New functionalities for the Drought Portal: standardized indices for soil moisture and streamflow drought

BART MOEKESTORM, MAAB ALTAYEB, DION VAN DEIJL, WILCO TERINK, AND GÉ VAN DEN EERTWEGH

Drought indices are valuable tools for assessing drought conditions across regions, as they allow for the comparison of anomalies over time and space and they can be calculated over various timescales. The drought portal (https://droogteportaal.nl) is an online platform providing historical, near-real-time and, for some variables, forecasted data on precipitation, evapotranspiration, soil moisture, groundwater, and discharge in the Netherlands. The portal currently features three drought indices: precipitation, precipitation deficit, and groundwater. Drought indices for soil moisture and streamflow are not yet implemented, but they might be added in the future. In order to investigate whether the addition of soil moisture and streamflow drought indices provides additional value, this article outlines the potential of adding the Standardized Soil Moisture Index (SSMI) and the Standardized Streamflow Index (SSI) to the portal as well as the challenges related to data availability and handling missing values.

Artikel

Introduction

A meteorological drought is a natural hazard with far-reaching consequences that impacts water availability, ecosystems, agriculture, and economies on a global scale (Katipoğlu, 2023; Yang, 2010). Drought can be defined as a precipitation deficit compared to an average situation for a specific period (Yihdego et al., 2019). Drought is considered a creeping disaster, as it propagates from one hydrological system to another, affecting the entire hydrological cycle. This makes understanding droughts challenging as it not only depends on the atmospheric conditions, but also on the hydrological processes that feed moisture to the atmosphere and cause the storage of water and runoff to streams (Van loon, 2015). Human activities, such as pumping groundwater from wells for irrigation and/or drinking water production, can exacerbate drought.

Droughts are often classified into four categories or stages (Mishra and Singh, 2010, and Figure 1):

- Meteorological drought: a period of insufficient precipitation to balance evapotranspiration, resulting in a large precipitation deficit.
- Soil moisture drought: a period with declining soil moisture, affecting crops and vegetation.

- Hydrological drought: Lowering groundwater tables followed by decreased streamflow in rivers and streams compared to the normal situation.
- Socio-economic drought: insufficient water supply to satisfy the water demand.

In recent years, particularly in 2018, 2019, 2021, and 2022, the Netherlands has experienced severe droughts (de Gier, 2021). These droughts led to numerous negative impacts on the environment and society. Consequently, the government began to set limits in terms of water use (van den Eertwegh et al., 2019; 2021). Climate change is expected to cause more frequent and prolonged droughts in the future (van Dorland et al., 2023). Therefore, it is essential to understand droughts and their severity and, if possible, effectively mitigate the negative effects.

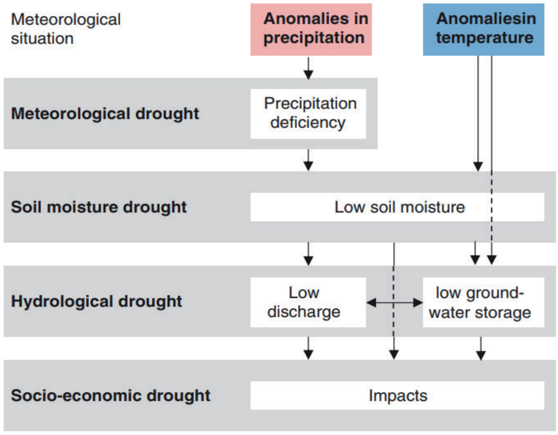

Figure 1 Theoretical progradation of drought through different stages of the hydrological system obtained from (Van loon, 2015).

The evaluation of drought relies on understanding the factors that cause it and its impacts. Droughts are primarily assessed using parameters such as intensity, severity, duration, and areal extent. These parameters were integrated into drought indices (Eden, 2012). These drought indices are valuable indicators of drought conditions in various regions of the world (Tijdeman et al., 2020; Svensson et al., 2017; Svoboda et al., 2016).

In response to the growing threat of droughts in the Netherlands, KnowH2O with partners KWR, Stella Spark, and Hoefsloot Spatial Solutions developed the drought portal (https://droogteportaal.nl), which is currently supported by InformatieHuis Water (IHW). This online platform provides historical and near-real-time information on drought conditions in the Netherlands. Initially, it was focused on the high sandy soils of the South, Central, and East of the Netherlands, but now it extends to almost the entire country. The drought portal aims to offer an overview of these conditions by enabling water authorities and water users’ access to vital data, forecasts, and analyses. It thereby serves as a tool to support water managers in their operational (short-term) and strategic (long-term) decision-making process to mitigate the impacts of droughts. The drought portal uses standardized indices to provide information on the drought condition for each measurement location. Standardized indices show the deviation of a hydrological variable (e.g., precipitation and groundwater levels) from its normal conditions, and enable a comparison of the characteristics of historical drought events over time.

To date, three indices have been implemented in the drought portal, which are the Standardized Precipitation Index (SPI), Standardized Precipitation minus Evapotranspiration Index (SPEI), and Standardized Groundwater Index (SGI) (van Huijgevoort et al., 2022). Drought indices for soil moisture and streamflow, however, remain absent. These indices are crucial for assessing drought conditions and the progression from surface water to the subsurface to the groundwater systems. One reason for their absence is the limited availability and quality of long-term data on streamflow and soil moisture, which are needed to calculate reliable drought indices. This study seeks to address this issue by adding new functionality to the drought portal, introducing standardized indices for soil moisture (SSMI) and streamflow (SSI).

