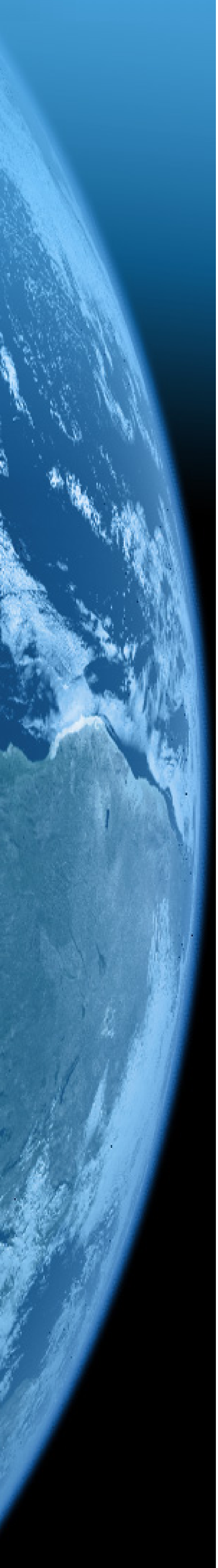

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Weekly Periodicities in Climatology

Master Thesis

February 2008

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Weekly periodicities in climatology

Master Thesis at the Institute for Atmospheric and Climate Science at "Eidgenössische Technische Hochschule" (Federal Institute of Technology) (ETH) (IACETH). This institute is part of the Department of Environmental Sciences (D-UWIS).

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Semester: Autumn 2007

Supervised by IAC Professor Ulrike Lohmann and PhD student Andreas Mühlbauer

Thanks

We cordially thank the follwing persons:

Dominik Auf der Maur (proofreading), Caroline Baumgartner (proofreading), Tracy Ewen (proofreading), Reto Knutti (hints for the autocorrelation in simulations), Bettina Kuster (mental succour), Ulrike Lohmann, Massimo Merlini (statistical hints), David Masson (proofreading), Andreas Mühlbauer, Hans Richner [Richner, 2007], Ariane Ritz (mental succour), Stefan Ritz (proofreading), Claudia Ryser (proofreading), Christoph Schär (6 and 8-day-week), Marc Wüest (handyman)

Date and time of the LaTeX-run: Wednesday 27$^{\text{th}}$ February, 2008 at 15:28

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Chapter 1

Introduction

The Intergovernmental Panel on Climate Change (IPCC) report, 2007 has caused a big interest regarding global climate change in the media, politics and society. Great effort has been undertaken and is still on going to understand the mechanism of climate change and the anthropogenic impact on it [Bäumer and Vogel, 2007].

One approach for a better understanding of the anthropogenic effects on climate could be the analysis of the 7-day-periodicities in meteorological data. Since there is no natural long-term 7-day-cycle known, one can consider the weekly anomalies in meteorological data-sets as human made. A few studies have focused on this topic (section 1.1 on the following page).

One objective of this master thesis is to check if there are similar weekly periodicities in Switzerland as Bäumer and Vogel (2007) found in Germany. Therefore, precipitation, temperature and daily sunshine duration data from several measurement stations are analysed.

Questions to be answered are the following: are there any differences between stations north or south of the Alps? How do these weekly periodicities—if there are any at all—change over time? Is the signal amplitude getting stronger with increasing industrial activity and pollution? Or are these weekly differences just coincidence?

Another focus is given on the weekly regime of Particulate Matter (PM). Bäumer and Vogel (2007) showed that the influence has to be at least on a mesoscale-α (phenomenon with a range of 200–2,000 km across), due to the fact that at mountain stations the weekly periodicity was also found. They suppose that the connection between a microscale to a mesoscale phenomena has to be an indirect aerosol effect.

1.1 Research that has been done on weekly cycles

The research on weekly cycles is not a new issue. Already in the late twenties of the last century Ashworth (1929) analysed the precipitation data from England between 1890 and 1920. He detected that there was 13% less rainfall on Sundays than on the average of all days. It was believed that the weekend reduction of smoke and hot gases from English factories was responsible for the decrease in precipitation. Referring to this, Ashworth (1933) wrote in his Nature article: "In a factory town Sunday is a day of reduced smoke pollution and concurrently Sunday is, in the long run, the day of least rainfall of any day of the week."

In the 1960s, various authors debated whether Tuesdays, Thursdays, or Saturdays, if any day of the week, were the wettest in London, England [Schultz *et al.*, 2007]. But no consensus was reached, in part owing to the different observing stations, time periods, and methodologies employed by these authors, as well as the lack of statistical testing [Schultz *et al.*, 2007].

Later studies on this topic were not less contradictory. The only agreement between the different groups seemed to be a weekly cycle in air pollutants (e. g. PM with less then $10\,\mu$m in aerodynamic diameter (PM_{10}) or ozone).

- Dettwiller (1968) found that the precipitation on weekdays was significantly higher than on weekends in five French cities. 30 years later Bäumer and Vogel (2007) found the contrary in Germany.

- Simmonds and Kaval (1986) found a weekly cycle in Melbourne, Australia, where the precipitation on weekdays was significantly higher than on weekends.

- Gordon (1994) showed through an analysis of satellite microwave sounding data (from the years 1979–1992) a significant but very small weekly temperature cycle for the northern hemisphere.

- Simmonds and Keay (1997) found weekly cycles in temperature and precipitation in Melbourne for the period 1960–1994. They attributed these to local heat emissions.

- Brönimann and Neu (1997) detected weekend-weekday differences in the near-surface ozone concentration depending on the meteorological conditions in Switzerland.

- Cerveny and Balling Jr. (1998) identified weekly cycles of precipitation and tropical cyclone maximum wind speed over the North-West Atlantic region and explained this with the help of an air pollution index that also showed a weekly cycle. Furthermore they detected that the difference of day and night wind speed in tropical cyclones reveals a weekly periodicity.
- Beaney and Gough (2002) found weekend-weekday differences of ozone and temperature in Toronto. As they did not find these difference in the data of a remote station they concluded that it has to be a local phenomenon.
- Marr and Harley (2002) detected weekend-weekday differences of ozone, VOCs and NOx (in 1980–1999) at several stations in California.
- Cerveny and Coakley (2002) identified a weekly cycle of CO_2 at Mauna Loa, Hawaii. However at the South Pole they did not find a 7-day cycle.
- Delene and Ogren (2002) and Jin *et al.* found weekly periodicities of aerosol optical properties at different locations in North-America.
- Beirle *et al.* (2003) analysed satellite data and found significant weekly cycles of tropospheric NO_2 over many industrialised regions.
- Forster and Solomon (2003) detected a weekend effect in the daily temperature range in different regions.
- Tsai (2005) found differences of the visibility and the PM_{10} concentration between weekdays and weekends in Taiwan.
- Shutters (2006) reported weekly cycles of various chemical variables and of wind speed in Phoenix, Arizona.
- Gong *et al.* (2006) found increasing weekly cycles in various meteorological parameters (e. g. temperature and precipitation) in China.
- Bäumer and Vogel (2007) showed that climatological variables in Germany have an unexpected weekly distinction. They chose data from 1991 to 2005 from the "Deutscher Wetterdienst" (German Weather Service) (DWD)

In contrast, other studies found no statistically significant signal between weekday and weekend precipitation. For example:

- Cehak (1982) in Vienna, Austria

- Horsley and Diebolt (1995) in five Midwestern US cities
- De Lisi *et al.* (2001) along the Northeast Corridor
- Wilby and Tomlinson (2000) at 92 stations in the United Kingdom

Schultz *et al.* (2007) state that there is no significant weekly precipitation cycle at all: “Daily precipitation records for 219 surface observing stations in the United States for the 42-year period 1951–1992 are investigated for weekly cycles in precipitation. Results indicate that neither the occurrence nor amount of precipitation significantly depends upon the day of the week.” They confirm the result of De Lisi *et al.* (2001) who did not find a significant weekly precipitation cycle along the Northeast Corridor. They even question the results of a study with the satellite derived precipitation estimates by Cerveny and Balling Jr. (1998) due to “the potential problems in estimating precipitation from Microwave Sounding Unit (MSU) data [Spencer, 1993], as well as questionable causal links between their data sets”.

This thesis is organised as follows: Chapter 2 focuses on a few hypothesised theories, that try to explain how a weekly cycle could come into being. Chapter 3 focuses on the methods applied hereinafter. In Chapter 4 the results will be presented and discussed in Chapter 5. Chapter 6 is reserved for a short conclusion and an outlook.

Chapter 2

Theory

Probably the oldest scientific theory about precipitation manipulation by humans is the inducement of convection. Referring to this Ashworth (1929) writes: "In a confined manufacturing area, such as the town of Rochdale, with a large number of factories burning quantities of coal of the order of 500 to 10,000 tons a day, it is not unlikely that the volume of heated gases which rises is sufficient to give that uplift to the atmosphere which is required to provoke an increase of rain." At that time it was already known that a slight uplift to the air—such as caused by the passage of the wind over a small elevation of the land in a flat country—augments the precipitation. In this context Ashworth (1929) states: "This effect on an uplift to the air may be looked for over a collection of mill chimneys from which a considerable upward current of hot gases issues for a third to a half of the 24 hours." He also assumes that there might be another possible effect which triggers precipitation: "There is also the probability that the fine flue dust ejected by the draught up the chimney may supply an abundance of the nuclei which promote the formation of rain [. . .]."

In cloud physics, the hypothesis—by supplying additional cloud condensation and ice nuclei, pollution downwind from urban centres would increase precipitation occurrence, precipitation amount, or both—has been supported for a long time. Research since the late 1980s, however, suggests that anthropogenic aerosols may decrease precipitation occurrence and amount because pollution particles cause the same amount of cloud water to be distributed among more droplets, hence the droplets are smaller and less likely to grow to precipitation-sized particles. The hypothesised result is that precipitation is less likely to occur [Schultz *et al.*, 2007]. Bäumer and Vogel (2007) conclude: "Since also cloud amount and precipitation are modified in the course of a week, we suppose that the indirect aerosol effects on cloud properties and precipitation play an important role. The prevalent ideas about coherences between an increase in aerosol particle number, an increase in cloud droplets number but a decrease of their radii, and a following decrease of precipitation but longer cloud lifetimes, is not reflected by our results."

Gong *et al.* (2007) hypothesised that the changes in the atmospheric circulation may be triggered by the accumulation of PM_{10} through diabatic heating of the lower troposphere. During the early part of a week the anthropogenic aerosols are gradually accumulated in the lower troposphere. Around midweek, the accumulated aerosols could induce radiative heating, likely destabilising the middle to lower troposphere and generating anomalously vertical air motion and thus resulting in stronger winds. The resulting circulation could promote ventilation to reduce aerosol concentrations in the boundary layer during the later part of the week. Corresponding to this cycle in anthropogenic aerosols, the frequency of precipitation, particularly the light rain events, tends to be suppressed around midweek days through indirect aerosol effects. This is consistent with the observed anthropogenic weather cycles, e. g. more (less) solar radiation near surface, higher (lower) maximum temperature, larger (smaller) diurnal temperature range, and fewer (more) precipitation events in midweek days (on weekends) [Gong *et al.*, 2007].

Not only the amount of aerosols influence the meteorology. It also depends on whether these aerosols can act as Cloud Condensation Nuclei (CCN) and on their size distribution:

- Dusek *et al.* (2006) detected that aerosol size distribution, particularly that of fine aerosols, plays a significant role in the nucleation of cloud particles which is one of the primary mechanisms of indirect aerosol effects. Furthermore they found that the size matters more than chemistry for the cloud-nucleating ability of aerosol particles.

- An experimental study by Yin *et al.* (2000) investigated the effect of giant CCN on the development of precipitation in mixed-phase convective clouds. Their results showed that the strongest effects of introducing giant CCN occur when the background concentration of small nuclei is high, as it is in continental clouds. Under these conditions, the coalescence between water drops is enhanced due to the inclusion of giant CCN. This leads to an early development of large drops in the lower parts of the clouds. In maritime clouds, where the background concentration of small nuclei is low, the effect of the giant CCN is smaller and the development of precipitation is dominated by the droplets formed on large nuclei.

These results show that it is not trivial to determine the important parameters that have to be analysed in the following. Due to the fact that only PM has been analysed systematically over a longer time period and a certain range, the data used for the computations in Results Chapter, Section 4.2 Particulate Matter, on page 19 are PM_{10} and PM with less then $1\,\mu$m in aerodynamic diameter (PM_1).

Chapter 3

Methods

3.1 Data Origin

Switzerland has an automatic meteorological network since 1978. From some stations longer time series are available [ANETZ, 1980; Zellweger, 1983]. All meteorological data are provided by the Federal Office of Meteorology and Climatology (MeteoSwiss). PM is measured by the “Nationales Beobachtungsnetz für Luftfremdstoffe” (National Observation Network for Foreign Air Contaminants) (NABEL) and the data are provided by the “Bundesamt für Umwelt” (Federal Office for the Environment) (BAFU) and the “Eidgenössische Material Prüfungsanstalt” (Material Science & Technology) (Empa).

The data for Germany are available from the DWD.

In this work only daily values are considered which are mostly computed from ten minutes values.

To facilitate the handling, all measured values used in the computations are stored in a database (details in Appendix A on page 65).

3.2 Data Evaluation

Climatological variables have different fluctuations caused by diurnal and seasonal cycles and diverse weather conditions.

For the analysis of a 7-day cycle, it is advisable to filter these cycles, primarily diurnal and seasonal ones. Considering only daily values, the diurnal cycle does not matter anymore.

3.2.1 Running Mean

A simple method to filter out these fluctuations is to compute the deviation to a running mean.

This deviation (δ_d) is computed as follows:

$$\delta_d = v_d - \frac{1}{\Delta} \sum_{i=d-\frac{\Delta-1}{2}}^{d+\frac{\Delta-1}{2}} v_i \tag{3.1}$$

The given measured value at day d is given as v_d, then the mean of the Δ days—which has to be odd—around the day d are subtracted (Equation 3.1). Bäumer and Vogel (2007) set Δ to 31 days.

In GNU R (R) this is realised with the function `gleitendesmittel.R` (Appendix, Section B.1 on page 67). The result is a new time series, which contains the daily deviation from the running mean and is called the “time series of deviation” (δ).

3.2.2 Grouping by weekdays

The “time series of deviation” (δ) can be grouped by weekdays. This gives 7 time series ($\delta_{\text{weekday}_w}$), one for each weekday (Equation 3.2).

$$\begin{aligned}
\delta_{\text{Monday}_w} &= \{\delta_d | d \text{ is Monday}\} \\
\delta_{\text{Tuesday}_w} &= \{\delta_d | d \text{ is Tuesday}\} \\
&\vdots \\
\delta_{\text{Sunday}_w} &= \{\delta_d | d \text{ is Sunday}\}
\end{aligned} \tag{3.2}$$

Calculating the mean of each group provides the deviation for every weekday ($\bar{\delta}_{\text{weekday}}$) (Equation 3.3).

$$\bar{\delta}_{\text{weekday}} = \frac{1}{w_{\text{end}} - w_{\text{begin}} + 1} \sum_{w=w_{\text{begin}}}^{w_{\text{end}}} \delta_{\text{weekday}_w} \tag{3.3}$$

It is also possible to group the measured values directly by weekdays. The result is a distribution in both cases.

3.2.3 Several Stations

There are two possibilities to compute $\bar{\delta}_{\text{weekday}}$ if there are data available from more than one station.

1. Group directly by weekday, as described in 3.2.2 on the preceding page

2. First aggregate the data for each single day and then group them by weekday

The number of the δ_{weekday} is higher in the first case (by a factor of the number of stations).

3.2.4 Plots

If the time dependence is neglected, δ_{weekday} can be considered as a distribution, so it is possible to calculate e. g. the standard deviation and standard error and plot the weekly cycle with errorbars.

3.2.5 Tests

With δ_{weekday} as a distribution it is possible to run a statistical test, e. g. Wilcoxon test one sided, of the maximum mean against the one with the minimum—this corresponds to the amplitude of the weekly cycle. Due to the fact that more than two groups exist (equal to the number of weekdays) an analysis of variance might be more appropriate, e. g., with the Kruskal-Wallis test.

If a time series (δ or v) of a station correlates with another one, they are not independent and therefore to group them directly by weekday (Section 3.2.3 on the facing page item 1) is not correct for the tests mentioned previously. To check whether the time series from the different stations correlate with each other, they can be tested against each other. It is important to test only the filtered time series. In R this can be done with the function `cor.test` and is realised in the program `korrelation.R`, Appendix, Section B.2 on page 68.

Another simple way to compare whether or not there is a weekly cycle, is to assume a 6-day-week and a 8-day-week. To distinguish between the "weeks" the following names for the weekdays are chosen:

6-day-week Jeroboam, Rehoboam, Methuselah, Shalmanazar, Balthazar and Nebuchadnezzar[1]

7-day-week Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday[2]

[1]Names of wine bottles

[2]It is difficult to explain where these names come from

8-day-week Bo, Hamm, Slink, Potato, Woody, Sarge, Etch and Lenny[3]

3.2.6 Periodogram

A periodogram is an estimate of the spectral density of a signal. It allows certain frequencies in a time series to be detected—unless there are any at all. A weekly cycle in the daily measured values provides a peak at the frequency of $\frac{1}{7}$ and at the multiples of it.

3.3 Simulation

Another plausibility check can be done by comparing the results with a random process. Different methods are used to create a random sequence. The target of all these methods is to create a new time series with the same length and the same characteristic as the original one but without a possible weekly cycle. The simulation can be based on the original time series with the measured values or on the "time series of deviation".

3.3.1 Random

There are two ways to create a new absolutely random series with the same length and standard deviation as the original time series.

- A random order of the time series
- A distribution with the same standard deviation and length as the time series

3.3.2 Autocorrelation

The time series has an autocorrelation, because a meteorological measured value often depends on the preceding value. The new time series (a_k) is computed as follows: the first entry is set to the mean of the original time series $\bar{\delta}$. The next entry is then computed from the entry before and a random

[3] Names of Debian releases

part (equation 3.4).

$$
\begin{aligned}
a_1 &= \bar{\delta} \\
a_2 &= a_1 \cdot \varrho + (1-\varrho) \cdot r_1 \\
a_3 &= a_2 \cdot \varrho + (1-\varrho) \cdot r_2 \\
&\vdots \\
a_n &= a_{n-1} \cdot \varrho + (1-\varrho) \cdot r_{n-1}
\end{aligned} \tag{3.4}
$$

r_i is a random number from a distribution with the same standard deviation as the original time series and ϱ is the autocorrelation of it. The autocorrelation ϱ is the estimated measure of association of the time series with itself shifted by one day, which corresponds to one entry. In R this is realised with the function `cor.test` as follows:

```
rho <- cor.test(timeserie[1:(length(timeserie)-1)],
  timeserie[2:(length(timeserie))])$estimate
```

Setting the autocorrelation to a arbitrary value is useful for comparison (e. g. 0 and 0.9).

It is not advisable to do these simulations with the measured values because they have a seasonal cycle.

3.3.3 Take Samples

The time series created in Section 3.3.2 on the preceding page could lack a feature describing the original time series. Another approach is to create a new time series (s_k) with samples from the original time series, which then exhibits the same length as the week. The procedure is shown in Equation 3.5:

$$
\begin{aligned}
&\text{First week of the new time series} && \begin{cases} s_1 = \delta_{r_1+1} \\ s_2 = \delta_{r_1+2} \\ \quad\vdots \\ s_w = \delta_{r_1+w} \end{cases} \\
&\text{Second week of the new time series} && \begin{cases} s_{w+1} = \delta_{r_2+1} \\ s_{w+2} = \delta_{r_2+2} \\ \quad\vdots \\ s_{w+w} = \delta_{r_2+w} \end{cases} \\
&\text{Third week of the new time series} && \begin{cases} s_{2w+1} = \delta_{r_3+1} \\ \quad\vdots \end{cases}
\end{aligned} \tag{3.5}
$$

r_i is a random number between 0 and the length of the time series minus the length of the week and w is the length of the week.

