

Statistical Modelling of Flood Events

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Abstract

Many extreme runoff distributions are not homogeneous, as they are often regarded in flood frequency analysis. The aim of this article is to identify the different homogeneous subsets in a heterogeneous distribution and to identify the mechanisms behind the heterogeneity.

The identification of the different subsets in a full dataset is carried out by the use of an analytical method based on a likelihood criterion. This method is applied to runoff maxima from flood basins in Europe and Russia.

The results of the investigations presented in this article show that in large regions of the case study areas the heterogeneity of an extreme runoff distribution is not so much determined by climatic mechanisms or by characteristics of a catchment, but apparently by other factors. Heterogeneity in the south-eastern part of Russia, however, might be explainable by the influence of weakened typhoons.

1. Introduction

For water management it is fundamental to have information on what flood conditions can be expected. This is needed in order to anticipate adequately to floods. Development of land or civil structures like dikes, bridges, embankments, drainage facilities, etcetera, have to be build with an idea of the magnitude and frequency of natural threats in mind. To this purpose frequency analysis is used. Based on annual maxima or partial duration series, a relation between return period and the extreme runoff can be developed.

The frequency analysis should come up with the best relation between the data and a statistical distribution. The outcome of the analysis can be used for practical goals concerning events within the domain of the data set and events of a larger scale than the extremes measured. In the last case the highest observed results are of the most importance and should be treated accordingly. In this project it is investigated whether the splitting of flood data into different distributions gives better results for the up-tail interpolation.

Flood frequency is liable to uncertainties and errors. The data used are prone to measurement errors and also the different distributions used only approach reality. This should be kept in mind when analyzing the results.

To extrapolate beyond the size of the data set a good representation of the data sample is needed. The traditional way to force the flood data into a model is using a distribution which fits the range with measured data best.

One of the most widely used distributions is the Gumbel method, but there are many more. When different distributions are used a goodness-of-fit criterion can be used to select the best method. Having chosen a distribution, extrapolations and consequently predictions are made on what can be expected.

In this approach the data are regarded as being homogeneous meaning originating from one and the same population. This is not necessarily the case as extremes can be caused by

different mechanisms. It could well be that a mixed distribution composed of a number of different homogeneous distributions give a better fit.

When the full annual dataset is regarded as a mixture of two or more subsets with different distributions it is possible to explain the inclination point or jump observed in many extreme value distributions. This was a reason to investigate whether or not this could be attributed to clear physical mechanisms.

The usefulness of splitting annual flood data into two distributions has been demonstrated by Alila and Mtiraoui [2002]. They analysed the Gila River basin in the south-western United States. For this one river basin they found two storm types to give clear different flood frequency curves, namely from monsoons and frontal rain. The scope of their research was limited to only one catchment and thereby considering only one climatic situation.

To make a better prediction it is necessary to look at the physical properties of the phenomenon that produced the different sample points (i.e. extremes). In this aspect better results can be expected when regarding the data sample as being a product of different mechanisms and thus paying more attention to the physical nature of the flood data. When a single distribution is applied to the data, the weight of the lower extremes is overrated; a more sophisticated method should pay more attention to the upper tail values, giving more accurate predictions on extreme flood frequencies.

The need of a different approach has been recognized by Cunnane in 1989:

‘...there are cases where a model which recognizes different physical flood producing mechanisms might have to be considered’.

Also Klemes (2000) and Alila and Mtiraoui (2002) pointed out the need for a different approach, considering the physical nature of hydrological processes.

The river basins observed in this analysis may be subject to changing circumstances. For example over the years changes in river routing, land use or climate have occurred. In the case these changes are significant this will lead to a non-stationary dataset of (annual) maxima, which in turn will lead to non-homogeneity. These non-stationary datasets can easily be identified within a statistical margin by one or more of the tests available like the Spearman rank test and the Range test. The river basins identified as non-stationary should be left out when investigating the heterogeneity.

The data used in this project originate from Western-Europe, Byelorussia and eastern Russia and cover several decades.

From the territories that were investigated a variety of different flood causing mechanism were to be expected. Some of the mechanisms producing floods are for example: Convective rain, rain on frozen soil, thunder storms, hurricanes, snow melt or changes in runoff routing. If it can be determined which mechanism produces an extreme, a better understanding of the complexity is within hand and a better analysis can be made on a basis of runoff data without making a complete physical survey of the hydrological processes.

This paper is build up as follows. First the heterogeneity in the flood frequency distributions will be described, followed by an overview of the study area and the possible mechanisms behind the heterogeneity. Next the results will be discussed and the article will be completed with conclusions and recommendations.

2. Heterogeneity in flood frequency distributions

In flood frequency analysis there is a need for a prediction over a much larger timescale than the data sample covers. Mathematical predictions beyond the length of this data sample have only limited validity. Nonetheless there is a need for an insight in the probability of hydrological extremes.

The build up of a flood is influenced by different processes. This is in general reason enough not to regard a sample as a product of one homogeneous distribution. It can not be described by a simple equation consisting of two or three parameters.

The heterogeneity of a runoff system is known and subject of investigation for some time. In most cases this is done by analyzing many aspects of the system.

Among others this has been done by Webb and Betancourt (1992) who made an analysis of the non-heterogeneity in the Santa Cruz River in Arizona. They concluded that different floods occurred under different ENSO (El Nino/Southern oscillations) conditions. Another interesting study has been made by Archer (1989). He proved that floodplain conditions and particular storm types result in different flood events.

These investigations proved the need for a wider use of a heterogeneous approach towards flood frequency analysis. Furthermore the greater scale on which different mechanisms play a role has not really been investigated. In the past only one flood basin at a time has been regarded. It would be very interesting to take a closer look to more flood basins and find out whether they have characteristics in common depending on their climatic condition, size and geological location.

3. Study area and probable causes of heterogeneity

For this paper flood data from different regions were used. The Pacific Institute of Geography, Far-Eastern Branch of Russian Academy of Sciences in Vladivostok provided the flood data from Eastern Russia.

The studies targeted on three main regions the Eastern Russian, Byelorussia and Western Europe. More specific the territories investigated in Eastern Russia are the Amur Basin, the Primorye region, the Baikal region, the Ankara basin, the Lena basin and the Yenisei basin. These studies used historical data, in most cases consisting of annual flood data from several decades. The catchments from which flood data were obtained are all smaller than 10,000 km². With catchments of a bigger size the flood genesis is a more complex process.

In Eastern Russia cyclones appear over or near the territories and cause floods. These cyclones occur only in summer and not in early spring. But not all the high water extremes are caused by a cyclone. An attempt has been made to identify the floods caused by cyclones.

In all of the catchments extremes were linked to their temporal occurrence, i.e. whether they originated from typical spring events such as snow melt combined with rain or storm events in summer.

