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Comparison of the New Drought Index with various well-known drought indices

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Abstract:
This article introduces the New Drought Index (NDI) to a wide scientific and professional society. This index, relatively simple to apply, was published by Bonacci et al. in Croatia in 2022 and international journals in 2023. Thus far, it has been tested in many countries on four continents. The main strength of NDI is that it uses only two parameters: precipitation and air temperature for a certain time period (month, season, or year). In this research, NDI was tested on a monthly basis for two Croatian regions, continental (meteorological station Donji Miholjac) and coastal region (meteorological station Split). The results were compared with those of drought severity obtained using the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Rainfall Anomaly Index (RAI), and Aridity Index (AI). The period of analysis was between 1981 and 2022. The best correlation was between both regions' NDI and SPEI (> 0,7).

Keywords:
New Drought Index; Standardized Precipitation Index; Standardized Precipitation Evapotranspiration Index; Rainfall Anomaly Index; Aridity Index

1 Introduction

Most proposed drought indices rely on precipitation data for a certain period. A lack of precipitation and more frequent dry periods with no precipitation are likely to result in drought episodes. Several meteorological indices use only one parameter, either directly or indirectly. Primarily, it is monthly, seasonal, or annual precipitation; however, similarly, data on monthly, seasonal, or annual discharge or groundwater levels can be used. This group of indices can be represented by the Standardized Precipitation Index (SPI) and other indices based on it: Standardised Streamflow/Discharge Index (SSI or SDI), and Standardised Groundwater Level Index (SGI or SWI). However, other meteorological and climatological parameters should not be disregarded. Because the most prominent impact of climate change is the increasing air temperature, including air temperature in the quantification of drought could lead to a significant improvement. A few years ago, Vicente-Serrano et al. proposed the Standardized Precipitation Evapotranspiration Index (SPEI) that introduced evapotranspiration into the original SPI [1]. However, in 2009, SPI was recommended by the World Meteorological Organization as a method suitable for use worldwide, regardless of climatic or topographical features [2].

A problem is always encountered when deciding which indicators or indices are the most appropriate for drought quantification. The question is whether a specific index is suitable for a given location, area, basin, or region. Similar to the definition of drought, no unique indicator or index is the most appropriate for all climate regions (arid, Mediterranean, or moderate climate regions), all types of droughts (agricultural, meteorological, or hydrological drought), or different sectors (water management, agriculture, water supply, etc.).

Several questions must be answered to determine the most appropriate index. However, the most straightforward method is often selected because it requires the least amount of data. However, long reliable data series of complex and specific parameters are often unavailable. Simple drought indices that are sensitive to climate, space, and time have certain advantages. Large-scale drought management with significant spatial and temporal variability should be considered. Complex composite (or modelled) indicators are often difficult to implement daily because of the large number of parameters that are often unavailable. Thus, these methods are more suitable for scientific purposes [3].

This article aims to introduce the New Drought Index (NDI) to a broad scientific and professional society. This index, which is relatively simple to apply, was published in 2022 in a Croatian scientific journal [4] and in 2023 in an international scientific journal [5] by Bonacci et al. In a short time, it was cited or used in more than 15 papers published in international journals. The only parameters required are the precipitation and air temperature for a certain period (month, season, or year). Thus far, in Croatia, the method has been tested in calculating drought severity between 1948 and 2020 for two meteorological Croatian stations: Split-Marjan and Zagreb-Grič. Another study was conducted on two islands: Lastovo Island in the southern Adriatic and Lošinj Island, situated 277 km north. The data series used in the calculation was for a 63 year period (1961-2023) [6].

In this article, the calculation of drought severity using NDI will be compared with similar meteorological drought indices: two-parameter methods, Aridity Index (AI) and SPEI, and one-parameter method, Rainfall Anomaly Index (RAI) and SPI, which can all be used to monitor drought that affects agriculture, natural water resources, the environment, etc.

2 Methodology

2.1 Materials and methods

2.1.1 Study area

Two climatologically distinct regions were selected to test the applicability of the proposed drought method (Figure 1). The first is in eastern Croatia, represented by the Donji Miholjac meteorological station. According to the Köppen climate classification, this region has a moderately warm and humid climate, with warm summers (Cfb) [7]. In this region, the mean annual precipitation between 1981 and 2022 was 718 mm, and the mean annual temperature during the same period was 11,6 °C. The second representative region is the southern region, located along the Adriatic Coast, and represented by the Split meteorological station. According to the Köppen climate classification, this region has a moderately warm and humid climate, with warm summers (Csa) [7]. The mean annual precipitation between 1981 and 2022 was 780 mm, and the mean annual temperature of the same period was 16,7 °C.

Figure 1. Study area with position and attitude of the relevant meteorological stations

The global impacts of climate change, particularly increasing air temperature, are being experienced in Europe. Previous investigations have shown homogeneous annual precipitation data series for both regions, and the mean annual air temperature has increased significantly since the 1990s [8]. A positive air temperature anomaly, defined as the difference from the average air temperature of the study period, prevailed during the 21st century in both regions (Figures 2a) and 2b)).

