF curves, *Journal of Flood Risk Management*, Online, DOI: 10.1111/jfr3.12164, 2015.

3) Pingping LUO, Bin He, Kaoru Takara, Yin E Xiong, Daniel Nover, Weili Duan, and Kensuke Fukushi, Historical Assessment of Chinese and Japanese Flood Management Policies and Implications for Managing Future Floods, *Environmental Science & Policy (SCI Journal, 2015 Impact Factor: 3.54)*, Vol.48, 2015, pp. 265-277, DOI: 10.1016/j.envsci.2014.12.015.

Ans: We have added two of the above-mentioned references (2,3 see page 10 &11) in the paper. All three references will also be added in our next publication on the precipitation extremes in southern Pakistan.

Response to Report #3

Anonymous Referee #5

We would like to thank anonymous Referee #5 for the critical review and comments. The step-by-step responses to the main reservations of the referee are as follows.

1. The manuscript lacks novelty. It seems to be just an application of widely-used methods in a new region. The authors said “the POT method was never used to analyze the risk of temperature extremes in Sindh” and repeated this point several times in their response. However, please remember “Just because it has not been done before is no justification for doing it now.” (by Peter Attiwill, Editor-in-Chief, Forest Ecology and Management.)

Ans: Yes, we mention in the paper that the POT method is applied for the first time in Pakistan but this is not the only reason we used it. Our main goal is the risk assessment of the temperature extremes in the region, which are responsible for the deaths of thousands of people almost every year. We clearly mention an example of such an events in our paper on page 1, lines 33-35. This study is conducted focusing on the need of the planning and adaptations in southern Pakistan. The local administrators, policy makers, and other stakeholders (Energy sector, agriculture sector, water management authority, port authorities etc) want to have a clearer picture of the statistics of hot extremes in the region. Extreme Value Theory, thanks to its universality, provides more robust information than ad-hoc approaches on return times of dangerous events.

POT method is preferred for this study because of its popularity and efficient use of data in evaluating the risks for relatively shorter datasets (Lucarini et al.,2016 ; Coles 2001 ; Holmes and Moriarity,1999; Davison and Smith, 1990).

Our results are informative of the spatial patterns of extremes. The results and maps of this paper will be displayed in a freely available web-tool SindhX developed for the policy makers [www.sindhX.org]. This tool will be available online after the publication of our results. Our results will not only contributes to the regional planning, but can also be useful for the ongoing EU projects (SUCCESS, CSCCC), World Bank project (Sindh Resilience Project) and mega construction projects like China-Pakistan Economic Corridor (CPEC).

Clearly, the sparse network of weather stations and lack of long-term data are the main limitations of this study.

We agree with the reviewer’s statement that in general “Just because it has not been done before is no justification for doing it now”. But we honestly do not see why this applies to this study. This would be the case if a) the region we are investigating is of no interest, and this seems blatantly untrue; or b) the method we are using is mathematically ill-defined or of no interest; this also seem unlikely.

References

Coles, S.: An Introduction to Statistical Modeling of Extreme Values, Springer London, London., 2001.

Davison, A. C. and Smith, R. L.: Models for Exceedances over High Thresholds, J. R. Stat. Soc. Ser. B, 52(3), 393–442, doi:10.2307/2345667, 1990.

Holmes, J. D. and Moriarty, W. W.: Application of the Generalised Pareto Distribution to wind engineering, J. Wind Engineering and Industrial Aerodynamics 83, 1– 10, 1999.

Lucarini, V., Faranda, D., Freitas, A.C.M., Freitas, J.M., Holland, M., Kuna, T., Nicol, M., Todd, M., Vaienti, S.: Extremes and Recurrence in Dynamical Systems, John Wiley & Sons Inc, 2016.

https://europeanunion.pk/?page_id=550

https://ec.europa.eu/europeaid/projects/sindh-union-council-and-community-economic-strengthening-support-success_en

<http://projects.worldbank.org/P155350?lang=en>

<https://www.dawn.com/news/1305179>

2. I agree with Referee #3 on his/her main points, especially for the suggestion of trend detection. Detailed test for stationarity in the observed data should be given because possible trend and abrupt changes will have great influence on the results. Referee #2 also pointed out that “The notion of return level is defined for stationary time series, that is without any cycles nor trends”.

The author said “-- considers the stationary extreme value analysis due to short duration of the data (33 years)”, I can't agree on this. The study period is from 1980 to 2013. In fact, the recent 3 decades are the periods that are with the most evident changes of temperature. What's more, In Fig 4 (page 10) of Rasul et al. (2012), it shows a sharp rise in temperature during the first decade of 21st century. Besides, in Figure 11 (page 19), it also shows significant increase in heat wave frequency in Sindh at $\geq 40^{\circ}\text{C}$ & $\geq 45^{\circ}\text{C}$.

Rasul, G., Afzal, M., Zahid, M., Ahsan, S. and Bukhari, A.: Climate Change in Pakistan Focused on Sindh Province., Technical Report No. PMD-25, 2012. It is also cited in the manuscript.

Ans: We clearly mention in the paper page 4, between lines 151-158 about the trend detection. We mentioned also in previous responses to Referee #2 and #3 that trends are tested and are insignificant in such a short time interval. Stationarity is investigated using Augmented Dickey Fuller (ADF) test on all time series (Dickey and Fuller, 1979). The trends are tested with Mann-Kendall test. The results are not shown since the paper already contains many tables, but they are provided now in a supplementary material. Referee #2 has accepted our response on the use of stationary

model.

In this region, observations without gaps are only available for a short duration of 33 years. Frei and Schär (2001) showed in their study that the length of climate record is critical for a trend detection and long-period records are beneficial for the trend analysis of rare events. We intend to do the non-stationary temperature analysis for future work with the centennial NCEP reanalysis [Compo et al., 2011].

Figure 4 (page 10) of Rasul et al. (2012), is showing a time series of area weighted annual averages for mean daily temperatures in Pakistan. This figure includes annual temperature values of entire Pakistan, not only Sindh (our study area) from 1960 to 2010. Figure 11 (page 19), shows average frequency of heat waves over entire Sindh under limited conditions (at $\geq 40^{\circ}\text{C}$ & $\geq 45^{\circ}\text{C}$ for 5,6,7 consecutive days) from 1960 to 2009. Both figures are showing average trends with different durations and cannot be compared with this paper results. One must not assume that there are significant trends in the data just on the basis of these figures.

We remark that temperature extremes vary from one station to another in this region. The policy makers do not agree to implement adaptations just on the basis of analysis of extremes on spatially averaged temperature data, while it is important to study the stations individually for supporting more efficiently the definition of risk assessment.

References:

Compo, G.P., J.S. Whitaker, P.D. Sardeshmukh, N. Matsui, R.J. Allan, X. Yin, B.E. Gleason, R.S. Vose, G. Rutledge, P. Bessemoulin, S. Brönnimann, M. Brunet, R.I. Crouthamel, A.N. Grant, P.Y. Groisman, P.D. Jones, M. Kruk, A.C. Kruger, G.J. Marshall, M. Maugeri, H.Y. Mok, Ø. Nordli, T.F. Ross, R.M. Trigo, X.L. Wang, S.D. Woodruff, and S.J. Worley, 2011: The Twentieth Century Reanalysis Project. *Quarterly J. Roy. Meteorol. Soc.*, 137, 1-28. <http://dx.doi.org/10.1002/qj.776>

Dickey, D. A. and Fuller, W. A. 1979: Distribution of the Estimators for Autoregressive Time Series With a Unit Root, *J. Am. Stat. Assoc.*, 74(366), 427, doi:10.2307/2286348.

Frei, C., and C. Schär, 2001: Detection probability of trends in rare events: Theory and application to heavy precipitation in the Alpine region. *J. Climate*, 14, 1568–1584.

Groisman, P. Y., R. W. Knight, D. R. Easterling, T. R. Karl, G. C. Hegerl, and V. N. Razuvaev, 2005: Trends in intense precipitation in the climate record, *J. Clim.*, 18, 1326 – 1350.

3. The authors gave too many detailed results (figures and tables) of the intermediate process, but just showing the results is not enough, more discussion should be given. What are the spatial patterns in the shape and scale parameters for the observed data, ERA interim and other data in Fig 4? What about Fig 8 and 9? This kind of analysis should be added. Besides, some of the figures or tables may be given as supplement.

Ans.: We gave detailed results in order to address an audience that might be not so familiar with this method. It first analysis for extremes using POT in Pakistan, so that it is clear that some of our potential readers might be not so familiar with this method. Note that many studies on climate extremes (including what reported in the IPCC reports) do NOT use extreme value theory (in the 2012 special IPCC report on

extremes, EVT is vaguely mentioned and basically no results based on it are reported there). Therefore, we prefer to give all the possible details.

The shape parameters of all datasets are negative at all stations (Fig 4). This is described on page 8, lines 297-308. The spatial pattern of scale parameter in all datasets is added on page 8 between lines 310-315.

Figure 8 and 9 are made for the detailed spatial overview of the temperature extremes in Sindh so that all stakeholders can see the return values in each station. We have added more explanation of Figures (8 and 9) on page 10, lines 371 - 394.

Table containing the mean climatic characteristics of Sindh is given as a supplement material.

4. The “Summary and conclusion” section is too long. The authors should concentrate on the main results and conclusions of the current research. The introduction section is also too long and should be shortened. E.g. the sixth paragraph of “Summary and conclusion” should be deleted, which is suitable for the introduction part.

What’s more, the main conclusions are too specific, concentrating on some detailed data/facts. Earth System Dynamics is an international journal, the results and conclusion part should report more meaningful findings to the scientific community.

Ans: The “Summary and conclusion” and “Introduction” part have been revised.

This is a maiden study of probability of occurrence of extremes in the region using extreme value theory. It seems to us that it makes sense to report them in detail. The findings are meaningful not only for the region but neighboring countries like India, Iran, and for many ongoing EU, WB and Chinese projects (SUCCESS, CSCCC, Sindh Resilience Project, CPEC) in Sindh. Clearly, there is much scope for understanding the dynamical processes behind such extremes, but this is well beyond of the goal of the present paper.

5. The bias correction method. The bias correction formula introduces the information of observed data which will surely improve the results of ERA data. On the one hand, we don’t need the ERA data when observed data are available for the past, so the bias correction method proposed by the authors seems to be not necessary; on the other hand, we need ERA or other reanalysis data to project future climate extremes. However, this method needs the observed data to make the correction. What’s the usage of this bias correction method?

As mentioned earlier the observations network is too sparse in the region and it is very difficult to have long-term reliable data. We could hardly achieve appropriate observational data of nine weather stations for this study. We tested ERA Interim to use it as an alternative for the regions within Sindh lacking data.

