Forest climatology: estimation and use of daily climatological data for Bavaria, Germany

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Abstract

Long-term daily climatological data are important to study forest damage and simulate tree growth, but they are scarce in forested areas because observational records are often scarce. At the eight Bavarian forest sites, we examined six interpolation methods and established empirical transfer functions relating observed forest climate data to the climate data of German weather stations. Based on our comparisons, a technique is developed and used to reconstruct 31-year daily forest climatological data at six forest sites. The reconstructed climate data were then used to calculate four meteorological stress factors which are of importance to forest studies. Finally, the uncertainties, temporal and spatial variation of these stress factors were discussed.

Keywords: Interpolation; Comparison; Empirical transfer functions; Weather stations; Forest climate stations; Meteorological stress factors; Reconstruction

1. Introduction

Forests are influenced to a very large extent by local meteorological and climatological conditions. The numerous ecological processes (photosynthesis, evapotranspiration, respiration, decomposition, etc.) are closely related to meteorological conditions. Recently, forest damage in Europe has been more and more emphasised (Mueller-Edzards et al., 1997). Meteorological stress factors (i.e., drought, high and low temperature, frost, etc.) are considered as the possible causes. To study these processes and possible causes, accurate forest climatological data are needed for the site of interest. However, the use of climatological data for ecological modelling and diagnostics has been hindered by three fundamental problems. First, climatological data are rarely available for the exact location of interest. Second, climatological data may be needed at varying time scales, from days to years, depending upon the use to be made of the data. Third, the interpolated data may be not accurate. The best method to solve the problems is to establish a larger network of forest climate stations. Based on this idea, the Bavarian State Institute of Forestry has set up 22 forest climate stations in typical forest areas throughout Bavaria since 1991. These forest climate stations are located in forest clearings with a diameter of at least four times the height of old trees. Clearly, measurements from above the canopy would be best but require costly measuring towers and intensive technical support. To date this could not be put into practice in Bavaria.
In other parts of Europe there are similar problems. In 1985, a Level I forest monitoring network was set up but did not include forest climate stations. An assessment of the 10-year monitoring results showed that forest climatological observations are very important, because climate interpolated from weather stations of various countries were not available (Hendriks et al., 1997). Due to this limitation, in 1995 a Level II intensive monitoring network was established. The 22 Bavarian forest climate stations were included in this Level II monitoring network (Preuhsler et al., 1996).

Due to early establishment of these forest climate stations in Bavaria, some of the forest climate stations have been operational for 5 years. We use this 5-year forest climate data set to examine the accuracy of various interpolation techniques, establish appropriate empirical transfer functions, develop available interpolation model and reconstruct 31-year (1965–1995) daily forest climatological data at Bavarian forest sites.

Interpolation methods used to estimate annual and monthly climatological data include inverse distance weighting (Cressman, 1959; Shepard, 1968; Barnes, 1973), optimal interpolation and kriging (Bussieres and Hogg, 1989; Daley, 1991) and splines (Hutchinson and Gessler, 1994; Hulme and New, 1997; Luo et al., 1998), but the interpolation techniques used for daily climatological data are scarce (Huth and Nemesova, 1995). One reason for this is that although these methods are usually satisfactory when calculating monthly or longer period averages, applying individual daily estimates show significant errors (DeGaetano et al., 1995; Xia, 1999). Another cause is that some techniques are time consuming and complex, e.g., optimal interpolation and kriging (e.g., ordinary kriging, cokriging, detrended kriging, universal kriging). Kriging requires examination of the experimental variogram and selection of the most suitable type of model, e.g., Gaussian, linear, exponential, by eye for each day. The model is then fitted to data points using a weighted least-squares fit (Cressie, 1985; Nalder and Wein, 1998). Clearly this amount of work is too computationally expensive for reconstruction of a 31-year daily data set. Therefore, these methods (e.g., kriging, optimal interpolation) were abandoned.

Bussieres and Hogg (1989) used distance weighting schemes (i.e., Barnes interpolation, Cressman interpolation, Shepard interpolation, statistical interpolation) to interpolate daily precipitation in Canada and showed that these estimates were accurate. Wallis et al. (1991) used the closest station method (CSM) to estimate daily precipitation in the United States. Hutchinson (1998) used thin plate splines (TPS) to interpolate the daily precipitation in Switzerland and discussed the different TPS models. For the other meteorological variables (i.e., daily mean air temperature), distance weighting and multiple regression techniques are also used (Kemp et al., 1983; Kunkel, 1989; Russo et al., 1993; DeGaetano et al., 1995; Huth and Nemesova, 1995; Bolstad et al., 1998; Dodson and Marks, 1997).

Based on our experiences for monthly mean climate data (Xia et al., 1999b,c), we selected Barnes (BAR) (Barnes, 1973) and Cressman method (CRE) (Cressman, 1959). In addition, we compared the CSM (i.e., Running et al., 1987; Wallis et al., 1991), multiple regression technique (i.e., Russo et al., 1993; Bolstad et al., 1998), SHE (Shepard, 1968) and TPS (i.e., Wahba, 1990; Hulme and New, 1997).

