Supplementary Materials

Four Sections are formed in the order of their connections to the Sections of the paper:

1. **Illustrative Figures**
2. **Discussion of the statistical analysis based on small samples**
3. **Box plots of the five dryness indices**
4. **Statistical parameters of the best quadratic fittings**

1. Illustrative Figures

The year-to-year evolution of the dryness indices is not analyzed in the paper, but it is presented for the two complex indices, DI and VWI.

The dryness index (DI) is the most complex index among the five applied ones in the present research. Therefore, fluctuations of the four additive terms of DI are presented in Figure S1. All values are based on the observed and interpolated data averaged for the 22 wine regions of the country. Note that the applied mm/m^2 unit is identical to the mm, reminding us of the observation of transpiration measured by lysimeters.

As shown in Figure S1, the interannual fluctuations are relatively high with no unequivocal linear trend, valid for 20 years.

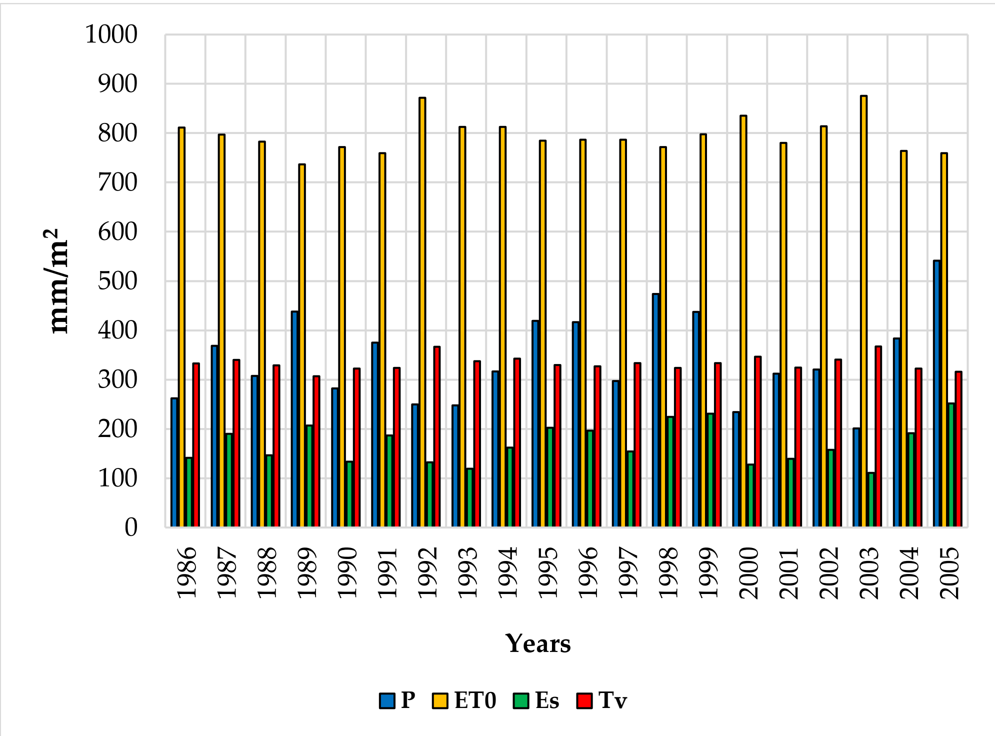


Figure S1. Components of the Dryness Index in the vegetation period averaged for the 22 wine regions of the country. P – precipitation, ET0 – potential evapotranspiration, Es – evaporation from the soil, and Tv –transpiration from the plant. The vertical axis unit (mm/m^2) is equivalent to mm.

VWI is an informative index comparing the precipitation of the vegetation period to the potential evapotranspiration of the same part of the year, the interannual fluctuation of this index is displayed in Figure S2.

The proportion of the income side of water balance, i.e. precipitation, varies between 20% and 70% of the potential evapotranspiration.

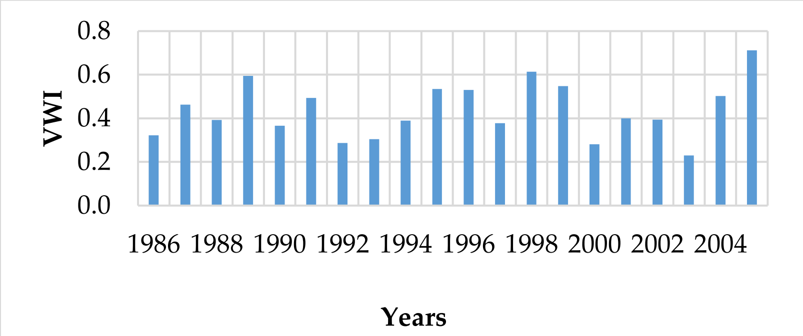


Figure S2. Interannual fluctuations of the Vineyard Water Indicator (VWI) in the vegetation period averaged for the 22 wine regions of Hungary.