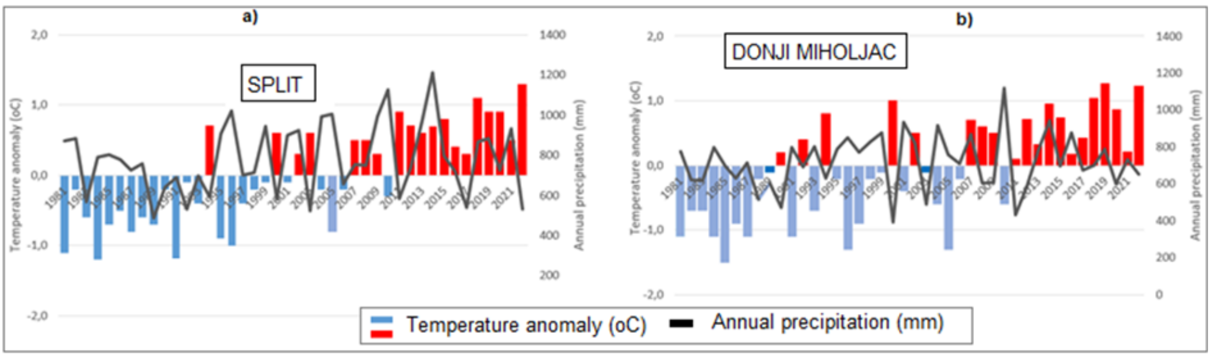


Figure 2. Annual precipitation and temperature anomaly of the period 1981-2022: a) for Split meteorological station; b) for Donji Miholjac meteorological station

In addition, previous drought analyses in Croatia confirmed the significant temporal variability and spatial diversity of drought occurrence. Croatia can be divided into three homogeneous regions: Central North, Eastern, and Southern (Figure 1) [9].

2.1.2 New Drought Index (NDI)

The first published proposal of NDI was in 2021 by Bonacci et al. [4; 5]. The climatological parameters necessary to define NDI values are precipitation and air temperature at different timescales. The basis of this index is that potential and/or actual evapotranspiration plays a crucial role in the water balance and, consequently, drought occurrence [10]. Additionally, increasing air temperature is the most persistent impact of climate change.
NDI presumes that drought severity is driven by a deficit in precipitation (below the average in a certain area) and increasing air temperature (above the average air temperature in a certain area). Therefore, NDI is expressed as follows:

$$NDIi = [(Pi - Pav)/SP] - [(Ti - Tav)/ST] \quad (1)$$

Where *Pi* is the precipitation in year or month *i*; *Pav* is the average value of the analysed series of precipitation in the obtained period; *SP* is the standard deviation of the analysed series of precipitation; *Ti* is the mean temperature in year or month *i*; *Tav*, is the average value of the analysed series of air temperature data in the analysis period; *ST* is the standard deviation of the analysed series of air temperatures.
The proposed classification of the *NDI* values relies on *SPI* and *SPEI* ranges for moderate droughts from −1,0 to −1,49; severe droughts from −1,5 to −1,99; and extreme drought for values less than −2,0 [6].

2.1.3 Aridity Index (AI)

AI is an old method developed by De Martonne in 1925 [11]. It is a two-parameter method that defines the ratio of precipitation to the mean temperature or evapotranspiration. It can be used not only as a drought index but also to classify the climate regime of a certain region. The possible values of AI are all positive and are given in five classes of aridity, as shown in Table 1. This study used evapotranspiration instead of air temperature in the following equation for *AI* calculation:

$$AI = P/PET \quad (2)$$

Where *P* is the precipitation in the year or month; *PET* is the potential evapotranspiration in the year or month.

2.1.4 Rainfall Anomaly Index (RAI)

RAI was developed in the 1960s by Van Rooy [12]. It uses normalised precipitation data at various timescales (months, seasons, or years) obtained from a particular meteorological station.
The positive and negative signs are related to positive and negative precipitation anomalies, respectively. Seven classes of drought severity are used, ranging from 3,0 to -3,0 (Table 1). Two equations exist for *RAI* calculation depending on the anomaly [13]:

$$RAI = 3\left(\frac{Pi - Pav}{M - Pav}\right) - \text{positive anomalies} \quad (3.1)$$

$$RAI = -3\left(\frac{Pi - Pav}{L - Pav}\right) - \text{negative anomalies} \quad (3.2)$$

Where *Pi* is the maximum precipitation for month or year in obtained period; *Pav* is the mean precipitation from the series of maximums; *M* is the average of the 10 highest values in the series, and *L* is the average of the 10 lowest values. Here, ±3 is a standardization factor that limits the anomalies within the range from −3 to +3 through a unity-based scaling, ensuring an asymmetrical distribution.

2.1.5 Standardized Precipitation Index (SPI)

McKee et al. (1992) developed *SPI* for the USA) [14]. It uses historical precipitation data series for a specific location and calculates the probability of precipitation at different timescales, frequently between 1 and 48 months (or even longer, but frequently between 1–24 months). The required length of a precipitation data series is at least 20 years; however, longer time series are more reliable [15]. Drought events are indicated when the results of *SPI* become negative and smaller than −1,0. *SPI* values between 1 and -1 indicate ‘normal’ conditions, whereas positive values higher than 1 present wet conditions.
SPI is based on the normalised gamma distribution of precipitation and presents several standard deviations of an average value. It can be used for various timescales, often between 1 and 24 months, depending on the purpose of the drought analysis.
SPI has defined limit values that depend on the relative frequency of drought, which enables the comparison of values for various locations or regions, as shown in Table 1. The equation used in *SPI* calculation is:

$$\mathrm{SPI} = \frac{1}{\sigma}\left(\sum_{i=1}^{n}(Pi - Pav)\right) \tag{4}$$

Where *Pi* is the precipitation in the year or month; *Pav* is the average value of the analysed series of precipitation in the obtained period; *σ* is the standard deviation of the data series. *SPI* calculation can be performed using an *SPI* generator [16].
Different timescales are included along with the precipitation deficit accumulated during each drought. Negative *SPI* values represent the accumulated precipitation deficit for each drought event as the sum of the monthly precipitation deviations from the mean during a drought event [14]. The same cumulative precipitation frequencies were valid for *SPEI* and *NDI*.