Empirical transfer function method significantly improved the estimates of monthly mean forest climate data at eight Bavarian forest sites (Xia et al., 1999b) since it can include local climate information (Karl et al., 1990; Wigley et al., 1990; Hewitson and Crane, 1992a,b; Hewitson, 1994; Winkler et al., 1997; Kidson and Thompson, 1998). The ability of this technique to estimate daily forest climate data and reconstruct a 31-year daily forest climate data at Bavarian forest sites will be assessed in this study. In order to use these reconstructed forest climate data (e.g., air temperature), we calculate the four meteorological stress factors related to the forest study and analyse their uncertainties, temporal and spatial variation. Our main study objectives are

1. comparison of interpolation techniques at eight forest climate stations,
2. development and use of empirical transfer functions, and
3. reconstruction and application of 31-year daily forest climate data.

### 2. Data and methods

#### 2.1. Data

Details of the data used in this study can be obtained from Xia et al. (1999a,b,c) because the same data set was used. Therefore, we give a brief description only.
Fig. 1. Thirty-two German weather stations and eight forest climate stations (●) used in this study.

Distribution of 32 weather stations with complete observational records for the period from 1965 to 1995, and eight forest climate stations with observed records (2–5 years) for the period 1991–1995 are shown in Fig. 1. An square root transformation was used for daily precipitation, because transforming daily precipitation data in this way can reduce its skewness and/or improve precipitation prediction (Hutchinson et al., 1993; Kidson and Thompson, 1998).

2.2. Interpolation methods

2.2.1. Shepard method

In the Shepard (1968) method, interpolated values are computed from a weighted sum of the observations corrected by a locally computed increment. The details of calculation can be seen from Bussieres and Hogg (1989). A predetermined maximum radius (we used 100 km in this study) limits the number of the observational stations and the computed increment is based on local slopes as determined by a least-squares fit in orthogonal directions.

2.2.2. Closest station method

The CSM is simple. Usually the closest station was identified, and the data at a specific site were replaced with data from the closest station. The observations from this station were adjusted by the ratio of the long-term means for precipitation, and
by a constant lapse rate (0.65°C/100 m) for air temperatures.

2.2.3. Multiple linear regression (MLR)

A regional regression model was based on a first-degree polynomial (Russo et al., 1993):

\[ G_i = a_0 + a_1 x + a_2 y + a_3 z \]  

(1)

where \( G_i \) is the estimated daily climatological variable, \( a \) the fit regression coefficients, \( x \), \( y \) and \( z \) are \( x \)-direction distance, \( y \)-direction distance and elevation, respectively.

2.2.4. Thin plate splines

TPS and kriging are formally equivalent but are formulated differently (Wahba, 1990; Hutchinson and Gessler, 1994). TPS are defined by minimising the roughness of the interpolated surface subject to the data having a predefined residual. Kriged surfaces are defined by minimising the variance of the error of estimation, which is normally dependent on a preliminary variogram analysis. TPS is usually accomplished automatically by choosing both the order of the derivative, which defines the surface roughness and the amount of data smoothing that is required to minimise the generalised cross-validation. If there are \( n \) data values \( G_i \) at positions \( x_i \) then it can be supposed that

\[ G_i = f(x_i) + \varepsilon_i \quad (i = 1, 2, \ldots, n) \]  

(2)

where \( f(x_i) \) is a function to be estimated from the observations \( G_i \). Error term \( \varepsilon_i \) contains not only the measurement errors, but also purely local variability that is of much smaller scale than the resolution of any model to be fitted. \( x_i \) are commonly co-ordinates in three-dimensional Euclidean space. Because TPS uses three-dimensional co-ordinates, it includes effect of environmental lapse rate (e.g., air temperature) on interpolated variables. Details can be found in Daley (1991) and Luo et al. (1998).

2.2.5. Barnes and Cressman method

BAR and CRE are distance weight interpolation methods. The computing details are given by Bussieres and Hogg (1989), and these two methods have been used for comparison of interpolation methods (Xia et al., 1999c) and reconstruction of monthly mean forest climate data (Xia et al., 1999b).

2.3. Assessment criteria

As a test of the accuracy of each method, mean absolute error (MAE) and mean error (ME) are used as evaluation criteria (Hulme et al., 1995; Willmott and Matsuura, 1995). MAE provides a measure of how far the estimate can be in error, ignoring sign, and ME indicates the degree of bias.

2.4. Empirical transfer functions and examination of their stabilities

Wigley et al. (1990) used empirical transfer functions to obtain sub-grid-scale information from coarse-resolution general circulation model (GCM) output. They found that most of variance explained arises from the area average of air temperatures or precipitation which is the predictand: in other words, if the temperature, say, at a location is to be estimated, the best predictor is generally the area average temperature. Therefore, a univariate regression analysis (Kemp et al., 1983; Kim et al., 1984; Wigley et al., 1990) was used. It is defined as follows:

\[ X_F = a + bX_W \]  

(3)

where \( a \) (offset) and \( b \) (slope) are the regression coefficients, \( X_F \) the measured climatological data at a site, and \( X_W \) the climatological data interpolated from the German weather stations to this site. These regression equations were called empirical transfer functions. In order to eliminate the influence of seasonal variation on the accuracies of estimated forest climate data, daily forest climate data pooled over 4–5 years for each month were used. Therefore, 12 regression equations were established for each variable and forest climate station.

