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Effect of evapotranspiration parameterisation on the Palmer Drought Severity Index

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ABSTRACT

The aim of the study is to compare two popular parameterisations of potential evapotranspiration, applied in computation of the Palmer Drought Severity Index. Among other differences, Thornthwaite method considers bare soil, whereas Blaney–Criddle method estimates evapotranspiration after specification of a given plant. Monthly PDSI series in the April–October growing season of maize are analysed at five stations in Eastern Hungary for the period 1901–1999. When using Blaney–Criddle method both the inter-annual and inter-monthly variability, i.e. standard deviation and auto-correlation decrease. Trends and regression coefficients to hemispheric temperature changes are smaller for latter parameterisation, as well. Synchronous correlation among the stations also decreases in this latter approach, whereas normality of the distribution remains valid in majority of months and stations.

1. Introduction

The increasing awareness of the effects of drought has led to a large number of regional and large-scale studies in various climatic regions (Dai et al., 1998, 2004; Wilhite, 2000; Domonkos et al., 2001; Panu and Sharma, 2002; Svoboda et al., 2002; Pongrácz et al., 2003; Stefan et al., 2004; van der Schrier et al., 2006, 2007; Blenkinsop and Fowler, 2007; Marsh et al., 2007).

Several drought indices have been used to analyse onset and duration of drought, recently overviewed e.g. by Heim (2002). The Palmer Drought Severity Index (PDSI) is one of the most widely applied indices for quantification of droughts all over the world (Szinell et al., 1998; Lloyd-Hughes and Saunders, 2002; Dai et al., 2004; van der Schrier et al., 2007). A comprehensive overview of the calculation procedures to derive the PDSI and its monthly increment, the *Z*-index is found in Palmer (1965, 1968), Alley (1984) and van der Schrier et al. (2006, 2007).

The PDSI is such an index of meteorological drought, values of which are calculated from of precipitation and temperature, as well as water capacity of soil for the actual and preceding periods. PDSI is standardised for different regions and time periods, which is useful in common assessment for a wide area with different climate. If PDSI values are negative (positive), they indicate dry (wet) period, while those around zero denote near-average water balance. Palmer considered ±4 as a threshold value of extremity (Palmer, 1965).

Some former studies (Horváth, 2002; Jankó Szép et al., 2005; Mika et al., 2005; Makra et al., 2002, 2005) have already analysed various features of PDSI in different sectors of Hungary. These papers reflect several aspects of PDSI and the key international literature sources on the field exhibit a 40-year long history since Palmer's historical paper in 1965.

The study aims at examining if an alternative approach to the potential evapotranspiration, i.e. the Blaney–Criddle approach may strongly affect some of the features having been established in the above papers. For this purpose, two versions of PDSI are compared, differing only in estimating the potential evapotranspiration. The Thornthwaite (1948) method operates with meteorological variables, irrespectively to the vegetation, i.e. potential evapotranspiration is estimated as evaporation of bare surface, only. In spite of this, the Blaney–Criddle method (Alley, 1984) uses plant constants to estimate potential evapotranspiration. To specify this methodology, maize is selected as typical for managed vegetation of the country. The study area is the plain area of the Tisza River in Eastern Hungary.

2. The study area and data of analysis

2.1. The study area

Similarly to our former studies dealing with the Palmer Index (Horváth, 2002; Makra et al., 2002, 2005; Mika et al., 2005), the

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present analysis is also based on monthly PDSI times series of Miskolc, Nyíregyháza, Debrecen, Kecskemét and Szeged on the plain catchment area of the Tisza River in Eastern Hungary (Fig. 1) for the period 1901–1999. Selection of the region is motivated by its important agricultural activity, by repeated drought and inundation. Natural protection is also crucial, since 70–80% of the area is covered by managed vegetation.

Hereinafter, results of the growing season, i.e. for April–October are analysed. In some cases, every second month (April, June, August and October) is only presented, considering the strong autocorrelation of the PDSI.

2.2. The Palmer Drought Severity Index

2.2.1. Computation of PDSI

Calculation of the Index, consisting of five steps, is described in a few papers (Palmer, 1965; Alley, 1984; Karl, 1986). The procedure considers monthly precipitation, temperature and soil water capacity conditions. Basic concepts and steps of computation are as follows:

Step 1: *Hydrological Accounting*. Computation of PDSI begins with a climatic water balance using series of monthly precipitation and temperature records. An empirical procedure is used to account for soil water storage by dividing the soil into two arbitrary layers. The upper layer is assumed to contain 25 mm of available water at field capacity. The loss from the underlying layer depends on the initial water content, as well as on the computed *potential evapotranspiration* (*PET*) and *the Available Water Capacity* (*AWC*) of the soil system. In the present calculations of PDSI, AWC values of 100 mm are used for all stations, even with, possibly, different soil types. Runoff is assumed to occur, if and only if, both layers reach their combined water capacity, *AWC*. In addition to *PET*, three more potential terms are used and defined as follows: *Potential Recharge* is the amount of water required to bring the soil to its water holding capacity. *Potential Loss* is the amount of water that could be lost from the soil by evapotranspiration during a zero precipitation period. *Potential Runoff* is defined as the difference between precipitation and Potential Recharge.