2.1.6 Standardized Precipitation Evapotranspiration Index (SPEI)

This method was developed by Vicente-Serrano et al. in 2010 [1]. It relies on the *SPI* method, but also includes the air temperature. Thus, the index considers the effect of temperature on drought development through basic water balance calculations. Possible time steps are between 1 and 48 months or more (such as *SPI*). Previous investigations of drought in Croatia confirmed that the most appropriate drought index in Croatian meteorological conditions *SPEI* owing to the potentially significant increasing trends of air temperature [17,8]. Potential evapotranspiration was calculated using the Thornthwaite equation. *SPEI* has defined limit values equal to those of the *SPI* method, making it easier to compare the two methods.
The procedure for calculating *SPEI* is similar to that used for *SPI*. However, *SPEI* uses the difference between precipitation and reference evapotranspiration (*P – ETo*) rather than precipitation. Equation (4) then changes to the following form:

$$\mathrm{SPEI} = \frac{1}{\sigma}\left(\sum_{i=1}^{n}((Pi - EToi) - (Pav - EToav)\right) \tag{5}$$

Where *Pi* is the precipitation in the year or month *i*; *Pav* is the average value of the analysed series of precipitation in the obtained period; *EToi* is potential evapotranspiration of the year or month; *EToav* is the average value of the analysed series of potential evapotranspiration in the obtained period; σ is standard deviation of data series.
As presented in Table 1, SPI and SPEI have the same classification of drought: negative values smaller than -1,0 designate droughts of different severity ranges. RAI has a similar classification, but the range of moderate and severe drought classes is more comprehensive, leading to more rigorous criteria for extreme drought (≤ −3,0). AI has a completely different scale for drought severity. All values are positive, ranging between 0,65 and 0,05 or smaller.

Table 1. Limit values for the *SPI*, *SPEI*, *RAI*, and *AI*

Classification	*SPI*, *SPEI*, *NDI* [1; 6; 14; 20]			*RAI* [12]	Classification	*AI* [11]
	Range	Cumulative precipitation frequencies	Probability of event			
Extremely wet	≥ 2,0	0,977 to 1,000	2,3	≥ 3,0	Hyper-arid	< 0,05
Very wet	1,50 to 1,99	0,933 to 0,977	4,4	2 to 2,99	Arid	0,05 to 0,20
Moderately wet	1,00 to 1,49	0,841 to 0,933	9,2	1,0 to 1,99	Semiarid	0,2 to 0,5
Normal	−0,99 to 0,99	0,159 to 0,841	68,2	0,5 to (−0,5)	Sub-humid-dry	0,50 to 0,65
Moderately dry	−1,49 to (−1,00)	0,067 to 0,159	9,2	−1,00 to (−1,99)	Humid	> 0,65
Very dry	−1,99 to (−1,50)	0,023 to 0,067	4,4	−2,00 to (−2,99)	---	---
Extremely dry	≤ −2,0	0,000 to 0,023	2,3	≤ −3,0	---	---

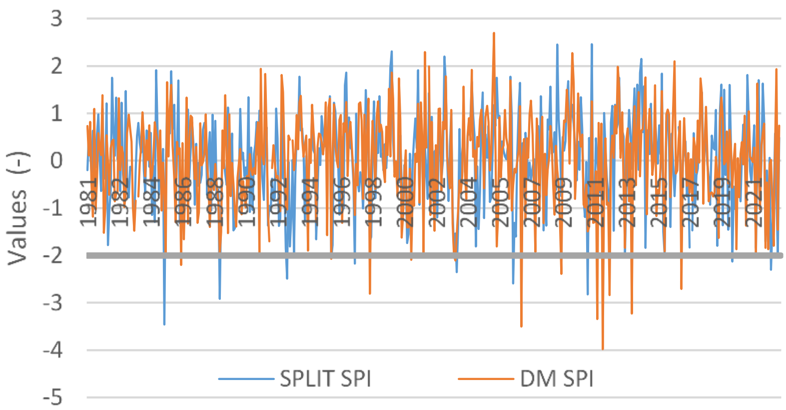
SPEI was calculated using the *SPEI* R package, which consists of a set of functions for computing potential evapotranspiration and several widely used drought indices, including *SPEI* [18].

2.1.7 Statistical methods

The methods used to compute the similarities or dissimilarities between variables (drought indices) were different correlation analyses suitable for determining whether the correlations were significant. Two correlation coefficients were applied, Spearman and Pearson, to detect correlations between the five sets of quantitative continuous variables (drought index values). The Pearson correlation coefficient corresponds to the classical linear correlation coefficient, whereas the Spearman correlation coefficient is based on the rankings of observations and not on their values. Therefore, the two coefficients have different statistical backgrounds.
The described methods were applied to data series of precipitation, air temperature, and evapotranspiration obtained in two Croatian regions presented by meteorological stations, Split and Donji Miholjac in the same time period between 1981 and 2022 on a monthly basis.