In order to examine stabilities of these empirical transfer functions, we used a cross-validation process. We used 4 (3) years data for each month, leaving out all the years of the series one after other (e.g., to combine January 1991, 1992, 1993 and 1994 to form a new data set) to calibrate the regression equations at a forest climate station, and then used these calibrated equations and the left year data (e.g., January 1995) to estimate forest climate data at this station, finally calculate the averaged correlation coefficients between observed and estimated data for left year of data. Therefore, we have 12 regression equations for each
variable and each forest climate station. We compared the change of correlation coefficients for the calibrated to independent data for each climatological element and each month. If the change is small, the regression equation is stable; otherwise, the equation is not stable. Additionally, we will use the cross-validation to investigate the ME statistics in Section 3.2.1.

2.5. Reconstruction method

The reconstruction technique consists of two parts. First, we used TPS, as implemented in the ANUSPLIN package (Hutchinson, 1997) to interpolate air temperatures at 32 weather stations to the six forest sites where forest climate stations were installed. TPS were chosen as a basic interpolation method, because we found that it can provide more accurate estimates for near-surface air temperatures and is appropriate for three-dimensional interpolation. Second, we used the empirical transfer functions to modify these interpolated air temperatures. These empirical transfer functions vary from month to month, from site to site and from meteorological variable to meteorological variable. Therefore, 216 empirical transfer functions were used in this study.

2.6. Quality control of reconstructed data

Because we used the empirical transfer functions to reconstruct long-term daily maximum temperature $T_{\text{max}}$, daily minimum temperature $T_{\text{min}}$, and daily mean air temperature $T_{\text{m}}$, respectively, the relationship between $T_{\text{max}}$, $T_{\text{min}}$ and $T_{\text{m}}$ may not satisfy the requirement that $T_{\text{min}} < T_{\text{m}} < T_{\text{max}}$. If this case occurs, the quality of reconstructed air temperatures is questionable. Therefore, a final quality control is needed (Carlson et al., 1994; Meek and Hatfield, 1994; DeGaetano et al., 1995).

A very small percentage (<5%) of the reconstructed data values were flagged as erroneous in this study. In such cases, a manual adjustment was made for air temperatures. Usually, we assume the estimates of daily mean temperature are precise because of small MAE and the large explained variances for empirical transfer functions, then, we mainly adjust daily maximum temperature or daily minimum temperature. If $T_{\text{min}}$ ($T_{\text{max}}$) is adjusted, $T_{\text{min}}(T_{\text{max}}) = 2T_{\text{m}} - T_{\text{max}}(T_{\text{min}})$. Finally, the adjusted daily forest climate data can be used to calculate the temperature stress indices and to provide an input for the forest growth models.

3. Results and discussion

3.1. Comparisons of methods

3.1.1. Mean absolute error

Average results (averaged in time and spatially) of MAE between observed and estimated data at eight forest climate stations are summarised in Table 1. In general, MAE is smaller than 1.4°C for daily maximum temperature and mean air temperature, is smaller than 0.9 hPa for daily water vapour pressure, and is smaller than 1.7°C for daily minimum temperature for all six techniques. TPS yields the lowest MAE for all variables except for wind speed. SHE gives more accurate estimates for wind speed. Wind speed estimates using the SHE method are significantly different from the other methods at the 5% level. Estimates of precipitation using TPS are significantly different from the other methods (except for MLR) at the 5% level ($t$-test). For air temperatures and water vapour pressure, MLR estimates are as accurate as the TPS methods, but 15% of regression equations are not significant at the 5% level so that they cannot be used for daily minimum temperature. Therefore, MLR should be used with caution in this study area. According to this analysis, TPS is the more accurate interpolation technique for air temperatures, water vapour pressure and precipitation, and SHE is the more accurate method for wind speed.

3.1.2. Temporal variation of mean absolute errors

We used TPS method (SHE method for wind speed) to interpolate the data of 32 German weather stations.
Seasonal variation of MAE and ME between estimated and observed: (a) $T_{\text{max}}$; (b) $T_{\text{min}}$; (c) $T_{\text{m}}$; (d) $e$; (e) $u$; (f) $P$, averaged across eight forest sites for the period 1991–1995.

to eight forest sites, and used observed forest climate data to calculate MAE and ME for the period from 1991 to 1995. The averaged results of eight forest climate stations are shown in Fig. 2. For daily maximum temperature, MAE is largest in winter and smallest in summer, ranging from 1.0°C in December to 0.6°C in July (Fig. 2a), however, for daily minimum temperature, MAE is smallest in winter and largest in summer, ranging from 1.7°C in May to 1.0°C in January (Fig. 2b). For daily mean temperature, seasonal variation of MAE is smaller, and MAE ranges from 1.0°C in August to 0.8°C in November (Fig. 2c). MAE of water vapour pressure is largest in summer and smallest in winter, ranging from 0.9 hPa in July to 0.2 hPa in December (Fig. 2d), however, MAE of wind speed is largest in winter and smallest in summer, ranging from 1.6 m/s in January to 1.1 m/s in July (Fig. 2e). Seasonal variation of MAE is consistent with that of water vapour pressure (wind speed), i.e., small (large wind speed) water vapour pressure in winter has lower (higher) estimated errors and large (small wind speed) water vapour pressure has higher (lower) estimated errors. MAE of precipitation is largest in summer and smallest in spring and autumn, ranging from
ME are positive for all variables except precipitation. This means that the TPS method overestimates daily maximum temperature, minimum temperature, mean air temperature and water vapour pressure and underestimates daily precipitation; the SHE method overestimates daily wind speed (Fig. 2). This overestimate may be due to forest effect of daily maximum, minimum, mean temperature and wind speed, because the air temperatures (wind speed) within forests are lower (smaller) than outside of forests.