Our analysis wishes to show two things 1) ERA Interim is “as it is” not a good enough datasets to look at extremes in this region. The statistics of extremes is

completely wrong. Note that reanalysis datasets are often used to construct climatologies (and to study climate change). 2) If we correct the first two moments of the ERA-Interim climatology so that it matches the observed ones (this amounts to correcting the bulk statistics, or the vast majority of the events), in many cases we are still unable to describe well enough the statistics of extremes. Bias correction methods tailored at extremes are needed, instead, if one wants to use ERA-Interim data to look meaningfully at extremes.

List of all changes in the manuscript

Changes according to Reviewer # 2

- Lines 364-365, p10, “the” is removed.
- Line 429, p11, “But” is replaced with “still”.
- Line 442, p12, word “yet” is added to complete the sentence.
- $\Delta\sigma$ is added in the caption of table 3, p18.

Changes according to Reviewer # 4

- The continuous line number is provided.
- The introduction section is modified.
- Lines 92- 110, p3, the objectives are modified and revised.
- It has been formatted, p17.
- Background is removed, p20.
- Background is removed, p21.
- Lines 384-385 and 417 – 419 added on p10 & p11.
- Two suggested references by the reviewer are added on p10 &11.

Changes according to Reviewer #5

- Lines 151-158, p4, trend detection is explained. Mann Kendall trend test is also included for testing the presence of trends.
- Lines 297-308 & 310-315, p8, the spatial patterns of the shape and scale parameters in all datasets are explained.
- Lines 371-394, p10, more explanation of Figures (8 and 9) are added.
- The “Summary and conclusion” and “Introduction” part have been revised.

Return Levels of Temperature Extremes in Southern Pakistan

Maida Zahid¹, Richard Blender¹, Valerio Lucarini^{1,2} and Maria Caterina Bramati³

1. Meteorological Institute, University of Hamburg, Hamburg Germany

2. Department of Mathematics and Statistics, University of Reading, Reading, UK

3. Department of Statistical Science, Cornell University, New York, United States

Correspondence to: Maida Zahid (maida.zahid@uni-hamburg.de)

Abstract. Southern Pakistan (Sindh) is one of the hottest regions in the world and is highly vulnerable to temperature extremes. In order to improve rural and urban planning, it is useful to gather information about the recurrence of temperature extremes. In this work, return levels of the daily maximum temperature T_{max} are estimated, as well as the daily maximum wet-bulb temperature TW_{max} extremes. We adopt the Peaks over threshold (POT) method, which has not yet been used for similar studies in this region. Two main datasets are analyzed: temperatures observed in nine meteorological stations in southern Pakistan from 1980 to 2013, and the ERA Interim (ECMWF re-analysis) data for the nearest corresponding locations. The analysis provides the 2, 5, 10, 25, 50 and 100-year Return Levels (RLs) of temperature extremes. The 90% quantile is found to be a suitable threshold for all stations. We find that the RLs of the observed T_{max} are above 50°C in northern stations, and above 45°C in the southern stations. The RLs of the observed TW_{max} exceed 35°C in the region, which is considered as a limit of survivability. The RLs estimated from the ERA Interim data are lower by 3°C to 5°C than the RLs assessed for the nine meteorological stations. A simple bias correction applied to ERA Interim data improves the RLs remarkably, yet discrepancies are still present. The results have potential implications for the risk assessment of extreme temperatures in Sindh.

Key words

Extreme temperature, return levels, peak over threshold, Generalized Pareto Distribution, declustering.

1 Introduction

Extreme maximum temperature events have received much attention in recent years, because of the associated dangerous impact on the increased risk of mortality (IPCC, 2012). Additionally, climate change scenarios suggest that in most regions the probability of occurrence of extremely high temperature is very likely to increase in the future (Sheridan and Allen, 2015). An example of the potential impact of raising maximum temperatures is the recent heat wave in southern Pakistan (Sindh), which occurred between June 17th and June 24th 2015 and broke all the records with a death toll of 1400 people, and over 14000 people hospitalized. The temperatures in different cities of the Sindh region were in the range of 45°C - 49°C during the event (Imtiaz and Rehman, 2015). Karachi had the highest number of fatalities (1200 people approximately). The Pakistan Meteorological department issued a technical report stating a very high heat index (measuring the heat stress on humans due to high temperature and relative humidity) during this heat wave (Chaudhry et al., 2015).

In summer, Sindh becomes very hot and with the arrival of a monsoon the humidity increases in the region (Chaudhry and Rasul, 2004). The extremely hot and humid conditions can have lethal effects, and can impact the overall human habitability of a region (Pal and Eltahir 2015). The human body generally maintains the

44 temperature around 37°C. However, the human skin regulates at or below 35°C to release heat (Sherwood and
45 Huber, 2010). Under [combined high temperatures and high](#) levels of moisture content in the atmosphere, the
46 human body cannot maintain the skin temperature below 35°C and can develop ailments like hyperthermia, heat
47 strokes and cardiovascular problems. Hyperthermia is a condition where extremely high body temperature is
48 reached, resulting from the inability of the body to get rid of the excess heat. Hyperthermia can occur even in the
49 fittest human beings, if [exposed for at least six hours](#) to an environment where wet-bulb temperature is greater
50 than 35°C.

51

52 [This study devotes special attention to Sindh \(23.5° N – 28.5° N and 66.5°E - 71.1°E\) because of its exposure to](#)
53 [the frequent and intense temperature extremes in the past \(Zahid and Rasul, 2012\). It is bounded on the west by](#)
54 [the Kirthar Mountains, to the north by the Punjab plains, on the east by the Thar desert and to the south by the](#)
55 [Arabian Sea \(Indian Ocean\), while in the center there is a fertile land around the Indus river. Cotton, wheat, sugar](#)
56 [cane, rice, wheat and gram crops are cultivated near banks of the Indus River \(Chaudhry and Rasul, 2004\).](#)
57 [Cotton is the cash crop of the country. High population density, limited resources, poor infrastructure and high](#)
58 [dependence of the local agriculture on climatic factors, mark this region as highly vulnerable to the impacts of](#)
59 [climate change. The Intergovernmental Panel on Climate Change \(IPCC\) scenarios estimates for this region an](#)
60 [increase in the temperature of the order of 4°C by the end of 2100. This may significantly reduce crop yields, and](#)
61 [cause huge economic losses to the country \(Islam et al., 2009; Rasul et al., 2012; IPCC, 2012, 2014\).](#)
62 [Furthermore, the risks of heat strokes, cardiac arrest, high fever, diarrhea, cholera and vector borne diseases](#)
63 [might increase.](#)

64

65 Extreme value theory (EVT) provides the statistical basis for increasingly widespread quantitative investigations
66 of extremes in climate studies (Coles, 2001, Zhang et al., 2004; Brown et al., 2008; Faranda et al., 2011; Acero
67 et al., 2014). The peaks over threshold (POT) approach aims at describing the distribution of the exceedances of
68 the stochastic variable of interest above a threshold. Under very general conditions, the exceedances are
69 asymptotically distributed according to the Generalized Pareto Distribution (GPD). GPD has remarkable
70 properties of universality when the asymptotic behavior is considered (Lucarini et al., 2016), while one can
71 expect that the threshold level above which the asymptotic behavior is achieved depends on the characteristics of
72 the analyzed time series. In particular, when looking at spatial fields, the threshold level depends on the
73 geographical location.

74

75 In this study, we have chosen [to analyze the temperature extremes in the Sindh region taking the point of view of](#)
76 [threshold exceedances associated to the GPD family of distributions, because the statistical inference provided by](#)
77 [the POT method](#) provides a more efficient use of data and has better properties of convergence when finite
78 datasets are considered [with respect to alternative methods for the analysis of extremes, such as the block maxima](#)
79 [method, which is used to fit the observed data to the generalized extreme value \(GEV\) distribution](#) (Lucarini et
80 al., 2016). Additionally, we are here interested in investigating the actual tails of the distributions [and not the](#)
81 [statistics of e.g. yearly maxima](#), the POT approach is [indeed](#) more appropriate. [While the POT method has been](#)
82 [applied for studying temperature extremes in different regions of the world \(Burgueño et al., 2002; Nogaj et al.,](#)
83 [2006; Coelho et al., 2007; Ghil et al., 2011\), to our knowledge, it has never been used to analyze the statistics of](#)
84 [temperature extremes in Sindh. Thanks to the properties of universality of the GPD distribution \(Lucarini et al.](#)

2016), the POT approach can in principle provide reliable estimates of return periods and the return levels also for time ranges longer than what is actually observed. This information and this predictive power can be beneficial for policy makers and other stakeholders. Since, it is exactly the kind of information planners need when, e.g., designing infrastructures that are deemed to last a very long time. Note that commonly used, more empirical approaches to the study of extremes, as those more used for assessing the ‘moderate extremes’ (IPCC, 2012), do not have any property of universality and might have weak predictive power.

It is useful to consider two indicators of extremely hot conditions: (1) temperature extremes T_{max} , and (2) Wet-bulb temperature extremes TW_{max} . Therefore, we estimate the return levels of T_{max} and TW_{max} over different return periods during summer (May-September) in Sindh. We apply the POT method on the observational data of the nine weather stations provided by Pakistan Meteorological Department, and the ERA Interim re-analysis data of European Center for Medium range Weather Forecast (ECMWF) model for the corresponding grid points from 1980 to 2013. ERA Interim re-analysis data are generally very good at replicating also trends in temperature percentile (Cornes and Jones, 2013). Nonetheless, it is in principle not obvious that ERA Interim data can simulate well meteorological extremes, as reanalysis are constructed in such a way that typical conditions are well reproduced. This is why we look at how well ERA Interim data performs in the target area against observations. If the ERA Interim dataset characterizes well the extremes, it could be an option for the regions within Sindh where no observational data is available. Furthermore, a standard bias correction is applied on the ERA Interim data to assess whether removing the bias in the bulk of the statistics improves substantially representation of the return levels of extremes. Given the shortness of the datasets, as we will show later, it is appropriate to analyze the extremes without taking into considerations possible long-term trends (Frei and Schär, 2001); see also the discussion in Felici et al. (2007). The provision of POT-based information on stationary extremes is already quite relevant in terms of impacts for the public and private sector as it fills a big data gap in Sindh. A possibility for investigating time dependency in the temperature extremes comes for considering the centennial NCEP reanalysis (Compo et al., 2011) and using suitable bias correction procedures. Such an analysis is not performed at this stage as we focus on observational data.

The paper is organized as follows. In Section 2 we present the datasets we study and the statistical methods we use for assessing the properties of extremes. In Section 3 we show and discuss the main results. In Section 4 we make a summary of the main findings and present our conclusions and perspectives for future investigations.

2. Data and Methodology

2.1 Meteorological station data

The daily maximum temperature and relative humidity data recorded at nine meteorological stations in Sindh from 1980 to 2013 are provided by the Pakistan Meteorological Department (see Table 1). We select nine stations, which contain a negligible amount of missing values after 1980, and are suitable for the POT analysis (Figure 1). An additional criterion is that only those stations are chosen where no changes occurred in measuring instruments during the last 33 years (Brunetti et al., 2006). None of the station data shows gaps with duration

123 longer than two days, which are treated by replacing the missing value with the average of the two previous
124 values.