3 Results

Figure 3 presents the results with distinguished values of extreme drought events calculated using *SPI*, *NDI*, *SPEI*, *RAI*, and *AI* [19].



Standardized Precipitation Index (*SPI*)

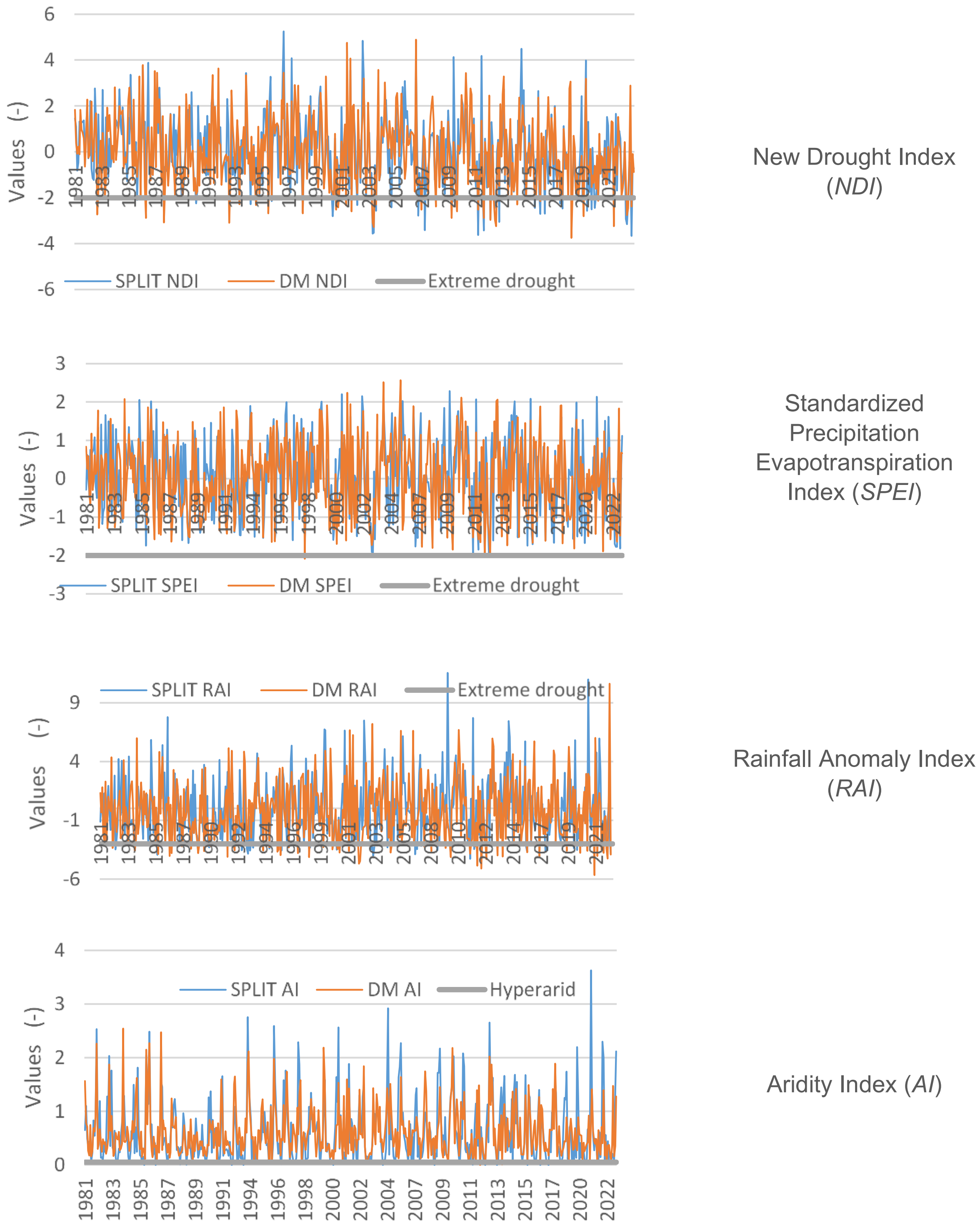


Figure 3. Monthly values of drought indices (*SPI*, *NDI*, *SPEI*, *RAI*, *AI*) for the period 1981–2022 for both meteorological station

Spearman and Pearson correlations were applied to compare the results obtained using different well-known drought indices with *NDI*.