3.1.3. Spatial variation of mean absolute errors

Usually, the spatial distribution of MAE of meteorological variables is determined by elevation, land surface covering, slope inclination, slope orientation and the density of the station network (i.e., Bussieres and Hogg, 1989). We used MLR to study the relationship between MAE and these physical factors. As we have only eight forest climate stations, none of the regression equations were significant at the 5% level for all variables. We selected three forest climate stations, station Altdorf (located in a plain area), station Riedenburg (located in a valley), and station Ebersberg (foothills of the Alps). MAE and ME of variables at these stations are listed in Table 2. For daily air temperatures, MAE are larger at the valley and hill stations than at the plain station because of topographic effects, although TPS considers the influence of lapse rates. For water vapour pressure, MAE is larger at the valley station than at the plain station and the hill station. For wind speed, MAE is largest at the valley station. For precipitation, MAE is much larger at hill station than at valley and plain stations. The results are similar for ME.

3.1.4. Meteorological stress factors

The purpose of estimating forest climatological data is for use in forest studies (i.e., forest damage), therefore, the accuracy of the predicted meteorological stress factors (see Appendix A) must be discussed. We used the TPS method to interpolate the data from 32 German weather stations to the six forest sites (we exclude Freising and Schongau stations because of short observational records), and then used these interpolated data and observed data to calculate the meteorological stress factors. The results from the statistical examination are listed in Table 3.

Predicted and observed heat and winter indices are not significantly different at the 10% level for all six examined stations, even though the predicted heat and winter indices are warmer than observed ones. This is consistent with previous comparisons (Fig. 2) where predicted daily air temperatures are higher than the observed station temperatures.

Examination of the late frosts (LF) and summer indices (SI) shows significant difference (at the 10% level) between the predicted and observed indices for all six examined forest climate stations (Table 3). The predicted SI are significantly higher than the observed SI ($t$-test, $D_0$: 10). Although MAE between predicted and observed air temperature are not large ($MAE < 1°$C), the predicted SI cannot be used because of their inaccuracy. The differences between predicted and observed LF are largest among these meteorological stress factors (Table 3). The results show that the predicted and observed LF are significantly different at all six stations. The predicted LF are as 2–4 times smaller than the observed ones except for Mitterfels station. The large difference is related to the large MAE (1.3–1.7°C) of daily minimum temperature (Fig. 2b). Thus, predicted LF cannot be used to study forest damage for all six forest climate stations.

The above analysis shows that while some predicted stress factors (i.e., HI) can be estimated from the interpolated climate data, but some predicted stress factors (i.e., LF) cannot, because of significant differences. Therefore, careful examination of predicted stress factors is necessary for the study of forest damage when predicted forest climatological data are used. These conclusions are consistent with those of Bolstad.
Table 3
Observed and predicted LF (°C days) and SI (°C days) based on observed daily minimum and mean temperatures, respectively, and the data sets which are interpolated by using TPS at six forest climate stations

<table>
<thead>
<tr>
<th>Station</th>
<th>Observed</th>
<th>Predicted</th>
<th>Mean value, $\alpha = 0.1$ (t-test)</th>
<th>Variance, $\alpha = 0.1$ (F-test)</th>
<th>Correlation, $\alpha = 0.1$ (t-test)</th>
<th>n (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LF based on daily minimum temperatures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Altdorf</td>
<td>$-15.0$</td>
<td>$-7.4$ NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>4</td>
</tr>
<tr>
<td>Altoetting</td>
<td>$-19.4$</td>
<td>$-3.6$ S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>4</td>
</tr>
<tr>
<td>Ebersberg</td>
<td>$-24.3$</td>
<td>$-6.2$ S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>5</td>
</tr>
<tr>
<td>Landau</td>
<td>$-7.2$</td>
<td>$-3.3$ NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>4</td>
</tr>
<tr>
<td>Mitterfels</td>
<td>$-39.3$</td>
<td>$-46.1$ NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>5</td>
</tr>
<tr>
<td>Riedenburg</td>
<td>$-29.4$</td>
<td>$-9.0$ S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>5</td>
</tr>
</tbody>
</table>

SI based on daily mean temperatures

<table>
<thead>
<tr>
<th>Station</th>
<th>Observed</th>
<th>Predicted</th>
<th>Mean value, $\alpha = 0.1$ (t-test)</th>
<th>Variance, $\alpha = 0.1$ (F-test)</th>
<th>Correlation, $\alpha = 0.1$ (t-test)</th>
<th>n (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altdorf</td>
<td>1826</td>
<td>1935 S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>4</td>
</tr>
<tr>
<td>Altoetting</td>
<td>1768</td>
<td>2013 S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>4</td>
</tr>
<tr>
<td>Ebersberg</td>
<td>1697</td>
<td>1870 S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>5</td>
</tr>
<tr>
<td>Landau</td>
<td>1911</td>
<td>2029 S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>4</td>
</tr>
<tr>
<td>Mitterfels</td>
<td>1266</td>
<td>1213 NS</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>5</td>
</tr>
<tr>
<td>Riedenburg</td>
<td>1662</td>
<td>1857 S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>5</td>
</tr>
</tbody>
</table>

et al. (1998). Their predicted and observed phenologies and whole canopy respirations were significantly different at four of the five stations. Although MAE between predicted and observed air temperatures are much smaller in our study ($<1.7^\circ$C) than those in their study ($<3.0^\circ$C), some estimated stress factors can still not be used.

