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Reconstruction of potential evaporation for water balance studies

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ABSTRACT: A large number of environmental management decisions such as the remediation of a mine site require the best possible knowledge of the water balance of the site or the catchment area. For precipitation a large number of observations exists and usually some data are available which are more or less representative for the precipitation conditions in the catchment. However, to close the water balance knowledge about evaporation is also required. This is usually not available from observations. Also bulk formulas cannot be used to reconstruct evaporation for a sufficiently long time, since observations of the input variables are limited as well. In this article an approach is presented showing how local potential evaporation may be reconstructed from other local and non-local atmospheric variables for which long-term observations are available. The method is demonstrated for the planned artificial lakes in the closed down mine sites in the Geiseltal (Germany) and aims at the estimation of the probability distribution of the difference between precipitation and evaporation for the surface water balance.

KEY WORDS: Statistical downscaling · Meteorological water balance · Remediation of mining areas

1. INTRODUCTION

A number of environmental management decisions require an accurate knowledge of the water balance of a catchment area, a lake, or some other region of interest. For instance, one option to remediate a surface mine site is the flooding of the corresponding area. The artificial lakes generated this way may later serve as recreational areas, a solution which is favored, e.g., for the former surface mining areas in Eastern Germany (Umweltamt Merseburg 1993).

A remaining question for applying this type of remediation is the probability of whether those artificial lakes can sustain their water levels within a given interval or whether an additional (permanent) water supply will be necessary to keep the water levels stationary. This probability is directly related to the long-term climatological water balance of the mine site or the catchment. In particular it is essential to know how often (on average) an excess or lack of yearly evaporation over yearly precipitation can be expected and how these numbers relate to the total water balance of the catchment. Additionally, the average duration of wet and dry periods may give an indication of the magnitude of the expected fluctuations of the water levels around their mean value.

A frequently used approach to obtain such information is to initiate measurement campaigns for limited time periods in which the most important constituents of the water balance of the site are measured as well as possible. Additionally, a few other sporadic measurements might be available which may help in the decision process. However, such measurement campaigns are extremely expensive, and the conclusions which can be drawn from these campaigns are limited. For example, the measurements might be taken within a year which was exceptionally cold and wet. The conclusion from the measurements might then support a positive water balance, although inspection of data

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from other years would not justify such a conclusion. It is therefore essential to put the conclusions drawn from such a measurement campaign into a long-term framework and to assess them with respect to the long-term water balance.

In this paper we present a statistical approach for the estimation of the precipitation minus evaporation contribution to the long-term water balance and its probability distribution. We suggest that the approach may be useful in assessing the conclusions drawn from measurement campaigns and may help to put them into a long-term framework. The approach is demonstrated for the example of the planned artificial lakes in the Geiseltal (Germany) and is based on linking measurements available for a limited period only (e.g., from measurement campaigns) with operational data and large-scale observations available for a much longer period. The study is structured as follows: In Section 2 we briefly discuss the water balance of a lake and the approximations we applied for this study. In Section 3 a short description of the Geiseltal and the project is given, while data and methods are presented in Section 4. Our results are presented in Section 5. A summary and discussion are given in Section 6.

2. THE WATER BALANCE

The water balance of a lake can be expressed by the rate of change of the water level h

$$\frac{\partial h}{\partial t} = P + D - E - R \qquad (1)$$

Here t represents time, P is the precipitation, E is the evaporation, D is the condensation at the lake surface, and R is the runoff, which includes contributions from surface runoff, ground water, and leakage and may therefore be negative if, for instance, ground water or water from a river system is supplied to the lake. Averaged over a long period, D is small (e.g., Hartmann 1994) and will be neglected in the following.

To obtain a stationary water level, the rate of change of h should be zero when averaged over a longer period, or in other words, we do not want the water level to fluctuate too much around its mean value. Eq. (1) then reduces to

$$R = P - E \qquad (2)$$

which states that the difference between precipitation and evaporation must be balanced by runoff or, if $P - E$ is negative, by additional permanent water supply either from ground water, river systems or other sources. Therefore, $P - E$ represents a key variable for assessing the water balance of a lake. In the following, our analyses and discussions are limited to $P - E$.