Table 2. Correlation matrix (Spearman)

DONJI MIHOLJAC					
Variables	*AI*	*SPI*	*SPEI*	*NDI*	*RAI*
AI	1,000	0,806	0,800	0,684	0,726
SPI	0,806	1,000	0,965	0,742	0,826
SPEI	0,800	0,965	1,000	0,855	0,817
NDI	0,684	0,742	0,855	1,000	0,689
RAI	0,726	0,826	0,817	0,689	1,000
SPLIT					
Variables	*AI*	*SPI*	*SPEI*	*NDI*	*RAI*
AI	1,000	0,521	0,469	0,326	0,533
SPI	0,521	1,000	0,915	0,556	0,973
SPEI	0,469	0,915	1,000	0,726	0,907
NDI	0,326	0,556	0,726	1,000	0,548
RAI	0,533	0,973	0,907	0,548	1,000

Table 3. Correlation matrix (Pearson)

DONJI MIHOLJAC					
Variables	*AI*	*SPI*	*SPEI*	*NDI*	*RAI*
AI	1,000	0,694	0,746	0,656	0,663
SPI	0,694	1,000	0,943	0,720	0,784
SPEI	0,746	0,943	1,000	0,857	0,809
NDI	0,656	0,720	0,857	1,000	0,692
RAI	0,663	0,784	0,809	0,692	1,000
SPLIT					
Variables	*AI*	*SPI*	*SPEI*	*NDI*	*RAI*
AI	1,000	0,640	0,657	0,496	0,677
SPI	0,640	1,000	0,942	0,762	0,934
SPEI	0,657	0,942	1,000	0,865	0,931
NDI	0,496	0,762	0,865	1,000	0,757
RAI	0,677	0,934	0,931	0,757	1,000

Both methods showed a high correlation between *NDI* and other drought indices, but the most correlated indices were *NDI* and *SPEI*. According to the Spearman correlation matrix, it was $R > 0{,}7$; and according to the Pearson matrix, it was $R > 0{,}8$. Based on these results, further analysis of the correlations between extreme droughts was provided for *NDI* and *SPEI*. The correlation between *AI* and *NDI* was the lowest ($R < 0{,}7$). However, a significant difference was observed between the correlation coefficients for the Split region ($0{,}4 < R < 0{,}5$) and Donji Miholjac region ($0{,}65 < R < 0{,}7$) calculated using both methods. This can be explained by the weaknesses of *AI* which lie in its slow reaction in specific regional climates. In addition, *AI* does not consider the meteorological conditions of the previous months/years [2] and has no negative values in its classification.

Different precipitation regimes, from wet to dry [1; 6; 14; 20], are presented in Table 1, and a different range of *SPEI* values (between < -2,0 and > 2,0) is related to cumulative precipitation frequencies. A presentation of the cumulative precipitation frequencies is given in Figure 4, which shows that most of the months between 1981 and 2022 had normal precipitation regimes designated at the Split and Donji Miholjac meteorological stations (grey squares). Precipitation regimes classified as dry and wet (red and blue squares, respectively) were much less frequent on a monthly basis. The dry and wet regimes included all three classification levels (moderate, very, and extreme). The procedure included ranking all data values in descending order and calculating the cumulative precipitation frequencies corresponding to certain probabilities. As shown in Table 1, the obtained values between 0 and 0,159 were characterized as moderately, very, and extremely dry with event probabilities of 9,2; 4,4; and 2,3 respectively.

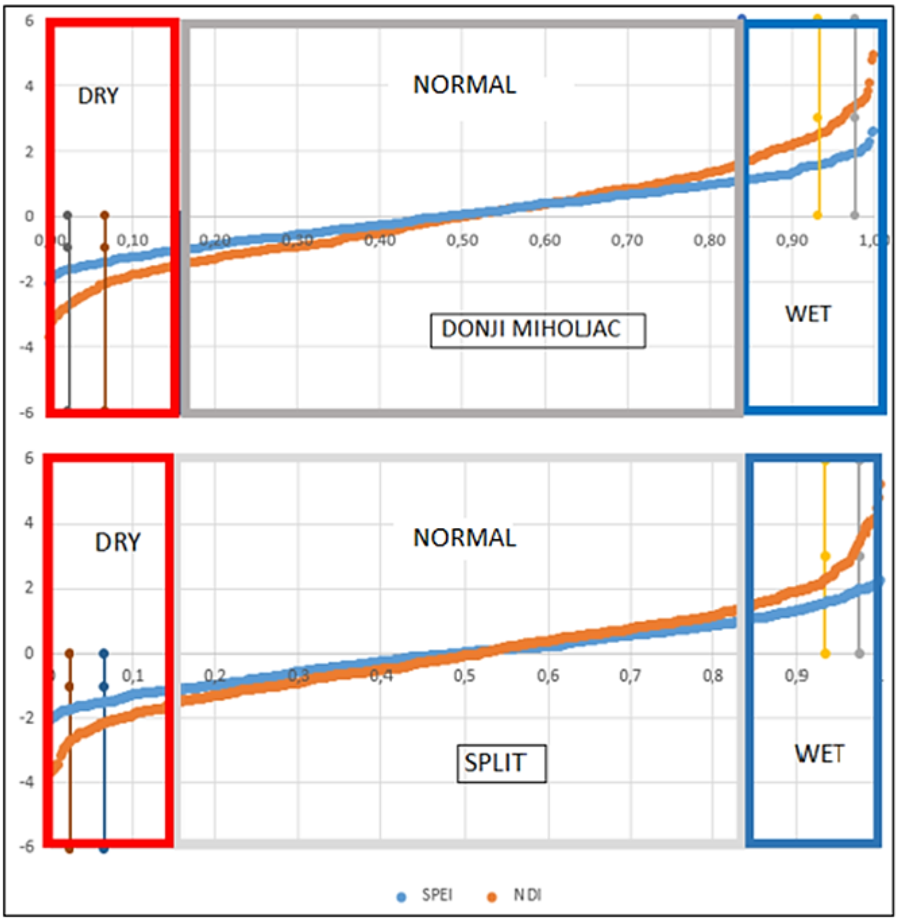


Figure 4. Cumulative precipitation frequencies as a basis for ranging different precipitation regimes for both meteorological station

For water management and risk analysis owing to extreme hydrological events driven by climate change impacts, the most important are precipitation regimes classified as very dry (values between −1,99 and −1,50) and extremely dry (values smaller than −2,0) characterised by severe precipitation deficit.

