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Characterization of the temporal variability of Estonian mean precipitation series

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Abstract. Values of mean precipitation have been estimated from time series obtained using 15- and 30-day totals of the daily precipitation, measured at 40 stations throughout Estonia over a 45-year period (1961–2005). Six series were studied using different spatially averaged scales. The temporal variability of each series was fitted using an autoregressive and integrated moving-average (ARIMA) model of type IMA(0,1,1). The fitted model was non-stationary but allowed a formal decomposition into a stationary white noise and a non-stationary random walk component. The standard deviation of the stationary component was then used to define a 95% range of variability for the precipitation that divides the distribution into three regimes, a central and two outlying parts. We herein present simple statistics for each of these three regimes.

Key words: precipitation, Estonia, ARIMA model, temporal variability.

1. INTRODUCTION

Studies of precipitation in Estonia first took place in the 19th century and have been reviewed in a number of milestone publications [1,2]. More recently, significant contributions were made by Jaagus [3,4], while other authors have studied the extreme weather conditions of the past few years [5–9].

Indeed, extremes of precipitation have become a popular focus of many studies carried out during the past twenty years, owing to the increased likelihood of more frequent and longer periods of intense weather conditions in the 21st century [10]. Ecosystems, and society as a whole, are both clearly affected by extremes of high and low rainfall. Floods, which result from torrential or long-lasting rainfall events, cause particular damage, as do long periods of drought during the warm season, when water is crucial for transpiration in plants, causing disruption to both ecosystems and agriculture. It is therefore important to understand variations in precipitation in greater detail.

A number of different definitions of extreme conditions exist. For example, the Intergovernmental Panel on Climate Change (IPCC) states that extremes "are commonly considered to be the values exceeded 1%, 5%, or 10% of the time (at one extreme) or 90%, 95%, or 99% of the time (at the other extreme). Heavy precipitation is defined as daily amounts greater than the 95th (or for 'very heavy', the 99th) percentile." [[10]]. The joint working group on the detection of climate change of the World Meteorological Organization Commission for Climatology (WMO-CCL) and the Research Programme on Climate Variability and Predictability (CLIVAR) has recommended indices to be used to characterize surface data [[11]], eleven of which are related to precipitation. Many studies have used day-count indices, based on the distribution of daily precipitation either at fixed thresholds, or using percentiles as thresholds [[12–14]]. Other indices in common use are the maximum length of a dry or wet spell [[15,16]], or annual total precipitation on wet days. Most of these indices do not really reflect the extremes of precipitation, since these occur too rarely to allow their reliable statistical study, justifying the investigation of other diagnostic measures that may be more appropriate for extreme conditions [[16]]. The amount of precipitation at a given location over a given time interval is a random variable that is best described by a probability distribution. The gamma probability density is usually taken to be a suitable approximation of precipitation histograms [[17,18]], but its accuracy often depends on the temporal resolution of the measured data in question [[12]].

The summation of data over time is a simple means of building up statistics of precipitation for different meteorological stations. It is easier to identify patterns for longer periods than for daily or shorter ones. For instance, by extending the period of summation of the rainfall, we can investigate the lower end of the frequency distribution more reliably.

The main advantage of the summation, or accumulation of data, is that a (usually) bimodal histogram may be converted into a unimodal one, thereby enabling the use of the Box-Cox transform to convert the initially asymmetric sample into a normally distributed (i.e., Gaussian) one. Empirical models are generally used where the exact physical relationships used to describe the temporal variability are unknown in any particular case, although it is nevertheless essential to have some idea of the approximate structure of the variability. This is frequently the case for climatological series. Models enable us to describe the current variability of the climate more precisely. Herein, our main aim is to show that time series of precipitation can be described by means of a statistical model that is formally composed of stationary white noise (WN) and non-stationary random walk (RW) components. This distinction enables us to develop a scheme for identifying a stationary regime, accounting for 95% of the total precipitation in various regions in Estonia. To achieve this, we used daily series obtained using two running time intervals of 15 and 30 days.

