Chapter 2
Trend and Season

Polynomials, moving averages and straight lines—the latter two describe the decrease and increase of temperature in the last two centuries—are considered. The warming in the last 20 years is substantiated. The effect of auto-correlation on standard significance tests is discussed. The study of monthly data gives rise to introduce the notion of a seasonal component and of seasonally adjusted data. Finally, we plot the course of oscillation (fluctuation) of a climate variable and search for trends or patterns.

2.1 Trend Polynomials. Moving Averages

A trend component describes the long-term variation of a time series. A comparatively rough and little sophisticated method is to fit polynomials (of lower order) to the whole time series Y_t, $t = 1, \ldots, n$, of observed annual data. Here, n is the number of years. See Figs. 1.1, 1.2, 1.3, 1.4, 1.5 and 1.6 for fourth-order polynomials

$$p_t = b_0 + b_1 \cdot t + b_2 \cdot t^2 + b_3 \cdot t^3 + b_4 \cdot t^4, \quad t = 1, 2, \ldots, n. \tag{2.1}$$

The residuals from the fitted polynomial are given by $e_t = Y_t - p_t$. A goodness-of-fit measure is calculated from the mean sum of the *squared residuals* (MSQ) by

$$RootMSQ = \sqrt{\frac{1}{n} \sum\nolimits_{t=1}^{n} e_t^2}.$$

The smaller the measure, the better the fit of the polynomial. Due to $\bar{e} \approx 0$ the measure *RootMSQ* is approximately equal to the standard deviation of the residuals e_t. Table 2.1 shows that the *RootMSQ*- values decrease with increasing order k. This decrease is very slow for precipitation and stronger for temperature. For temperature at Hohenpeißenberg and in Karlsruhe, the biggest drop is from order

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Table 2.1 Annual temperature means

	Bremen				Hohenpeißenberg			
	Temperature		Precipitation		Temperature		Precipitation	
k	R	r_1	R	r_1	R	r_1	R	r_1
1	0.719	0.30	1.05	0.02	0.824	0.26	1.64	0.21
2	0.717	0.29	1.05	0.02	0.757	0.12	1.62	0.19
4	0.681	0.21	1.03	−0.00	0.754	0.11	1.62	0.18
6	0.675	0.20	1.01	−0.04	0.737	0.06	1.59	0.16
	Karlsruhe				Potsdam			
	Temperature		Precipitation		Temperature		Precipitation	
k	R	r_1	R	r_1	R	r_1	R	r_1
1	0.790	0.31	1.35	0.01	0.733	0.21	0.95	−0.08
2	0.707	0.14	1.35	0.01	0.724	0.18	0.95	−0.08
4	0.692	0.11	1.34	0.00	0.712	0.15	0.95	−0.09
6	0.672	0.06	1.32	−0.05	0.702	0.14	0.95	−0.09

Order k of the polynomial and resulting goodness-of-fit R = RootMSQ. Further, the auto-correlation $r_1 = r_e(1)$ of the residual series e_t is listed

$k = 1$ (straight line) to order $k = 2$ (parabola)—more than from $k = 2$ to 4, 6. For temperature, the auto-correlations $r_e(1)$ of the residuals are distinctly positive, meaning that the fit p_{t+1} stays—by tendency—on the same side of the observed value as the fit p_t does. The same is true with precipitation only at Hohenpeißenberg.

The $r_e(1)$-values for precipitation in Bremen, Karlsruhe, and Potsdam are ≈ 0, but that was already the case with the $r(1)$-values of the original series Y, see Table 1.3.

Next, we compare the fitted polynomials (of order $k = 1, 2, 3$) for three stations. For the sake of comparability, we take 116 years (1893–2008) only and center the curves around $\bar{Y}$; that is, we are plotting in Fig. 2.1 the values $p_t - \bar{Y}$, $t = 1, \ldots, 116$. The curves run nearly identical over the 116 years. That is, the annual temperature means—when approximated by polynomials—run remarkably parallel at the three stations.

Further, Figs. 1.1, 1.2, 1.3, 1.4, 1.5 and 1.6 contain—as trend curves—*centered* moving averages m_t over $k = 11$ years. Putting $k = 2 * l + 1$, for estimating the trend m_t we form the time interval $[t - l, t + l]$ of k points, with the time point t as the center, and extend the average over the k years, but with weight $1/2$ for the endpoints; that is

$$m_t = \frac{1}{2 * l} \cdot \left[\frac{1}{2} \cdot Y_{t-l} + Y_{t-l+1} + \cdots + Y_t + \cdots + Y_{t+l-1} + \frac{1}{2} \cdot Y_{t+l} \right]. \qquad (2.2)$$

Remark. The variables m_t or p_t, according to Eqs. (2.1) or (2.2), are predictions (interpolations) for Y_t. Note that they use information from observations before and after time point t. Let us call this approach the *standard regression approach* for