Figure 5 shows the correlation between *NDI* and other indices for extreme drought events. Comparing the correlations for all monthly values presented in Table 3, the correlation coefficients of extremes were lower but still > 0,5, and *NDI* had the highest correlation with *SPEI*. The correlations of other variants were much lower: < 0,2 and < 0,4 for Split and Donji Miholjac, respectively.

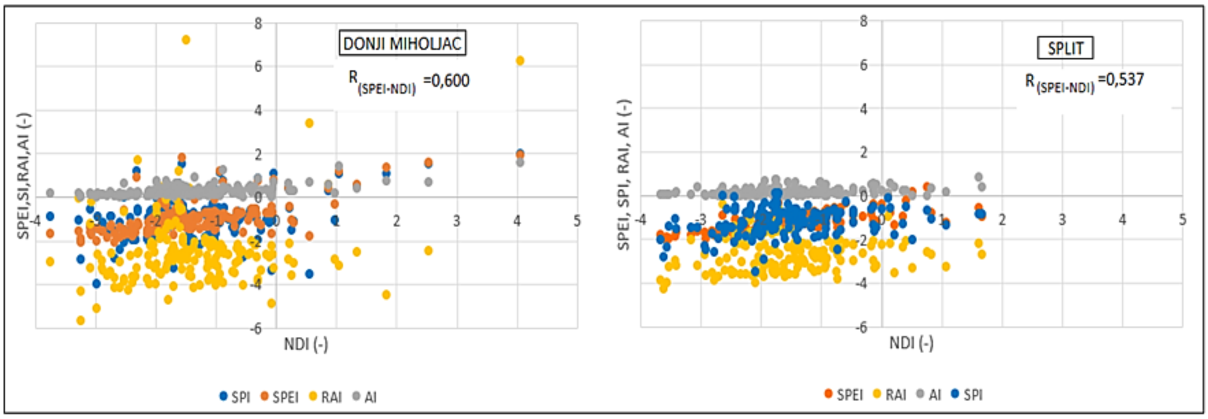


Figure 5. Correlation between NDI and other indices for extreme drought events for both meteorological station

4 Discussion

At both meteorological stations, a statistically significant increase in air temperature was previously determined with no significant annual change in precipitation (Figure 2) [8]. The time step for calculating drought indices is one month, which is frequently used to determine the first indication of drought occurrence (deficit in precipitation and soil moisture). Monthly values of drought indices (*SPI*, *NDI*, *SPEI*, *RAI*, *AI*) for the period 1981-2022 for both meteorological stations, presented in Figure 3, showed a more frequent occurrence of extreme drought calculated using *NDI* and *RAI* with values of indices lower than −2,0. In addition, a high correlation between these two methods could be expected, but the results showed a better correspondence *NDI* with *SPEI*. There are two reasons for this: Both indices use two meteorological parameters, precipitation and air temperature, and they have a better correlation in the range of normal precipitation regimes, with precipitation frequencies between 0,159 and 0,841 (Table 1, Figure 4). The obvious divergence of the results in the range of dry and wet conditions favours NDI; extreme values are more pronounced. However, the timing of extreme values have good correspondence [22].

The highest correlations between *NDI* and *SPEI* were confirmed using two correlation coefficients, Spearman and Pearson (Tables 2 and 3), which showed very similar values, particularly for data obtained from the continental part of Croatia (Donji Miholjac meteorological station).

However, the correlations among *NDI*, *RAI* and *SPI* were also respectable, regardless of the specific characteristics of the methods. This leads to the recommendation that a multi-index approach for drought-severity estimation is the most appropriate. No ideal global drought index exists [22; 23]. Focusing on extreme drought severity, the correlation coefficients of monthly values were lower than those of the complete data series. In this case, the dataset was much smaller, and a large portion of the data related to the normal precipitation regime was omitted. Again, very similar values were obtained for the continental and Mediterranean parts of Croatia; however, more frequent extremely wet periods in the continental part of the country were detected by all drought indices (Figure 5).

To summarise, the tested drought indices *NDI*, *RAI*, *SPEI*, *SPI*, and *AI* have strengths and weaknesses (Table 4). Most have the same characteristics, such as simplicity of calculation. Some of them are one-parameter indices with two-sided views. On the one hand, this guarantees simplicity, and on the other, this can be disadvantageous in future periods of increasing air temperatures on a global scale. The main strength of *NDI* is its simple calculation, and thus far, it has proven its applicability in different climates and geographical regions on the four continents. In addition to Croatia [4; 6; 24], it has been applied in China, Brazil, the USA, India, Afghanistan, Pakistan, Iran, Mexico, and Slovakia [25-38].