3. THE GEISELTAL LAKES

3.1. The Geiseltal area

The Geiseltal valley (51.3° N, 11.9° E) is located in Eastern Germany, about 20 km south of Halle and 40 km west of Leipzig. The occurrence of lignite in this area was first mentioned in 1698, while industrial surface mining did not start until 1890. In the 100 yr from 1890 to 1990 roughly 1.4×10^9 t of lignite were produced and roughly the same amount of overburden was moved. The mining finally stopped in 1993, leaving an area of roughly 90 km^2 for remediation. The valley is located at the edge of the Querfurter Platte such that surface runoff into the valley is considered to be small. It is provided by only a few creeks, some of which fall dry during summer.

3.2. The project

Extensive investigations and studies elaborating the options for the remediation of the Geiseltal area have been performed (e.g., Umweltamt Merseburg 1993, KZG 1995, 1996). For several economical, technical and safety purposes it was finally suggested that flooding the mine site remains the only possible option (Umweltamt Merseburg 1993). All efforts currently undertaken therefore aim at the preparation of the flooding of the site with roughly 410×10^6 m^3 of fresh water, which in the following 15 yr will generate an artificial lake of nearly 20 km^2. This so-called Geiseltal lake will finally represent the twelfth largest lake by size within Germany.

To augment the natural rise of ground water, it is planned to supply additional fresh water for several years from the river Saale via a pipeline system. So far it is not entirely clear whether this artificial and extensive water supply will be necessary on a permanent basis or if fresh water supply for a limited time may be sufficient. Presently there are a number of projects addressing this central question. In the long run, the development of the infrastructure, landscape and the geohydrological and climatological conditions are the key variables to assess in order to find an optimal solution to this problem.

4. DATA AND METHODS

4.1. Data. ***4.1.1. Monthly amounts of evaporation:*** Monthly potential evaporation amounts E in mm mo^{-1} were provided by the UTK Zeitz for the period 1965–1995. The data were obtained from CUI GmbH Halle and were estimated from the monthly mean values of the saturation water vapor pressure difference Δe in hPa at the water surface and the global radiation G in J cm^{-2} using the empirical bulk formula for monthly mean values (DWD 1997)

$$E = (0.327\,\Delta e + 0.00055\,G - 0.035)n \qquad (3)$$

where n is the number of days per month. The input data to Eq. (3) were obtained from regular observations of the National German Weather Service (DWD) taken at Halle-Kröllwitz and Bad Lauchstädt, which were available for the period 1965–1995. The data were prepared by the DWD for this particular project and may be considered as being representative for the Geiseltal area (DWD 1997). In the following we will refer to these data as 'observed' evaporation.

4.1.2. Monthly amounts of precipitation: For this study monthly precipitation amounts were provided by the UTK Zeitz for the period 1851–1995. The data were obtained from CUI GmbH Halle on the basis of daily precipitation amounts at the locations Mücheln and Frankleben of the precipitation measuring network of the DWD. The data were quality checked and compared with the measurements of neighboring stations and can be considered as representative for the Geiseltal area. A systematic correction was applied to account for a systematic error of the precipitation measuring devices used (Richter 1995).

4.1.3. Potential predictors of the statistical model: The following data were used as potential predictors for the statistical model: (1) Monthly mean air temperatures from 1851–1996 provided by the UTK Zeitz. The data are based on the observations of the DWD at the weather stations Halle and Mücheln/Frankleben. (2) North Atlantic Oscillation Index (NAOI) from 1899–1995. This index represents the difference between sea level pressure (SLP) at Lisbon (Portugal) and Stykkisholmur (Iceland) in winter. A high index generally coincides with westerly winds and mild winters in Europe (Hurrell 1995).