3.3.4 Evaluation

The weekdays are matched to each of these new time series. The first entry in the time series is Monday (Jeroboam or Bo depending on the length of the week) the second Tuesday (Rehoboam or Hamm) and so on.

To receive the amplitude of the average weekly cycle one has to subtract the weekday with the minimum mean value from the one with the maximum mean value. Repetitions of this procedure allow a histogram of the amplitudes to be made.

Storing the mean of each weekday from a few runs allows the simulated weekly cycle to be compared with the original one.

To compare the different tests presented in Section 3.2.5 on page 11, the same procedure as for the amplitude is used with the p-values of each test. Thus one can make a histogram of the p-values.

Chapter 4

Results

4.1 Explanatory Notes to the Results

4.1.1 Fundamental Assumption

First of all—before the results are computed—one has to make sure that the assumption “there is no natural seven-day cycle” is true. Therefore it is appropriate to have a look at the “Witterungslagen nach Schüepp” (‘synoptical weather classification by Schüepp’). This is a classification based only on dynamics. It classifies the weather conditions in 8 main-groups which then subsequently are grouped in 5 subgroups. In this Chapter, for practical reasons, only the 8 main-classes are considered, which are:

- “Hochdrucklage” (high pressure condition) (H)
- “Flache (mittlere) Druckverteilung” (weather conditions with a flat pressure distribution) (F)
- “Tiefdrucklage”(low pressure condition) (T)
- “Westströmung” (west stream) (W)
- “Nordströmung” (north stream) (N)
- “Ostströmung” (east stream) (O)
- “Südströmung” (south stream) (S)
- “Mischlage” (M)

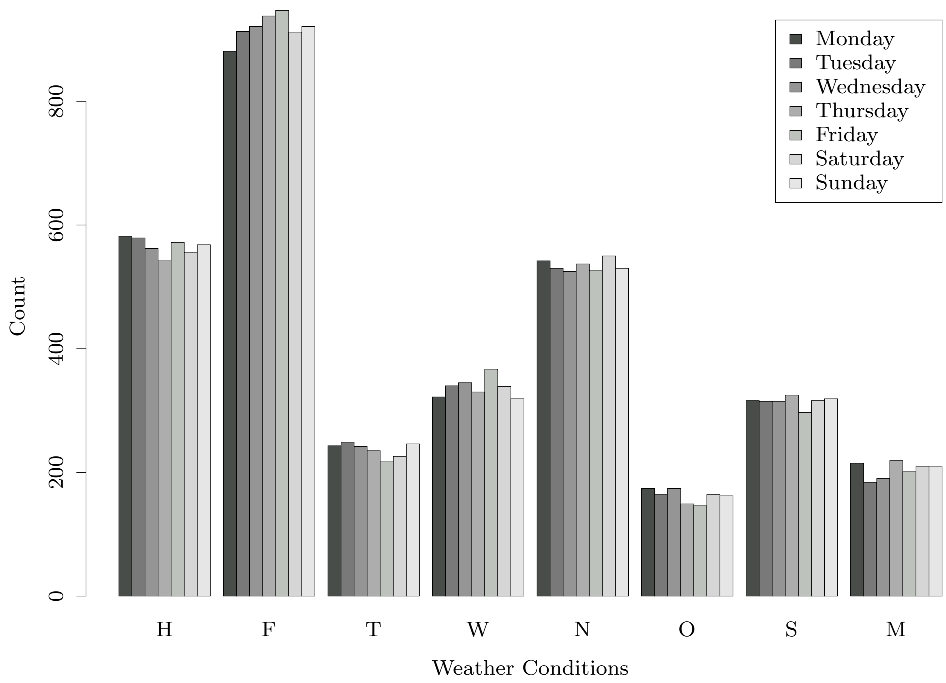


Figure 4.1: Distribution of the different weather conditions (since 1945) per weekday

H, F, T are called 'convective conditions' and W, N, O, S are called 'advective conditions'. They all refer to the situation at the 500 hPa-layer, while M can have either strong winds on the ground or higher up as a jetsteam.

The count of the several "Witterungslagen" per weekday since 1945 shows that there is no dynamical 7-day cycle (Figure 4.1) so that the assumption from above is consequently correct.

4.1.2 Stations and their Aggregation

In the following Chapters the meteorological-data are used from: Bargen (SH), Bière, Binningen, Col du Grand St-Bernard, Egolzwil, Genève, La Brévine, Lugano, Männlichen, Matro, Mosen, Passo del S. Gottardo, Schaffhausen, Schüpfheim, Segl-Maria, Sion, Zollikofen and Zürich (Figure 4.2 on the next page). This 18 CLIMAP-stations provide temperature values since 1864.

The PM_{10} values are derived from NABEL-stations which are located in: Basel, Bern, Lugano and Zürich. The measurements go back to the year 1998. For the sommer 2007 the station Jungfraujoch is also available.

The availability of the PM_1-data is of a shorter time series, namely since

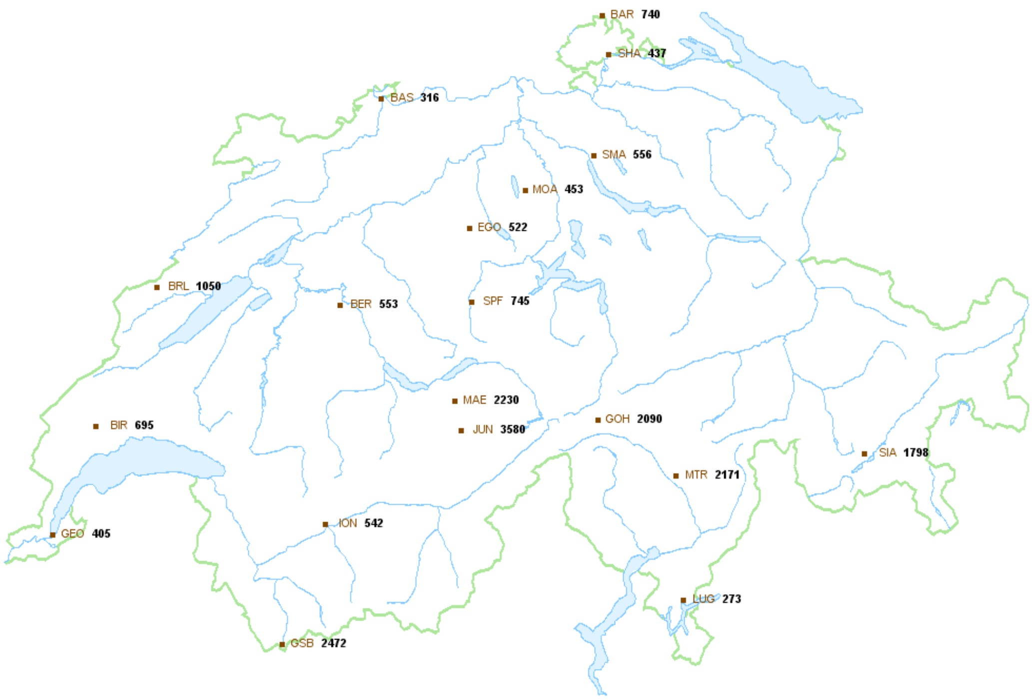
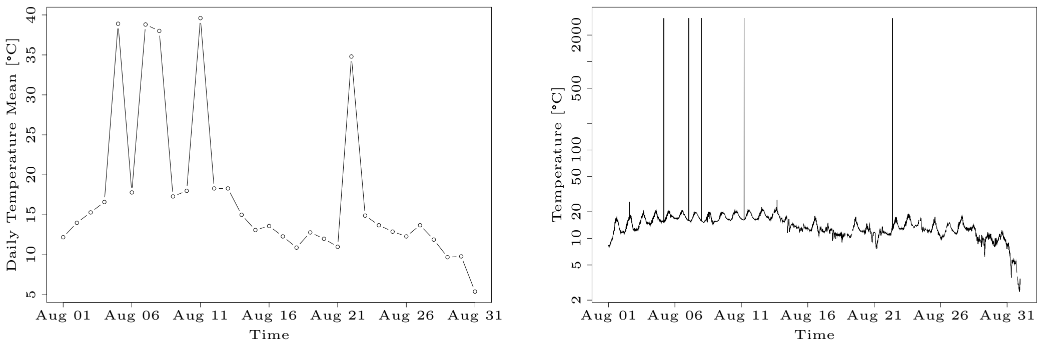


Figure 4.2: Stations with meter above sea level: Bargen (SH) (BAR), Bière (BIR), Binningen (Basel) (BAS), Col du Grand St-Bernard (GSB), Egolzwil (EGO), Genève-Observatoire (GEO), Jungfraujoch (JUN), La Brévine (BRL), Lugano (LUG), Männlichen (MAE), Matro (MTR), Mosen (MOA), Passo del S. Gottardo (GOH), Schaffhausen (SHA), Schüpfheim (SPF), Segl-Maria (SIA), Sion (ION), Zollikofen (Bern) (BER) and Zürich (SMA)



(a) Daily values (b) 10 minutes values

Figure 4.3: Temperature 2 m above ground in August 2003, recorded at Matro.

2003. The geographical coverage is also smaller and consists of only three stations: Basel, Bern and Lugano. Hereinafter the PM_1-values between March 2003 and December 2006 are analysed.

Usually the data of these stations are aggregated and the mean over all stations is used for further calculations. This allows results which reflect the entire area of Switzerland to be generated. This might smooth a possible local weekly course. To be on the safe side—regarding this "aggregation problem"—each of the 18 stations is always considered and also separately tested.

4.1.3 Faults in the Data and Data Handling

All meteorological data are derived from the Java application to get data from MeteoSwiss (CLIMAP). Some of them can not be true. E. g. the temperature series of Matro contains some very high daily temperature values (exceeding 35°C). They are based on wrong 10 minutes values with a temperature of 3108.2°C (Figure 4.3). Therefore all extreme values in precipitation, daily mean temperature, daily minimum and maximum temperature had had to be manually checked for plausibility check: all values that exceed the Swiss all-time record have been dropped and those which are in the range of it have been carefully analysed. Another method to detect wrong values is to look for the outliers in the "time series of deviation".

Even by removing the sparse existing incorrect data, the results do not change significantly. Only in the precipitation results, it does observably diminish the errorbars.

When a station contains more than 20% unavailable data in a considered period, the station drops out automatically for this period.

As long as not stated otherwise, the analysed time series refer to the deviation from the 31-day running mean. This allows, e. g., to make a correlation test between the stations without testing the seasonal cycle. The resulting smaller standard deviation leads to narrower errorbars and the statistical tests reveal better results (due to the filtered time series).

4.2 Particulate Matter

Bäumer and Vogel (2007) hypothesised that the indirect aerosol effect is responsible for weekly cycles in meteorological data. Therefore PM_{10} and PM_1 are analysed first.

4.2.1 General Aspects of Particulate Matter Data

Since there are no PM_{10} values available before 1998, a comparison with earlier periods is not possible. Nevertheless—thanks to the correlation between suspended matter and PM_{10}—there are facilities to convert one into the other. Based on the suspended matter measurements the BAFU computed the PM_{10} values back until 1988. In this longer time series one can recognise a clear decreasing trend over the last 20 years, especially in the cities. The BAFU reckons also that the maximum PM_{10}-pollution was around 1970. For this reason the further analysis of longer meteorological time series (in the following Sections) often consider the period between 1960 and 1990 [BUWAL, 2005].

One assumes that the small particles of the PM_{10}-fraction have more influence on clouds than the bigger ones (Chapter 2 Theory on page 6).

4.2.2 PM_{10}

Figure 4.4 on the next page shows the weekly course of PM_{10}. Data since January 1998 have been evaluated from the five NABEL-stations mentioned before. The range between the maximum on Wednesday and the minimum on Sunday is almost $7\,\mu\mathrm{g\,m^{-3}}$.

The Kruskal-Wallis test over the seven weekdays (on the average over all stations) reveals a significance at very high level with a p-value of $6 \cdot 10^{-29}$. This means that there is a weekly cycle which can hardly be coincidence. In fact every single station shows a highly significant ($\alpha = 0.3\%$) weekly cycle (Table 4.1 on the following page).

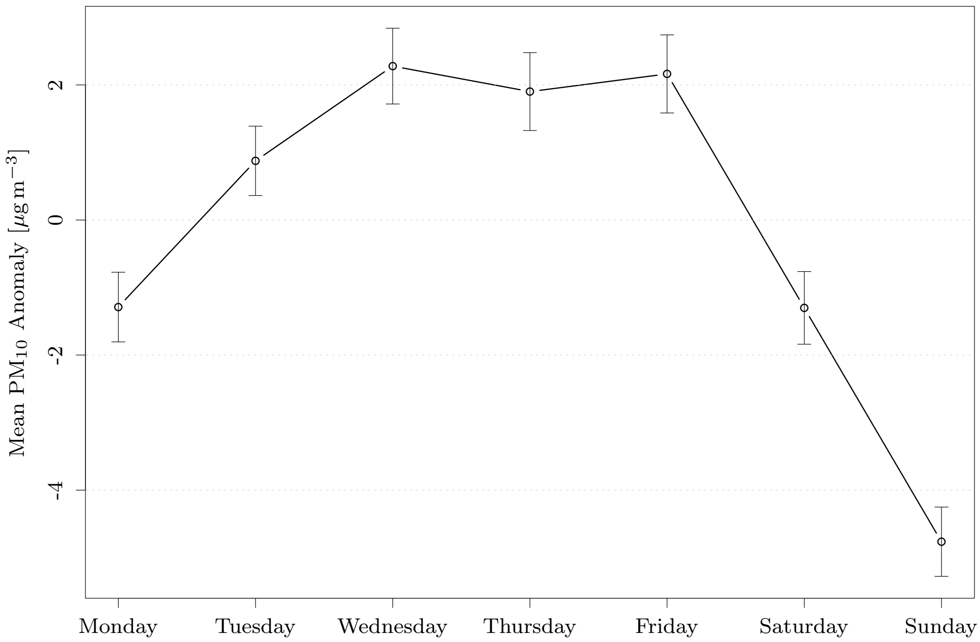


Figure 4.4: Weekly cycle of PM_{10} anomaly averaged over the following stations: Basel, Bern, Lugano, Zürich. Period: 1998-01-01 to 2006-12-31. Errorbars: ± 1 standard error.

Table 4.1: PM_{10}. Period: 1998-01-01 to 2006-12-31. p-values of the Kruskal-Wallistest.

Station	p-value
Basel	$2.30 \cdot 10^{-10}$
Bern	$1.09 \cdot 10^{-66}$
Lugano	$3.98 \cdot 10^{-11}$
Zürich	$1.77 \cdot 10^{-19}$
Average	$6.00 \cdot 10^{-29}$

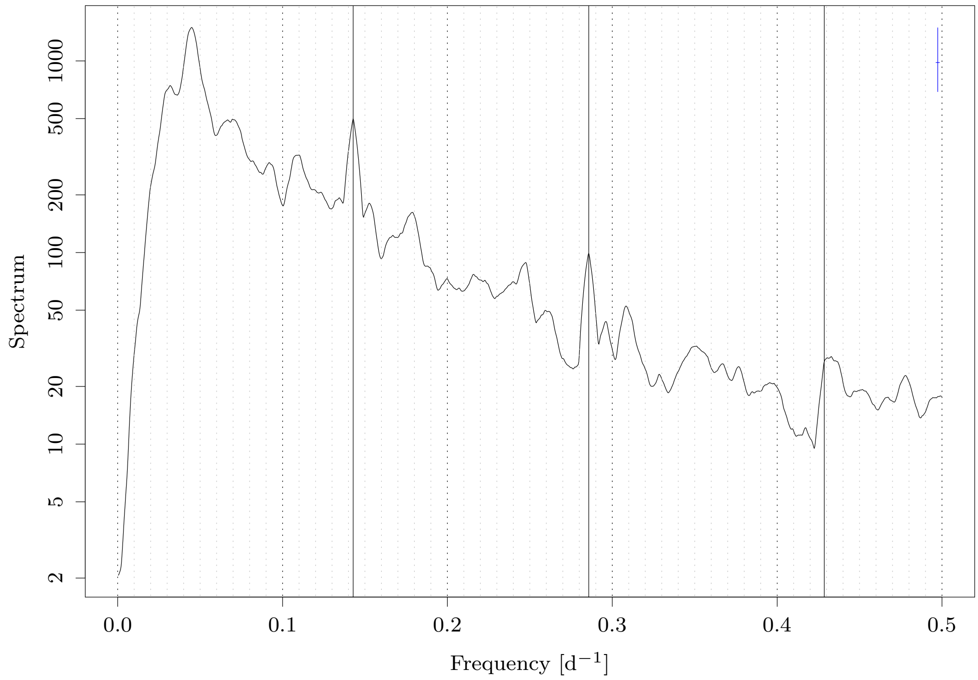


Figure 4.5: Smoothed periodogram of PM_{10}. Bandwidth=0.00243. Period: 1998-01-01 to 2006-12-31.
The first peak is at $\frac{1}{31}\,\mathrm{d}^{-1}$ because smaller frequencies are filtered out through a 31-day running mean.
Peaks at $\frac{1}{7}\,\mathrm{d}^{-1}$ and the multiples of it point to a 7-day cycle in PM_{10}.
"The cross emblem in the upper right corner of the plot represents the bandwidth of the smoother (cross-piece) and the upper and lower bounds of a pointwise 95% confidence interval for the spectral density about the plotted curve (vertical line of the cross)" [Smith, 1999, page 49].

The Fourier Analysis on the time series of the PM_{10} deviation from the running mean provides a periodogram which yields a clear peak at $\frac{1}{7}\,\mathrm{d}^{-1}$ and the multiples of it (vertical black lines in Figure 4.5) that in turn marks the 7-day cycle.

Assuming a 6 or an 8-day-week the amplitudes become at least 3 times smaller. The range for an 8-day-week is almost $1.9\,\mu\mathrm{g\,m}^{-3}$ while for a 6-day-week it is only around $1.1\,\mu\mathrm{g\,m}^{-3}$ (Figure 4.6 on the following page).

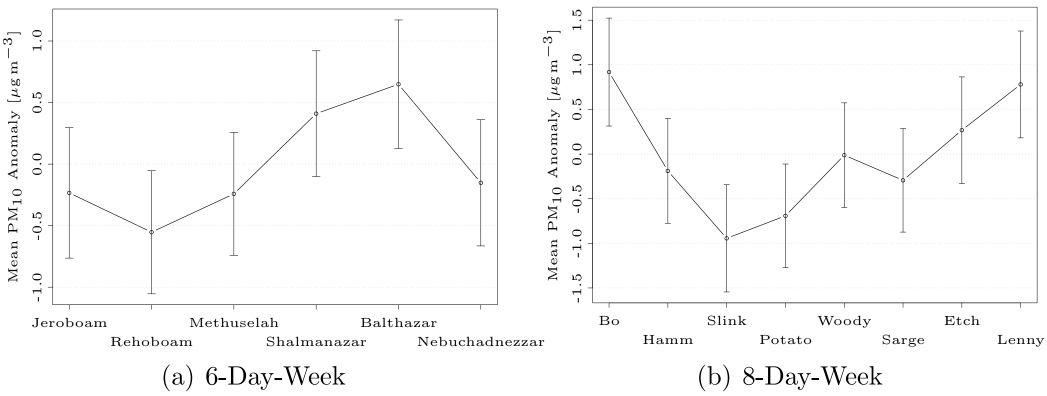


Figure 4.6: Weekly cycle of PM_{10} anomaly averaged over the following stations: Basel, Bern, Lugano, Zürich. Period: 1998-01-01 to 2006-12-31. Errorbars: ±1 standard error. Note that the range of the ordinate varies.

4.2.3 PM_1

The weekly course of PM_1 has an amplitude of about 2.9 $\mu g\,m^{-3}$. Applying the Kruskal-Wallis test on it, reveals a high significance ($\alpha = 0.3\%$) with a p-value of 2.165e-06. The minimum falls on Sunday. From then on there is a constant ascent to the maximum on Friday (Figure 4.7(a) on the next page).