Step 2: *Climatic Coefficients*. This is accomplished by simulating the water balance for the period of available weather records. Monthly coefficients are computed as proportions between climatic averages of actual vs. potential values of evaporation, recharge, runoff and loss, respectively.

Step 3: *CAFEC Values*. The derived coefficients are used to determine the amount of precipitation (I) required for the Climatically Appropriate For Existing Conditions (*CAFEC*), i.e. "normal" weather during each individual month.

Step 4: *Moisture Anomaly Index*. Difference between the actual and the *CAFEC* precipitation is an indicator of water deficiency or surplus in that month and station, expressed as $D = P - I$. These departures are converted into indices of moisture anomaly as $Z = K(j)D$, where $K(j)$ is a weighting factor for the month j, also accounting for spatial variability of the departures (D).

Step 5: *Drought Severity*. In the final step the Z-index time series are analysed to develop criteria for the beginning and ending of

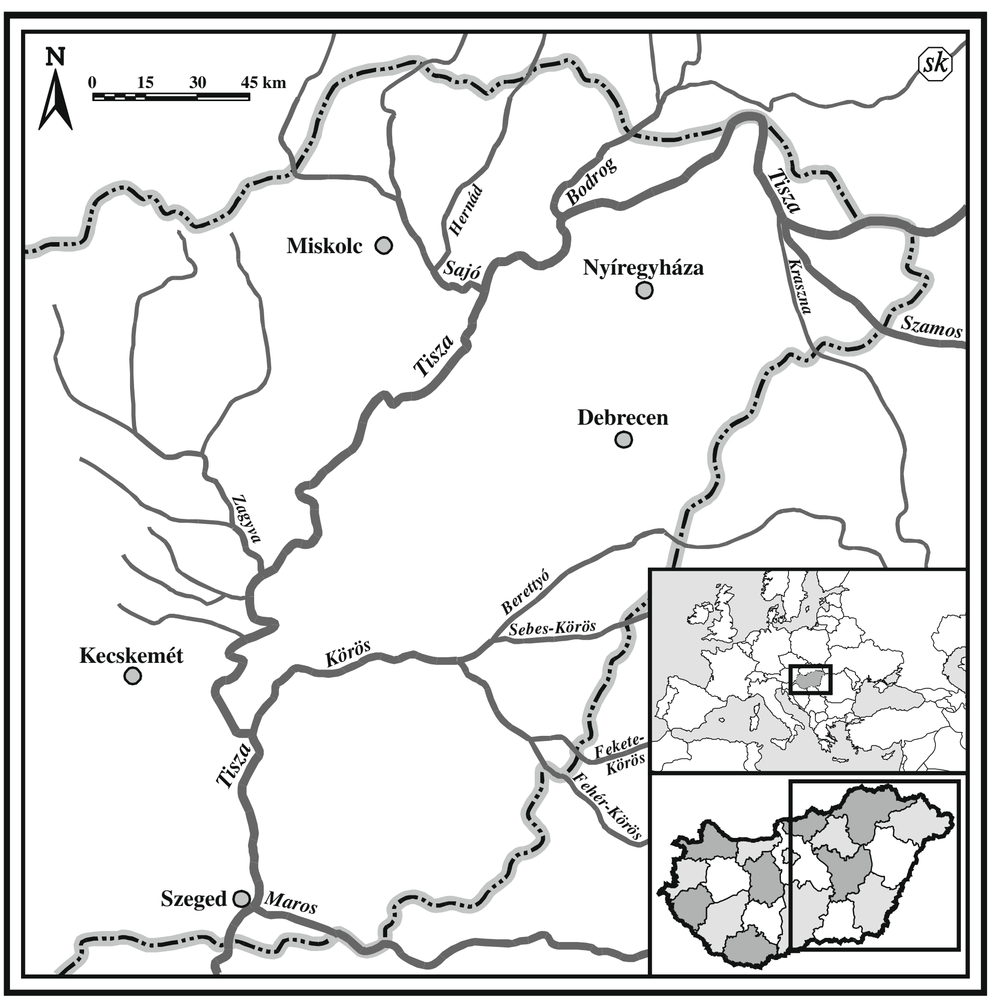

Fig. 1. The study area with the five investigated stations in East Hungary.

drought periods and an empirical formula for determining drought severity, such as:

$$X_j = 0.897X_{j-1} + Z_j/3,$$

where Z_j is the Moisture Anomaly Index and X_j is the value of PDSI for the jth month.

