DOI: 10.31577/ahs-2022-0023.01.0010

ACTA HYDROLOGICA
SLOVACA

Volume 23, No. 1, 2022, 89 – 98

Observations from the Western Carpathians and Pannonian Plain show that rainfall return levels need to be adjusted to account for rising dew-point temperature

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Rainfall records from a total of 526 rain gauges located in the western part of the Carpathian Mountains and the adjacent Pannonian Plain were analyzed. Estimation of extreme rainfall totals with various return periods is essential for reliable design of hydraulic infrastructure. The ongoing climate change brings additional challenges to the estimation of rainfall return levels. In this paper, we compared stationary vs. non-stationary generalized extreme value distributions (GEV) for 2-, 5-, 10-, 25-, 50-, and 100-year return levels of 24-h rainfall determined from annual maxima series. The fundamental question we seek to answer in this paper is whether the stationarity-based design concept is adequate under changing climate conditions because the statistical parameters of probability distribution become dependent on dew-point temperature. Our analyses revealed that the projected return levels tend to increase with decreasing return periods. For instance, the 100-year return levels need an adjustment by ~6.64% (CI: -1.03% +14.95%), while the stationary 5-year return periods of 24-h precipitation totals need to be adjusted by up to ~10.5% (CI: -3.61% +21.24%). Our investigations showed that in ~60% of the analyzed sites the current return levels might need an adjustment to account for the rising dew-point temperature. The presented results may have implication for regional water management planning and flood risk assessment.

KEY WORDS: rainfall, non-stationarity, GEV, return period, return level

Introduction

Climate extremes, including heavy precipitation and extreme air temperatures have substantially increased in the past few decades (Onderka and Pecho, 2021; Lakatos et al., 2020; Alexander et al., 2006; Vose et al., 2005). Global warming increases average air temperature, which in turn enhances atmospheric water holding capacity (Onderka and Pecho, 2021). It is now recognized that these changes are responsible for higher frequency and/or intensity of extreme rainfall (Ganguli and Coulibaly, 2017; Agilan and Umamahesh, 2016). Rainfall extremes and their statistical properties are important for proper estimations of design values in numerous engineering infrastructures such as urban drainage systems, bridges, railways, highways, rain harvesting systems and road culverts can be designed more economically when the frequency of extreme rainfall is known (Yan et al., 2021; Lakatos et al., 2020; Onderka et al., 2020; Bara et al., 2009; Faško et al., 2000). Rainfall extremes can studied at a range of spatial and temporal scales (AghaKouchak et al., 2013; Diffenbaugh and Giorgi, 2012; Jakob, 2013; Kharin et al., 2007). A substantial reduction in the return period of an annual maximum precipitation amount with frequent occurrence of extreme rainfall events is predicted by the end of the 21st century (IPCC 2012). O'Gorman (2015) found a dependency between mean and extreme precipitation on air temperature. This dependency has been ascribed to physical relation known as the Clausius–Clapeyron relation (O'Gorman and Schneider, 2009; Wasko and Sharma, 2015; 2017; Onderka and Pecho, 2021), according to which, increased water-holding capacity of warmer air intensifies heavy rainfall at a rate of approximately 7–8% °C −1 of warming. Lenderink et al. (2017) found that in the Netherlands, extreme precipitation of sub-hourly up to the 6-h durations have increased above the Clausius–Clapeyron relation. Similar results are reported by other authors in Switzerland (Ban et al., 2015), Germany (Berg et al., 2013), the UK (Blenkinsop et al., 2015), in Australia (Schroeer and Kirchengast, 2018; Wasko and Sharma, 2015; 2017), North America (Shaw et al., 2011) and in China (Miao et al., 2015). This pattern of increasing annual extremes with air temperature is not valid for every place on the Earth. Observations published in relevant literature suggest that this relation is region-specific. For instance, in India (Ali and Mishra, 2017) and northern Australia (Jones et al., 2010) negative rates have been reported. Consequences of climate change often lead to altered intensity, duration or frequency of all rainfall extremes. Cheng and AghaKouchak (2015) showed that a stationary climate assumption may lead to underestimation of extreme precipitation by as much as 60%, and that such underestimation ultimately may increase the risk of floods and failure of infrastructure. For example, the return level with a T-year return period represents an rainfall amount that has a 1/T chance of occurrence in any given year (Lakatos et al., 2020; Cooley et al., 2007). However, infrastructure design concepts still rely on stationary return levels, which assume no change in the frequency of extremes over time (Cheng and Aghakouchak, 2015; Agilan and Umamahesh 2018; Sarhadi and Soulis 2017). The concept of frequency analysis inherently implies mutually independent rainfall events.