4.2. Methods. The objective of the applied statistical approach is to obtain a best-guess reconstruction of that part of the variability of the predictands which is externally controlled by the variability of a number of predictors for which long-term observations are available. This externally induced part of the variability of the predictands may be considered deterministic or predictable to the extent that the predictors are predictable. A standard statistical approach to this end is regression:

$$y(t) = \sum_{i=1}^{N} a_i x_i(t) + b + n(t) \qquad (4)$$

Here y represents the predictand, x_i a number of N potential predictors, and n the residuals or that part of the variability of the predictands which is not controlled by the predictors. The residuals could also be considered as the model's error and should have a Gaussian distribution if the x_i are adequate predictors of y. The coefficients a_i and b are usually fitted by a least-squares method. Within the context of this study the approach may be considered as a simple (univariate) case of the so-called statistical downscaling approach (von Storch et al. 1993).

5. RESULTS

5.1. Potential evaporation

From the simplified water balance (Eq. 2) it can be inferred that a key variable controlling the water balance of a lake is given by the difference between precipitation and evaporation, $P - E$. If $P - E$ is positive, it must be balanced by an adequate runoff, and if it is negative, additional water supply in the form of ground water or surface water from rivers etc. is necessary to keep the lake's water level stationary. Since the $P - E$ balance may vary seasonally, the key variable to address is the annual amount of $P - E$.

For our purposes precipitation observations were available from 1851 onwards, while estimations of evaporation were available only from 1965. Although, we are primarily interested in $P - E$, in the following we first focus on the reconstruction of evaporation amounts. Later, the evaporation data derived this way are used in combination with the precipitation measurements to obtain a reconstruction of $P - E$.

5.1.1. Analysis of available evaporation data

One of the key variables for assessing the stationarity of the water level of an artificial lake is the *annual* amount of $P - E$. However, precipitation, evaporation, and the difference between the two may vary seasonally. To find out which months primarily determine the annual amount of evaporation and to gain insight into the typical intra-annual fluctuations, the evaporation time series E_t was rearranged into a vector time series

$$\vec{\boldsymbol{E}}_{\tilde{t}} = \left(E_{\tilde{t},1}, E_{\tilde{t},2}, \ldots, E_{\tilde{t},12}\right) \qquad (5)$$

where the 2 new time indices $\tilde{t}$ and $1\ldots12$ represent the year and the month respectively. Subsequently, an empirical orthogonal function (EOF) analysis (e.g., von Storch & Zwiers 1999) of the vector time series (Eq. 5) was performed.

The results of this analysis are shown in Fig. 1. The first EOF explains almost 44% of the total intra-annual variance. With the exception of December the anomalies are either all negative or all positive throughout the year, with the largest anomalies occurring in the summer months July and August. The sum of the evaporation anomalies over all months is 83 mm. The dominant intra-annual signal in the evaporation data thus reflects the fact that the year in its entirety has either too high or too low evaporation. However, the yearly amount of anomalous evaporation is basically controlled by the evaporation in summer. The structure of the second EOF pattern is slightly more complicated. However, the essential point is that the yearly amount of anomalous evaporation of this pattern is almost zero. Therefore, this pattern is not important for the reconstruction of the annual mean water balance. The third EOF basically shows above-normal evaporation in the first half of the year and below-normal evaporation in the second half of the year or vice versa. It accounts for roughly 10% of the total variance. Again anomalies are largest in summer.

In summary, the intra-annual variability of the evaporation is largest in summer. The variability of the annual amount of evaporation is therefore to a large part determined by the variations of the evaporation in summer. A large fraction of the intra-annual variations of evaporation averages out when the annual amounts of evaporation are determined.