The equation indicates that PDSI of a given month strongly depends on the conditions of the previous months and on the moisture anomaly of the actual month. This fact implies strong auto-correlation of PDSI.

Monthly time series of temperatures and precipitation, as input data of the Index, exhibit inhomogeneity due to changes in observation times, transfer of stations and other possible factors. Homogenisation of the monthly temperature and precipitation data is performed by the statistical procedure of MASH (Multiple Analysis for Homogenisation) elaborated in the Hungarian Meteorological Service (Szentimrey, 1995, 1999). The essence of the procedure is a break-point analysis assuming that all real changes of the local macro-climate occur in a smooth way; hence any significant break-point of the series should be corrected. The MASH procedure and software is used in several other countries, as well (WMO, 2004).

2.2.2. Two methods for estimating potential evapotranspiration

Calculation of PDSI may differ in the way of how potential evapotranspiration is estimated. Palmer used the formula of Thornthwaite in his Index for calculating potential evapotranspiration (Thornthwaite, 1948); however, application of the Blaney–Criddle method offered alternative assessment later (Alley, 1984). The first method considers evapotranspiration as a climate variable, without specific vegetation, whereas the second approach reflects some specifics of the vegetation, as well. Thereinafter, the two methods of calculating potential evapotranspiration, required for computing PDSI, are briefly specified.

The *Blaney–Criddle* (B–C in the followings) *method* belongs to the group of empirical methods, mainly used in agricultural and water management calculations. The method estimates the quantity of water utilised by vegetation (*CU* = *consumptive water use*) which equals to the potential evapotranspiration (*PET*):

$$CU = PET = k.c.p(0.46T + 8)\ [\text{mm day}^{-1}] \tag{1}$$

where T is daily average temperature (°C); c is a constant, depending of daily minimum of relative humidity, wind speed and relative humidity; p is a coefficient depending of geographical latitude, which represents average daily ratio of sunshine duration per latitude. Value of k, as a plant factor, is location-specific. The expression $(0.46T + 8)$ in Eq. (1) is the average value of *PET*, which is improved by c in order to make its value more precise.

When using the B–C method for calculating potential evapotranspiration, a so called reference plant should be considered. For this aim, the selected reference plant is maize, since it is characteristic for the investigated region (Mika et al., 2001), and its quickly developing leaf surface is also similar to several other agricultural plants, from transpiration point of view, as well.

The *Thornthwaite* (Th in the followings) *method* is based on the experience that potential evapotranspiration (*PET*) is competently determined by temperature. The procedure can be used for calculating *PET* sums of large regions; however, it does not explicitly reflect its dependence from air humidity and windiness. Its formula, simplified by Thornthwaite is:

$$PET = 1.6 \cdot \left(\frac{10 \cdot T}{I}\right)^a \tag{2}$$

where T is monthly average temperature (°C), while I is the so called heat index,

$$I = \frac{12}{5} \cdot T^{1.514}, \tag{3}$$

whereas the exponent a can be calculated as follows:

$$a = 6.75 \cdot 10^{-7} I^3 - 7.71 \cdot 10^{-5} \cdot I^2 + 1.792 \cdot 10^{-2} \cdot I + 4.9239 \cdot 10^{-1} \tag{4}$$

The two methods for calculating potential evapotranspiration can modify our results published in former studies, although we received strong significant correlation ($0.86 < r < 0.98$) between monthly PDSI data sets calculated with Th and B–C methods (Mika et al., 2005). In this paper PDSI series considering: (a) B–C method; and (b) Th method are compared for the period 1901–1999 at the above five stations. Eight further aspects (see titles of Section 4) are presented to characterise the differences in PDSI caused only by the evapotranspiration method.

At the end of description of the key process of our paper, i.e. the PDSI computation, we must admire that all our computations use the traditional way of PDSI where the constants of the process are used, as it had been set by Palmer (1965). Since then, the so-called self-calibrated PDSI (scPDSI) has been defined in the literature which improved the 'traditional' PDSI (Wells et al., 2004). This improvement means that the empirical weighting factors, described above, are individually set according to climate of the given station. However, these parameter-settings are performed to provide long-term balances which also depend on the applied evapotranspiration methodology. This "self-calibration" of the PDSI would also obscure the effects of the evapotranspiration processes, as well.

2.3. Further data

2.3.1. Soil moisture estimation

The calculated PDSI values were compared to the soil moisture content (SMC) of the upper 1 m soil layer, quantified for a shorter period, 1901–1990, in an independent way (Dunkel, 1994; Jankó Szép et al., 2005). The latter data were available for three stations of the region: Nyíregyháza, Debrecen and Szeged. Computation of SMC also considers daily changes of the water balance, but it parameterises evapotranspiration (both the potential and the real ones) in a different way. The original source of data (Dunkel, 1994) also contains some verification against the data of a direct soil moisture measuring network.