Therefore, more accurate estimated forest climate data are needed for calculating various meteorological stress factors (i.e., LF). Empirical transfer functions may be an appropriate method, because they show large improvement for monthly mean forest climatological data (Xia et al., 1999b).

3.2. Empirical transfer function development

We develop simultaneous relationships between the interpolated data (i.e., the predictors) and observed forest climate data (i.e., the predictands) for a particular forest site. We use a univariate regression to develop separate functions for each predictand and each month. These functions can implicitly incorporate the effects of land cover (i.e., forest), local topography and geography.

3.2.1. Explained variance

The strongest statistical relationships between the predictands and predictors is for daily maximum temperature, mean air temperature and water vapour pressure at the eight Bavarian forest climate stations, as indicated by the large explained variances. Normally, the explained variances are larger than 0.90 for most of eight forest sites. For daily minimum temperature, the statistical relationship between observed values and interpolated values is also strong, usually the explained variances are larger than 0.88 for all eight forest climate stations. The statistical relationship between observed and interpolated precipitation and wind speed is weak (explained variance is smaller than 0.8 except precipitation at two sites).

Since a major problem evident in the previous sections is MAE and ME, the cross-validation process described in Section 2.4 was used to investigate both these errors. The examination results of independent samples (year 1995) show that the transfer functions greatly reduce MAE and ME for all climate variables except for precipitation, particularly minimum air temperature, mean air temperature and wind speed at the five examined stations (Altdorf, Altoetting, Ebersberg, Landau, Riedenburg).

3.2.2. Regression equations (transfer functions)

The averaged regression coefficients $(a, b)$ at the eight forest climate stations are shown in Table 4. For daily minimum temperature and mean temperature, $a$ (offset) is negative for all months, and $b$ (slope) is not significantly different from unity for all months at the 5% level (Table 4). Therefore, $a$ can approximately
represent the forest influence on daily minimum temperature and mean air temperature. The effect is $-1.3$ to $-0.9 \degree C$ in summer and $-0.8$ to $-0.6 \degree C$ in winter. For wind speed, $a$ is not significantly different from zero at the 5% level. It is clearly shown that forest reduces wind speed by 49–62% at eight forest sites (Table 4). For daily maximum temperature, the forest effect is smaller than 0.8 (Table 4). For daily maximum temperature, the forest reduces wind speed by 49–62% at eight forest sites.

For wind speed, $a$ and $b$ for the summer (offset is also negative but slope is significantly different from unity). Thus, these effects can be included by the $a$ and/or $b$ of the empirical transfer functions. For water vapour pressure and precipitation, the offset and slope include the forest effect as well. These results are based on the average of eight forest sites. In practice the forest effect on daily air temperatures, water vapour pressure and wind speeds varies from site to site.

3.2.3. Importance, temporal stability and spatial availability of empirical transfer functions

A summary of the errors obtained from seven forest climate stations is presented in Fig. 3. The empirical transfer functions greatly reduce the errors between observed and estimated values for all meteorological variables except daily precipitation. When empirical transfer functions were used, MAE were reduced by 40–90% for daily wind speed depending on the different forest climate stations (Fig. 3e), 20–60% for daily minimum temperature (Fig. 3b), 30–70% for daily mean temperature (Fig. 3c), and less than 40% for daily maximum temperature and water vapour pressure for all forest climate stations except for forest climate station Schongau (Fig. 3a and d). The improvements of empirical transfer functions vary from site to site, and from variable to variable. But for daily precipitation, MAE were hardly reduced (Fig. 3f) by the use of empirical transfer functions.

The analysis shows that the empirical transfer functions are important for estimating daily minimum temperature, mean air temperature and wind speed. They also improve the estimates of daily maximum temperature and water vapour pressure, although the improvement is not significant. However, they cannot improve the estimates of daily precipitation. In addition, the empirical transfer functions can also hardly improve the estimates of all six variables at Mitterfels mountain forest climate station.