For the European datasets with annual flood extremes an attempt is made to see whether the extremes could be related to high water level history. A distinction is made between annual flood extremes that are preceded by a period of relatively high runoff and annual flood extremes that are preceded by a period of relatively low runoff.

For both the Eastern Russian data as well as all of the available European datasets have been split into two distributions by regarding the high annual flood extremes and the low annual flood extremes as different distributions. This method divides the dataset into two subsets with different distributions without knowing the actual mechanisms

4. Methods, mechanisms and results

4.1. Methods for the mixture of different flood distributions

The assumption that the dataset is not a homogenous one can be supported with the mixed distribution method. The extremes are separated into different groups, corresponding to their different distributions. The distributions of the subsets can be calculated according to one of the different flood frequency distributions like the ones stated by Gumbel or Pearson.

The probability of a random extreme being part of one of the subsets can be calculated by dividing the number of data points from the subset by the total number of data. The total distribution can be calculated with equation 1.

$$P_{mixed}(x > X) = P_1(x > X) \cdot \alpha_1 + P_2(x > X) \cdot \alpha_2, \quad (1)$$

where $P_1(x > X)$ and $P_2(x > X)$ are the probabilities of exceedance of the respective populations of annual flood extremes and α_1 and $\alpha_2 (= 1 - \alpha_1)$ are the probabilities that an extreme event draws from one of the two populations. Another method based on the assumption of independent subsets is the Multi-Component distribution. This method can be applied when two flood peaks can be identified in one year, each caused by a certain mechanism. The product of the exceedance probability in that case is calculated as:

$$P_{mc}(x \geq X) = P_1(x \geq X)P_2(x \geq X), \quad (2)$$

where $P_1(x \geq X)$ and $P_2(x \geq X)$ are the exceedance probabilities of the different populations flood data.

These methods are useful tools for fitting heterogeneous distributions. The identification of the different physical mechanisms is a second problem. This can be done by using additional information on mechanisms involved, for example the seasonality of the flood extreme or the weather system causing the flood extreme.

4.2. Possible mechanisms behind the flood extremes

a. Physical mechanisms

As a cause for the heterogeneity in the annual flood extremes, different mechanisms have been analysed.

A logical hypothesis for the appearance of data with a different background in the data sample is that the annual extreme results from a different weather mechanism. This can e.g. be extremes from melting water in spring, convective rain in the summer, cyclones

In the case the data sample with annual flood extremes consists of different mechanisms an attempt can be made to split accordingly.

The different physical mechanisms analyzed are:

Seasonal: The annual flood extremes are divided into two subsets. The criterion for the division is the date. One set containing spring values, another summer values.

Cyclone/Non cyclone: The complete set is divided into a set which extremes can be related to a cyclone and a set of which the extremes do not relate to cyclones. The search for weather mechanisms of this kind is only interesting in the Eastern Russian coastal regions, where

cyclones actually occur. To identify the cyclones geopotential maps have been used together with data from the *Joint Typhoon Warning Centre*. The identification of a cyclone brings several difficulties. First of all standards have to be set to identify a cyclone and furthermore the limited availability of data makes it hard to come up with more than only a few cases of annual extremes caused by a typhoon in the dataset.

Floods without clear history/floods with clear history: When looking into the history of a flood extreme, it can either be an extreme following a period of high water or an extreme following a period of relative calm river discharge.

The analytical criterion used to determine whether a flood extreme was preceded by a period of high water is the following: The annual flood peak is not preceded in the tailing month by a peak of more than one quarter of the height of the annual flood peak itself. This again gives two different subsets of extremes.

b. Character of probability distributions

Another option for finding different distributions behind the flood extremes is looking into the character of the probability distribution. In many cases the shape of the observations in a Gumbel probability plot does not give a straight line but shows a curvature. This deviating shape could well be because of the existence of two different distributions. A method to identify two distributions behind the annual flood extremes is described here.

From the dataset consisting of annual flood extremes, two subsets are formed. One subset exists of the highest extremes, the other of the lowest extremes. Besides an analytical method it is also possible to make splits visually, regarding an inflection point in the graph as a threshold. Though this method is not very objective therefore a more statistical approach has been used in this paper.

This method based on a division in high and low extremes analyses the data statistically, without physical information on the different mechanisms. Two methods are considered.

The first method is splitting the data set into two parts after they are arranged from the lowest annual extreme ascending to the highest extreme; fit a distribution to each one of the thus formed datasets. The distribution used in this research is the Gumbel distribution. (eq. 3)

$$f_{\mu,\beta}(x) = \frac{1}{\beta} e^{-\frac{x-\mu}{\beta}} e^{-e^{-\frac{x-\mu}{\beta}}} \quad (3)$$

The equations for the estimation of the shape and scale parameters $\tilde{\beta}$ and $\tilde{\mu}$ used in the Likelihood calculation are given by equations 4 and 5.

$$\tilde{\beta} = \frac{s\sqrt{6}}{\pi} \quad (4)$$

$$\tilde{\mu} = \bar{X} - 0.5772\tilde{\beta} \quad (5)$$

where \bar{X} and s are respectively the mean and the standard deviation of the data sample. Subsequently the likelihood is calculated. (eq. 6, 7) This is done for the dataset with the highest extremes as well as for the dataset with the lowest results, both values are added. (eq. 8)

$$L_1 = \log\left(\frac{1}{N} \sum_{i=1}^N f_{1,\beta,\mu}(x_i)\right) \quad (6)$$

$$L_2 = \log\left(\frac{1}{M} \sum_{j=1}^M f_{2,\beta,\mu}(x_j)\right) \quad (7)$$

$$L = L_1 + L_2 \quad (8)$$

This protocol is repeated for every possible split of the dataset into two sets. The best location for the split is the position that gives the highest likelihood.

A second method also provides a point at which the data can be split into high and low extremes. This method calculates the likelihood of two mixed distributions. Both distributions are again calculated with one end of the dataset. A distribution is fitted to each end of the dataset in the same way as described previously; next the mixture of the two distributions is calculated. (eq. 9)

$$f_{\mu_1,\beta_1,\mu_2,\beta_2}(x) = \alpha_1 f_{\mu_1,\beta_1}(x) + \alpha_2 f_{\mu_2,\beta_2}(x) \quad (9)$$

where α_1 and α_2 are the weight factors representing the size of each dataset, determined by the number of extremes in the subset divided by the total amount of extremes in the dataset. Consequently the total likelihood is calculated. (eq. 10)

$$L = \log\left(\frac{1}{N} \sum_{i=1}^N f_{\beta_1,\mu_1,\beta_2,\mu_2}(x_i)\right) \quad (10)$$

Again this is repeated for every possible split in the total dataset and the best point for splitting is regarded as the point with the highest likelihood.

4.3 Results

With the several areas and the associated numerous data sets used to gain insight in the advantages of regarding more than one mechanism, the following results have been found.