Table 4. Strengths and weaknesses of the tested drought indices [2; 21]

Index	Strengths	Weaknesses
AI	• Easy calculation • Two inputs: precipitation and air temperature • Various time scales	• Does not consider carry-over of dryness from year to year • May be slow to react in certain climates
RAI	• Easy calculation • Only one input: precipitation • Various timescales	• Requires a serially complete dataset with estimates of missing values • Only one input: precipitation • Variations within the year must be small compared with temporal variations
SPI	• Easy calculation • Only one input: precipitation • Possibility of using poor data sets • Applicability in all climate regimes • Various time scales • Available computer program	• Only one input: precipitation • Questionable application to areas with long periods without precipitation
SPEI	• Two inputs: precipitation and air temperature • Index appropriate when looking at the impact of climate change under various future scenarios. • Available computer program • Applicable for all climate regimes	• Dataset for both temperature and • precipitation should be complete • Rapidly developing drought scenarios may not be identified quickly
NDI	• Two inputs: precipitation and air temperature • Easy calculation • Suitable for application in increasing temperature conditions	• Not sufficiently tested • Dataset for both temperature and precipitation should be completed

5 Conclusions

This research was conducted to test Bonacci's recently developed New Drought Indicator (*NDI*) (2021) by comparing its results with those of well-known and established meteorological drought indices. This study assumed that the data series of monthly precipitation and air temperature obtained in the two regions over 42 years (1981-2022) were reliable for research. NDI has strengths similar to those of other prominent indices, but more testing on large spatial and temporal scales is required. To evaluate drought indices, they should be analysed in terms of the damage caused by the drought. It is a very complex task and, at this moment, has still not been sufficiently explored.

References

[1] Vicente-Serrano, S. M.; Begueria, S.; López-Moreno, J. I. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 2010, 23 (7), pp. 1696-1718. https://doi.org/10.1175/2009JCLI2909.1

[2] World Meteorological Organization. *Handbook of Drought Indicators and Indices, (WMO-No. 1173)*. Geneva: World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016.

[3] Hayes, M.; Svoboda, M.; Wall, N.; Widhalm, M. The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. *Bulletin of the American Meteorological Society*, 2011, 92 (4), pp. 485-488.

[4] Bonacci, O.; Bonacci, D. Prijedlog nove metode za analizu suša. *Hrvatske vode*, 2022, 30 (119), pp. 1-16.
[5] Bonacci, O.; Bonacci, D.; Roje-Bonacci, T.; Vrsalović, A. Proposal of a new method for drought analysis. *Journal of Hydrology and Hydromechanics*, 2023, 71 (1), pp. 100-110. https://doi.org/10.2478/johh-2022-0030
[6] Bonacci, O.; Žaknić-Ćatović, A.; Roje-Bonacci,T: Prominent Increase in Air Temperatures on Two Small Mediterranean Islands, Lastovo and Lošinj, Since 1998 and Its Effect on the Frequency of Extreme Droughts. *Water*, 2024, 16 (22), 3175. https://doi.org/10.3390/w16223175
[7] Šegota T.; Filipčić, A. Köppenova podjela klima i hrvatsko nazivlje. *Geoadria*, 2003, 8 (1), pp.17-37. https://doi.org/10.15291/geoadria.93
[8] Tadić, L.; Brleković, T.; Potočki K.; Leko-Kos, M. Application of principle component analysis on drought indicators of three Croatian representative regions. *E-gfos: Electronic Journal of the Faculty of Civil Engineering Osijek*, 2021, 12 (22), pp. 41-55.
[9] Santos, F. J. et al. Drought Characterization in Croatia Using E-OBS Gridded Data. *Water*, 2023, 15 (21), 3806. https://doi.org/10.3390/w15213806
[10] Bonacci, O. On the role of hydrology in water resources management. In: *The Basis of Civilization - Water Science?* December, 2003, Rome, Italy, International Association of Hydrological Sciences (IAHS) Publication; 2004, 286, pp. 88-94.
[11] De Martonne, E. Traité de Géographie Physique. *A Colin*, 1927, 3.
[12] van Rooy, M. P. A Rainfall Anomaly Index Independent of Time and Space, Notos. *Weather Bureau South Africa*, 1965, 14, pp. 43-48.
[13] Ekpetere, K.O. et al. Estimating Rainfall Anomalies with IMERG Satellite Data: Access via the IPE Web Application. *Remote Sensing*, 2024, 16 (22), 4137. https://doi.org/10.3390/rs16224137
[14] McKee, T. B.; Doesken, N. J.; Kleist, J. The Relationship of Drought Frequency and Duration to Time Scales. In: *Proceedings of the 8th Conference on Applied Climatology*. January 17-22, 1993, Anaheim, USA, American Meteorological Society; 1993.
[15] Guttman, N. B. Accepting the Standardized Precipitation Index: A calculation algorithm. *JAWRA Journal of the American Water Resources Association*, 2007, 35 (2), pp. 311-322. https://doi.org/10.1111/j.1752-1688.1999.tb03592.x
[16] National Drought Mitigation Center. SPI Generator [software]. University of Nebraska-Lincoln. Accessed: October 14, 2024. Available at: https://drought.unl.edu/Monitoring/SPI/SPIProgram.aspx
[17] Tadić, L.; Brleković, T.; Hajdinger, A.; Španja, S. Analysis of the Inhomogeneous Effect of Different Meteorological Trends on Drought: An Example from Continental Croatia. *Water*, 2019, 11 (12), 2625. https://doi.org/10.3390/w11122625
[18] Beguería, S.; Vicente-Serrano, S. M.; Reig, F.; Latorre, B. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 2014, 34 (10), pp. 3001-3023. https://rmets.onlinelibrary.wiley.com/doi/full/10.1002/joc.3887
[19] Antolović, M. *Usporedba različitih metoda za ocjenu suše/Comparison of different drought indices*. [master thesis], Josip Juraj Strossmayer University of Osijek, Faculty of Civil Engineering and Architecture, Osijek, Croatia, 2022. Accessed: October 5, 2024. Available at: https://repozitorij.gfos.hr/islandora/object/gfos%3A2082
[20] European Drought Observatory Indicator. Standardized Precipitation Index (SPI). Accessed: November 4, 2024. Available at: https://drought.emergency.copernicus.eu/data/factsheets/factsheet_spi.pdf
[21] Naumann, G. et al. Comparison of drought indicators derived from multiple data sets over Africa. *Hydrology and Earth System Sciences*, 2014, 18 (5), pp. 1625-1640. https://doi.org/10.5194/hess-18-1625-2014
[22] Salehnia, N. et al. Estimation of meteorological drought indices based on AgMERRA precipitation data and station-observed precipitation data. *Journal of Arid Land*, 2017, 9, pp. 797-809. https://doi.org/10.1007/s40333-017-0070-y