Observed and estimated LF and SI are agreed well for all five examined forest sites. The examination of mean values and variances shows that observed and estimated values are not significantly different at the 10% level for all five stations. However, they are significantly correlated at the 10% level (Table 5). This means that there is no significant difference between observed and estimated for LF and SI for all five forest sites. The estimated daily forest climate data can thus be used for the studies of forest damage. This is a great improvement for the diagnostic studies of forest damage, as a result of using empirical transfer functions. The difference between observed and estimated

<table>
<thead>
<tr>
<th>Variable</th>
<th>January</th>
<th>February</th>
<th>March</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>August</th>
<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression coefficient $a$</td>
<td>$T_{max}$ ($\degree C$)</td>
<td>$-0.55$</td>
<td>$-0.45$</td>
<td>$-0.37$</td>
<td>$-0.72$</td>
<td>$-0.88$</td>
<td>$-0.91$</td>
<td>$-0.97$</td>
<td>$-1.13$</td>
<td>$-1.12$</td>
<td>$-0.55$</td>
<td>$-0.50$</td>
</tr>
<tr>
<td>$T_{min}$ ($\degree C$)</td>
<td>$-0.76$</td>
<td>$-0.87$</td>
<td>$-0.95$</td>
<td>$-1.11$</td>
<td>$-1.04$</td>
<td>$-1.09$</td>
<td>$-1.08$</td>
<td>$-1.25$</td>
<td>$-1.22$</td>
<td>$-0.88$</td>
<td>$-0.77$</td>
<td>$-0.74$</td>
</tr>
<tr>
<td>$T_{m}$ ($\degree C$)</td>
<td>$-0.64$</td>
<td>$-0.66$</td>
<td>$-0.66$</td>
<td>$-0.78$</td>
<td>$-1.06$</td>
<td>$-0.96$</td>
<td>$-0.98$</td>
<td>$-0.91$</td>
<td>$-0.88$</td>
<td>$-0.70$</td>
<td>$-0.66$</td>
<td>$-0.65$</td>
</tr>
<tr>
<td>$e$ (hPa)</td>
<td>$0.34$</td>
<td>$0.24$</td>
<td>$0.09$</td>
<td>$0.21$</td>
<td>$0.20$</td>
<td>$0.48$</td>
<td>$0.66$</td>
<td>$0.24$</td>
<td>$0.31$</td>
<td>$0.25$</td>
<td>$0.10$</td>
<td>$0.17$</td>
</tr>
<tr>
<td>$u$ (m/s)</td>
<td>$0.03$</td>
<td>$0.09$</td>
<td>$0.21$</td>
<td>$0.08$</td>
<td>$0.26$</td>
<td>$0.17$</td>
<td>$0.15$</td>
<td>$0.04$</td>
<td>$0.09$</td>
<td>$0.03$</td>
<td>$-0.13$</td>
<td>$0.04$</td>
</tr>
<tr>
<td>$\sqrt{P}$ (mm$^{1/2}$)</td>
<td>$0.40$</td>
<td>$0.35$</td>
<td>$0.51$</td>
<td>$0.31$</td>
<td>$0.35$</td>
<td>$0.26$</td>
<td>$0.44$</td>
<td>$0.39$</td>
<td>$0.36$</td>
<td>$0.39$</td>
<td>$0.35$</td>
<td>$0.35$</td>
</tr>
</tbody>
</table>

Table 4
Regression coefficients $a$ and $b$ averaged across eight sites for $T_{max}$, $T_{min}$, $T_{m}$, $e$, $u$ and $P$
mean values is smaller than 11% for LF at all five stations. There is almost no difference between observed and estimated mean SI for all five stations.

The differences between observed and estimated mean heat and winter indices become smaller, when the empirical transfer functions were used. Thus, the empirical transfer functions improve the estimation accuracies for the mean heat and winter indices at five stations, even though the improvement is not as large as that for LF and SI.

We used a cross-validation process as described in Section 2.4 to examine the stabilities of these empirical transfer functions for five sites (Freising and Schongau stations with less than 4 years of observational records, and Mitterfels mountain station was excluded) and all variables except for daily precipitation, because the empirical transfer functions cannot improve its estimate. The results indicate that for daily maximum temperature, daily minimum temperature, daily mean temperature and water vapour

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**Fig. 3.** MAE between observed and estimated: (a) $T_{\text{max}}$; (b) $T_{\text{min}}$; (c) $T_m$; (d) $e$; (e) $u$; (f) $P$ at seven sites (TF: transfer function; Alt: Altdorf; AOE: Altoetting; EBE: Ebersberg; FRE: Freising; LAN: Landau; RIE: Riedenburg; SOG: Schongau).
Table 5
Observed and estimated late frosts and SI based on observed daily minimum temperatures and mean temperatures, respectively, and the data sets which are estimated by using empirical transfer functions for five sites

<table>
<thead>
<tr>
<th>Station</th>
<th>Observed</th>
<th>Estimated</th>
<th>Mean value, ( \alpha = 0.10 ) (t-test)</th>
<th>Variance, ( \alpha = 0.10 ) (F-test)</th>
<th>Correlation, ( \alpha = 0.10 ) (t-test)</th>
<th>n (years)</th>
</tr>
</thead>
</table>
| LF based on daily minimum temperatures
| Altdorf    | −15.0    | −15.0     | NS                                      | NS                                     | S                                        | 4         |
| Altoetting | −19.4    | −17.9     | NS                                      | NS                                     | S                                        | 4         |
| Ebersberg  | −24.3    | −21.7     | NS                                      | NS                                     | S                                        | 5         |
| Landau     | −7.2     | −7.8      | NS                                      | NS                                     | S                                        | 4         |
| Riedenburg | −29.4    | −26.2     | NS                                      | NS                                     | S                                        | 5         |
| SI based on daily mean temperatures
| Altdorf    | 1862     | 1860      | NS                                      | NS                                     | S                                        | 4         |
| Altoetting | 1768     | 1767      | NS                                      | NS                                     | S                                        | 4         |
| Ebersberg  | 1697     | 1698      | NS                                      | NS                                     | S                                        | 5         |
| Landau     | 1911     | 1912      | NS                                      | NS                                     | S                                        | 4         |
| Riedenburg | 1662     | 1661      | NS                                      | NS                                     | S                                        | 5         |