2.3.2. Hemispherical mean temperature

Comparison of PDSI with the global climate tendency requests data on mean temperature (<T>) of the Northern hemisphere and those for air temperature contrast between continents and oceans (ΔT). They are derived from air temperature data over the continents (Jones, 1994 and updated) and over the oceans (Folland et al., 1984 and updated), considering the proportionality of the two surface-types. The original updated time series are available from internet: http://cdiac.esd.ornl.gov/trends/temp/jonescru/jones.html. Since air temperature data sets over the oceans are available till 1988 (Folland et al., 1984 and updated), ΔT for the 1989–1999 period between is estimated from regression with <T>. This estimation indicates significant connection only in monotonously warming (or cooling) periods. Data of the last 11 years were estimated from the northern hemispheric mean temperature using the clearly warming periods of 1917–1943 and 1976–1988, i.e. altogether 40 years (Jones et al., 2000).

3. Methods

3.1. Tests of normality

Monthly PDSI series exhibited normal distribution in the majority of months and stations (Mika et al., 2005) with the B–C method. Results of normality tests performed by the χ^2-test for the whole 1901–1999 period are presented in Section 4.1.1 for the monthly PDSI values in April–October, computed by both B–C and Th methods.

3.2. Inter-serial, temporal and spatial correlation

Correlation coefficient generally characterises sign and strength of linear relationship between two variables. In our study there are three different ways of how these variable pairs are selected:

Inter-serial correlation is used to assess whether both PDSI versions may be interpreted as a soil moisture indicator. For this purpose series of the given PDSI version is correlated to the soil moisture content (Section 4.1.2).

Temporal correlation (auto-correlation) is determined to check whether the vegetation affects the strong memory of PDSI caused by the recursive manner of its derivation (Section 4.4.1). Six-monthly auto-correlation coefficients are compared for this purpose.

Spatial correlation is used to examine effect of vegetation on spatial diversity of PDSI, exhibiting statistical dependence at the different stations of the region. This dependence is interpreted by spatial correlation between the 10 possible pairs of stations (Section 4.4.2).

3.3. Trend and regression

Regression coefficient is another quantitative characteristics of the linear relationship between two variables, indicating how much (and to which direction in its natural or standardised unit) the dependent variable would change, in average, if the independent variable changed by one unit of its dimension.

Specific way of regression is the *linear trend,* where sequence of time stands for the independent variable. Section 4.2 displays such applications of regression.

Another example of regression is demonstrated in Section 4.3.1 where the two PDSI series are compared after Gauss-filtering. Regression coefficient between them indicates which PDSI version changed more radically in the 20th century, compared to the other one.

3.4. Method of slices

Three variable regressions are incorporated into an approach applied in Section 4.3.2. Method of "slices" (Mika, 1988; Horváth, 2002) is used to investigate connections between regional climatic elements and two hemispheric temperature characteristics, i.e. the average temperature ($<T>$) and air temperature difference between continents and oceans (DT) for the period 1901–1999. The original time series are sliced into sub-periods of the same length, and regression analysis is fulfilled using time averages of the 5, 9, 13, 17 and 21-year long sub-periods, defined to randomise the possible data inhomogeneity. Linear regression connecting the regional variable Y, to the above global indices, $<T>$, and DT, is as follows:

$$Y = Y_o + (\delta Y/\delta < T >) < T > +(\delta Y/\delta \mathrm{DT})\mathrm{DT} \qquad (5)$$

The aim of "slicing" is to quantify the connections being non-significant on the year-by-year basis, not distorting the original coefficients. The temperature interval covered by the "slices" is 0.5 K. Regression coefficients are calculated by the method of least squares. Student's *t*-tests of the regression coefficients are performed. Hemispheric mean temperature and continent–ocean contrasts are derived from air temperatures above the oceans (Folland et al., 1984 and updated) and above the continents according to updated series of Jones (1994). The updates are taken from the Internet with reference to Jones et al. (2000); (http://cdiac.esd.ornl.gov/trends/temp/jonescru/jones.html).

Regression coefficients found and validated by Student's *t*-tests at 95% and 80% probability levels we considered real ones. Those of 80% significance are listed only with their sign. If more then half of the cases (3 out of 5) yielded coefficients on at least 80% significance, the average coefficient was calculated as mean of the five slices' coefficient.

3.5. Gauss-filtering

Long-term tendencies of PDSI with B–C method is presented by Makra et al. (2005), using Gauss-filtering. Section 4.3.1 examines if the lack of vegetation (Th method) modifies these trends. Weights of the Gauss-filtering within the considered 11-year "window" are 0.200, 0.177, 0.122, 0.065, 0.027 and 0.009 for the central year and for its two-sided neighbours of ±1, ±2, ±3, ±4 and ±5-year distance, respectively. Sum of the 11 weights is equal to 1.