Material and Methods

This study employs hydrological models to address the challenges of missing data and insufficient time series lengths, aiming to enhance data series completeness and mitigate the observational dataset limitations. It focuses on calculating two standardized indices: The Standardized Soil Moisture Index (SSMI) and the Standardized Streamflow Index (SSI). The methodology, as shown in Figure 2, begins with the setup of the Hydrus-1D and WALRUS models and proceeds to the calculation of the SSMI and SSI indices, with additional details provided in the subsequent subsections.

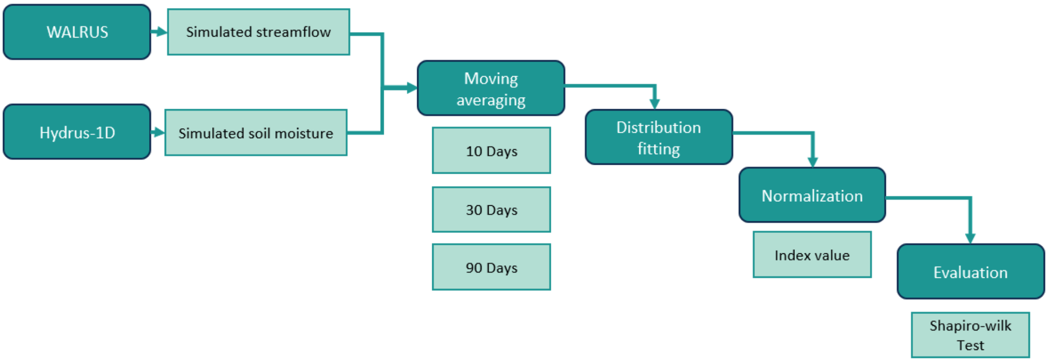

Figure 2 Schematic overview of soil moisture and the streamflow indices calculations.

Hydrus-1D model
For this project, soil moisture monitoring locations were used that were part of the “Droogte zandgebieden” project (van den Eertwegh et al., 2019). The volumetric soil moisture sensors were installed as shown in Figure 3 for each location (van Dam and Gooren, 2021). To determine the Standardized Soil Moisture Index (SSMI), a time series record of around 30 years of soil moisture content data is needed. As the longest soil moisture time series available on the Drought Portal spans only five years, which is insufficient for calculating the SS-MI, a simulated 30-year time series generated by a Hydrus-1D model was used instead (Šimůnek et al., 2008). The modeled timeseries were validated using the available sensor data.
The Hydrus-1D model was set up using the Phydrus python package (Collenteur et al., 2019) using the BOFEK (Heinen, 2021) soil profiles for the specific location with the corresponding soil physical parameters from the Staringreeks (Heinen et al., 2020). The column was simulated to a depth of 120 cm with the sensors situated at a depth of 15 and 30 cm. To simulate the flow of water in the soil, the soil hydraulic model of van Genuchten (van Genuchten, 1980) is used. The soil surface has been set to an atmospheric boundary condition with surface runoff. The lower boundary of the modeled soil column was set to be free draining and, therefore, it experiences no influence of the groundwater or capillary rise of soil moisture. The column was assumed to have a standard grass vegetation on top and used meteorological forcing from the nearest KNMI station.

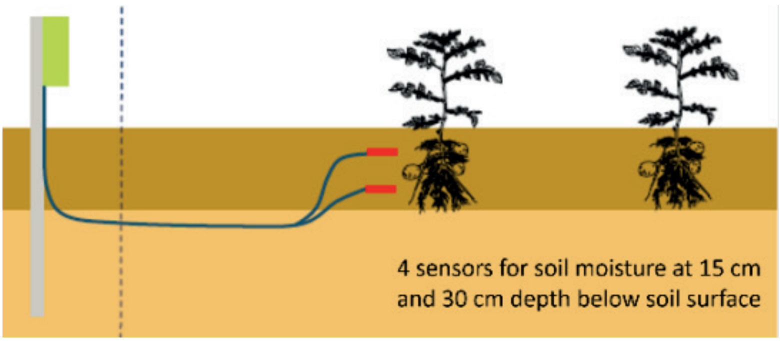

Figure 3 Soil moisture measurement setup, adjusted from van Dam and Gooren (2021).

The model results were validated using sensor measurement data (2019-2024). Performance was evaluated using the Pearson correlation coefficient as we have no interest in the bias of the model due to the statistical nature of the index. To further improve the model, the use of different BOFEK-profiles was explored for each location. When the model performance was considered satisfactory (Pearson correlation > 0.7) the index was calculated. This threshold was arbitrarily set for the purpose of this project, taking into account the model performance of previous models (Heinen et al., 2022).

WALRUS model

Similar to SSMI, the SSI also requires at least 30 years of data to ensure that the distribution of streamflow is well-represented. However, the observed streamflow time series for the Hupsel Brook catchment contains missing values. To address this issue, we utilized the WALRUS model (Brauer et al., 2014) to simulate streamflow at the Hupsel Brook outlet. WALRUS was chosen because it has been developed for free-drainage lowland areas, making it suitable for this study. We set up WALRUS using daily meteorological data (e.g., precipitation and reference evapotranspiration) obtained from the Hupsel Brook weather station. The catchment characteristics, such as soil type, were obtained from Brauer et al. (2014). Then, WALRUS was auto calibrated to obtain the optimal parameter set. The calibration was performed over the period of 1994 to 2024 (for more details, see Altayeb 2024). Model performance was quantified with the Nash Sutcliffe efficiency (NSE), Percent of Bias (PBIAS), and Root Mean Square Error (RMSE).