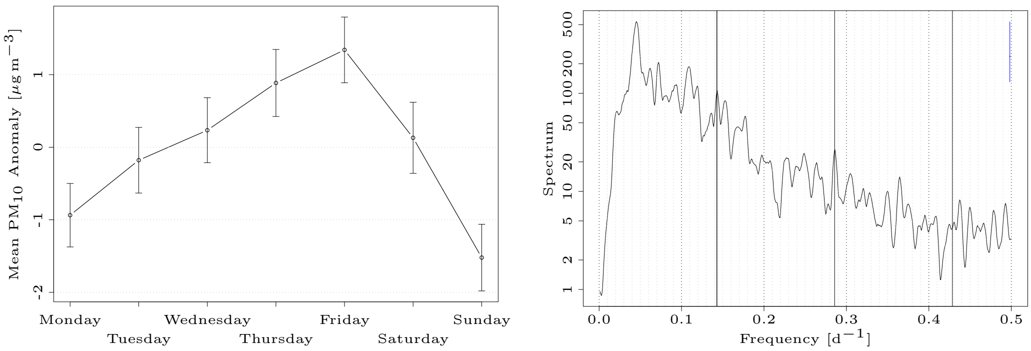
The Fourier Analysis on the PM_1-values (Figure 4.7(b) on the facing page) provides a periodogram which yields a clear peak at $\frac{1}{7}\,d^{-1}$ and the multiples of it. This underlines the result from the Kruskal-Wallis test, which show that the PM_1 weekly course is statistically significant.

The analysis of this result, by assuming a 6 and an 8-day-week (and by doing preceding procedure again), reveals apparent smaller amplitudes as for the regular week. For a 6-day-week it is about $1.1\,\mu g\,m^{-3}$ and for the 8-day-week it is $0.7\,\mu g\,m^{-3}$. In both cases the Kruskal-Wallis test reveals no significance: neither for the shortened week (p-value is 0.64) nor for the extended week (p-value is 0.92)

4.3 Temperature

4.3.1 Temperature Anomaly for the Time Period between 1992 and 2007

The analysis of the temperature anomaly for the 15 years from 1992 to 2007 reveals no significance: even if there is a small amplitude of 0.15 K



(a) Weekly cycle of PM_1 anomaly. Errorbars ± 1 standard error.

(b) Smoothed Periodogram with bandwidth=0.00176.

Figure 4.7: PM_1 for following stations: Basel, Bern, Lugano. Period: 2003-01-01 to 2006-12-31

between the maximum on Wednesday and the minimum on Sunday (Figure 4.8 on the next page), the Kruskal-Wallis test reveals a p-value of 0.805 which means that this weekly course is not significant. Even when applying this test to each of the 18 stations, none provides a significant weekly cycle in temperature—not even at the 10% level, all p-values are greater then 0.1. This result can be confirmed by applying the “6-8-week-day-test” and with several simulations (Section 4.10 on page 44).

Examining the periodogram of the temperature deviation (Figure 4.9 on page 25) no peak can be detected at $\frac{1}{7}\,\mathrm{d}^{-1}$ and its multiples. Therefore it seems to be quite coincidental to assume a 7-day-cycle in temperature.

4.3.2 Temperature Anomaly since 1865

Considering the plots since 1865 (Figure 4.10 on page 26) one can not recognise a clear weekly trend which lasts for more than 30 years. The amplitudes however are—during the considered 140 years—more or less around 0.12 K.

4.3.3 Temperature Anomaly for a 30 Year Time Period starting at 1960

Considering the time period with the highest PM_{10} air pollution (Section 4.2 on page 19) the weekly course reveals a maximum on Monday and a minimum on Sunday. The amplitude between the two is 0.07 K. It is remarkable that, by doubling the considered time period, the amplitude almost bisects (Table 4.2 on the following page).

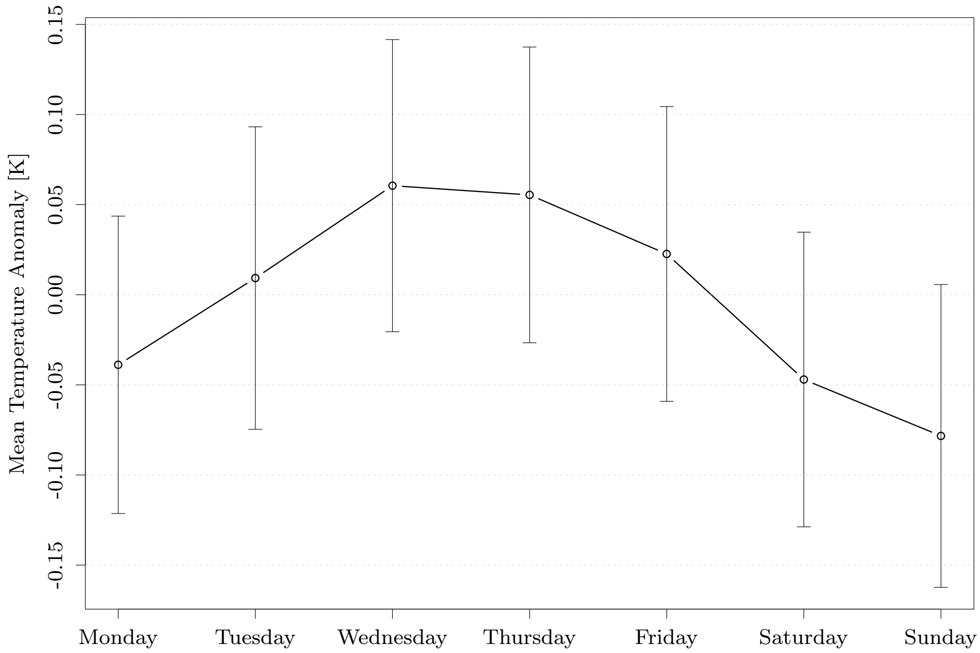


Figure 4.8: Weekly cycle of temperature (2 m above ground) anomaly averaged over all stations. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error.

Table 4.2: Amplitudes of weekly temperature anomalies. 15 vs. 30 year periods

15 years	amplitude	amplitude	30 years
1872–1886	0.132	0.12	1870–1899
1887–1901	0.218		
1902–1916	0.113	0.02	1900–1929
1917–1931	0.098		
1932–1946	0.103	0.07	1930–1959
1947–1961	0.102		
1962–1976	0.141	0.07	1960–1989
1977–1991	0.055		
1992–2006	0.139		
average	0.122	0.072	average

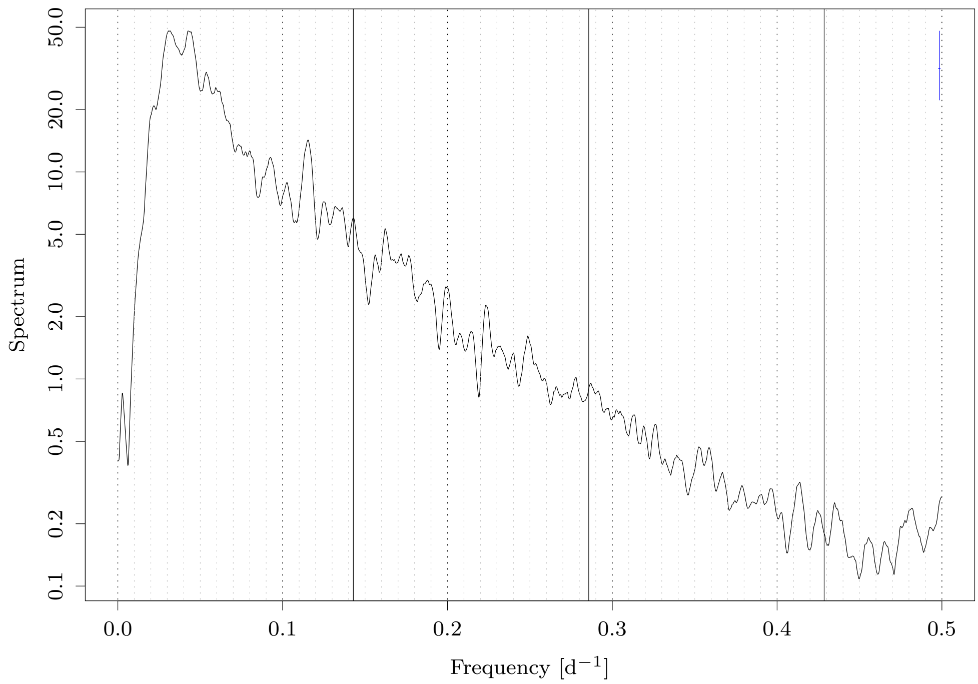
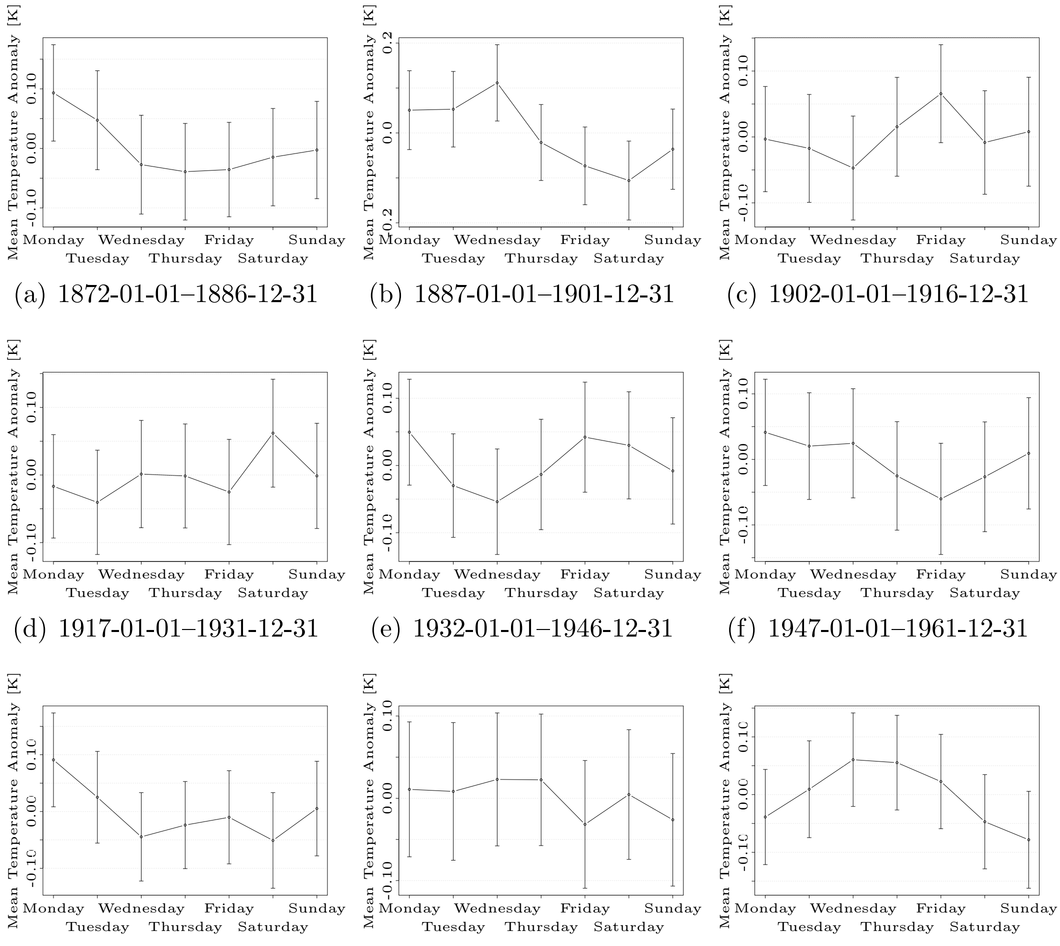


Figure 4.9: Smoothed periodogram of temperature (2 m above ground). Bandwidth=0.00146. Period: 1992-01-01 to 2006-12-31
The high peak at $\frac{1}{31}\,\mathrm{d}^{-1}$ is because smaller frequencies are filtered out through a 31-day running mean. The very first peak at $\frac{1}{365}\,\mathrm{d}^{-1} \approx 0.003\,\mathrm{d}^{-1}$ reflects the not perfectly filtered seasonal cycle.
No peak can be detected at $\frac{1}{7}\,\mathrm{d}^{-1}$ and its multiples.
"The cross emblem in the upper right corner of the plot represents the bandwidth of the smoother (cross-piece) and the upper and lower bounds of a pointwise 95% confidence interval for the spectral density about the plotted curve (vertical line of the cross)" [Smith, 1999, page 49].



(a) 1872-01-01–1886-12-31 (b) 1887-01-01–1901-12-31 (c) 1902-01-01–1916-12-31

(d) 1917-01-01–1931-12-31 (e) 1932-01-01–1946-12-31 (f) 1947-01-01–1961-12-31

(g) 1962-01-01–1976-12-31 (h) 1977-01-01–1991-12-31 (i) 1992-01-01–2006-12-31

Figure 4.10: Weekly cycles of temperature anomaly since 1865 in 15 year time steps. Average over all stations. Errorbars: ±1 standard error. Note that the range of the ordinate varies from period to period.

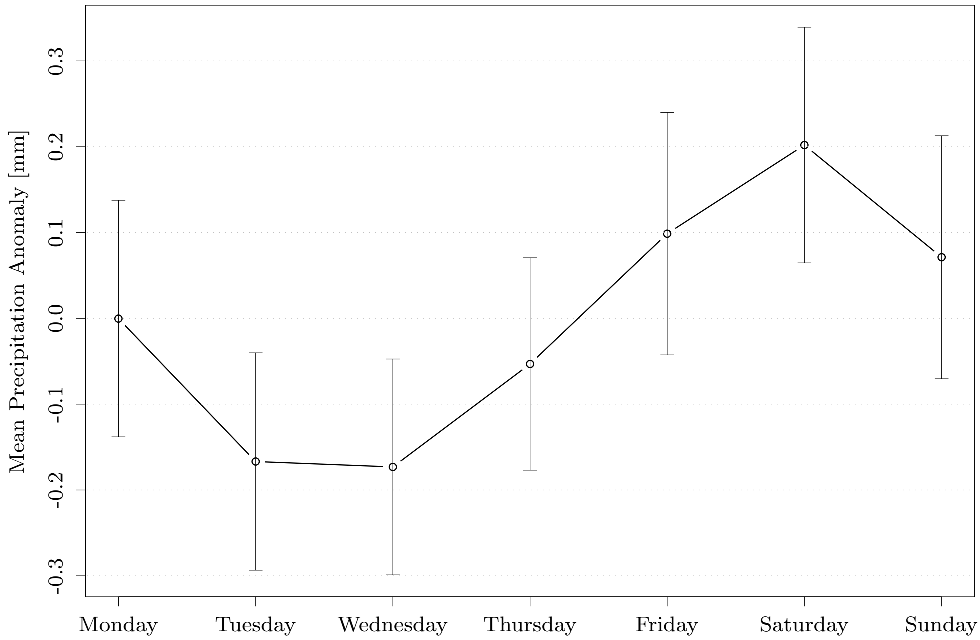


Figure 4.11: Weekly cycle of daily precipitation (5:40 to 5:40 UTC) anomaly averaged over all stations. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error.

4.4 Precipitation

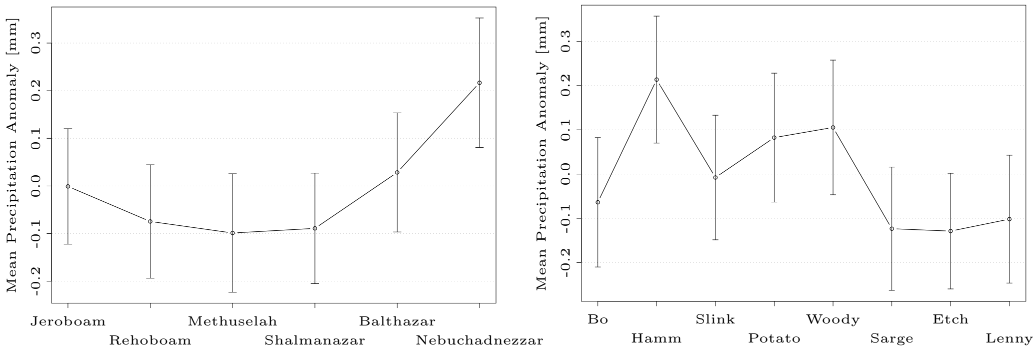
The weekly course in the mean precipitation anomaly reveals a minimum on Wednesday and a maximum on Saturday which leads to an amplitude of more than 4 mm (Figure 4.11). According to the errorbars one could assume that this cycle could be significant: the errorbars of Wednesday and those of Sunday do not overlap. But the Kruskal-Wallis test reveals another result: the aberrations from the medians are not significant.

The second test—with the assumed 6 and 8-day-weeks—reveals similar amplitudes as the regular week and the errorbars of the maximum and the minimum do not overlap either (Figure 4.12 on the following page).

Moreover with an appropriate model one can point out that such a weekly course—with an amplitude in the same range—can simply be simulated (Section 4.10 on page 44).

4.4.1 Precipitation in the Past for 15 Year Time Series

Going back into the past—in 15 year time steps—the maximum and the minimum seem to vary arbitrarily. The weekly anomaly range in precipita-



(a) 6-Day-Week (b) 8-Day-Week

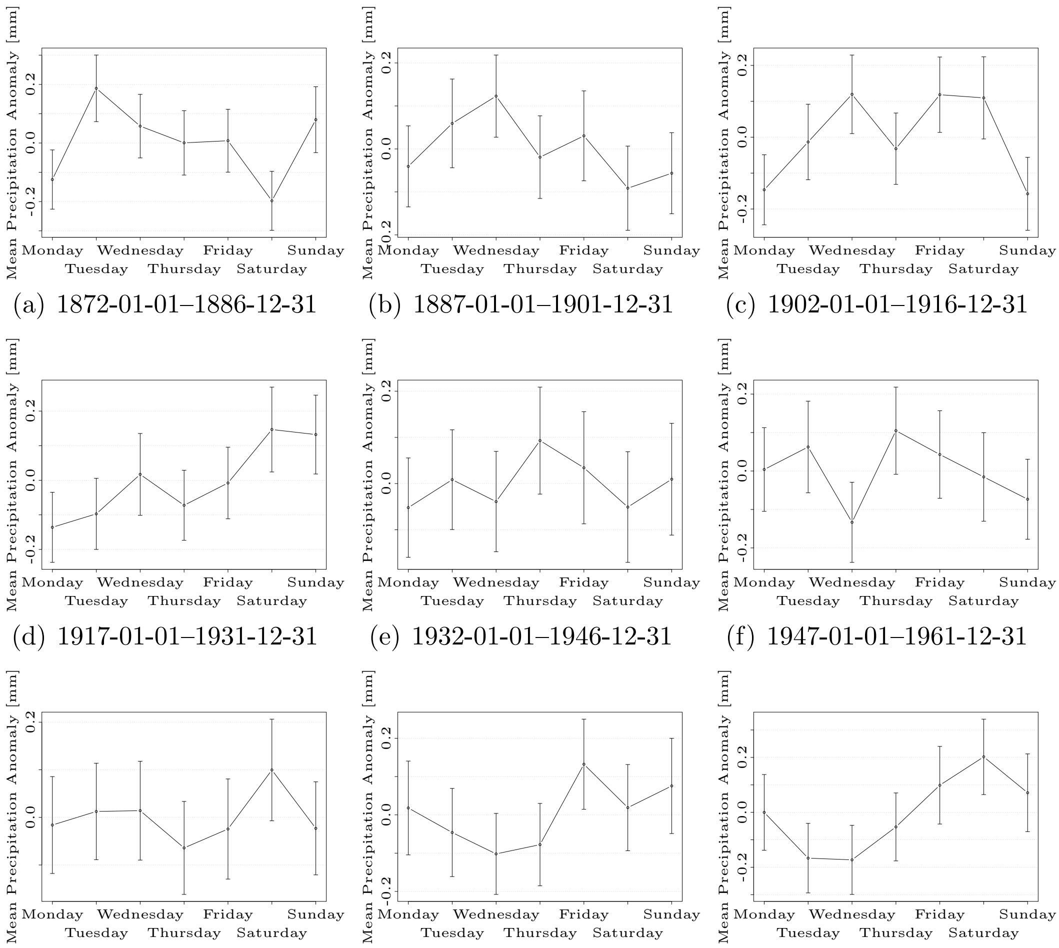
Figure 4.12: Weekly cycles of daily precipitation (5:40 to 5:40 UTC) anomaly averaged over all stations for different lengths of weeks. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error. Note that the range of the ordinate varies.

tion between 1992 and 2006 is almost 0.4 mm. Compared to the past this is remarkably high. Only in the period between 1872 and 1886 does the amplitude yield a similar range (Figure 4.13 on the facing page).