Seasonal

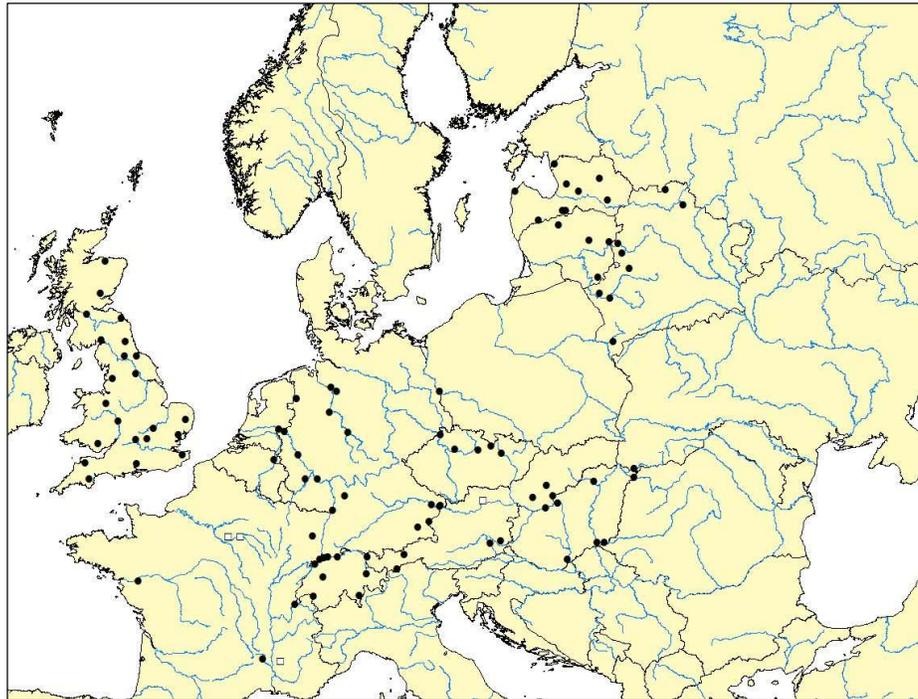
Splitting on a basis of the date of occurrence of extremes has not resulted in a satisfactory improvement on the statistical distribution of extremes.

For the European data it can be said that in almost all cases, the vast majority of the annual extremes fall within the spring period, as can be seen in figure 1. When looked at the individual datasets, the extremes beyond the spring period are too few to fit a statically valid distribution to them. Therefore it is not possible to speak of a mixture of distributions on a basis of the seasonality of the flood extremes.

In the few cases (figure 1.) that indeed a considerable number of the flood extremes do take place beyond the spring season, an analysis has been made by using a probability plot of the data. A representative graph of one of these cases can be seen in figure 2. If a distribution is fitted to each of the datasets, no statistical evidence can be found of two different distributions.

The conclusion on the observed datasets of extremes from Eastern Russia [figure 3] is a little different. For these data in a considerable amount of locations the majority of the flood extremes fall beyond springtime in the summer. Thus the locations in the Russian catchments can be divided into two groups, one group in which the spring extremes are predominant and one group in which summer extremes are predominant.

In a number of these datasets there are both a considerable amount of summer and a considerable amount of spring extremes, but again like in figure 2 no proof for the existence of the unique distributions can be found.



- Most floods occur in spring
- Most floods occur outside spring

FIGURE 1. The seasonality of flood extremes in Europe.

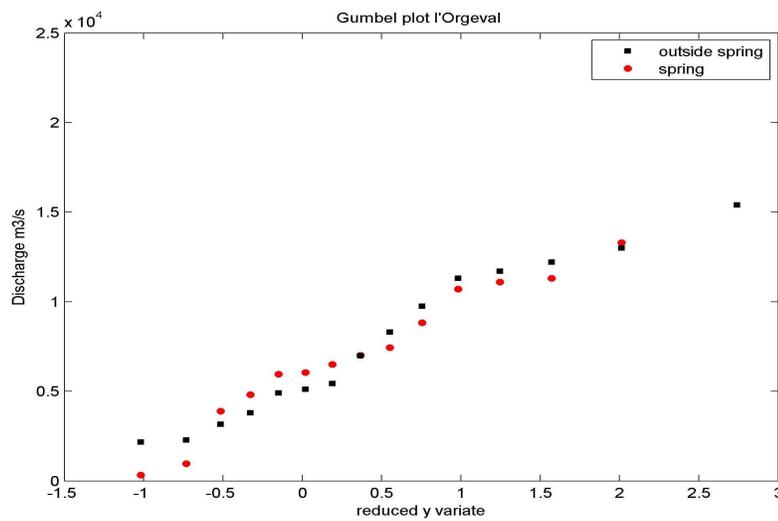


FIGURE 2. Frequency curve of annual floods classified by season. (L'orgeval, le Theil FR.)

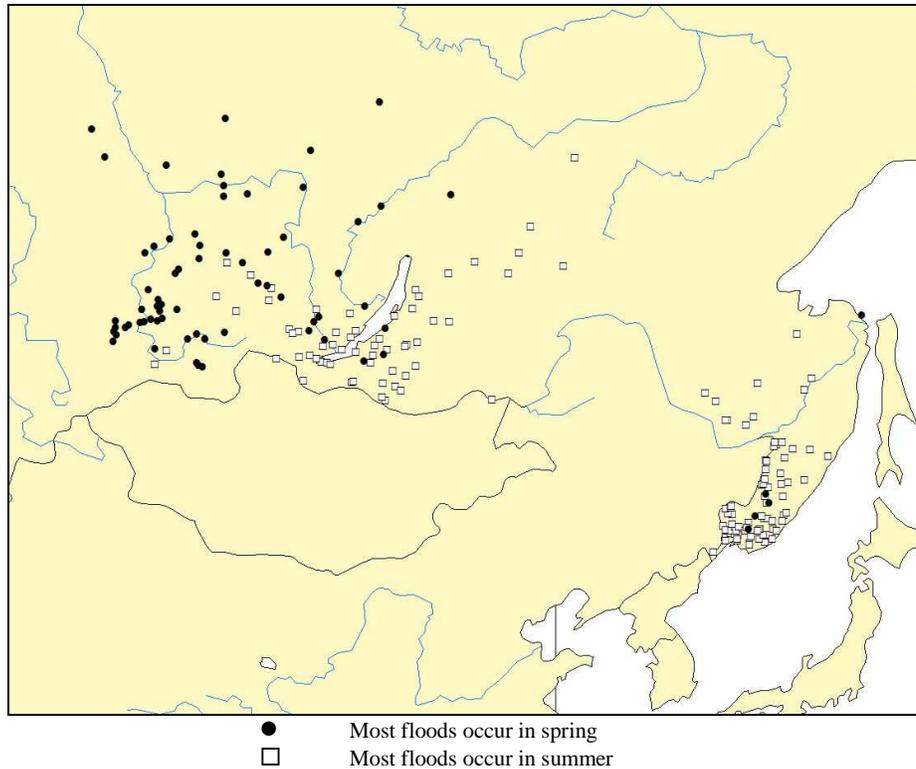


FIGURE 3. The seasonality of flood extremes in Asian Russia

Cyclone / Non cyclone

An attempt has been made to identify the floods caused by a tropical cyclone. In several cases floods could be connected to tropical cyclones, although these cyclones did not always result in annual maxima¹. This connection of flood data connected to a cyclone could only be made in the far eastern coastal region of Russia.