SSMI and SSI calculations

Standardized indices like SSMI and SSI quantify the state of the hydrological system by comparing current conditions to historical values. The index shows the deviation of the hydrological variable from normal conditions and it classifies the extremity of events.
With the indices, both wet and dry conditions can be investigated, where positive values indicate wet conditions, and negative values indicate dry conditions (see Table 1). These indices also track the intensity, duration, spatial extent, and propagation of drought over time across different locations.

Table 1 *Standardized index values for drought classification. Index values, the associated category, and the probability of occurrence.*

Index value	Category	Probability
2.00 or more	Extremely wet	2.3%
1.50 to 1.99	Severely wet	4.4%
1.00 to 1.49	Moderately wet	9.2%
0 to 0.99	Mildly wet	34.1%
0 to -0.99	Mild drought	34.1%
-1.00 to -1.49	Moderate drought	9.2%
-1.50 to -1.99	Severe drought	4.4%
-2.00 or less	Extreme drought	2.3%

For calculating the indices, we use a methodology similar to the SPI. In general, calculating the index involves three main steps: First, the average is taken for data over the time scale of interest to filter out the effect of a single extreme event. Second, a statistical distribution is fitted to data. Lastly, the fitted values are transformed to a standard normal distribution with a zero mean and one standard deviation to get the index value (see Figure 4) (Tijdeman et al., 2020).

In the present study, we calculated SSMI and SSI as follows: First, we used Hydrus-1D and WALRUS to generate 30 years of simulations data that was then averaged using a moving average window for different time scales (10, 30, and 90 days). Then, we fitted the distributions to the data. For SSMI, the parametric normal, beta, gamma, and Pearson3 distributions as well as the non-parametric kernel density estimation approach were evaluated. It is important to critically evaluate the distributions throughout the year as they may differ as shown in Figure 5. While, for the SSI, Generalized Extreme Value, Generalized Logistic, Pearson Type III, and Tweedie distribution were evaluated. The selection of these distributions reflects the variability and characteristics of both the soil moisture and streamflow data, which often exhibit non-normal and highly variable behavior depending on local climatic and hydrological conditions. We used the Shapiro-Wilk test (Shapiro & Wilk, 1965) to assess whether the calculated SSI and SSMI datasets were normally distributed or not based on a null hypothesis (p-value > 0.05). This test was applied to daily SSMI and SSI over a 30-year period. Specifically, for each calendar day, we created a time series consisting of 30 values. The Shapiro-Wilk test was then conducted for each day, yielding a series of p-values. To compare the distributions, we calculated the rejection rate as the proportion of days with p-values less than 0.05.

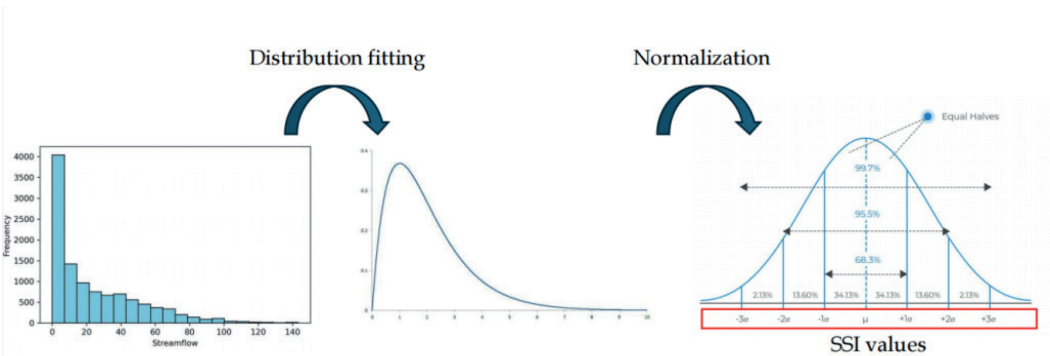

Figure 4 *Overview of calculation steps for calculating standardized indices based on aggregated data.*

The SSI approach has recently been extended to calculate and visualize this index in an operational setting for 40 streamflow measurement locations managed by the waterboards Brabantse Delta, De Dommel, Limburg, Rijn en IJssel, and Vallei en Veluwe (Terink et al., 2024).

Results

Soil moisture

The final model results show a sufficient model result (r>0.7) for the locations Wijhe, Barneveld, Lettele, Harreveld, and Eibergen. Figure 6 compares the model results for the Eibergen location in the Hupsel catchment with the measurements. From the figure, it is apparent that the Hydrus-1D model does not accurately represent the values measured by the sensors. An explanation for this may be that the use of generalized BOFEK soil profiles does not capture the spatial variability of the measurement location. For the final index, however, it is more useful if it indicates the value for a larger area rather than a point measurement. Moreover, the model assumption of a freely draining soil profile (no capillary rise) and the use of uncalibrated sensors influence the model results.

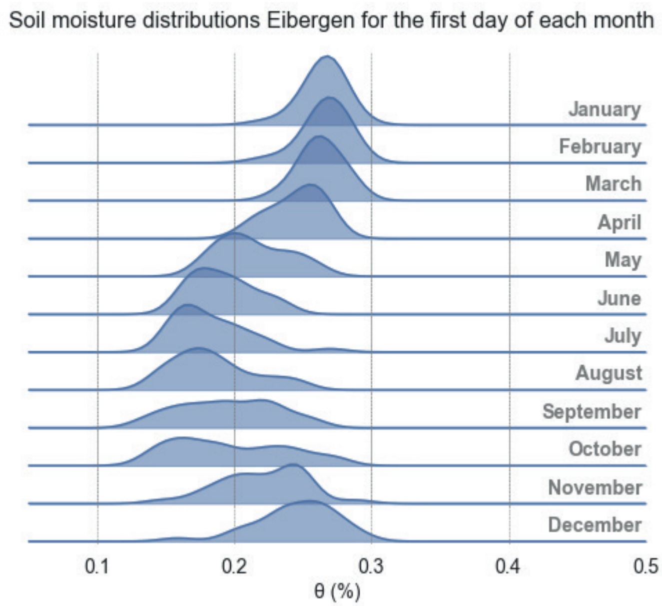

Figure 5 *Soil moisture distributions on the first day of each month over the year based on a period of 30 years.*