125

126 The temperature data are discretized unevenly with intervals up to 1 degree Celsius. Deidda and Puliga (2006)
127 proposed a Monte Carlo approach for addressing this issue. They showed that finite resolution in precipitation
128 data affects the convergence of parameter estimation in the extreme value analysis. They suggested generating
129 many synthetic datasets by adding numerical noise to the original data, and then providing the best estimate of
130 the parameters of the extreme value distributions by averaging over all the best fits obtained in each synthetic
131 dataset. Following their suggestion, we produce **high-resolution** data to compensate the effect of discretization
132 and thus to improve the convergence of the estimator. In order to convert the temperature readings to higher
133 resolution, we add a uniform random variable in the interval $[-0.5, 0.5]$. The main property of this noise is that
134 $\text{round}(T+r) = T$, where T is the temperature with 1-degree resolution and ‘*round*’ is the numerical function,
135 which maps the interval $[T-0.5, T+0.5]$ to T . Thus, adding the noise does not perturb the information content of
136 the observations. This procedure is applied to all temperature data, irrespective of the actual resolution, and
137 replicated 100 times using a Monte Carlo approach. For each synthetic dataset, we perform the statistical best fit
138 described later in the paper and then average the results. We check the influence of this noise parameterization
139 and find no significant bias in the return level estimates. The advantage of adding a noise is to avoid the spurious
140 statistical effects associated to the presence discrete values assigned to the temperature readings. Using the
141 described bootstrap method we reduce such problem without biasing the data.

142

143 **2.2 ERA Interim re-analysis data**

144

145 The gridded daily maximum temperature and relative humidity data of ERA Interim re-analysis is obtained from
146 the ECMWF Public Datasets web interface (<http://apps.ecmwf.int/datasets/>). The ERA Interim is generated by
147 the European Center for Medium range Weather Forecast (ECMWF) model with resolution $0.75^\circ \times 0.75^\circ$ (Dee et
148 al., 2011). **The gridded data are then extracted at the closest grid points of all stations, for the period 1980-2013**
149 **(Figure 1). The latitude and longitude of the ERA Interim stations are displayed in Table 1.**

150

151 The extreme temperatures analysis is restricted to the summer season (May-September) over a period of 33 years.
152 **We have tested the datasets by applying the Mann-Kendall test; the results show that trends are not significant in**
153 **such a short time interval.** One of the main requirements for performing the POT analysis is assuming the
154 stationarity of the time series. Therefore, as in Bramati et al. (2014), the Augmented Dickey Fuller (ADF) test of
155 stationarity is performed on all time series (Dickey and Fuller, 1979). In all cases we find no sign of long-term
156 correlations in the data. Short-term correlations (daily time scale) typically lead to clusters of extreme values and
157 are studied by computing the extremal index θ in all time series and treated using the associated standard
158 declustering technique (see more details in Section 2.4).

159 **2.3 Wet-bulb temperature calculations**

160

161 The wet-bulb temperature measures the heat stress better than other existing heat indices, because it establishes
162 the clear thermodynamic limit on heat transfer that cannot be overcome by adaptations like clothing, activity and

163 acclimatization (Pal and Eltahir, 2015; Sherwood and Huber, 2010). Here, we use an empirical equation
164 developed by Stull (2011) to measure the wet-bulb temperature.

165

$$166 \quad TW = T \operatorname{atan}(\alpha_1 \sqrt{RH + \alpha_2}) + \operatorname{atan}(T + RH) - \operatorname{atan}(RH + \alpha_3) + \alpha_4 (RH)^{\frac{3}{2}} \operatorname{atan}(\alpha_5 RH) - \alpha_6$$

167
168 (1)
169
170

171 where TW is the wet-bulb temperature [$^{\circ}\text{C}$], T is the temperature [$^{\circ}\text{C}$], and RH is the relative humidity [%]. This
172 relationship is based on an empirical fit, as in Stull (2011), where the coefficient values are $\alpha_1 = 0.151977$, $\alpha_2 =$
173 8.313659 , $\alpha_3 = -1.676331$, $\alpha_4 = 0.00391838$, $\alpha_5 = 0.023101$, and $\alpha_6 = 4.686035$. Equation (1) covers a wide range
174 of relative humidity and air temperatures with an accuracy of 0.3°C .

175

176 **2.4 Peaks over Threshold**

177

178

179 In order to determine the return levels of extreme maximum temperatures and maximum wet-bulb temperatures,
180 the peaks over threshold (POT) approach is applied to the data obtained from the meteorological stations in
181 Sindh, and from the ERA Interim archive.

182

183 Multi-occurrence is an important characteristic of extreme climatic events and is referred to as clustering.
184 Clusters are consecutive occurrences of above threshold events. It is important to post process the clustered
185 extremes in order to take into account the assumption of weak short time correlation between extreme events,
186 which is crucial for our statistical analysis. We have treated the clusters using the concept of Extremal Index (EI)
187 (see Newell, 1964, Loynes, 1965, O'Brien, 1974, Leadbetter, 1983, Smith, 1989, Davison and Smith, 1990). The
188 Extremal Index θ measures the degree of clustering of extremes. It ranges between 0 and 1, ($\theta = 0$ means strong
189 clustering and dependence, $\theta = 1$ absence of clusters and independence). Leadbetter (1983) interprets $1/\theta$ as the
190 mean number of exceedances in a cluster.

191

192 The extremal index θ can be estimated in two different ways. Here, we apply the 'intervals estimator' automatic
193 declustering by Ferro and Segers (2003). A positive aspect of this method is that it avoids the subjective choice of
194 cluster parameters. The main ingredient is the use of an asymptotic result for the times between threshold
195 exceedances. The exceedance times are split into two types, a set of vanishing intra-exceedance times within the
196 clusters, and an exponentially distributed set of inter-exceedance times between clusters. The method is iterative,
197 starting with largest return times and stops when a limit for the inter-exceedance times is reached. The standard
198 errors of the estimated parameters is obtained by a bootstrap procedure. In this study, once we select appropriate
199 value for the threshold (see below) the extremal index value is ≤ 0.5 in all the considered time series. Therefore,
200 it is necessary to decluster the extremes by choosing the largest event in each cluster, before fitting it to the GPD.

201

202 As mentioned before, we use as statistical model for the exceedances over threshold the Generalized Pareto
 203 Distribution (GPD), which is characterized by two parameters, the shape ξ and the scale σ . The GPD for
 204 exceedances $x - u$ of a random variable x reads as

$$205 \quad G(x) = 1 - \left[1 + \xi \left(\frac{x - u}{\sigma} \right) \right]^{-\frac{1}{\xi}} \quad (x > u, \xi \neq 0), \quad (2)$$

206 where u is the threshold. The shape parameter ξ determines the tail behavior while the scale parameter σ
 207 measures the variability. For a negative shape parameter, $\xi < 0$, the distribution is bounded (Weibull distribution),
 208 for vanishing shape parameter, $\xi = 0$, the distribution is exponential, and for a positive shape parameter, $\xi > 0$, the
 209 distribution has no upper bound (Pareto distribution).
 210

211
 212 In particular, for a negative shape parameters $\xi < 0$ the GPD has the upper bound

$$213 \quad A_{max} = u - \sigma / \xi \quad (3)$$

$$214 \quad G(x) = 0 \quad (x > A_{max}, \xi < 0)$$

215 where A_{max} is an absolute maximum (Lucarini et al., 2014). In general, the best estimate for the two parameters
 216 shape ξ and scale σ depend on the threshold u (Coles, 2001). The choice of the optimal threshold for performing
 217 statistical inference from a time series is crucial. Choosing a very large value for u reduces the number of
 218 exceedances to a few values, inflating the variance of the estimators, so that the analysis is unlikely to yield any
 219 useful results. On the other hand, choosing a too small value for u would violate the asymptotic nature of the
 220 model, with a possible biased estimation and wrong model selection (Coles, 2001), see details later in Section
 221 3.1. The shape ξ , the scale σ and the return levels are estimated using the Maximum Likelihood Estimator (MLE)
 222 using the R software (R Development core team 2015), which also provides an estimate of the standard error of
 223 the estimates.
 224

225
 226 Additionally, we wish to investigate the N - years return levels x_N , which are exceeded on the time scale of N
 227 years (Coles, 2001) and can be expressed as

$$228 \quad x_N = u + \frac{\sigma}{\xi} \left[(N n_y \zeta_u)^\xi - 1 \right], \quad (4)$$

229 where N represents the return period in years, n_y is the number of observations per year, ζ_u is the probability of
 230 an individual observation exceeding the threshold u , the shape parameter is ξ and the scale parameter is σ .
 231
 232
 233

234 2.5. Bias Correction Method

235 A simple bias correction is applied to each ERA Interim time series through a rescaling that adjust the first two
 236 moments (mean and variance) to the sample moments calculated for the corresponding observations. Therefore,
 237 the bias correction is applied to the entire time series and it is not tailored to the extreme events only. The idea is
 238 to check whether by adjusting the properties of the bulk of the statistics we improve the skill of the ERA Interim
 239 dataset [considerably](#) in describing extreme events. The bias corrected ERA Interim time series x is expressed as
 240

241

$$x = \bar{z} + \frac{y_{ERA} - \bar{y}}{\sigma_y} \sigma_z \quad (5)$$

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where y_{ERA} is the ERA Interim time series, \bar{y} and σ_y its mean and standard deviation, whereas \bar{z} and σ_z are the mean and standard deviation of the meteorological station temperatures. The properties of extremes are commonly assumed to be closely controlled by the first two moments of the underlying distribution - e.g. the IPCC (2012) relates changes in the properties of extremes to changes in the mean and in the standard deviation of the underlying distributions - EVT clarifies that, in fact, only a loose link exists between true extremes and the bulk of the events. Note that the proposed method of bias corrections has no impact on the estimates of the shape parameter, while it affects the scale and location parameters, thus impacting at any rate the return levels.

251

3. Results and Discussion

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3.1 Threshold Selection

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The threshold selection is the first step in a POT analysis. One needs to test whether the asymptotic regime is reached, i.e. whether one is choosing true extremes. It must be noted that EVT does not predict where (in terms of quantiles) one should expect the asymptotic regime to start. This can be investigated by checking whether the best fits of the shape parameter ξ and the modified scale parameter $\sigma^* = \sigma_u - \xi u$ are stable with respect to increases in the chosen value of u (Sacrotto and MacDonald, 2012). The optimal threshold u is selected as the lowest value where the two parameters are invariant in order to reach the asymptotic limit (Coles, 2001 and Furrer et al., 2010). This choice allows for having as many data as possible for performing the statistical inference, thus having lower variance for the estimators of the parameters. Figure 2 shows the parameter stability plots of the T_{max} reading for Karachi, as an example to explain the threshold selection procedure.