One should notice that the Gauss-filter has no such exposed role among the other filters, as the Gaussian distribution does among the continuous distributions. Nevertheless, this filter is often applied in the case of climatic time series, as well.

4. Results

4.1. Effect of evapotranspiration on the statistical distribution and physical interpretation of PDSI

4.1.1. Normality of the distribution

Majority of the months and stations exhibit normal distribution in both PDSI data sets (Table 1). Ratio of deviation from normality at the 95% and 80% probability levels is 7/35 and 14/35 for the B–C version, respectively. The same ratio for the Th version is almost identically 7/35 and 13/35, respectively. This means that the way of computing evapotranspiration does not influence the fact that although majority of the cases correspond to the normality, frequency of deviations from it is also higher than it should be in the case of a true, undisturbed Gaussian ensemble.

Table 1
Significance levels of deviation from normal distribution according to the χ^2-test at the five stations.

1901–1999	Test	Apr	May	Jun	Jul	Aug	Sep	Oct
Miskolc	Th		*10*				*15*	
	B–C		*12*					*16*
Nyíregyháza	Th				*8*			
	B–C			**2**	**0.4**	*14*		*8*
Debrecen	Th		*19*					**2**
	B–C			**1**	**0.02**	**0.1**	6	
Kecskemét	Th	**4**			**2**	**5**	**0,04**	**1**
	B–C				*11*			
Szeged	Th		*20*		**5**			*16*
	B–C				**2**	6	**2**	

Empty cells: no significant difference from normality; *italics:* probability of normality is ⩽20% but >5%; **bold:** probability of normality is ⩽5%.

4.1.2. Correlation with the soil moisture content

PDSI series computed by the B–C version exhibited close relation with the independent series of monthly soil moisture content, SMC (Mika et al., 2005). On the basis of linear regression coefficients the index values could also be expressed in physical units of water content in the upper 1 m soil layer.

With except of the May–June peak of precipitation, correlation coefficients are somewhat higher for the B–C method than for the Th method. The most common feature of both PDSI series is that they exhibit strong correlation with the SMC in all 7 months, analysed (April–October). Although SMC is an independent estimation of soil moisture, the correlation between SMC and PDSI may as strongly influenced by the given methodology of the soil moisture estimation, as by the way of computing evapotranspiration in the PDSI. Therefore, the above relation surely does not mean that B–C is better than Th in this respect.

For the standardised regression coefficients between PDSI values, calculated with the B–C method and moisture content, it can be established that they are very similar in each of the 7 month and three stations (Nyíregyháza, Debrecen, Szeged) (Table 2). Unit change of PDSI calculated with the Th method is connected to the SMC series with slightly lower standardised regressions than those calculated with the B–C method.

4.2. Effects of evapotranspiration on the short-term variability of PDSI

4.2.1. Linear trends

Linear trends of the two PDSI versions are presented in Table 3 for every second month of the growing season from April to October. Proportion of significant trends is not too high, according to the *t*-test at the 95% probability level, but the uniformly negative tendency is worth for attention. This means, that soil of the examined region was characterised with slow drying out in the 20th century.

Comparing absolute values of the trends, obtained by the Th and B–C methods in the given 99-year long time sequence, one can find that the previous one is generally stronger. From among the 20 pairs (i.e. five stations and 4 months) there are only 5 months, at two stations, where PDSI with B–C evapotranspiration estimation show steeper linear decrease than the same values for the Th evaporation estimation. This means that the previous approach confined the drying tendency during the 20th century to some extent.

4.2.2. Variance of original and de-trended series

Comparison of variances (i.e. squares of the standard deviation) between the two methods is demonstrated in Fig. 2. Height of the columns indicates the total variance, whereas smaller white parts at their bottom part show the contribution of the above linear trends on the variance. The larger part of the columns can be interpreted as inter-annual variability of PDSI.

Monthly variance of PDSI with the Th method is higher in each station than those with the B–C method. Although, the individual differences are generally not significant according to the *F*-test, the B–C approach could slightly decrease the inter-annual variability of PDSI.

4.3. Effects of evapotranspiration on long-term variability of PDSI

4.3.1. Time-evolution of Gauss-filtered series in the 20th century

Linear trends are just rough first approximations of the tendency. Results of Gauss-filtering, with the same 11-year window as specified above in Section 3.5, are presented by Makra et al. (2005) for the B–C version. Here we give a quantitative comparison of the smoothed Th and B–C series by their regression coefficients (Fig. 3).

In majority of the stations and months the regression coefficient is higher than 1.0. This means that smoothed changes of the Th version are generally steeper than those for the B–C version. The only exception is Miskolc characterised by its most northern position within the region, surrounded by hills in 3 months from the four indicated.

In some cases the coefficient is higher than 1.2, indicating that lack of vegetation would add more than 20% to the drying tendency of the 20th century in theses months and locations.