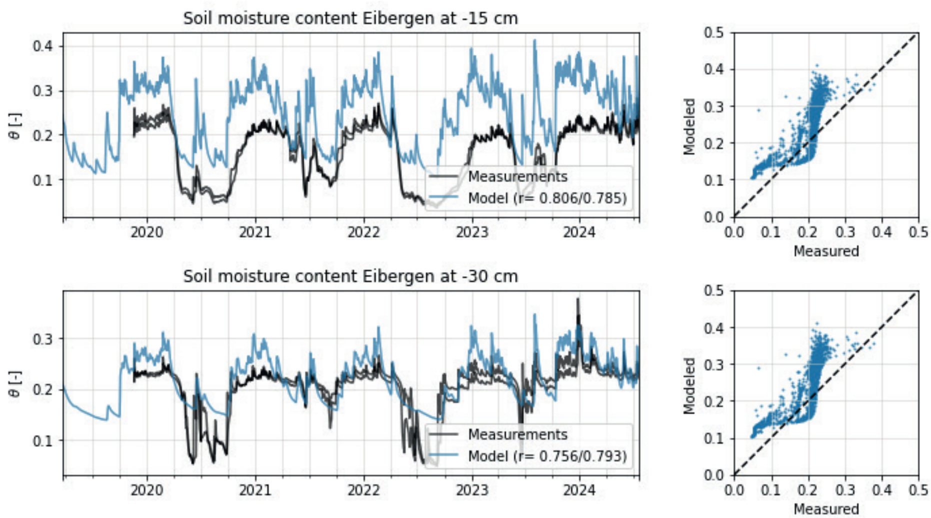

Figure 6 *Modeling results (in blue) compared to the soil moisture measurements (in black) for the location in Wijhe.*

The addition of groundwater and capillary rise to the model may improve the results for some of the locations. For the index calculation, we are not interested in the exact value that the model produces. The probabilistic nature of the index causes any systematic bias to be ignored when calculating a final index. The standard bias observed in Figure 6 does not influence the final index value.

For each distribution, the rejection rate indicated the percentage of days for which the distribution was unsuitable. The Pearson3 distribution has the best performance, only exceeding a rejection rate of 10% once.

The Kernel density estimation approach was solely fitted based on the data and will, therefore, always produce a good fit to the data. The use of this approach was compared to the parametric approaches by assessing the spread in the minimum value. The spread in minimum values can be compared to the expected spread of the index to assess if the index behaves as expected. Kernel density estimated overestimates the minimum index values, while the Pearson3 was in the right range. The different calculated indices using these two methods are shown in Figure 7. In this figure, it can be seen that the index calculated with the Pearson3 methods has unexplained negative peaks that can be explained by an unsuitable distribution at the specific day. On the other hand, the Kernel Density Estimation underestimates the positive peaks compared to the results from the Pearson3 distribution. The final index time series was created using the Kernel Density Estimation approach and can be found in Figure 10.

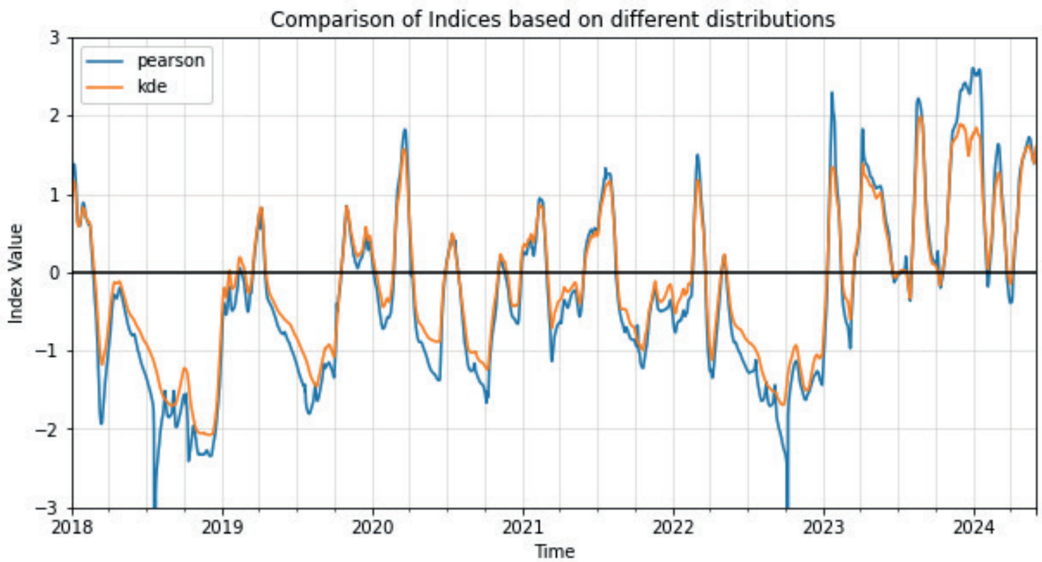

Figure 7 *Calculated index time series for the monitoring location near Wijhe. The blue line indicates the index for which the distributions are described with the Pearson3 distribution. For the orange line, the distribution is described with Kernel Density Estimation (KDE).*