2. SHORT DESCRIPTION OF THE AVAILABLE DATASET

In the current study we consider precipitation data obtained from 40 meteorological, hydrological, and precipitation monitoring stations owned by the Estonian Meteorological and Hydrological Institute, the locations of which are shown in Fig. 1. Precipitation was measured during at least 98% of the days at these stations over the period 1961–2005; however, 23 of these stations took measurements continuously without interruptions. Any gaps in the data were filled using values taken from the nearest station. Every day at 18:00 UTC, the raw data were summed for the previous 24 hours. All measurements were made using Tretyakov precipitation gauges [5]. The measured values were known to be consistently slightly smaller than the actual precipitation, so a 'wetting correction' was applied at the stations to the raw data from 1966 onwards as over the whole former USSR. The resulting inhomogeneity in the time series, however, is insignificant compared with the variance.

Before carrying out the analysis of the time series, we first obtained the 15- and 30-day sums of the precipitation data. These sums were calculated for the mean precipitation over the whole of Estonia (averaged over 40 stations), but also for individual stations and averaged for the western, central, and eastern regions. The regions were defined as in [9], and based on values of percentiles of the cold half-year distribution of daily precipitation. The town of Võru was selected for its liability to flash flooding, at any time of the year [19], due to the proximity of Lake Tamula. The largest single 24-hour precipitation in a town (131 mm) was also measured at Võru, in July 1988. In contrast, Vilsandi was the region with the lowest precipitation.

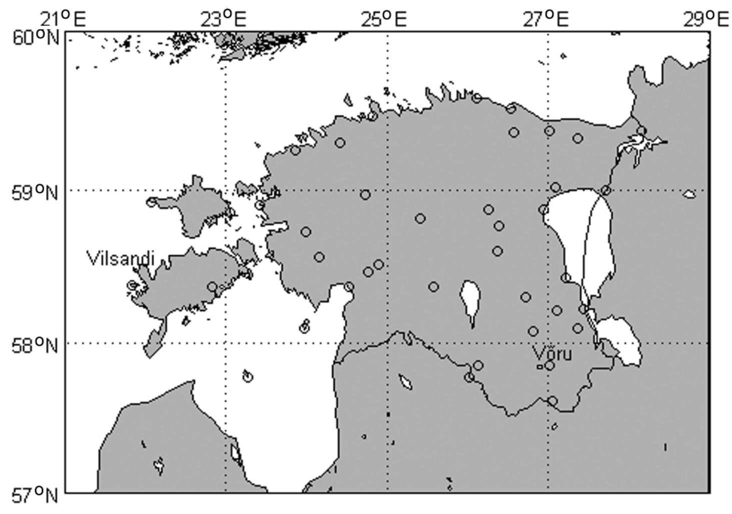

Fig. 1. Locations of 40 precipitation monitoring stations in Estonia, including Vilsandi and Võru.

3. METHOD

The raw summed 15- and 30-day series appear to be highly asymmetrical and the Box-Cox transform was therefore applied to obtain a symmetrical, near-normal distribution for modelling:

$$\xi(t) = \frac{x(t)^{\lambda} - 1}{\lambda}, \tag{1}$$

where $x(t)$, $t = 1, \ldots, n$ is the time series (in mm) and $\xi(t)$ the transformed variable. The value of the parameter λ was adjusted so that $\xi(t)$ was near-normally distributed.

The method of fitting an autoregressive integrated moving average (ARIMA) family model [20] uses an autocorrelation function as a primary tool for selecting an appropriate type of the model. We shall show that the correlation between consecutive increments of accumulated precipitation series as a function of the increment interval enables one to select an appropriate model (see also [21,22]). We first divided the raw series into τ subseries (i.e., the number of corresponding increment intervals), and the subseries thus obtained were numbered accordingly. The time series $\xi(t)$ $(t = 1, 2, 3, \ldots, n)$ could be decomposed into τ subseries of increments as follows:

$$\eta_{\tau,j}(t) = \xi((t+1)\tau + j) - \xi(t\tau + j), \tag{2}$$

where τ is the increment interval, $j = 1, 2, 3, \ldots, \tau$ denotes the subseries, and t the time: $t = 1, 2, 3, \ldots, n_1$, where $n_1 = [n/\tau] - 1$. The square brackets indicate a rounding off to the lower integer. The raw series were divided into τ subseries, each having n_1 terms. The autocovariance of the j-th subseries for a lag of $k = 0, 1, \ldots, m$ was calculated as

$$C_{\tau,j}(k) = \frac{1}{n_1 - k} \sum_{i=1}^{n_1 - k} (\eta_{\tau,j}(i) - \bar{\xi}_{\tau,j})(\eta_{\tau,j}(i+k) - \bar{\xi}_{\tau,j}). \tag{3}$$

Here, $\bar{\xi}_{\tau,j}$ represents the sample mean value of the subseries j. In the present study, we are interested in the behaviour of the correlation between consecutive increments only, i.e., for $k = 1$. Because each value of j denotes a subseries of non-overlapping increments, a representative value for the correlation coefficient $r_{\tau}(1)$ may be obtained by averaging over all the subseries:

$$r_{\tau}(1) = \frac{1}{\tau} \sum_{j=1}^{\tau} \frac{C_{\tau,j}(1)}{C_{\tau,j}(0)}. \tag{4}$$

An example of the correlations $r_{\tau}(1)$, computed for central Estonia for a 15-day cumulative precipitation for increments of up to 100 days, is shown in Fig. 2. The same correlation is computed for the corresponding transformed

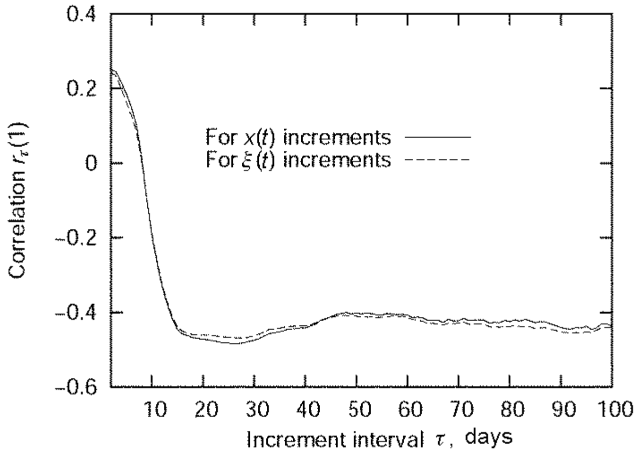

Fig. 2. Correlation between consecutive increments as a function of the increment interval τ for two series of 15-day sums of precipitation in central Estonia.

series (i.e., $\xi(t)$), in order to confirm that the correlation was not affected by the Box-Cox transform.

Figure 2 shows that the correlation decreases down to a lag of 15 days and then reaches an approximate saturation level. This characteristic results from the use of the 15-day running summation used to construct the precipitation series. Important information for the selection of a suitable model and time step to describe long-range variability may be obtained by considering the behaviour of the coefficients at larger intervals τ. For $\tau > 20$ days, the curves oscillate around a nearly constant value $(r_\tau(1) \approx -0.45)$. The correlation between consecutive increments over τ coincides with the first autocorrelation of the subseries over the intervals τ. In this case, the autocorrelations for longer lags $(r_\tau(k), k > 1)$ appear to be nearly zero (not shown). This suggests that the first-order moving-average (MA(1)) model is appropriate for describing the relationship between the increments (see [20] for details):

$$\xi_j(t) - \xi_j(t-1) = a_j(t) - \theta_j a_j(t-1), \quad (5)$$

where $a_j(t)$ is white noise and θ_j is the fitted coefficient. It is important to note that t is not expressed in days but in intervals of length τ.