The frequency of rainfall extremes has been changing and is likely to continue to change in Slovakia in the future (Onderka et al., 2020). Therefore, concepts and models that can account for non-stationary analysis of climatic and hydrologic extremes are needed (e.g. Cooley 2013; Parey et al., 2010; Salas and Obeysekera, 2014). Katz et al. (2002) present non-stationarity in extremes in terms of changing quantiles (also termed "effective return levels"), which vary as a function of time to keep a constant probability of an extreme event. Alternatively, Rootzén and Katz (2013) introduced the concept of "Design Life Level" to quantify the probability of exceeding a fixed threshold during the design life of a project.

To our best knowledge, non-stationarity of 24-h rainfall annual maxima induced by changing climate has not been considered in Slovakia so far. Thus our intention here is to present the first results obtained from non-stationary modeling of return levels of 24-h rainfall with respect to rising air and dew point temperatures with an emphasis placed on a comparison with a stationary set up.

Material and methods

Data sources

Our investigations are based on data collected at 526 rain gauges located throughout the investigated region (Slovakia), i.e. encompassing the northern part of the Pannonian Plain and the adjacent western Carpathian Mountains. The rain gauges are located throughout a broad range of altitudes ranging from 97 up to 2634 m a.s.l. The average distance between the rain gauges is 9.2 km. The analyzed time series span over 40 years and cover the time period 01/1981–12/2020 (Table 1). The choice of rain gauges was based on the length of the available time-series and their quality so that we did not have to fill in missing data nor remove suspicious observations. The 24-h rainfall totals were measured in standard rain gauges operated by the national weather service (Slovak Hydrometeorological Institute). The amount of precipitated water in the rain gauges is measured on a daily basis at 0600 UTC. The capture area of a rain gauge is 500 cm^2. The auxiliary data on near surface dew-point and dry-bulb temperatures were downloaded from the reanalysis ERA5 database in the form of monthly averages of near surface dew-point and dry-bulb air temperatures. The ERA5 data were downloaded from the Copernicus Climate Data Store via the Application Programme Interface CDS API (https://cds.climate.copernicus.eu).

Identification of return levels under stationary and non-stationary conditions

The term return level refers to the magnitude of the daily rainfall event. The return period is the frequency of

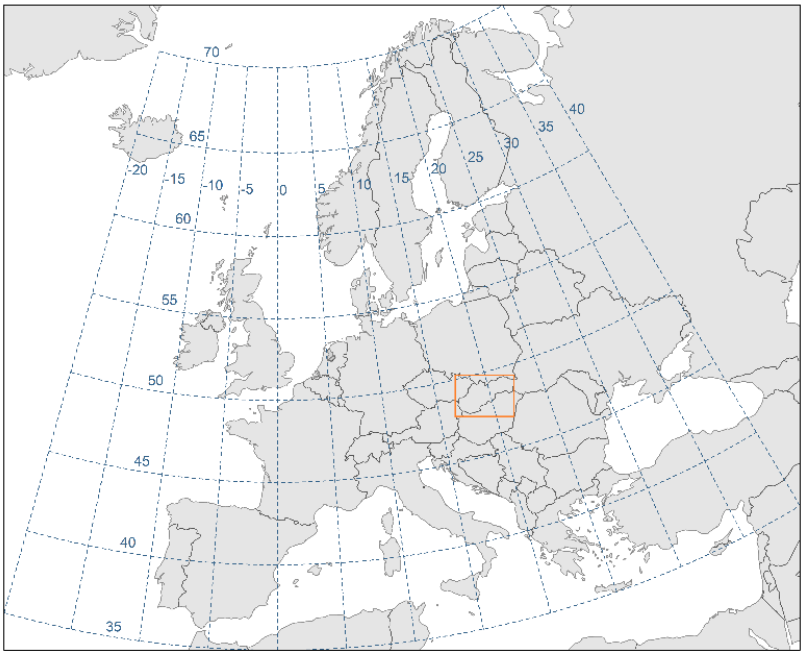

Fig. 1. Location of the investigated region – the rectangle encompasses the western part of the Carpathians Mountains and the adjacent Pannonian Plain.