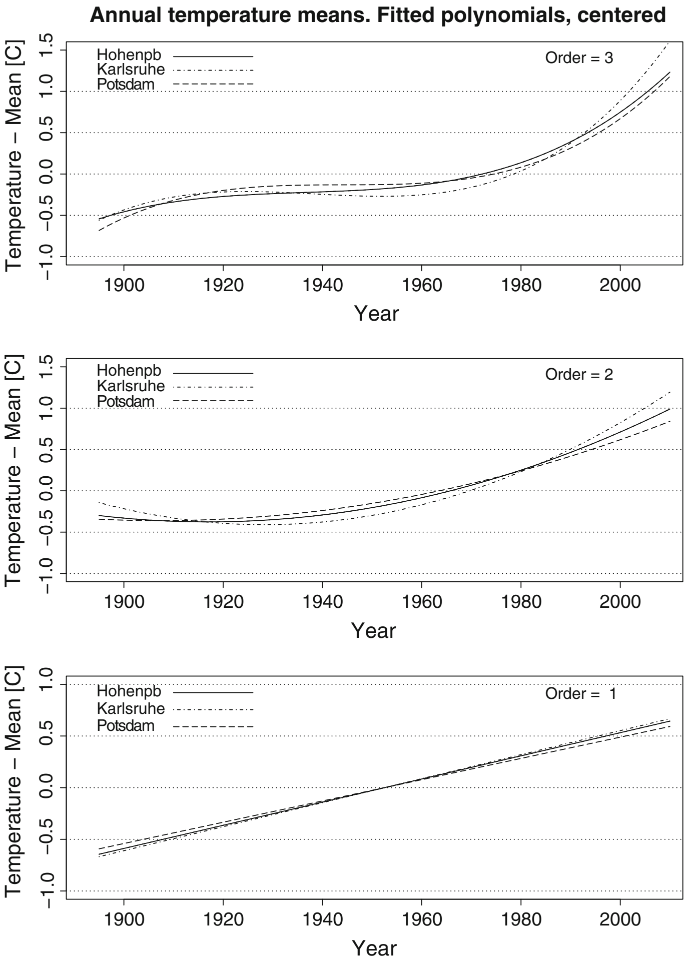

Fig. 2.1 Fitting polynomials of order 1, 2, and 3 over the years 1893–2008, each time for the three stations Hohenpeißenberg, Karlsruhe, Potsdam. Each curve is centered around the total mean $\bar{Y}$ for the station

prediction. Within the context of climatological time series (which are continuously updated) a *forecast* approach for prediction seems to be more appropriate. Here, for predicting Y_t, only observations *before* time point t are employed. This is—for instance—the case with left-sided moving averages, growing polynomials, or autoregressive algorithms, which will follow in Chaps. 4, 5, and 8.

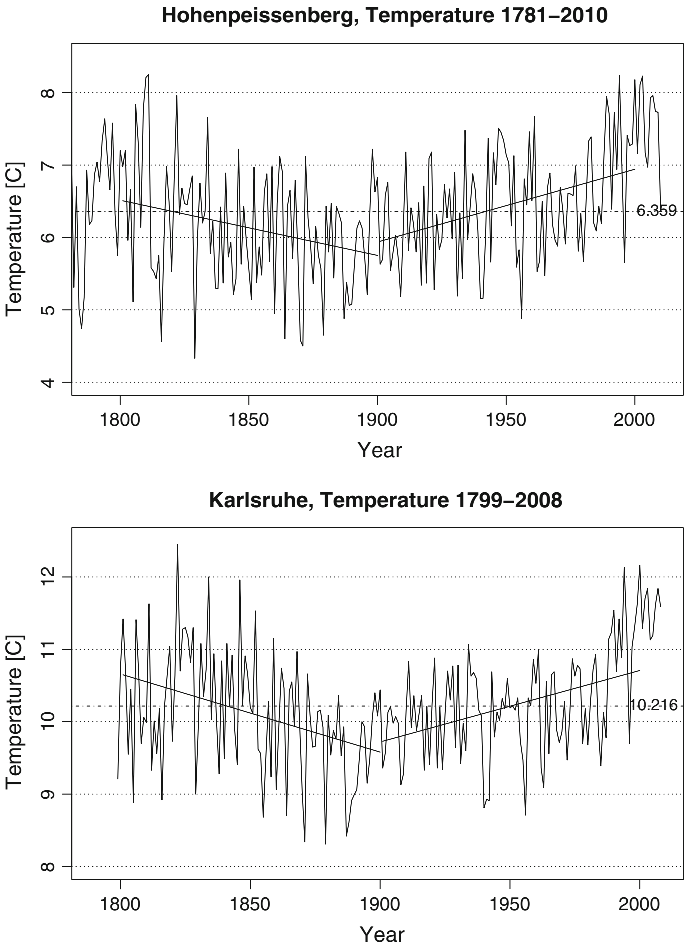

Fig. 2.2 Annual temperature means (°C) Hohenpeißenberg, 1781–2010 (*top*), Karlsruhe, 1799–2008 (*bottom*); with *straight lines* fitted for each century and with the total mean (*horizontal line*). Compare also Schönwiese (1995, Abb. 12)

2.2 Temperature: Last Two Centuries—Last Twenty Years

In this section, we study the long-term trend of temperature over the last two centuries. For this investigation, only the series of Hohenpeißenberg and of Karlsruhe are long enough. While temperature decreases in the nineteenth century, it increases in the twentieth century, see Fig. 2.2.

The regression coefficients (slopes) $b = b(Temp|Year)$ of the two—for each century separately fitted—straight lines $p_t = a + b \cdot t$ are tested against the hypothesis

Table 2.2 Statistical measures for the temperature (°C) of the last two centuries

	Hohenpeißenberg					
Period	n	Mean value	Standard deviation	Regression b*100	Correlation r	Test T
Nineteenth century	100	6.129	0.843	−0.763	−0.262	0.271
Twentieth century	100	6.445	0.747	1.006	0.390	0.423
	Karlsruhe					
Period	n	Mean value	Standard deviation	Regression b*100	Correlation r	Test T
Nineteenth century	100	10.114	0.845	−1.079	−0.370	0.398
Twentieth century	100	10.219	0.689	0.988	0.416	0.457

The regression coefficient b is multiplied by 100, r is the dimension-free version of b, T the test statistic (2.3)

of a zero slope. The level 0.01-bound for the test statistic T,

$$T = \frac{|r|}{\sqrt{1-r^2}}, \quad r = b \cdot \frac{s(Year)}{s(Temp)}, \tag{2.3}$$

is $t_{98,0.995}/\sqrt{98} = 0.265$. Herein, the correlation coefficient r is the dimension-free version of b.

1. As Table 2.2 informs us, the negative trend in the 19th century and the positive trend in the twentieth century are statistically confirmed (at Hohenpeißenberg and in Karlsruhe). The test assumes uncorrelated residuals $e_t = Y_t - p_t$. This can be substantiated using the auto-correlation function of the e_t (not shown, but see Chap. 4 for similar analyses).

2. The total temperature means m_1 and m_2 of the two centuries do not differ very much from each other and from the total mean m of the whole series, see Table 2.2.

The increase of temperature in the 20th century is statistically significant in Potsdam, too. In Bremen, however, we have a nearly horizontal trend line over this time period (consult Fig. 2.3 and Table 2.3).