Following our hypothesis, the increment interval was chosen following diagnostic tests made using the portmanteau statistic [20]. Each of the τ subseries models was tested separately. The correlation between the terms in the series decays slowly as the distance between the terms increases. This in turn is more favourable for the application of the MA(1) model between the series increments if a longer increment interval is used to extract the subseries. The detailed method for estimating the parameter θ_j and for the diagnostic test for the subseries models are described elsewhere [20].

Each subseries model depends on two parameters, θ_j and the variance of residuals $\sigma^2_{a,j}$. We herein use the values of these parameters, averaged over the subseries and denoted as $\overline{\theta}$ and $\overline{\sigma^2_a}$, to characterize the range of the precipitation data.

Equation (5) is the first-order integrated moving-average model for the increments. Integration leads to an IMA(0,1,1) model for the precipitation values of ξ [20]. Its advantage for the current approach is that it can be formally decomposed into a stationary white noise and a non-stationary random walk component, i.e,

$$\xi(t) = b(t) + z(t), \tag{6}$$

where $b(t)$ is WN. The RW term can be written as

$$z(t) = \sum_{i=1}^{t} u(t), \tag{7}$$

where $u(t)$ is also a WN signal and is independent of $b(t)$. Knowledge of the parameters $\overline{\theta}$ and $\overline{\sigma^2_a}$ enables us to compute the variances for the WN process σ^2_b and the generator of the RW process σ^2_u:

$$\sigma^2_b = \overline{\theta}\,\overline{\sigma^2_a}, \quad \sigma^2_u = (1-\overline{\theta})^2\,\overline{\sigma^2_a}. \tag{8}$$

The term $b(t)$ in Eq. (6) represents the stationary part of the model, meaning that its variance does not vary with time. It can therefore be determined on the basis of the model, fitted using an arbitrary τ from the approximate region of saturation, shown in Fig. 2. We may thus select an interval τ depending on the outcome of the diagnostic test. If the number of subseries that pass the portmanteau test at the 99% level is reasonably high (90% of the subseries used in the following examples), the approach may then be considered to be statistically applicable.

Equations (8) highlight an important property of the fitted non-stationary IMA(0,1,1) model. The value of $\overline{\theta}$, lying between 0 and 1, is itself a measure of stationarity. For values near 1, the variance of the WN component approximately equals the sample variance $\sigma^2_{a,j}$, signifying that the modelled series is nearly stationary and the range of its variability can be reasonably well approximated by a stationary characteristic. For lower values, Eqs (8) imply a relative increase in σ^2_u. The range of variability is then less stationary.

In our case we have $\overline{\theta} \approx 0.9$, suggesting that the sample range is reasonably well contained within the interval from $\overline{x} - 2\sigma_b$ to $\overline{x} + 2\sigma_b$. Due to the approximately Gaussian distribution of the transformed variable ξ, this interval should contain approximately 95% of the values of summed precipitation. The actual percentage will be discussed in the following section.

4. RESULTS

4.1. Precipitation regime of the 15- and 30-day sums

Some results that characterize the range of summed precipitation data for Estonia are shown in Tables 1 and 2. Values have been computed for six daily series over a total of 45 years, averaged over geographical regions of different sizes. The first four series correspond to averages over the whole of Estonia, Western Estonia, Central Estonia and Eastern Estonia, respectively. The results for two local series at the stations of Võru and Vilsandi are also shown. Table 1 contains the results for precipitation series summed over 15 days, and Table 2 for those summed over 30 days.

Table 1. Values of the ARIMA-model approximation and the Box-Cox transform parameters for the 15-day summed precipitation in Estonia

No.	Variable	Estonia	W Estonia	C Estonia	E Estonia	Võru	Vilsandi
1	λ	0.4850	0.4815	0.4874	0.4289	0.3779	0.4592
2	σ_u/σ_b	0.12	0.11	0.11	0.14	0.13	0.12
3	$\bar{x}$, mm	26.7	24.5	29.1	25.8	25.6	23.4
4	$s_{\min}$, mm	2.3	1.3	2.0	2.3	1.1	0.1
5	$s_{\max}$, mm	68.7	67.3	77.1	69.0	79.6	68.8
6	$x_{\max}$, mm	121.4	133.4	141.1	140.9	204.3	129.1
7	$f(x < s_{\min})$	0.0230	0.0244	0.0225	0.0267	0.0267	0.0119
8	$f(x > s_{\max})$	0.0242	0.0209	0.0216	0.0249	0.0253	0.0247
9	ρ	0.79	1.00	0.85	1.08	1.59	0.88

