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ABSTRACT

Increasing drought is considered one of the major threats associated with climate change in central Europe. To provide an objective, quantitative tool that represents current drought conditions, the Czech Drought Monitor System (CzechDM) was established in 2012. Like other drought monitoring systems worldwide, the CzechDM uses several approaches to provide drought data. However, the CzechDM is unique internationally due to its utilization of a network of voluntary reporters (farmers) who complete a weekly online questionnaire to provide information about soil water content and the impacts of drought on crop yield. In this study, the results from the questionnaires from individual farms were aggregated by district. Reporters' data were compared and validated with the outputs of the SoilClim model (a core tool of the CzechDM) and with other drought monitoring tools, such as the water balance model, the soil water index and the evaporative stress index. The soil water content estimated by the reporters was significantly correlated (on average $r = 0.8$) with the outputs of the SoilClim model. Conversely, the correlation between the drought impacts on yield estimated by the reporters and the SoilClim outputs was lower (on average $r = 0.4$), suggesting that *in situ* observations by farmers provide additional insights into the occurrence of drought impacts. Importantly, it was found that farmers reported significant drought impacts on yield earlier in the season than any other methods (models or remote sensing). The main findings of this study are that the drought monitoring provided by reporters is a useful and reliable component of the CzechDM. We conclude that weekly reports by farmers represent a significant enhancement to drought monitoring and have potential for use in developing automated approaches that combine *in situ*, modeling and remote sensing data within a data fusion or machine learning framework.

Abbreviations: ALEXI, atmosphere–land exchange inverse model; ASCAT, advanced scatterometer; AVISO, water balance model; AWP, drought intensity defined as a difference between predicted and real drought values (within this study for a soil depth 0–0.4 m); $AWR_{0-0.4}$, relative soil saturation for a soil depth 0–0.4 m; $AWR_{0-1.0}$, relative soil saturation for a soil depth 0–1.0 m; AzDW, arizona drought watch; CFSR, climate forecast system reanalysis; CzechDM, Czech drought monitor; DIR, drought impact reporter; EDO, European drought observatory; ESI, evaporative stress index; LST, land surface temperature; MODIS, moderate resolution imaging spectroradiometer; NDMC, national drought mitigation center; PDSI, palmer drought severity index; SPI, standardized precipitation index; SPEI, standardized precipitation-evapotranspiration index; SSM, surface soil moisture; SWC_{rep}, soil water content observed by reporters within CzechDM; SWI, soil water index; VIC, variable infiltration capacity model.

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1. Introduction

Drought, as a manifestation of climate change, is a natural hazard and a worldwide problem (Wilhite et al., 2007; Hou et al., 2017). As has been observed many times, drought is notoriously difficult to define and to characterize properly as it is happening (Redmond, 2002; World Meteorological Organization, 2006) given its gradual onset, long duration, large spatial extent, and cross-boundary effects (Blauhut et al., 2015). Although drought can be defined in various ways, it has multidisciplinary impacts, e.g., economic (Logar and van den Bergh, 2013; Ding et al., 2011), environmental (Crausbay et al., 2017) and social impacts (Wilhite and Vanyarkho, 2000), as well as direct and indirect impacts (Gil et al., 2013). All these impacts influence various sectors, including agriculture, energy production and public water (Blauhut et al., 2015; Stahl et al., 2016). The impacts of drought can be classified into a number of different categories (Stahl et al., 2012), but research and the public interest focus mainly on agricultural sector impacts (Blauhut et al., 2015) and on water management and water resources.

The importance of drought monitoring is associated with a better understanding of drought occurrence, onset, extent and intensity, which could help to mitigate drought-related impacts, including economic losses (Wilhite, 1993), and to facilitate management or adaptation in the agricultural (Shrum et al., 2018), forestry (Bussotti and Pollastrini, 2017) and water management (Fisher et al., 2017) sectors.

Studies of existing drought monitoring systems that are available to the public have already been published, and they summarize current operational or proposed monitoring systems (e.g., Zink et al. 2016, Trnka et al. 2020). Most of the existing drought monitoring systems use indices such as the standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), or (self-calibrated) Palmer drought severity index (PDSI) (used by both the US Drought Monitor and the European Drought Observatory (EDO). Other systems use soil moisture percentiles derived from hydrologic model simulations (US Drought Monitor), the hydrologic model LISFLOOD for soil moisture estimations (EDO) or the variable infiltration capacity (VIC) model (systems established in India and Africa) (Svoboda et al., 2002; Zink et al., 2016; Horion et al., 2012).

There are also projects and monitoring systems that specialize in capturing drought impacts. In the USA, the impacts of droughts are recorded by the National Drought Mitigation center (NDMC), where the Drought Impact Reporter (DIR) is a tool for recording observations of drought impacts reported by various sources (Smith et al., 2014). The NDMC uses an online service that is open to the public and can be used to search for impacts in several categories (e.g., agriculture, water supply, wildfire, tourism). The DIR is both a historic archive of impacts and a gage of what kind of impacts are primarily of interest to contributors and news reporters (Smith et al., 2014). Impact data can help to improve the understanding of drought vulnerabilities and can therefore be used for developing and targeting mitigation strategies (Hayes et al., 2011; Wilhite et al., 2007). Information about drought impacts can also be used to support more precise relief allocation decisions and inform policy and planning priorities. In the agricultural sector, for example, drought impact reports are provided to USA Drought Monitor staff by the Farm Service Agency field personnel and by county extension agents, which are both seen as credible and professional sources of information (Lackstrom et al., 2013). In the US, additional local drought monitoring systems also exist. For example, the Arizona Drought Watch (AzDW) is designed to collect qualitative information about drought impacts in six categories: water, agriculture, livestock, society, tourism, and ecology. AzDW includes an online drought impact reporting system and was created mainly as a reaction to the demand for high-quality, local-level drought impact data to make decisions about drought declarations, status, and relief funds (Meadow et al., 2013).

Within Europe, extensive datasets of drought impacts have been collected (Stahl et al., 2016), including close to 5000 impact reports from 33 European countries developed using journal articles, books, newspaper articles, various reports and other sources. These datasets can fill information gaps about drought impacts and provide a useful data source for studies connecting the hydrological characteristics of droughts. However, Stahl et al. (2016) also highlighted the need to monitor variables in addition to precipitation (e.g., soil moisture, for improved impact-specific drought indicators). In the central and southeastern European states, drought impacts have been monitored and collected within the DriDanube project. The target states collected data from publicly available sources (newspapers and journals) in five categories (agriculture, forestry, soil systems, wildfires and hydrology) during the 1981–2016 period (Jakubinsky et al., 2019). Another significant monitoring effort in Europe is the MARS (Monitoring Agricultural Resources) bulletin, which provides widespread monitoring services and information; each bulletin includes a set of maps (areas of concern) depicting extreme weather events (including droughts or rain deficits) that have occurred in Europe during the analysis period and their impacts on crops (Seguini et al., 2019).

In the Czech Republic, the Czech Drought Monitor (CzechDM) surveys not only drought duration and occurrence information (using modeling approaches, remote sensing data and ground data from meteorological stations) but also drought impacts on yield. Reporters (farmers) subjectively observe soil moisture and especially drought impacts on the yields of given crops weekly and provide information from numerous localities in real time throughout the whole year (Trnka et al., 2020). These observations are unique in Europe and provide new and deeper insights into drought evaluation and management.

The main goals of this study are to (1) process the data from reporters who monitored drought (soil water content) and drought impacts on weekly yields during the 2015–2018 period; (2) evaluate the reporters' estimated soil water content data through comparisons with models and indices used for drought monitoring; and (3) evaluate the reporters' estimated drought impacts on crop yield using models and other parameters of drought observations. For goal (1), we hypothesize that the data from reporters (the soil water content and drought impacts on yield) are usable and that the information about drought impacts on yield in particular will provide new insights and information about drought occurrence (i.e., we expect low correlations between the observed impacts by reporters and the outputs of models and indices). Consequently, for goal (2), we hypothesize that the soil water content and drought impacts on yield observed by reporters will be variably correlated with the outputs of the SoilClim model (and other models and methods of drought monitoring) over given periods (years). Finally, for goal (3), we expect that a lower number of reporters in each district will result in lower correlations with the modeled values.

2. Materials and methods

We used weekly estimated soil water content (SWC_{rep}) and estimated drought impacts on yield data from reporters from various sites in the Czech Republic (16 districts and 57 sites on average) from 2015 to 2018. The SWC_{rep} and reported impacts were evaluated and compared with the SoilClim model, the AVISO model, the soil water index (SWI) and the evaporative stress index (ESI).

2.1. Reporters

The CzechDM reporters are farmers who were nominated by the Agriculture Chamber of the Czech Republic to monitor drought occurrence and drought impacts. The main task of these reporters was to make weekly observations of drought conditions and to share the information through an online questionnaire (accessible to the general public in the Czech language at www.intersucho.cz/dotaznik, attached as Supplement 1). Their participation was based on voluntary cooperation, which implies that the number of reporters varied from week to week and over the years. The questionnaire consisted of 15 questions, and completing the questionnaire took ca. 15 min. The first three questions were related to soil moisture conditions (the current situation, the last three months, and the change since the last report) were followed by questions focusing on the specific observed impacts on key crops. More details about the reporters' tasks have been described previously (Trnka et al., 2020).