2. Discussion of the Statistical Analysis Based on Small Samples

Statistical results obtained from small samples are often questioned without considering the effects of sample size on Type I or Type II errors of the statistical decisions based on small samples. In the case of our quadratic fitting, two questions should be discussed, and both are related to the fact that the quadratic regressions are being investigated from a small sample. The questions are as follows: Can we accept the established connections? Why do we expect quadratic connections instead of linear ones?

Concerning the first question, we may read in the statistical textbooks (e.g. [66], see among the References in the paper) that there are two types of errors in statistical decisions, which should either accept or reject a so-called zero hypothesis. In our case, the zero hypotheses is that there is no real difference between the variances compared by the F-test; in other words, there is no correlation between x and y in the expected form. In this case, the Type I error is that we reject the zero hypothesis, although that is true. In other words, we claim that the connection exists, whereas it does not. On the other hand, the error of Type II is that we do not recognize that the zero hypothesis is false, erroneously concluding that there is no connection in the specified form.

In general, it is impossible to decrease both the 'alpha' likelihood of Type I and the 'beta' likelihood of Type II errors, but we can partly influence their likelihood depending on principal or practical aspects. Most often, we decide about the significance level, i.e. allowed 'alpha' likelihood of Type I error, which in practice is 10, 5 or 1 %. As explained by [67: p. 11] (see in the paper), the' beta' likelihood depends on the selected 'alfa', the sample size and the strength of the effect that may cause rejection of the zero hypotheses. The lower alpha is selected, the higher the beta likelihood of Type II error remains. In the case of a fixed 'alpha', the smaller the sample, the higher the likelihood of Type II error occurring.

In our case, we can regulate the likelihood of false conclusions that a given quadratic relation is valid. Of course, even in the case of variables that are totally independent of each other, we may receive significant F values. Hence we may be convinced of the reality of the connections if the frequency of significant relationships is much higher than the selected 'alpha' threshold.

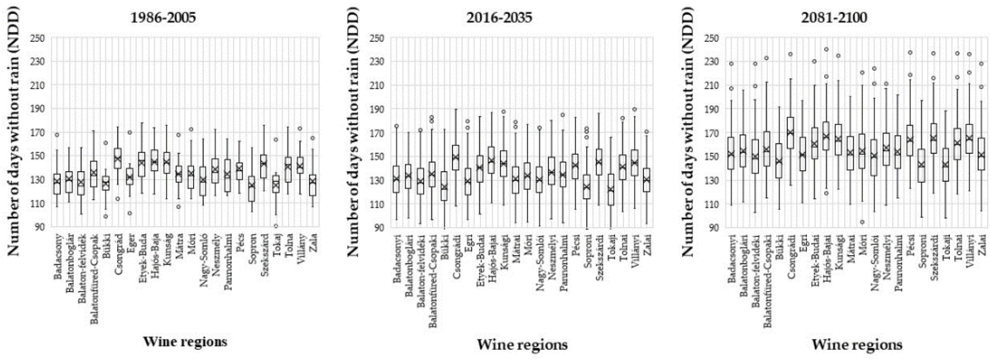
As will be presented in Tables 5 and 6 of the paper, the rates of significant quadratic correlation are over 50% in the case of the samples containing 17 elements, whereas the same for the smaller samples was above 25 %, so the frequency of statistical significance is by 10 and 5 times higher than the random probability, i.e. 5%! In conclusion, even with these small samples, we can rely on the established quadratic relationships, although we could find further connections if having much larger samples.

The answer is relatively simple concerning why quadratic regression is expected to be realistic, not even investigating the linear correlation. Based on common sense, one can expect that the yield in extremely dry and extreme wet situations should be low, whereas the maximum yield may be produced in moderately wet vegetation periods. This assumption is validated by all significant quadratic relationships where the coefficients of the quadratic term (a) are negative, i.e. all parabolas are located up-side-down (see Tabs S1, S2 and S3 in Section 4 of this Supplement and Figs. 9-11 of the paper for the strongest correlations)

3. Box Plots of the Five Dryness Indices

In this Section, Box-plots of the five Dryness indices are presented to illustrate the statistical distribution of the simulated indices averaged for the grid points of each wine region. For the overwhelming majority of the indices and the regions, the range of the indices is wider in the future 20 years than in 1986-2005.