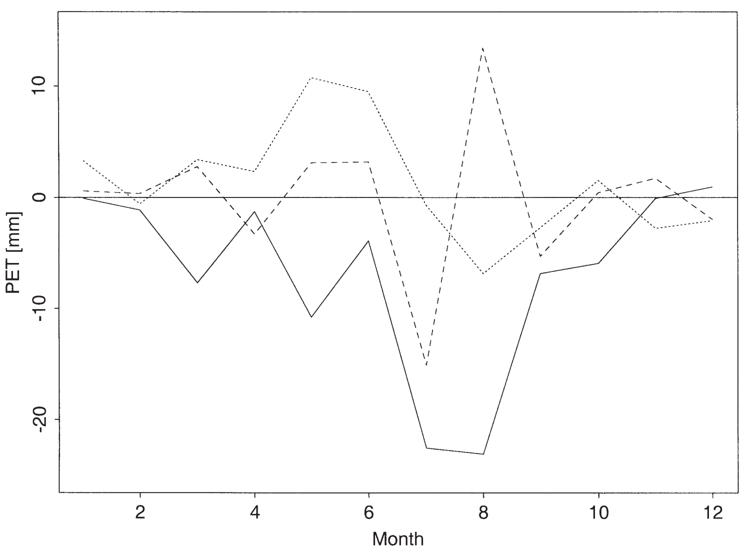

Fig. 1. Patterns of EOF 1 (solid), EOF 2 (dashed), and EOF 3 (dotted) of monthly amounts of evaporation. The x-axis represents the month of the year, the y-axis typical deviations from the amount of evaporation in the respective month. Note that the mean annual cycle was removed prior to the analysis and that the sign of the patterns is arbitrary. The first EOF explains 44%, the second EOF explains 16% and the third EOF explains 10% of the total intra-annual variance of evaporation

5.1.2. Fitting the statistical model

Evaporation is constrained by the surface water supply, the energy available to provide the latent heat of vaporization, and the ability of the surface air to accommodate water vapor (e.g., Hartmann 1994). Potential evaporation is the maximum evaporation possible for a wet surface (e.g., from a lake) in the given atmospheric conditions. For a water surface the evaporation is usually rather close to potential evaporation; however, (small) deviations may occur if, e.g., a reed or algae are present. Among the atmospheric variables, the most important factors controlling evaporation are air temperature, wind speed and the overall synoptic situation (e.g., cloud cover, radiation). Within the proposed statistical model we therefore tried to relate evaporation to these atmospheric variables or eventually proxies of these variables if no direct long-term measurements were available.

For the air temperatures, observations were available back to 1851 at a number of stations in the vicinity of the Geiseltal. Here we used a homogenized record which best represented the local conditions in the Geiseltal. Since we were interested in the annual amount of evaporation, we concentrated on 2 predictors obtained from this data set, the annual mean temperature and the average July and August temperatures. The latter is henceforth referred to as summer temperature and was chosen on the basis of the results of our EOF analysis (Section 5.1.1), which showed that a large fraction of the variability of the annual evaporation could be explained by anomalous evaporation in July and August (Fig. 1).

Since no other long-term observations were available, we chose the NAOI as a proxy for both the wind speed and the overall atmospheric synoptic conditions. Using the NAOI in our statistical approach allows the evaporation to vary not only in response to local air temperatures but also to the general state of the atmospheric circulation.

Using these predictors and the annual amount of evaporation as the predictand, 3 simple statistical models were fitted. All 3 models have the general structure (Eq. 4). In order to keep these models simple and to avoid over-fitting, the maximum number of potential predictors was limited to 2 in each model. A list of predictors used in the single models, the best-guess estimates of the model parameters and the correlation of the fits are given in Table 1. All models were fitted for the period 1965–1995. The correlation of the fit increases from 0.68 for

Table 1. Predictors and parameters of the statistical models. R_f: correlation of the fit. See Section 4.2 for description of approach

Model	x_1 (°C)	x_2 (hPa)	a_1 (mm °C^{-1})	a_2 (mm hPa^{-1})	b (mm)	R_f
1	Annual mean temperature	–	82.59	–	45.78	0.68
2	Mean summer temperature	–	56.43	–	–224.54	0.78
3	Mean summer temperature	NAOI	43.28	14.33	24.75	0.84

Model 1, which is based only on annual mean temperature, to 0.84 for Model 3, in which the annual amount of evaporation is related to the summer air temperature and the NAOI.