the event. Return periods are usually identified by analyzing rainfall annual maxima series (AMS), where the largest event of one year is considered to be independent of the largest event from any other year (Bedient et al., 2008). In a purely statistical sense, extremes in rainfall or any other natural phenomenon can be broadly categorized either as stationary and non-stationary (Ragno et al., 2019; Cheng et al., 2014; Cheng and Aghakouchak, 2015). In a stationary model, the mean, variance, and distribution of extremes do not change over time or with respect to other covariates. In a stationary model, observations are assumed to have a probability distribution function with constant parameters. On the contrary, when non-stationarity of the extremes is assumed, the parameters of the underlying probability distribution function change in response to a given covariate (Ragmo et al., 2019). First, we identified annual maxima of 24-h rainfall in each of the time series. This was accomplished by identifying the highest 24-h rainfall total for each calendar year of the record. As the investigated period covers the years 1981-2020, each rain gauge provided 40 maximum 24-h rainfall totals. The time-series of annual maxima from each of the 526 rain gauges were then analyzed to detect non-stationarity with respect to time and dew-point temperature. In this paper, we applied the generalized framework named Process-informed Non-stationary Extreme Value Analysis (ProNEVA) Software Package, Version 2.0 developed by Cheng et al. (2014) and further described with practical applications in Regno et al. (2019). A non-stationarity component is often defined as a temporal dependence of the observed extremes on another physical variable. Incorporating a physical control into the statistical analysis is possible when there is strong evidence (empirical or theoretical) that the physical covariate can alter the statistics of the extremes. Since it is recognized that increasing air temperature intensifies the development of convective storms (Onderka and Pecho, 2021) the temporal trend in near-surface dew point temperature is considered here as a plausible physical covariate for explaining non-stationarity of rainfall extremes. For a stationary model, the cumulative distribution function of the GEV is defined as

$$F_{GEV}(x) = exp\left[-\left(1+\xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-1/\xi}\right] \qquad (1)$$

where F_{GEV} is defined for $\{x: 1 + (\xi(x-\mu)/\sigma) > 0\}$, $-\infty < \mu < \infty$, $\sigma > 0$. and $-\infty < \xi < \infty$, where μ is the location parameter, σ is scale parameter, and ξ is the shape parameter (Cheng and Aghakouchak 2015; Smith et al., 2001). The stationary GEV model can be extended to a non-stationary GEV by allowing the parameters of the distribution function in Eq. 1 to vary with a chosen physical covariate x_{cov} or simply with time t. Then, the non-stationary probability density function can be defined as

$$F_{GEV}(x|x_{cov}) = exp\left[-\left(1+\xi(x_{cov})\left(\frac{x(x_{cov})-\mu(x_{cov})}{\sigma(x_{cov})}\right)\right)^{-1/\xi(x_{cov})}\right] \qquad (2)$$

where μ is the location parameter, σ is scale parameter, and ξ is the shape parameter are assumed to be dependent on the covariate x_{cov}. Here, we allowed only the location parameter μ to be covariate-dependent. As pointed out by Ragno et al. (2019), it is difficult to precisely estimate the shape parameter ξ even for the stationary GEV distribution, in this paper only the location parameter μ was allowed to depend on a covariate. The location parameter is therefore defined as a linear function of the covariate.

$$\mu(x_{cov}) = \mu_0 + \mu_1 x_{cov} \qquad (3)$$

where x_{cov} is a covariate and μ_0 and μ_1 are estimated parameters. The parameters of the selected non-stationary GEV distribution were estimated using the Bayesian approach described e.g. in Ragno et al. (2019), AghaKouchak et al. (2013) or Cheng et al. (2014).

Covariate selection – time vs. dew point temperature

Time is the most frequently used covariate in non-stationary modeling of rainfall extremes (Yan et al., 2021; Agilan and Umamahesh, 2016; Ragno et al., 2019). An important advantage of using time as a covariate in non-stationary GEV is that we can project the return levels for a projected time horizon. However, before blindly applying time as a covariate in our analyses it is necessary to justify its utilization as a covariate in non-stationary distribution functions. Our hypothesis was that time can be considered as a covariate only if another physically plausible covariate (e.g. dew-point temperature) co-varies linearly with time (Ganguli and Coulibaly, 2017; Onderka and Pecho, 2021; O'Gorman and Schneider, 2009; Wasko and Sharma, 2015; 2017). If a non-linear temporal trend in dew-point temperature was detected, the parameters in Eq. 3 would need to be adjusted to account for a non-linear temporal evolution of the physical covariate (e.g. using higher order polynomials). In such cases, time as a single covariate could not be used. Therefore, a linear temporal trend in the covariate series is a pre-requisite for using time as a covariate in the non-stationary distribution function. It is well a known fact that summertime rainfall extremes are physically linked to the atmosphere's water holding capacity (Zhang et al., 2019; Onderka and Pecho, 2021; Wasko and Sharma, 2015; 2017). A dependency between the frequency and intensity of extreme rainfall and mean near-surface air and dew-point temperatures has been observed in a growing number of studies (e.g. Ganguli and Coulibaly, 2017; Onderka et al., 2021; O'Gorman and Schneider, 2009; Wasko and Sharma, 2015; 2017). This dependency is physically explained by the relationship between saturated vapor pressure and air temperature, known as the Clausius–Clapeyron relation. Because extreme rainfall apparently scales with dew-point temperature better than with dry-bulb temperature (Zhang et al., 2019; Onderka and Pecho, 2021) in this paper we focused on the temporal evolution of dew-point temperature first.