The reporters within this study evaluated drought and soil water conditions at the cadaster(s) level, and the results were subsequently averaged over the area of a district. In each district, the drought situation was reported by 1 or more reporters (10 at most) independent of each other (the average number of reporters in one district was four). For the current study, we used data from 16 districts from which the reporters sent reports from 2015 to 2018 and continuously if possible. The selected districts represent mainly areas that experience a long-term negative water balance during the year. A large fraction of the observational sites were in regions where the soils were experiencing a negative water-balance regime, with 100 sites at deficits of up to −100 mm and three districts representing areas with even more severe negative water balances (of −100 up to −300 mm); Fig. 1.

To evaluate the reporters' data on soil moisture, we used the answers to the first question from the questionnaire: 'What is the state of soil moisture in the layer 20 cm from the surface?' The responses were averaged (if there was more than one reporter in a district) and compared with outputs of the SoilClim and AVISO models and with SWI and ESI data at weekly time steps for the 2015–2018 period. The responses were provided on a five-point scale where a value of 1"" indicates that the soil is dry and dusty to the touch, and a value of ""5 indicates that the soil is close to being fully saturated with water.

To evaluate the estimates of drought impacts on yields, we used the answers to seven questions, e.g., 'Estimate the drought impacts on the yield of winter cereals'. The drought impacts on winter cereals and winter rape were averaged, and those on spring cereals in the first half of the vegetation period (March, April, May, and June) were also averaged for each week. The drought impacts on sugar beet, potato and maize yields were averaged over July, August, September, and October in given week. The drought impacts on permanent grasslands were averaged in given weeks over the entire vegetation period. These averages were done because the observed impacts were almost similar for winter and spring cereals and in summer part of the year for late (summer) crop. The questionnaire responses were provided on a 6-point scale, where 1 indicates no effect of drought and thriving vegetation; 2 indicates no effect of drought but worse vegetation conditions for other reasons; and 3, 4, 5 and 6 indicate various yield losses (<10%, 10–30%, 30–40% and >40%, respectively). Before the harvest, the reporters estimated their expected yield loss, which means that the questionnaire relied on their professional estimates based on vegetation conditions (e.g., the amount and strength of offshoots). The yield loss reported after the harvest was the current value calculated by the reporters according to the average yields from the last three years. These estimated impact data were compared and evaluated with the outputs of the SoilClim and AVISO models and with the SWI and ESI values.

2.2. SoilClim

The SoilClim model (Hlavinka et al., 2011) was designed as an advanced tool for the identification of soil climate regimes at a daily time step. The model simulates the soil water content in two defined layers as a result of the balance between the inflow (e.g., infiltration) and outflow (e.g., evapotranspiration, percolation, runoff) components

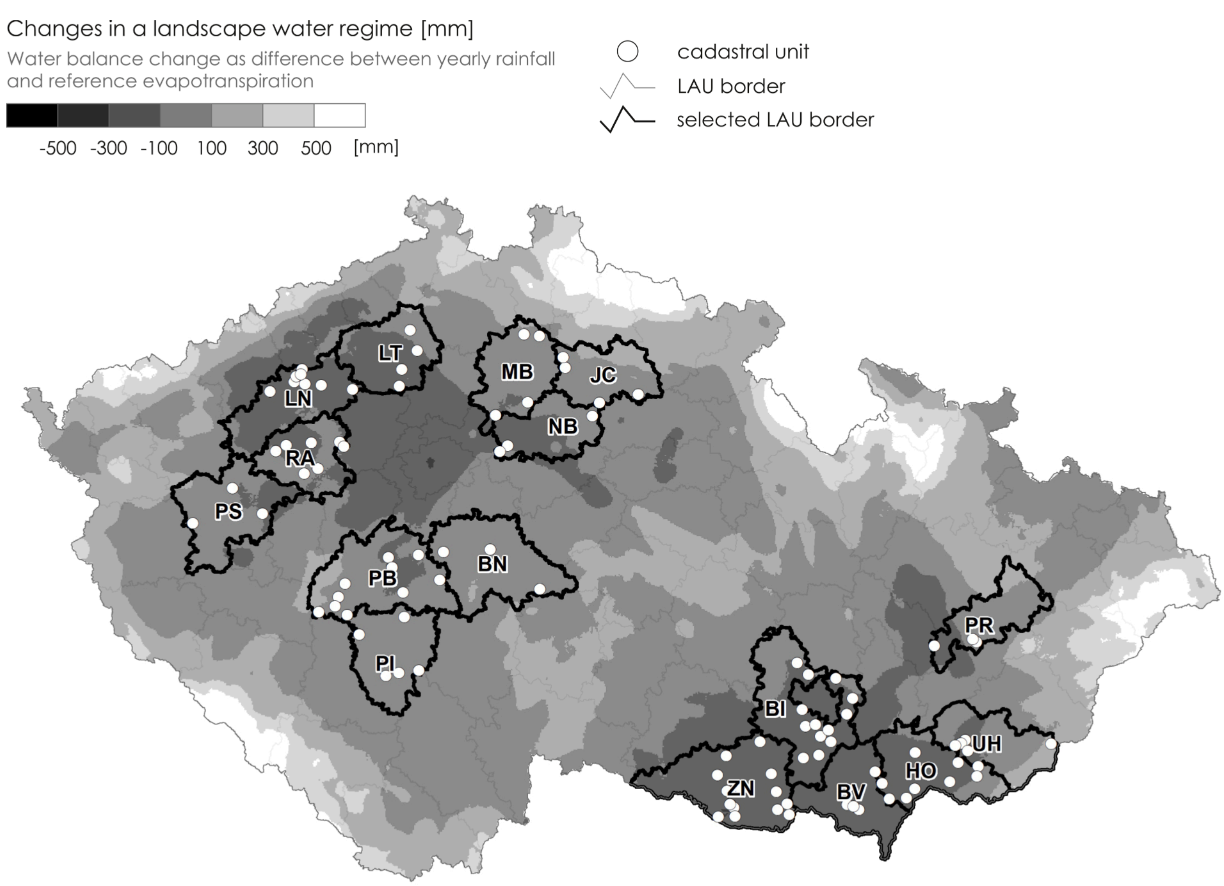

Fig. 1. The Czech Republic. The indicated districts (black outlines) include all observational plots at the cadaster level (white dots) used in this study. Changes in the landscape water regimes were calculated for one year, and data from 1981 to 2010 were used. The district abbreviations are: BN = Benešov, BI = Brno venkov, BV = Břeclav, HO = Hodonín, JC = Jičín, LT = Litoměřice, LN = Louny, MB = Mladá Boleslav, NB = Nymburk, PI = Písek, PS = Plzeň sever, PR = Přerov, PB = Příbram, RA = Rakovník, UH = Uherské Hradiště, ZN = Znojmo.

of the water balance. SoilClim works at a daily time step and requires the maximum and minimum air temperature, global solar radiation, precipitation, vapor pressure and wind speed as meteorological inputs, as well as basic information about the soil properties (soil type map after Tomášek 2007) and dynamically simulated vegetation cover (and related crop coefficients), and multiple vegetation cover types (e.g., spring and winter field crops or permanent grasslands) (Řehoř et al., 2021; Hlavinka et al., 2011). The SoilClim model also considers runoff, deep percolation, simplified macropore water flows with a modified cascade principle (Allen et al., 1998).

Two SoilClim indicators were used to evaluate the reporters' data in this study: i) the relative available water content at soil depths of 0–0.4 m ($AWR_{0–0.4}$) and 0–1.0 m ($AWR_{0–1.0}$); the AWR describes the current relative soil saturation over 500 m grids, where 0% represents the wilting point and 100% represents field capacity. And ii) the drought intensity in the 0–0.4 m topsoil (AWP); the AWP value represents a probabilistic interpretation of the actual AWR value in relation to all AWR values occurring in the given grid between 1961 and 2010 during the same period of the year. The final output of the AWP describes the current probability of the frequency of a given soil water content on a specific day and is classified into a seven-stage scale of drought intensity (from <S0 – no drought risk to S5 – extreme drought) (Trnka et al., 2020).

2.3. AVISO

The AVISO model is an agrometeorological information system used at the Czech Hydrometeorological Institute. The basic output of the model is the soil water content (in 0–1.0 m) in percent of available water capacity. The actual deficit is computed as a sum of difference between precipitation and evapotranspiration of current day and soil water deficit at the end of the last day. The soil water content in percent of available water capacity is then calculated by means of actual soil water deficit value between two main hydrolimits - field moisture capacity and wilting point. The input data for this model are the air temperature, vapor pressure, sunshine duration, wind speed, and precipitation, as well as the values of soil texture characteristics (available water capacity, field capacity and wilting point). The modeled surface was set to a reference grass (Allen et al., 1998), and one soil type was applied – medium-heavy soils (Kohut et al., 2009). The main difference between the SoilClim and AVISO models is a significant generalization of vegetation cover and soil conditions within the AVISO calculations (the model uses only one vegetation cover type and one soil type). The AVISO model is then dependent mainly on meteorological parameters (primarily precipitation and temperature). The calculation of outputs is run each year (from the 1st January) with very low default values of soil water deficit. Subsequently, the outputs for winter and early spring are not sufficiently representative and within this study used data from the start of April till the end of the year. Although the cumulative indices of soil moisture are useful for characterizing the drought severity in critical development stages (Piniewski et al., 2020), both models (SoilClim and AVISO) used in this study indicate current soil water status each week. The outputs of this model (the soil water content in percent of available water capacity) used in this study are for a soil depth of 0–1.0 m and are indicated as AVISO within the text.