In the scope of this paper the question is whether the annual maxima caused by a tropical cyclone can form a different subset with a specific distribution. This can only be done when more than a few data points are identified as being part of these cyclone-related-maxima. Unfortunately this can not be done, the number of data points making up this subset is simply too little.

It may be possible that a different mechanism makes up the probability graph of annual maxima in the far eastern region, but it can not be concluded from the datasets investigated.

Floods without clear history/floods with clear history

Another possibility investigated was the existence of two different flood mechanisms related to their runoff characteristics, more specific extremes with a flood history and extremes without a flood history.

¹ Mixed distribution and multicomponent functions with applications to hydrology by Alexander Bakker

The method used was based on the interpretation of flood records. When the water level preceding the annual flood meets two criteria; the first that it is higher than a third of the annual flood level and second that it precedes the annual flood by no more than a month; it is considered to be a flood with flood history. For example the first flood peak in figure 4 is considered as a flood due to the preceding high water levels. In contrast the second flood peak has almost no preceding high water; only the base flow is making up the river runoff and is considered a flood peak without history. For the several datasets that were analysed this way, this criterion gave two considerable subsets.

Subsequently the two subsets were analysed, whether it could be made probable they have clearly different distributions. This was done by using a Gumbel probability plot (fig. 5), the same way as in figure 3. The two subsets do not show any evidence of being part of different distributions.

Although the results should be treated with care, there are assumptions that might not be discarded easily. The criteria chosen to determine whether an annual flood has a flood history are arbitrary and differ for each flood basin. More investigations are necessary.

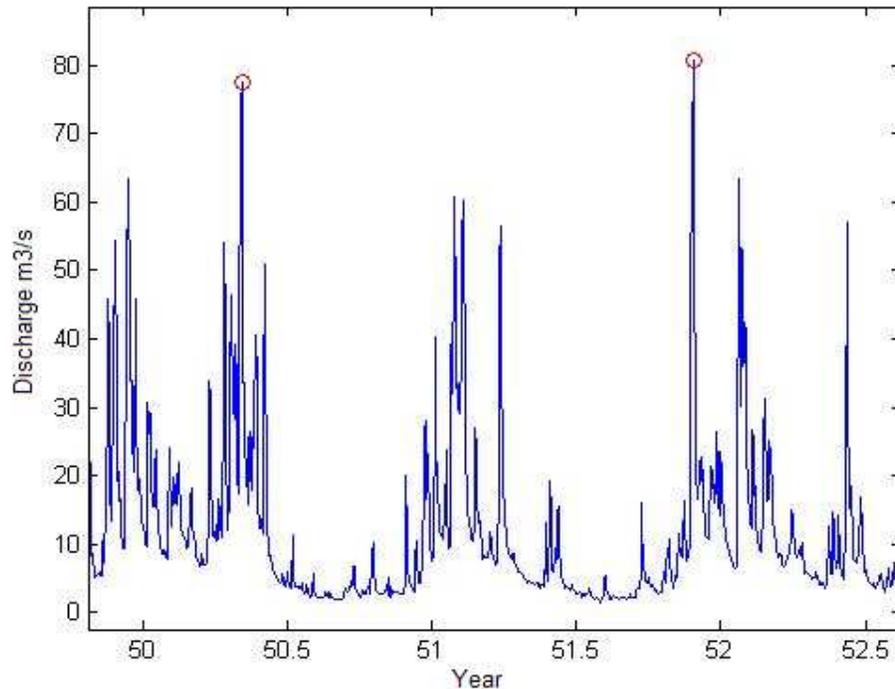


FIGURE 4. Part of a flood record with highlighted annual extremes. (Bedford Ouse, Bedford GB)

High / low extremes

The clearest differences in distributions were obtained when the extremes are split according to the high and low extremes.

When splitting on an obvious inflection point on the probability graph of extreme values useful results were obtained. Two subsets could be formed one from the lower extremes and one with the higher results. These two subsets in most cases have clearly different distributions.

For determining the inflection point an objective analytical method was necessary. The two methods used are based on the maximum likelihood, as described previously in this paper.

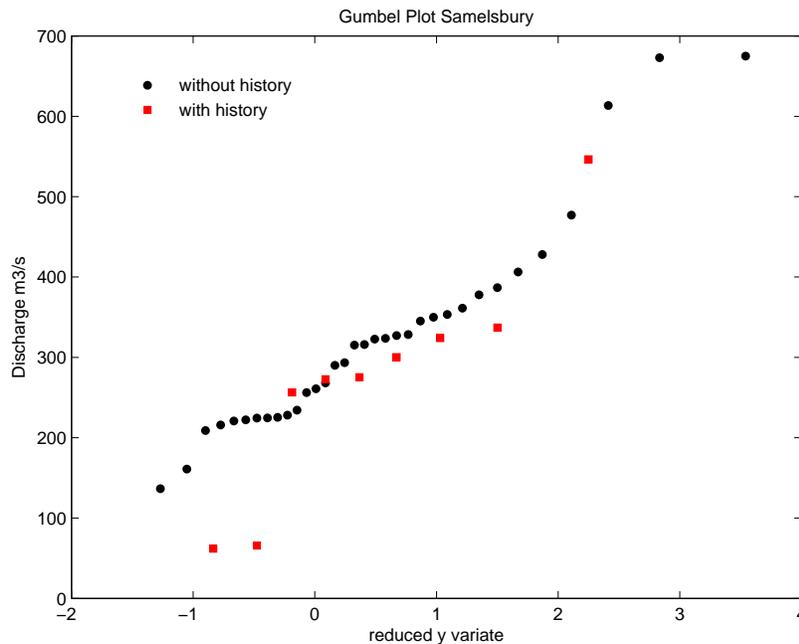


FIGURE 5. Gumbel plot of extremes with and without flood history. (Samelsbury, Ribble GB)

These two methods give very useful results; the inflection point is defined accurately by the highest likelihood, as can be seen in figure 6. In the upper part of the graph a Gumbel plot is depicted. The corresponding likelihood of a split at a specific position is depicted in the lower part of the graph, according to the two methods; using a mixture of two distributions and the use of two different distributions. The line drawn in the Gumbel plot is calculated by using a mixture of distributions.