Table 2
Dimensionless regression coefficients (Ky/σy) between Dunkel's soil moisture content (SMC), standardised by its standard deviation, and the given PDSI versions (B–C or Th), 1901–1990. Unit change in B–C mean slightly stronger change in the standardised SMC.

SMC_{stand}/PDSI	April	May	June	July	August	September	October
Nyíregyháza							
B–C	**0.33**	**0.35**	**0.39**	**0.39**	**0.37**	**0.36**	**0.38**
Th	*0.32*	*0.35*	*0.36*	*0.37*	*0.34*	*0.32*	*0.33*
Debrecen							
BC homog	**0.31**	**0.31**	**0.37**	**0.39**	**0.35**	**0.36**	**0.35**
Th homog	*0.30*	*0.31*	*0.35*	*0.36*	*0.33*	*0.31*	*0.31*
Szeged							
BC homog	**0.30**	**0.34**	**0.37**	**0.37**	**0.33**	**0.34**	**0.35**
Th homog	*0.28*	*0.31*	*0.33*	*0.33*	*0.29*	*0.28*	*0.30*

Table 3
Linear trends of PDSI (1/100 years) in both Th and B–C versions for 1901–1999. Significant trends at 5%, according to the *t*-test, are **bold** set (Contribution of the trends to the variance is shown in Fig. 2.).

Station	April		June		August		October	
	Th	**B–C**	**Th**	**B–C**	**Th**	**B–C**	**Th**	**B–C**
Miskolc	−2.1	**−2.1**	−1.3	−1.5	−1.4	−1.5	−2.0	−1.9
Nyíregyháza	**−2.3**	−1.6	−1.2	−0.7	−1.4	−1.2	−2.2	−1.8
Debrecen	−1.7	−1.6	−0.6	−0.7	−0.5	−0.7	−1.5	−1.7
Kecskemét	**−3.3**	**−2.5**	−2.0	−1.2	−2.2	−17	**−3.7**	−2.2
Szeged	**−3.3**	**−3.1**	**−2.5**	−1.7	−1.7	−0.9	−2.4	−2.0

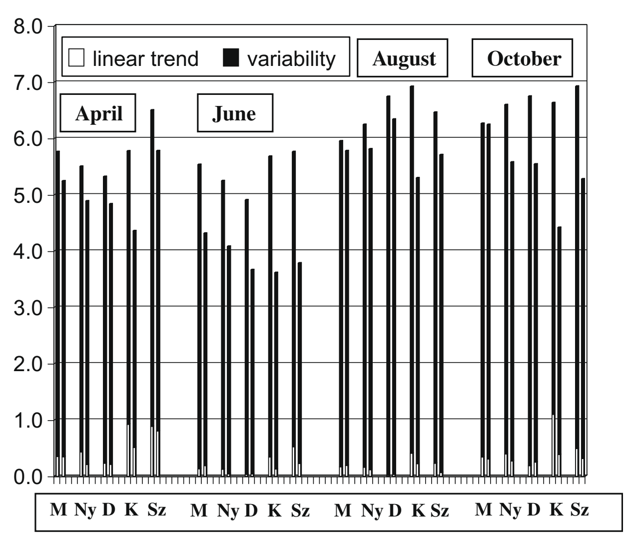

Fig. 2. Variance of monthly PDSI values in the five stations (M – Miskolc, Ny – Nyíregyháza, D – Debrecen, K – Kecskemét, Sz – Szeged) as a sum of contribution from the linear trends (see in Table 3) and the inter-annual variability. Left column of each pair is the Thorthwaite version, right side is the Blaney–Criddle version. The latter variance is always smaller, mainly due to the inter-annual differences. Role of linear trends is rather small in the total variance.

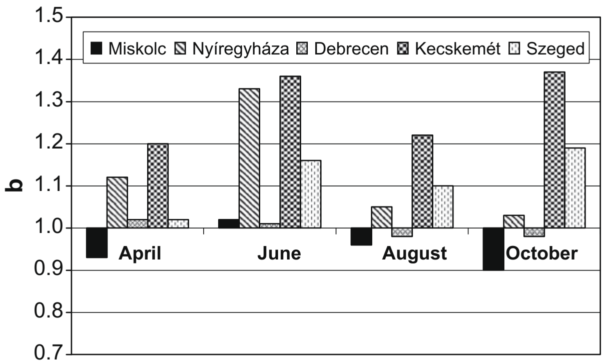

Fig. 3. Regression coefficients between Gauss-filtered PDSI series with 11 years window in the two different versions, in 1906–1994. In the given consideration Th version is the dependent variable, and B–C version is the independent variable. Regression >1.0 mean stronger changes in Th version than in the B–C during the investigated period.