The 22 wine regions exhibit similar characteristics, with a slight difference in the same distribution (Figure S3). The box diagrams for the NDD show that in the near and distant future, the range of occurrence of the data will be significantly broader; we can count on a more significant standard deviation and more extremes. However, at the same time, the differences between the wine regions will not change.

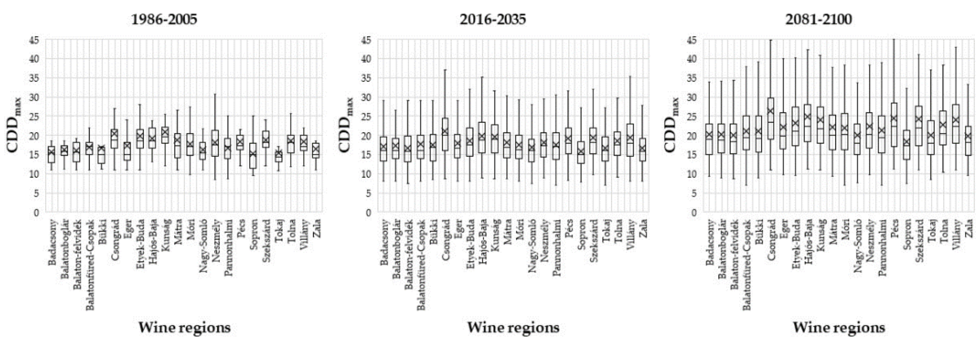


(a) (b) (c)

Figure S3. Box diagrams indicating the frequency distribution of the number of rain-free days (NDD) for 22 Hungarian wine regions and three periods. Diagram S3a characterizes the recent period 1986-2005, S3b refers to the near future 2016-2035 period, while S3c refers to the distant future period, 2081-2100.

The sum of rain-free days typical for the vegetation period numerically characterizes drought occurrence. If there are many days without precipitation, the frequency of occurrence of drought increases significantly. We can expect 90-180 rain-free days in Hungary during the growing season.

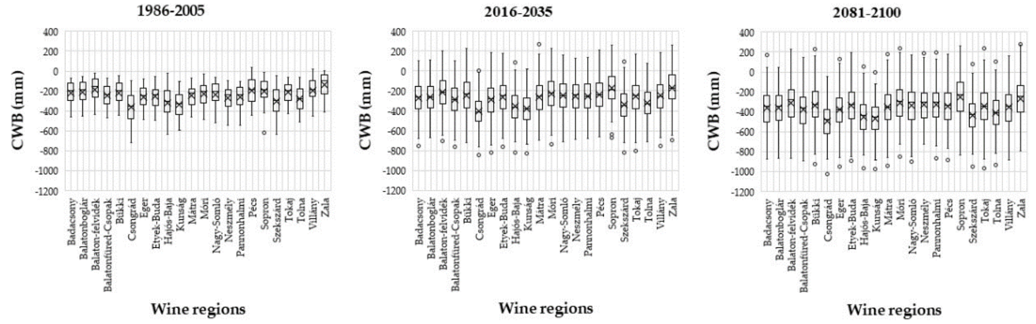
The box diagrams for the 22 Hungarian wine regions show that in the near future, but especially in the distant future, the range of occurrence of the data will be significantly more expansive, whereas the differences between the wine regions will not change. All 22 wine regions in Hungary have a similar character, with a slight difference and can be characterized by the same distribution (Figure S4).



(a) (b) (c)

Figure S4. Box diagrams indicate the frequency distribution of the maximum number of consecutive dry days (CDD_{max}) for 22 Hungarian wine regions and three periods. Diagram S4a characterizes the recent period 1986-2005, S4b refers to the near future 2016-2035 period, while S4c refers to the distant future period, 2081-2100.