The result is unambiguous. The dataset is divided into two subsets with both clearly different distributions. In figure 7 the two datasets are plotted separately in the same graph. As can be seen they form two clearly different distributions, as opposed to the situation in for example figure 5 where no different distributions could be found.

Unfortunately not in every case the result is as clear as in the situation shown above. The two methods give contradicting results and there is no clear inflection point to identify.

In figure 8 the results are shown when the same methods are applied to a data set from Chancy. The optimum inflection point based on the method that gave the best likelihood from the sum of likelihoods of the two distributions is clearly different from the optimum inflection point when the likelihood of the fitted mixed distribution is applied.

It could well be that like in the case depicted in figure 8; there are not multiple distributions which can be identified.

With the method discussed above two different cases can be identified, a case in which clearly two different subsets with a corresponding distribution can be found and a case where there seems to be only one distribution. When there are clearly two subsets like in figure 6 the

splitting of the datasets is regarded as useful. This is partly a visual method; a more analytical method is presented further on.

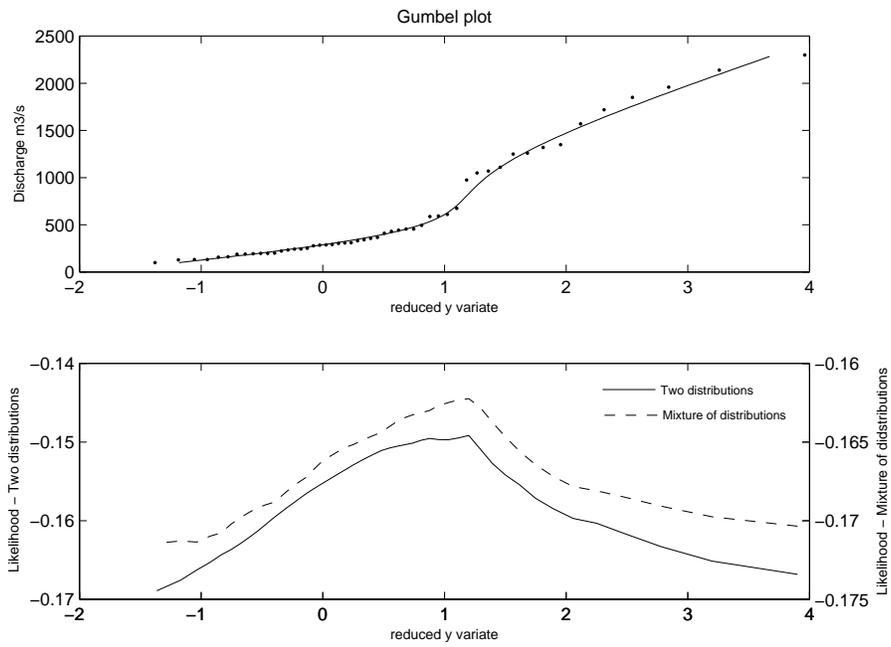


FIGURE 6. Gumbel Plot with likelihood (Arsenyevka-Yakovlevka RU)

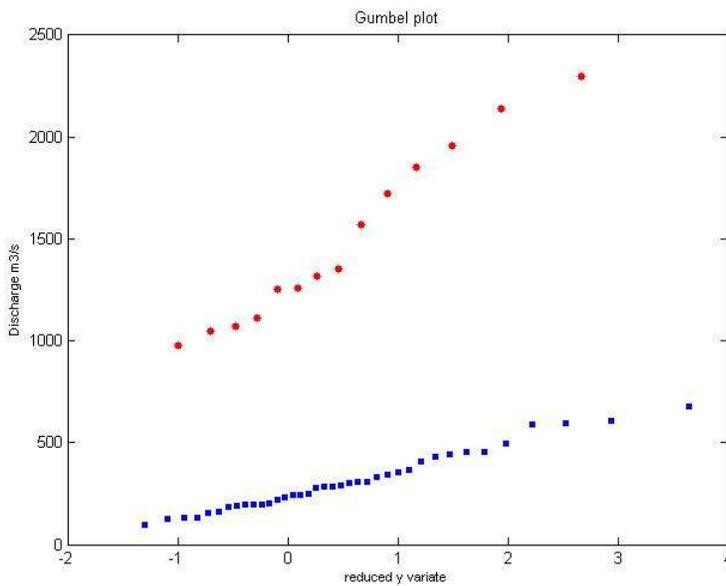


FIGURE 7. Gumbel plots of two subsets. (Arsenyevka-Yakovlevka RU)

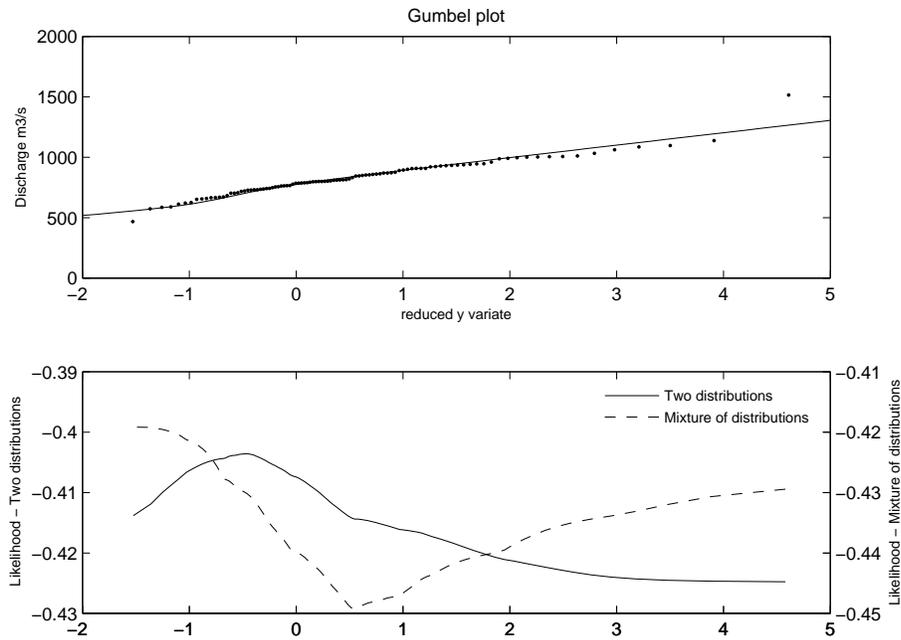


FIGURE 8. Gumbel plot with Likelihood. (Rhone, Chancy CH)

For every available dataset it is analysed in which of these two categories it falls. The results are arranged according to their territory in table 1 and are geographically depicted in figure 9. The different measure stations per region are depicted in figure 10.