$\boxed{\textbf{R 2.1}}$ Plot of annual temperature means, together with straight lines fitted for the nineteenth and twentieth century separately, see Fig. 2.2 (bottom). The straight line is produced within the user function `tempger` (for `lm` and `predict` see also R 1.3). The output is written and stored on the file `C:/CLIM/Tempout.txt`.

```
attach(karlsTp)

postscript(file="C:/CLIM/KarlsT12.ps",height=6,width=20,horiz=F)
sink("C:/CLIM/Tempout.txt")         #Output on file Tempout.txt

quot<- "Karlsruhe,  Temperature 1799-2008"; quot
Y<- Tyear/100;    "annual means in Celsius"
cylim<-  c(8.0,12.5);  cabl<- c(8:12)
plot(Year,Y,type="l",lty=1,xlim=c(1790,2008),ylim=cylim,
   xlab="Year",ylab="Temperature [C]",cex=1.3)
```

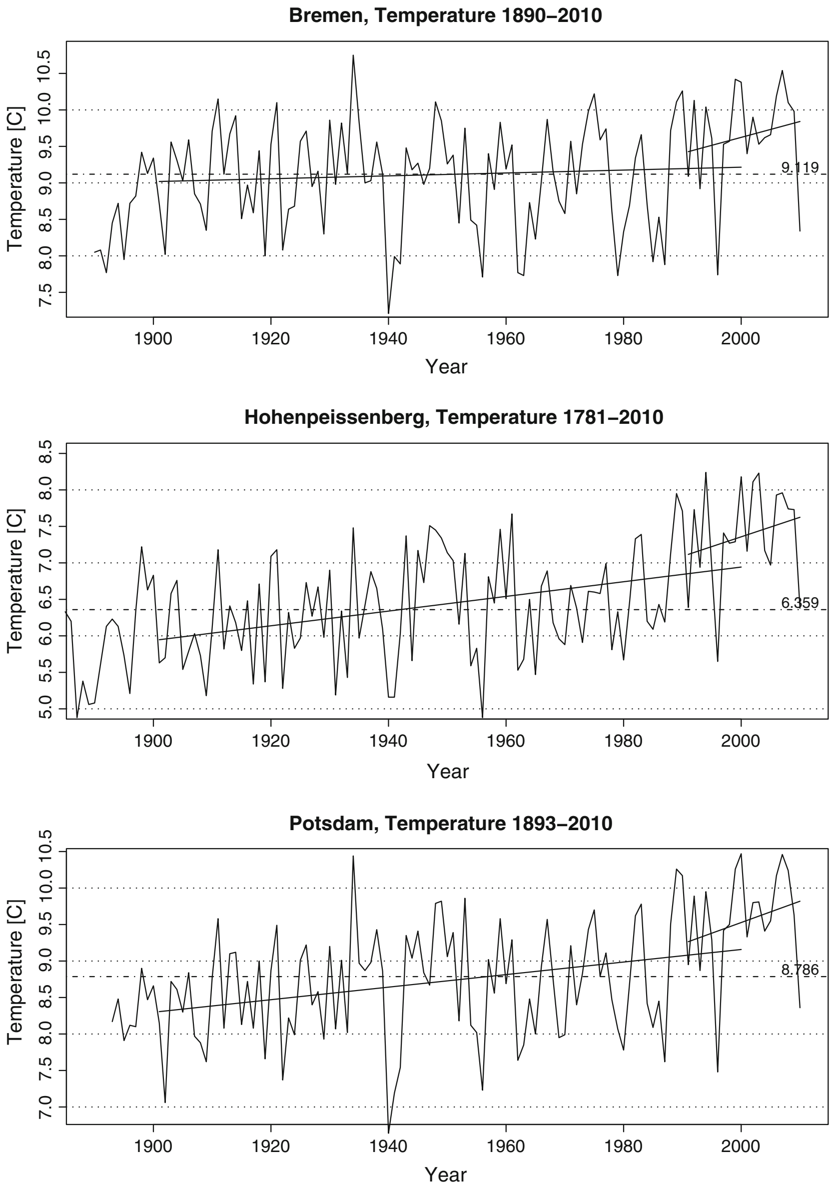

Fig. 2.3 Annual temperature means (°C). Bremen 1890–2010, Hohenpeißenberg 1781–2010 (here 1885–2010 is shown), Potsdam 1893–2010; with *straight line* fitted for the twentieth century. The *fitted line* for the 20 years 1991–2010 is also shown

Table 2.3 Statistical measures for the temperature (°C) of the last century and of the last 20 years 1991–2010

Period	n	Mean value	Standard deviation	Regression b*100	Correlation r	Test T	Upper limit
	Bremen						
Twentieth century	100	9.117	0.738	0.198	0.077	0.077	
1991–2010	20	9.634	0.699	2.177	0.184		9.372 (16)
	Hohenpeißenberg						
Period	n	Mean value	Standard deviation	Regression b*100	Correlation r	Test T	Upper limit
Twentieth century	100	6.445	0.747	1.006	0.390	0.423	
1991–2010	20	7.370	0.699	2.677	0.226		6.553 (17)
	Potsdam						
Period	n	Mean value	Standard deviation	Regression b*100	Correlation r	Test T	Upper limit
Twentieth century	100	8.732	0.804	0.860	0.310	0.326	
1991–2010	20	9.542	0.730	2.919	0.237		9.066 (16)

The regression coefficient b is multiplied by 100, r is the dimension-free version of b, T the test statistic (2.3). The upper limit refers to the 99 % confidence interval (2.4); in brackets the number of years (out of 20) with a temperature mean above the upper limit

```
title(main=quot)
abline(h=cabl,lty=3);  abline(h=mean(Y),lty=4)
text(2008,mean(Y),trunc(mean(Y)*1000)/1000,cex=0.8)   #total mean

#---------------------------------------------------------------
tempger<-  function(Year,Y,A,B){  #compute and plot straight line
Y0<- Y[A:B]; Year0<- Year[A:B]
tpger0<- lm(Y0~Year0);   tpg0<- summary(tpger0)
lines(Year0,predict(tpger0),lty=1)              #plot fitted line
return(tpg0)                                     #return summary
}

"19th century"
Jbeg<- 2;   A1<- Jbeg+1; B1<- Jbeg+100;
tpg1<- tempger(Year,Y,A1,B1); tpg1                #print summary

"20th century"
A2<- Jbeg+101; B2<- Jbeg+200;
tpg2<- tempger(Year,Y,A2,B2); tpg2                #print summary

dev.off()
```

Output from R 2.1 Excerpt from results written on the file `C:/CLIM/Tempout.txt`, for Karlsruhe, Temperature.