$\bar{x}$ is the mean precipitation sum, $s_{\min}$ and $s_{\max}$ are the lower and upper boundaries of the stationary regime, $x_{\max}$ is the maximum value of cumulated precipitation, f is the percentage of summed precipitation values outside the boundaries and ρ is the ratio of upper outliers to the stationary range.

Table 2. Corresponding values of the ARIMA-model approximation and the Box-Cox transform parameters for the 30-day summed precipitations

No.	Variable	Estonia	W Estonia	C Estonia	E Estonia	Võru	Vilsandi
1	λ	0.4903	0.4918	0.5056	0.3985	0.2920	0.4496
2	σ_u/σ_b	0.13	0.12	0.14	0.12	0.12	0.10
3	$\bar{x}$, mm	53.3	49.1	58.3	51.6	51.2	46.8
4	$s_{\min}$, mm	11.4	8.6	11.5	10.8	8.4	6.3
5	$s_{\max}$, mm	115.9	111.4	127.9	118.4	134.8	114.7
6	$x_{\max}$, mm	177.5	175.3	209.8	181.4	224.9	199.0
7	$f(x < s_{\min})$	0.0247	0.0239	0.0266	0.0282	0.0216	0.0250
8	$f(x > s_{\max})$	0.0245	0.0237	0.0252	0.0274	0.0313	0.0291
9	ρ	0.54	0.62	0.70	0.59	0.71	0.78

The first row contains the values for the parameter λ in the Box-Cox transform. The second row shows the ratio of the standard deviations σ_u/σ_b for the series in (6). This measures the relative significance of the nonstationary RW component. The low value of this ratio (which turns out to be about 0.1 in all cases) reasonably justifies the description of the range of variability by means of the stationary component in (6).

The third row contains the mean value $\bar{x}$ of the precipitation series over the period of analysis. The previously observed [9] difference between the regions for the two periods of summation may clearly be seen; the values for the central region are higher than they are for the other regions, while the western region has the lowest values.

The fourth and fifth rows show the values for $s_{\min} = \bar{x} - 2\sigma_b$ and $s_{\max} = \bar{x} + 2\sigma_b$ used to determine the lower and upper boundaries of the proposed range of precipitation. Hereafter, these thresholds are called the soft minimum ($s_{\min}$) and the soft maximum ($s_{\max}$) respectively. The lower boundary for the 15-day sums ranges between 1 and 2.5 mm, showing that two-week periods of drought are quite frequent in Estonia. The lower boundary for the 30-day cumulated series ranges between 6 and 12 mm, indicating that these longer dry periods are more likely in Western Estonia.

The upper boundary ranges between 67 and 80 mm for the 15-day sums, which is within 85% of the half of the equivalent value for the 30-day summation. This indicates that two-week precipitation periods are significantly more frequent than those that cover a complete month.

In a normal distribution, 95% of the sample lies within two standard deviations of the sample mean, and our approximation via the Box-Cox transform rests on this assumption. This can be tested relatively simply for the summed precipitation data. The sixth row shows the precipitation maxima observed over the corresponding periods of summation. These values are significantly higher than our soft thresholds, and nearly twice the estimated soft maxima. Frequencies of outliers outside the lower and upper soft thresholds collected during the 45 years of our analysis are shown in the seventh and eighth rows, respectively. Each category covers around 2.5% of the data, in reasonable agreement with our assumption. The distribution of outliers is also reasonably symmetrical for the spatially averaged series, albeit with two clear exceptions.