Pressure, the empirical transfer functions are stable, but for daily wind speed, empirical transfer functions are not stable (not shown). In addition, we discussed the spatial applicability of empirical transfer functions. We used the observed data and interpolated data (Ebersberg station) to establish empirical transfer functions, and then we used these functions and interpolated data (Altoetting station, 80 km distant with the similar topography and same species) to estimate climate data and calculate MAE and ME. The results show large errors for all six variables at Altoetting station. It means that, these empirical transfer functions, established in a forest region, cannot be applied to other forest regions. Finally, we perform an analysis to assess how much data is required to determine reliable empirical transfer functions. We used Ebersberg station as an example, separating 5 years of data into 4, 3 and 2 years of observational data, leaving out all the years of the series one, two and three after the other, and then used the cross-validation as described in Section 2.4 to investigate the change of correlation coefficients. The results show that small change of correlation coefficients can be given for 4 years of observed data, hence, 4 years of data may be required to establish reliable transfer functions.

![Fig. 4. Seasonal variation of MAE averaged across seven sites for \( T_{\text{max}} \), \( T_{\text{min}} \), \( T_{\text{m}} \), \( e \) and \( u \) when the empirical transfer functions were used.](image)
3.2.4. Accuracy of estimated data

The MAE averaged across seven stations (except for Mitterfels station) are shown in Fig. 4. Usually, the estimated errors ranged from 0.49°C in September to 0.69°C in February for daily maximum temperature, ranged from 0.66°C in December to 0.94°C in May for daily minimum temperature, and ranged from 0.41°C in December to 0.5°C in May for mean temperature (Fig. 4). Errors less than 1°C can thus be expected for air temperatures. Errors ranged from 0.17 hPa in December to 0.6 hPa in August for water vapour, and for wind speed ranged from 0.26 m/s in September to 0.40 m/s in April (Fig. 4). These estimated forest climate data are relatively accurate, when we compared the estimates of climatological data without the empirical transfer functions.

Of the seven forest sites, the low elevation site (e.g., Landau) has smaller errors while the high elevation site (e.g., Schongau) has larger errors. For daily minimum temperature, the forest site Riedenburg has large errors because of its location in a valley.

3.3. Reconstruction and application of 31-year forest climate data

3.3.1. Temporal and spatial variation of near-surface air temperature

Firstly, we used the method described in Section 2.5 to reconstruct 31-year forest climate data at six of the eight forest sites except for Freising and Mitterfels stations. Secondly, we use the quality method presented in Section 2.6 to correct the erroneous data. The reconstructed near-surface air temperatures in January and July (averages of all days for these 2 months) are presented in Fig. 5. The temporal variations of air temperatures at six forest climate stations are relatively consistent, although there are differences among the stations. The coldest years are 1979, 1985 and 1987 (Fig. 5a), and the warmest years are 1976, 1983, 1991 and 1994 (Fig. 5b). Near-surface air temperatures are different at six forest sites. The differences between stations are not large in January, but it is very large in July. Generally speaking, low elevation sites have higher near-surface air temperatures (e.g., Altdorf) and high elevation sites have lower near-surface air temperatures (e.g., Schongau). The largest difference may be up to 3°C.

3.3.2. Temporal and spatial variation of stress indices

3.3.2.1. Heat index

HI (see Appendix A) describes the possible effect of high temperatures on forest trees. The calculated HI at the six forest sites is shown in Fig. 6a. The largest index occurred in 1976, 1983, 1992 and 1994. These years are warmest when the variation of near-surface air temperatures is analysed at the six forest sites (Fig. 5a). This means that HI is closely relating to the anomalies of the regional climates.

The heat indices at the six forest sites are very different from each other (Fig. 6a). Heat indices at forest sites Ebersberg and Schongau are much smaller than those at the other four sites for the anomaly year 1976, 1983 and 1994. Thus, high temperatures may not damage the forest trees at these two forest sites, because they are located on the high elevation ridges (station Ebersberg: 540 m, station Schongau: 780 m), and maximum temperatures are lower at the two sites than the other four sites. Clearly, local climates greatly modify the heat indices at the two sites. Therefore, the interactions between regional (global) climate anomalies and local environments may greatly affect local heat indices, but regional climate anomalies influence the whole study area and local environments affect only a specific forest site.

3.3.2.2. Late frost

LF (see Appendix A) describes the average intensity of LF damage to trees. It is presented in Fig. 6b for the six forest sites. The strongest LF occurred in 1973, 1982 and 1984, with relatively strong LF also occurring in 1977 and 1992. The LF is very different at six forest sites, it varies from site to site, and from year to year (Fig. 6). The Landau site experiences fewer LF because of its low elevation, and Schongau site located on a high elevation ridge and Riedenburg site located in the valley experience more frequent LF because of the high elevation and valley topography. Valley floors will often be colder than ridge sites because cold air drainage and radiation cooling will lead to a temperature inversion.