Nevertheless the Kruskal-Wallis test does not reveal a significance for the average over all stations nor for a single one. This applies to all analysed time periods (Table 4.3 on page 30).

4.4.2 Precipitation for Time Series of 30 Years

The analysis of 30 year time series does not reveal large differences compared to those of 15 years. Every timestep provides a graph with a divers look. The one between 1960 and 1990—which corresponds to the time period with the highest PM_{10} pollution—has an amplidude of a little bit more than 1 mm (Figure 4.14 on page 31). All errorbars overlap with each other and the Kruskal-Wallis test does not reveal a significance. Compared to the 6 and 8-day-week the amplitudes are all in the same range—around 1 mm: the amplitude of the 8-day-week exceeds the regular one while the 6-day-week does not.



(a) 1872-01-01–1886-12-31 (b) 1887-01-01–1901-12-31 (c) 1902-01-01–1916-12-31

(d) 1917-01-01–1931-12-31 (e) 1932-01-01–1946-12-31 (f) 1947-01-01–1961-12-31

(g) 1962-01-01–1976-12-31 (h) 1977-01-01–1991-12-31 (i) 1992-01-01–2006-12-31

Figure 4.13: Weekly cycles of precipitation anomaly averaged over all stations since 1872 in 15 year time steps. Errorbars: ±1 standard error. Note that the range of the ordinate varies from period to period.

Table 4.3: p-values of the Kruskal-Wallis test on precipitation anomaly. The values are separated by time periods and stations

Periods Stations	1872– 1886	1887– 1901	1902– 1916	1917– 1931	1932– 1946	1947– 1961	1962– 1976	1977– 1991	1992– 2006
Bargen (SH)	0.64	0.41	0.98	0.55	0.92	0.69	0.9	0.41	0.26
Binningen	0.45	0.12	0.78	0.49	0.83	0.85	1	0.99	0.82
Col du Grand St-Bernard	0.54	0.32	0.56	0.49	0.43	0.83	0.87	0.55	0.82
Egolzwil	0.93	0.34	0.78	0.99	0.91	0.91	0.53	0.5	0.93
Genève	0.61	0.22	0.41	0.4	0.84	0.56			
La Brévine	0.89	0.79	0.86	0.91	0.95	0.67	0.85	0.68	0.44
Lugano	0.97	0.22	0.88	0.14	0.77	0.65	0.97	0.79	0.7
Matro		0.72	0.25	0.56	0.76	0.73	0.57	0.8	
Mosen		0.21	0.82	0.73	0.68	0.94	0.52	0.99	0.25
Männlichen	0.99	0.65	0.9	0.87	0.83	0.68	0.3	0.74	0.45
Passo del S. Gottardo			0.35	0.54	0.56	0.81			
Schaffhausen			0.79	0.67	0.89	0.63	0.97	1	0.5
Schüpfheim	0.78	0.97	0.96	0.99	0.71	0.88	0.32	0.84	0.65
Segl-Maria	0.35	0.65	0.91	0.72	0.89	0.67	0.69	0.79	0.68
Zollikofen	0.18	0.37	0.95	0.97	0.17	0.97	1	0.93	0.76
Zürich	0.14	0.54	0.91	0.41	0.91	0.44	0.7	0.99	0.58
Average over stations	0.37	0.41	0.4	0.83	0.74	0.8	0.99	0.81	0.34

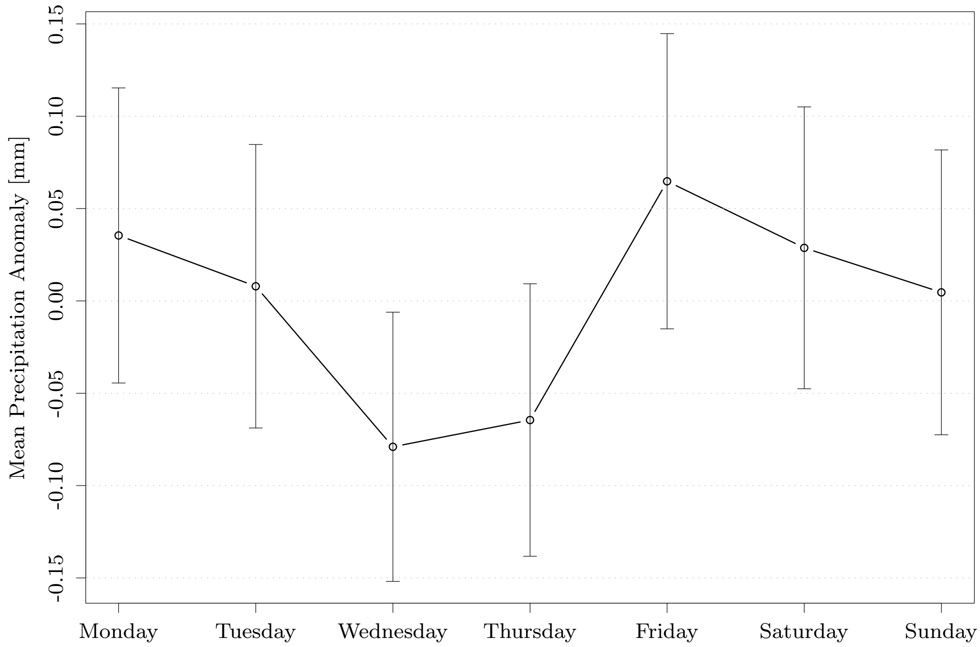


Figure 4.14: Weekly cycle of daily precipitation (5:40 to 5:40 UTC) anomaly over 30 years, averaged over all stations. Period: 1960-01-01 to 1989-12-31. Errorbars: ±1 standard error.

Table 4.4: Daily temperature range ($T_{\max} - T_{\min}$) anomalies. Amplitudes and p-values of the Kruskal-Wallis test in 15 year time steps.

Period	Amplitude [K]	p-value
1932-1946	0.144	0.389
1947-1961	0.167	0.127
1962-1976	0.134	0.832
1977-1991	0.132	0.621
1992-2006	0.094	0.933

4.5 Daily Temperature Range

4.5.1 15 Year Steps

The weekly cycle of the temperature range ($T_{\max} - T_{\min}$) between 1992-01-01 and 2006-12-31 reveals an amplitude of 0.094 K. The maximum is on Friday and the minimum on Sunday. Table 4.4 shows the p-values of the Kruskal-Wallis test and compares the amplitudes between the different time periods. The latter seem to get smaller with time. But due to the fact that none of the periods analysed provide a statistically significant weekly course, this change over time can just be arbitrary as well.

The test with the 6 and the 8-day-week unveil vaguely the same amplitudes as the regular week.

4.5.2 30 Year Steps

Looking backwards—in 30 year steps—reveals that there has never been a significant weekly cycle in temperature range in Switzerland since 1887. This applies both to the average over all stations and to every single station except Bargen (between 1947 and 1976). The latter reveals—in the indicated time period—a p-value of 0.030, which is indeed significant ($\alpha = 5\%$) but not highly significant ($\alpha = 0.03\%$).

The amplitude comparison between the 6, 7 and 8-day-weeks shows that the regular week does not yield higher amplitudes than the 6 and 8-day-week—this holds in the past as well as to date (Table 4.5 on the facing page).

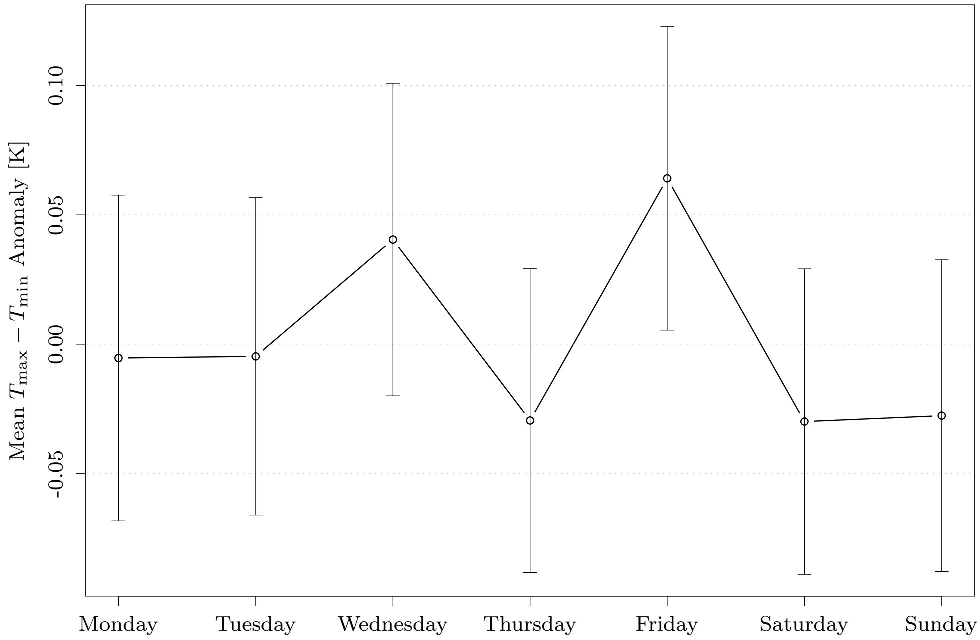


Figure 4.15: Weekly cycle of daily temperature range ($T_{\max} - T_{\min}$) anomaly averaged over all stations. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error.

Table 4.5: Daily temperature range ($T_{\max} - T_{\min}$) anomalies. Amplitudes for a 6, 7 and 8-day-week in 30 year time steps.

	Amplitude [K]		
Period	6-day-week	7-day-week	8-day-week
1887–1916	0.076	0.089	0.033
1917–1946	0.066	0.086	0.114
1947–1976	0.051	0.152	0.074
1977–2006	0.075	0.065	0.181

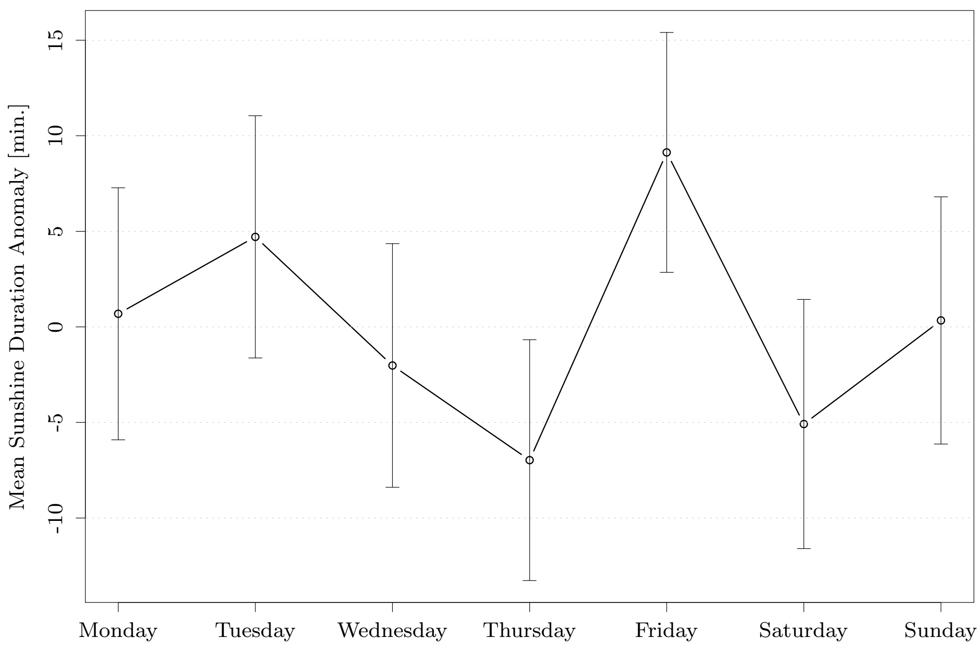


Figure 4.16: Weekly cycle of daily sunshine duration anomaly averaged over all stations. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error.

Table 4.6: Daily sunshine duration anomalies. Amplitudes and p-values of the Kruskal-Wallis test for a 6, 7 and 8-day-week. Period: 1992-01-01 to 2006-12-31

parameter	6-day-week	7-day-week	8-day-week
Amplitude [minute]	10.65	16.1	20.66
p-value	0.85	0.49	0.29

4.6 Sunshine Duration

Considering the period between 1992 and 2007, Friday was the day with the highest sunshine duration while Thursday had the lowest. The mean difference is 16.1 minutes. (Figure 4.16)

The Kruskal-Wallis test implies no significance for this cycle. The same is true for the test with the shortened and extended weeks: the amplitudes are of the same range as for the normal week (Table 4.6). A look into the past and applying “6-8-week-day-test” shows that an amplitude of this range is absolutely normal and therefore could easily be random.

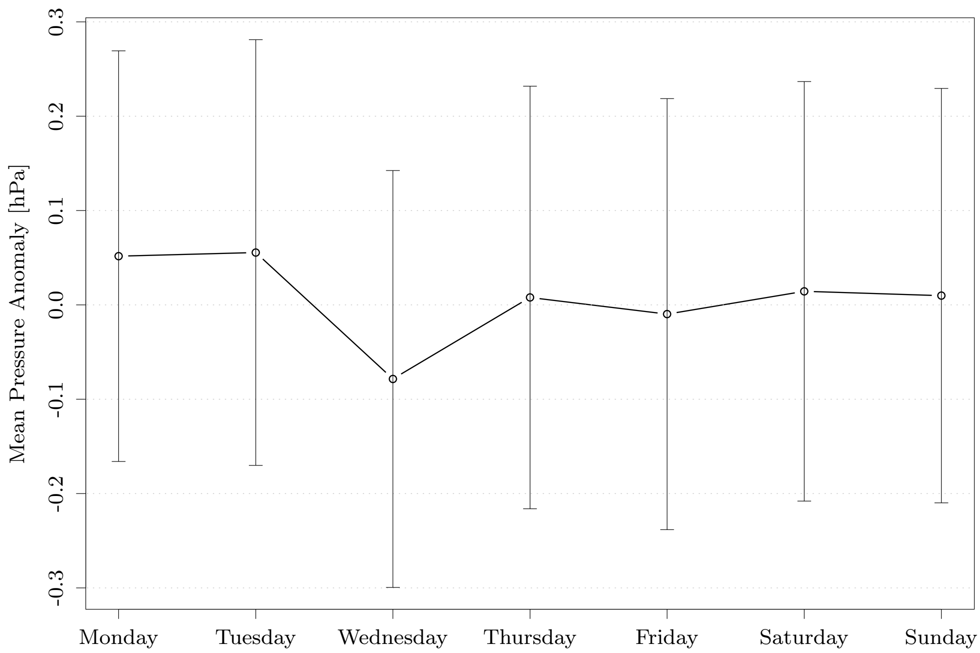


Figure 4.17: Weekly cycle of pressure anomaly averaged over all stations. Period: 1992-01-01 to 2006-12-31. Errorbars: ±1 standard error.

4.7 Pressure

The weekly pressure course has an amplitude of 0.134 hPa (Figure 4.17). As Figure 4.1 on page 16 at the beginning of this Chapter permits to assume, the pressure cycle is not significant. The Kruskal-Wallis test results in a p-value of 0.99 and the 6 and 8-day-week cycles deliver 5 times higher amplitudes than the regular week, namely almost 0.7 hPa. In this respect it would be more justified to assume a 6 or 8-day periodicity than a 7-day cycle.

4.8 Four Seasons

Considering the weekly temperature and precipitation anomalies for each season (Spring, Summer, Autumn, Winter), no significant cycle can be detected either. This can be verified by the application of a Kruskal-Wallis test (p-values for precipitation in Table 4.7 on the next page).

Figure 4.18 on page 37 shows the precipitation anomaly per season, for the period between 1960 and 1990. The comparison of the plots visualises, that the maximum and minimum change rather coincidentally among the seasons while the weekly range remains approximately the same. The weekly range

Table 4.7: Daily precipitation anomalies. p-values of the Kruskal-Wallis test since 1870 in 30 year steps by season.

	p-values			
Periods	Spring	Summer	Autumn	Winter
1870-01-01–1899-12-31	0.127	0.164	0.992	0.243
1900-01-01–1929-12-31	0.900	0.351	0.501	0.836
1930-01-01–1959-12-31	0.625	0.990	0.514	0.773
1960-01-01–1989-12-31	0.961	0.831	0.992	0.505

Table 4.8: PM_{10}. p-values of the Kruskal-Wallis test by season. Period: 1998-01-01 to 2006-12-31

Season	p-value
Spring	$2.41 \cdot 10^{-12}$
Summer	$1.51 \cdot 10^{-06}$
Autumn	$8.32 \cdot 10^{-07}$
Winter	$8.05 \cdot 10^{-04}$

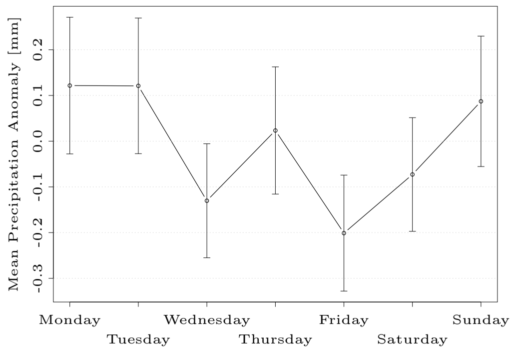
varies is between 0.27 an 0.34 mm which is distinctly higher than the average over all seasons together. However the dataset is four times smaller. Compared to the amplitudes of the 15 year periods they are nothing particular.

PM_{10} reveals a significant weekly cycle for each season (Table 4.8).

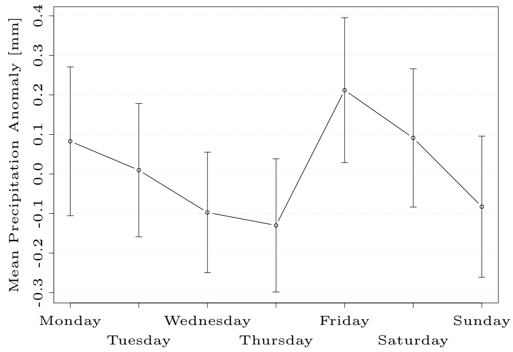
The amplitudes however vary sizeably between 4.78 μg m^{-3} for summers and 9.20 μg m^{-3} for springs (Figure 4.19 on page 38). It is remarkable that in summer, while PM_{10} reveals its smallest amplitude, precipitation reveals its highest one.