The ninth row shows the ratio of the range that contains 2.5% of the upper-end outliers to the range that remains between the soft boundaries, which contains 95% of all the observations:

$$\rho = (x_{\max} - s_{\max})/(s_{\max} - s_{\min}). \tag{9}$$

The ratio signifies that extremely intense precipitation, although rare, may exceed $s_{\max}$ more than twice. This implies that the range of outliers must be given independent consideration, in addition to the consideration of stationary values.

4.2. Outliers: floods and droughts

The thresholds based on WN are only 'soft' limits. Real outliers (RW) are very rare and far from these thresholds, as seen in Tables 1 and 2. The difference between s_{max} and x_{max} is between 52 and 125 mm for 15-day, and 62 and 90 mm for 30-day series.

The smallest 15-day sums of precipitation (Table 3) for Estonia were below 0.1 mm. Most of these occurrences were not agricultural droughts, because the growing season had not yet begun. Values above 100 mm occurred only in July 1978, in August 1987, and in August 2005, pointing to periods of flooding for the country as a whole (a total of 22 days). At some individual stations, however, more days of local flooding have been recorded. Võru recorded 3 consecutive days of flooding in mid-July 1993, when the 15-day cumulated precipitation exceeded 200 mm (204). Võru experiences flash flooding throughout the year, not only because of the abundant outflow from Lake Tamula, but also because of its exposure to southern cyclones that can bring extreme rainfall.

We cannot use the same threshold values for the 30-day and 15-day summations, since no drought of 0.1 mm was ever observed for any 30-day period and an excessive number of readings above 100 mm were counted (1030 days). We have therefore adjusted the threshold values for the 30-day calculations to 2.3 mm and 160 mm, in order to yield the same number of events as for the 15-day calculations. Thus, drought periods were identified in March 1972 and September 2002 for the 30-day sums. The first period was very long, with little rain measured at several stations, but this is not apparent from the 15-day results. Floods occurred in September 1978 and August 1987, extending the periods of flooding already identified from the 15-day results. Dry spells occurred between April and October, and wet ones only in July, August and September, when the local sea was already warm.

If we compare the three regions on the basis of their stationarity thresholds and accumulation maxima, then their regional grouping is also valid: Western

Table 3. Extremely wet and dry periods in Estonia, 1961–2005. The date is the τ-th day. The number in brackets indicates the number of τ-day periods. The dryness thresholds for the 15- and 30-day calculations are 0.1 and 2.3 mm, respectively

15-day long dry periods	30-day long dry periods	At least 100 mm of rain per 15-day periods	At least 160 mm of rain per 30-day periods
11.–12.04.1963 (2)	3.–25.03.1972 (23)	17.–20.07.1978 (4)	1.–5.09.1978 (5)
6.–9.04.1974 (4)	3.–5.09.2002 (3)	8.–21.08.1987 (14)	15.–17.09.1978 (3)
22.–25.05.1976 (4)		12.–14.08.2005 (3)	21.–23.09.1978 (3)
21.–22.03.1980 (2)		16.08.2005 (1)	16.–25.08.1987 (10)
23.03.1986 (1)			29.08.1987 (1)
1.–2.10.2000 (2)			
20.08.2002 (1)			

and Eastern Estonia generally experience less precipitation than the central region using these time scales. It was difficult to define $s_{\min}$ for Vilsandi for 15-day sums, even after performing the Box-Cox transform, because too many periods contained no precipitation at all (196 events, 1.2%) to allow a reliable normal distribution.

5. DISCUSSION AND CONCLUSIONS

We have herein defined statistics for describing the variability of precipitation in Estonia in terms of 15- and 30-day periods of summation. We first examined the temporal variability of the series by fitting a statistical model in order to characterize its variability. An IMA(0,1,1) model suitably describes long-range variability in the summed precipitation data, and can be formally decomposed into a stationary white noise contribution and a non-stationary random walk contribution. This means that the long-term precipitation regime can be described in terms of three distinct ranges. The first and narrowest of these accounts for about 2.5% of the occurrences of dry weather in Estonia. The second covers about 95% of the observations made during the past 45 years. This range may be described on the basis of a sufficiently large number of observations. The third range corresponds to excessive precipitation, and accounts for 2.5% of observations. Nevertheless, these outliers account for only a small fraction of the measured sums, and they span a large range of values in comparison to the central range.