The square root of `R-squared = 0.137` equals the absolute value 0.370 of the coefficient of correlation in Table 2.2. The t-value −3.945 divided by $\sqrt{98}$ equals the absolute value 0.398 of the test statistic T.

```
"19th century"
Call:  lm(formula = Y0 ~ Year0)
Coefficients:
             Estimate Std. Error t value  Pr(> t|)
(Intercept) 30.07826    5.0611     5.943  4.29e-08 ***
Year0       -0.010788   0.002735  -3.945  0.00015  ***
---
Signif. codes:  0  *** 0.001 ** 0.01 * 0.05 . 0.1   1
Residual standard error: 0.7894 on 98 degrees of freedom
Multiple R-squared: 0.137,  Adjusted R-squared: 0.1282
F-statistic: 15.56 on 1 and 98 DF,  p-value: 0.0001500
```

Effective Sample Size

When applying tests and confidence intervals to time series data, the effect of auto-correlation should be taken into account. To compensate, the sample size n is to be reduced to an *effective* sample size n_{eff}. As an example we treat the confidence interval for the true mean value μ of a climate variable, let us say the long-term temperature mean. On the basis of an observed mean value $\bar{y}$, a standard deviation s and an auto-correlation function $r(h)$, see Sect. 3.3 below, the $(1-\alpha) * 100\,\%$ confidence interval (assuming a large n) is

$$\bar{y} - u_0 \cdot \frac{s}{\sqrt{n_{eff}}} \le \mu \le \bar{y} + u_0 \cdot \frac{s}{\sqrt{n_{eff}}}, \quad u_0 = u_{1-\alpha/2}, \tag{2.4}$$

with u_γ being the γ-quantile of the $N(0, 1)$-distribution, and with

$$n_{eff} = \frac{n}{1 + 2 \cdot \sum_{k=1}^{n-1} (1 - (k/n)) \cdot r(k)} \approx \frac{n}{1 + 2 \cdot \sum_{k=1}^{n-1} r(k)} \quad [n \text{ large}];$$

see Brockwell and Davis (2006, Sect. 7.1), von Storch and Zwiers (1999, Sect. 6.6). For an AR(1)-process with an auto-correlation $r = r(1)$ of first order we have to put $r(k) = r^k$, cf. Appendix B.3, and obtain

$$n_{eff} = n \cdot \frac{1-r}{1+r} \quad [n \text{ large}]. \tag{2.5}$$

The Last Twenty Years

We have the further result

3. The average m_3 over the last 20 years is significantly larger than the twentieth century mean m_2 (and larger than the total mean m too; 0.01 level). That is immediately confirmed by a two sample test, even after a correction, due to auto-correlation. The warming in the last two decades is well established by our data.

To make this result **3.** more explicit, we construct a 99 % confidence interval around the long-term temperature mean μ acc. to (2.4) (where the auto-correlation is taken into regard). Then we count, how many of the last 20 yearly means lie above the upper limit.

Example Hohenpeißenberg: With $n = 230, r = 0.295, m = \bar{y} = 6.359, s = 0.844$ we are led by Eq. (2.5) to $n_{eff} = 125.21$ and thus to a 99 % confidence interval [6.165, 6.553].

For all three stations in Table 2.3, at least 16 of the last 20 yearly temperature means lie above the upper 99 % confidence limit, reinforcing the result **3.** above. Among the exceptions are always the colder years 1991, 1996, 2010.

The *winter* temperatures show the same pattern, but in a weakened form. The fall and the rise of the straight lines are no longer significant (see result **1.**), at least 13 of the last 20 winter temperature means lie above the upper 99 % limit of (2.4) (see result **3.**). So, the warming in the winter months of the last decades is not so strongly pronounced in our data.

2.3 Precipitation

The precipitation records start in the last quarter of the nineteenth century. To sketch their course over the last 120 years, we divide this time period into three intervals, namely

1891–1950 (Potsdam 1893–1950), 1951–1990 and 1991–2010 (Karlsruhe 1991–2008).

Then we calculate—for each time interval separately—the average of annual and of winter amounts. Further, a parabola is fitted over the whole 120 years. Figure 2.4 and Table 2.4 reveal a general increase of precipitation toward the second half of the last century. They show a drastic increase of the annual and the winter amounts from the first to the second time interval at Hohenpeißenberg (weaker in Bremen and in the winter data Karlsruhe), followed by a decrease to the third. The Table 2.4 reports the corresponding 2-sample t-test statistics. Note that the standard deviations are roughly between 1.0 (Po) and 1.7 (Ho) for the annual data, and between 0.4 and 0.5 for the winter data, cf. Table 1.3. Taking the maximal value of 0.27 for the auto-correlation into regard (and the correction formula in 2.2), the upper 5 % bound for the absolute value of the t-test statistic is at most $t_{34-2,0.975} = 2.04$ (and at least $u_{0.975} = 1.96$, of course). Thus, statistically significant changes are:

- from the first to the second time interval at Hohenpeißenberg (annual and winter data) and in Bremen (annual data),
- from the second to the third interval at Hohenpeißenberg (winter data).