The fits for all models are optimized with respect to the sample used. Thus, the obtained correlations are biased and it is necessary to validate the proposed models with independent data. Usually, this is done by splitting the data into a fit and a validation period, and the quality of the model is assessed by the correlation between the modeled data and the data from the validation period which have not been used in establishing the statistical model (e.g., von Storch et al. 1993). Since the evaporation time series used in this study is too short for the application of this technique, a cross-validation approach is used instead (e.g., Michaelsen 1987, Heyen et al. 1998): If the data are available at N time steps, N models are fitted each time using the information from $N-1$ time steps. For each model, the predictand of the Nth time step is estimated from the predictor at the same time step by regression. Finally, the N estimations are compared with the observations of the predictand.

The result of the cross-validation for Model 3 is presented in Fig. 2. Generally, there is good agreement between the 2 time series. Especially the low-frequency variability is captured reasonably. To assess the agreement between the modeled and the observed evaporation quantitatively we computed the correlation of the validation R_v and the Brier-based score β. The latter is defined as

$$\beta = 1 - \frac{\mathrm{Var}(y_{obs} - y_{est})}{\mathrm{Var}(y_{obs})} \qquad (6)$$

(e.g., Heyen et al. 1998). Here y_{obs} and y_{est} represent the observations and the estimations of the predictand and Var() denotes the variance. If $\beta = 1$ observations and estimations of the predictand from the proposed model are identical; if $\beta = 0$ the error of the estimations has the same size as the variance of the observations (Livezey 1995). In our case we obtained $R_v = 0.79$ and $\beta = 0.55$ (Table 2).

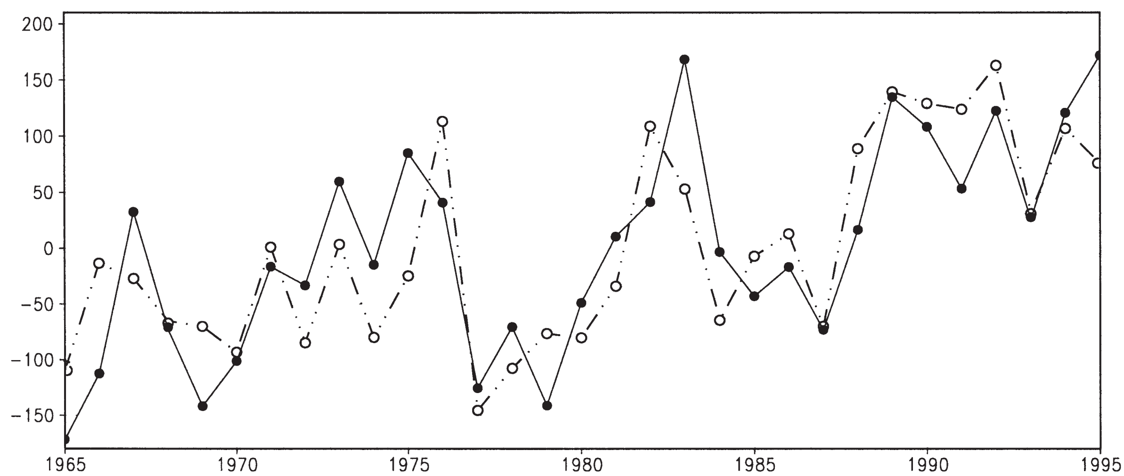

Fig. 2. Annual amounts of observed evaporation (dashed) and of evaporation estimated from Model 3 (solid) in mm. A mean value of 791.5 mm was subtracted from both curves

Table 2. Validation of Model 3. R_v: validation correlation coefficient; β: Brier-based score. See Section 5.1.2 for more details

	Model 3	95% level	99% level
R_v	0.79	0.33	0.44
β	0.55	0.10	0.18

The significance of these results was tested using a Monte Carlo approach: A first-order autoregressive process [AR(1) process] (e.g., von Storch & Zwiers 1999) was fitted to the observations. The lag-1 autocorrelation $\rho(1)$ was computed and the standard deviation of the driving noise σ_N was estimated from the residuals. Subsequently, 10 000 random realizations of an AR(1) process with $\rho(1)$ and σ_N were generated and compared with the observations. The upper 5% quantile of the correlations obtained in this way yields a measure of the 95% confidence level. Provided the correlation between the evaporation obtained from the cross-validated statistical model and the observed evaporation is larger than the 95% quantile, this correlation may be regarded as statistically significant. The results of this analysis for the correlation and the Brier-based score are presented in Table 2. The cross-validated model was found to be significant at the 99% level, and we conclude that the model is sufficiently skillful and able to reproduce the observed low-frequency variability of the annual amount of evaporation in the Geiseltal.

