Eidgenössische Technische Hochschule Zürich
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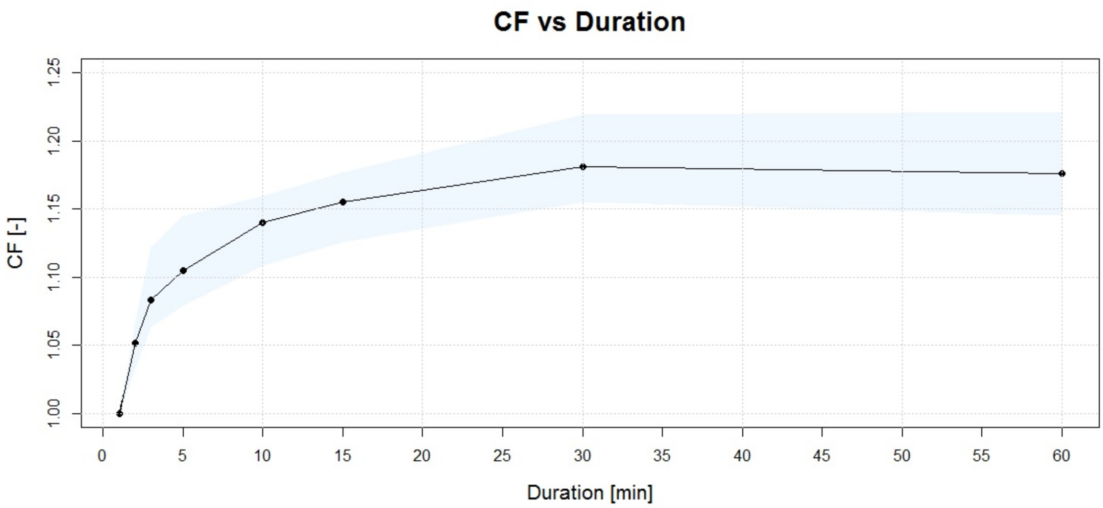
Maximum Precipitation Measurement Bias due to Fixed Time Interval Sampling



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January 7, 2019

MSc Project on Water Resources Management
Spring Semester 2017

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Eidgenössische Technische Hochschule Zürich
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Abstract

Measurement underestimation is something that could lead to potential damages, more concern should be considered when these measurements are used for the design of structures that compromise social and economic aspects if flawed. That is the case for maximum precipitation measurements and their use for hydraulic structure and flood designs. The Hershfield Factor, HF, a correction factor which increases the underestimated precipitation measurement by a factor of 1.13 is used for this purpose, it was nevertheless derived using a daily scale. In this project, a one minute resolution precipitation data set, composed of several Iowa stations, was used to test different outcomes when dealing with a sampling procedure that uses a fixed time interval. Inasmuch as this data has a really fine resolution of one minute, it was used as the "true" rain intensity. It was therefore aggregated from the original one minute resolution into different higher time durations by also taking into consideration all possible sampling starting points in time. This way, the sampling behavior was simulated and thus the existing bias associated to it was known. With the use of a peak over threshold analysis, depth duration frequency curves, DDF, for the simulated different sampling outcomes were computed. By means of these DDF curves, a bias was computed and expressed in this project as a correction factor, which as the HF, should be used to correct the likely underestimated maximum precipitation value which was initially measured.

Contents

1. Introduction

Maximum precipitation depths and their frequency in time, is information used for hydraulic structure or flood design. Meaning that there is an utter importance in having this data well characterized for their proper implementation. Inasmuch as incorrect measured values or underestimation of these could lead to potential flawed designs or have other social or economic consequences. The fact of dealing with storm events, which are intrinsically random in terms on when to expect maximum intensities, leads to a potential bias when measuring rainfall.

In this project, the main study lies on characterizing the bias associated with rainfall measurements due to their fixed time interval sampling (i.e. every five minutes, hour, or day). What is the effect that different measuring starting points in time have on this bias, namely, what is the right time, if there is one, at which measurements should start recording, in order to capture the true maximum depth for a given duration of a storm event.

From what it was commented above, it is not likely that the time at which the maximum rain intensity occurs is known beforehand, and thus the likelihood of capturing the true maximum intensity decreases by the amount of starting points that a fixed time interval sampling has, which depends on the tipping bucket time resolution (i.e. 60 starting positions for a 60 minute duration using a 1 minute sampling interval).

Solutions to this extreme rainfall intensity underestimation have already been presented. Hershfield and Wilson, 1961, [1] proposed the so called $Hershfield\ Factor$ (HF), a correction factor equal to 1.13 used to increase and correct the recorded extreme rainfall intensity of a given duration, due to the probability of underestimating the value when measured.

Some other studies include the statistical analysis between true maximum intensities and the ones obtained with fixed time intervals (Simon Michael Papalexiou , Yannis G. Dialynas , Salvatore Grimaldi, 2016 [2]), by using an impressive amount of hourly precipitation data.

For this project, I analyzed 1 minute precipitation data from the ASOS Network (Automated Surface Observing System), processed by the Iowa Environmental Mesonet[1]. Using these data, I delved into this associated bias in rainfall measurements, and asses if the HF is indeed suitable to use as a correction factor. I also investigate what are the consequences in calculating a correction factor using precipitation data sets with coarser time resolutions.

[1] `https://mesonet.agron.iastate.edu/request/asos/1min.phtml`

2. Project Objectives and Data Set

The main reason of this project was that of finding an empirical formulation that describes and corrects the measurement underestimation of maximum precipitation depths due to the existing bias when sampling with a fixed time interval.

This goal described above, was accomplished by analysing two different resolution data sets. The first one from the United States of America, more specifically from Iowa Counties (IEM[2]), being an ASOS data set, with a 1 minute time resolution and 0.254 mm as tip sensitivity. The second one from Cantons of Switzerland (MeteoSwiss IDAWEB[3]), which consisted of data with a 10 minute time resolution and a tip sensitivity of 0.1 mm.

Both data sets were measured with a tipping bucket rain gauge, which tips when the aforementioned measurement resolution is collected. They also count with internal data loggers with the time resolutions specified before.

2.1. Analyzed Stations

The location of each of the analyzed stations is shown in Figure 1 . Table 1 and 2 show some representative data of the Iowa and Swiss stations respectively.

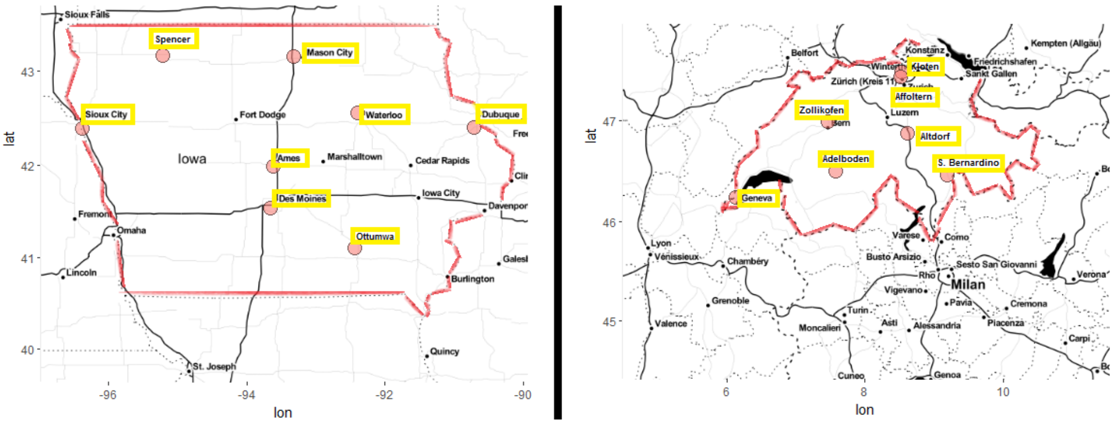

Figure 1: Locations of the Iowa Stations are displayed in yellow on the left map and on the right map, also in yellow, the location of the Swiss stations is presented

It has to be noted that the stations were chosen to be analyzed depending on their data availability, namely, the stations which had the most data length where chosen for this project. Another important aspect that was also taken, was that they were chosen so that all stations together, depending on the data set, should cover more area to analyze, and not remain in one single spatial point throughout the analysis.

As seen already on Table 1 and 2, the time length on average for the stations located in Iowa was 10 years and 34 years for the Swiss stations. However, in terms of real data length, The Iowa stations had 4 times more data points than the Swiss stations, even though they measured only 1/3 of what the Swiss stations had as time record.