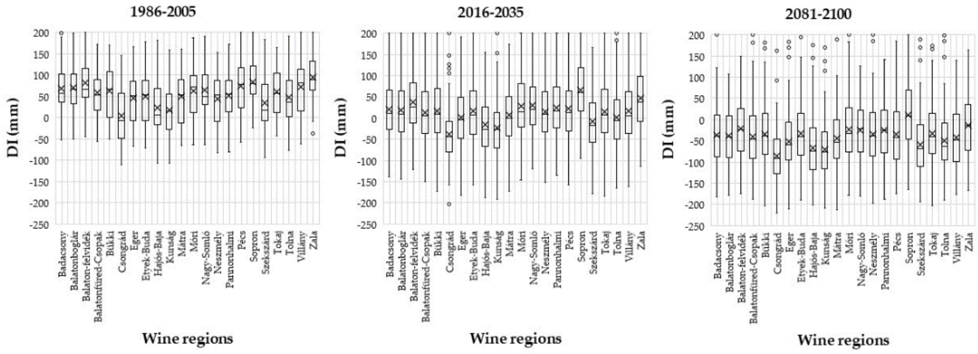
The box diagrams show that in the near and distant future, the range of occurrence of the data will be significantly more expansive, and the occurrence of extreme values will increase. The occurrence of extreme values in the negative range will be significantly more frequent in the future than in the positive range. The differences between wine regions are not significant (Figure S5).



(a) (b) (c)

Figure S5. Box diagrams indicating the frequency distribution of the climatic water balance (CWB) for 22 Hungarian wine regions and three periods. Diagram S5a characterizes the recent period 1986-2005, S5b refers to the near future, 2016-2035 period, while S5c refers to the distant future period, 2081-2100.

The box plots for the 22 Hungarian wine regions show that the data range will be more comprehensive in the near and distant future. All 22 Hungarian wine regions have a similar character, with a slight difference, and can be characterized by the same distribution (Figure S6). Due to the more frequent occurrence of DI<-100 values, at the same time, the differences between individual wine regions do not change.



(a) (b) (c)

Figure S6. Box diagrams indicating the frequency distribution of the dryness index (DI) for 22 Hungarian wine regions and three periods. Diagram S6a characterizes the recent period 1986-2005, S6b refers to the near future 2016-2035 period, while S6c refers to the distant future period, 2081-2100.

The VWI box diagrams for the 22 Hungarian wine regions show that in the near and distant future, the range of occurrence of the data will be more comprehensive, and at the same time, the occurrence of extreme values will increase. At the same time, the differences between wine regions are insignificant, i.e. we cannot separate or group wine regions based on the Vineyard Water Indicator; the 22 Hungarian wine regions follow a similar distribution (Figure S7).

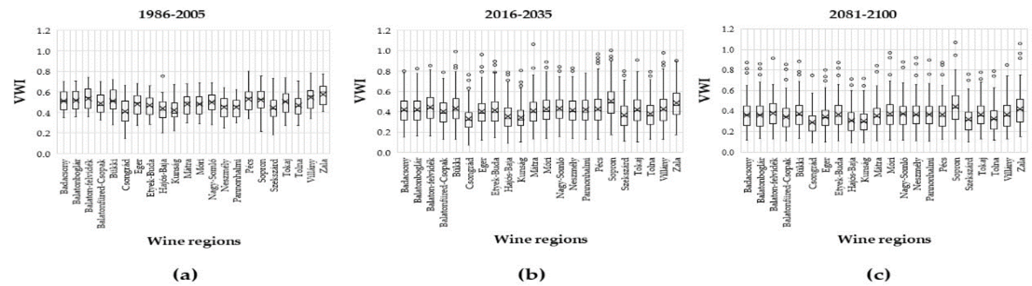


Figure S7. Box diagrams indicating the frequency distribution of the vineyard water indicator (VWI) for 22 Hungarian wine regions and three periods. Diagram S7a characterizes the recent period 1986-2005, S7b refers to the near future, 2016-2035 period, while S7c refers to the distant future period, 2081-2100.

4. Statistical Parameters of the Best Quadratic Fittings

The results of the best regression fits of the variables are shown in Table S1 for the 2005-2017 period. In this way, we obtained 110 quadratic connections, but the table presents only those connections for each dryness index, which are characterized by the highest significance of their "explained" variance.

Table S1. The regression coefficients (a, b, c), level of significance (p) and explained variance (R^2) presented the best fit between the given drought index and yield fluctuations in the 2005-2021 period. The a, b and c are related to the terms of the $y = ax^2+bx+ c$ formula.