Streamflow

We calibrated the WALRUS model from 1995 to 2024 to generate the best parameter set, and we simulated the streamflow for the Hupsel Brook catchment. The results showed that WALRUS performed well in simulating the streamflow at Hupsel outlet, resulting in an NSE of 0.75, RMSE of 0.65 mm/d and PBIAS of 2%. To validate the model performance under different hydrological conditions, we selected one dry year (2018) and one wet year (2010). Using the calibrated parameter set, we evaluated the model's performance for both years. The validation results indicated that the model performs well for both the dry (NSE of 0.83 (Figure 8)) and wet conditions (NSE of 0.8 (Figure 8)). Using the simulated streamflow, we calculated the SSI for different timescales of 10, 30, and 90 days using the four selected distributions (Tweedie, Pearson3, Generalized logistic and Generalized extreme value). Based on the Shapiro wilk test, we selected the distribution that resulted in the lowest rejection rate, which was the Generalized extreme value distribution.

Having long streamflow records at the Hupsel catchment allowed for a detailed comparison between the Standardized Streamflow Index (SSI) calculated from both simulated and observed values across various timescales (10, 30, and 90 days) as illustrated in Figure 9. The analysis showed that simulated SSI values tended to overestimate negative SSI, especially during extreme droughts like those in 2018. In addition, the simulated SSI displayed more fluctuation than the observed SSI. However, despite these differences, the simulated values generally captured the overall variation well, particularly for SSI-1 and SSI-3.

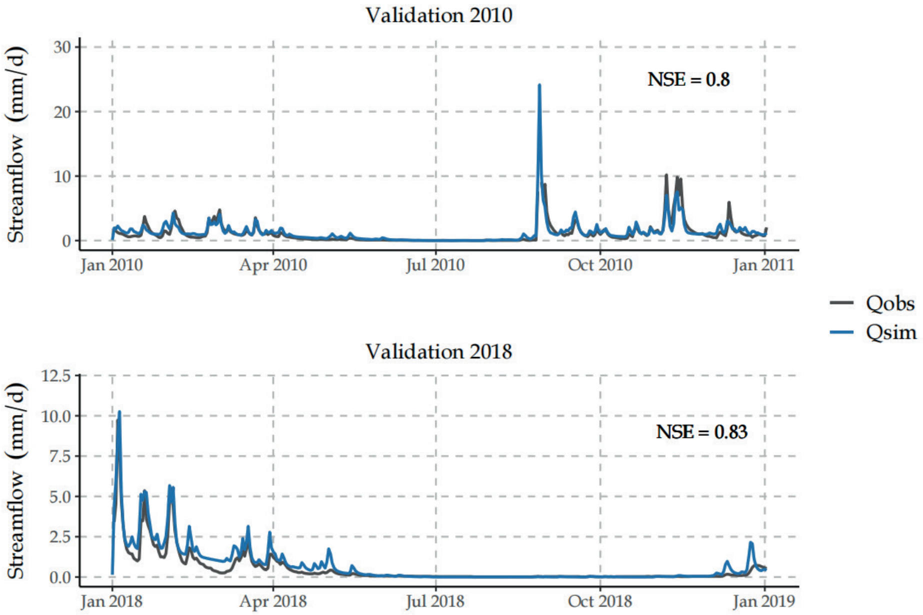

Figure 8 *WALRUS model validation results for the wet year of 2010 and the dry year of 2018.*