2.4. Soil water index-SWI

The soil water index (SWI), originally developed at Technical University Wien (Wagner et al., 1999) and later developed by other research groups (Bauer-Marschallinger et al., 2018), uses an infiltration model that describes the relationship between the surface and soil profile soil moisture as a function of time. The algorithm is based on a two-layer water balance model that estimates the profile soil moisture from surface soil moisture data retrieved from the radar backscattering coefficients measured by the ASCAT (Advanced Scatterometer) instrument onboard the MetOp (Meteorological Operational) satellites. In this model, the water content of the reservoir layer is described in terms of an index that is controlled only by the past soil moisture conditions in the surface layer such that the influence of the measurements decreases with time. The SWI is derived from surface soil moisture (SSM) values based on a temporal filtering method. An important parameter used to model infiltration into deeper soil layers to calculate the SWI is the characteristic time length, called the T-value; the higher the T-value is, the smoother the SWI and the deeper the represented layer (Bauer-Marschallinger et al., 2018). In this study, 15-day T-values were used to represent 0–0.4 m soil depth and are indicated as SWI.

2.5. Evaporative stress index-ESI

The evaporative stress index (ESI) represents the standardized anomalies (z-scores) of the actual to reference evapotranspiration ratio ($fRET = ET_a/ET_o$), where ET_a is determined from the land-surface temperature (LST)-driven atmosphere–land exchange inverse (ALEXI) model. ALEXI is a diagnostic modeling system that exploits the morning LST rise signal to derive the components of the surface energy balance with a two-source energy balance scheme (Norman et al. 1995; Anderson et al. 1997; 2007). The version of the model used in this study is based on the approximation of the LST morning rise by the MOD11A1 day/night retrieval dataset from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the Terra satellite ((Hain and Anderson, 2017). Additional inputs describing the meteorological conditions necessary to solve the surface energy balance and to compute the FAO-56 ET_o (Allen et al., 1998) were obtained from the Climate Forecast System Reanalysis (CFSR). The ESI product used in this study is available at a weekly temporal resolution in the form of two composites with 0.05° (~5000 m) spatial resolution: a 4-week composite, which has the ability to capture shorter-term drought events, and a 12-week composite, which has the potential to indicate agricultural as well as hydrological droughts. The 12-week values are used in this study and are indicated as ESI in the text. The values of ESI were download for this study from external online database serviglobal.net.

2.6. Statistical analyses and validation

Correlation coefficients (r) and p-values (p) were used as the basic indicators of correlations, statistical significance, and deviation among all parameters. The coherency between given data series was evaluated at the 95% and 99% confidence levels according to Schönwiese (1985). The coherence analysis is used to evaluate dependencies in given periodic elements (Brázdil, 1986). In this study, the periodic elements of given weeks were considered (specifically from 2, 4, 8, 16, 32, and 64 weeks cycles up to trend components) and help us better see the coherency among series mainly in trend components. The SWC_{rep} and reported impacts were evaluated using data from the SoilClim model ($AWR_{0–0.4}$, $AWR_{0–1.0}$ and AWP); data from the AVISO model; and values of SWI and ESI at weekly time steps. Analyses were performed with the statistical/programming tool R 3.6.1. (R: A Language and Environment for Statistical Computing 2022R: A Language and Environment for Statistical Computing, 2022) and with AnClim software for time series analysis (Štěpánek P., 2008).

3. Results

The number of active reporters increased from 22 reporters on average for the Czech Republic in 2014 to 197 reporters in 2018 (Fig. 2) (Table 1). In line with this increase, the number of active districts increased from 17 in 2014 to 62 in 2018. The total number of districts in the Czech Republic is 76, and the area of one district is equal to one LAU (local administrative unit) in the European Union system. The number of registered reporters (including active and nonactive reporters) also grew to more than 500 in 2018 (Table 1). The numbers of active reporters and

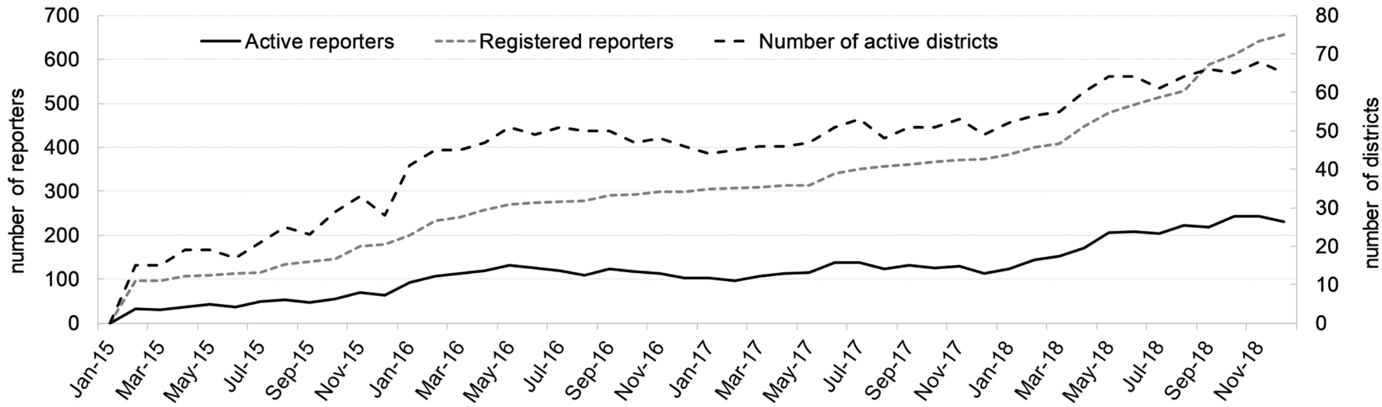

Fig. 2. Number of active reporters (dark gray), active districts (gray) and registered reporters (light gray) from 2015 – 2018 in the Czech Republic.

Table. 1
Development of the average numbers of active and registered reporters and districts throughout the Czech Republic from 2014–2018.

	2014	2015	2016	2017	2018
Active reporters	22	45	105	109	197
Number of districts with active reporters	17	22	48	49	62
Registered reporters	40	118	268	339	512

active districts changed over the years and increased mainly in the spring and summer months.

Data from 2014 were not included in this study because the number of reporters was too low, there were many data gaps, and reporting ended after the crop vegetative period ended (in October 2014). In this study, we show the numbers of reporters in order to provide a better overall perspective on the growth of CzechDM activity since cooperation with reporters began. Since February 2015, observations by reporters have been collected regularly throughout the entire year, thus providing a consistent, robust and continuous database.

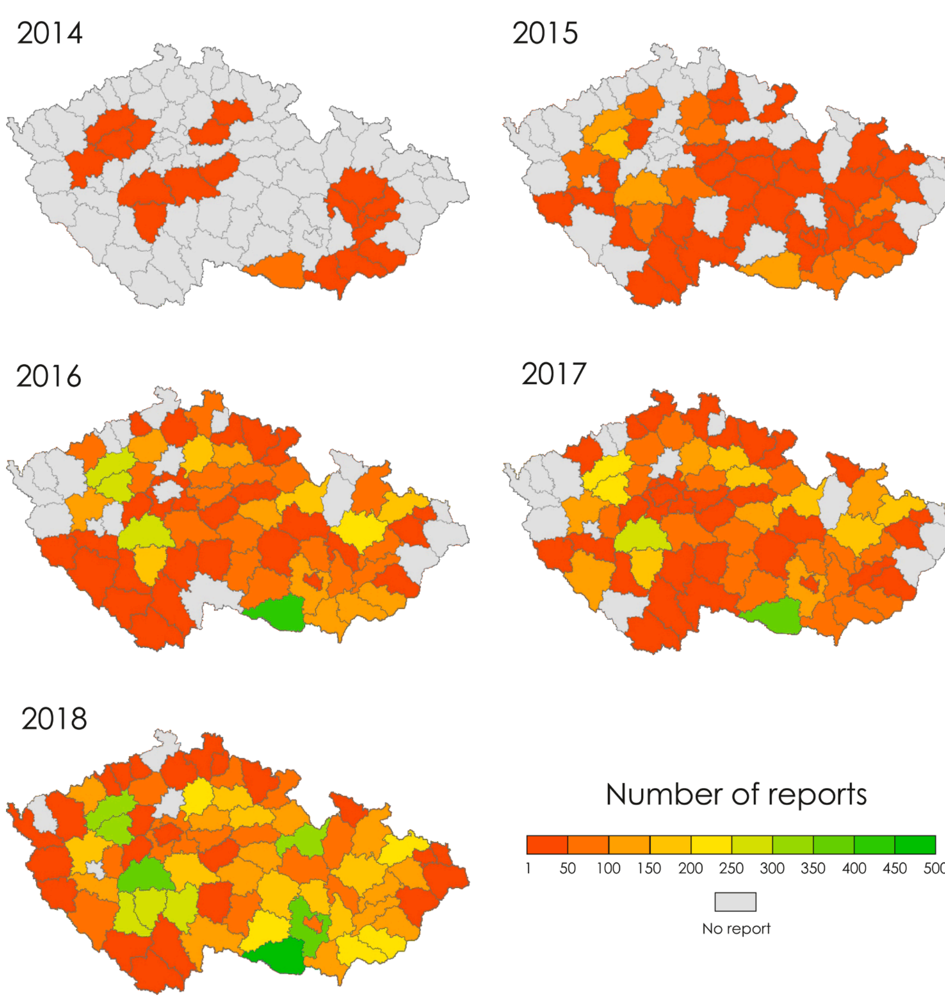

Fig. 3. Total number of all received from reporters monitoring soil water content and drought impacts on field crops from 2014 to 2018.