[2] https://mesonet.agron.iastate.edu/request/asos/1min.phtml
[3] https://gate.meteoswiss.ch/idaweb/

Station	Data Length [Years]	Data Calculated Average Annual Precipitation [mm/year]	Average Annual[a] Precipitation [mm/year]
Des Moines	15.31	860	906
Sioux City	14.38	694	704
Dubuque	14.30	901	923
Waterloo	11.82	847	876
Ottumwa	9.17	1,039	942
Spencer	8.78	661	749
Mason City	8.57	811	894
Ames	8.08	946	910

Table 1: Iowa Stations Description (1min Resolution)

[a] `http://www.usclimatedata.com/climate/iowa/united-states/3185`

Station	Data Length [Years]	Data Calculated Average Annual Precipitation [mm/year]	Average Annual[a] Precipitation [mm/year]
Altdorf	36.03	1,127	1,500
Kloten	35.78	956	800
Zollikofen	33.13	1,002	900
Cointrin	33.13	901	900
S. Bernardino	33.13	1,404	1,700
Affoltern	33.13	994	800
Adelboden	33.13	1,296	1,300

Table 2: Swiss Stations Description (10min Resolution)

[a] `http://www.meteoswiss.admin.ch/product/output/climate-data/monthly-annual-maps-processing/precip/mean/1999/precip_mean_1999_yy.pdf`

Tables 1 and 2 also include an average of the yearly precipitation. One of this calculated with the analyzed data sets and the other taken from the websites cited on the tables. This in order to asses the accuracy of the data sets, with respect to what its published on the official weather sites.

In the following section (sec.3), a detailed explanation on how these data was processed, manipulated and analysed is explained and how with the use of a Peak Over Threshold (POT) analysis an extreme rainfall intensity bias due to fixed measurement intervals could be estimated for a given duration.

3. Methods

The two countries' data sets, from section 2.1, had to pass for several filtration steps, before being ready for any sort of analysis.

The taken steps were thus, firstly the removal of precipitation depths that could have come from snow events, secondly a procedure to fill in missing precipitation from time periods during storm events was also implemented. A third step was that of, declusterizing storm events from each station data set. The last steps consisted on analyzing these declusterized storms and with their data do a POT analysis which will be then further used to compute a bias. It most be noted that in this project work, the bias will be expressed as a correction factor, CF, that will be needed to increase underestimated maximum precipitation depth values for a given duration.

3.1. Data Preparation

3.1.1. Depth from Snow Removal

The first topic discussed here, is that related to the removal of depth that could potentially come not from rainfall but from a snow event. The procedure was quite simple and it consisted mainly in setting a threshold of 0°C (32 F), so that all values above it will be taken as liquid precipitation. The main reason of doing that is due to the fact that further analysis for computing the bias, will delve with precipitation depth and not depth from snow. It had to be assumed that snow would be present at that temperature.

3.1.2. Missing Precipitation Values

It comes as no surprise that when dealing with data containing large amount of data points due to its time granularity and their large time records, there will be some missing precipitation values. Some of these missing depth values could fall in the middle of a storm, and thus a filling-in procedure of rain depth values was needed. For sake of completion this procedure was then also implemented in order to set the data for analysis.

The filling procedure, therefore consisted on firstly finding on the huge data sets, missing periods of time. Out of these, the next step was to find which ones fell in the middle of a storm. In order to do that, an implementation was taken, this consisted on taking the missing periods between a storm higher than 10 min but lower than 90 min, since having less than those periods would not really consist of too much data loss, and having more than 90 minutes would already be considered as having another event between storms.

After locating the missing periods of time inside a storm between the aforementioned time ranges, a rate was computed. Meaning that if the missing precipitation, P was located at time t, the rate (eq. 1) would be then computed from $P(t_{-30})$ to $P(t_{+30})$, and then used to fill the missing time interval.

$$Intensity = \frac{\sum_{-30}^{30} P(t)}{60min} \tag{1}$$

Where Intensity is given in $[mm * min^{-1}]$

3.2. Data Processing

3.2.1. Storm Separation

Here the main focus was that of, as the title suggests, separate storm events from each station data set. The purpose of it was to, first, make all events independent from each other, in this case useful by the fact that the main interest is to obtain maximum depths which are not correlated to other events.

In order to do so, a dry period of 60 minute between events was proposed. It was chosen to be this value, due to the fact that increasing dry period times, showed to introduce more variability in storm events, since the process would cluster depth values that may likely be coming already from when the storm has stopped.

The previously mentioned step would just separate the storms, there was a second filtration step however, that would truly ensure that each storm event was independent from each other. This consisted on using only storm events which had as a total precipitation depth for the whole duration a value higher than 10 mm in depth. This was also handy for the POT analysis needed to be done described in section 3.3. The storm events with values bellow this threshold would be thus discarded and not taken for further analysis.

3.2.2. Storm Data Manipulation

Once all the storms were separated, the data manipulation process could start. This consisted on changing each storm event resolution by aggregating depth in time. Namely, going from 1 minute time resolution to 5, 10, 15, 30, and 60 minutes and from the 10 minute resolution data set, aggregating it to a 20, 30, 40 and 60 minute resolution. By doing so, different precipitation depths for different durations were thus known.

The aggregation step, however, was not only dealing with one time aggregation for a wanted duration (i.e. one aggregation set when going from 1 to 60 min), inasmuch as we wanted to delve within all different possibilities in which a measurement could start. Thus, a simulated sampling procedure was implemented, this consisting of different time fixed intervals, which also had different starting sampling points in time. Every different starting point in time will be creating a different aggregated data set.

In order to summarize what it has been told here, Table 3 and 4 serves to enlighten how many aggregation sets were to be expected depending on the wanted duration for the Iowa and the Swiss data sets respectively.

Fixed Interval Sample Length [Minutes]	Starting Points in Time (No. Sets) [-]	Maximum Intensities Calculated per Storm [-]	True Maximum Intensities per Storm [-]
60	60	60	1
30	30	30	1
15	15	15	1
10	10	10	1
5	5	5	1

Table 3: Aggregation sets gotten, depending on the fixed time interval for sampling used (1 min resolution data)

Fixed Interval Sample Length [Minutes]	Starting Points in Time (No. Sets) [-]	Maximum Intensities Calculated per Storm [-]	True Maximum Intensities per Storm [-]
60	6	6	1
40	4	4	1
30	3	3	1
20	2	2	1

Table 4: Aggregation sets gotten, depending on the fixed time interval for sampling used (10 min resolution data)

In Table 3 and 4 the number of maximums that we would be expecting for every fixed interval sample length is also included . This will become important in the *POT* section, were we use the maximum depth values for the analysis of the data. Furthermore, there is also a column indicating the true maximum depth values per fixed interval length (duration), since there is just one true maximum depth value characterizing each storm event for a given time duration. Hence, the likelihood of measuring this true maximum depth will depend on when did the sampling started in time and on how many sampling starting points do we have in time.

This likelihood was simulated so that for every storm, there would be a rain depth sampling initiating at different times, which would either be at t_0, meaning at the time when the storm began, or with an offset at t_0, which would depend on the desired duration D. For example, taking the 1 minute resolution data set and 5 minutes as duration, the starting positions would be $t = \{0, -1, -2, -3 - 4\}$, or $t = \{0, ..., -D + 1\}$. It has to be noted, that the offset being equal to $-D$, would yield the same aggregated set as starting with t_0.

For the Swiss 10 minute resolution data sets, this was a bit different, since we could just move in time with the same resolution of the data set, meaning every 10 minutes, that is why the number of starting points in time differ, as seen in Table 4, where for 60 minutes there is just 6 different starting points and not 60, such as with the Iowa sets.

3.2.3. Storm Data of Interest

The data processed as described in the previous section, served mainly to extract data that was needed for the *POT* analysis, out of which the bias was computed.

From each station, the data set was separated in storms, out of each storm a maximum was then located for every fixed time interval sample fabricated (as seen in Table 3). The maximum of the maximum depths was also found from the same storm with different starting sampling positions (every starting position has an associated maximum depth value), this was then the corresponding true maximum depth of a certain duration for a given storm.

For example, in figure 2 below, the dotted lines represent the aggregated series, namely rain depth every 15 min for this particular example. In this figure, it can be seen that by starting the simulated sampling procedure with a 10 minute offset from t_0, the expected depth maximum for a 15 min duration is lower than if starting the sample at t_{-13}, where actually the true maximum intensity for 15 min duration is going to happen.