Various approaches have been proposed to relate annual rainfall extremes to increasing dew-point temperatures (or another appropriate variable). For instance, Westra et al. (2013) use a global approach, i.e. they applied the global mean temperature to scale global rainfall extremes. Poschlod and Ludwig (2021) used the average temperature of the European continent to account for the fact that the sources of water attributing to rainfall in Europe originate from regional moisture transfers (Keune and Miralles, 2019); local temperatures have been used by Onderka and Pecho (2021) in event-based analyses of rainfall intensities (Onderka and Pecho, 2021). Bisselink and Dolman (2008) described a dynamic rainfall recycling model using re-analyses data from ERA40. Based on their investigations for the Central European region, the recycling ratio for the summertime season (J- J-A) is a function of spatial scale.

However, the principle sources of rainfall water for atmospheric precipitation are the evaporated water from the land surface and water bodies such as lakes and oceans. The proportion these two sources of precipitation water contribute to the observed rainfall in an investigated area is usually unknown. For instance, it is estimated that only some 10 to 20 % of rainfall water falling on the Central European region comes from the same area where the rainfall is observed. This implies that the origin of rainwater is mostly attributable to soil moisture evaporated from land surface outside the vicinity of an investigated rain gauge (Poschlod and Ludwig, 2021; Keune and Miralles, 2019; Bisselink and Dolman, 2008).

In this paper we averaged the temporal trends calculated for near surface dew-point temperature series (ERA5 reanalysis data) over a rectangle encompassing the entire investigated region of the western Carpathians and the most northern part of the Pannonian Plain (bottom left corner coordinates: longitude 16.75, latitude 47.75; upper right corner coordinates: longitude 22.75, latitude 49.75, see Fig. 1). First, the temporal trend was calculated separately for each grid point of the ERA5 reanalysis dew-point temperature data. Trends were esimated only on summertime data (JJA). A global trend was then constructed by averaging the individual local (grid point) trends. The global average trend was used as a proxi covariate in the non-stationary GEV analyses for each of the 526 rain gauges.

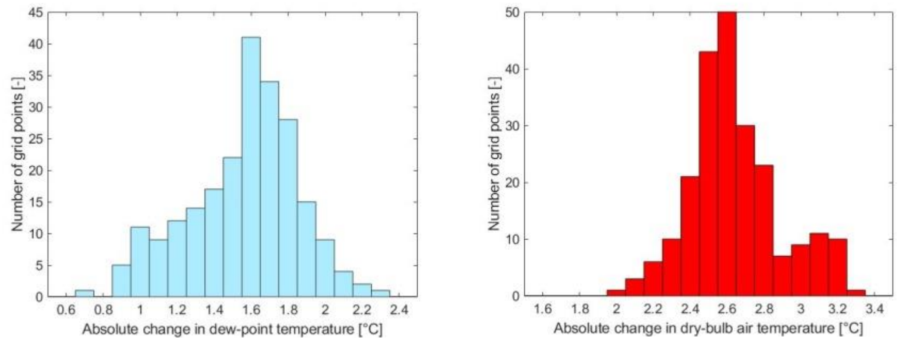

Fig. 2. Histograms of temporal changes (period 1981–2020) in summertime (JJA) near surface dew-point temperature (left) and dry-bulb temperature (right) determined from ERA5 data (n = 225 grid points). The median absolute change in summertime dew-point temperature over the investigated period is 1.6°C, and the median change in summertime dry-bulb temperature is 2.6°C.