Each reporter observed one or more localities, so the number of collected reports is different from the number of reporters; it ranged from 50 to 400 on average for the entire country in 2014 – 2018 (Fig. 3). The districts with the highest number of reporters and of reports with continuous and long-term observations are in the areas of southern Moravia and central Bohemia. These districts were used for validation in this study, and the number of reporters in each district moved from two to eight reporters (Table 2).

3.1. Reported soil water content (SWC_{rep})

The SWC_{rep} was evaluated by comparison with $AWR_{0–0.4}$, $AWR_{0–1.0}$, AWP, AVISO, SWI and ESI data (Table 2). The validation tests showed high and statistically significant correlations between SWC_{rep} and $AWR_{0–0.4}$ ($r_d = 0.8$, r_d – correlation coefficient for all districts), $AWR_{0–1.0}$ ($r_d = 0.7$) and SWI ($r_d = 0.7$). The correlations of the mentioned parameters were statistically significant at α=0.001 for all studied districts. Lower, yet still significant, correlation coefficients were obtained from the validation with AWP and AVISO ($r_d = 0.5$ same for both variables). The lowest correlation was detected with ESI ($r_d = 0.3$), but the correlations for most districts were still significant at α=0.001.

The temporal changes in SWC_{rep} and the other drought indices are displayed for the Rakovník district, where the number of reporters was the most consistent and the dataset was the most robust throughout the entire study (Fig. 4). The average number of reporters in each week was 6. The strongest correlation ($r = 0.86$, $p = 0.000$) in this district was obtained between SWC_{rep} and $AWR_{0–0.4}$. The weakest correlation ($r = 0.3$, $p = 0.027$) was obtained between SWC_{rep} and ESI.

The coherence analysis between SWC_{rep} and $AWR_{0–0.4}$, $AWR_{0–1.0}$ and SWI showed high and stable coherency (in all districts) for long-term periods. For these characteristics, the coherency also exceeded the 95% and 99% confidence levels in long-terms periods for all studied districts. The coherency analysis revealed notably high variability between SWC_{rep} and AWP and ESI within the districts. For some districts, the coefficients exceeded the 95% and 99% confidence levels for long-term periods, while in other districts, there was almost no coherency or the coherence coefficients were low. No coherency or very low coherency coefficient values were obtained from the analysis between SWC_{rep} and AVISO in all districts (Fig. B). The coherence coefficients showed similar trends as the correlation coefficients for the same paired datasets (SWC_{rep} with $AWR_{0–0.4}$, $AWR_{0–1.0}$ and SWI), especially over long-term periods and trend components (specifically for periods of 4 months or longer).

3.2. Impacts assessed by reporters

The reported impacts were validated through comparisons with $AWR_{0–0.4}$, $AWR_{0–1.0}$, AWP, AVISO, SWI and ESI data (Table 3). The validation results showed the highest correlation between the reported impacts and the ESI values ($r_d = 0.73$). The correlation coefficients were constant in all districts, and all were significant at α=0.001. High and significant correlation coefficients were also detected between the reported impacts and the AVISO outputs, for which the correlations were 0.71 on average across all districts. All tested relationships were statistically significant, with r values ranging from 0.43 to 0.89 among districts. Another parameter used for elaboration of the reported impacts was $AWR_{0–1.0}$. The relationship between the reported impacts and $AWR_{0–1.0}$ had high but variable correlation coefficients ($r_d = 0.6$); they ranged from 0.3 (not significant) to 0.72 (significance at α=0.001). The parameters $AWR_{0–0.4}$, AWP and SWI showed little agreement with the reported impacts, with correlation coefficients of 0.4, 0.22 and 0.36, respectively. The lowest statistically significant correlation was found between the reported impacts and AWP in 7 of the 16 districts.

The results from the representative district of Rakovník are presented (Fig. 5). The comparisons resulted in the highest correlations for the ESI, AVISO and SoilClim data ($AWR_{0–1.0}$ m) ($r_d = 0.73$, 0.7 and 0.62, respectively). These correlations were statistically significant at α=0.001, and the same level of significance was also calculated for the parameters $AWR_{0–0.4}$ and SWI (with lower correlation coefficients). A significant but weak correlation (α= 0.05 and $r = 0.26$) was detected for one of the SoilClim parameters, AWP.

The coherence analysis between the reported impacts and the outputs of the SoilClim model (all three parameters, $AWR_{0–0.4}$, $AWR_{0–1.0}$ and AWP) and SWI showed various values of coherence coefficients at short time scales and at long time scales. In some districts, the coherency exceeded the 95% and 99% confidence levels in 16-week periods. For other districts, the coherency was low or showed a decreasing long-term trend. High coherency was detected between the reported impacts and the ESI and AVISO. The coherency was high in 8-week and longer periods as well as between the trends of both parameters, and the results exceeded the 95% and 99% confidence levels (Fig. C). The results showed stable and high coherency in trends between the same datasets

Table. 2
Correlations between the soil water content as estimated by reporters and the outputs of the SoilClim model ($AWR_{0–0.4}$, $AWR_{0–1.0}$, AWP), evaporative stress index (ESI), soil water index (SWI) and AVISO model in 2015–2018, and the average number of reporters in each district.

District	No. of reporters/ average	Reported soil water content vs. AWR_0–40 r	AWR_0–100 r	AWP r	ESI r	SWI r	AVISO r
Benešov	2	0.77***	0.72***	0.53***	0.30***	0.72***	0.59***
Brno venkov	3	0.71***	0.64***	0.33***	0.15	0.67***	0.32***
Břeclav	2	0.81***	0.62***	0.45***	0.01	0.66***	0.40***
Hodonín	3	0.66***	0.58***	0.24*	0.06	0.63***	0.31***
Jičín	3	0.81***	0.74***	0.61***	0.63***	0.81***	0.72***
Litoměřice	2	0.84***	0.70***	0.59***	0.33***	0.72***	0.63***
Louny	5	0.77***	0.59***	0.65***	0.27***	0.64***	0.48***
Mladá Boleslav	3	0.82***	0.78***	0.68***	0.46***	0.75***	0.65***
Nymburk	2	0.78***	0.70***	0.52***	0.38***	0.74***	0.58***
Písek	4	0.78***	0.68***	0.58***	0.15**	0.53***	0.41***
Plzeň sever	3	0.87***	0.71***	0.65***	0.44***	0.69***	0.61***
Přerov	2	0.81***	0.60***	0.36***	0.30***	0.68***	0.55***
Příbram	6	0.76***	0.63***	0.56***	0.32***	0.51***	0.57***
Rakovník	6	0.86***	0.66***	0.71***	0.30***	0.71***	0.60***
Uherské Hradiště	3	0.86***	0.67***	0.55***	0.24**	0.72***	0.56***
Znojmo	8	0.84***	0.69***	0.57***	0.21**	0.70***	0.51***

* Significant at α= 0.05.
** significant at α=0.01.
*** significant at α=0.001%.