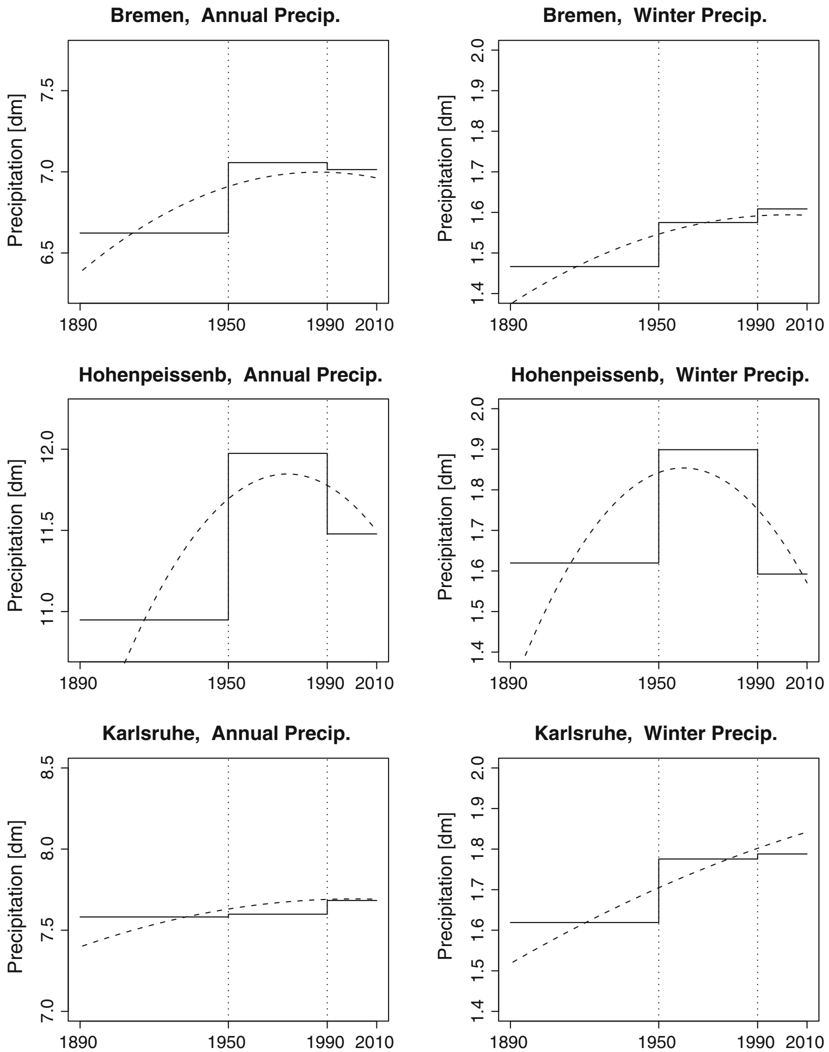

Fig. 2.4 Annual (*left*) and winter (*right*) precipitation amounts (dm), averaged over each of the 3 sections of the time period 1891–2010 (Bremen, Hohenpeißenberg), 1891–2008 (Karlsruhe). A parabola is fitted to the 120 yearly data. Notice that the y-axes on the *right* have the same range 1.4–2.0 (dm); the y-axes on the *left* have different ranges, but the ranges have the same width of 1.5 (dm)

Table 2.4 The table gives the annual and the winter precipitation amounts in (dm), for the three time intervals (1) 1891–1950, (2) 1951–1990, (3) 1991–2010, with the three mean values and with the two 2-sample t-test statistics for the changes from (1) to (2) and from (2) to (3)

Station	Mean 1	Mean 2	Mean 3	Test 1 → 2	Test 2 → 3
Bremen annual	6.623	7.057	7.014	2.23	−0.13
Bremen Winter	1.467	1.575	1.609	1.07	0.22
Hohenpb annual	10.95	11.97	11.48	2.92	−1.14
Hohenpb Winter	1.620	1.899	1.592	2.52	−2.42
Karlsruhe annual	7.582	7.599	7.683	0.06	0.22
Karlsruhe Winter	1.619	1.776	1.788	1.38	0.08
Potsdam annual	5.837	5.965	5.986	0.66	0.07
Potsdam Winter	1.249	1.336	1.384	1.11	0.47

2.4 Historical Temperature Variations

Statistical results are formal statements; they alone do not allow substantial statements on the earth warming. Especially, a prolongation of the upward lines of Figs. 2.2 and 2.3 would be dubious. An inspection of temperature variability of the last millenniums reveals that a trend (on a shorter time scale) could turn out as part of the normal variation of the climate system. See Schönwiese (1995), von Storch and Zwiers (1999).

Figure 2.5 shows temperature variability of the last 8,000 years, adopted from Schönwiese (1995), estimated by the method of oxygen-isotopes from Greenland's ice drill cores. Especially, we recognize distinctly cold and warm time periods, denoted by A–E in Fig. 2.5.

2.5 Monthly Values

The march of temperature and of precipitation over the 12 months of the year is plotted as histogram in Fig. 2.6. Hereby—for each specific month—the total average of n monthly values is calculated (n the number of years). In the case of temperature the histograms of the four stations (three are shown) show a rather similar form, with a somewhat lowered and compressed form for Hohenpeißenberg. In the case of precipitation, the wet months June and July at Hohenpeißenberg and the dry months February, March, and October in Potsdam attract attention.

According to Malberg (2007) the histogram of precipitation in Fig. 2.6 at the stations Hohenpeißenberg and Potsdam reflects more a continental (and less an oceanic) type of climate.

R 2.2 Six histograms of the total monthly averages for temperature and precipitation at three stations, see Fig. 2.6. Within the user function `monthTP` the (user)

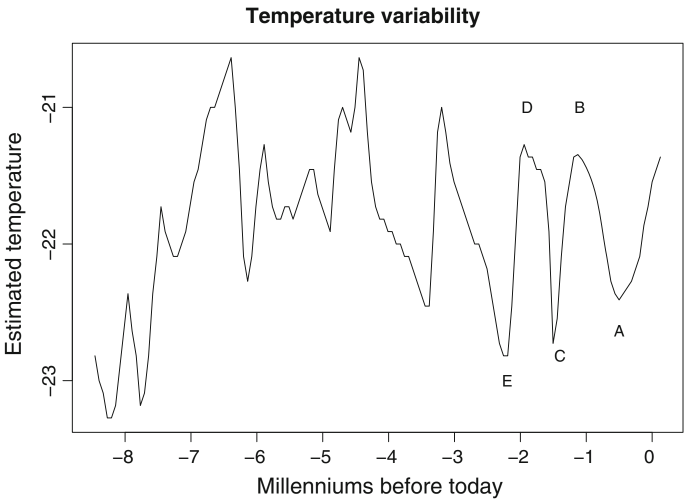

Fig. 2.5 Temperature variability of the last 8,000 years, qualitative curve; adopted from (Schönwiese (1995), Abb. 26). *A* (1500–1700), *B* (800–1000), *C* (450–800), *D* (200 BC–200 AD), *E* (1200 BC–600 BC)