4.3.2. Correlation to hemispheric mean temperature

The drying tendency, demonstrated in the previous sections can be understood only if comparing to the global climate processes, instead of simple sequence of time, only. (This does not mean, however, that water balance could not be influenced by those local interventions that are just casual functions of time. Such effects, nevertheless, are not involved into the PDSI process operating, e.g. with the same water holding capacity, or soil layer thickness.) Comparison of local PDSI to hemispheric mean temperature, <*T*>, and continent–ocean contrast, DT, is numerically performed by the method of slices (Section 3.4).

The detailed results for the B–C version of PDSI are displayed by Horváth (2002). Here we focus on comparison of the two versions, without presenting parallel details concerning the Th version. Key figures of this comparison are presented in Table 4, in which number of all significant partial regression coefficients (4 months at five stations) between the corresponding PDSI values and the hemispheric parameters are displayed together with the averages of all regression coefficients ($\Sigma/5$: together for the significant and non-significant ones).

Similarly to the results with the B–C method, significant negative regression coefficients (*PDSI*/*T*) dominate the partial relation between the PDSI with Th method and the hemispheric mean temperature. The average coefficient is also strongly negative. This means drying tendency parallel to the warming of the 20th century, including long-term fluctuations of the latter series, as well. Comparing the two versions, one may establish that the negative tendencies are slightly more dominant in the case of the Th version (bare soil) considering the proportion of the significant signs and the average coefficients, as well.

Sign of the significant coefficients regarding the continent–ocean air temperature contrast ($PDSI/\Delta T$) is balance between positive and negative effects, whereas the mean coefficient (including again the non-significant ones, as well) are negative in both the Th and B–C versions. Here the average coefficients differ more characteristically, but it would not be easy to interpret without detailed physical interpretation.

Putting together the overall proportionality of significant coefficients, one may establish slightly more significance in case of the B–C version. While Th exhibits 5 + 51 = 56 significant coefficients for *PDSI*/*T* and 17 + 14 = 31 ones for $PDSI/\Delta T$, the version with the B–C approach is characterised by 8 + 53 = 61 and 18 + 21 = 39 significant coefficients, respectively. Maybe this is also connected to the fact of the smaller inter-annual variability in the latter case, which, in turn, opens wider space to the statistical governance of global climate tendencies. However, the more frequent significant coefficients themselves do not mean stronger sensitivity of PDSI in the case of B–C computation of evapotranspiration, since the average negative *PDSI*/*T* coefficients is stronger for the Th version by ca. 15% ($-2.28\ K^{-1}$ vs. $-1.92\ K^{-1}$).

4.4. Effects of evapotranspiration on the temporal and spatial correlation of PDSI

4.4.1. Six-monthly auto-correlation

The high values of auto-correlation, coming from the recursive definition of the PDSI, remain significant even after the time difference of 6 months (0.3–0.7) for the B–C version (Mika et al., 2005). Within these ranges, slightly lower values of the auto-correlation are observed in the summer half-year, due to the higher variability of (partly convective) precipitation.

Analysis of the 6-monthly auto-correlation of PDSI derived with the two methods is performed by numerical comparison of the auto-correlation values (R_6^{Th}/R_6^{B-C}). Results of this operation are shown in Fig. 4. Each sample includes total frequency for all five stations and 12 months, i.e. 60 cases, since the semi-annual lag spreads beyond the growing season, anyway.

Ratios above 1.0 indicate stronger auto-correlation of the Th version compared to that with the B–C version of evapotranspiration. Such relation is valid in overwhelming majority of the cases. Hence, the latter way of evapotranspiration leads to weaker and less frequent appearance of very long-lasting drought or inundation. In other words, this approach maintains wider diversity of soil moisture conditions at a given site of the region.

4.4.2. Spatial correlation

Finally, the spatial diversity, investigated by comparing the spatial correlation of synchronous PDSI patterns, derived with one or the other method of estimating evapotranspiration is analysed. The values of the spatial correlation coefficients calculated for the 10 station-pairs of the five stations and the 7 months are between 0.13 and 0.80, with low values only in the case of the two most distant stations Miskolc and Szeged, characterised by rather different topography. Correlation coefficients of the Th version served for basis of the spatial classification received by factor analysis, is based on much more stations with shorter series (Horváth,

Table 4
Relative sensitivity of the PDSI data sets calculated with the B–C and the Th methods, in relation to the hemispherical mean temperature (T) and the continent–ocean air temperature contrast (ΔT). April, June, August and October months are considered. Number of regression coefficients is 100 for both hemispherical variables, separately. This means, e.g. 8 + 53 = 61% of significance for PDSI/*T* in the B–C version.

Station month	Relative sensitivity 1/K	Blaney–Criddle			Thornthwaite		
		[a]sign. + sign	[a]sign. − sign	[b]Σ/5	[a]sign. + sign	[a]sign. − sign	[b]Σ/5
Five stations, A–J–A–O months	**PDSI/T**	8	53	−***1.92***	5	51	−***2.28***
	PDSI/ΔT	18	2s1	−***0.60***	17	14	−***0.06***

[a] Sign. = significant at least at the 80% level.
[b] Σ/5: Average of all (significant and non-significant) coefficients of PDSI/*T* and PDSI/ΔT.