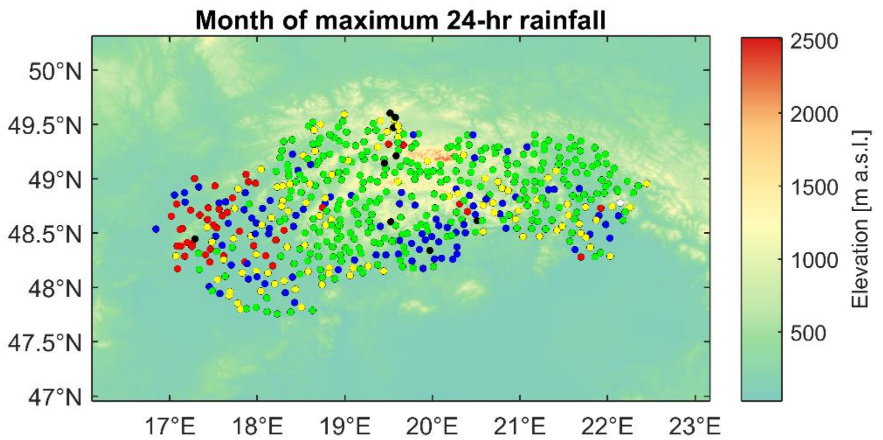

Fig. 3. Distribution of months (median values) with the highest rate of annual 24-h maxima. The following color-coding was applied to distinguish between months: black = May; blue = June; green = July; yellow = August; red = September.

Goodness of fit

Four goodness-of-fit measures were calculated to test the performance of the models. The tests were used to facilitate the selection a parsimonious model, i.e. a model showing a sufficient level of performance efficiency with the minimum number of parameters. The models were compared based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the Root Mean Square Error (RMSE). The Akaike Information Criterion (AIC) is formulated as

$$AIC = 2(D - L) \quad (4)$$

where D is the number of parameters of the statistical model and L is the log-likelihood function. The model associated with a lower AIC is considered a better fit. The Bayesian Information Criterion (BIC) is defined as

$$BIC = D\ ln(N) - 2L \quad (5)$$

where N is the length of records. Similar to AIC, the model with lower BIC results a better fit. In addition to AIC and BIC, the Root Mean Square Error (RMSE) was calculated. A time series was declared non-stationary if AIC, BIS and RMSE concurrently satisfied the three following conditions: $AIC_{NonStat} < AIC_{Stat}$; $BIC_{NonStat} < BIC_{Stat}$; $RMSE_{NonStat} < RMSE_{Stat}$. As summarized in Table 2, we used all three criteria to identify non-stationary series of annual rainfall maxima. First we compared the percentage of rain gauges with stationary and non-stationary series based on comparison of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the root mean squared errors (RMSE). Note that the last column in Table 1 indicates the percentage of rain gauges satisfying the condition that all three criteria of non-stationarity are satisfied concurrently. The further statistical analyses are based on the concurrent satisfaction of the three criteria.

By analyzing the temporal aspects when a rainfall maximum occurs we found that the annual maxima occur mostly in the summer months between June and September, as shown in Fig. 3 with an apparent spatial pattern. In the south-western portion of the investigated region the annual maxima occur predominantly in May and September, whereas the month of July dominates in the rest of the region. Therefore the trend analysis of the ERA5 near surface dew point temperature series was conducted only for the summer months (June, July and August). The trend analysis of dew point temperature revealed that, over the period 1981–2020, the average near surface dew-point temperature increased linearly by 1.6°C (Fig. 2). The use of time as a covariate in non-stationary GEV analysis is therefore justified. Recalling the C-C scaling rate of ~7% per every degree of dew-point temperature, the 1.6°C increase in dew point should roughly correspond to 11.2% increase in rainfall extremes. Table 2 summarizes the comparison of the stationary and non-stationary approach. The corresponding histograms of changes in return levels between the stationary estimates (1981–2020) and the non-stationary estimates projected for the time horizon 2040 are shown in Figure 4. The 2-year return levels increased by 13.39% and the 100-year return levels increased by 6.64%. In general, the return levels tend to increase with decreasing return period. Similar results were obtained by Ganguli and Coulibaly (2017) who compared intensity-duration-frequency curves constructed for non-stationary conditions with current design standards in Canada. They found that return periods (10 years or less), which are values typical for urban drainage design require an update of up to ~7%. For longer recurrence intervals (50–100 years) the authors conclude that updates ranging from 2 to 44% are needed. Figure 5 shows the overall distributions (histograms) of the simulated 2-, 5-, 10-, 20-, 50- and 100-year return levels. The percentage changes in return levels are shown in maps (Fig. 6).