[23] Yihdego, Y.; Vaheddoost, B.; Al-Weshah R. A. Drought indices and indicators revisited. *Arabian Journal of Geosciences*, 2019, 12, 69. https://doi.org/10.1007/s12517-019-4237-z

[24] Bonacci, O.; Žaknić-Ćatović, A.; Roje-Bonacci, T.; Bonacci, D. Assessing the Effects of Climate Change on the Hydrology of a Small Catchment: The Krapina River near Kupljenovo. *Water,* 2025, 17 (9), 1403. https://doi.org/10.3390/w17091403

[25] Gu, X. et al. A Study of Drought and Flood Cycles in Xinyang, China, Using the Wavelet Transform and M-K Test. *Atmosphere*, 2023, 14 (8), 1196. https://doi.org/10.3390/atmos14081196

[26] Weaver, S. M. et al. A Case Study of Drought during Summer 2022: A Large-Scale Analyzed Comparison of Dry and Moist Summers in the Midwest USA. *Atmosphere*, 2023, 14 (9), 1448. https://doi.org/10.3390/atmos14091448

[27] Soni, A. K. et al. Future Projection of Drought Risk over Indian Meteorological Subdivisions Using Bias-Corrected CMIP6 Scenarios. *Atmosphere*, 2023, 14 (4), 725. https://doi.org/10.3390/atmos14040725

[28] Sidiqi, M.; Kasiviswanathan, K. S.; Scheytt, T.; Devaraj, S. Assessment of Meteorological Drought under the Climate Change in the Kabul River Basin, Afghanistan. *Atmosphere*, 2023, 14 (3), 570. https://doi.org/10.3390/atmos14030570

[29] Mo, C. et al. Evolution of Drought Trends under Climate Change Scenarios in Karst Basin. *Water*, 2023, 15 (10), 1934. https://doi.org/10.3390/w15101934

[30] Munir, S.; Shirazi, S. Ali. Long-term drought analysis and hazard assessment using SC-PDSI in the Punjub, Pakistan. *Pakistan Journal of Science*, 2023, 75 (4), pp. 652-659.

[31] Ayoubi, T.; Reinhardt-Imjela, C.; Schulte A. Assessment of Water Resources under Climate Change in Western Hindukush Region: A Case Study of the Upper Kabul River Basin. *Atmosphere*, 2024; 15 (3), 361. https://doi.org/10.3390/atmos15030361

[32] Pekárová, P. et al. Sensitivity of runoff due to changes in the characteristics of the water balance in the Danube River region. *Journal of Hydrology and Hydromechanics*, 2023, 71 (4), pp. 399-412. https://doi.org/10.2478/johh-2023-0033

[33] Mohammad, N.; Hejazizadeh, Z. The effects of climate change on increasing the risk of drought in Tehran using CMIP6 scenarios. *Water and Soil Management and Modeling*, 2024, 4 (2), pp. 133-148. https://doi.org/10.22098/mmws.2023.12563.1252

[34] Kim, S. U.; Seo, D.-Il. Comparison of the drought return periods by univariate, bivariate probability distribution, and Copula function under SSPs scenarios. *Research Square*, 2024, preprint. https://doi.org/10.21203/rs.3.rs-4759014/v1

[35] Arganis, M.; Preciado, M.; de Luna, F. New Drought Index Implementation at Station 15130, Valle de Bravo, Mexico. *Hidraulica*, 2024, 1.

[36] Zeybekoglu, U. Comparative drought analysis in Amasya and Merzifon with ZSI, PNI and NDI under transitional climatic conditions. *Dynamics of Atmospheres and Oceans*, 2025, 110, 101556. https://doi.org/10.1016/j.dynatmoce.2025.101556

[37] Zeng, F. et al. Modeling short-term drought for SPEI in Mainland China using the XGBoost model. *Atmosphere*, 2025, 16 (4), 419. https://www.mdpi.com/2073-4433/16/4/419

[38] Weaver, S. M.; Lupo, A. R.; Hunt, S.; Aloysius, N. Refining Drought Assessment: A Multi-Dimensional Analysis of Condition Monitoring Observer Reports in Missouri (2018–2024). *Atmosphere* 2025, 16 (4), 389. https://doi.org/10.3390/atmos16040389