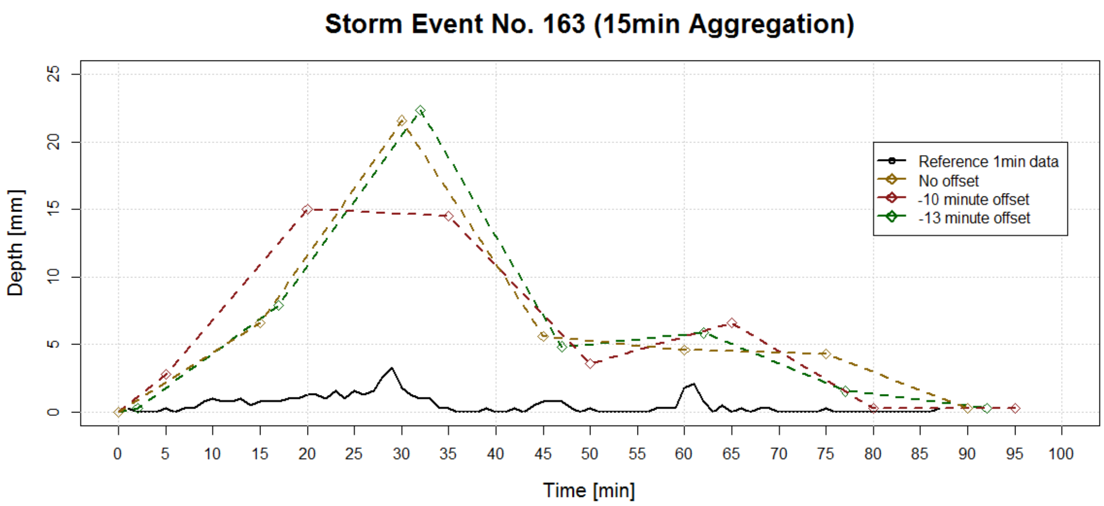

Figure 2: Depth vs Time of an independent storm event, aggregation from 1 min to a 15 min resolution. The dotted lines indicate depth every 15 min of 3 different starting sampling points and the solid line indicates the 1 minute data set

All maximum depth values were then averaged. Again, in this example from the figure, the average would be done out of the 15 maximum depths, which were gotten from the different starting points in time when sampling the storm with a 15 minute fixed time interval. Out of these 15 maximum depth values, confidence intervals, *CI*, around the mean were also computed.

The last important data needed was the true maximum, which in figure 2 is shown by the green dotted line, which is a maximum depth value for a 15 min duration case, for this specific storm example.

In summary, for each storm a true maximum depth, a mean maximum depth from all different starting sampling points and a confidence interval were computed.

3.3. Peak Over Threshold Analysis

This section describes how the *POT* analysis was carried on by using the maximum depth data obtained as described in the previous sections.

One of the main differences between a *POT* analysis and an annual maximum analysis, is that for the former, uses several peaks per block (usually a year), whereas in the latter, there is one maximum per block, generating an annual maxima series.

With a annual maximum approach, correlation should not be a problem, inasmuch as every event is largely separated in time. That is not the case for a *POT* analysis where the input of maximums should be chosen in such a way that these are not correlated through each other. This was achieved by doing the storm separation, as described in section 3.2.1, and so this declusterization ensured that each maximum was independent to other maximums obtained for the analysis.

The first calculation step, was to fit the variables described in section 3.2.3, the mean of the maximum precipitation depths per storm for each duration, the true maximum precipitation depth per storm for each duration, and the confidence intervals, to a Generalized Pareto Distribution, *GDP*, using a maximum likelihood estimator. Theoretical quantiles, Q_{Theo}, are computed from the fitted GDPs, and the probabilities, p_j of the events, j, were computed by using the plotting position estimator proposed by Hosking, 1995, [3] shown in equation 2, where n is the total number of events. The expected precipitation level, was computed from the theoretical quantiles, which are function of the return period which is also function of the estimated event probabilities. Thus, the return precipitation level vs return period plot is described by $(T(p), F^{-1}(p))$, where F^{-1} is the fitted quantile function. The return period, T, (eq. 4) was computed by taking into consideration the average number of events per block (per year), meaning that this return period differs to the annual maximum return period that would be obtained by just one maximum event per year.

$$p_j = \frac{j - 0.35}{n} \tag{2}$$

$$Q_{Theo,j} = F^{-1}(p_j) \tag{3}$$

$$T = \frac{1}{events/year * (1 - p)} \tag{4}$$

A return precipitation level of a maximum precipitation expected for 5, 10, 15, 30, and 60 minute durations for the stations in Iowa was computed. For the Swiss stations, the estimated maximum return levels where computed for the 20, 30, 40 and 60 minute duration. Hence, *DDF* curves were constructed out of this information for different return periods, which were 2, 5, 10 and 20 years for both, the Iowa and the Swiss stations.

The *POT* analysis was in part carried out with the use of an R package (The POT Package[4]), and the nomenclature from the formulas used in this section were taken from the reference manual.

[4] `http://pot.r-forge.r-project.org/`

3.4. Bias Computation

This section comprises all the information gathered from the previous ones. The DDF curves derived from the POT analysis will be used in a straightforward calculation to compute the bias associated to maximum precipitation depth measurements and finally estimate the correction factor needed for a given duration.

Whit the DDF curves, one can visually asses what was the expected maximum depth for a given duration. This, however, will be different depending on which information was used to construct the curves. For example, when using the true maximum depth, the return level expected for a given duration should be higher than when using a DDF curve which was derived from data containing just the means of the maximum depths.

Use Figure 3 bellow as an example. It shows a DDF curves plot, containing two important pieces of information. The first one is the true maximum depth for all the durations, H_{true}, represented here as a dotted line and red square points. The second piece of information is, the mean of the maximum depths, $\bar{H}$, which is represented as a solid line with red poins. Around it, are the confidence intervals, also calculated from fitting a GPD to these data, and not with the CI of the GPD, namely it is the sampling variability the one plotted in blue and not the fitting uncertainty.

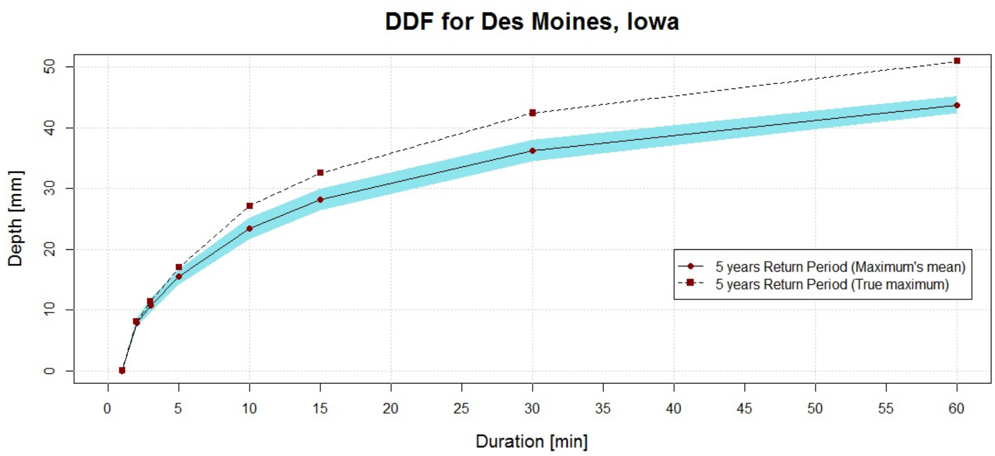

Figure 3: Depth Duration Frequency curves of Des Moines, Iowa for a 5 year return period. The curves displayed here correspond to the true maximum depth and mean of the maximum depths.

Now that the reader has a graphical representation of what values are going to be compared, the following formula calculates the bias and expresses it, as mentioned before, as a corrector factor:

$$CF = \frac{H_{true}(duration)}{\bar{H}(duration)} \tag{5}$$

Where CF is the correction factor needed to apply to maximum precipitation measurements for a wanted duration. Other nomenclature is as stated before.

4. Results and Discussion

For this part, there will be given a higher importance to the results that were obtained with the 1 minute resolution data set, namely, those results obtained from the stations in Iowa. The Swiss station results were used in order to make a comparison between a coarser and a finer resolution. It is nevertheless important to remember that the purpose of this work was that of deriving an empirical formulation to assess the bias coming from different resolution lengths. It is also intuitive to think that the best results will thus be derived from the finer resolution data set, inasmuch as these contain a higher resemblance to the true storm and rainfall nature.

In the following sections, this will be discussed, and this empirical formula of a correction factor will be presented, as well as a fast test using Iowa data sets for fabricating a 10 min resolution data, to see if we can obtain similar results as with the Swiss data sets.

4.1. Data Processing

For the storm separation procedure, the declusterization part in which we obtained independent events, the results are shown in Tables 5 and 6 bellow, for the Iowa and the Swiss stations respectively. These tables show how many storms were gotten per analyzed time series of each station, and how many storm events remained after the filtering procedures were implemented. These tables also indicate what was the average number of events per year in each of those analyzed stations.