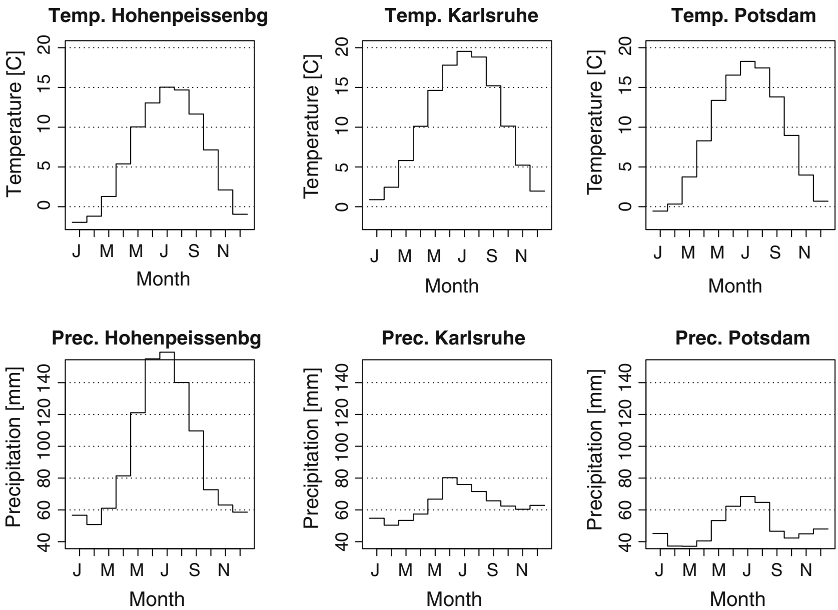

Fig. 2.6 March of temperature in °C (*top*) and precipitation in mm (*bottom*) over the calendar year, plotted for the three stations Hohenpeißenberg (until 2010), Karlsruhe (until 2008), Potsdam (until 2010). The truncated precipitation values for Hohenpeißenberg are: June 154.9, July 159.2

function `plotTP` is called. The latter produces a step function plot. Note that we put `plm[13] = plm[12]` with respect to the last (twelfth) step. The x-axis (`side=1`) with the initial letters is labeled by `axis` and `labels`. All six `read.table` commands of R 1.1 are needed.

```
postscript(file="C:/CLIM/MonthTP.ps",height=8,width=20,horiz=F)
par(mfrow=c(2,3),pty="s")          #2x3 pictures of square size

plotTP<- function(mo,ttext,cylim,tylab,cabl){
plmo<-c(mo,mo[12])          #plmo[13]: right corner of last step
x<- seq(0.5,12.5,by=1)
plot(x,plmo,type="s",                          #step function plot
  xlim=c(0.5,12.5),ylim=cylim,xaxt="n",xlab="Month",ylab=tylab)
axis(side=1,at=c(1:12),
  labels=c("J","F","M","A","M","J","J","A","S","O","N","D"))
title(main=ttext,cex=1.1);  abline(h=cabl,lty=3)
}
monthTP<- function(mon12,ttext,cylim,tylab,cabl){
mon12.mat<- as.matrix(mon12)                    #mon12 as matrix
mon12.me<- colMeans(mon12)                      #monthly means
plotTP(mon12.me,ttext,cylim,tylab,cabl)
}
#--------------------------------------------------------------
cylim<- c(-2,20); tylab<- "Temperature [C]"
cabl<- c(0,5,10,15,20)
mon12<- data.frame(hohenTp[,3:14])/10           #select jan-dec
monthTP(mon12,"Temp. Hohenpeissenbg",cylim,tylab,cabl)
mon12<- data.frame(karlsTp[,3:14])/10
monthTP(mon12,"Temp. Karlsruhe",cylim,tylab,cabl)
mon12<- data.frame(potsdTp[,3:14])/10
monthTP(mon12,"Temp. Potsdam",cylim,tylab,cabl)

#----Similarly with precipitation-----------------------------

dev.off()
```

To judge a temperature value in a specific month, we have to compare it with the value, which is predicted by the trend and by the seasonal component.

This comparison is illustrated by Fig. 2.7, which presents the 36 monthly temperature means Y_t of three succeeding years. The trend-component $\hat{m}_t$ is gained by building moving averages over 13 months, that is, by employing six preceding and six following months. The seasonal component $\hat{s}_t$ consists of the total averages of each month, as shown in the histogram of Fig. 2.6 (left, top)—centered at a mean value zero. The trend and season-component is then given by

$$\hat{Y}_t = \hat{m}_t + \hat{s}_t,$$

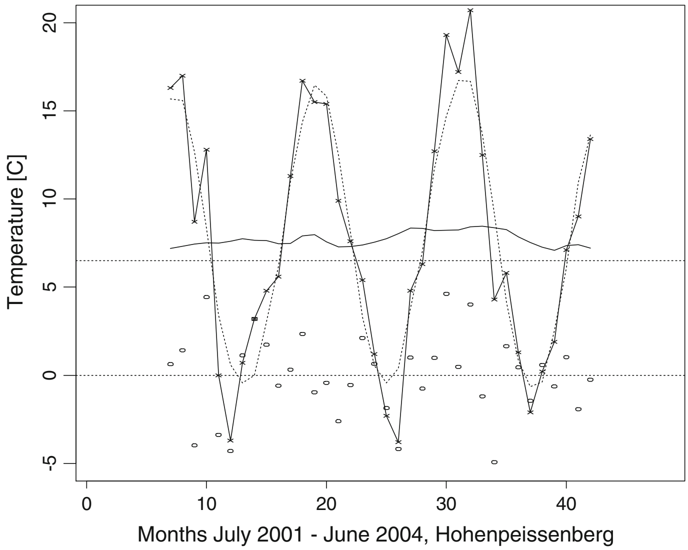

Fig. 2.7 The 36 monthly temperature means Y_t ($\times$) at Hohenpeißenberg, July 2001–June 2004. In addition, with a trend-component (*inner solid line*—) and trend+season-component ($\cdots$), as well as residuals therefrom (o)

also called *prediction* for Y_t. The *residuals*

$$e_t = Y_t - \hat{Y}_t$$

reveal, for which months the trend- and seasonally adjusted temperature values are too high (then with a positive residual) or too low (then with a negative residual).