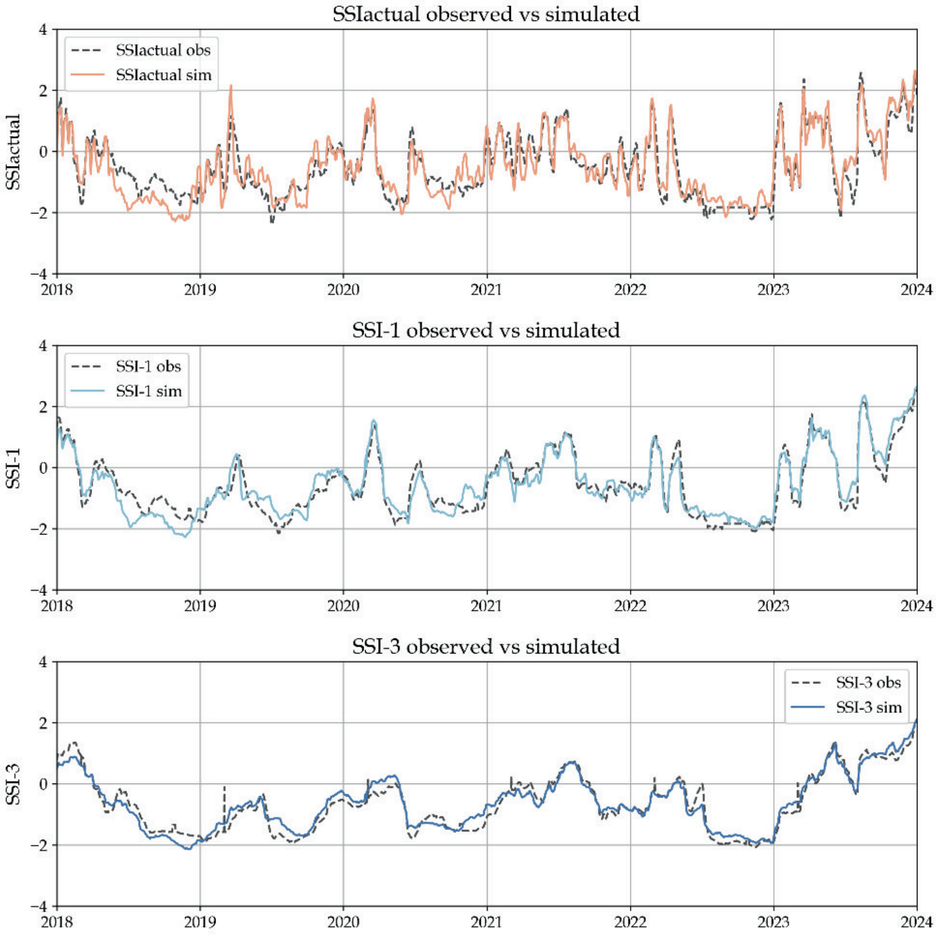

Figure 9 Comparison between the SSI values calculated using the observed streamflow values (filled) and the simulated values calculated using GEV distribution and for different averaging timescales (10 days for SSI actual, 30 days for SSI-1, and 90 days for SSI-3).

Drought propagation

The addition of the standardized soil moisture index and the standardized streamflow index to the Drought Portal filled the remaining gaps and provided indices for the different stages of drought. By comparing the indices at the different stages of drought, we obtained an overview of the propagation of drought through the system. Figure 10 shows the different indices for measurements within the Hupsel catchment. The peak in SPI and SPEI toward an index value of 0, which was observed in fall 2018, shows that the situation is back to normal from a meteorological point of view. The other index values show that the system, however, is still in a state of drought. This indicates that the systems need more precipitation and/or time to go back to a normal state; this illustrates the lag and memory of the system, as one would expect from the aspect of hydrology, and demonstrates the need for different indices.

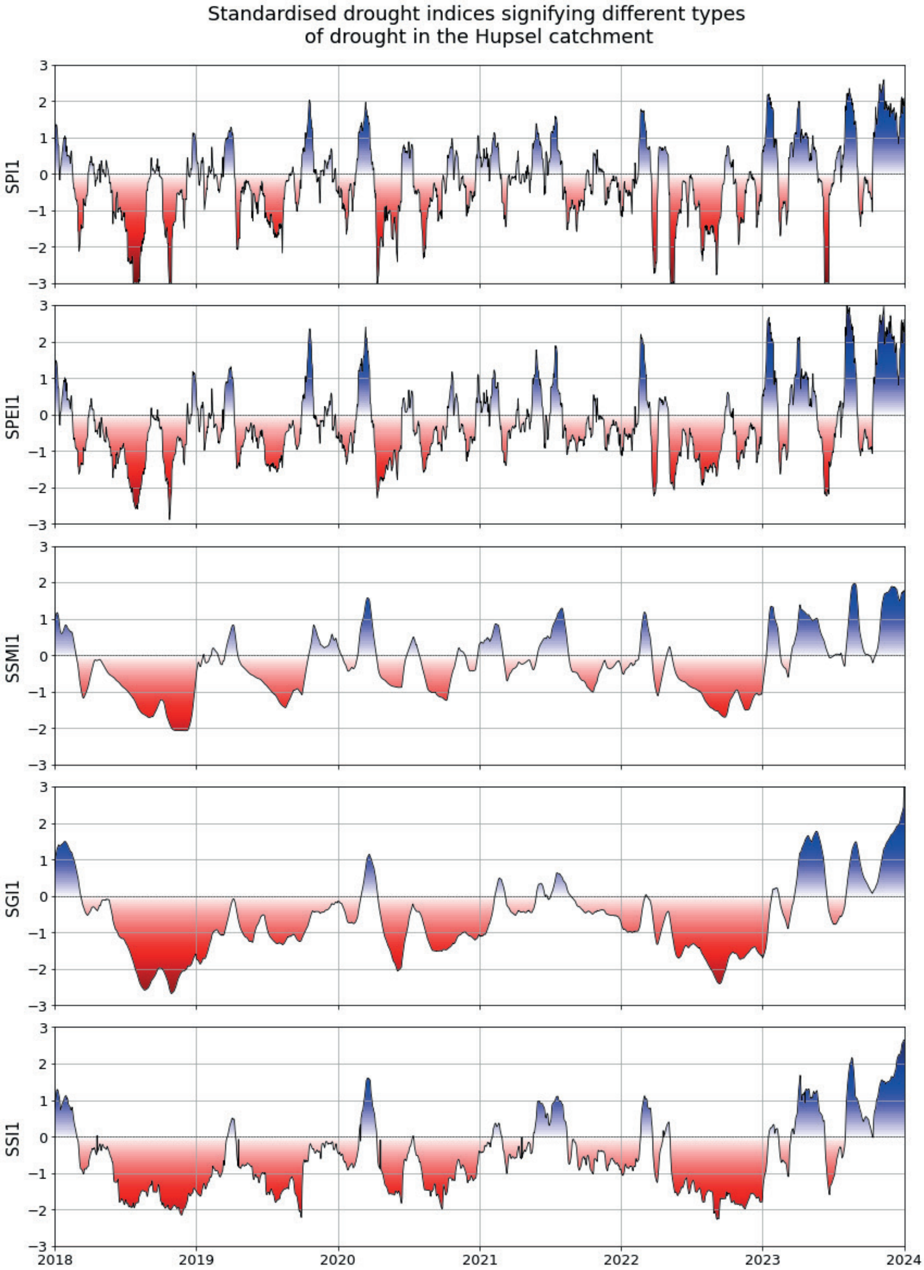

Figure 10 *Standardized indices showing the different types of droughts within the Hupsel Brook catchment (using a 30 day averaging timescale).*

Discussion

For Hydrus-1D, the influence of groundwater is neglected, and a free-draining profile is assumed. In this way, the index is solely influenced by meteorological forcing. It is recommended to add the groundwater influence to the model to improve model performance and calculate indices that are more in line with observed field conditions. Due to the probabilistic nature of the index, systematic biases in the Hydrus-1D results are ignored when calculating the final SSMI values. Pearson's correlation is used to assess model goodness-of-fit. A threshold of 0.7 is set arbitrarily. It is recommended to further investigate this threshold and to develop additional metrics to evaluate the model performance in an operational setting.