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In addition to diagnostic plots of the modified scale parameter σ^* and the shape parameter ξ , the mean residual life plot is used to select the appropriate threshold for the POT analysis (Davison and Smith, 1990). The idea is to select the lowest value of the threshold when the plot is approximately linear. In the case of the Karachi data for T_{max} , the plot appears to be linear and stable for $u = 36^\circ\text{C}$, indicating $u = 36$ as the most suitable threshold for the POT analysis (Figure 3). We observe that the 90% quantile is an appropriate threshold for all the station data, as well as the ERA interim datasets, and for both T_{max} , and TW_{max} .

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3.2 GPD Fit

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The goodness of fit is evaluated by Quantile-Quantile (Q-Q) plots and hypothesis testing. The Q-Q plot analysis is performed for the stations observed, the ERA Interim, the bias corrected ERA Interim daily T_{max} and TW_{max} . The Q-Q plots of the observed T_{max} show that the GPD fits well in most stations. However, in a few stations like Jacobabad, Mohenjo-daro, Padidan and Chhor the empirical values show slight deviation from the modeled values. In spite of minor deviations at some stations, still most of the exceedances are well fitted by the model. The Q-Q plots of the observed TW_{max} also fits well to the model in all stations.

279 The Q-Q plots of the empirical ERA Interim T_{max} and TW_{max} data reveals substantial differences with respect to
280 the corresponding GPD fits. The empirical values of the higher quantiles are deviating from the theoretical
281 quantiles in all stations. However, if the higher quantiles are disregarded, then stations like Jacobabad, Mohenjodaro,
282 Rohri, Padidan, Nawabshah, Chhor, and Badin fits very well with the model. The Q-Q plots of the bias
283 corrected ERA Interim T_{max} , and TW_{max} show better results than the ERA Interim. We notice that the T_{max} of the
284 ERA Interim and bias corrected ERA Interim fits better than the TW_{max} if the highest quantiles are ignored,
285 indicating the bias procedure is, as expected, unable to treat correctly the statistics of the largest events.

286

287 In order to assess the goodness-of-fit, we apply the Kolmogorov-Smirnov (K-S) test and Anderson-Darling (A-D)
288 test to the data of meteorological stations, ERA Interim, bias corrected ERA Interim T_{max} and TW_{max} . The p-
289 values indicate a good performance of the fit procedure. Table 2 shows the results of the K-S and A-D statistics
290 of the T_{max} and TW_{max} in all the data sets.

291 3.3 Parameter Estimates

292

293 Here, we analyze the shape parameter ξ , the scale parameter σ , and threshold u for all considered datasets. The
294 standard errors of the shape ξ and the scale σ parameters are given in Table 3. The spatial distribution of the
295 shape parameter ξ and the scale parameter σ of the GPD in Sindh are shown in Figure 4. The shape parameters ξ
296 are negative in all datasets at all stations. This is hardly surprising, as meteorological and physical processes
297 make sure that the temperature cannot grow locally without control. One finds a certain degree of
298 variability across stations in the estimated value of the shape parameter. In the case of the observed
299 T_{max} one obtains for ξ estimates ranging between -0.418 and -0.223, while for TW_{max} the range is between -0.323
300 and -0.177, so that values slightly closer to zero are found, thus allowing for larger excursions towards very high
301 values with respect to the case of the extremes of the actual temperature. When looking at the bias corrected ERA
302 Interim data, the range of values for the shape parameter of T_{max} (TW_{max}) is between -0.305 to -0.002 (-0.18 and -
303 0.01). While there is a good match in the spatial patterns of the estimates for the observative vs ERA Interim
304 datasets, the presence of values much closer to zero in the second case suggests the presence of some
305 inadequacies in the representation of extremes in the reanalysis. This is not entirely unexpected, as reanalysis are
306 constructed in such a way that typical conditions are well reproduced. Note that our simple bias correction
307 procedure, while not impacting the estimates of the shape parameters, allows for improving the estimates of the
308 return levels, as discussed below.

309

310 The scale parameters σ measures the variability of the GPD distributions. The highest values of the scale
311 parameters σ of T_{max} and TW_{max} are observed at stations such as Jacobabad, Padidan, Karachi, Hyderabad and
312 Chhor in all datasets. This indicates that the variability of temperature extremes is higher at these stations, and
313 one can expect higher return values of T_{max} and TW_{max} here having similar shape parameter and same threshold
314 according to Equation 4. The scale parameters σ of the observed T_{max} range from 2.08 to 2.76, and the TW_{max} are
315 in 1.86 to 2.76. In the ERA Interim analysis, the scale parameter σ of T_{max} is between 1.00 - 1.95, and TW_{max} in
316 0.74 - 1.75. We observe a difference in the scale parameters of both the observed, ERA Interim T_{max} and TW_{max} .
317 We find that, unsurprisingly, the scale parameters of the bias corrected ERA Interim data are much closer to those
318 estimated for T_{max} and TW_{max} using the station data. In the bias corrected ERA Interim T_{max} the scale parameters

319 σ are in 1.50 - 2.75, while for TW_{max} are in a range 1.40 – 2.40 (Figure 4). All the temperature scale parameters
320 are in degree Celsius.
321

322 **3.4 Absolute Maxima** 323

324 Once the shape parameters ξ , the scale parameters σ , and the thresholds u are determined, it is possible to
325 compute the theoretical absolute maxima using Eq. (3) (Section 2.4). Theoretical absolute maxima can be
326 compared with the observed ones for each station to better understand whether our fits are in agreement with the
327 observed data. The daily maximum temperature T_{max} and the maximum wet-bulb temperature TW_{max} (station
328 data, the ERA Interim, and the bias corrected ERA Interim) have negative shape parameters ξ at all stations. This
329 means that according to Eq. (2) in section 2.4, the probability distribution function (pdf) is bounded by the
330 maximum values. These maximum values are the theoretical upper limits predicted by the GPD fit. The analysis
331 shows that the observed absolute maxima T_{max} and TW_{max} at all stations of the three data sets are below the
332 theoretical absolute maximum, as expected (Figure 5). This gives us confidence on the quality of our fit. The
333 following piece of information can also be derived: assume that one observes in the future an extreme event
334 larger than the maximum inferred in the present dataset; this may suggest some non-stationarity in the most
335 recent portion of the dataset.
336

337 **3.5 Return Levels** 338

339 The return levels (RLs) are computed considering various return periods (2, 5, 10, 20, 50, 100-year). *As remarked
340 above, using a statistical approach based on the universality of EVT, we are able to extrapolate the results for
341 time horizons longer than the one for which observations are taken. Clearly, uncertainties grow when longer time
342 horizons are considered.* The return level plots of the stations observed, the ERA Interim, the bias corrected ERA
343 Interim daily maximum temperature T_{max} and daily maximum wet-bulb temperature TW_{max} are displayed in
344 Figures 6 and 7. The values of the RLs follow the north-south gradient of the climatic mean temperatures. The
345 northern part of the Sindh (Jacobabad, Mohenjo-daro, Rohri, Padidan, and Nawabshah) are hotter than the
346 southern part (Hyderabad, Chhor, Karachi, and Badin).

347
348 The 2, 5, 10, 20, 50, 100-year RLs estimated in Sindh for station observed T_{max} at time reach over 50°C in
349 Jacobabad, Mohenjo-daro, Padidan, Nawabshah, and over 45°C in Rohri, Hyderabad, Chhor, Karachi, Badin.
350 The corresponding ERA Interim T_{max} return levels are at least 3°C to 5°C lower in all stations, while having
351 correct representation of the geographical variability of the field. As example, the RLs of 42°C at Badin has a 3-
352 year return period in the observations T_{max} , but a 30-year return period in ERA Interim (Figure 6).

353
354 The RLs of TW_{max} are above 35°C in all meteorological stations. As for the ERA Interim, the RLs of TW_{max} are
355 greater than 30°C for all the stations except Karachi, which has RLs less than 30°C. Here, we see again that the
356 RLs of the ERA Interim TW_{max} are lower than the RLs of station TW_{max} . Going again to the Badin stations, the 4-
357 year return period observed for TW_{max} is 38°C, while the ERA Interim dataset show the same RL in a 15-year
358 return period (Figure 7).

359

360 The bias corrected ERA Interim T_{max} and TW_{max} , show some improvements in the RLs at all stations. When
361 looking at the Nawabshah, Hyderabad, Karachi, and Badin stations, the RLs agree with those obtained from the
362 station data in the range 5-100 years, while disagreements exist in the range 2-5 years. In the rest of the stations,
363 the bias corrected data RLs are closer to those of the station data, yet not statistically compatible with them.
364 When looking at the wet-bulb temperature TW_{max} analysis, the RLs of the bias corrected ERA Interim show some
365 overlap with those derived from station observations in Mohenjo-daro, Hyderabad, Chhor, and while no overlap
366 is found in the other stations. One understands that the proposed simple bias correction methods improves the
367 quality of the representation of extremes by ERA Interim, but many discrepancies remain (Figures 6 and 7).

368

369 We also plot the station and bias corrected ERA Interim T_{max} , and TW_{max} return levels spatially for the 5, 10, 25
370 and 50-year return periods (Figures 8 and 9), as a detailed spatial overview of the temperature extremes in Sindh
371 might be of interest to the policy makers. The spatial return levels of the station and bias corrected ERA Interim
372 T_{max} shows differences in temperature; the hottest stations have the highest return levels. We notice that for
373 Jacobabad, Mohenjo-daro, Padidan, Nawabshah the return levels are between 50°C-53.6°C and for Rohri,
374 Hyderabad, Chhor, Karachi, and Badin are between 45°C - 50°C in 5 to 50 years return period (Figure 8). These
375 extreme temperatures can impact the yields because crops are very sensitive to temperature variations, and even a
376 rise of one degree Celsius can cause detrimental changes in the phenological stages of the crops (Hatfield and
377 Preuger, 2015). Every crop has a certain limit to tolerate the temperature. When temperature exceeds this limit,
378 the crop yield is drastically reduced. Abbas et al., (2017) notices 33% decrease in major crops of Sindh due to
379 warmer and drier weather. Karachi and Badin are expected to decrease rice cultivation, hatching of fisheries, and
380 mangroves forest surrounding these cities. Furthermore, temperature extremes can have serious threat to cotton,
381 wheat, and rice yields in Rohri and Mohenjo-daro areas due to increased crop water requirements.

382

383 In summer, the temperature and humidity increase to an extent that there are high chances of a rapid pests spread
384 in the crops. Temperature extremes not just directly impact the quantity and quality of grains, but can also be a
385 reason of urban flooding affecting the agriculture lands (Luo et al., 2015). Sindh produces cotton, wheat, rice,
386 mango, banana, and dates, so a correct estimate of temperature extremes is very important.