The "record summer" 2003 (months no. 30–32 in Fig. 2.7) is salient because of the above-average temperature values in June and August. Accordingly, the residual values are distinctly positive. Cold months (in relation to trend+season) were September, November, and December 2001, as well as especially October 2003—the latter with an extremely negative residual.

More sophisticated prediction/residual procedures for monthly data are presented in Chap. 5.

2.6 Oscillation in Climate Series

Besides the trend, it is also the oscillation (fluctuation) of a climatological series, in which we are interested. First, we want to visualize the oscillation of the *annual* temperature and precipitation values. To this end, we build moving 10-years blocks $[t-9, t]$, $t = 10, \ldots, n$, calculate for each block the standard deviation sd(t) = $\hat{\sigma}(t)$

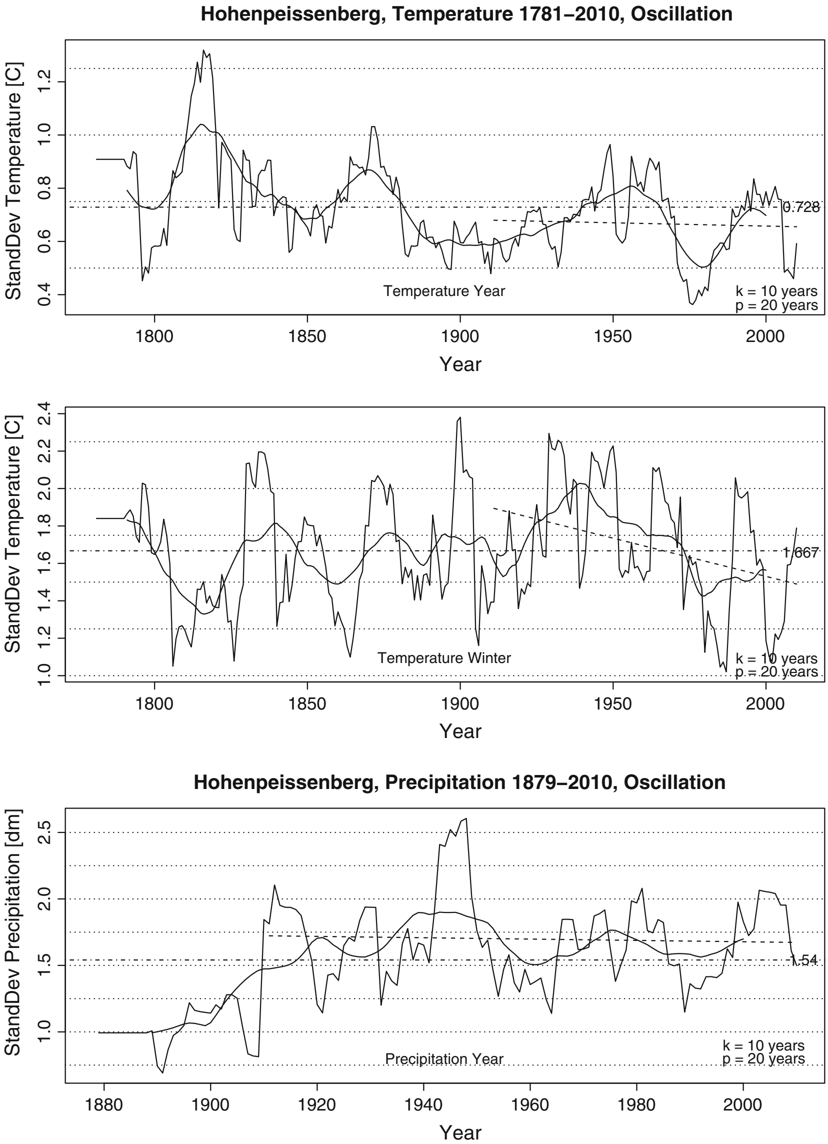

Fig. 2.8 Oscillation of annual climate values at Hohenpeißenberg. Standard deviation sd(t), calculated for 10-years blocks $[t-9, t]$, plotted over years t. Further: smoothing by 20 years moving averages (*inner solid line*), *straight line* fit for the last 100 years (*dashed line*), and the total mean (*horizontal dashed-dotted line*). Shown are yearly and winter temperature means, yearly precipitation amounts (from *top* to *bottom*)