Station Name	Data Length [Years]	Total No. of Storms $\left[\frac{\#}{DataLength}\right]$	No. of Separated Storms [#]	Storms per Year $\left[\frac{\#}{Year}\right]$
Des Moines	15.31	2,817	408	27
Sioux City	14.38	2,343	294	20
Dubuque	14.30	3,015	364	25
Waterloo	11.82	2,205	293	25
Ottumwa	9.17	1,892	288	31
Spencer	8.78	1,483	154	18
Mason City	8.57	1,653	207	24
Ames	8.08	1,659	208	25

Table 5: Iowa Stations, Storm Separation Table

Station Name	Data Length [Years]	Total No. of Storms $\left[\frac{\#}{DataLength}\right]$	No. of Separated Storms [#]	Storms per Year $\left[\frac{\#}{Year}\right]$
Altdorf	36.03	12,874	1,071	30
Kloten	35.78	12,483	868	24
Zollikofen	33.13	11,843	853	26
Cointrin	33.13	10,713	809	24
S. Bernardino	33.13	8,767	1,060	35
Affoltern	33.13	11,714	837	25
Adelboden	33.13	13,612	1,181	36

Table 6: Swiss Stations, Storm Separation Table

For the stations in Iowa, about 10 to 13% of the total storms per series were used for the analysis, in the case of the Swiss stations, this number was around 8% of all the storms per station. On average, there were 25 events per year (As seen in Table 5 and 6). The events per year are important, since they were used to set up the threshold for the analysis and thus use them to properly calculate the return period in order to construct the DDF curves (as seen in equation 4).

It is also seen here, that the total depth per storm assigned as a requirement to be considered an event for the analysis, (10 mm as minimum depth per storm), worked fine for the storm separation purposes. We managed to obtain, on average, a similar amount of events per year, which are the ones required for the POT analysis. These separated events, were then the storms containing all the information such as the true maximum depth for all the wanted durations (5, 10, 15..., 60 min), the mean of the maximums, and the confidence intervals.

Take Ottumwa station as an example in Table 5, it has 288 separated, independent storms, it then means that this particular station had 288 true maximum depths, 288 maximum's mean, 288 upper CI, and 288 lower CI for every of the aforementioned durations, thus 288 times 4 times 5 data points. These set of data was then fitted to a GPD later on the POT analysis.

4.2. Depth Duration Frequency Curves

The construction of this curves was done, as commented in section 3.3, with the POT analysis, the resulting maximum rain intensity vs return period are shown from Figure 4 to 13. For this part, only the results of the Des Moines station will be shown and discussed.

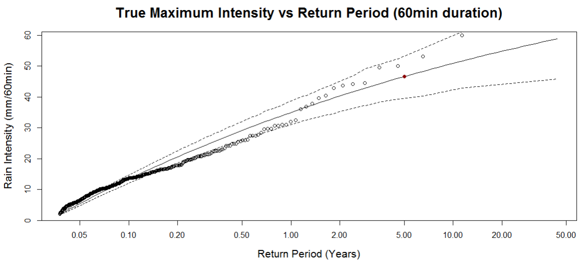

Figure 4: Des Moines True Maximum Intensity vs Return Period for a 60 min duration.

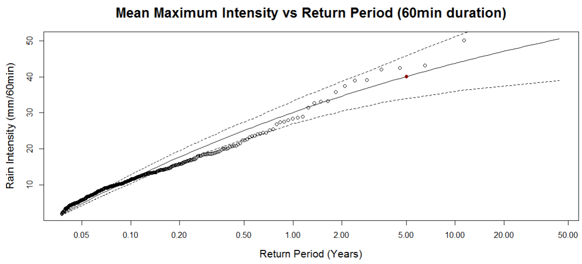

Figure 5: Des Moines Mean Maximum Depth vs Return Period for a 60 min duration.

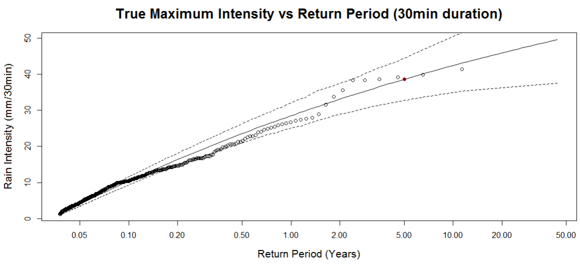

Figure 6: Des Moines True Maximum Intensity vs Return Period for a 30 min duration.

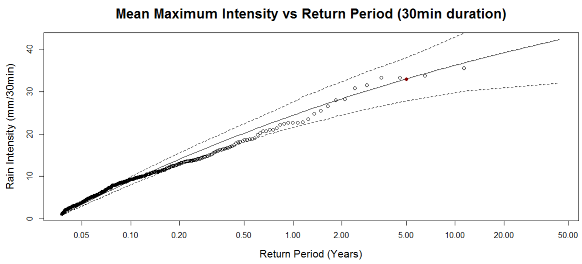

Figure 7: Des Moines Mean Maximum Intensity vs Return Period for a 30 min duration.

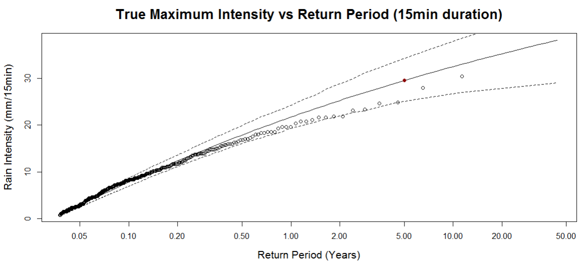

Figure 8: Des Moines True Maximum Intensity vs Return Period for a 15 min duration.

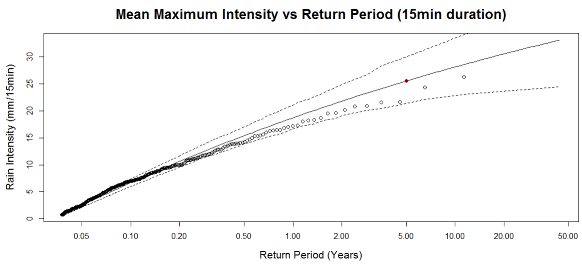

Figure 9: Des Moines Mean Maximum Intensity vs Return Period for a 15 min duration.

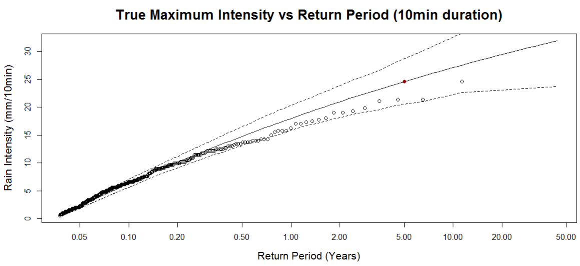

Figure 10: Des Moines True Maximum Intensity vs Return Period for a 10 min duration.

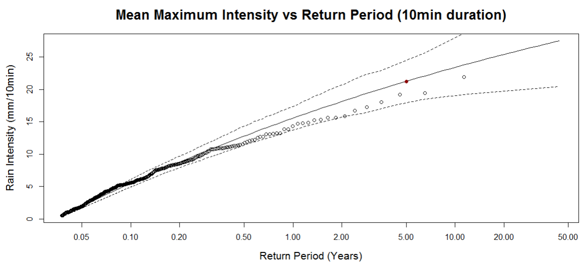

Figure 11: Des Moines Mean Maximum Intensity vs Return Period for a 10 min duration.

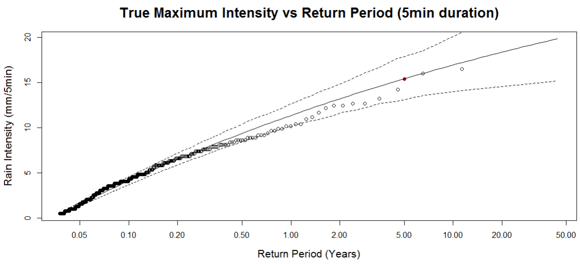

Figure 12: Des Moines True Maximum Intensity vs Return Period for a 5 min duration.

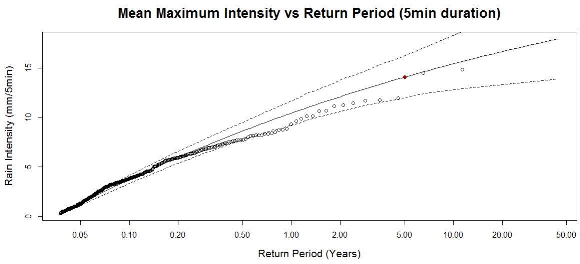

Figure 13: Des Moines Mean Maximum Intensity vs Return Period for a 5 min duration.

The Figures on the left show the true maximum intensity, whereas the ones on the right show their mean maximum intensity. It can already be seen that there is a clear underestimation when comparing a couple of curves derived from the same duration. For example, seeing Figure 6 and 7, which display the intensity duration vs return period of a 30 min duration, and looking for the intensity corresponding to a 5 year return period, it is noticeable that the values differ, being the true maximum intensity 38.5 mm/30min, and 33 mm/30min for the mean maximum intensity.