387

388 The spatial return levels of station and bias corrected ERA Interim TW_{max} for the 5, 10, 25 and 50-year return
389 periods show highest return level greater than 35°C at all stations (Figure 9). This is very serious for the human
390 health due to the working day hours of population in agriculture farms, building construction, and port activities.
391 Karachi and Badin being closet to the coast are at the highest risk of temperature extremes. Thus, an immediate
392 plan for adaptations is needed in Sindh to deal with such a hazard. The high values of TW_{max} also indicate high
393 levels of humidity in the region during summer, which is also proved by Kalim and Shouting, (2012), and
394 Freychet et al. (2015).

395

4. Summary and Conclusion

396

397 The main objective of this study is the assessment of the return levels of the extreme daily maximum
398 temperatures T_{max} and wet-bulb temperatures TW_{max} in southern Pakistan (Sindh). In addition, the performance of
399 the ERA Interim TW_{max} is compared to the weather station TW_{max} to assess its ability to estimate temperature
400 extremes in Sindh. Moreover, a simple bias correction is applied to the ERA Interim data to see whether
401 correcting the first two moments of its statistics helps in improving its performance in representing temperature
402 extremes.

403
404 The POT method is applied to the daily maximum temperature (T_{max}) and wet-bulb temperature (TW_{max}) data of
405 nine stations and to the corresponding nearest ERA Interim temperature data. After testing the asymptotic
406 statistical properties, the 90% quantile is found to be appropriate threshold choice for all datasets. The Q-Q plots
407 are used to assess the GPD fit, which results to be acceptable for both T_{max} and TW_{max} station data for all three
408 datasets. However, the bias corrected ERA Interim data shows improved GPD fits than the ERA Interim data.
409 The shape parameters ξ is in general negative at all stations. The scale parameters σ show high values in
410 Jacobabad, Padidan, Karachi, Hyderabad and Chhor indicating higher variability of temperature extremes in these
411 regions. The return levels (RLs) of T_{max} and TW_{max} are estimated for the 2, 5, 10, 25, 50, 100-year return periods
412 in all datasets. The RLs of T_{max} estimated using the meteorological station temperatures are greater than 50°C in
413 Jacobabad, Mohenjo-daro, Padidan, Nawabshah, and greater than 45°C in Rohri, Hyderabad, Chhor, Karachi and
414 Badin. While the RLs of TW_{max} in station data are larger than 35°C in the entire Sindh, when using ERA Interim
415 temperatures, they are estimated as greater than 45°C in Northern Sindh and greater than 40°C in southern Sindh.

416
417 Our results predict extremely high values of T_{max} and TW_{max} in the region. The T_{max} extremes contribute to an
418 increase rate of evaporation, which in turn may intensify the hydrological cycle causing precipitation events and
419 flooding (Cheema et al., 2012, Luo et al., 2015). Additionally, crops variety needs to be changed under such a hot
420 climate to avoid the risks of temperature extremes. The extremes of daily maximum wet-bulb temperature TW_{max}
421 are estimated as above the human survivability threshold 35°C throughout the region, so the risk of hyperthermia
422 is very high here. The most vulnerable people are those who are involve in the everyday outdoor activities like
423 farming, fishing, building construction, athletes, elderly and infants can have heat strokes, dehydration etc. The
424 human habitability in such a warm region is already at risk and one can expect that these issues will be worse in
425 future climate conditions.

426
427 We found that the RLs of station and ERA interim showed differences are between 3°C and 5°C for both shorter
428 and longer return periods due to the minor variations in the shape and scale parameters. Although the ERA
429 Interim dataset does not capture well the magnitude of the extremes, still it provides a good representation of
430 their spatial fields. The biases between the station and the ERA Interim data are rather relevant when one wishes
431 to address the impact of hot climatic extremes to human life and to active crop production in the region. It would
432 be of primary importance to understand the physical reasons behind such inconsistencies, which makes it hard to
433 use reasonably ERA without bias correction. Clearly, they might result either from a misrepresentation of local
434 processes dominated by near surface processes (namely, heat and water fluxes), or from an inadequacy of the re-
435 analysis in reproducing synoptic and sub-synoptic conditions responsible for extremely hot and humid conditions.
436 This matter is surely worth investigating but is well beyond the scope of this paper.

437

438 We applied a simple bias correction i.e. adjusting the mean and standard deviation to ERA Interim T_{max} and
439 TW_{max} data to check the improvements in return levels. We noticed that the bias corrected ERA Interim T_{max} and
440 TW_{max} gives the return levels closer to the meteorological stations observed ones than the original ERA Interim
441 return levels at all stations. Although the bias corrected ERA Interim shows a good correspondence with the
442 meteorological station data, yet statistically differences remain in most cases. Therefore, one must use more
443 advanced bias correction method for analyzing extremes precisely. We propose to repeat this analysis in GCMs
444 (CMIP5, CMIP6) and RCMs (CORDEX) to study the properties of extremes. All models use re-analysis as input,
445 and generate information of extremes, which involves biases that if not corrected, can lead to significant errors in
446 prediction of present and future extremes. Therefore, in order to reduce the uncertainties in impact assessment, it
447 is necessary to improve the re-analysis before using it in GCMs and RCMs.

448

449 The results have practical implications for assessing the risk of extreme temperature events in Sindh. All the
450 results are placed in a web-tool SindhX [www.sindhx.org] that will be freely available online soon after the
451 publication of this paper. The maps and graphs are prepared to guide the local administrations to prioritize the
452 regions in terms of adaptations like preparation of baseline contingency plans for dealing with strong heat waves
453 based on the current climatology. Such measures are not yet present in the territory and lead to many casualties
454 each year. Our results will not only contributes to the regional planning, but can also be useful for the ongoing
455 EU projects (SUCCESS, CSCCC), World Bank project (Sindh Resilience Project) and mega construction
456 projects like China-Pakistan Economic Corridor (CPEC).

457

458

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460

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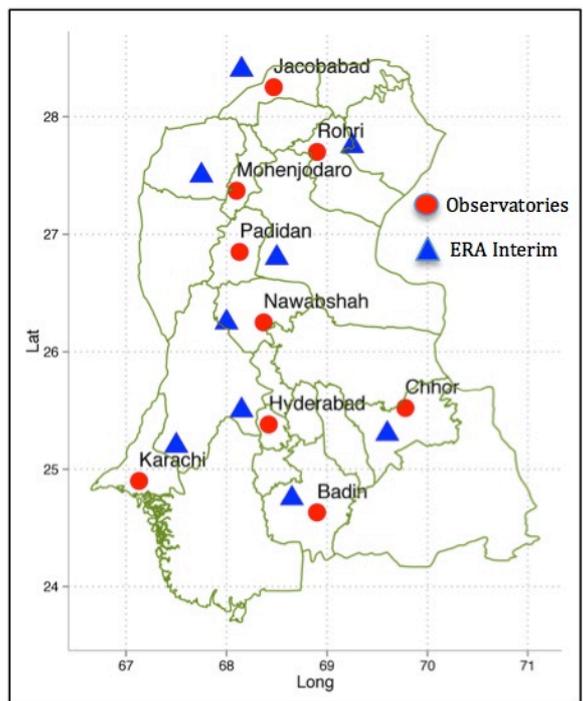


Figure 1: Study Domain (23.5 – 28.5° N , 66.5- 71.1°E)

Table 1. Code, Name, Geographic coordinates and Altitude of the stations.

Code	Name	PMD weather stations			ERA-Interim stations	
		Latitude	Longitude	Altitude (m)	Latitude	Longitude
JCB	Jacobabad	28° 18'N	68° 28'E	55	28 °4'N	68 °15'E
MJD	Mohenjo-daro	27° 22'N	68° 06'E	52.1	27°5'N	67 °75'E
RHI	Rohri	27° 40'N	68° 54'E	66	27°75'N	69 °25'E
PDN	Padidan	26° 51'N	68° 08'E	46	26°8'N	68 °5'E
NWB	Nawabshah	26° 15'N	68° 22'E	37	26°25'N	68 °0'E
HYD	Hyderabad	25° 23'N	68° 25'E	40	25°5'N	68 °15'E
CHR	Chhor	29° 31'N	69° 47' E	5	25°3'N	69 °6'E
KHI	Karachi	24° 54'N	67°08' E	21	25°2'N	67 °5'E
BDN	Badin	24° 38'N	68° 54'E	10	24 °75'N	68 °65'E

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Table 2. Results of the Kolmogorov-Smirnov Goodness of fit test and Anderson-Darling test between empirical and GPD fits.

Observed Tmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.947	0.340	0.996	0.139	0.941	0.385	0.928	0.306	0.666
Anderson Darling	Equality of probability distribution	0.553	0.978	0.654	0.857	0.157	0.649	0.233	0.869	0.145
ERA Interim Tmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.169	0.125	0.553	0.456	0.322	0.187	0.419	0.456	0.332
Anderson Darling	Equality of probability distribution	0.355	0.263	0.165	0.587	0.615	0.398	0.266	0.687	0.425
Bias corrected ERA Interim Tmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.452	0.4729	0.197	0.489	0.269	0.137	0.158	0.243	0.312
Anderson Darling	Equality of probability distribution	0.352	0.315	0.235	0.270	0.335	0.289	0.216	0.390	0.227
Observed TWmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.981	0.111	0.341	0.226	0.457	0.545	0.441	0.385	0.211
Anderson Darling	Equality of probability distribution	0.623	0.745	0.587	0.884	0.199	0.123	0.789	0.669	0.473
ERA Interim TWmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.712	0.564	0.955	0.425	0.258	0.134	0.856	0.497	0.222
Anderson Darling	Equality of probability distribution	0.236	0.474	0.516	0.219	0.356	0.117	0.537	0.464	0.613
Bias corrected ERA Interim TWmax										
Test Statistics	Null Hypothesis	P-value								
		JAC	MJD	RHI	PDN	NWS	HYD	CHR	KHI	BDN
Kolmogorov Smirnov	Equality of probability distribution	0.268	0.688	0.127	0.372	0.268	0.229	0.591	0.582	0.478
Anderson Darling	Equality of probability distribution	0.373	0.484	0.278	0.432	0.306	0.283	0.365	0.445	0.483