4.9 Summer 2007: a Case Study

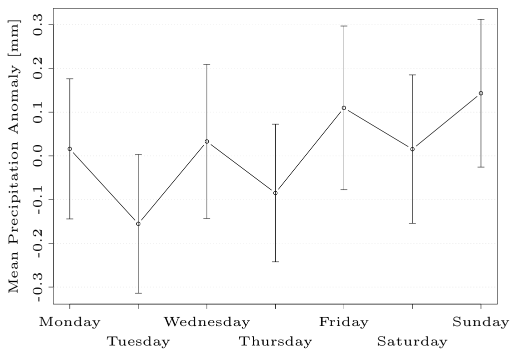
The summer 2007—here, only the time period between June 1$^{\text{st}}$ and September the 30$^{\text{th}}$ is considered—had particularly often sunny and warm weekends while the midweekdays often were colder, cloudier and with more precipitation. In the following temperature, sunshine duration, PM_{10}, atmospheric pressure and precipitation anomaly are analysed as well as the number of the sundry 'weather conditions' on each weekday. Furthermore we analyse these anomalies with the help of a spectral analysis and try to find a periodicity



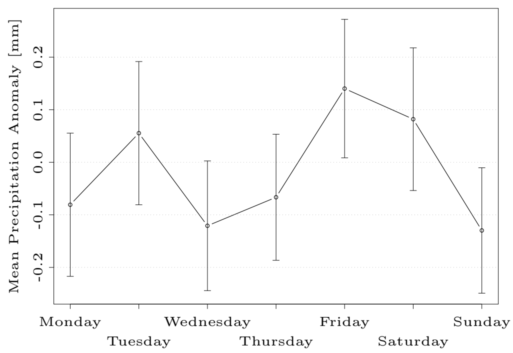
(a) Spring



(b) Summer



(c) Autumn



(d) Winter

Figure 4.18: Weekly cycles of daily precipitation (5:40 to 5:40 UTC) anomaly by season, averaged over all stations. Period: 1960-01-01 to 1989-12-31. Errorbars: ±1 standard error. Note that the range of the ordinate varies from period to period.

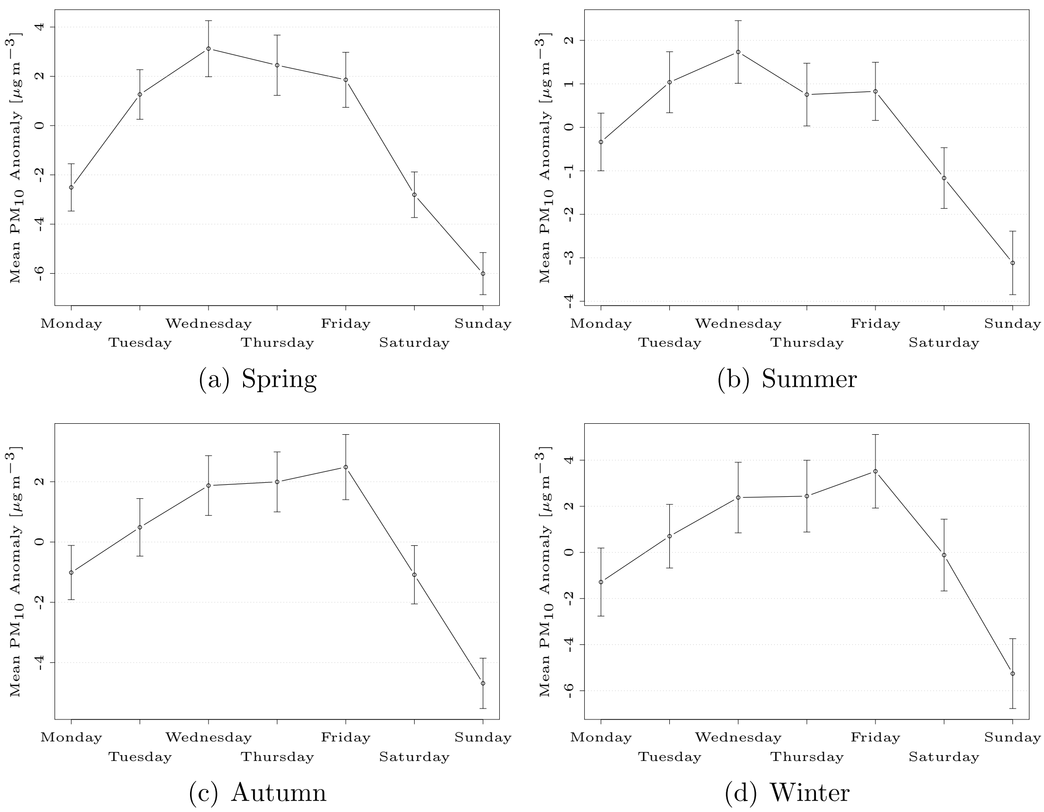
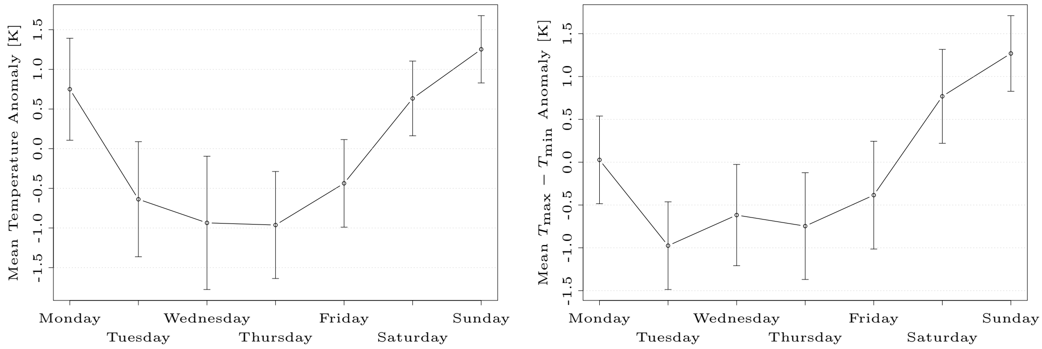


Figure 4.19: Weekly cycles of PM_{10} anomaly by season, averaged over the following stations: Basel, Bern, Lugano, Zürich. Period: 1998-01-01 to 2006-12-31. Errorbars: ±1 standard error. Note that the range of the ordinate varies from period to period.



(a) Mean temperature anomaly.

(b) Temperature range ($T_{\max} - T_{\min}$) anomaly

Figure 4.20: Weekly cycles of anomalies for summer 2007, averaged over the following stations: Binningen, Col du Grand St-Bernard, La Brévine, Lugano, Matro, Schaffhausen, Segl-Maria, Zollikofen, Zürich. Period: 2007-06-01 to 2007-09-30. Errorbars ±1 standard error.

by dint of a Fourier fitting curve.

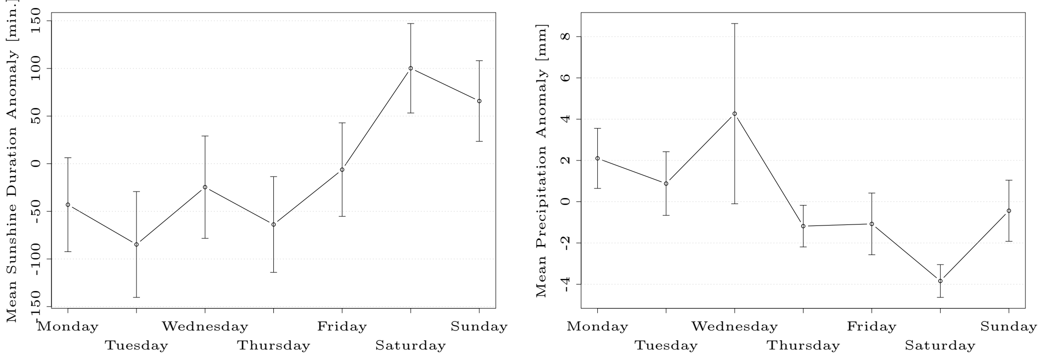
The temperature anomaly reveals a rather clear weekly cycle with an amplitude of more than 2.5°C (Figure 4.20(a)). The temperature minimum is on Thursday while the maximum falls on Sunday. Compared to the results for a longer time series, e. g., those in Section 4.3 on page 22 and those by Bäumer and Vogel (2007), who found an amplitude around 0.2°, this is more than 10 times larger.

The temperature range anomaly reveals a weekly course with a minimum on Tuesday and a maximum on Sunday (Figure 4.20(b)). Contemplating the amplitude one gets a range of more than two degrees.

The anomaly of the sunshine duration (Figure 4.21(a) on the following page) looks similar to the one with the temperature. The sunshine-maximum is on Saturday while the minimum falls on Tuesday. The amplitude is almost 200 minutes, so that generally there is exceeding three hours more sunshine on Sundays than on Tuesdays—at least during the summer 2007.

The anomaly in precipitation has its maximum on Wednesday and its minimum on Saturday (Figure 4.21(b) on the next page). The anomaly range exceeds 8 mm and is hence more than an order of magnitude higher than the amplitudes in a 15 year time series (Section 4.4 on page 27).

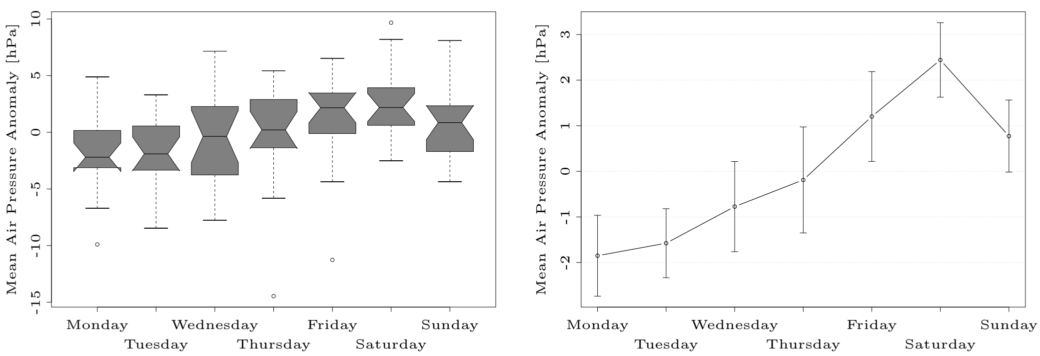
Saturday is the day with the highest mean in atmospheric pressure, the minimum falls on Monday. Compared to the longer time series, the range of about 4.5 hPa is extremely high (Figure 4.22 on the next page). The weekly cycle in the atmospheric pressure indicates the reason for the sunny



(a) Sunshine duration anomaly, averaged over the following stations: Binningen, Col du Grand St-Bernard, Lugano, Schaffhausen, Zollikofen, Zürich.

(b) Daily precipitation anomaly, averaged over the following stations: Binningen, Col du Grand St-Bernard, La Brévine, Matro, Schaffhausen, Segl-Maria, Zollikofen, Zürich.

Figure 4.21: Weekly cycles of anomalies for summer 2007. Period: 2007-06-01 to 2007-09-30. Errorbars ±1 standard error.



(a) Boxplot

(b) Errorbars: ±1 standard error

Figure 4.22: Weekly cycle of air pressure at sea level (QFF) for summer 2007, averaged over the following stations: Binningen, Lugano, Schaffhausen, Zollikofen, Zürich. Period: 2007-06-01 to 2007-09-30. Errorbars ±1 standard error.

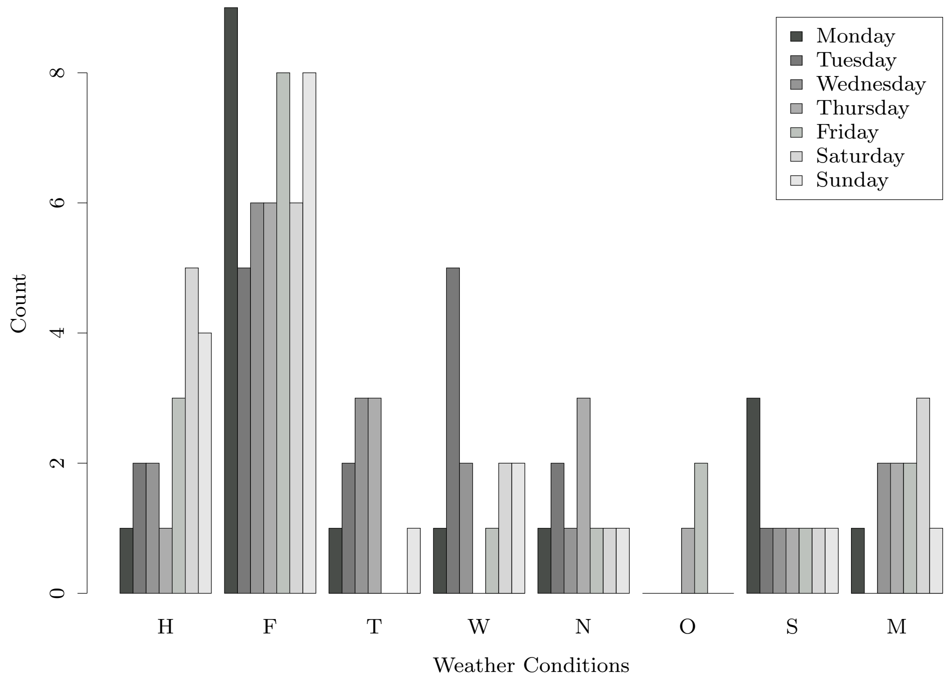


Figure 4.23: Distribution of the different weather conditions per weekday during the summer. Period: 2007-06-01 to 2007-09-30

and warm weekends during the summer 2007 and a look at the distribution of the 'weather conditions' per weekday (Figure 4.23) verifies the hypothesis that it has to be due to dynamical reasons.

The weekly course of PM_{10} is—compared with those of a longer time series (Section 4.2.2 on page 19)—rather unusual: the PM_{10} maximum falls on Monday and the minimum on Tuesday while the range is a little less than $4.5\,\mu\mathrm{g\,m^{-3}}$ (Figure 4.24 on the following page).

According to the Kruskal-Wallis test all these cycles except the PM_{10} are significant on a 10% level (p-values are in Table 4.9 on the next page).

A further analysis of the anomalies has been done in MATrix LABoratory, a numerical computing environment and programming language created by "The MathWorks" (MATLAB), by generating a fitting curve with help of the "general model Fourier 1" of the form:

$$f(x) = a_0 + a_1 \cdot \cos(x \cdot w) + b_1 \cdot \sin(x \cdot w)$$

For the temperature and the pressure anomaly the fitting curve reveals a periodicity of 7 days within the 95% confidence interval (Figure 4.25 on page 43 and Table 4.10 on the next page).

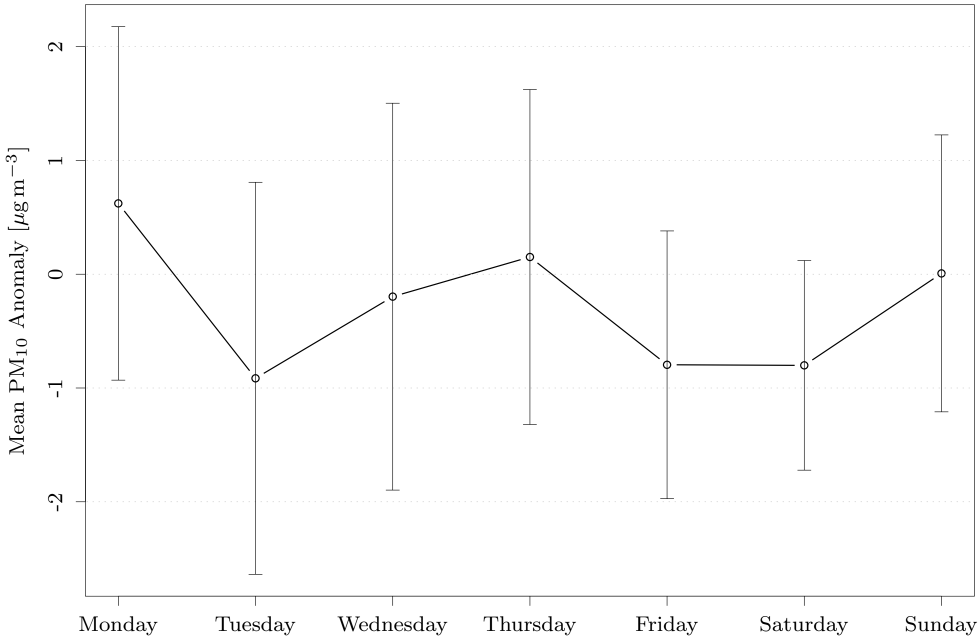


Figure 4.24: Weekly cycle of PM_{10} anomaly for summer, averaged over the following stations: Basel, Bern, Jungfrau, Lugano, Zürich. Period: 2007-06-01 to 2007-09-30. Errorbars ±1 standard error.

Table 4.9: p-values of the Kruskal-Wallis test for summer 2007. Period: 2007-06-01 to 2007-09-30.

Parameter	p-value
PM_{10}	0.964
pressure	$6.09 \cdot 10^{-3}$
precipitation	$4.19 \cdot 10^{-2}$
sunshine	$9.66 \cdot 10^{-2}$
temperature	$8.45 \cdot 10^{-2}$
temperature range	$3.33 \cdot 10^{-2}$

Table 4.10: Periodicities of the fitting curves for temperature and pressure anomalies during the summer 2007. Period: 2007-06-01 to 2007-09-30. In parentheses are the 95% confidence bounds

Parameter	Periodicities [d]	
Temperature	7.012	(7.094–6.931)
Pressure	6.991	(7.080–6.903)

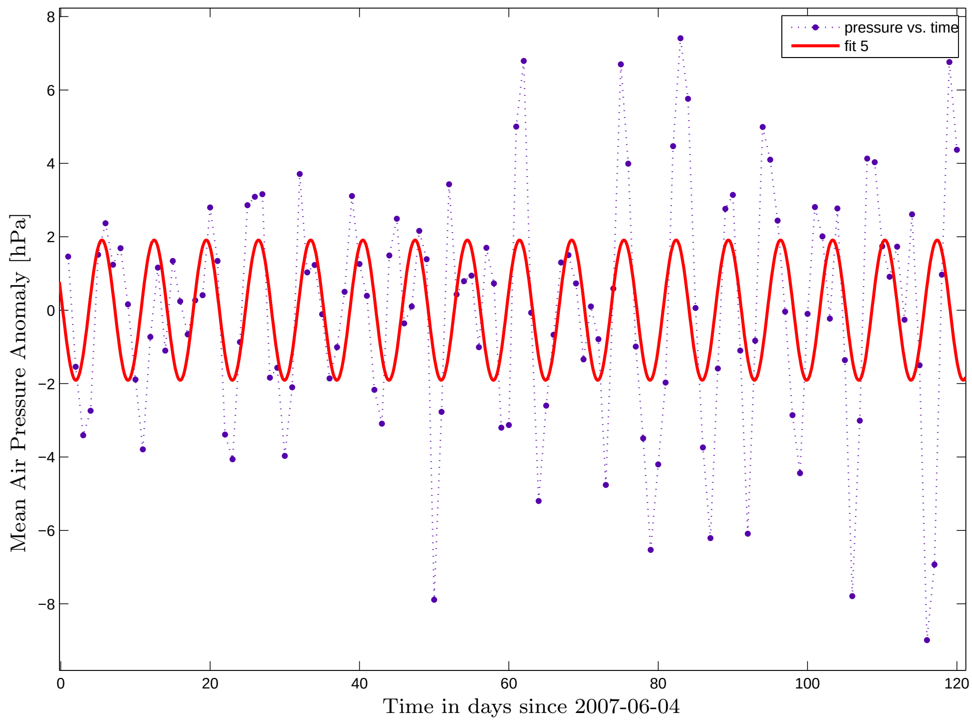
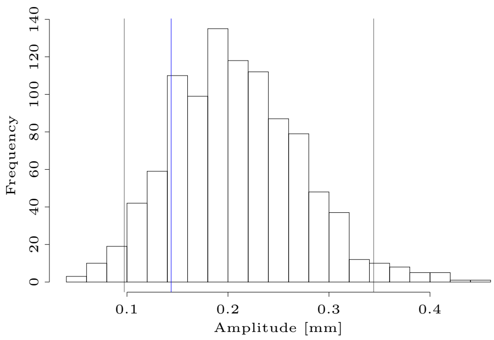
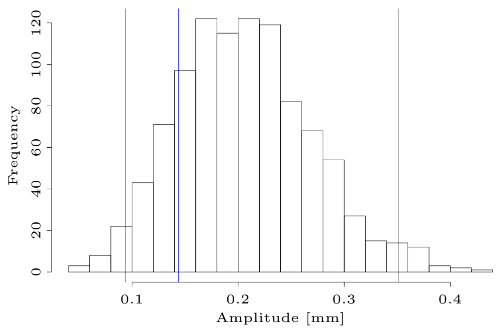


Figure 4.25: Fitting curve for air pressure at sea level (QFF) during the summer 2007. Period: 2007-06-01 to 2007-09-30.