5.1.3. Reconstruction of evaporation

The obtained statistical relationships were used to reconstruct the annual evaporation backward in time. (Fig. 3). Since the available observations of air temperature and of NAOI started in different years the lengths of the reconstructed time series differ. However, from all 3 reconstructions it can be inferred that there is a fairly good agreement between the observed and the reconstructed time series during the fit period. Especially the low-frequency variability is captured reasonably. Furthermore, since all 3 models capture the upward trend in annual evaporation starting around 1960 it can be concluded that this trend basically originates from a similar trend in air temperature. However, since this trend is best captured by Model 3, variations in the general circulation also contribute to the observed trend. Additionally, inspection of the temperature time series reveals that this trend is part of a low-frequency air temperature variation and that the 1960s were relatively cold while temperatures in the 1990s were similar to those observed around 1940. Provided the proposed statistical model holds, similar conclusions are valid for the annual evaporation. In this case the 1960s were characterized by below-normal evaporation, while the levels observed nowadays were typical for the years around 1940 as well.

5.2. Reconstruction of *P* – *E*

From the analyses in the previous section it became clear that the observed trend in the annual evaporation is probably only part of a low-frequency variation and that conditions observed during the 1990s were by no means special. As a next step, we combined the reconstructed evaporation time series with available annual precipitation time series to obtain an estimate of $P - E$ (Fig. 4). The striking feature of all 3 time series is that $P - E$ remains negative almost throughout the reconstruction period. In each time series there are only a few realizations for which precipitation exceeds evaporation.

The probability distribution of the 3 reconstructions is presented in Fig. 5. In all 3 cases the average excess of annual evaporation over precipitation is on the order of 200 mm yr^{-1}. This is in general agreement with the findings of DWD (1996), who found an average $P - E$ deficit of –173 mm yr^{-1} from directly available observational data for the time period 1971–1995. From Fig. 5 it can be further inferred that in roughly 1% of all cases the $P - E$ deficit was as large as –500 to –600 mm yr^{-1}. The probability that $P - E > 0$ is observed is only on the order of 1 to 3%.

6. SUMMARY AND DISCUSSION

For a large number of environmental management decisions as, e.g., within the context of the remediation of former surface mining sites in Eastern Germany, the knowledge of the local water balance is an important decision criterion. However, usually the water balance is not known from direct observations or measurements are only available for limited periods. In the present study an approach was presented to put the conclusions drawn from such a limited sample into the context of long-term changes and variability. This approach statistically links the evaporation to available large-scale and routine atmospheric observations. Assuming a time-invariant statistical relationship this allows the evaporation to be estimated for a sufficiently long time and yields a sample large enough to provide estimates of the probability distribution (i.e., the mean values, the variability, and the extremes) of $P - E$,