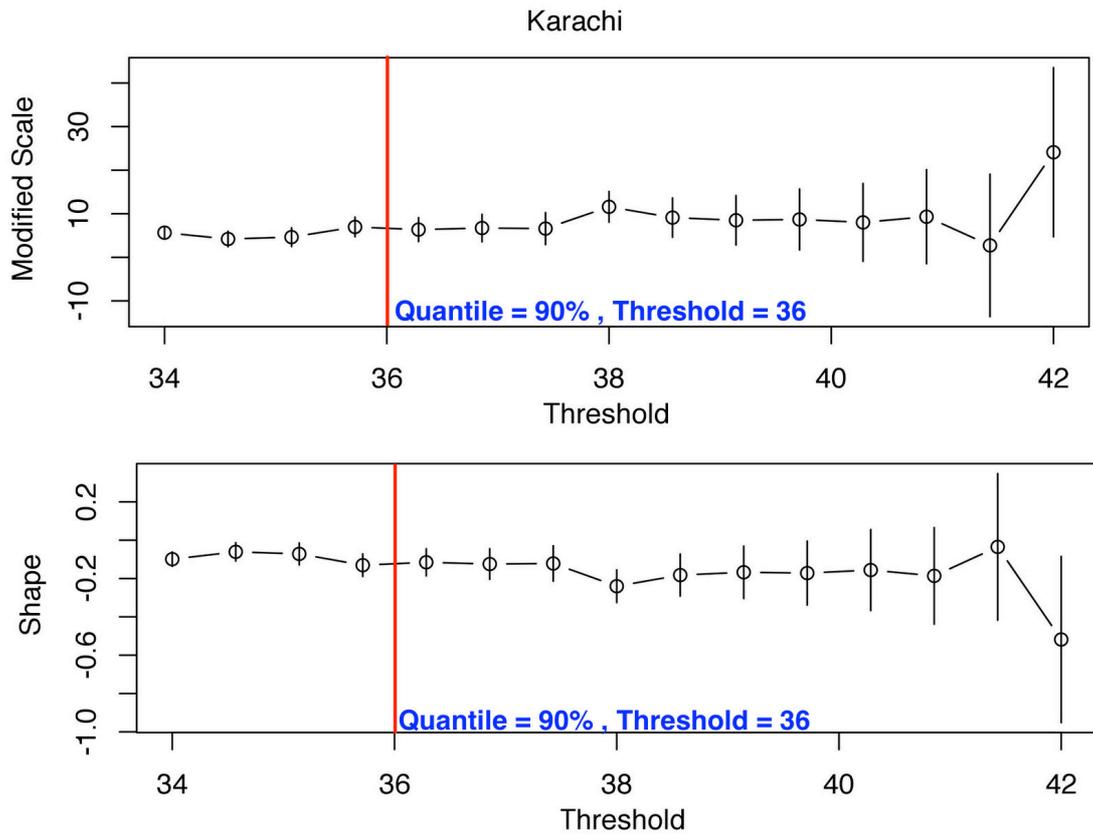
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Table 3. Estimated parameters shape ξ , scale σ and standard error $\Delta\xi$, $\Delta\sigma$ of all the data sets.

Station observed T_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.3875	-0.2550	-0.4182	-0.3261	-0.3323	-0.3292	-0.3108	-0.2225	-0.3292
Standard Error $\Delta\xi$	0.0317	0.0226	0.0226	0.0218	0.0208	0.0312	0.0371	0.0341	0.0312
Scale σ	2.7540	2.0819	2.3510	2.2144	2.1391	2.2286	2.5629	2.5685	2.2286
Standard Error $\Delta\sigma$	0.1421	0.1040	0.1075	0.1076	0.1031	0.1166	0.1462	0.1444	0.1166
ERA Interim T_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.1959	-0.1788	-0.2076	-0.2185	-0.2135	-0.3380	-0.2850	-0.0376	-0.2514
Standard Error $\Delta\xi$	0.0320	0.0348	0.0343	0.0287	0.0265	0.0316	0.0337	0.0508	0.0371
Scale σ	1.4643	1.3230	1.3440	1.5045	1.5630	2.0656	1.8497	1.3303	2.0410
Standard Error $\Delta\sigma$	0.0798	0.0739	0.0741	0.0788	0.0788	0.1082	0.0949	0.0908	0.1153
Bias Corrected ERA Interim T_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.1959	-0.1788	-0.2076	-0.2185	-0.2135	-0.3380	-0.2850	-0.0376	-0.2514
Standard Error $\Delta\xi$	0.0320	0.0348	0.0343	0.0287	0.0265	0.0316	0.0337	0.0508	0.0371
Scale σ	1.9834	1.7918	1.8205	2.0382	2.1164	2.7980	2.3081	1.8016	2.7636
Standard Error $\Delta\sigma$	0.1081	0.1001	0.1004	0.1068	0.1068	0.1467	0.1233	0.1229	0.1562
Station observed TW_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.1769	-0.1860	-0.2150	-0.2157	-0.2164	-0.3231	-0.2423	-0.2190	-0.1867
Standard Error $\Delta\xi$	0.0383	0.0354	0.0347	0.0442	0.0266	0.0269	0.0347	0.0368	0.0322
Scale σ	2.7590	2.0454	1.9600	2.0780	1.8572	2.3724	2.5126	2.3375	1.9032
Standard Error $\Delta\sigma$	0.1596	0.1146	0.1084	0.1289	0.0938	0.1191	0.1380	0.1328	0.1055
ERA Interim TW_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.0896	-0.0946	-0.0687	-0.1257	-0.1583	-0.1771	-0.0902	-0.0194	-0.1733
Standard Error $\Delta\xi$	0.0379	0.0293	0.0327	0.0342	0.0313	0.0377	0.0357	0.0359	0.0378
Scale σ	1.2879	1.2437	1.2311	1.4408	1.6104	1.6499	1.3423	0.6801	1.7886
Standard Error $\Delta\sigma$	0.0748	0.0660	0.0676	0.0804	0.0875	0.0959	0.0760	0.0398	0.1028
Bias Corrected ERA Interim TW_{max}									
Estimates	JCB	MJD	RHI	PDN	NWB	HYD	CHR	KHI	BDN
Shape ξ	-0.08961	-0.0946	-0.06870	-0.12570	-0.15831	-0.17711	-0.09017	-0.01942	-0.17332
Standard Error $\Delta\xi$	0.03786	0.02931	0.03275	0.03424	0.03134	0.03767	0.03571	0.03593	0.03782
Scale σ	1.35674	1.64650	1.75852	1.49477	1.52013	2.05281	2.14609	1.39943	2.15299
Standard Error $\Delta\sigma$	0.07878	0.08736	0.09651	0.08347	0.08254	0.11924	0.12145	0.08193	0.12370

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Figure 2. Modified scale (σ^*) and shape parameter (ξ) of the observed T_{max} ($^{\circ}\text{C}$) Karachi. The red vertical lines represent the selected threshold according to the station quantiles.

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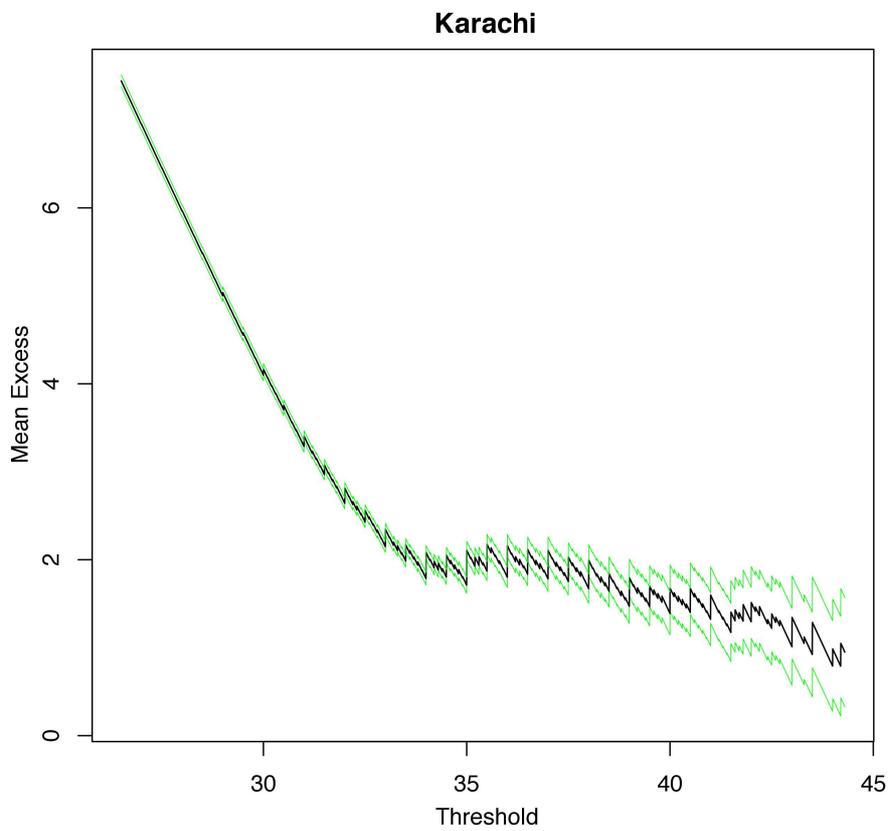


Figure 3. Mean residual life plot of the station observed T_{max} ($^{\circ}\text{C}$) Karachi.

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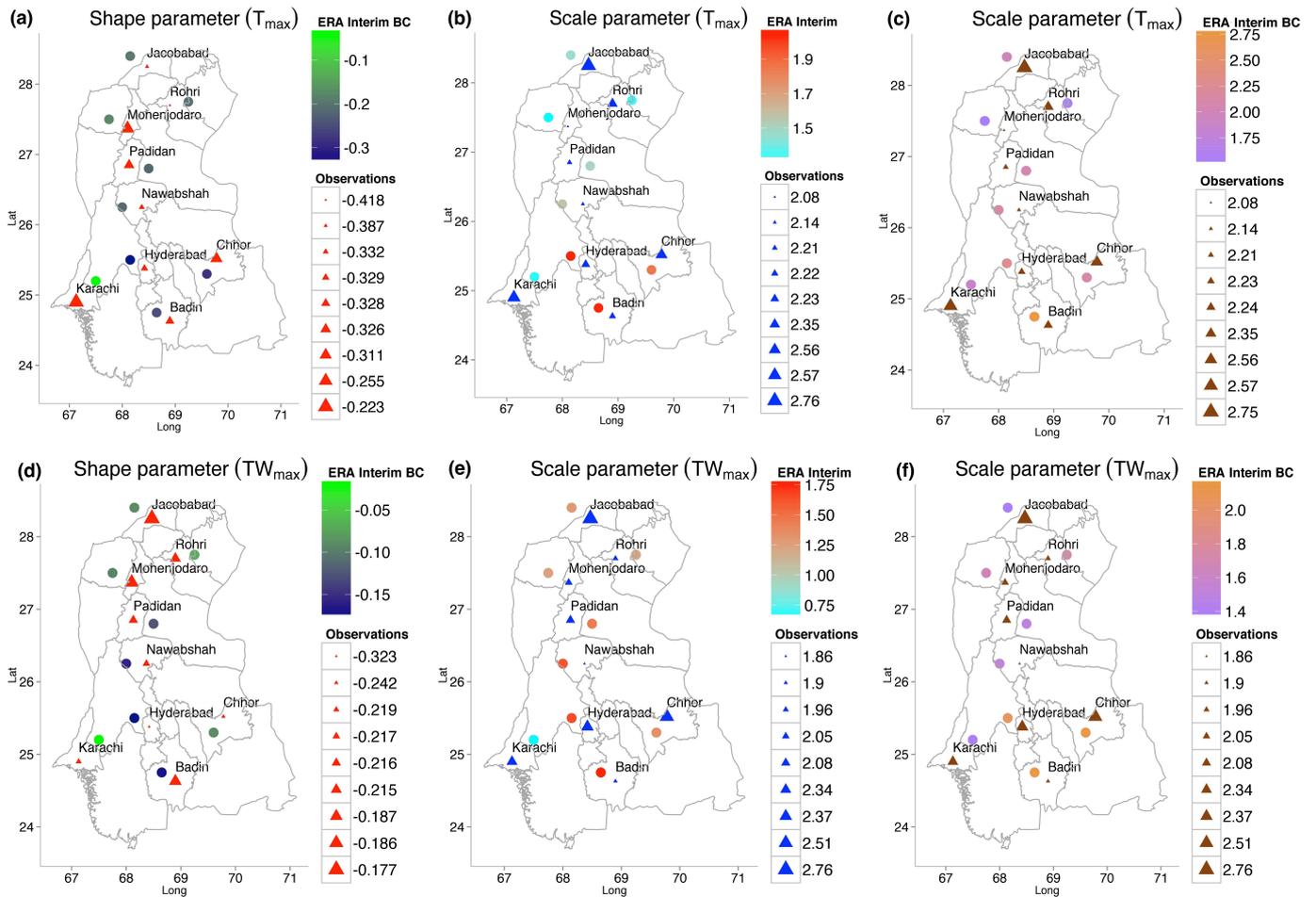


Figure 4. Spatial distribution of the shape parameters ξ and scale parameters σ of the station observed, ERA Interim, and bias corrected ERA Interim T_{max} (upper panel) and TW_{max} (lower panel) in degree Celsius.