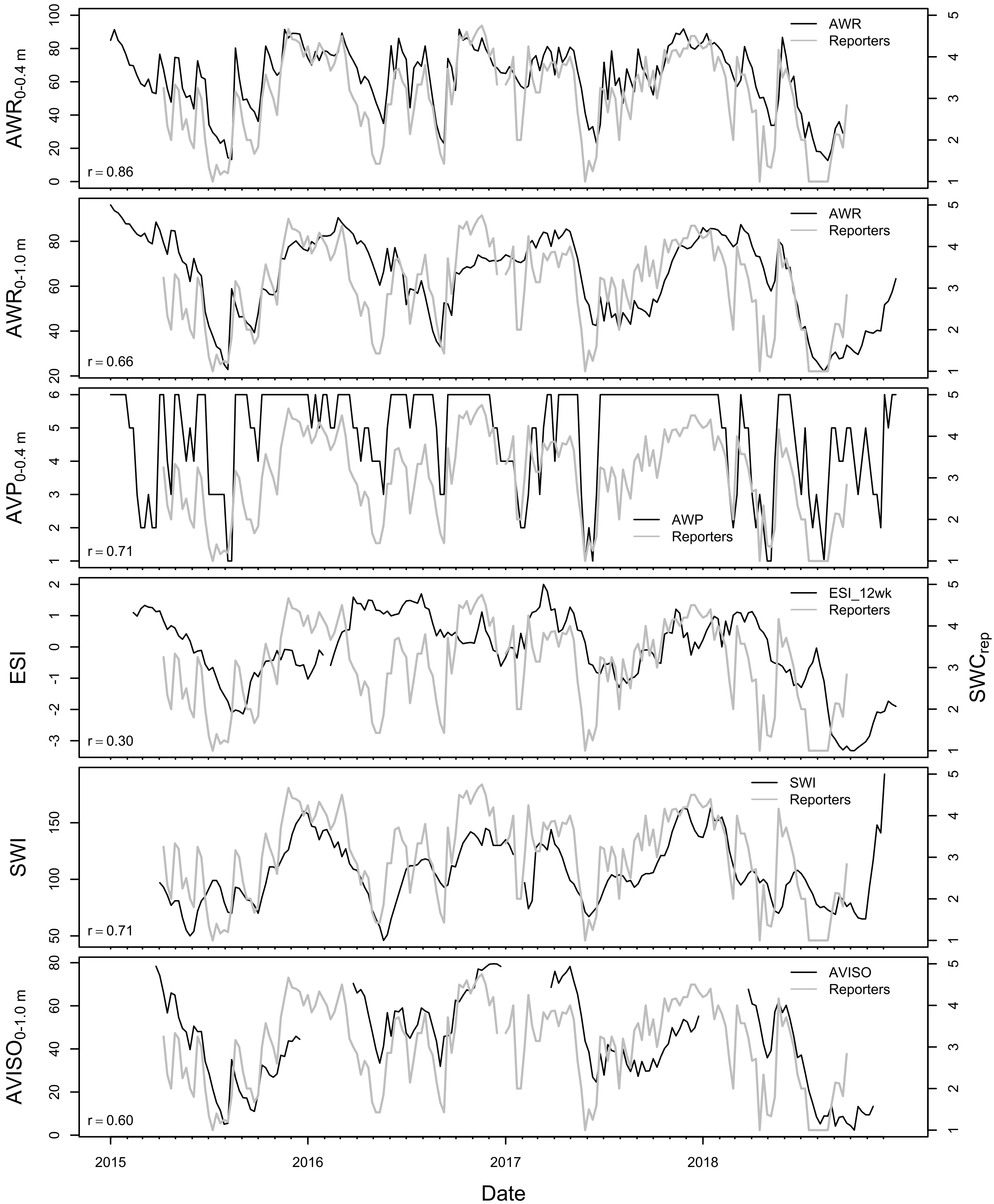

Fig. 4. Time series of soil water content as estimated by reporters (SWC_{rep}) and simulations by the SoilClim model, relative soil saturation at a soil depth of 0 – 0.4 m ($AWR_{0-0.4}$), relative soil saturation at a soil depth of 0 – 1.0 m ($AWR_{0-1.0}$), and drought intensity at a soil depth of 0 – 0.4 m (AWP); soil water index (SWI) at a soil depth of 0 – 0.4 m; evaporative stress index (ESI); and AVISO outputs at a soil depth of 0 – 1.0 m in 2015–2018 in the representative district of Rakovnik.

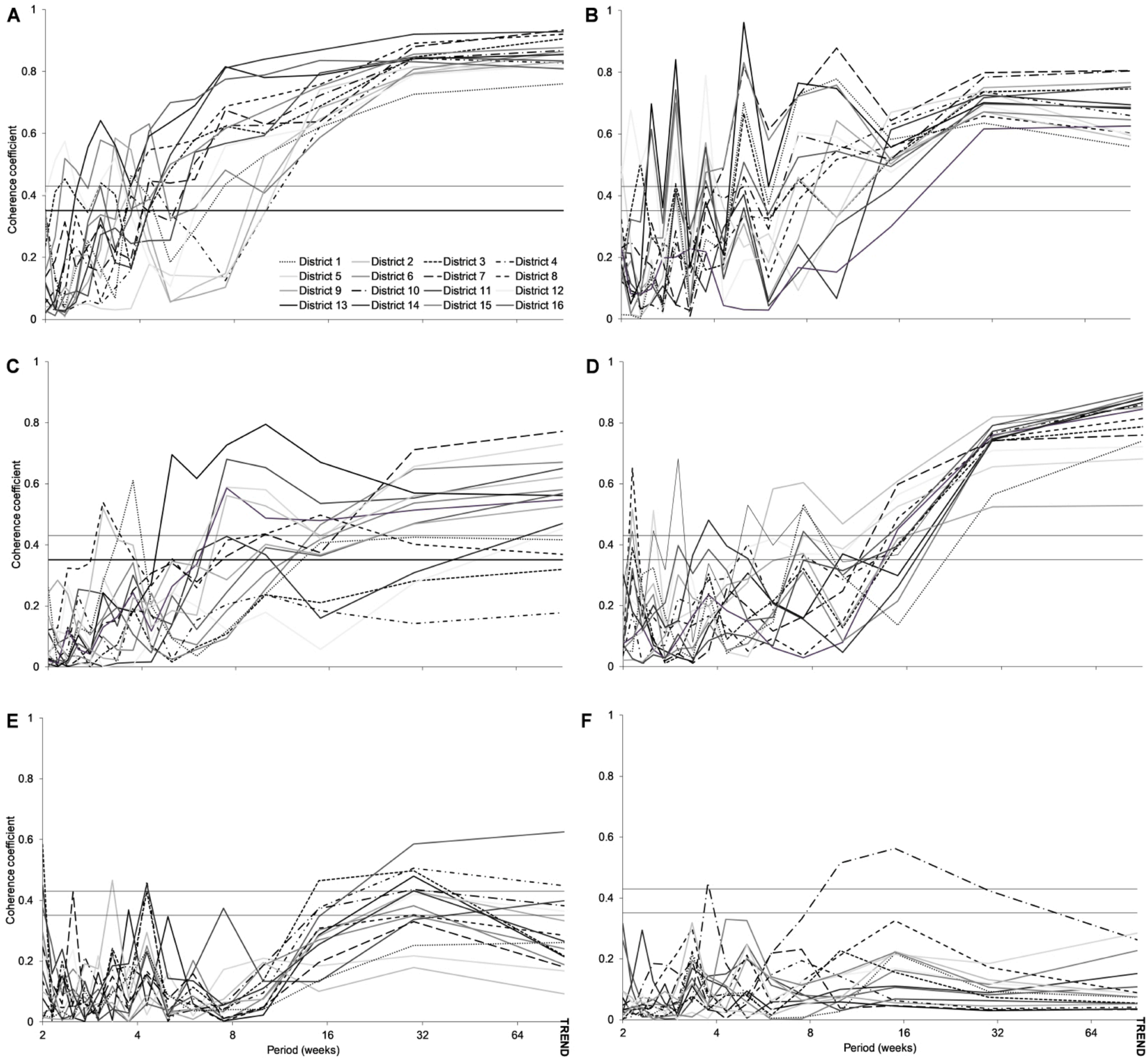

Fig. B. 1 Coherence analysis of soil water content observed by reporters (SWC_{rep}) with outputs of model SoilClim: relative soil saturation in topsoil layer and root zone layer: $AWR_{0-0.4}$ (A), $AWR_{0-1.0}$ (B) and drought intensity in top soil layer AWP (C). Coherence among SWC_{rep} with other parameters are displayed as following: D - Soil Water Index (SWI), E – Evaporative Stress Index - ESI, F – outputs of model AVISO. Black equal lines indicate 95% and 99% confidence levels. Different types of lines in each graph indicate data from all 16 districts used within this study.

(the reported impacts and the ESI and AVISO), just as the correlation coefficients showed. Stable trends were detected for long-term series and trend components (4 months and longer).

To better understand the links among the parameters used in this study, we also calculated the correlations among all indicators (Table 4). The correlation analyses revealed the strongest correlation between indicators from the two models (SoilClim and AVISO), i.e., the relative soil saturation at a soil depth of 0 – 1.0 m and the current deficit of soil water in mm at a soil depth of 0 – 1.0 m ($r_d = 0.88$). The outputs of the SoilClim model, especially $AWR_{0-0.4}$ (the relative soil saturation in the topsoil layer), showed strong correlations with the SWI ($r_d = 0.74$). The next strongest correlation was detected between the ESI and the AVISO model ($r_d = 0.69$). On the other hand, the correlation between the SWI and the ESI was weak. Only in two cases was the correlation between the model or index and the data from reporters stronger than the correlation between the remaining parameters (models and indices). The output of the SoilClim model, $AWR_{0-0.4}$, showed the strongest correlation with SWC_{rep} (average $r = 0.8$), and the ESI showed the next strongest correlation with the reported impacts (average $r = 0.73$). In all other cases, the correlations were stronger between pairs of models or indices. This means that reporter data provide new information about drought development; in particular, data about drought impacts on yield from reporters showed weak correlations with the SoilClim model data.

3.3. Number of reporters

In the studied districts, the average number of reporters ranged from 2-3 reporters (districts with a low number of reporters) to 4–8 reporters

Table 3
Correlations between the estimated impacts on yield from reporters and the outputs of the SoilClim model ($AWR_{0–0.4}$, $AWR_{0–1.0}$, AWP), evaporative stress index (ESI), soil water index (SWI) and AVISO model in 2015–2018, with the average number of reporters in each district.

District	No. of reporters/ average	Reported impacts vs. AWR_0–40 r	AWR_0–100 r	AWP r	ESI r	SWI R	AVISO r
Benešov	2	−0.49***	−0.69***	−0.17	−0.66***	−0.44***	−0.82***
Brno venkov	3	−0.29**	−0.62***	−0.09	−0.66***	−0.29**	−0.71***
Břeclav	2	−0.21*	−0.5***	−0.13	−0.65***	−0.15	−0.58***
Hodonín	3	−0.19*	−0.33***	−0.12	−0.76***	−0.25**	−0.43***
Jičín	3	−0.42***	−0.61***	−0.37***	−0.72***	−0.19*	−0.64***
Litoměřice	2	−0.43***	−0.71***	−0.19	−0.70***	−0.44***	−0.74***
Louny	5	−0.30***	−0.61***	−0.21*	−0.73***	−0.40***	−0.66***
Mladá Boleslav	3	−0.68***	−0.72***	−0.55***	−0.69***	−0.65***	−0.87***
Nymburk	2	−0.54***	−0.71***	−0.39***	−0.77***	−0.41***	−0.84***
Písek	4	−0.52***	−0.68***	−0.25**	−0.76***	−0.44***	−0.89***
Plzeň sever	3	−0.49***	−0.64***	−0.27**	−0.79***	−0.56***	−0.76***
Přerov	2	−0.26**	−0.61***	−0.04	−0.68***	−0.05	−0.63***
Příbram	6	−0.44***	−0.52***	−0.16	−0.82***	−0.33***	−0.84***
Rakovník	6	−0.51***	−0.62***	−0.26*	−0.73***	−0.46***	−0.70***
Uherské Hradiště	3	−0.23*	−0.38***	−0.05	−0.70***	−0.27**	−0.52***
Znojmo	8	−0.34***	−0.65***	−0.2	−0.78***	−0.38***	−0.66***

* Significant at α= 0.05.
** significant at α=0.01.
*** significant at α=0.001.