The usefulness of splitting into different datasets differs with every territory. In some territories it seems to be much more useful than others. Especially in the Primorye region and the Upper Amur basin interesting results are found. In a majority of the datasets in these regions it seems to be very plausible that more than one mechanism determine the river runoff.

Territory	Useful	Not useful	Useful (%)
Angara	17	14	55%
Baikal	16	25	39%
Lena	10	7	59%
Primorye	68	17	80%
Upper Amur	17	9	65%
Upper-middle Amur	83	29	74%
Yenisei	20	29	41%
Europe	30	42	42%

TABLE 1. Cases in which splitting into two subsets of full dataset seems useful

It should be noted that the result in table 1 for the European should be handled with suspicion. The European datasets come from such different situations that it is not valid to regard them as being part of the same system.

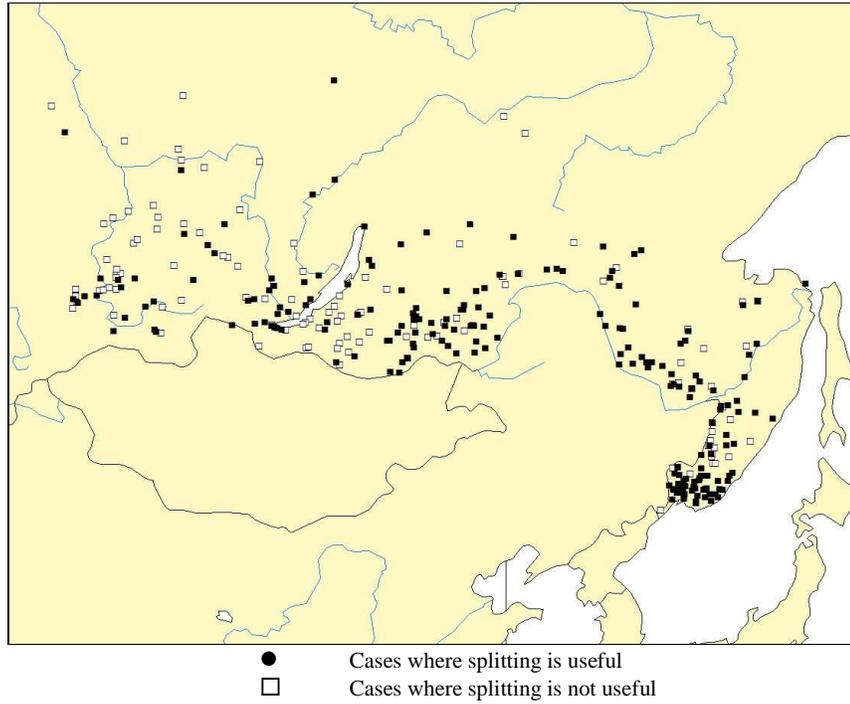


FIGURE 9. The usefulness of a division of the annual flood extremes in two distributions.

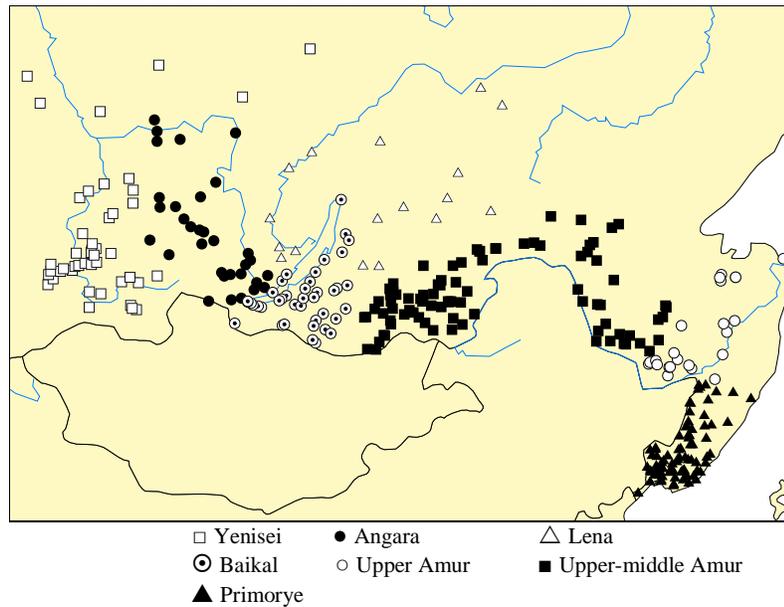


FIGURE 10. Measure stations per region

A property of this analytical method is that the different subsets cannot automatically be assigned to a specific mechanism like a cyclone, spring snow melt, a longer period of consecutive precipitation, etc. Further investigations are needed to determine the mechanism behind the different distributions within the same dataset of annual flood extremes.

4.4. Possible mechanisms behind the flood extremes

An interesting question is whether the position of the inflection point, this corresponds with a probability of exceedence, can be related to a runoff mechanism or a characteristic of the flood basin. One characteristic that could be investigated with the available data was the size of the catchment. The results are depicted in a scatter plot. [Figure 11]

The data are from 168 different catchments in Europe and in Eastern Russia. The data from both regions have been observed separately and give a similar view. Furthermore the distribution of the inflection points in Europe and Russia have been added.

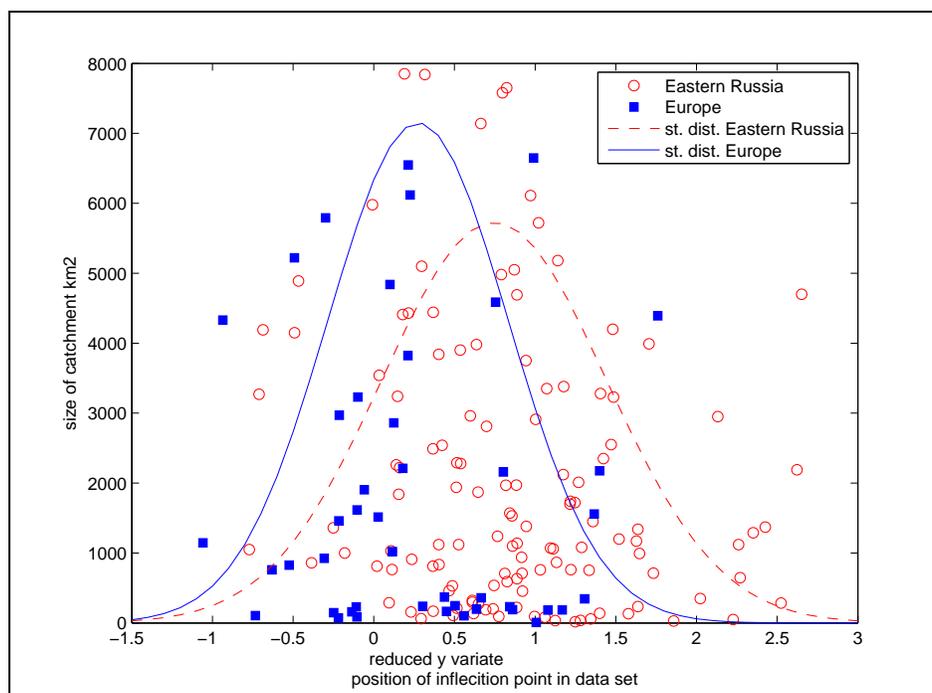


FIGURE 11. Scatter plot of the catchment size against the position of the division into subsets.