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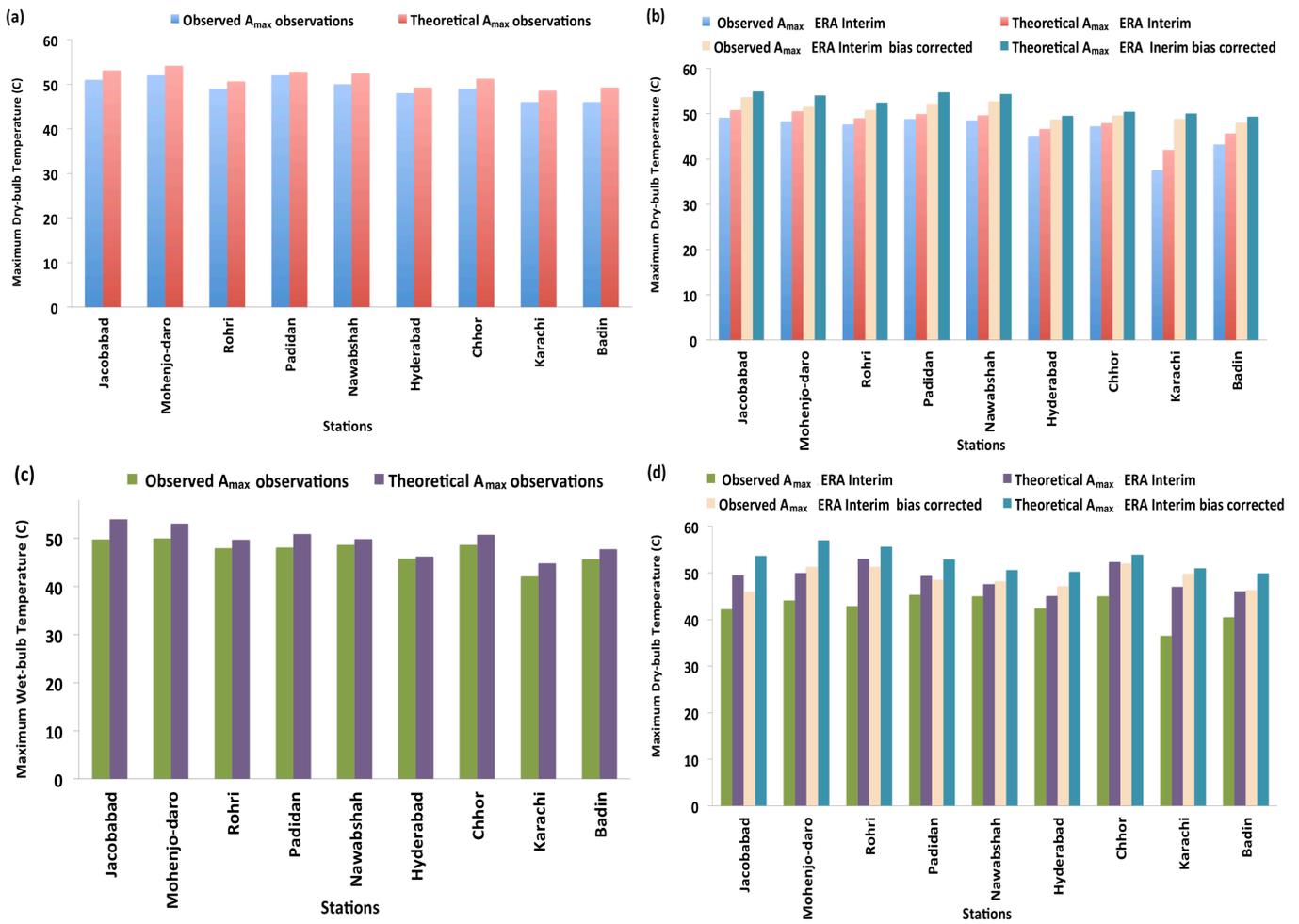


Figure 5. Absolute maxima A_{max} in degree Celsius (a) station observed T_{max} (b) ERA Interim and bias corrected ERA Interim T_{max} (c) station observed TW_{max} (d) ERA Interim and bias corrected ERA Interim TW_{max} .

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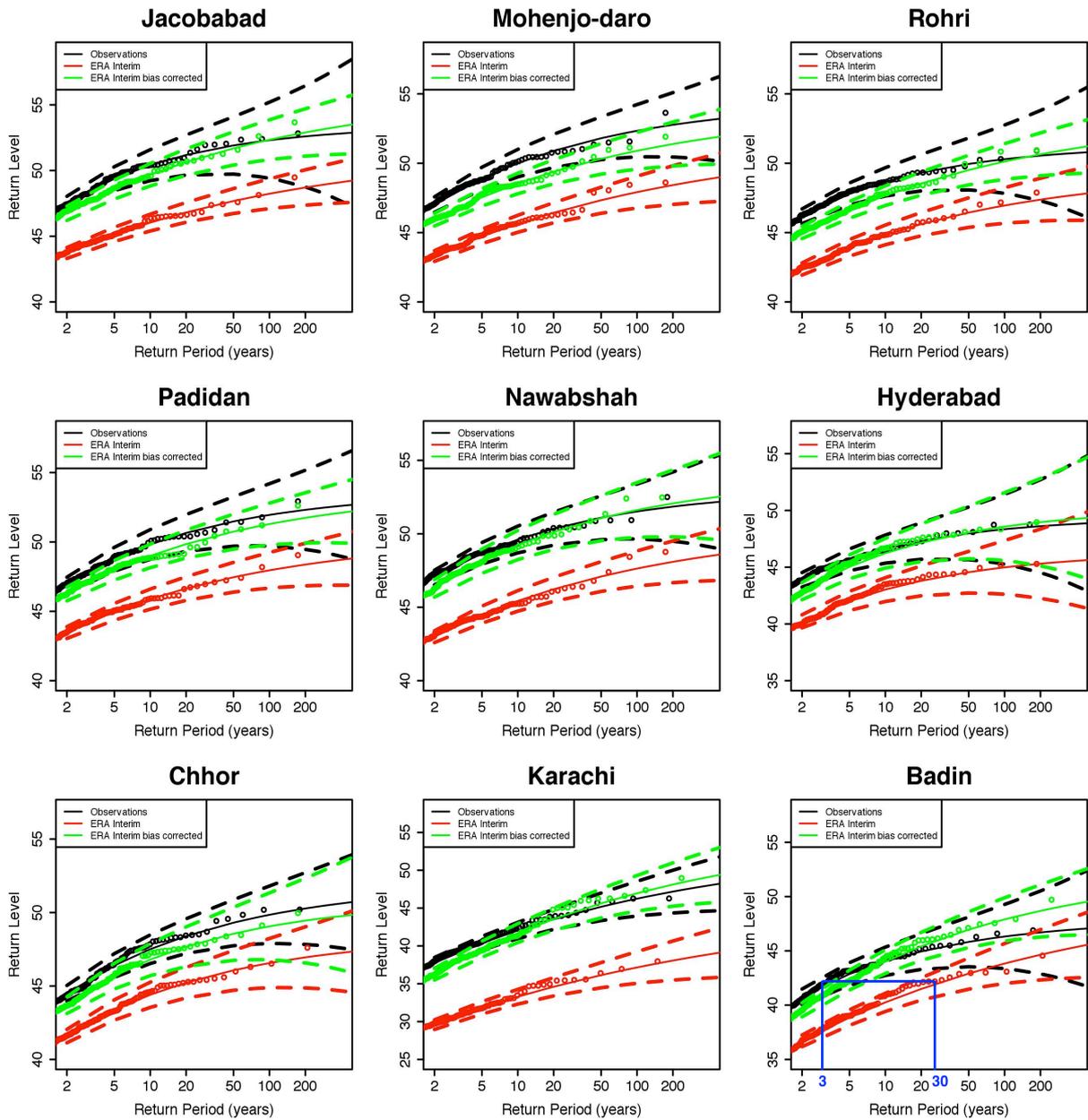


Figure 6. Return level plots of the station observed T_{max} (black) , ERA Interim T_{max} (red), and bias corrected ERA Interim T_{max} (green) in degree Celsius. The blue line is to show a difference in the observed and ERA Interim RLs.