The constructed *DDF* curves for Des Moines are then shown below in Figures 14, 15, and 16, which were derived by using the information from the figures above. The return periods plotted are for 2, 5, 10 and 20 years for Figure 14 and 15. The colored areas in Figure 15 correspond to the confidence intervals with respect to the sampling variation, and not with respect to the uncertainty due to the GPD fitting. Figure 14, which represents the true maximum depth, does not have this uncertainty since it is taken as the true value. The last figure of this bunddle, Figure 16, shows the comparison between the true maximum depths and the mean of the maximums of a same return period, in this case 20 years.

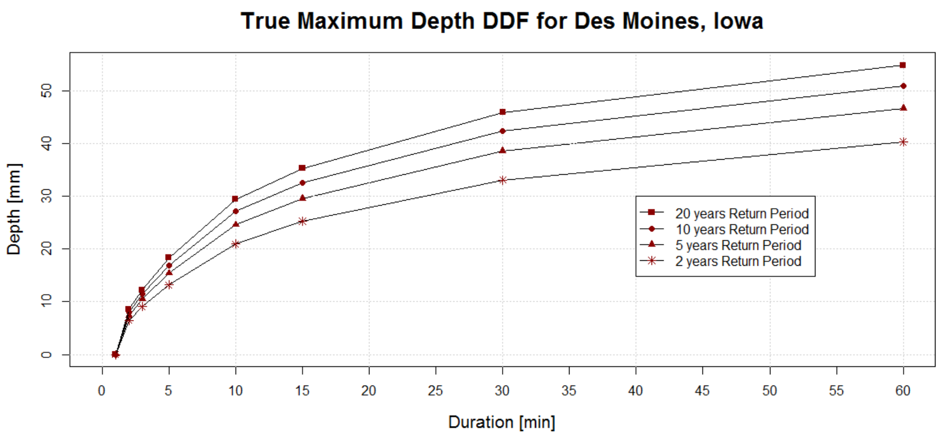

Figure 14: Depth Duration Frequency curves of Des Moines, Iowa for a 2, 5, 10 and a 20 year return period. The curves displayed here correspond to the true maximum depth.

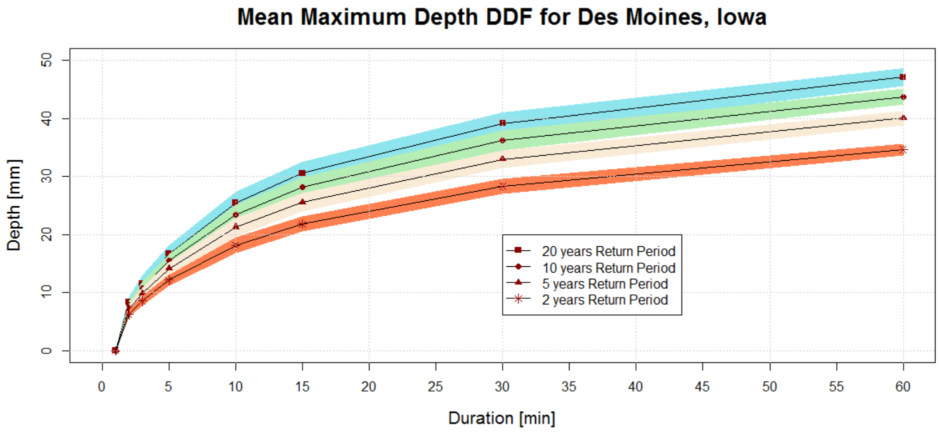

Figure 15: Depth Duration Frequency curves of Des Moines, Iowa for a 2, 5, 10 and a 20 year return period. The curves displayed here correspond to the mean of the maximum depths.

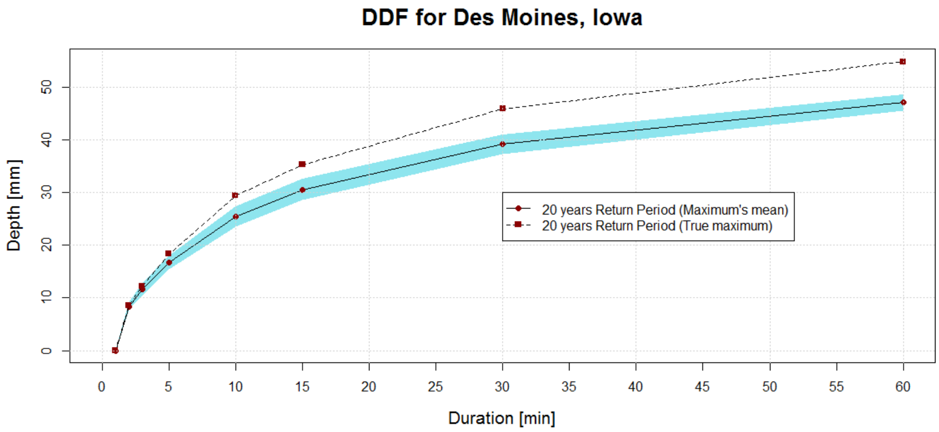

Figure 16: Depth Duration Frequency curves of Des Moines, Iowa for a 20 year return period.The curves displayed here correspond to the true maximum depth and mean of the maximum depths.

The same procedure was then applied for the Swiss stations, with the minor difference that for this case the data resolution of 10 minutes meant that when having a duration of 60 minutes, the mean of the maximums would have been computed with 6 maximum depth values and not with 60 such as in the 1 minute resolution Iowa data sets, since the sampling starting point in time could just be shifted as many times as the real duration was equal to, but with the minor difference that the possible shift to be done was relative to the data resolution, namely every 10 minutes. Other *DDF* curve plots are shown in the appendix A.2 and A.1 .

4.3. Correction Factor

4.3.1. Iowa Stations

Once that the pertinent calculations are done, the bias was then estimated. Using the information given by the DDF curves, like the one in Figure 16, that has both, the maximum and the mean maximum depths, a comparison is made.

This comparison, consisted as stated in equation 5, on getting to know the ratio between these two depths, the true maximum depth and the mean maximum depth for a given duration, and thus compute the factor that should be implemented in order to correct the maximum depth for a given duration.

The results obtained as CF are shown in the graph below for all the analyzed Iowa stations,

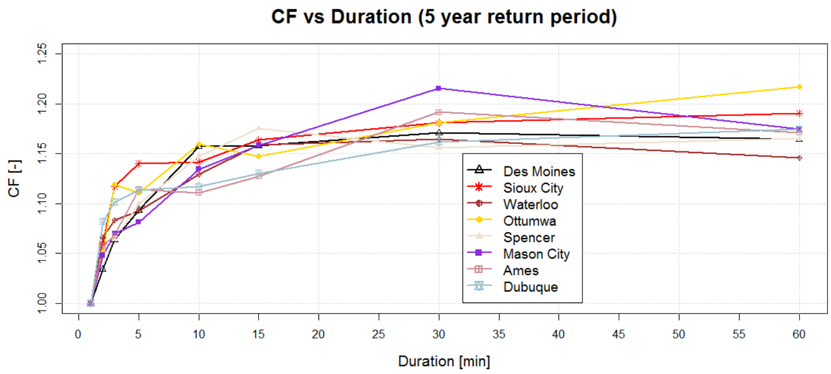

Figure 17: Iowa station Correction Factors vs Duration for a 5 year return period

All CF from the 8 stations from Iowa are plotted in here, the variation shown in here, is later taken as a type of confidence bounds for this type of analysis (For other return period CF see A.3).

When averaging all the results of these stations, and also including the results for all the other mentioned return periods, we obtained the following results presented in the graph bellow:

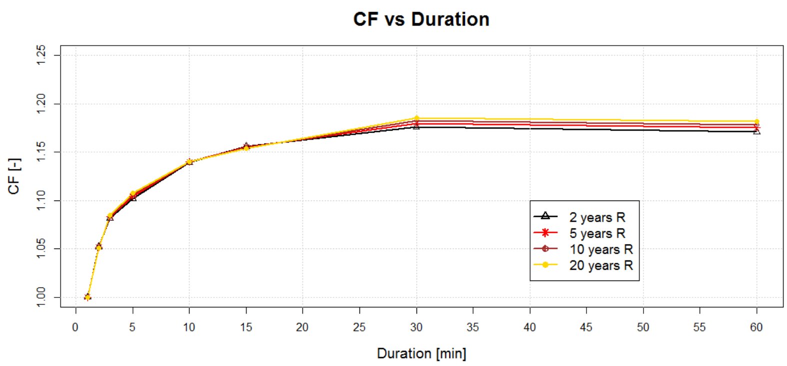

Figure 18: Averaged Iowa station Correction Factor vs Duration of all analyzed return periods.