(districts with an average or high number of reporters) (Table 2). The correlations between SWCrep and all studied indicators were 0.59, on average, in districts with 2-3 reporters. In districts with 4–8 reporters, the average correlation was 0.57 (between SWCrep and all model and index outputs). Similar results were obtained for the relationships between the reported impacts and all studied parameters. The average correlation coefficients were 0.49 for districts with 2-3 reporters and 0.53 for districts with 4–8 reporters. The correlation between SWCrep and the output of the SoilClim model, AWR0–0.4 (which was the highest detected correlation), changed gradually over time during 20-week periods. The correlation strengths declined, especially during the winter and spring months; the number of reporters in all districts was also lower during these periods (Fig. 6).

4. Discussion

The main goal of this study was to verify whether data about drought conditions collected by voluntary reporters could be considered objective and reliable information about drought occurrence that has the potential to be an integral part of drought monitoring. The principal finding of this study was that the data collected by reporters (specifically the estimated soil water content - SWC_{rep} and the estimated drought impacts on yield) were closely related to other independent and commonly used drought indicators. The SWC_{rep} values were highly correlated with outputs of the SoilClim model and the SWI. The reported impacts showed a lower correlation with the SoilClim model outputs but had significant correlations with the values of soil moisture estimated the AVISO model and the ESI.

Monitoring drought using various indices is currently common, and various methods and online tools for the public have previously been described and published (e.g., Zink et al. 2016, Trnka et al. 2020). The observation of drought impacts by voluntary reporters is still exceptionally unique at the international scale, and only a few systems around the world involve cooperation with reporters/volunteers. We assumed that there are two challenges involved in cooperating with reporters who work on a voluntary basis: i) keeping them active and ii) determining whether their work and observed data are reliable.

With regard to the first challenge, reporters (volunteers) often have differing motivations and interests, diverse technical capacities, and differing needs for regular communication and outreach; these factors hinder the sustained impact of reporting efforts (Lackstrom et al., 2013). One of the main motivations for the Czech reporters considered in this study was the long-term drought occurring at their locations. The effort required to initiate action and solve problems for the reporting system was high, mainly in the first years of the observations (2014 and 2015) and in southern Moravia and the central Czech Republic, where drought is clearly a long-term problem (Brazdil et al., 2007; Trnka et al., 2009). A noticeable increase in the number of reporters occurred after the significant and intensive drought in 2015 (Van Lanen et al., 2016; Trnka et al., 2020) which had negative impacts mainly in the agriculture sector (Bartosova et al., 2016). The average number of active reporters in the first half of 2015 was 36; in the second half of 2015, the number of active reporters increased to 53, and in 2016, the average number was 105. These trends confirm the experience of the Arizona Drought Watch (AzDW), where the intended users of AzDW were reluctant to report observations when they did not perceive drought impacts in their region (Meadow et al., 2013).

In developing a reliable and robust group of reporters, we greatly appreciate the support of the Agriculture Chamber of the Czech Republic (a nongovernmental organization), which provided us with contacts and organized a number of meetings and lectures with farmers and potential reporters. This cooperation with the chamber was a crucial point at the onset of the collaboration with the reporters. The number of reports from a given district depends, in the end, on the personal activity of each reporter; nevertheless, we did our best to remain in contact with the reporters (mainly through email correspondence and regular communication to keep them active). Building a system that is supported by experts substantially increases the probability that other drought impact observers will follow the lead of these experts and start to make routine contributions (Meadow et al., 2013). We expected that a higher number of reporters in a given district would also result in higher-quality information. However, the final correlations between the SWC_{rep} or reported impacts and the outputs of the SoilClim model and other indicators did not show any obvious dependence on the number of reporters. According to the correlations in the districts with a low number of reporters (2-3 reporters in each district; the average area of these districts is 1093 km^2) and in the districts with an average or high number of reporters (4–8 reporters in each district; the average area of these districts is 1259 km^2), it was not clear that a higher number of reporters resulted in higher correlations or that a low number of reporters resulted in specific and local information that was usable only for that cadastral area. The correlations between the SWC_{rep} and the

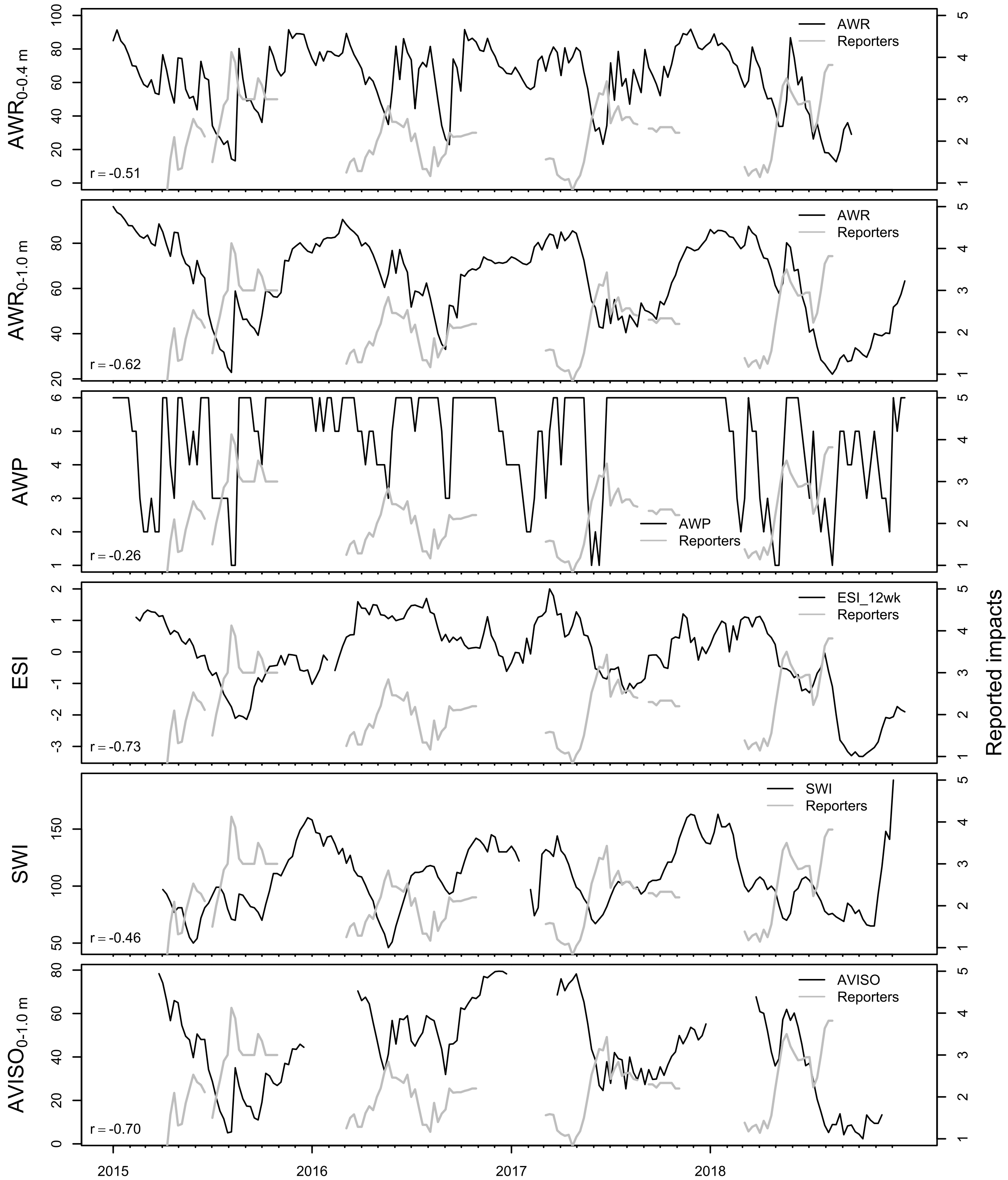

Fig. 5. Time series of reported drought impacts and simulations of the SoilClim model, relative soil saturation at a soil depth of 0.0–0.4 m ($AWR_{0-0.4}$), relative soil saturation at a soil depth of 0.0–1.0 m ($AWR_{0-1.0}$), and drought intensity at a soil depth of 0.0–0.4 m (AWP); soil water index (SWI) at a soil depth of 0 – 0.4 m; evaporative stress index (ESI); and AVISO model at a soil depth of 0 – 1.0 m in 2015–2018 in the representative district of Rakovnik.