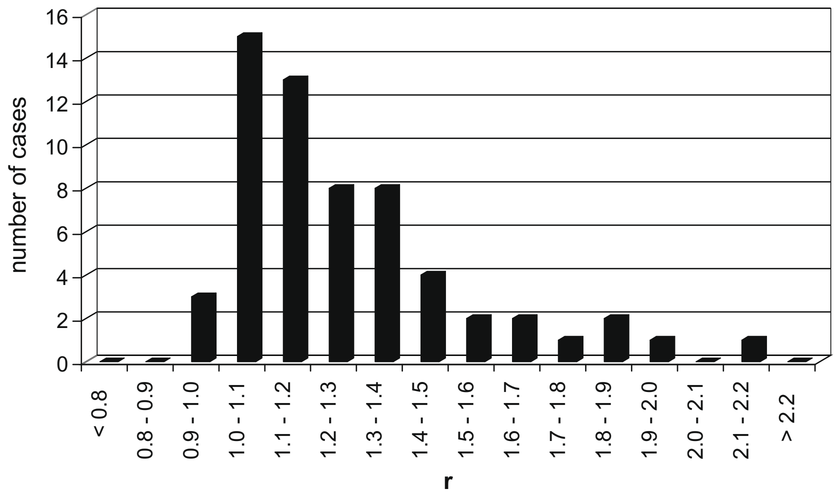

Fig. 4. Histogram of the ratio between the 6-month lag auto-correlation values, corresponding to the Th vs. the B–C methods. (The five stations and all the 12 months of the year are involved in this particular statistics.) Ratios above 1.0 indicate stronger auto-correlation for PDSI computed by the Th method.

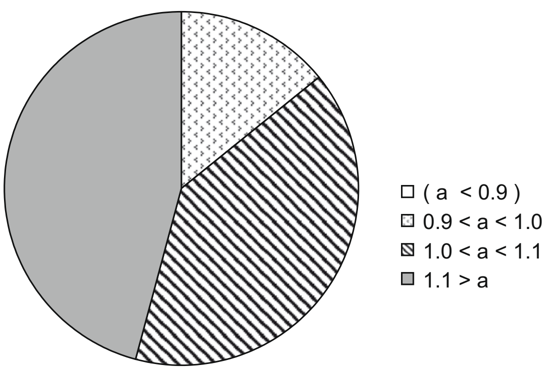

Fig. 5. Proportion between the spatial correlation coefficients of PDSI computed with the Th vs. the B–C method of evapotranspiration. Values $a > 1$ indicate stronger spatial correlation without plants, i.e. the Th method, than with the B–C (maize) version.

2002). The 2–3 regions obtained by that method indicate strong but not uniform spatial correlation of the Th version PDSI series.

Fig. 5 gives a simplified view on the behaviour of the spatial correlation accumulated for the five stations and the 7 months between April and October. Proportion of spatial correlation with the Th version and the B–C version is grouped according to its relation to the proportion equal to 1.0. Much larger part of the proportions is higher than 1.0, indicating the more developed spatial diversity (lower correlation) in the case of the B–C version of evapotranspiration.

5. Conclusion

The difference between PDSI data based on Thorntwaite's potential evapotranspiration from that calculated with the Blaney–Criddle method can be summarised as follows:

The majority of the monthly PDSI distributions can be considered normal, although proportion of non-normal cases is higher than the random selection. Deviation from normality does not depend on the way of computing evapotranspiration.

Strong linear connections between both the versions of PDSI series and the independent soil moisture content are established. The standardised regression coefficient between the soil moisture content and the PDSI is higher in the case of the B–C version of evapotranspiration, which is explained by the larger standard deviation of PDSI following the Th way of computing evapotranspiration.

The linear trends for the whole period decrease more intensively in the case of the Th approach.

The standard deviation following the Th is somewhat higher in each month, than those determined with the B–C approach. The inter-annual component of the variability is more important than the linear trends, although they are also somewhat stronger in the case of the Th approach.

Drying tendency of the 20th century, according to the Gaussian filtering, is also steeper in the Th version than in the case of the B–C approach.

The regression coefficients between PDSI and the hemispheric mean temperature are mostly negative in both versions. The significant coefficients, however, refer to a stronger relationship, that means that the unit change of the hemispheric temperature happens parallel to the 20% stronger drying out for Th version, than in the case of the B–C version.

Most of the temporal correlation coefficients are higher in the case of the Th approach than those determined by the B–C way of computing evapotranspiration.

Most spatial correlation coefficients are higher for the Thornthwaite version than those determined by the Blaney–Criddle evapotranspiration methodology.

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