Table 1. Percentage of rain gauges with stationary and non-stationary annual maxima series based on comparison of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the root mean squared errors (RMSE). The last column indicates the percentage of rain gauges satisfying the condition that all three criteria of stationarity are satisfied concurrently, i.e. AIC, BIC and RMSE of the stationary models are lower than for the non-stationary models

	$AIC_{stat}<AIC_{NonStat}$	$BIC_{stat}<BIC_{NonStat}$	$RMSE_{stat}<RMSE_{NonStat}$	$AIC_{stat}<AIC_{NonStat}$ and $BIC_{stat}<BIC_{NonStat}$ and $RMSE_{stat}<RMSE_{NonStat}$
Stationary AMS [%]	69.96	84.22	48.29	32.70
	$AIC_{Nonstat}<AIC_{Stat}$	$BIC_{Nonstat}<BIC_{Stat}$	$RMSE_{Nonstat}<RMSE_{Stat}$	$AIC_{Nonstat}<AIC_{Stat}$ and $BIC_{Nonstat}<BIC_{Stat}$ and $RMSE_{Nonstat}<RMSE_{Stat}$
Non-stationary AMS [%]	30.04	15.78	51.71	59.86

Table 2. **Percentage change [%] of stationary vs. non-stationary return levels simulated for the time horizon 2040. The statistics was calculated for rain gauges satisfying the non-stationarity criteria**

Return period	2-year	5-year	10-year	25-year	50-year	100-year
Min	-27.44	-23.86	-22.84	-22.21	-22.09	-22.19
Max	49.03	40.34	36.71	33.58	32.03	35.50
Kurtosis	0.21	0.69	1.11	1.64	1.92	2.23
Skew	-0.31	-0.53	-0.65	-0.68	-0.54	-0.27
P10	-4.18	-3.61	-2.31	-1.82	-1.53	-1.03
P50	13.39	10.49	9.25	7.81	6.92	6.64
P90	28.83	21.24	18.30	16.05	15.09	14.95
St.Dev.	13.44	9.99	8.58	7.53	7.26	7.43
Average	12.94	9.76	8.49	7.47	7.03	6.79

Table 3. **Global statistics of return levels (maximum likelihood values) calculated for the ensemble of stationary and non-stationary models for the time horizon 2040. The values are indicated in mm**

Return period	2-year	5-year	10-year	25-year	50-year	100-year
Min	27.35	36.72	42.66	50.04	53.65	56.35
Max	78.83	103.41	119.76	140.51	155.97	171.37
Kurtosis	2.57	4.43	5.30	5.11	4.09	2.88
Skew	1.30	1.57	1.64	1.54	1.35	1.15
P10	35.60	45.93	52.03	59.42	64.66	69.25
P50	41.36	52.30	59.85	69.31	76.84	84.35
P90	52.97	65.01	73.42	85.49	95.44	105.30
St.Dev.	7.61	8.59	9.52	11.28	13.20	15.77
Average	43.31	54.20	61.63	71.38	78.93	86.75

Table 4. **Return levels of the 24-hr rainfall [mm] projected for the time horizon 2040. The projections were performed for both the stationary and non-stationary conditions. ML stands for maximum likelihood estimates; the confidence interval of the ML estimates is defined as the 5th and 95th percentiles (P05 and P95). The percentage change (% change) was calculated as a 100*(RL2040/RLstat)**

	Return levels [mm]					
Rain gauge location	**2-years**	**5-years**	**10-years**	**25-years**	**50-years**	**100-years**
Bratislava – Koliba						
ML	46.74	56.95	64.11	73.64	81.08	88.79
P05	36.46	47.96	55.62	64.35	70.01	75.17
P95	56.6	69.18	79.04	95.55	108.54	125.04
% change	19	14.9	13.2	11.9	11.4	11.1
Bratislava – Airport						
ML	40.31	52.23	61.10	73.54	83.77	94.83
P05	28.78	41.36	49.99	61.34	68.27	74.53
P95	48.54	63.40	77.93	102.78	130.61	164.08
% change	21.2	14.3	11.3	8.6	7.1	6