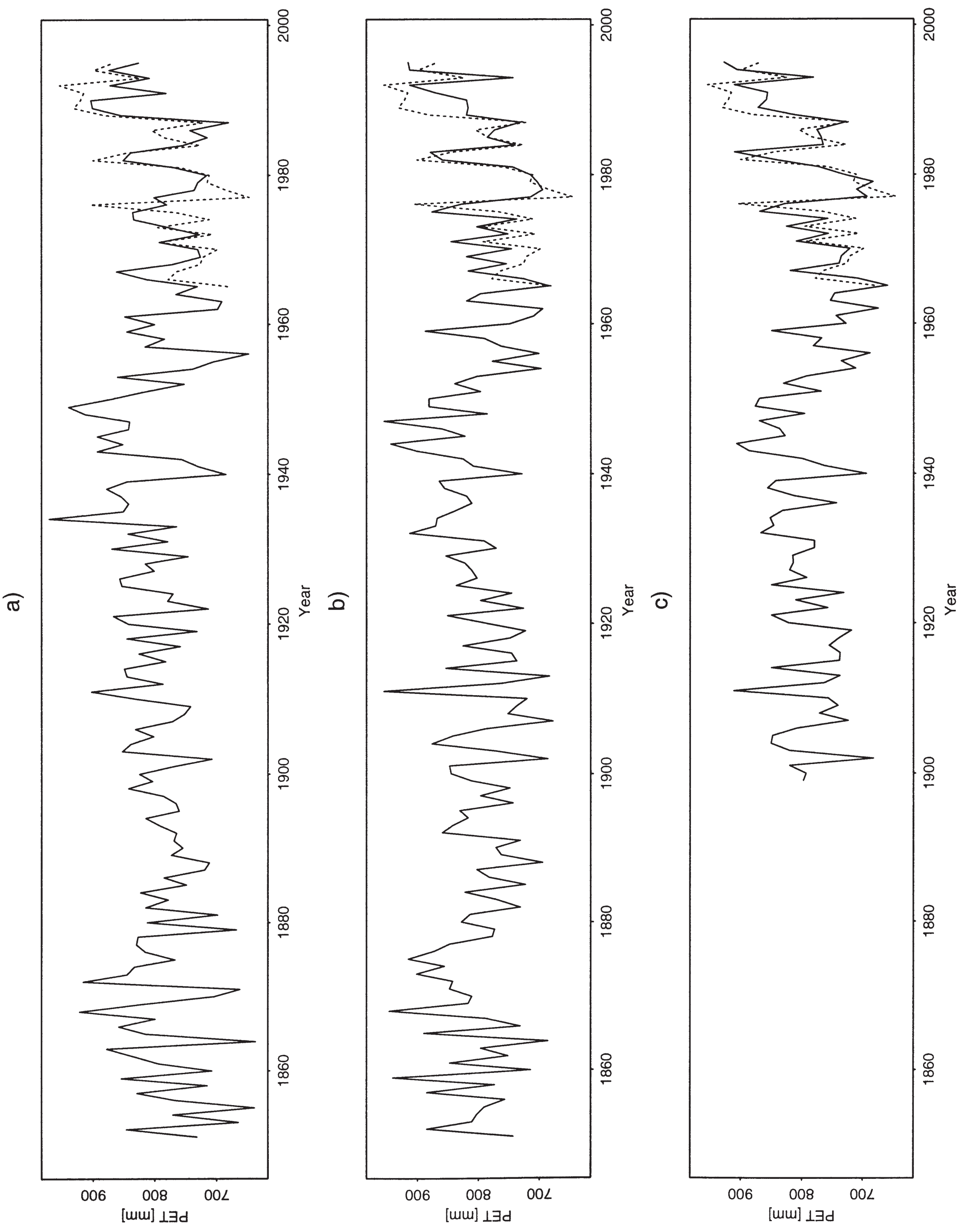

Fig. 3. Annual amount of evaporation obtained from (a) Model 1, (b) Model 2 and (c) Model 3 (solid) and observed annual evaporation amount (dashed)