SoilClim output ($AWR_{0-0.4}$) over 20-week periods varied with time in all studied districts (Fig. 6). The correlation strength declined specifically during winter and springtime, as did the number of reporters; the number of reporters increased during the entire observed period (2015–2018) but experienced localized declines in the winter. The lower correlations during winter may be due not only to the lower number of reporters but also to the difficulty in assessing the soil water content and to greater errors in the satellite data and model simulations during the

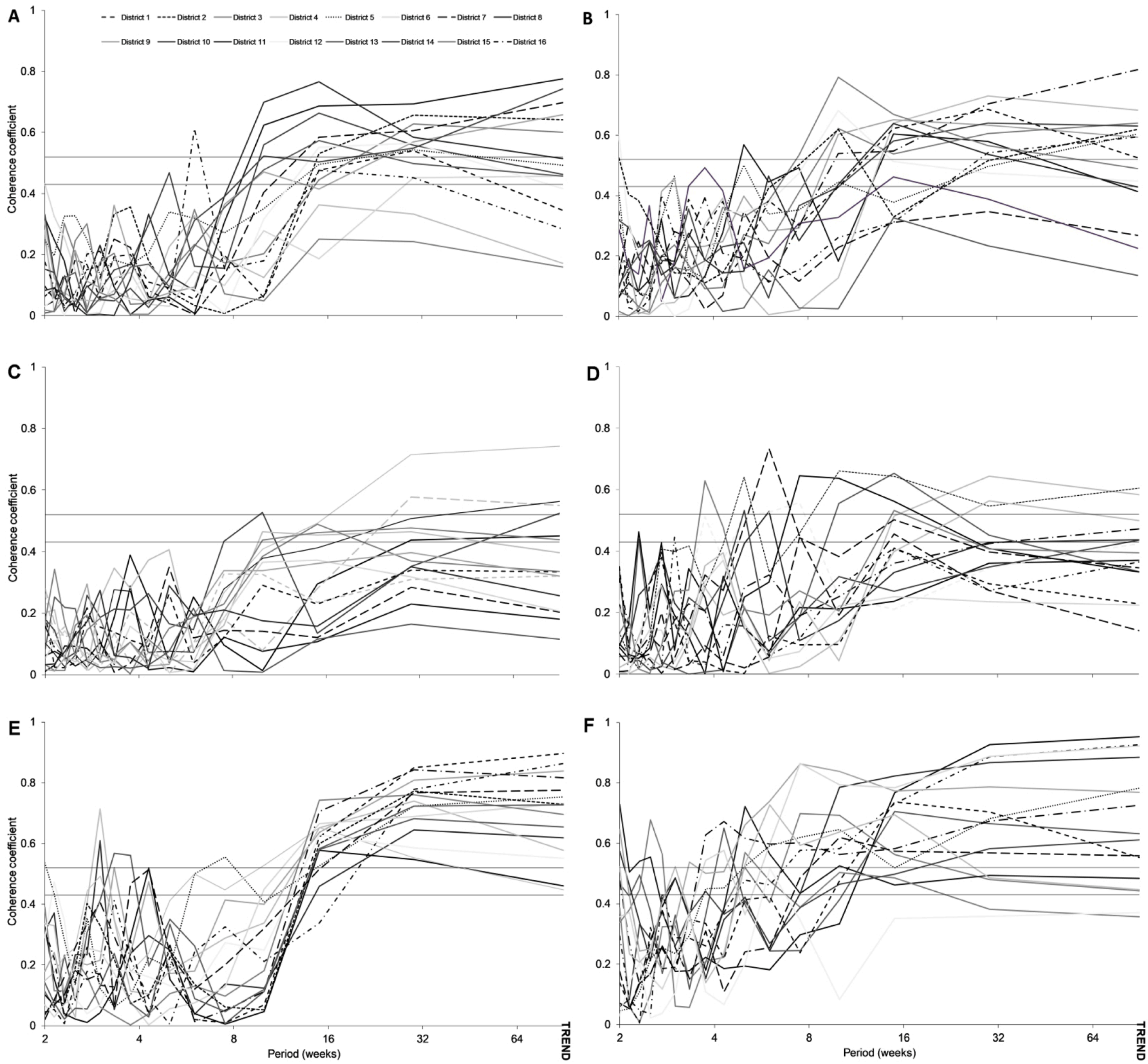

Fig. C. 1 Coherence analysis of drought impacts on yield observed by reporters with outputs of model SoilClim: relative soil saturation in topsoil layer and root zone layer: $AWR_{0–0.4}$ (A), $AWR_{0–1.0}$ (B) and drought intensity in top soil layer AWP (C). Coherence among reported imapcts with other parameters are displayed as following: D - Soil Water Index (SWI), E – Evaporative Stress Index - ESI, F – outputs of model AVISO. Black equal lines indicate 95% and 99% confidence levels. Different types of lines in each graph indicate data from all 16 districts used within this study.

winter months.

Currently, the CzechDM reporters provide data for three sectors: agriculture, fruit orchards and viticulture, and forestry. This study evaluated only data from reporters in the agriculture sector because these data are complete and do not have gaps. While the value of the impact data collected for agriculture has been clearly demonstrated (Lackstrom et al., 2013), there are also some attendant challenges and conflicts of interest that can complicate the interpretation of these data. For example, in the case of the USDM, there may be either direct or indirect financial benefits to those who may be impacted by drought in the form of mitigation funding, insurance payouts, or changes in revenue streams. On the other hand, other drought stakeholders might have political or economic disincentives for contributing critical information; there could also be reporters who are reluctant to report improving conditions because improvements could bring an end to federal aid (Lackstrom et al., 2013). Similar questions are faced by the CzechDM, and one of the motivations of this study was to evaluate the data from the reporters with independent methods, tools and models.

The SWC_{rep} data collected from the reporters showed the strongest correlation with the outputs of the SoilClim model; for $AWR_{0–0.4}$, the average correlation for all studied districts was 0.8, and for $AWR_{0–1.0}$ the average correlation for same group of districts was 0.7. While these values indicate that the reporter information was generally valid, they also mean that the information from reporters about soil water conditions did not provide new information to the CzechDM, as was hypothesized. However, the soil water content data collected by reporters are still one of the most useful data sources for independent validations of the SoilClim model.

Table 4
Correlation coefficient values for all parameters used in this study in all studied districts: outputs of the SoilClim model, relative soil saturation at a soil depth of 0 – 0.4 m ($AWR_{0–0.4}$), relative soil saturation at a soil depth of 0 – 1.0 m ($AWR_{0–1.0}$), and drought intensity at a soil depth of 0 – 0.4 m (AWP); soil water index (SWI), evaporative stress index (ESI) and AVISO outputs at a soil depth of 0 – 1.0 m.

	$AWR_{0–1.0}$/ AVISO	$AWR_{0–0.4}$/ $AWR_{0–1.0}$	$AWR_{0–0.4}$/ SWI	ESI/ AVISO	$AWR_{0–0.4}$/ AWP	$AWR_{0–0.4}$/ AVISO	$AWR_{0–1.0}$/ SWI	$AWR_{0–1.0}$/ESI	SWI/ AVISO	AWP/ SWI	AWP/ AVISO	$AWR_{0–1.0}$/ AWP	$AWR_{0–0.4}$/ ESI	ESI/ SWI	AWP/ ESI
District	r	r	R	r	R	r	r	r	r	r	r	r	r	r	r
Benešov	0.86***	0.8***	0.78***	0.75***	0.68***	0.63***	0.69***	0.56**	0.58***	0.43**	0.3*	0.37*	0.35*	0.3*	0.05
Brno venkov	0.91***	0.77***	0.74***	0.42**	0.6***	0.57***	0.58**	0.31	0.32**	0.35**	0.31**	0.34*	0	0.06	−0.18
Břeclav	0.89***	0.78***	0.77***	0.43**	0.59***	0.52**	0.63**	0.29	0.22**	0.36**	0.33**	0.36*	0.01	0.02	−0.05
Hodonín	0.91***	0.82***	0.76***	0.55**	0.52***	0.61***	0.62**	0.39*	0.31**	0.29*	0.31**	0.32	0.2	0.18	0.05
Jičín	0.96***	0.88***	0.85***	0.75***	0.73***	0.84***	0.76***	0.66***	0.69***	0.51**	0.65***	0.57**	0.52**	0.4**	0.38**
Litoměřice	0.93***	0.74***	0.78***	0.78***	0.73***	0.64***	0.66***	0.69***	0.54***	0.48**	0.53***	0.47**	0.36*	0.26*	0.31**
Louny	0.92***	0.65***	0.7***	0.73***	0.74***	0.54***	0.57**	0.69***	0.41**	0.45**	0.43**	0.37*	0.3*	0.21*	0.17
Mladá Boleslav	0.9***	0.84***	0.84***	0.84***	0.71***	0.77***	0.74***	0.71***	0.67***	0.47**	0.59***	0.5**	0.54**	0.43**	0.32**
Nymburk	0.93***	0.8***	0.81***	0.77***	0.68***	0.73***	0.69***	0.61***	0.61***	0.41**	0.51***	0.38*	0.35	0.25*	0.13
Písek	0.81***	0.74***	0.51**	0.84***	0.61***	0.53**	0.24**	0.44**	0.32**	0.39**	0.23	0.32*	0.25	0.23*	−0.02
Plzeň sever	0.9***	0.78***	0.7***	0.81***	0.66***	0.68***	0.56***	0.66***	0.54***	0.41**	0.4**	0.36*	0.46**	0.36**	0.19
Přerov	0.87***	0.8***	0.75***	0.73***	0.6***	0.7***	0.64***	0.48**	0.6***	0.3*	0.45**	0.39*	0.31	0.34*	0.22*
Příbram	0.54***	0.6***	0.69***	0.85***	0.66***	0.57***	0.39**	0.35**	0.45**	0.4**	0.22	0.17	0.33*	0.15	−0.01
Rakovník	0.87***	0.71***	0.67***	0.75***	0.68***	0.61***	0.45**	0.69***	0.44**	0.38**	0.33**	0.28*	0.44**	0.22*	0.11
Uherské Hradiště	0.94***	0.83***	0.76***	0.63***	0.55***	0.71***	0.65***	0.5***	0.46**	0.39**	0.29*	0.33**	0.25*	0.19	0.03
Znojmo	0.9***	0.76***	0.76***	0.43**	0.64***	0.53**	0.6***	0.31*	0.25**	0.4**	0.32**	0.36**	0	0.04	−0.1
Average	0.88	0.77	0.74	0.69	0.65	0.64	0.59	0.52	0.46	0.40	0.39	0.37	0.29	0.23	0.10

* Significant at α= 0.05.
** significant at α=0.01.
*** significant at α=0.001.