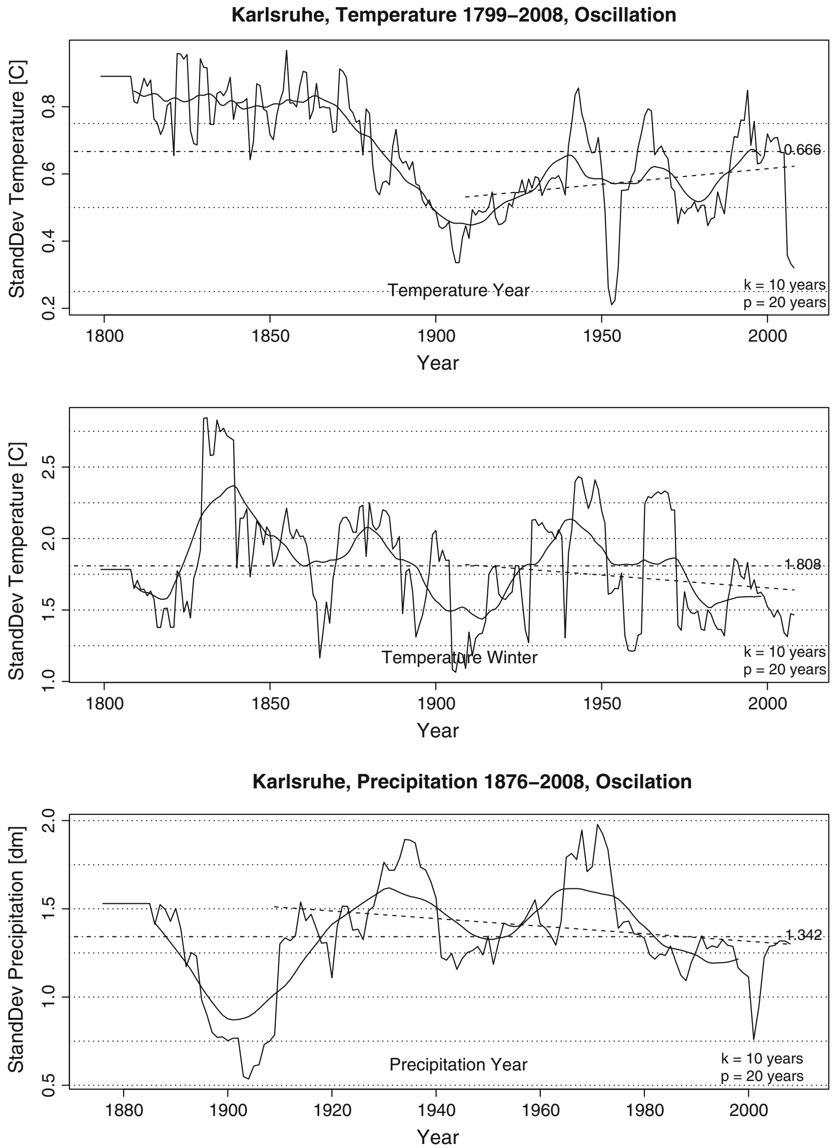

Fig. 2.9 Oscillation of annual climate values in Karlsruhe. Legend as for Fig. 2.8

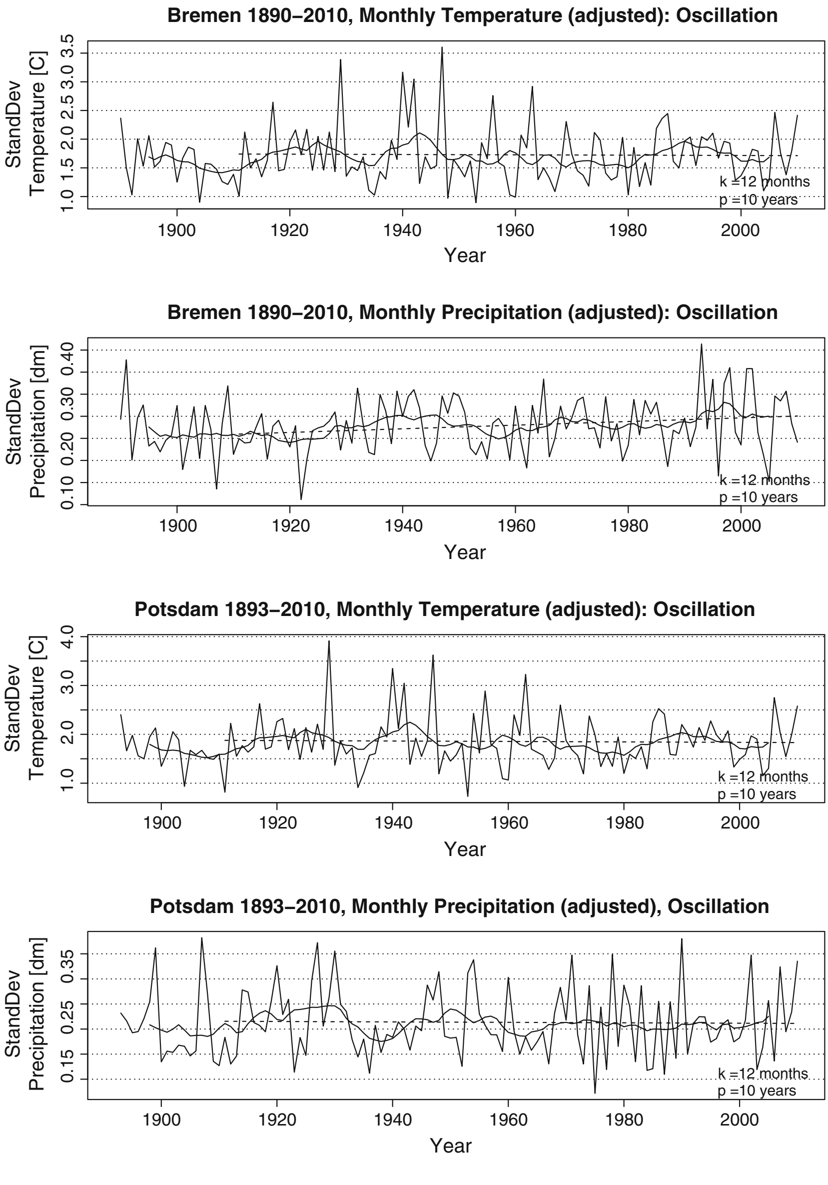

Fig. 2.10 Oscillation of (seasonally adjusted) monthly climate values, in Bremen and Potsdam. Standard deviation sd(t), calculated for calendar year t, plotted over the years t. Further: smoothing by 10 years moving averages (*inner solid line*), *straight line* fit for the last 100 years (*dashed line*)

and plot sd(t) over the years t. For Hohenpeißenberg (Fig. 2.8), Karlsruhe (Fig. 2.9), Bremen, and Potsdam (no Figs.), no definite common pattern can be detected, neither in the yearly nor in the winter data. Time periods with higher fluctuation follow those with lower fluctuation, without an apparent regularity and with little agreement between the stations. At least one could recognize a general lower oscillation around 1900 (except Fig. 2.8, middle). Further, perhaps against the expectation, the oscillation in the last 10 or 20 years is not very high. In Sect. 4.4, the oscillation in the annual precipitation series is analyzed by more sophisticated methods.

To quantify the oscillation of *monthly* climate values, we calculate for each calendar year the standard deviation sd(t), that is the standard deviation of the 12—seasonally adjusted—temperature means and precipitation sums, respectively. Once again, we plot sd(t) over the years t; see Fig. 2.10 for the stations Bremen and Potsdam. We do not discover clear-cut patterns, but with respect to temperature, we notice a good conformity of the Bremen and the Potsdam oscillation series sd(t).

The oscillation sd(t) shows no uniform trend over the last 100 years (see the straight line fit in Figs. 2.8, 2.9 and 2.10). The sign of the slopes differ between the four stations, and that is true for yearly and for winter temperature and precipitation, as well as for monthly precipitation. Only in the cases of monthly temperature we have an uniformly decreasing tendency (but the negative coefficients of slope are not significantly different from zero).

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