(a) The "time series of deviation" in random order (sample)



(b) Series with the same standard deviation and length as "time series of deviation"

Figure 4.26: Histograms of 1,000 simulated amplitudes for daily precipitation (5:40 to 5:40 UTC). The amplitude of the original time series (0.144) is at the blue line. 95% of the simulated values are within the marked vertical grey lines. Period: 1960-01-01 to 1989-12-31.

For all other parameters (anomalies of: precipitation, PM_{10}, sunshine duration) the fitting curve reveals no 7-day periodicity.

4.10 Simulations

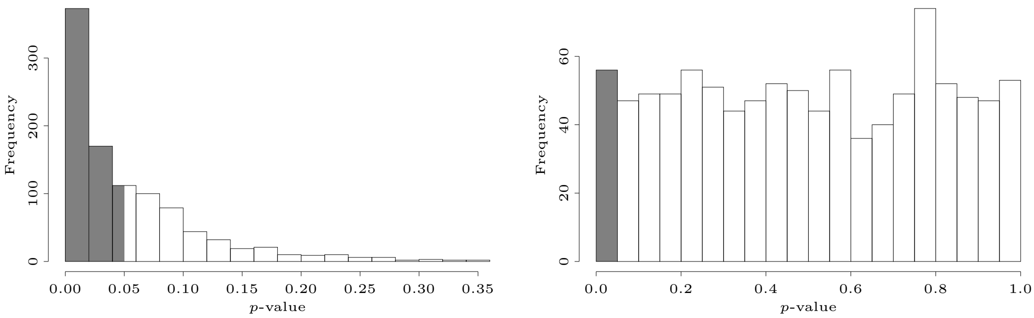
Simulations can be conducted with the measured values or the "time series of deviation". Likewise it is feasible to differentiate between 6, 7 and 8-day in the simulations.

For all simulations the "time series of deviation" is used and a 7-day-week.

4.10.1 Random Series

The two simulations described in the Methods Chapter, Section 3.3.1 on page 12, provide roughly the same results. In both cases the simulated mean amplitude is higher as the real one. Figure 4.26 shows the histogram of the simulated amplitudes for precipitation.

A histogram of the p-values reveals that in more than 70% of the simulations—the one sided Wilcoxon test—are significant ($\alpha = 5\%$). The distribution of the p-values is not uniform (Figure 4.27(a) on the facing page). In contrast to this the distribution of the p-values of the Kruskal-Wallis test is uniform and around 5% of the simulations are significant (Figure 4.27(b) on the next page).



(a) One sided Wilcoxon test (b) Kruskal-Wallis test

Figure 4.27: Histograms of p-values for 1,000 simulated daily precipitation (5:40 to 5:40 UTC) time series. Latter has the length and same standard deviation as "time series of deviation" for precipitation. Values below 5% are grey shaded. Period: 1960-01-01 to 1989-12-31.

The weekly cycles of the first 10 simulated time series indicate that both simulations create a time series with different characteristics than the original ones (Figure 4.28 on the following page). The original weekly cycle is always smoother than the simulated ones—no matter which meteorological parameter is considered. The original time series must therefore have a feature that both simulations do not include.

4.10.2 Autocorrelation

Figure 4.29 on the next page shows the histogram of the simulated amplitudes. The histogram of the time series with autocorrelation $\varrho \approx 0$ (Figure 4.29(a) on the following page) looks similar to the results of a random simulated series (Figure 4.26 on the preceding page). This applies also to the histogram of p-values (Figure 4.30(a) on page 47) and the weekly cycles of the first 10 time series (Figure 4.31(a) on page 47). This has to be the case, as it is basically the same.

In contrast, the mean amplitude of simulated series with higher autocorrelation is lower. The simulated mean amplitude of series with the same autocorrelation as the original series (for precipitation $\varrho = 0.357$) is only slightly lower than the original one (Figure 4.29(b) on the following page). However the simulations with the autocorrelation set to 0.9 are an order of magnitude smaller.

From the Figure 4.30 on page 47 it follows that the number of significant ($\alpha = 5\%$) simulations (grey shaded in the Figure) decrease with an increasing

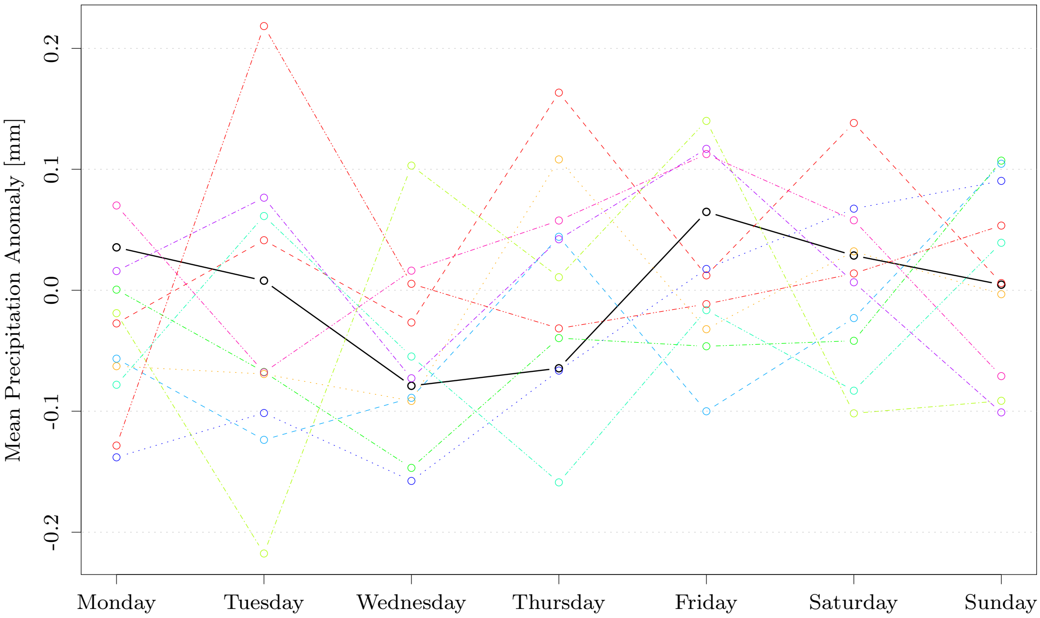
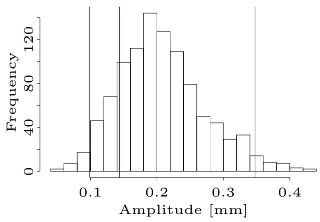
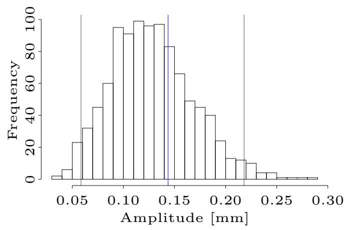


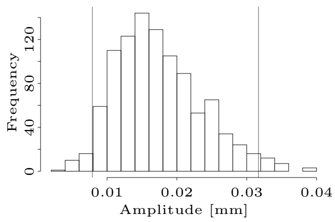
Figure 4.28: Weekly cycles of the first 10 simulated time series for daily precipitation (5:40 to 5:40 UTC). The thick black line is the weekly cycle of the original "time series of deviation", the dotted colour lines are simulated. Period: 1960-01-01 to 1989-12-31.



(a) Series with $\varrho \approx 0$

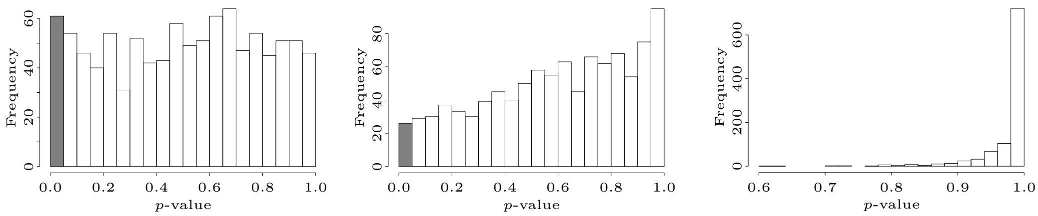


(b) Series with $\varrho \approx 0.36$. This corresponds to the one of the original precipitation series.



(c) Series with $\varrho \approx 0.9$

Figure 4.29: Histograms of 1,000 simulated amplitudes for daily precipitation (5:40 to 5:40 UTC). The amplitude of the original time series (0.144) is at the blue line. 95% of the simulated values are within the marked vertical grey lines. Period: 1960-01-01 to 1989-12-31.

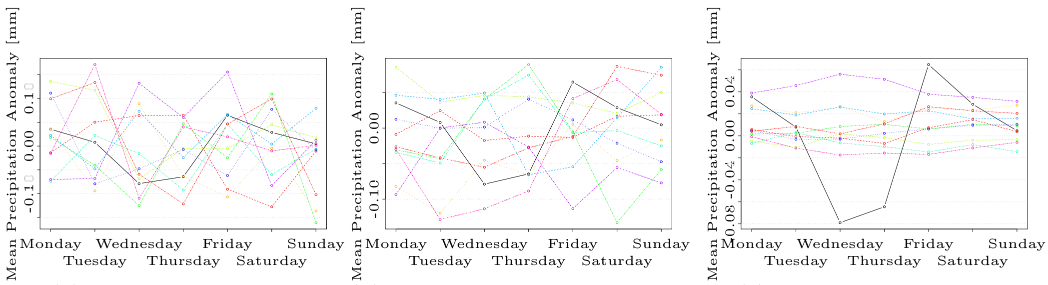


(a) Series with $\varrho \approx 0$

(b) Series with $\varrho \approx 0.36$. This corresponds to the one of the original series.

(c) Series with $\varrho \approx 0.9$

Figure 4.30: Histograms of p-values of the Kruskal-Wallis test of 1,000 simulated daily precipitation (5:40 to 5:40 UTC) time series with different autocorrelations (ϱ). Period: 1960-01-01 to 1989-12-31.



(a) Series with $\varrho \approx 0$

(b) Series with $\varrho \approx 0.36$. This corresponds to the one of the original series.

(c) Series with $\varrho \approx 0.9$

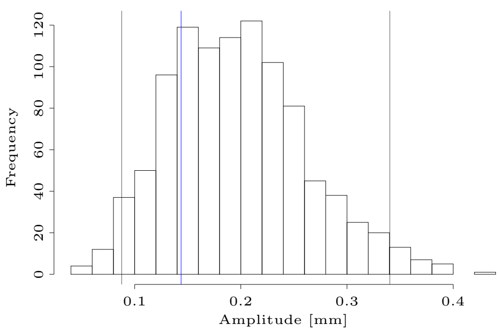
Figure 4.31: Weekly cycles of the first 10 simulated daily precipitation (5:40 to 5:40 UTC) time series. The thick black line is the weekly cycle of the original "time series of deviation", the dotted colour lines are simulated. Period: 1960-01-01 to 1989-12-31.

autocorrelation (ϱ). Around 60 of 1000 simulations have a p-value below 5% if the autocorrelation is 0 (Figure 4.30(a)), slightly more then 20 if the autocorrelation is 0.357 and 0 if the autocorrelation is very high (0.9).

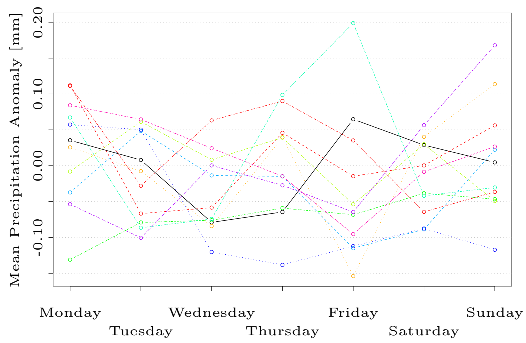
A higher autocorrelation smoothes the weekly cycle as shown in Figure 4.31.

4.10.3 Take Samples

If samples of the length of a week are taken from the time series, the mean simulated amplitude is slightly higher than the real one and the weekly cycle is as smooth as the original one (Figure 4.32 on the following page).



(a) Histograms of 1,000 simulated amplitudes for daily precipitation (5:40 to 5:40 UTC). The amplitude of the original time series (0.144) is at the blue line. 95% of the simulated values are within the marked vertical grey lines.



(b) Weekly cycle of the first 10 simulated time series for daily precipitation total (5:40 to 5:40 UTC). The thick black line is the weekly cycle of the original "time series of deviation", the dotted colour lines are simulated.

Figure 4.32: Simulated time series with samples out of the original time series, which then exhibits the same length as the week. Period: 1960-01-01 to 1989-12-31

Chapter 5

Discussion

5.1 Our Motivation and the Long Road to the Results

The main motivation surely was the results from Germany published by Bäumer and Vogel (2007). We were quite confident that one could find similar results for Switzerland too. Furthermore we wanted to provide a detailed look at the geographical differences and probable changes over time. Initially we hoped to find a spatial difference—at least between north and south of the Alps—and detect an increasing amplitude in weekly cycles over the course of time.

The fact that even to date many mechanisms in cloud physics still reveal a lot of open questions which have to be investigated made this working field additionally more interesting. As it was impossible to start a big field campaign and measure all human made effects on weather and climate within five months, we focused on achievable goals and started to analyse meteorological data from the archive.

5.1.1 Assumptions and Procedures

It is hard to overlook that—especially in the assumptions and the procedure—we rely heavily on the work of Bäumer and Vogel (2007):

- Considering 15 year time steps: Bäumer and Vogel (2007) had a good reason to do so. We did it mainly to be able to compare our results with theirs. By also analysing 30 year periods we tried to handle this coincidental fact.

- The 31-day running mean: it is quite hazardous to take 31 days for the moving average. Therefore we calculated all “time series of deviation” with a 7 and a 31-day running mean and the result is nearly identical. However, the 7-day running mean culls the dynamically induced weather conditions and flattens/minimises generally the “time series of deviation”. This can be seen very well in plots with temperature data.

5.1.2 Statistical Tests

Another point that we initially adopted from Bäumer and Vogel (2007) was the statistical test procedure. We advisedly did not take all available CLIMAP-data for our computation, to prevent getting a false statistical significance. Without further analysis of the independence among the stations we applied their method.Surprisingly the weekly amplitude in temperature anomaly remains nearly constant during the last 143 years, only the warmest and the coldest day in the week changes coincidentally. The crucial factor to reconsider our statistical methods was the fact that the one sided t-test of all stations always reveals a significance between the maximum and the minimum while for each single station it never did. The presumption suggests itself that the stations are not independent. This can be confirmed with a correlation test in R on the “time series of deviation”: it shows that the stations can indeed not be considered as independent.

This result led us to the idea to make a control by performing a “6-8-week-day-test” and with the help of simple simulations.

During the analysis of the precipitation data (with the t-test) we realised that many considered periods suddenly revealed a significance. The “6-8-week-day-test” and the simulations showed this too. As this was not the case in the analysis of the temperature time series, we assume that this sudden significance in the real data is due to higher scatter in the precipitation “time series of deviation” (chapter Results section 4.4 on page 27). By having a closer look at this “time series of deviation” we detected that the precipitation data are not distributed normally. Applying a Wilcoxon test instead of the t-test would have solved this issue. But the problem is more fundamental: we compare several groups—7 in a regular week—against each other. Every one has its own distribution. However, the t-test and the Wilcoxon test are appropriate for the comparison of two groups. The following gedanken experiment should show, why we have the opinion that in this case neither the t-test nor the Wilcoxon test is advantageous.

A little Gedanken Experiment

> Ten persons play with a six-sided dice. They successively roll the dice 100 times and count their points together. Now, the player with the highest score compares his dice distribution with that of the person who had the lowest score. As they all love statistics they immediately perform a one sided Wilcoxon test on these two distributions. By computing the p-values they want to figure out, whether this difference is significant or not. They are so fascinated by this game, that they play it all night long, all in all 1,000 times. But it was worthwhile as the result is surprising: in more than 800 games (exceeding 80%) the test revealed a significance at the 5% level[1].

It is obvious that the dice is not unfair and they just applied a wrong statistical method to figure out whether their scores differ significantly from each other.

The same problem occurs by testing the weekdays against each other. Another analogy to the weekday analysis is, that the person who throws the highest score and the one who throws the lowest one changes arbitrarily. So it is in our case: the weekday with the highest/lowest temperature- and precipitation anomaly changes during the last 143 years quite haphazardly.

In our case there is still a problem left with the autocorrelation in the "time series of deviation". Especially for temperature this correlation within the time series is very high and this in turn might influence the Kruskal-Wallis test negatively. The application of this test on our various simulations underlines this suspicion.

All in all one could say that—for this issue—the Kruskal-Wallis test seems to be the most eligible significance test that we know. But it is highly recommended to check the results carefully with other tests.

Since statistical tests are not always unproblematic and since we do not feel very comfortable basing all our results and statements only on one statistical test, we decided to do a few additional examinations.

5.1.3 Simulation

The simulations however are a good method of controlling. They are far too simple to call them a model. The simulation of the reality is not very accurate either, but nevertheless they provide a check whether a result is plausible or not. Applying the t-test on a random series divided by the

[1]For the end of the gedanken experiment see appendix C on page 77.

number of weekdays, and testing the maximum against the minimum, was then also how we figured out that the initially pursued path had to be wrong.

5.1.4 "6-8-Day-Test"

For the "6-8-week-day-test" one can say that, it is likely improbable that a 6, 7 and 8-day-cycle exists at the same time. Even if this were the case, it would for sure not be human made. Insofar it is a simple plausibility control to answer the question as to whether there is a human made weekly cycle or not.

5.1.5 What else did we do

At this point we have to admit that we really tried to do almost everything conceivable to find a weekly cycle in climatology. Besides the division in the four seasons we tried to find a cycle at least in one of the 8 different weather conditions. We thought that maybe Milano, Genova and Torino together could cause a 7-day precipitation cycle during a longer "Südströmung" (south stream). We even looked only at periods, in which "Hochdrucklage" (high pressure condition) and "Flache (mittlere) Druckverteilung" (weather conditions with a flat pressure distribution) last longer than 14 day and tried to find a weekly cycle, but without success.

Another basic approach to detect a 7 day cycle is by means of a Fourier-Model-fitting-curve in MATLAB. As we could not find anything in the "time series of deviation" for temperature data, we tried a different approach. This time the seasonal cycle is eliminated by subtracting the Fourier-Model-fitting-curve from the daily measured values. This results in residuals. The latter can be considered as a new "time series of deviation". Now, by performing a second fitting curve on this time series, it is possible to compute the periodicity of this fitting curve. No 7-day cycle could be found either.

5.2 Discussion of the Results

As we could not find any weekly periodicities in climatology, there is little left to discuss about weekly cycles. As a matter of fact the discussion leads mainly to the question of the right method of detecting a 7-day cycle. Depending on that, one finds a weekly cycle or not.

Nevertheless there are a few aspects concerning the "climate results" which might be interesting to discuss.

5.2.1 Anomalies since 1865

Considering the plots since 1865 (chapter Results on page 15ff) one expects that for the considered time period of 15 years the weekly cycles are arbitrary.

The anomaly ranges of all parameters do not increase over time and remain more or less “constant”. This can be considered as an indication, that the human made PM pollution is not responsible for a potential weekly cycle. The arbitrarily changing maximums and minimums in the last 50 years imply that there might be no human impact.

5.2.2 Summer 2007 (Case Study)

In longer time series the PM_{10} usually reveals a clear weekly cycle with a minimum on Sundays and an enhancement during the midweekdays (Results Chapter, Section 4.2.2 on page 19ff). For the summer 2007 the PM_{10} maximum occurs on Monday and the minimum on Tuesday (Results Chapter, Section 4.9 on page 36ff). This unusual result can be explained with the precipitation anomaly and the ‘weather conditions’—in fact they strongly relate to each other:

- On weekends there is hardly any precipitation while Tuesday is the day with the second highest rainfall during the week and the latter is responsible for the washout of the PM_{10} (Figure 4.21(b) on page 40).