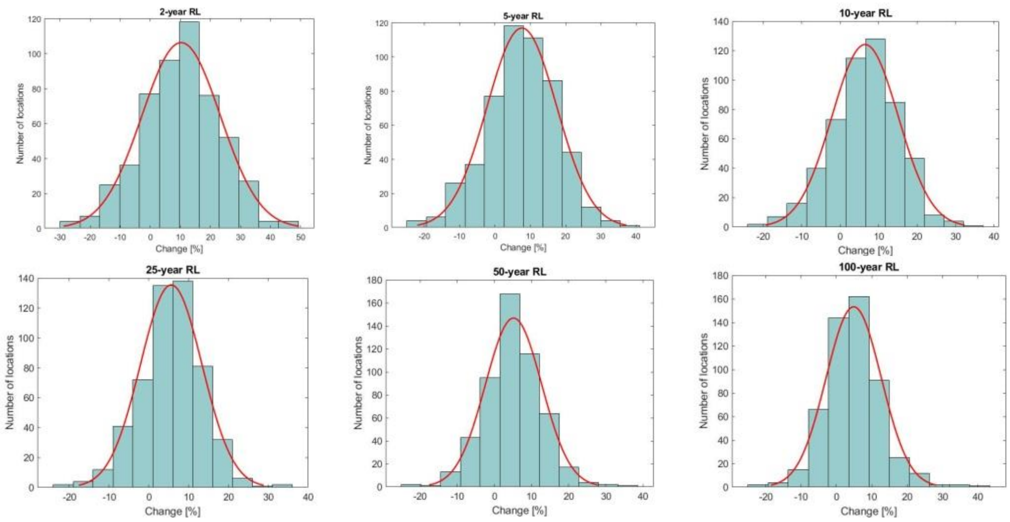

Fig. 4. Histograms with their normal pdf functions constructed for the changes in return levels. The percentage changes indicate the change between the stationary estimates (1981–2020) and the non-stationary estimates projected for the time horizon 2040.

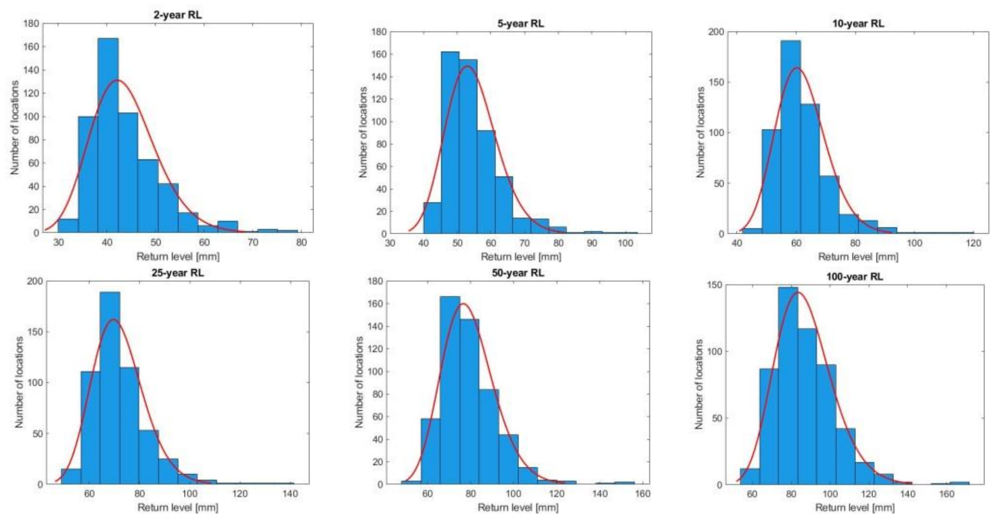

Fig. 5. Histograms with their log-normal pdf functions constructed for the 2-, 5-, 10- , 20-, 50-, and 100-year return levels (maximum likelihood estimates) simulated for the time horizon 2040.

It is important to note that in this study we related non-stationarity only to one physical driver, i.e. dew-point temperature.

In terms of other physical drivers related to convective precipitation that could be potentially used as a covariate in non-stationary GEV analyses, convergence, vorticity and vertical wind shear changes should be considered (Onderka and Pecho, 2021).In addition to these physical drivers, there are reports from other parts of the globe where atmospheric circulation modes, global and regional changes in air temperature, global carbon dioxide trends and the level of urbanization are recognized as being capable of affecting the non-stationary behavior of rainfall extremes in the future (Agilan and Umamahesh, 2016; Yan et al., 2021).

First, we focused on the appropriateness of using time as a single covariate to describe the non-stationary behavior of rainfall annual maxima series. To justify the use of time as a covariate, we used the temporal trend in summertime dew-point temperature as a plausible physical variable controlling the occurrence of summertime rainfall extremes.

Based on the presented analyses we can conclude that the stationarity-based concept may not be adequate for the design of hydraulic infrastructures under changing climate conditions because the parameters of probability distribution change with time.

In fact, an update of the present-day stationary estimates of rainfall return levels is needed to account for the rising dew-point temperature.