3.3.2.3. Summer index

Temporal variation of the SI at six forest sites is shown in Fig. 6c. The largest SI occurred in 1983, 1992 and 1994, this is relatively consistent with the regional warm anomalies (Fig. 5b). SI increases at all six forest sites from 1956 to 1995, this trend is consistent with a warm regional climate. SI is
different at each of the six forest sites. Low elevation sites have the larger SI (e.g., Altdorf, Landau) and high elevation sites have the smaller SI (e.g., Schongau).

3.3.2.4. Winter index. Winter index (WI) can be used to represent the severity of the winter. The coldest years were 1969, 1985 and 1987. The warmest year was 1974. WI also shows the difference between sites. This difference varies from year to year (Fig. 6d). Spatial variation of WI is similar to that of SI, but the difference between two sites is much smaller.

We compared the 31-year averaged values of four meteorological stress factors estimated with and without the empirical transfer functions. The averaged difference of the estimated index is 15% for SI and HI, 20% for WI and 40% for LF at six forest sites. These differences are not negligible because they are significant at the 5% level. Therefore, the use of air temperatures directly interpolated from weather stations may result in the inaccurate estimates of derived variables (e.g., LF).

3.3.3. Uncertainties of meteorological stress factors
The uncertainties can be divided into two groups of causes. The first source of uncertainty resulted from inaccuracies in the estimated near-surface air temperature. The average uncertainty is about 5–10% for daily maximum, minimum and mean temperatures but for individual sites uncertainty can be large (up to 20%
Fig. 6. The inter-annual variation of reconstructed (a) HI; (b) LF; (c) SI; (d) WI at six forest climate stations for the period from 1965 to 1995 (ALT: Altdorf; AOE: Altoetting; EBE: Ebersberg; LAN: Landau; RIE: Riedenburg; SOG: Schongau).
or more) for an individual year. The second source of uncertainty is a physiological one. Based on our knowledge, threshold values were chosen for the temperature stress indices: 0°C for the WI, 5°C for the SI, and 30°C for the HI. Effects of chosen threshold values on the relationships with defoliation are unknown. Furthermore, no difference was made between sensitivity for particular tree species, which also introduced some uncertainty, since the threshold values vary from tree species to tree species. In addition, it should be noted that these forest climate data measured in a forest clearing can introduce the large uncertainties, because they are not measured within a forest canopy or above a forest canopy.

Besides the four meteorological factors, we used daily mean temperatures to calculate growing-degree days, which is important for agriculture and forestry. In USA, the mean value of daily maximum and minimum temperature was used for daily mean temperature (McMaster and Wilhelm, 1997), although the mean temperatures calculated using hourly temperatures can improve the accuracy of predictions (Cross and Zuber, 1972). Because we have 15 min observational records at six forest sites, we compare daily mean temperature calculated by 15 min records to mean temperature calculated according to three standard observation times (7:30, 14:30, and 21:30 h) of German Weather Service, and average of daily maximum and minimum temperatures at six forest sites for the period from 1991 to 1995. We found that the difference between daily mean values according to 15 min records and three standard observational times is small. We determine to use daily mean temperature calculated by three standard observational times, because we believe that the value is more close to true daily mean temperature.

4. Conclusions

We observed significant differences in the accuracy of the BAR, CRE, CSM, MLR, SHE and TPS for prediction of the six climate variables. In general, TPS can give more accurate estimates of daily maximum temperature, minimum temperature, air temperature, water vapour pressure and precipitation, while the SHE is more accurate method for wind speed.

We developed the empirical transfer functions between observed and interpolated data using a univariate regression technique and examined their effects for all forest sites. The results show that empirical transfer functions improve the estimates of air temperatures, water vapour and wind speed for seven of the eight forest sites, particularly wind speed, daily minimum and mean temperature, since they include forest impacts on daily climatological data, as described in this paper. However, they cannot improve the estimate of daily precipitation for any forest site. The examination of LF and SI shows that the observed and estimated values are consistent for five forest sites, whereas, they are significantly different at the 10% level when empirical transfer functions are not used. Therefore, the empirical transfer functions are essential to estimate reliable climatological data for the forest sites.

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Appendix A. Calculation of the meteorological stress factors

In order to compare the accuracy of estimated climatological data, we define four stress indices (Hendriks et al., 1997):

1. Winter index (WI): it indicates the severity of the winter. This index equals the sum of daily mean temperature below 0°C in the period from 1 November to 31 March (unit: degree days).
2. Late frost (LF): late-night frost in spring may cause serious damage to trees when growth has just started and, buds and young shoots are very sensitive to frost. This parameter is defined as the sum of minimum temperature (below 0°C) in the period from 1 April to 30 June.
3. Heat index (HI): high temperatures may cause tree damage. It equals the sum of the differences between daily maximum temperatures in the growing season (from 1 April to 31 October) and a threshold
value of 30°C which is used in Bavarian Climate Atlas (BayForKlim, 1996).

4. Summer index (SI): this quality of the growing season is included, since it influences the potential photosynthetic activity and the ability to the tree to produce reserve assimilates for the purposes of defence and growth in the beginning of the next season. This factor is sum of the differences between daily mean temperatures during the growing season and a threshold value of 5°C.

References