- Probably more important however are the ’weather conditions’. The sunny and dry weekends (“Hochdrucklage” (high pressure condition)) make an accumulation of PM_{10} possible while the high number of “Westströmung” (west stream) on Tuesday cut back and dilute the aerosols (Figure 4.23 on page 41).

5.2.3 Simulation

Assuming that the weekly cycles are absolutely random, a good simulation should reveal approximately the same weekly amplitudes as in reality. If this is not the case, there must be a deficiency in the simulation. This deficiency can result simply because an important feature has been forgotten, or else the assumption of no weekly cycle is wrong.

In case the simulated amplitudes differ from reality, one can distinguish between two circumstances:

Overestimation The simulation has a higher amplitude, which can be reduced to a deficiency in the simulation.

Underestimation The opposite is the case. The simulated amplitude is smaller than in reality. The simulation ignores a forcing that could be an anthropogenically induced 7-day forcing. But it could be just as well an other forcing, like e. g., a dynamical one.

As shown in Results Chapter, Section 4.10.2 on page 45, the autocorrelation of the time series is an important feature. Nevertheless the inference that an underestimation of the simulated amplitude—that exhibits the same autocorrelation as the original time series—must be due to an anthropogenic forcing, is wrong. The amplitude could not be as high in the 6 and 8-day-week, if this was the case.

Generally one can say that simulations with a high autocorrelation usually underestimate the weekly amplitude while those without autocorrelation normally overestimate it. At this point one has to emphasise, that the so called "real autocorrelation" only looks at the preceding day, or the following day respectively. It therefore depends on the parameter whether this "real autocorrelation" reflects the original "time series of deviation" or not. The temperature e. g. displays a rather high autocorrelation ($\varrho = 0.81$). Various fluctuations underlie the real "time series of deviation"—despite the subtraction of the 31 running mean—e. g. dynamical ones, which last usually over several days. The dynamic cycle again force the "time series of deviation" literally towards a defined direction. It is very unlikely that a random simulation with an implemented autocorrelation of 0.8 would do so. The simulation with the "real autocorrelation" of precipitation ($\varrho = 0.36$) on the contrary reflects the reality quite well.

In all simulations the dynamical forcing is excluded, even though it is a very important factor for the weather conditions in the middle latitudes. As shown in chapter Results in section 4.9 on page 36 it can be the most important thing for a cycle—in this case weekly one.

5.2.4 Number of Significant Tests

Performing the three statistical tests (t-test, Wilcoxon test and Kruskal-Wallis test) on the precipitation data and counting the number of significant outputs reveals a similar result to the gedanken experiment (Section 5.1.2 on page 51): most of the t-tests—namely around 80 of 140—between the maximum and the minimum get significant (Figure 5.1 on the facing page). Regardless whether this test is applied on a 6, 7 or 8-day-week, it provides approximately the same picture. This result underlines our assumption, that this kind of statistical test is not appropriate for our study.

The Wilcoxon test reveals about half as many significant cases than the

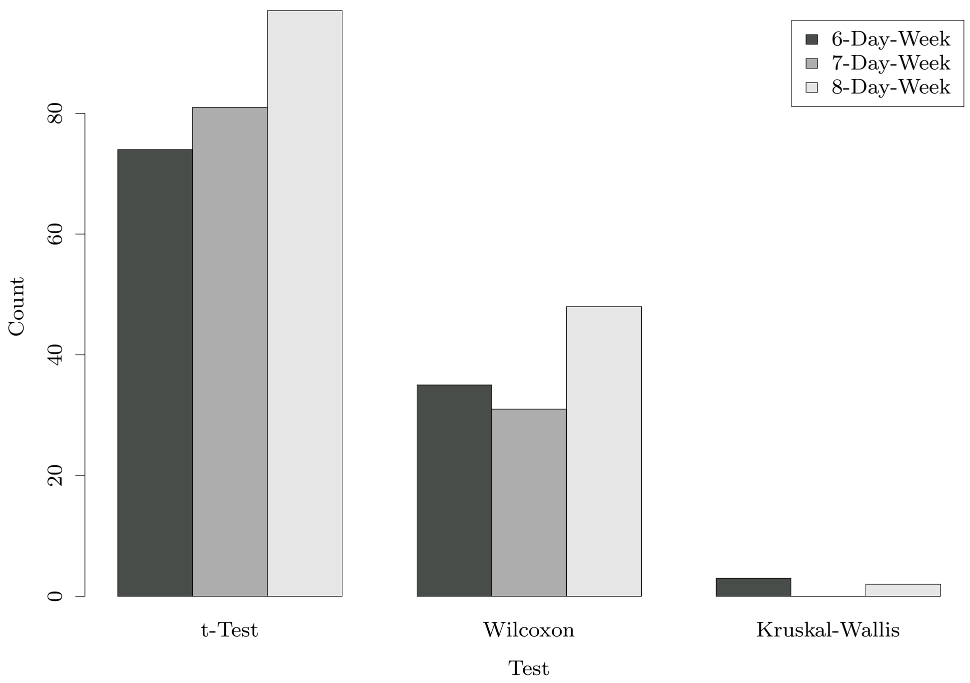


Figure 5.1: Number of siginificant tests (for $\alpha = 5\%$) on precipitation data in 15 years period steps between 1872-01-01 and 2006-12-31. The total amount of tests in every single bar is 140.

t-test does. Nevertheless the comparison with the 6 and 8-day-week provides even more significant cases. Insofar a 6-day cycle or an 8-day cycle would be more likely than a 7-day one. This might be true, but it underlines our results: there is no significant 7-day-cycle.

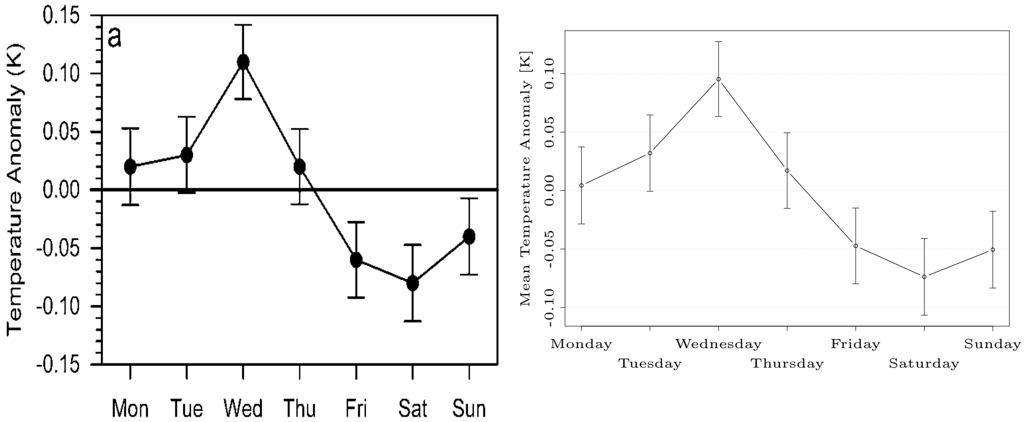
5.3 Faults in the Data and Data Handling

Series of measurements often do contain wrong values, this is bothersome but practically unavoidable. The question is, how to detect and eradicate them. The best would be to check the time series with the highest available resolution for wrong values. Due to the lack of a direct access to this data this was not possible for us.

The difference between a corrected series and the original series (contain wrong values) is normally not recognisable in the results (Results Chapter, Section 4.1.3 on page 18). In the weekly mean values of precipitation between 1992-01-01 and 2006-12-31 one mean is slightly higher and the standard deviation is much bigger in the uncorrected series. This is caused by the fact that one value in the precipitation series of Bargen (SH) is extremely high (1637.0 mm at 1998-11-29). There is no other fanciful value in this series. Normally there is more than one wrong value in a series, and they can be distributed evenly over the weekdays.

5.4 Comparison of our Work with Bäumer and Vogel (2007)

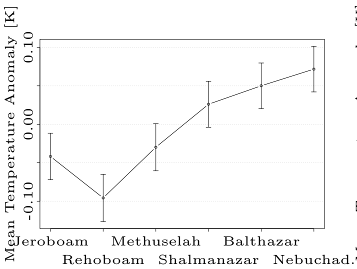
To make sure that our results, that differ from those of Bäumer and Vogel (2007) are not based on a lack of understanding on our part, we verified our computation-procedure by using the data from Germany (Figure 5.2 on the facing page). It is possible to reproduce their results by applying the same statistical proceeding.We could reproduce the weekly anomalies for each single station except for Hohenpeissenberg. Here our anomalies differ conspicuously from those of Bäumer and Vogel (2007).It is quite opaque, how this can come into being. Nevertheless this verification with the German WMO-data illustrates that our results are not a question of a wrong series (like e. g. Hohenpeissenberg), and it neither seems to be a question of region. It solely depends on, whether their method is correct or not. And assuming their method is correct would imply that there has to be—beside the 7-day cycle—also a 6 and 8-day cycle (Figure 5.3 on page 58). This is rather unprobable.



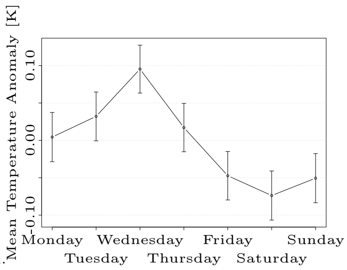
(a) Original Figure from Bäumer and Vogel (2007)

(b) Our reproduction of their result

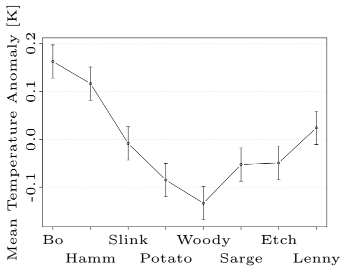
Figure 5.2: Verifying of our calculation procedure with the German stations: Aachen, Berlin-Tempelhof, Düsseldorf, Frankfurt/Main Flughafen, Helgoland, Hohenpeissenberg, Kahler Asten, Karlsruhe, Konstanz, Rostock-Warnemünde, Stuttgard-Echterdingen and Zugspitze.
The "time series of deviation" of all stations is grouped directly by weekday (assumption that the stations are absolutely selfcontained), no average over the stations.
Period: 1991-01-01 to 2005-12-31. Errorbars ± 1 standard error.



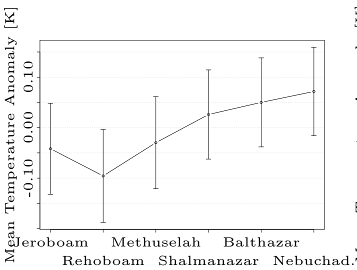
(a) 6-Day-Week. Amplitude is 0.17.



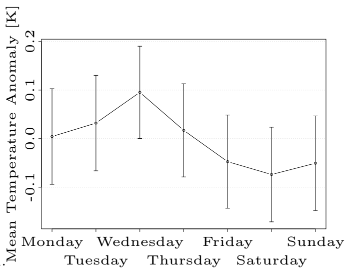
(b) 7-Day-Week. Amplitude is 0.17.



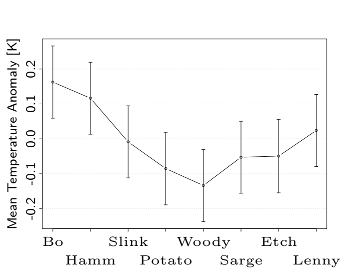
(c) 8-Day-Week. Amplitude is 0.30



(d) 6-Day-Week. Average over stations.



(e) 7-Day-Week. Average over stations.



(f) 8-Day-Week. Average over stations.

Figure 5.3: Weekly cycles of temperature anomaly for a 6, 7 and 8-day-week with the following German stations: Aachen, Berlin-Tempelhof, Düsseldorf, Frankfurt/Main Flughafen, Helgoland, Hohenpeissenberg, Kahler Asten, Karlsruhe, Konstanz, Rostock-Warnemünde, Stuttgard-Echterdingen and Zugspitze.
In the first row the "time series of deviation" of all stations is grouped directly by weekday (assumption that the stations are absolutely selfcontained), no average over the stations. In the second row a single time series is first computed with mean values for every single day.
Errorbars ±1 standard error. The range of the ordinate is from week to week different. Period 1991-01-01 to 2005-12-31. Errorbars ±1 standard error.

Chapter 6

Conclusion and Outlook

The amplitude of the 6, 7 and 8-day-week is more or less the same for one measured value in all periods. This indicates a random process.

The simulation shows the importance of dynamics or different processes not studied here. So it looks like the difference between weekdays is caused by the dynamics.

Nevertheless if there is an anthropogenic 7-day cycle effect it must be very small and it would be more or less impossible to find this signal. One method that has not used so far is to build an Autoregressive-Moving Average (ARMA)-model.

The results presented here indicate, that a weekly cycle in climatology is random. The PM_1 and PM_{10} values however provide a clearly significant 7-day course.

The simulations—that initially were created to have a plausibility control of the statistical tests—show additionally how important the dynamics are for weather. The case study for the summer 2007 further clarifies this issue.

In our opinion several studies that have been done on weekly cycles in climatology, apply a basic approach of methods which is not appropriate to detect a weekly cycle. However, this does not mean that it is absolutely impossible to detect one somewhere on this planet (this Masterthesis just focused only on measurements in Switzerland).

It would be interesting to analyse measurements from highly industrialised regions or big cities with a huge air pollution with a Kruskal-Wallis test and a "6-8-week-day-test". A comparison with simulations would likewise be very useful—next time maybe with methods a little more sophisticated. Another method is to build an ARMA-model.

Another aspect that might be interesting to consider more precisely are measurements in higher altitudes, like on the Jungfraujoch. The suspended matter measurements from the Jungfraujoch station (since 1998) do yield a significant weekly cycle, while the PM_{10}-data (only since 2006) do not. This result can be coincidence, but we also found several possible explanations, why this could the case.

Now, doing PM measurements in different altitudes over industrialised regions or megametropolises could be a way to find out whether weekly periodicities in climatology are possible or not. But maybe even one could not detect a 7-day cycle on the ground in PM, due to activities taking place 7 days a week around-the-clock.

For now we can just speak for Switzerland and say that, if there is a an anthropogenically induced 7-day cycle, it must be so small that it would be more or less impossible to detect.

To address the open questions in this and other studies, further research is needed.

Bibliography

[ANETZ, 1980] ANETZ. Schweizerische meteorologische Anstalt & Bundesamt für Landwirtschaft. Projekt ANETZ 1974-1980; (Automatisches meteorologisches Mess- und Beobachtungsnetz): Zusammenfassungen der Vorträge der ANETZ-Kolloquien, Nov. 1980.

[Ashworth, 1929] J. R. Ashworth. The influence of smoke and hot gases from factory chimneys on rainfall. *Quarterly Journal of the Royal Meteorological Society*, 1929.

[Ashworth, 1933] J. R. Ashworth. Rainfall and atmospheric pollution. *Nature*, 1933.

[Beaney and Gough, 2002] G. Beaney and W. A. Gough. The influence of tropospheric ozone on the air temperature of the city of Toronto, Ontario, Canada. *Atmospheric Environment*, 36(14):2319–2325, May 2002.

[Beirle *et al.*, 2003] S. Beirle, U. Platt, M. Wenig, and T. Wagner. Weekly cycle of NO_2 by GOME measurements: a signature of anthropogenic sources. *Atmospheric Chemistry and Physics*, 3:2225–2232, Dec. 2003.

[Brönimann and Neu, 1997] Stefan Brönimann and U. Neu. Weekend-weekday differences of near-surface ozone concentrations in Switzerland for different meteorological conditions. *Atmospheric Environment*, 31(8):1127–1135, Apr. 1997.

[BUWAL, 2005] BUWAL. Bundesamt für Umwelt, Wald und Landschaft. Feinstaub PM10 Fragen und Antworten zu Eigenschaften, Emissionen; Immissionen, Auswirkungen und Massnahmen, Dec. 2005.

[Bäumer and Vogel, 2007] Dominique Bäumer and Bernhard Vogel. An unexpected pattern of distinct weekly periodicities in climatological variables in Germany. *Geophysical Research Letter*, 34(3), Feb. 2007.

[Cehak, 1982] K. Cehak. Note on the dependence of precipitation on the day of the week in a medium industrialized city. *Archives for Meteorology, Geophysics, and Bioclimatology*, 30:247–251, 1982.

[Cerveny and Balling Jr., 1998] R. S. Cerveny and R. C. Balling Jr. Weekly cycles of air pollutants, precipitation and tropical cyclones in the coastal NW Atlantic region. *Nature*, 394(6700):561–563, Sep. 1998.

[Cerveny and Coakley, 2002] R. S. Cerveny and K. J. Coakley. A weekly cycle in atmospheric carbon dioxide. *Geophysical Research Letters*, 29(2):1028, Jan. 2002.

[Delene and Ogren, 2002] D. J. Delene and J. A. Ogren. Variability of aerosol optical properties at four North American surface monitoring sites. *Journal of the Atmosphric Sciences*, 59(6):1135–1150, Mar. 2002.

[De Lisi *et al.*, 2001] M. P. De Lisi, A. M. Cope, and J. K. Franklin. Weekly precipitation cycles along the northeast corridor? *Weather and Forecasting*, 16(3):343–353, 2001.

[Dettwiller, 1968] J. Dettwiller. Incidence possible de l'activite industrielle sur les precipitations a Paris, 1968.

[Dusek *et al.*, 2006] U. Dusek, G. P. Frank, L. Hildebrandt, J. Curtius, J. Schneider, S. Walter, D. Chand, F. Drewnick, S. Hings, D. Jung, S. Borrmann, and M. O. Andreae. Size matters more than chemistry for cloud-nucleating ability of aerosol particles. *Science*, 312:1375–1378, June 2006.

[Forster and Solomon, 2003] P. M. de F. Forster and S. Solomon. Observations of a "weekend effect" in diurnal temperature range. *Proceedings of the National Academy of Sciences of the United States*, 100(20):11225–11230, Sep. 2003.

[Gong *et al.*, 2006] Dao-Yi Gong, Dong Guo, and Chang-Hoi Ho. Weekend effect in diurnal temperature range in China: Opposite signals between winter and summer. *Journal of Geophysical Research-Atmospheres*, 111, Sep. 2006.

[Gong *et al.*, 2007] Dao-Yi Gong, Chang-Hoi Ho, Deliang Chen, Yun Qian, Yong-Sang Choi, and Jinwon Kim. Weekly cycle of aerosol-meteorology interaction over China. *Journal of Geophysical Research-Atmospheres*, 112, Nov. 2007.

[Gordon, 1994] A. H. Gordon. Weekdays warmer than weekends? *Nature*, 367(6461):325–326, Jan. 1994.

[Horsley and Diebolt, 1995] A. D. Horsley and J. Diebolt. The rainy weekend myth. *Weatherwise*, 1995.

[Jin *et al.*, 2005] M. L. Jin, J. M. Shepherd, and M. D. King. Urban aerosols and their variations with clouds and rainfall: A case study for New York and Houston. *Journal of Geophysical Research-Atmospheres*, 110, Apr. 2005.

[Marr and Harley, 2002] L. C. Marr and R. A. Harley. Spectral analysis of weekday-weekend differences in ambient ozone, nitrogen oxide, and non-methane hydrocarbon time series in California. *Atmospheric Environment*, 36(14):2327–2335, may 2002.

[R Development Core Team, 2007] R Development Core Team. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria, Apr. 2007. Version 2.5.0 (2007-04-23).

[Richner, 2007] Hans Richner. English geographical terminology, 2007.

[Schultz *et al.*, 2007] David M. Schultz, Santtu Mikkonen, Ari Laaksonen, and Michael B. Richman. Weekly precipitation cycles? Lack of evidence from United States surface stations. *Geophysical Research Letters*, Nov. 2007.