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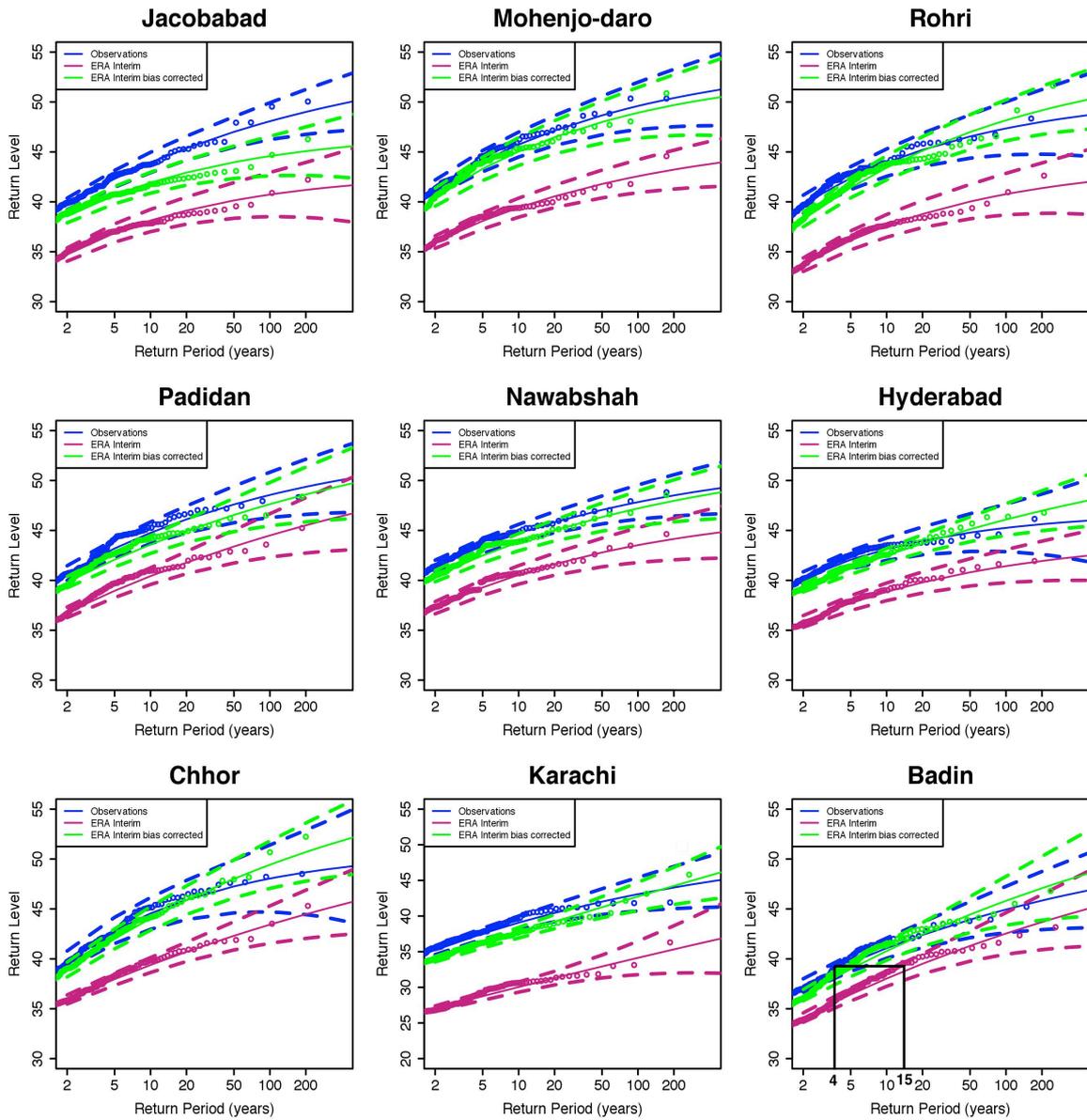


Figure 7. Return level plots of the station observed TW_{max} (blue), ERA Interim T_{max} (pink), and bias corrected ERA Interim T_{max} (green) in degree Celsius. The black line is to show a difference in the observed and ERA Interim RLs.

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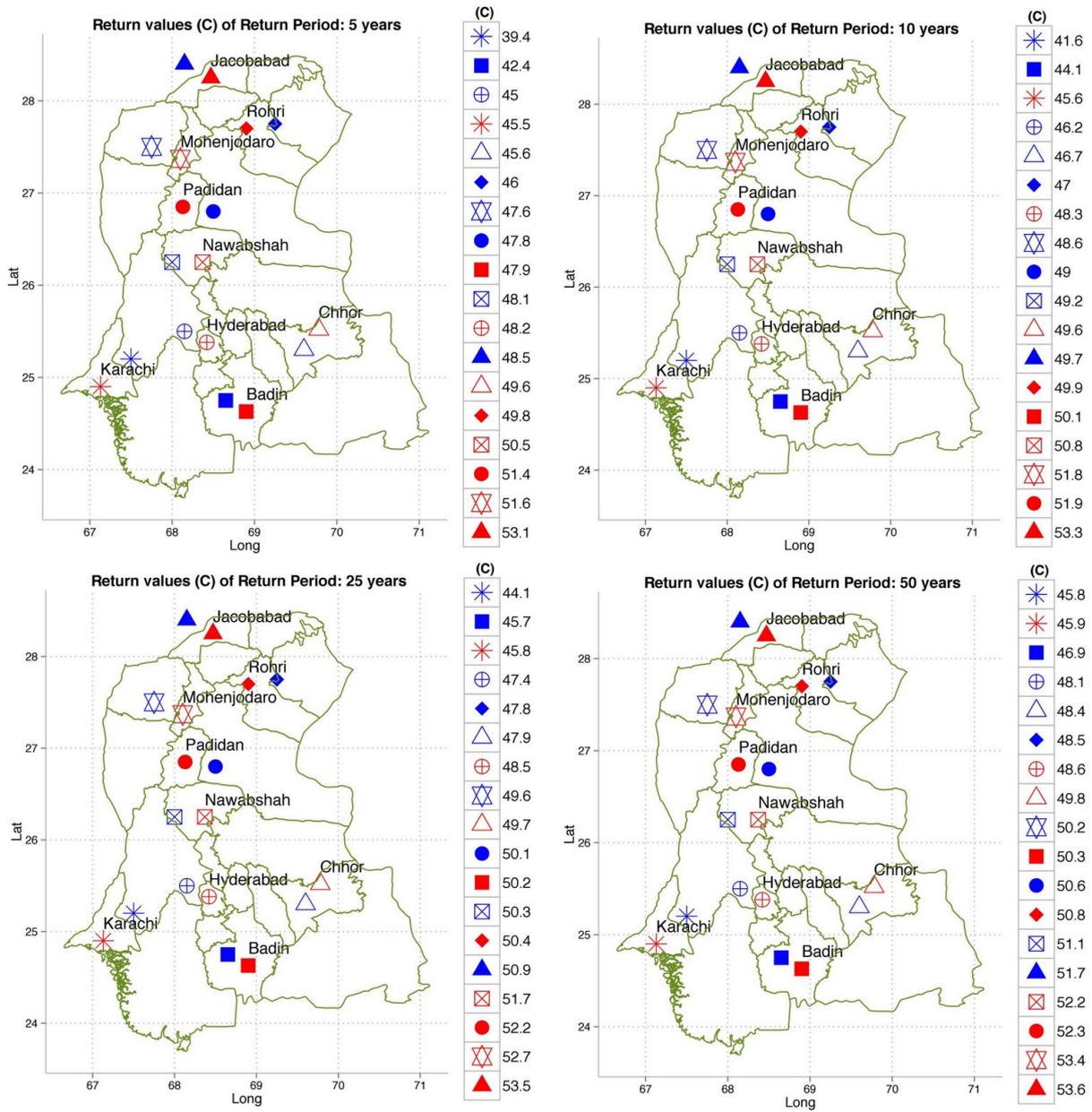


Figure 8. Spatial distribution of the station observed T_{max} (red) and bias corrected ERA Interim T_{max} (blue) return levels in degree Celsius corresponding to return periods of 5, 10, 25 and 50 years in southern Pakistan.

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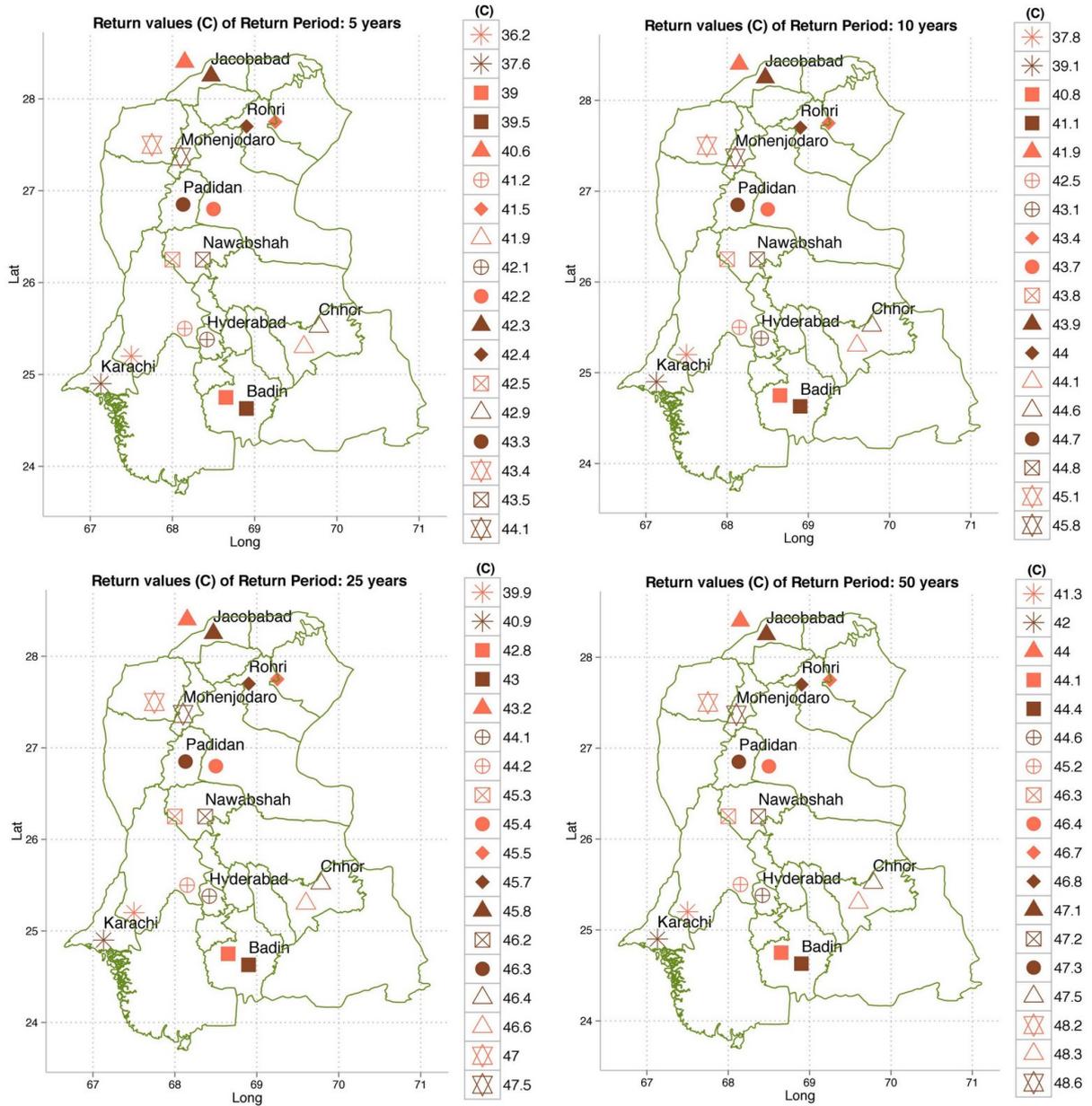


Figure 9. Spatial distribution of the station observed TW_{max} (brown) and bias corrected ERA Interim TW_{max} (orange) return levels in degree Celsius corresponding to return periods of 5, 10, 25 and 50 years in southern Pakistan.

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