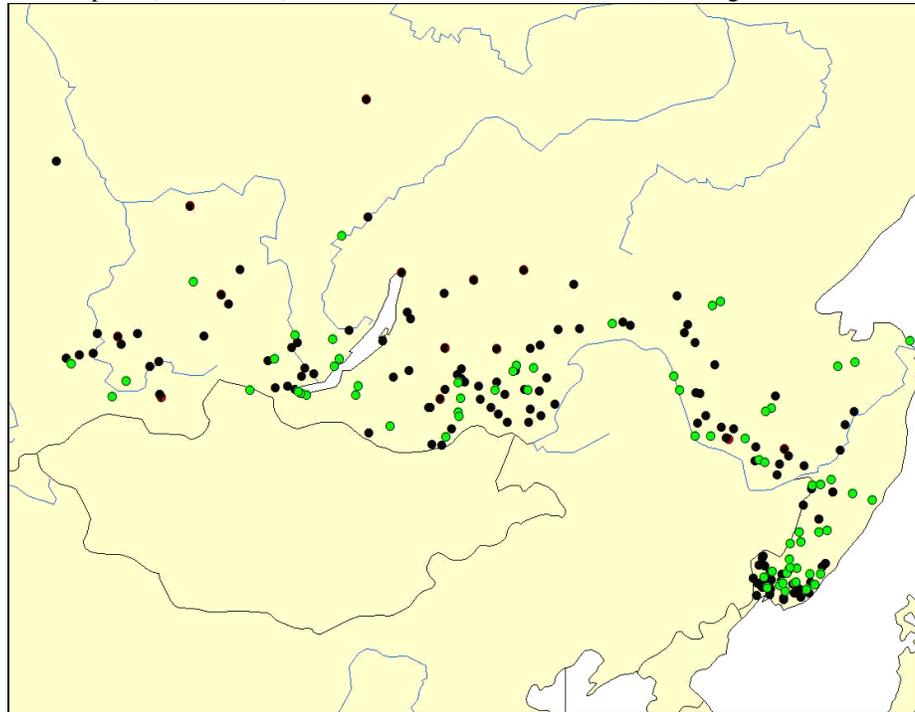
This gives no support for the hypothesis that there is a relation between the size of the catchment and the curvature of the probability graph.

Continuing with the same parameter, the position of the inflection point in the dataset, there are more questions that can be posed. Another interesting hypothesis is that the position of the inflection point is related to the geographical position of the measurements.

The expectation is that in the coastal region, the extreme weather types, like cyclones make up the dataset of the highest annual extremes. This dataset of high annual extremes is formed by relatively little number of data. Therefore it can be expected that the inflection point lies more at the right end of the graph.

So, for the coastal area it is expected that the position of the inflection point (as in figure 6) has a higher reduced-y-variate than inflection points corresponding to measurements more inland. The results are shown in figure 12.

This does not give a clear result; the different positions of the inflection point are not related to a specific geographical position. Although the datasets with a really low position of the inflection point (lower than 0) are not found in the southern and coastal regions.



- Inflection point higher than 0.9
- Inflection point lower than 0.9

FIGURE 12. Position of inflection Point in graphs where a split into two distributions is useful

4.5. Usefulness of the split

Another question investigated is the usefulness of splitting the dataset into two distributions in relation to the geographical position of the dataset. In figure 13 this is made visible.

The green dots, referring to a larger improvement of the fit, are more prevalent in the southern region than in the northern region. This gives the impression that in the southern region the runoff system is determined stronger by two different mechanisms than in the northern region.

This is also illustrated in figure 14, where in two graphs the geographical position of a measure point is plotted against the improvement of fit.

It can be seen that the longitude has no influence on the improvement of fit, but the latitude shows a pattern, similar to the map in figure 13. The southern points give more evidence of heterogeneity.

A possible explanation for the distribution of the measure points in the upper graph in figure 14 could be that the most southern points, around latitude 43, are influenced by tropical

depressions and cyclones. This gives two clear distributions and therefore a large improvement in treating them as such.

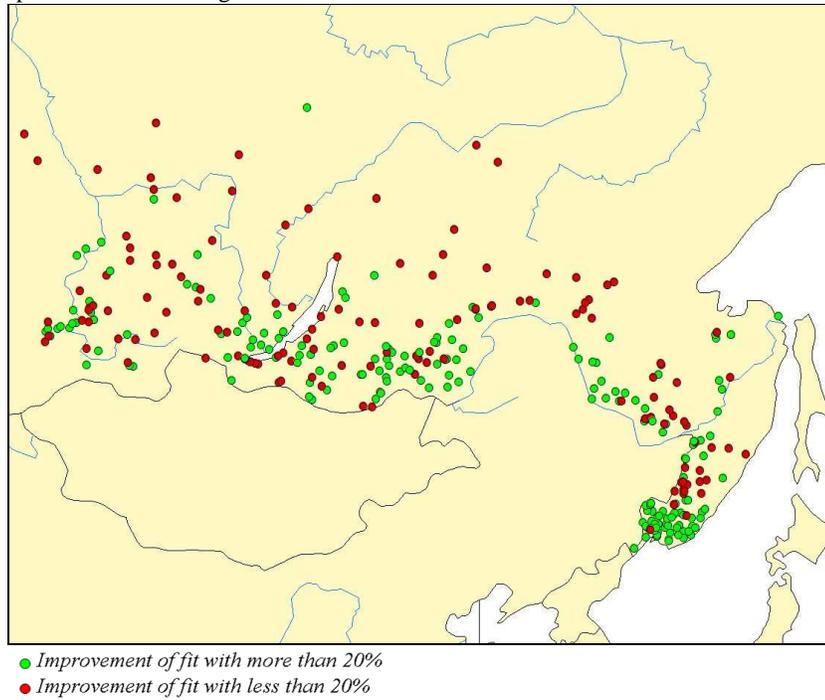


FIGURE 13. To what extent does a split into two distributions give a better fit than considering the dataset as a single distribution.