Dryness Indices	Wine Region	a	b	c	p	R^2
NDD	Szekszárd	-0.038	11.668	-891.242	p=0.003	0.565
CDD_{max}	Tolna	-0.095	5.042	-59.677	p=0.034	0.382
CWB	Szekszárd	-0.000	-0.074	-7.092	p=0.000	0.810
DI	Etyek-Buda	-0.002	0.218	4.651	p=0.000	0.753
VWI	Etyek-Buda	-78.962	-385.917	0.000	p=0.000	0.686

In the case of white grape varieties, Rhine Riesling and Chardonnay, we found the most significant relationships between the examined drought indicators and yield fluctuations. The fluctuation of the Italian Riesling yield shows a significant quadratic function relationship with the VWI, CWB, and DI, while the fluctuation of the Chardonnay yield shows the NDD, CWB and VWI variables. A significant quadratic relationship can be demonstrated between the Italian Riesling and Furmint wine grape varieties' yield fluctuations and the CDDmax, and NDD variables. The fluctuation of the Tramini cultivar is primarily determined by the NDD, while the CWB determines the fluctuation of the Pinot Gris.

From the examined variables, there is at least one outstandingly significant quadratic relationship in the case of all white wine grape varieties (Table S2).

Table S2. The regression coefficients (a, b, c), level of significance (p) and explained variance (R^2) presented the best fit between the given drought index and white wine grape yield fluctuations in the 2005-2021 period. The a, b and c are related to the terms of the $y = ax^2+bx+ c$ formula.

White Wine Grapes	Dryness Indices	Wine Region	a	b	c	p	R^2
Tramini	NDD	Hajós-Baja	-0.86	253.66	-18682.38	p=0.000	0.992
Italian Riesling	CDD_{max}	Balatonboglár	-2.20	81.21	-747.27	p=0.001	0.999
	NDD	Balatonboglár	-0.07	18.06	-1206.19	p=0.016	0.984
Pinot blanc	VWI	Pannonhalmi	-1389.71	1323.55	-304.99	p=0.003	0.997
Rhine Riesling	VWI	Pannonhalmi	-1159.02	1119.98	-261.01	p=0.027	0.973

	CWB	Sopron	-0.01	-4.88	-802.50	p=0.037	0.963
	DI	Nagy-Somló	-0.01	0.65	-8.87	p=0.048	0.952
Chardonnay	NDD	Tokaj	-0.65	160.28	-9810.73	p=0.010	0.990
	CWB	Zala	0.00	-1.06	-187.76	p=0.015	0.985
	VWI	Zala	-1701.03	1826.07	-479.62	p=0.025	0.975
Furmint	NDD	Zala	-0.25	65.53	-4325.62	p=0.036	0.964
	CDD_{max}	Neszmély	-0.00	0.00	0.00	p=0.042	0.958
Pinot gris	VWI	Sopron	-863.33	990.04	-276.39	p=0.015	0.985

The results show significant quadratic functional relationships for each white and red wine grape variety, at least with one dryness index and yield fluctuations (q/ha) at least at a 95% significance level (p≤5%).

Zweigelt and Syrah found the most significant relationships among red wine grape varieties between the studied drought indices and yield fluctuations. For the red wine grape varieties, CWB proved to be the best drought indicator; this index showed the closest relationship with the magnitude of yield fluctuations of Cabernet franc, Pinot noir, Syrah, and Zweigelt grape varieties. Cabernet Sauvignon shows a significant quadratic relationship with NDD, Lemberger with CDDmax, and Merlot with DI variables. In the case of the Syrah and Zweigelt grape varieties, a significant quadratic relationship can also be shown with the VWI, NDD, and CDD_{max} indices (Table S3).

Table S3. The regression coefficients (a, b, c), level of significance (p) and explained variance (R^2) presented the best fit between the given drought index and red wine grape yield fluctuations in the 2005-2021 period. The a, b and c are related to the terms of the $y = ax^2+bx+ c$ formula.

Red Wine Grapes	Dryness Indices	Wine Region	a	b	c	p	R^2
Cabernet franc	CWB	Bükki	-0.003	-2.851	-620.982	p=0.008	0.992
Cabernet Sauvignon	NDD	Villány	-0.136	39.890	-2920.334	p=0.009	0.991
Lemberger	CDD_{max}	Pécs	-0.711	25.747	-227.957	p=0.027	0.973
Merlot	DI	Balaton-felvidék	-0.036	4.220	-83.905	p=0.025	0.975
Pinot noir	CWB	Nagy-Somló	-0.011	-9.797	-2110.018	p=0.019	0.981
Syrah	CWB	Bükki	-0.009	-7.641	-1633.536	p=0.009	0.991
	VWI	Bükki	-12084.67	11321.58	-2619.430	p=0.048	0.952
Zweigelt	CWB	Balaton-boglár	-0.002	-2.235	-498.724	p=0.012	0.988
	NDD	Bükki	-0.067	16.546	-1016.159	p=0.022	0.978
	CDD_{max}	Villány	-1.524	55.175	-493.075	p=0.030	0.970