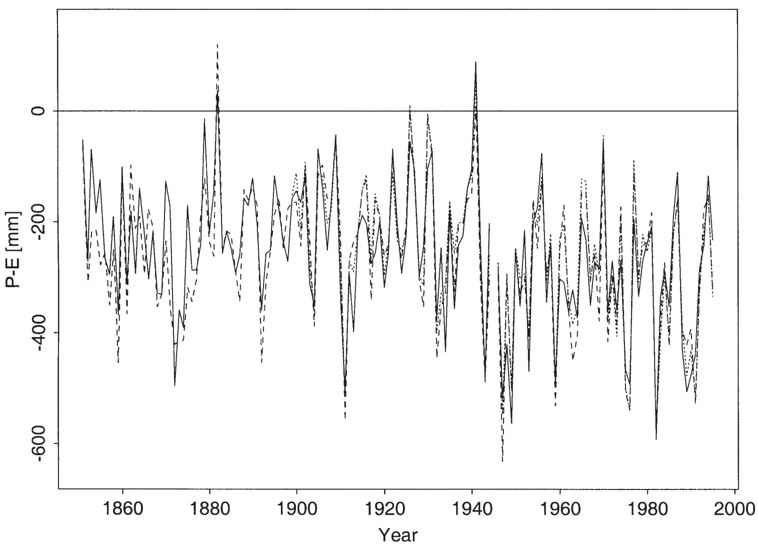

Fig. 4. Difference between the annual amounts of precipitation and evaporation obtained from Model 1 (solid), Model 2 (dashed), and Model 3 (dotted)

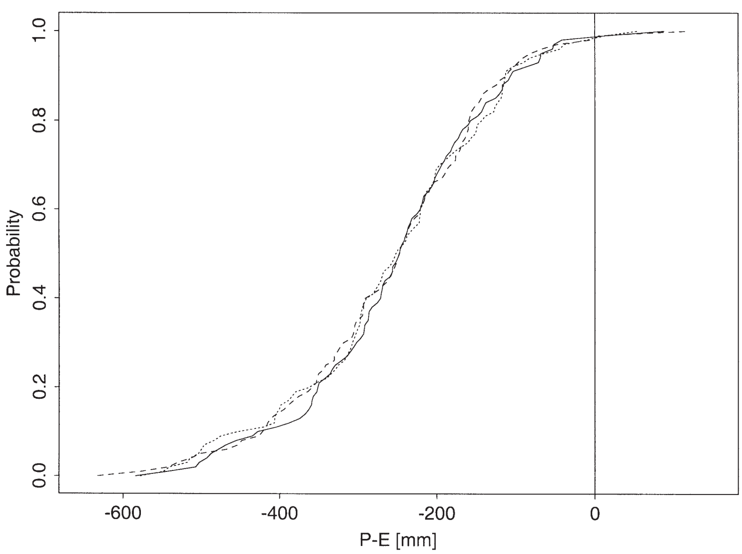

Fig. 5. Cumulative probability distribution of the difference between the annual amounts of precipitation and evaporation for Model 1 (solid), Model 2 (dashed), and Model 3 (dotted). The line $P - E = 0$ is also shown

which represents one key variable for assessing the water balance.

The approach is demonstrated for the example of the Geiseltal. It was found that a robust statistical relationship between evaporation, local air temperatures and the large-scale atmospheric circulation could be established. Based on the results of our analyses it was concluded that it is highly unlikely that an excess of annual precipitation over annual evaporation will be observed for the Geiseltal in most years.

Although the approach has proven to be successful for the reconstruction of the annual evaporation in this particular example, some limitations should be taken into account: (1) The statistical model was fit for a period in which data for both predictands and predictors were available. When the predictands are reconstructed backward in time from observations of the predictors, it is implicitly assumed that the statistical relation found for the fitting period holds for the entire reconstruction period. However, this is a general constraint when applying the presented technique. (2) A more severe constraint might arise from the fact that the suggested statistical model is partly based on local observations. Especially in the presence of strong spatial gradients, observations taken at a specific site are not necessarily representative for the entire area and the signal might be obscured by anomalous advection or turbulence processes. In this case a multivariate approach could be a solution since it considers spatial gradients and smoothes inhomogeneities or small-scale variability (variability at individual stations). (3) The probability for $P - E > 0$ may slightly change if other observations for P or other statistical models are used, but not by much. It remains highly unlikely that an excess of precipitation over evaporation will be observed in the yearly average for the Geiseltal. The results of this study suggest that additional permanent water supply would be necessary to maintain a quasi-stationary water level for the future Geiseltal lake. This water supply may be provided either naturally (e.g., ground water, aquifers) if these resources have sufficient capacity or artificially by, e.g., a pipeline system.

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