It can already be seen in Figure 18, that all the curves seem to be going for the same Correction Factor when increasing the duration, since that was the case, it was decided to average these CF values too, obtaining the following curve shown bellow in Figure 19, where the blue shadings indicate the variability between stations, namely the best and worst scenarios performed by the stations as seen in Figure 17, with the exception that in this case, every worst case and best case scenario was an average of all the return period worst and best case scenario values.

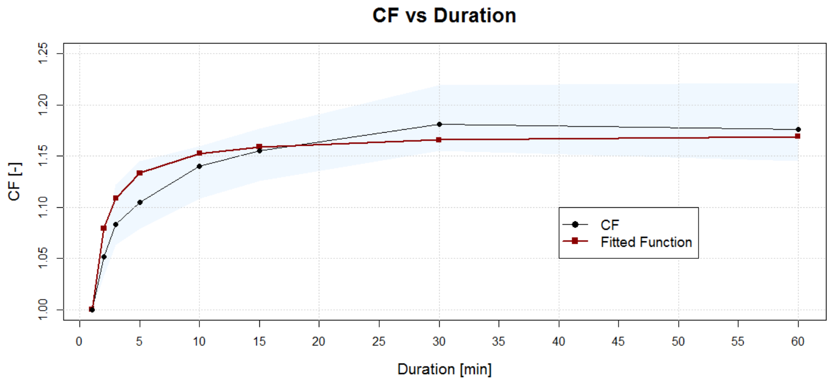

Figure 19: In black the Iowa station Correction Factor vs Duration, averaged from all return periods. In red the parabolic fitted function.

The proposed fitted function also shown in Figure 19, corresponds to a parabolic function with the following form:

$$CF_{fit} = \frac{a * b * Duration}{(1 + b * Duration)} \tag{6}$$

Where a=1.172303, and b=5.80371 min^{-1}.

It has to be noted, that at the duration equal to 1 minute, there is no bias, and therefore the $CF = 1$, this is due to the fact that the data used for this analysis was of 1 minute resolution, and it was considered as the true intensity and thus it should not contain any bias.

In the next section, the results obtained from the Swiss stations will be presented, These will be used to finally make a comparison between the two derived CFs.

4.3.2. Swiss Stations

The empirically derived CF that would be needed for the Swiss station are presented in Figure 20 bellow (For other return period CFs see A.4),

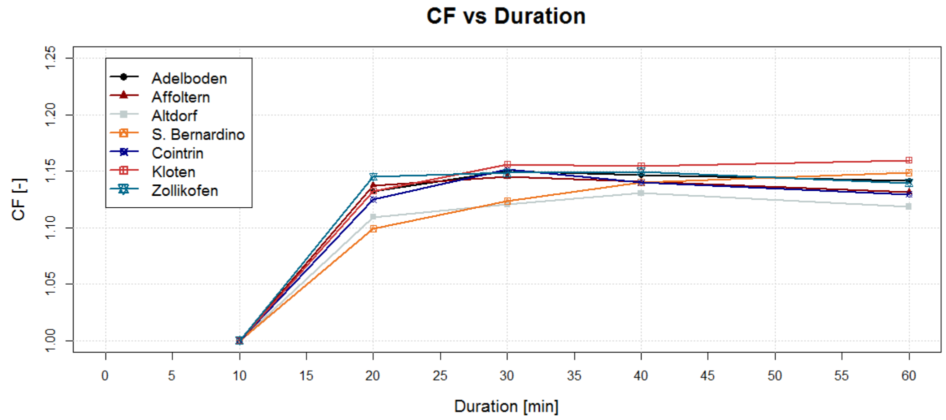

Figure 20: All Swiss station Correction Factors vs Duration for a 5 year return period.

By averaging all the station CFs and all 4 return period considered for the analysis, the following curve, presented in Figure 21, is obtained. The blue shadings such as in the case of the Iowa station CF results, show the uncertainty with respect to the stations, as seen in Figure 20, where the worst and best CF scenarios can be seen.

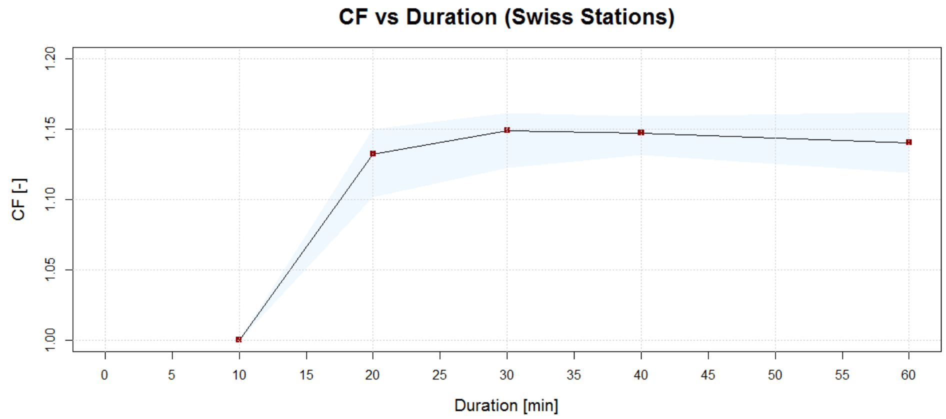

Figure 21: Swiss station Correction Factor vs Duration, averaged from all analyzed return periods.

It can already be seen that for these series, the CF for a 10 minute duration is equal to 1. Which should already be seen as not normal, since by referring to the empirically derived CF for the Iowa stations in Figure 19, we can see that at that duration we already have a CF equal to 1.14, meaning that this data set has more likely already a bias on its measurements. In order to make a fair comparison, the following section will be delving with a tiny experiment done with some Iowa stations, in order to compare if there are any differences between the two data sets with different resolutions.

4.4. Aggregation Test

Iowa data from 3 stations is aggregated from the original 1 minute resolution data to a 10 min resolution one. By choosing only one starting sampling point in time, and recording with a new sampling interval of 10 minutes for the whole time series. Obtaining thus, 3 new 10 minute resolution series, that in this example will be taken as original 10 min resolution data sets.

Those 3 new data sets of now 10 min in resolution, were analyzed as described already before in the Methods section. By firstly, filling in any missing depth value (raw data was the one aggregated), secondly, the storm separation procedure via choosing a dry period and filtering with respect to the total precipitation depth per storm, followed by the POT analysis for DDF curve derivation and finalizing with the bias computation.

The results that were obtained are shown in Figure 22 below, the previous Swiss CF results are also plotted in this graph, and as it can be seen, there is an existing resemblance between both series, the generated one from the Iowa 1 minute stations, and the Swiss data series, which consisted already of originally being a 10 min resolution data set. This would make us thus believe, that there is already a bias in the Swiss measurements, which is around 3% when compared with the CF derived from the Iowa data set. One could even argue that there would be a correction factor of the CF equal to 1.03 for the generated factor using a 10 minute resolution precipitation data.

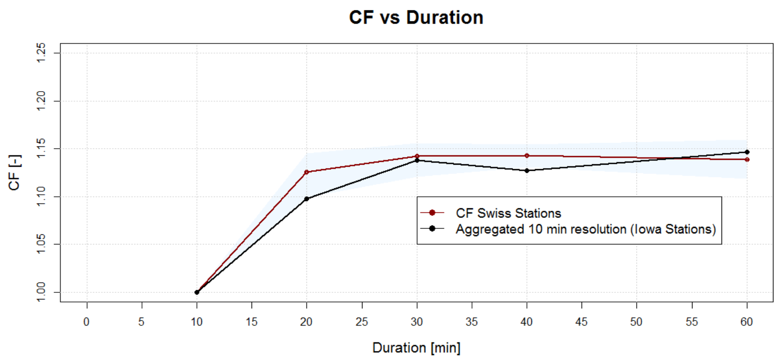

Figure 22: Correction Factor comparison between the generated 10 minute resolution Iowa series and original 10 minute resolution Swiss series. Both series for a 5 year return period.

As seen also bellow, in Figure 23, one can notice this previously mentioned underestimation of around 3% between both empirically derived CFs, where the one corresponding to the Iowa set, displays a higher correction factor needed, whereas that corresponding to the Swiss data set is clearly lower, and in some duration cases, there is an even higher underestimation than the 3% commented before.