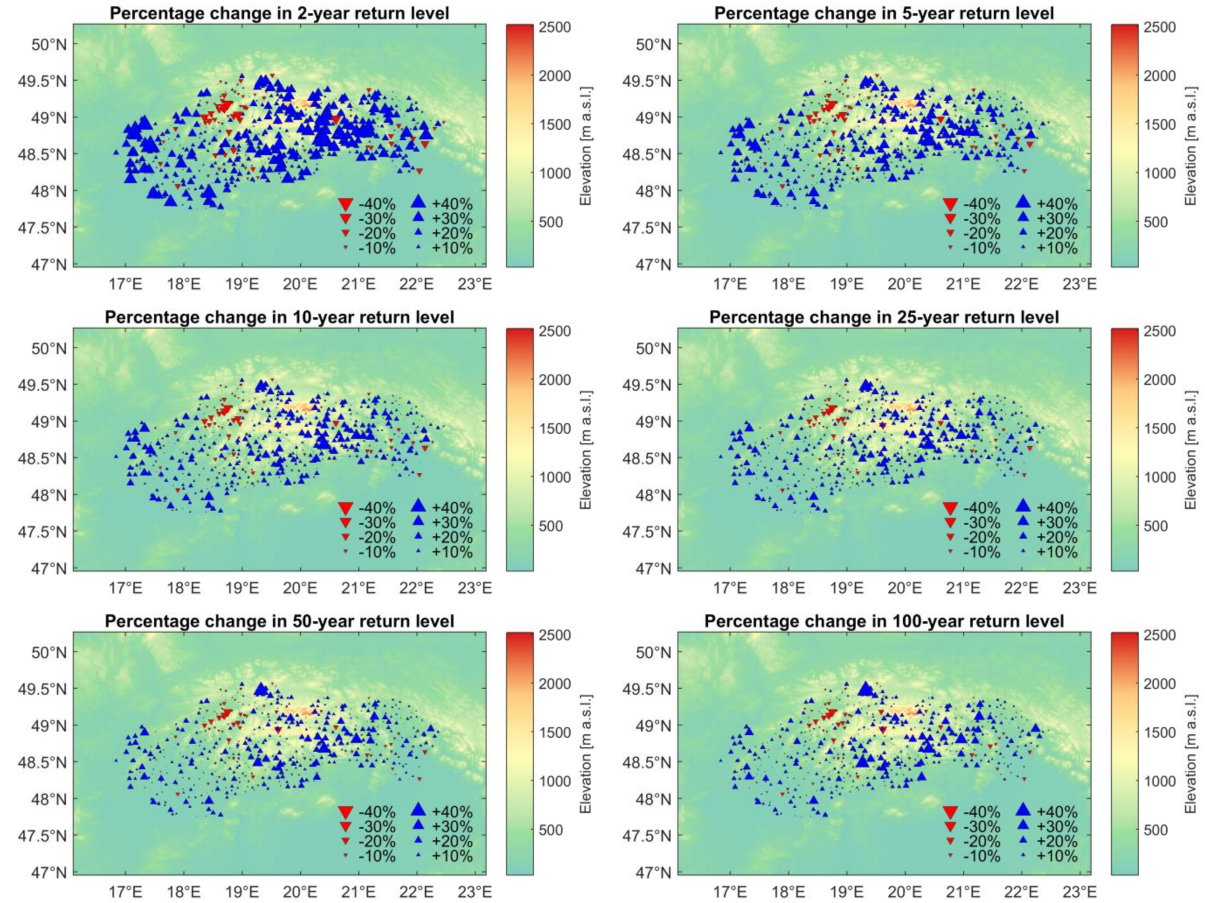

Fig. 6. Spatial distribution of the percentage changes in return levels. The percentage changes indicate the change between the stationary estimates (1981–2020) and the non-stationary estimates projected for the time horizon 2040.

Conclusions

The following conclusions can be drawn from this paper:

- Over the period 1981–2020, the average summertime near surface dew-point temperature in the investigated region increased by ~1.6°C
- Up to 60% of the investigated sites showed non-stationarity in rainfall annual maxima
- Changes in the projected return levels tend to increase with decreasing return periods
- By 2040, the 100-year return levels are likely to increase by ~6.64%
- The 2-year return levels might rise up to 13.39% by 2040

Acknowledgement

The research presented in this paper could not be accomplished without the following grants: „Scientific support of climate change adaptation in agriculture and mitigation of soil degradation (ITMS2014+ 313011W580), supported by the Integrated Infrastructure Operational Programme and funded by the ERDF; and the national VEGA grant No. 2/0003/21 "Complex analysis of the effects of rising air temperature on rainfall extremes in Slovakia".

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