[Schüepp, 1979] M. Schüepp. Witterungsklimatologie von M. Schüepp, 1979.

[Shutters, 2006] S. T. Shutters. Weekly periodicity of environmental variables in Phoenix, Arizona. *Atmospheric environment*, 40(2):304–310, Jan. 2006.

[Simmonds and Kaval, 1986] I. Simmonds and J. Kaval. Day-of-the week variation of rainfall and maximum temperature in Melbourne, Australia. *Arch. Meteorol. Geophys. Bioclimatol*, 36:317–330, 1986.

[Simmonds and Keay, 1997] I. Simmonds and K. Keay. Weekly cycle of meteorological variations in Melbourne and the role of pollution and anthropogenic heat release. *Atmospheric Environment*, 31(11):1589–1603, June 1997.

[Smith, 1999] Richard L. Smith. Time Series. Chapel Hill, NC 27599-3260, May 1999.

[Spencer, 1993] R. W. Spencer. Global oceanic precipitation from the MSU during 1979–91 and comparisons to other climatologies. *Journal of Climate*, 6:1301–1326, 1993.

[Tsai, 2005] Y. I. Tsai. Atmospheric visibility trends in an urban area in Taiwan 1961–2003. *Atmospheric Environment*, 39(30):5555–5567, Sep. 2005.

[Wilby and Tomlinson, 2000] R. L. Wilby and O. J. Tomlinson. The "Sunday Effect" and weekly cycles of winter weather in the UK. *Weather*, 55(7):214–222, 2000.

[Yin *et al.*, 2000] Yan Yin, Zev Levin, Tamir G. Reisin, and Shalva Tzivion. The effects of giant cloud condensation nuclei on the development of precipitation in convective clouds—a numerical study. *Atmospheric Research*, 53:91–116, 2000.

[Zellweger, 1983] R. Zellweger. Aufbereitung der ANetz–Wetterdaten für das Rechenprogramm DOE-2.1A, May 1983.

Appendix A

Database

For a simpler handling of the data all needed measured values are stored in a Object-Relational DataBase Management System (ORDBMS), more precise in a PostgreSQL database. The available tables, their fields and relations are shown in Figure A.1 on the following page.

Further documentations are available on the following webpage: `http://iacweb.ethz.ch/staff/kusterth/database`. There is also a webfrontend to get with a Structured Query Language (SQL) command data from the database—this is restricted to the ETH computer network. Another webfrontend has been created to load data into the database.

For a better performance connect directly to the database server on `iac-psql.ethz.ch`.

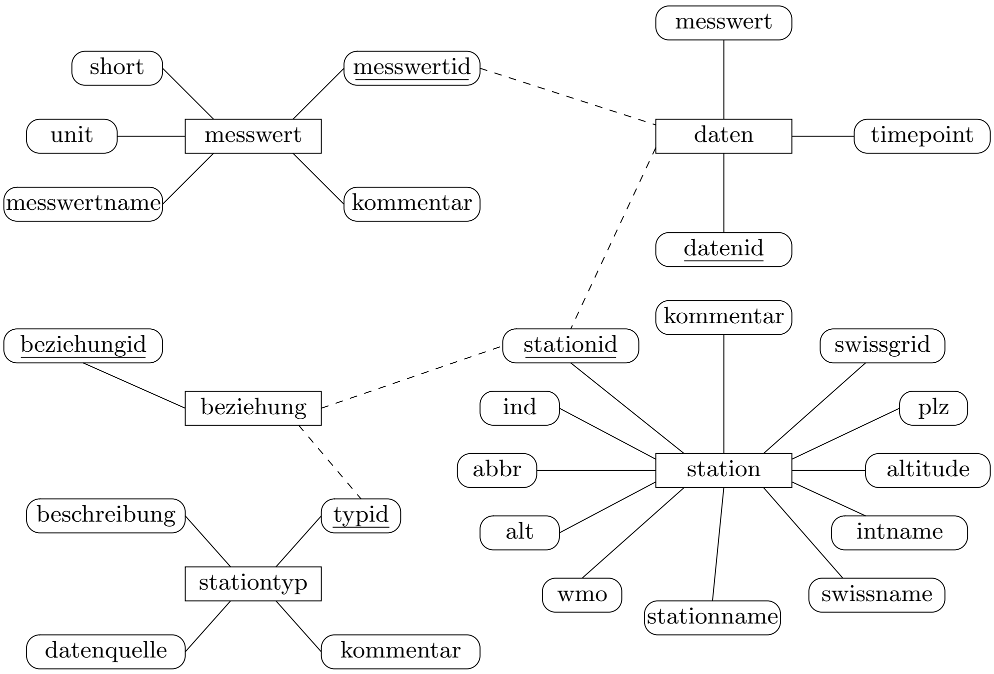


Figure A.1: Database structure. Rectangular boxes: table names. Rectangular boxes with rounded edges: field names. Underlined names: key fields

Appendix B

GNU R Programmes

The statistical evaluation is realised with GNU's Not UNIX (GNU) R. In the follwoing section the most important programs are listed.

B.1 gleitendesmittel.R

```
#!/bin/R

# R Funktion: Gleitendes Mittel berechnen
#
# Copyleft (GPL): Thomas Kuster, 11.10.2007
#
# Aufruf:
# Rueckgabewert <- gleitendesmittel([Vektor])
#
# Rueckgabewert:
# Vektor
#
# Funktion mit source("Dateiname") laden.
#
# Bespiel:
# source("gleitendesmittel.R") # Funktion einlesen
# mittel <- gleitendesmittel(daten[,3], 31) #
  Funktion aufrufen
# mittel
#

gleitendesmittel <- function(data, intervall)
```

```
{

# Randbereich kann nicht berechnet werden
randbereich <- (intervall-1)/2

# Intervall muss ungerade sein
if(round(randbereich,0)!=randbereich)
 {
  stop("Intervall muss ungerade sein!")
 }

cat("Intervall for Running Mean is:", intervall, "\n
   ")

laenge <- length(data)

# ganzer Vektor mit NA fuellen
mittel <- NA
mittel[laenge] <- NA

for(i in (randbereich+1):(laenge-randbereich))
 {
  mittel[i] <- mean(data[(i-randbereich):(i+
     randbereich)], na.rm=TRUE)
 }

return(mittel)
}
```

B.2 korrelation.R

```
# Korrelation der Stationen untereinander
   untersuchen

# Aufruf z.B. wie folgt:
# /usr/local/bin/R-2.5.0 --no-save < ./
   autokorrelation.R > log.log

source("einstellungen_lib.R")
source(paste(lib, "einlesen_umwandeln.R", sep=""))
#source(paste(lib, "gleitendesmittel.R", sep=""))
```

```

intervall <- 31

# Wieviele Wert sind mindestens notwendig in der
    Datenreihe
anteil <- 0.5

# Ab welchen cor Stationen ausgeben?
corlimit <- 0.3

output <- c("PDF", "Xfig")

## From-To-Date for SQL Query
von_sql <- "1992-01-01"
bis_sql <- "2006-12-31"

## SQL Querys
# Temperature 2m over ground 12 Deutsche Stationen
#sql_mit_var <- quote(paste("SELECT timepoint,
    swissname, messwertname, unit, messwert FROM
    daten INNER JOIN station ON daten.stationid=
    station.stationid INNER JOIN messwert ON daten.
    messwertid=messwert.messwertid AND daten.
    timepoint BETWEEN '", von_sql, " 00:00:00' AND
    '", bis_sql, " 00:00:00' AND messwert.
    messwertname LIKE 'Lufttemperatur 2 m Ã¼ber Boden
    ; Tagesmittel' AND daten.stationid IN (1876,
    1882, 1883, 110637, 110501, 110384, 110400,
    110015, 110427, 110727, 110170, 110738) ORDER BY
    daten.timepoint", sep=""))

# Temperature 2m over ground Schweiz
#sql_mit_var <- quote(paste("SELECT timepoint,
    swissname, messwertname, unit, messwert FROM
    daten INNER JOIN station ON daten.stationid=
    station.stationid INNER JOIN messwert ON daten.
    messwertid=messwert.messwertid INNER JOIN
    beziehung ON daten.stationid=beziehung.stationid
    INNER JOIN stationtyp ON beziehung.typid=
    stationtyp.typid AND daten.timepoint BETWEEN '",
    von_sql, " 00:00:00' AND '", bis_sql, " 00:00:00'
```

```
AND messwert.messwertname LIKE 'Lufttemperatur 2 m Ã¼ber Boden; Tagesmittel' AND stationtyp.beschreibung LIKE 'Messwerte ab 1865' ORDER BY daten.timepoint", sep=""))

# Precipitation Schweiz
sql_mit_var <- quote(paste("SELECT timepoint, swissname, messwertname, unit, messwert FROM daten INNER JOIN station ON daten.stationid=station.stationid INNER JOIN messwert ON daten.messwertid=messwert.messwertid INNER JOIN beziehung ON daten.stationid=beziehung.stationid INNER JOIN stationtyp ON beziehung.typid=stationtyp.typid AND daten.timepoint BETWEEN '", von_sql, " 00:00:00' AND '", bis_sql, " 00:00:00' AND messwert.messwertname LIKE 'Niederschlag; Tagessumme 0540 - 0540 Folgetag' AND stationtyp.beschreibung LIKE 'Messwerte ab 1865' ORDER BY daten.timepoint", sep=""))

sql <- eval(sql_mit_var)

cat("SQL Query:\n", sql, "\n", sep="")

## Daten holen und korrekt formatieren
daten <- einlesen_umwandeln(sql, intervall)

## einzelne Stationen in Liste ablegen
datenliste <- new.env()
for(swissname in levels(daten$swissname)) {
  befehl <- (paste("datenliste$`", swissname, "` <- daten[(daten$swissname==swissname & !is.na(daten$swissname)),]", sep=""))
  eval(parse(text=befehl))
 }
datenliste <- as.list(datenliste)

## cor.test Messwert
cat("== cor.test Messwert ==\n")
cortest <- list()
i <- 1
```

```
for(ref in datenliste) {
 #cat("== Station: ", as.character(ref$swissname[1]), " ==\n", sep="")
 laenge <- length(ref$messwert)
 limit <- laenge*anteil
 messwertref <- ref$messwert
 laengeeffref <- length(na.omit(messwertref))
 if(laengeeffref>limit) {
  messwertref <- as.ts(messwertref)
  for(vergleich in datenliste) {
   #cat("Vergleich ", as.character(ref$swissname[1]), " mit ", as.character(vergleich$swissname[1]), "\n", sep="")
   messwertvergleich <- vergleich$messwert
   laengeeffver <- length(na.omit(messwertvergleich))
   if(laengeeffver>limit) {
    messwertvergleich <- as.ts(messwertvergleich)
    #print(cortest)
    text <- paste(as.character(ref$swissname[1]), " (", laengeeffref, " von ", laenge, ") vs. ", as.character(vergleich$swissname[1]), " (", laengeeffver, " von ", laenge, ")", sep="")
    cortest[[i]] <- list(text=text[1], test=cor.test(messwertref, messwertvergleich, na.rm=TRUE))
    i <- i+1
    cat("*")
   } else {
    # Kein cor.test da limit erreicht
    cat("0")
   }
  }
 } else {
  #cat("Mehr als 10% der Werte sind NA -> mache kein cor.test\n")
  cat("0")
 }
 cat("\n\n")
}

# Alles ausgeben
```

```
print(cortest)

## cor.test Abweichung
cat("== cor.test Abweichung ==\n")
cortest <- list()
i <- 1
for(ref in datenliste) {
 #cat("== Station: ", as.character(ref$swissname[1]), " ==\n", sep="")
 laenge <- length(ref$abweichung)
 limit <- laenge*anteil
 messwertref <- ref$abweichung
 laengeeffref <- length(na.omit(messwertref))
 if(laengeeffref>limit) {
  messwertref <- as.ts(messwertref)
  for(vergleich in datenliste) {
   #cat("Vergleich ", as.character(ref$swissname[1]), " mit ", as.character(vergleich$swissname[1]), "\n", sep="")
   messwertvergleich <- vergleich$abweichung
   laengeeffver <- length(na.omit(messwertvergleich))
   if(laengeeffver>limit) {
    messwertvergleich <- as.ts(messwertvergleich)
    #print(cortest)
    text <- paste(as.character(ref$swissname[1]), " (", laengeeffref, " von ", laenge, ") vs. ", as.character(vergleich$swissname[1]), "(", laengeeffver, " von ", laenge, ")", sep="")
    cortest[[i]] <- list(text=text[1], test=cor.test(messwertref, messwertvergleich, na.rm=TRUE))
    i <- i+1
    cat("*")
   } else {
    # Kein cor.test da limit erreicht
    cat("0")
   }
  }
 } else {
  #cat("Mehr als 10% der Werte sind NA -> mache kein cor.test\n")
```

```
  cat("0")
 }
 cat("\n\n")
}

# Alles ausgeben
print(cortest)

cat("== Stationen mit:", corlimit, "\n")
anzahl <- 0
totalanzahl <- 0
corwert <- numeric()
for(station in cortest) {
  if(station$test$estimate<corlimit) {
   print(station$text)
   print(station$test$estimate)
   anzahl <- anzahl + 1
  }
 totalanzahl <- totalanzahl + 1
 corwert[totalanzahl] <- station$test$estimate
}

cat("= Anzahl mit cor<", corlimit, ":", anzahl, "von ", totalanzahl, "\n")

vonbis <- as.character(range(daten$timepoint))
vonbis <- paste(vonbis[1], "_", vonbis[2], sep="")
filename <- paste("korrelation", vonbis, format(Sys.time(), "%Y_%m_%d_%H%M"), sep="_")

for(geraet in tolower(output)) {
 cat("== Plotausgabe ==\n")
 x11 <- FALSE
 if(geraet=="x11") {
  x11 <- TRUE
  cat("Ausgabe auf Bildschirm (X11)\n")
 }
 if(geraet=="pdf") {
  pdf(paste(filename, ".pdf", sep=""))
  cat("Ausgabe (PDF) in ", filename, ".pdf\n", sep="")
```

```
  }
  if(geraet=="xfig") {
   xfig(paste(filename, "_%03d.fig", sep=""))
   cat("Ausgabe (Xfig) in ", filename, "_%03d.fig\n", sep="")
  }
  hist(corwert, breaks=20)
  if(!x11) dev.off()
}

cat("== Warnings ==\n")
warnings()
```

```
rho <- cor.test(timeserie[1:(length(timeserie)-1)], timeserie[2:(length(timeserie))])$estimate
```

B.3 wuerfeln.R

```
anzahlspieler <- 10 # Anzahl Spieler
laenge <- anzahlspieler*100 # Totale Anzahl die gewuerfelt wird
wiederholungen <- 1000 # Wieviel mal spielen

t.t <- numeric(wiederholungen)
w.t <- numeric(wiederholungen)
k.t <- numeric(wiederholungen)

for(i in 1:wiederholungen) {
 wuerfeln <- as.integer(round(runif(1000, min=0, max=1)*6+0.5))
 spieler <- rep(1:anzahlspieler, laenge/anzahlspieler)

 meandaten <- tapply(wuerfeln, spieler, mean)

 maxpos <- spieler==which.max(meandaten)
 minpos <- spieler==which.min(meandaten)

 t.t[i] <- t.test(wuerfeln[maxpos], wuerfeln[minpos], alternative="greater")$p.value
```

```
 w.t[i] <- wilcox.test(wuerfeln[maxpos], wuerfeln[
    minpos], alternative="greater")$p.value
 k.t[i] <- kruskal.test(wuerfeln, spieler)$p.value
}

# Wieviele Tests sind signifikant
summary(t.t<0.05)
summary(w.t<0.05)
summary(k.t<0.05)
# ... hoch signifikant
summary(t.t<0.003)
summary(w.t<0.003)
summary(k.t<0.003)

pdf("wuerfeln.pdf")
hist(t.t, main="Histogram\nt-test one sided", xlab="
   p-value")
hist(w.t, main="Histogram\nWilcoxon-test one sided",
    xlab="p-value")
hist(k.t, main="Histogram\nKruskal-Wallis-test",
   xlab="p-value")
dev.off()

xfig("wuerfeln_%03d.fig")
hist(t.t, main="Histogram\nt-test one sided", xlab="
   p-value")
hist(w.t, main="Histogram\nWilcoxon-test one sided",
    xlab="p-value")
hist(k.t, main="Histogram\nKruskal-Wallis-test",
   xlab="p-value")
dev.off()
```

Appendix C

End of the Gedanken Experiment

The Rest of the gedanken experiment, the beginning is in chapter Discussion section 5.1.2 on page 51.

> They knew, that this could not be possible. Based on the assumption that the dice is fair, the statistical test should reveal only as much percentage of significant cases as the significant level was set. Here it should be around 50 (corresponds to $1,000 \cdot 0.05$).
>
> They still were arguing with each other as the morning had already begun. As they could not sleep anyway without solving this problem, they decided to call a friend who was mathematician. Latter suggested to try once the Kruskal-Wallis-test because it can be applied on a group of distributions. And behold, their friend was right: the new test revealed for an $\alpha = 5\%$ around 50 significant cases and as α was set to 0.3% they counted 4 significant cases, which is near by 3. This is exactly what they expected from a good test, see also chapter Results section 4.10 on page 44.

Appendix D

Glossar

ARMA Autoregressive-Moving Average

ANETZ "Automatisches Stationsnetz" of "Schweizerische Meteorologische Anstalt" (SMA) (automatical meteorological gauging stations network of SMA)

BAFU "Bundesamt für Umwelt" (Federal Office for the Environment)

BUWAL "Bundesamt für Umwelt Wald und Landschaft"

Former name of the BAFU

CLIMAP Java application to get data from MeteoSwiss

CCN Cloud Condensation Nuclei

DWD "Deutscher Wetterdienst" (German Weather Service)

Data are available online: `http://www.dwd.de/de/FundE/Klima/KLIS/daten/online/nat/index_standardformat.htm`

O "Ostströmung" (east stream)

Empa "Eidgenössische Material Prüfungsanstalt" (Material Science & Technology)

ETH "Eidgenössische Technische Hochschule" (Federal Institute of Technology)

F "Flache (mittlere) Druckverteilung" (weather conditions with a flat pressure distribution)

GNU GNU's Not UNIX

Project with the target to develop a complete free operating system (http://www.gnu.org)

GPL General Public License (http://www.gnu.org/licenses/gpl.html)

H "Hochdrucklage" (high pressure condition)

IACETH Institute for Atmospheric and Climate Science at ETH

IPCC Intergovernmental Panel on Climate Change

M "Mischlage"

MATLAB MATrix LABoratory, a numerical computing environment and programming language created by "The MathWorks"

MeteoSwiss Federal Office of Meteorology and Climatology

MSU Microwave Sounding Unit

N "Nordströmung" (north stream)

NABEL "Nationales Beobachtungsnetz für Luftfremdstoffe" (National Observation Network for Foreign Air Contaminants)

NABEL is a corporate project from "Bundesamt für Umwelt Wald und Landschaft" (BUWAL) and Empa

ORDBMS Object-Relational DataBase Management System

PM Particulate Matter

PM_1 PM with less then 1 μm in aerodynamic diameter

$PM_{2.5}$ PM with less then 2.5 μm in aerodynamic diameter

PM_{10} PM with less then 10 μm in aerodynamic diameter

PostgreSQL PostgreSQL an ORDBMS

http://www.postgresql.org

QFF Current air pressure in hPa, reduced to sea level by mind the real temperature circumstances

R GNU R

A statistics program. Used the same language as S (R is 'GNU S'), licence: General Public License (`http://www.gnu.org/licenses/gpl.html`) (GPL) [R Development Core Team, 2007]

S "Südströmung" (south stream)

SMA "Schweizerische Meteorologische Anstalt"

Former name of the MeteoSwiss

SQL Structured Query Language

A database computer language

T "Tiefdrucklage"(low pressure condition)

W "Westströmung" (west stream)

WMO World Meteorological Organization