A comprehensive statistical description of the first and third ranges is difficult to achieve because it is based on so few observations. Nonetheless, droughts and floods have a significant impact locally, signifying that a satisfactory description of extreme precipitation conditions requires a different treatment in comparison with that afforded to normal conditions.

We have shown that both the cumulated series remain within some fixed interval for 95% of the time. These intervals are representative of the current climate. Non-stationarity in the cumulated series is mainly caused by changes in extreme precipitation. The wings on either side of the probability distribution (each covering 2.5%) can be considered to be outliers of the current climate. This classification may prove to be useful for characterizing the variability of the climate in the future. The reliability of our approach can easily be tested as new observations become available. Cases where these threshold limits are exceeded can be classified as rare occurrences of extreme weather.

Using the ARIMA model, we have identified enough outliers to provide reliable statistics. The thresholds chosen in [6] implied that average precipitation exceeded 10 mm per day during the 10-day periods, considerably more than our value of 4–5 mm per day, but our summation period is also longer.

Our finding that the outliers should be treated separately also helps to explain the apparent absence, in earlier research, of statistically significant trends in monthly precipitation in Estonia [4], despite the fact that extreme weather conditions have become more frequent [9]. Thus, there have been changes in the regimes in the wings of the precipitation distribution, but not in the stationary central regime.

Further investigation is necessary to establish whether our analysis can be applied to other regional climates. Although the Box-Cox transform is almost certainly inappropriate for overwhelmingly dry climates, its application in more balanced climates may yield better results.

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Üks võimalus iseloomustada Eesti sademeterežiimi

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Eesti sademete aegridu, mis on kogutud 15 ja 30 päeva summadena, on uuritud selleks, et leida karakteristikut, mis sademete ulatuse järgi võiks antud maakohta iseloomustada. Selleks on sobitatud statistiline mudel, mis kirjeldab muutlikkuse pikaajalist iseloomu. Sobiva mudeli iseärasuseks on asjaolu, et see on vaadeldav kahe lihtsa statistilise protsessi summana. Neist üks on valge müra. Tänu sellele saab eraldada statsionaarse ala, mille ulatusse mahub 95% sademete rea vaatlustest. Sellega saame sademete kogumise read tinglikult jagada kolme ossa, millest keskmise jaoks on piisavalt andmeid, et seda statistiliselt iseloomustada. Külgmised režiimid vastavad suurtele hälvetele ja kumbki sisaldab ligikaudu 2,5% vaatlustest. Nende olemasolu on oluline sademete kliima kirjeldamisel, aga nende statistilised karakteristikud on raskesti määratavad, sest viimaste esinemissagedus on väike. See tähendab, et statsionaarse osa ulatus ja ekstreemsete sademete hulgad on statistilisest seisukohast kaks eri asja. Suurte hälvete esinemissagedust ja jaotust on vaja eraldi uurida, et saada sademete statistilisest iseloomust täielikumat teavet.

Statsionaarsest 95% osast nii suuremate kui väiksemate väärtuste piirkonnas üle jäävat 2,5% juhtudest võib nimetada erinditeks. ARIMA mudeli rakendamine võimaldab meil määrata ka läved erindite määramiseks. Need läved tulevad suhteliselt “pehmed” kliima ekstreemumid, sest tõeliselt ekstreemsed nähtused asuvad kaugel jaotuse tiibadel. 15-(30-) päevaste sademesummade jaoks on valge müraga kirjeldatav (statsionaarne) sademehulk suurusjärgus 67–80 (111–135) mm, juhuslike hälvete tõttu tekkinud tõeliste ekstreemumite kaugus jääb jaotuse 95% keskosa ülemisest piirist veel 55–125 (62–90) mm kaugusele.