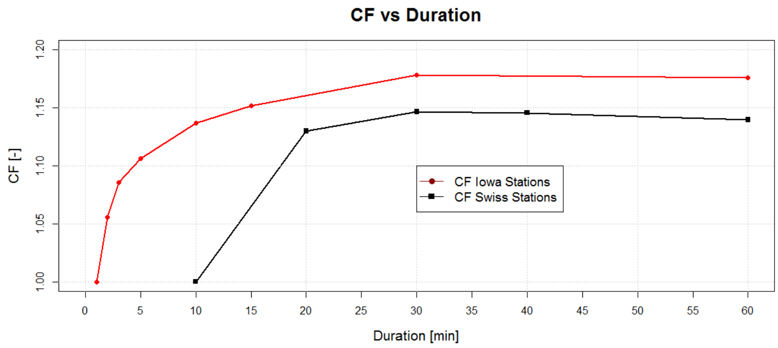

Figure 23: Correction Factor comparison between Iowa and Swiss series, derived from their original data resolutions.

This results, clearly show, that there is already some bias associated in the 10 minute resolution data set. Meaning that if an analysis of this type should be carried out in order to estimate a systematical underestimation due to depth measurements, one should notice that there will be some bias propagation due to coarser sample resolutions.

5. Conclusion

The goal of this project work was that of finding the associated bias existing when measuring precipitation depths. With the use of these findings, an empirical formulation that describes and quantifies the missing precipitation depth due to this measurement underestimation, was computed. This formula, was represented as a correction factor needed to be implemented on a measured maximum precipitation depth for a given duration.

This correction factor, should be considered as a reliable practical tool to correct depth measurements, inasmuch as it was derived by using a fine resolution of 1 minute data (Iowa stations). Not only that but, a comparison was also done using a correction factor derived from a 10 minute resolution data set (Swiss stations), which clearly showed an underestimation when comparing it to the 1 minute data derived correction factor.

In order to prove whether these findings were station specific, an aggregation test, using 1 minute data and aggregating it to a 10 minute resolution data, was also performed. The resulting correction factor from this fabricated 10 minute resolution series, showed similar results to those of the Swiss station correction factor. Meaning that there is indeed a bias that is not taken into consideration, when deriving a correction factor with coarser time resolutions.

The implementation of this factor becomes important depending on the hydraulic structure or flood design that needs to be carried on. Meaning that, for designs were the required volume of precipitation that needs to be used depends on a low return period, and lower durations, the Hershfield Factor of 1.13 is already doing fine, and could not really represent any risks by using a correction factor or not. However, when these design precipitation volumes have a magnitude in which there is a huge depth difference between not correcting the measurements or correcting them, then a correction factor derived with fine data resolution should be definitely implemented.

References

[1] Hershfield, D.M. (1961). Estimating the probable maximum precipitation. ASCE Journal of the Hydraulics Division 87, 99-106

[2] Papalexiou, S. M., Dialynas, Y. G., Grimaldi, S. (2016). Hershfield factor revisited: Correcting annual maximum precipitation. Journal of Hydrology, 542, 884-895. doi:10.1016/j.jhydrol.2016.09.058

[3] Hosking, J. R. M. and Wallis, J. R. (1995). A comparison of unbiased and plotting-position estimators of L moments. Water Resources Research. 31(8), 2019–2025

A. Appendix

A.1. DDF Iowa Stations

Displayed below are the Depth Duration Frequency curves of all true maximum depths from the -Iowa stations for all 4 analyzed return periods.

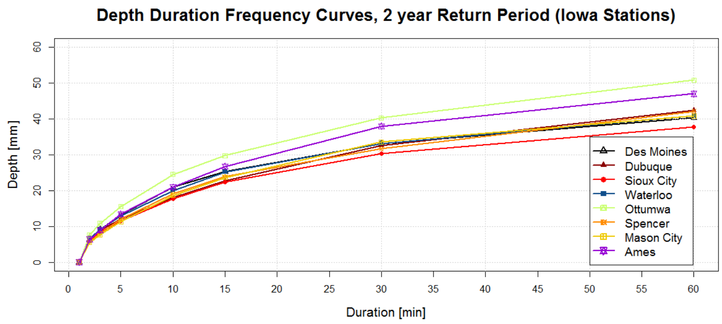

Figure A.1: Depth Duration Frequency curves of a 2 year return period for all analyzed Iowa stations.

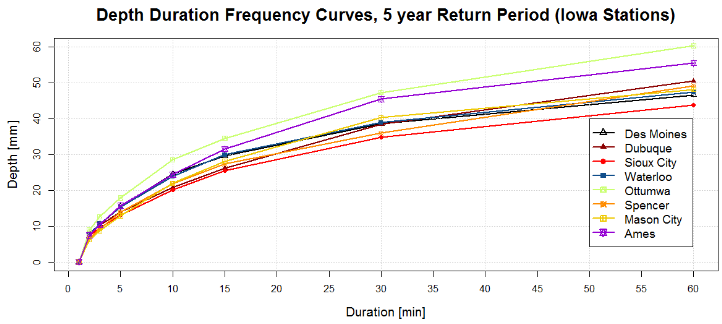

Figure A.2: Depth Duration Frequency curves of a 5 year return period for all analyzed Iowa stations.

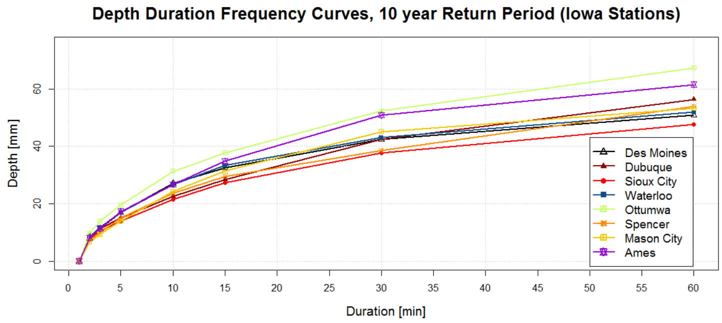

Figure A.3: Depth Duration Frequency curves of a 10 year return period for all analyzed Iowa stations.

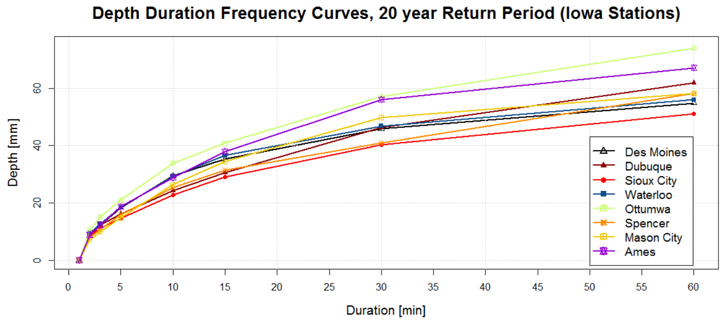

Figure A.4: Depth Duration Frequency curves of a 20 year return period for all analyzed Iowa stations.

A.2. DDF Swiss Stations

Displayed below are the Depth Duration Frequency curves of all true maximum depths from the Swiss stations for all 4 analyzed return periods.

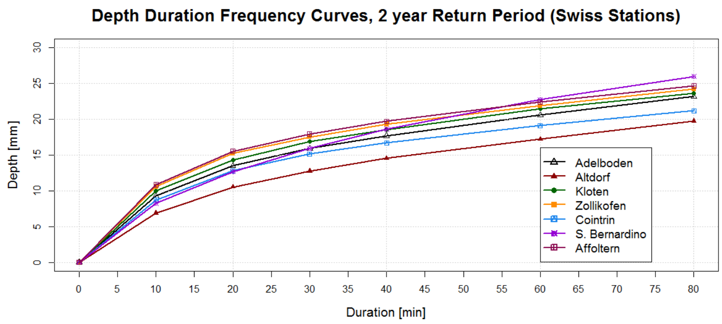

Figure A.5: Depth Duration Frequency curves of a 2 year return period for all analyzed Swiss stations.

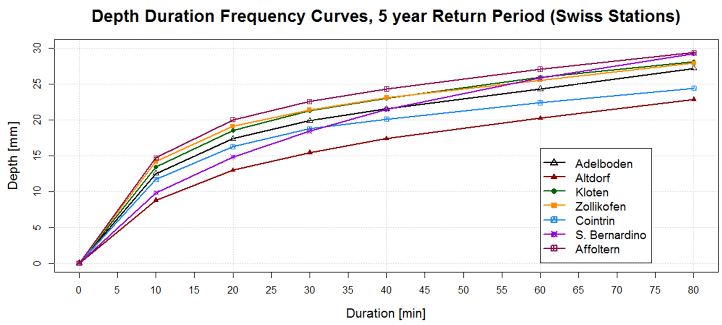

Figure A.6: Depth Duration Frequency curves of a 5 year return period for all analyzed Swiss stations.