The WALRUS model performed well for the dry and wet periods. However, it uses preprocessing functions to linearly interpolate missing streamflow data, including during calibration. However, in cases with long periods of missing data, as in this study, this interpolation can reduce the accuracy of streamflow simulations. It has been implemented in the recent operational setting of the SSI calculation and visualisation (Terink et al., 2024).

Deciding what distribution is the best fit to derive the soil moisture and the streamflow indices is not straightforward. Although you can assess the distribution fit and the statistical behavior of the chosen distribution, an objective comparison between the parametric and non-parametric methods is difficult. If you solely focus on parametric distributions, the best way to compare the distributions is to compare the goodness-of-fit indicated by the Shapiro-Wilk test. For SSMI, the Pearson 3 distribution showed to be the best fit. You can, however, argue whether it is appropriate to fit a unimodal distribution to data that tends to show bimodal or multimodal characteristics (Vidal et al., 2010), which is also highlighted in Figure 7. The main advantage of the non-parametric Kernel Density Estimates (KDE) is that it offers more flexibility and can describe the multimodality of the distribution (Carrão et al., 2016; Tijdeman et al., 2020). Some disadvantages, however, should be carefully considered. The KDE approach can be prone to over- or under-smoothing and it has difficulty handling data that goes beyond the range of observations. This means that it has difficulty assigning the right probability to the most extreme values (Tijdeman et al., 2020). These differences are also highlighted in Figure 7. The above-mentioned disadvantage of KDE is one reason as to why it has not been used in the SSI calculation. Moreover, for the standardized streamflow index (SSI), the sensitivity of the index to the chosen method and distribution highlights the complexity of selecting an appropriate approach for drought monitoring and characterization (Tijdeman et al., 2020). While non-parametric methods often provide a better fit for SSI calculations, they tend to underestimate the magnitude and spread of negative SSI values and exhibit higher uncertainty bounds (Tijdeman et al., 2020). This trade-off underscores the need for the careful consideration of both parametric and non-parametric methods in drought analysis, but nonparametric methods may be considered less suitable for SSI calculation in drought analysis due to their high uncertainty (Tijdeman et al., 2020).

The user should carefully evaluate the different evaluation criteria and choose based on what is most suitable for the application at hand as, objectively, no single best method can be selected. The most important thing is that the end user is correctly informed about the strengths and weaknesses of the chosen method so that the limitations of the final index are clear (Tijdeman et al., 2020).

Conclusions

This study demonstrates that a simple Hydrus 1D model, based on local BOFEK soil profiles and driven solely by meteorological data, can effectively simulate historical time series for at least five of the investigated locations. Furthermore, the WALRUS model proved effective in simulating streamflow for the Hupsel catchment. Among the tested distributions, KDE appeared to be the most suitable option for SSMI. While, for SSI, Generalized Extreme Value distribution is the best fit.

Implementing the SSMI and SSI in the portal will provide users with a consistent view of the hydrological system's current state and help explore historical trends and spatial characteristics. These indices will support water authorities and stakeholders in understanding and responding to various drought impacts, including effects on agriculture, ecosystems, and water resources.

Acknowledgements

We would like to express our gratitude to Erik Tijdeman, Paul Torfs, and Gert van den Houten as well as Claudia Brauer and Jos van Dam for their invaluable guidance and support throughout this process.

Literature

Altayeb, M. (2024) Standardized streamflow index for the drought portal; Internship Report.

Brauer, C., Torfs, P., Teuling, A., & Uijlenhoet, R. (2014) The Wageningen lowland runoff simulator (WALRUS): Application to the Hupsel brook catchment and the Cabauw polder; *Hydrology and Earth System Sciences*, 18, 4007–4028.

Carrão, H., Russo, S., Sepulcre-Canto, G., & Barbosa, P. (2016) An empirical standardized soil moisture index for agricultural drought assessment from remotely sensed data; *International Journal of Applied Earth Observation and Geoinformation*, 48, 74–84.

Collenteur, R., Brunetti, G., and Vremec, M. (2019) Phydrus: Python implementation of the hydrus-1d unsaturated zone model; version 0.2.0. software.

de Gier, L. (2021) Hydrological drought forecasting in the Netherlands with a rainfall-runoff model and forecasted weather data; Master's thesis, WUR.

Eden, U. (2012) Drought assessment by evapotranspiration mapping in Twente, the Netherlands; Master's thesis, University of Twente.

Heinen, M., Bakker, G., & Wösten, J. H. M. (2020). Waterretentie-en doorlatendheidskarakteristieken van boven-en ondergronden in Nederland: de Staringreeks: Update 2018 (No. 2978). Wageningen Environmental Research.

Heinen, M., Brouwer, F., Teuling, K., and Walvoort, D. (2021) Bofek2020 - bodemfysische schematisatie van Nederland: update bodemfysische eenhedenkaart; Wageningen Environmental Research.

Heinen, M., van Dam, J., Bartholomeus, R., de Wit, J., van den Eertwegh, G., and Hack-ten Broeke, M. (2022). Vergelijking metingen bodemvochtgehaltes met swap-wofost simulaties. KLIMAP.