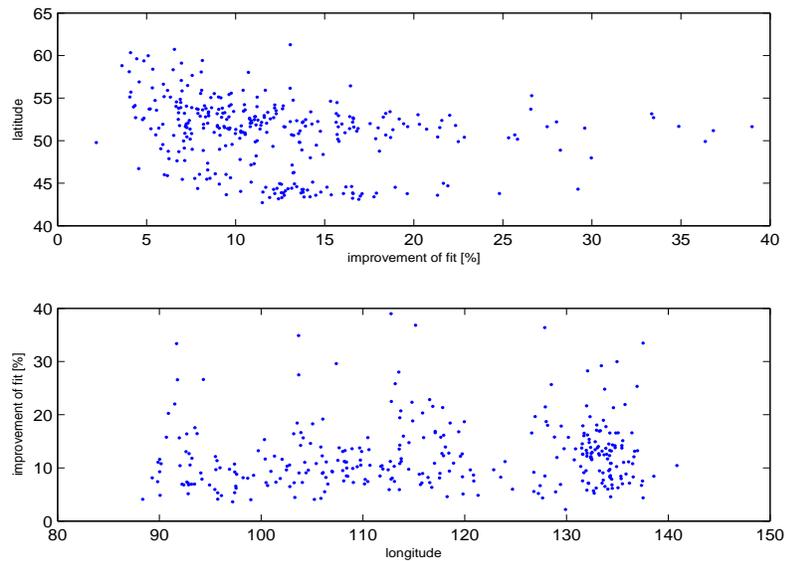


FIGURE 14. Improvement of the fit against the longitude and latitude.

The measure points around latitude 52 are subject to more diverse system. There are datasets that give clear sign of heterogeneity (improvements over 10%) and others give an image of homogeneity (small improvements)

The heterogeneous dataset around latitude 52 can originate from different mechanisms. One cause for heterogeneity can be both summer and spring runoff give annual extremes, another can be summer runoff and died-out cyclones cause heterogeneity, and yet another cause can be the characteristics of the runoff-basin.

This last possibility, the catchment characteristics, is the most plausible, because if origin of the heterogeneity lay in the presence of different weather mechanisms, there would be some regional uniformity. This is not the case the homogenous runoff-basins are situated next to runoff-basins which show heterogeneity.

The most northern points, north of latitude 52, correspond to a system where little to no heterogeneity exists.

So, there is a mixed image, on one hand there is a geographical factor determining the heterogeneity. The most northern points and the most southern points give a clearly different situation. And on the other hand the division of heterogeneous and homogenous catchments around latitude 52 does not seem to be related to a geographical factor.

A second method which also gives a measure of the usefulness of splitting the dataset into two different datasets with a corresponding distribution is presented in figure 15. The method used is derived from the Gumbel distribution. When the split of the dataset is made according to the method using likelihood, the two new datasets are distributed according to the Gumbel method. The two distributions each have a different slope in the Gumbel graph. These two slopes are divided by each other.

The more the result of this division deviates from 1, the more it can be concluded that there are two unique distributions.

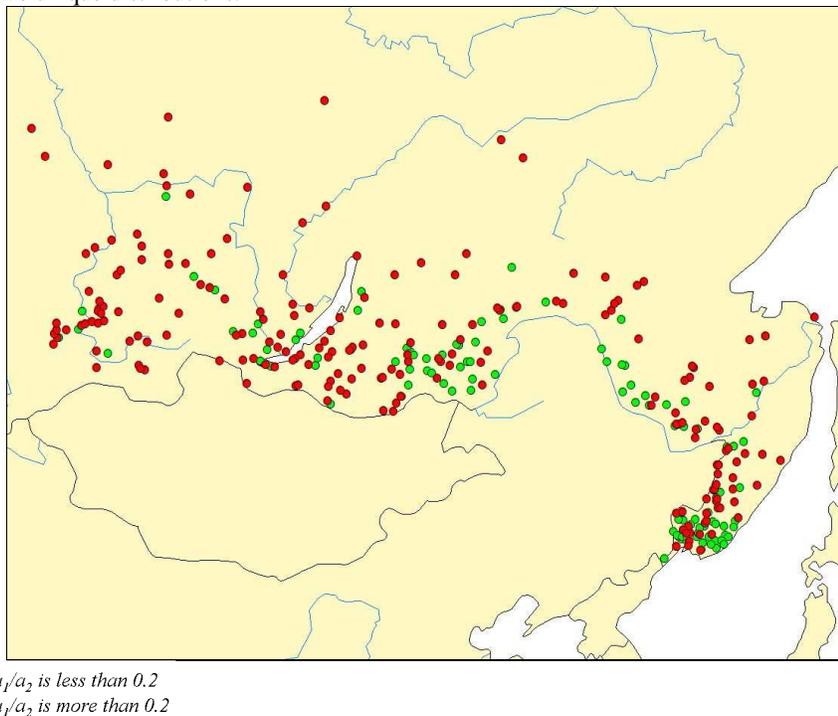


FIGURE 15. The division of the slopes of the two distributions

Again it can be seen that for a measure point in the north, it is less likely to see two clear different distributions.

Besides the geographical position and the size of the catchment there are more characteristics that can be of influence to the presence of multiple runoff mechanisms such as the slope of the catchment, the water volume in a catchment, the roughness of a river bed, etc;

5. Conclusions

In traditional flood frequency analysis it is assumed that the flood distribution is homogeneous, in many cases this is not true. In a majority of the datasets, with annual flood data, investigated in this paper, it is possible to detect heterogeneity. To test the heterogeneity, an analytical method has been developed. The method uses a maximum likelihood criterion to determine objectively what the best transition point is, and how strongly a heterogeneous approach is an improvement as compared to a homogeneous approach of the dataset.

To connect a mechanism to the different subsets found in the heterogeneous subsets, a number of possibilities have been investigated. Analysis has been made to connect heterogeneity to seasonality, i.e. whether the flood extremes can be connected to spring runoff or to summer runoff. Another mechanism investigated is the influence of cyclones.

There was no hard evidence found that the origin of this heterogeneity lays at one of these climatic or weather related mechanisms. A split of the dataset into a subset of the lowest annual extremes and a subset of the highest extremes, does lead to two clearly differently distributed subsets. The distinctive form of heterogeneity is seen in the distribution as a threshold behavior. Above a certain runoff level, the distribution seems to change.

This leads to the conclusion that the extreme runoff distribution is not so much determined by climatic mechanisms or by the conditions of the catchment, but apparently by other factors. From the investigations it is shown that in some regions heterogeneity of annual flood extremes is a more prevalent feature than in other regions. For the situation in Russia, it can be observed that the heterogeneity is stronger in the southern, coastal areas compared to more inland areas, probably caused by the influence of weakened typhoons.

6. Recommendations

It is advisable to collect data on temperature, rainfall, snowfall and also more catchment characteristics like slope, soil conditions etc. More research is needed towards the question to what extent the heterogeneity is a result of catchment characteristics.

Rather than splitting the data to two subsets each with a unique distribution, it might be useful to split the set in more than two subsets. Also more examination on the threshold behaviour can be carried out, as for what exactly causes the higher runoff extremes to belong to a different distribution.

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