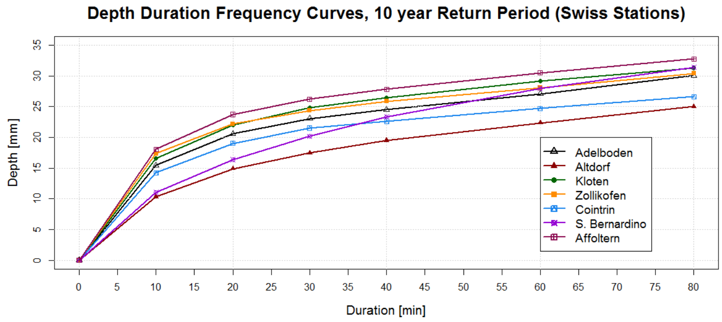

Figure A.7: Depth Duration Frequency curves of a 10 year return period for all analyzed Swiss stations.

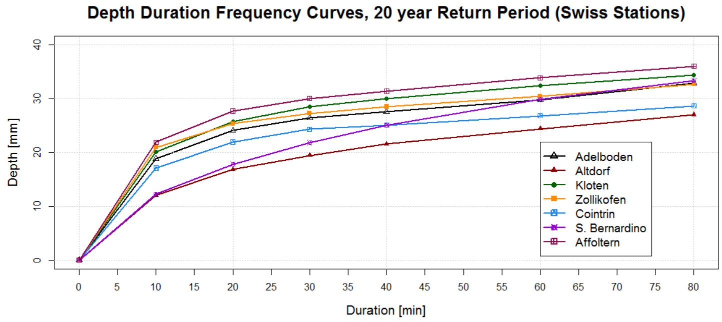

Figure A.8: Depth Duration Frequency curves of a 20 year return period for all analyzed Swiss stations.

A.3. CF Iowa Stations

Displayed below are the Correction Factor vs Duration plots of the Iowa Stations for all analyzed return periods.

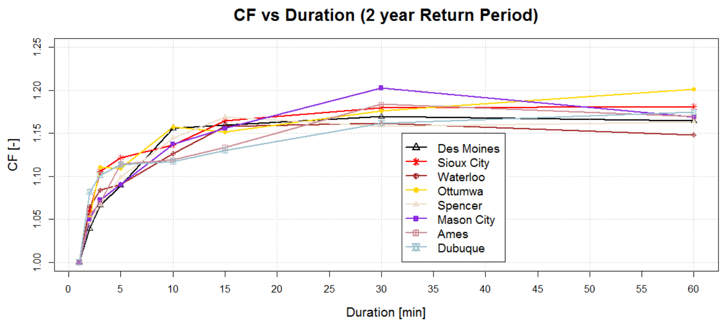

Figure A.9: Correction Factor vs Duration of a 2 year return period for all analyzed Iowa stations.

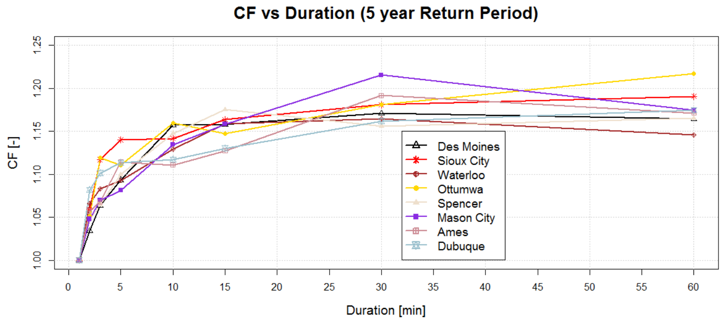

Figure A.10: Correction Factor vs Duration of a 5 year return period for all analyzed Iowa stations.

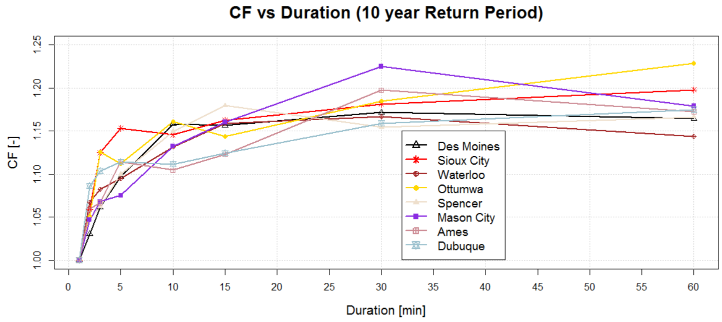

Figure A.11: Correction Factor vs Duration of a 10 year return period for all analyzed Iowa stations.

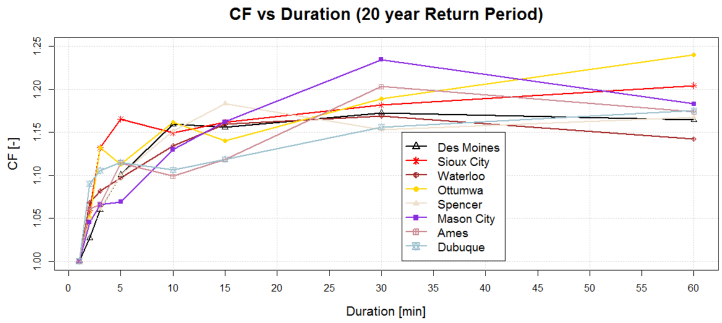

Figure A.12: Correction Factor vs Duration of a 20 year return period for all analyzed Iowa stations.

A.4. CF Swiss Stations

Displayed below are the Correction Factor vs Duration plots of the Swiss Stations for all analyzed return periods.

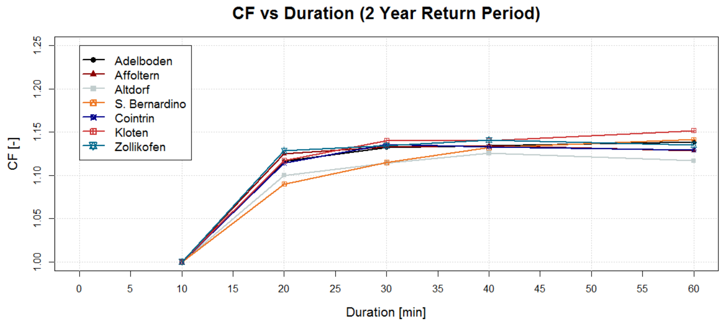

Figure A.13: Correction Factor vs Duration of a 2 year return period for all analyzed Swiss stations.

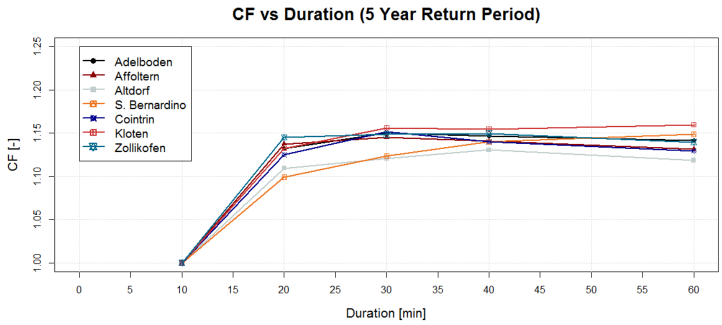

Figure A.14: Correction Factor vs Duration of a 5 year return period for all analyzed Swiss stations.

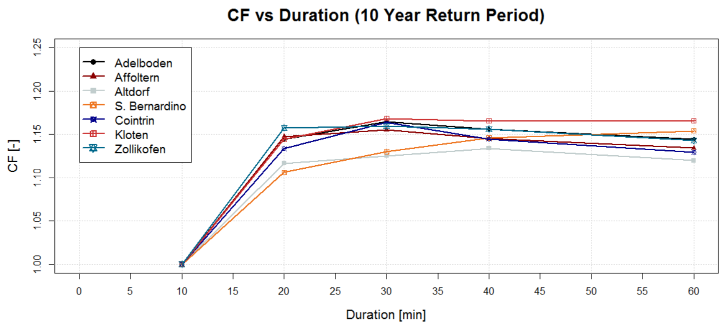

Figure A.15: Correction Factor vs Duration of a 10 year return period for all analyzed Swiss stations.

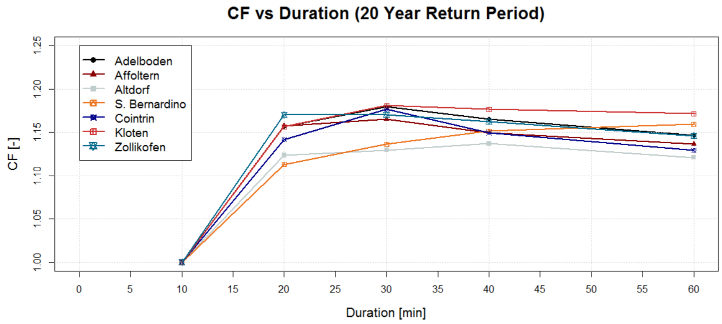

Figure A.16: Correction Factor vs Duration of a 20 year return period for all analyzed Swiss stations.

A.5. Code

`https://github.com/edghyhdz/precipitation_bias`