Katipoğlu, O. M. (2023) Prediction of streamflow drought index for short-term hydrological drought in the semi-arid Yesilirmak basin using wavelet transform and artificial intelligence techniques; *Sustainability*, 15, 1109.

Mishra, A. K., & Singh, V. P. (2010) A review of drought concept; *Journal of Hydrology*, 391, 202–216.

Parker, B., Lisonbee, J., Ossowski, E., Prendeville, H., & Todey, D. (2023) Drought assessment in a changing climate: Priority actions and research needs;

Šimůnek, J., van Genuchten, M. T., and Šejna, M. (2008) Development and applications of the hydrus and stanmod software packages and related codes; Vadose Zone Journal, 7(2):587–600.

Svoboda, M., Hayes, M., & Wood, D. (2012) Standardized precipitation index: User guide;

Svoboda, M. D., Fuchs, B. A., et al. (2016) Handbook of drought indicators and indices; Volume 2, World Meteorological Organization, Geneva, Switzerland.

Svensson, C., Hannaford, J., & Prosdocimi, I. (2017) Statistical distributions for monthly aggregations of precipitation and streamflow in drought indicator applications; *Water Resources Research*, 53, 999–1018.

Terink, W., van Deijl, D., & van den Eertwegh, G. (2024). Droogte en droogval van beken in zandgebieden van Nederland. Berekening en visualisatie van de 'Standardized Streamflow Index' en beek droogval in een operationele setting in het kader van droogteportaal.nl; KnowH2O rapport. https://edepot.wur.nl/680041

Tijdeman, E., Stahl, K., & Tallaksen, L. M. (2020) Drought characteristics derived based on the standardized streamflow index: A large sample comparison for parametric and nonparametric methods; *Water Resources Research*, 56, e2019WR026315.

van Dam, J. C., & Gooren, H. P. (2021). Bodemvochtmetingen in zandgebieden van hoog Nederland;

van den Eertwegh, G., Bartholomeus, R., de Louw, P., Witte, F., van Dam, J., van Deijl, D., Hoefsloot, P., Clevers, S., Dimmie Hendriks, M. v. H., Hunink, J., Mulder, N., Pouwels, J., & de Wit, J. (2019). Droogte in zandgebieden van Zuid-, Midden- en Oost-Nederland. Rapportage fase 1: Ontwikkeling van uniforme werkwijze voor analyse van droogte en tussentijdse bevindingen.

van den Eertwegh, G., de Louw, P., Witte, J.-Ph., van Huijgevoort, M., Bartholomeus, R., van Deijl, D., van Dam, J., Hunink, J., America, I., Pouwels, J., Hoefsloot, P., & de Wit, J. (2021). Droogte in zandgebieden van Zuid-, Midden- en Oost-Nederland. Eindrapport (fase 3): het verhaal – analyse van droogte 2018 en 2019 en bevindingen.

Van Dorland, R., Beersma, J., Bessembinder, J., Bloemendaal, N., Van Den Brink, H., Brotons Blanes, H., & Van Der Wiel, K. (2023). KNMI national climate scenarios 2023 for The Netherlands; KNMI: De Bilt, The Netherlands.

van Genuchten, M. T. (1980). A closed-form equation for predicting the hydraulic conductivity of unsaturated soils; Soil Science Society of America Journal, 44(5), 892–898.

van Huijgevoort, M., Brakkee, E., de Wit, J., van Deijl, D., van den Eertwegh, G., & Bartholomeus, R. (2022) Uniform inzicht in droogte met behulp van indices; Stromingen, 28(1).

Van Loon, A.F. (2015) Hydrological drought explained; *Wiley Interdisciplinary Reviews*, Water, 2, 359–392.

Yang, W. (2010) Drought analysis under climate change by application of drought indices and copulas; Portland State University.

Yihdego, Y., Vaheddoost, B., & Al-Weshah, R. A. (2019) Drought indices and indicators revisited; *Arabian Journal of Geosciences*, 12(3).

Samenvatting Nieuwe functionaliteiten voor het droogteportaal: gestandaardiseerde indexen voor bodemvocht en afvoer

Voor een goed inzicht in de huidige droogtesituatie en de progressie daarvan, is het belangrijk om de verschillende typen droogte in kaart te brengen. In dit project testen we een gestandaardiseerde index voor zowel bodemvocht (SSMI) als afvoer (SSI) voor het droogteportaal (https://droogteportaal.nl). We maken hiervoor gebruik van realtime veldmetingen en modelsimulaties. Voor het berekenen van de SSMI gebruiken we de veldmetingen om een Hydrus-1D-model te valideren omdat de tijdreeks van veldmetingen niet lang genoeg is om een index op te berekenen. Voor de SSI wordt het WALRUS-model gebruikt om de gaten in de afvoerdata te vullen en waar nodig te verlengen. Voor beide indexen worden er verschillende statistische verdelingen geëvalueerd om de best passende verdeling voor de data te vinden. De indexen kunnen worden gebruikt om de verschillende hydrologische systemen op een uniforme manier te benaderen en helpen om keuzes te maken om de impact van droogte te verminderen.

Auteurs

BART MOEKESTORM
Intern KnowH2O
bart@moekestorm.nl

MAAB ALTAYEB
Intern KnowH2O
maabalbager@gmail.com

DION VAN DEIJL
KnowH2O
deijl@knowh2o.nl

WILCO TERINK
KnowH2O
terink@knowh2o.nl

GÉ VAN DEN EERTWEGH
KnowH2O
eertwegh@knowh2o.nl