The reported impacts showed weaker correlations with the outputs of the SoilClim model than SWC_{rep} (the correlation values for the three SoilClim parameters were low). This confirmed our hypothesis that the drought impacts observed by reporters would provide new insights and new information. A good example of the importance of reported impacts occurred during 2018, when all the indicators of drought showed favorable conditions during spring (specifically in March, April and May). For example, $AWR_{0–0.4}$ and $AWR_{0–1.0}$ (the relative soil saturation in the topsoil and root zone layer) reached saturation values of 50 – 80% and 60 – 80%, respectively, which means that the soil moisture still provided a good or sufficient water supply for plants. Reporters, however, identified the cumulative impacts of drought beginning in early March, and predicted yield declines of up to 10%. The reported impacts either did not change or worsened, and the expected yield decline during April was 10–30%. Finally, the situation became serious in May, when most of the reporters observed moderate and sporadically severe drought impacts, and the expected yield decline increased to 30–40%. During that time, the SoilClim model (and other tools) also showed deterioration, but these signs were one or two months late compared to the reported impacts. During that spring, the information provided by reporters was sufficient to allow for subsequent planning and management interventions for farmers and revealed a better view of the whole drought process during the 2018 growing season, especially in the early spring. An explanation why this happened right in 2018 could be the fact that drought in 2017 was intensive; the winter of 2017/2018 was warm, with little precipitation; the river levels were low after the winter; and there was a significant soil moisture deficit starting in February 2018. Although the relative soil saturation (the AWR in the topsoil and root zone layer) was calculated by the SoilClim model to be sufficient, the soil was not sufficiently saturated with water, and the landscape was not ready for a new upcoming vegetation period; evidently, the reporters were aware of these conditions. Cumulative drought indices should describe the drought impacts observed by reporters more precisely. The following study will analyze the drought impacts on specific crops in given localities (at cadastre unit). The planned study will also use the cumulative indices (calculated by the SoilClim model) for better understanding the reporteŕs impacts.

The reported impacts were strongly correlated with the ESI, which has been found to be a leading indicator of developing and persistent water and/or vegetation stress during times of drought in other studies (Anderson et al., 2016a, 2016b). Based on actual ET components, including transpiration, ESI inherently captures signals of vegetation health and functioning. The results also showed the difference (low correlation) among ESI and SWI values, which is not surprising, because both indices describe drought from different perspectives. Generally, the SWI is derived from surface soil moisture and describes the soil moisture in specific soil depths, at the same time ESI describes the anomaly of the ratio between actual and reference evapotranspiration. As such, SWI points to the soil moisture at a given depth, while ESI results from the soil moisture across the entire root zone. The reported impacts were also strongly correlated with the AVISO model output, which describes the soil water content (in 0–1.0 m) in percent of available water capacity. Of the SoilClim model outputs, $AWR_{0–1.0}$ was most strongly correlated with the reported impacts. This result is expected since the moisture conditions in the root-zone layer (0–1.0 m) are more strongly correlated with vegetation conditions and observed drought impacts than those in the topsoil layer (0–0.4 m). The correlations between both models and impacts observed by reporters showed slightly different values of correlation coefficients, which was expected. Despite the short period (4 years) of analysis, the difference in correlation is not so significant and the success of each model is approximate. All results also showed there is no one best method for determining the drought, so the approach is based on the convergence of evidence of specific techniques. Combining various data sources has potential and integrating particular approaches for improved drought impact forecasting can evolve various pathways and at various stages in the drought information system. The methods to

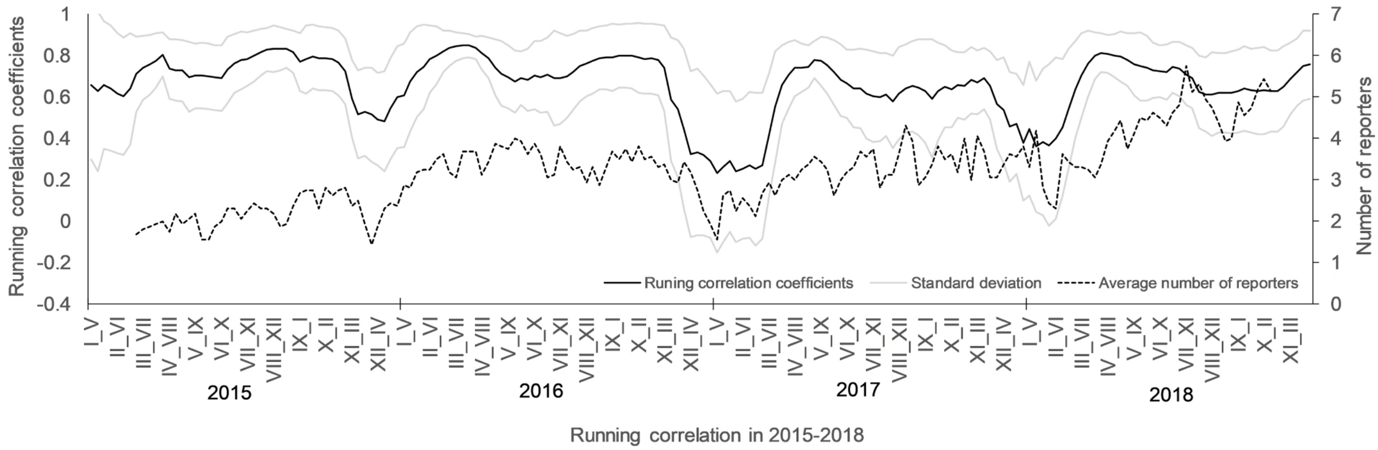

Fig. 6. Running correlation between the SWC_{rep} and the SoilClim model output, the relative soil saturation at a soil depth of 0 – 0.4 m ($AWR_{0–0.4}$) over 20-week periods in all studied districts. The black line indicates the average value of the running correlation; the gray lines indicate the standard deviations of the running correlations; and the dashed line indicates the average number of reporters in all studied districts.

do so can roughly be categorized into machine learning approaches and model-data integration techniques, which allows us to establish the most suitable drought impacts diagnostic or identify the key drivers of agricultural drought and their impacts on yield (Crocetti et al., 2020).

5. Conclusions

Drought monitoring practices that do not include drought impacts are not comprehensive. Systematic and quantitative information about the environmental and socioeconomic impacts of drought is often missing from drought planning and management (Stahl et al., 2016), and historical drought impacts have led to crucial progress in developing measures to reduce vulnerability to drought hazards (Knutson et al., 1998; Wilhite et al., 2000, 2007). Most empirical studies of drought impacts have focused on agricultural crop production, which is direct, immediately observable, well understood, and easy to quantify (Wilhite et al., 2000). The CzechDM is also aimed mainly at agricultural impacts; nevertheless, regular agricultural monitoring provides many benefits for drought management planning and negotiations with state agencies during ongoing drought events as well as for understanding the historical development of drought impacts. Our results showed that observations of drought impacts on plants and of the soil water content provided by reporters are valuable and necessary for drought monitoring. The drought impact data provided by voluntary reporters were validated, and they were the most strongly correlated with parameters describing the soil water content in the root zone layer (0 – 1.0 m). On the other hand, the soil water content as observed by reporters was most strongly correlated with soil water indicators for the topsoil layer (0 – 0.4 m). The validation results revealed a weaker correlation between the reported impacts and the SoilClim model (but high correlations with the independent indices and models) and strong correlations between the SWC_{rep} and the SoilClim model and other independent indicators of drought. These results confirmed that the data and observations from reporters are robust and objective and should be part of the Czech Drought Monitor system. We believe that drought impact observations from voluntary reporters provide new insights into drought development and, in certain years, could detect the start of a drought earlier or more accurately than other tools for drought monitoring.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices

A: Online questionnaire for reporters, accessible on website of CzechDM in Czech language in period 2014 - 2018. Since 2019 the drought impacts questions changed (first four questions remain the same), questionnaire became more detailed and included questions on individual crop. Questionnaire is online for reporters every week since Monday to Thursday (https://www.intersucho.cz/cz/dotaznik/).

1. What is the state of soil moisture in the layer 20 cm from the surface?

- soil is dry and dusty by touch, without possibility to make any form
- soil is drier by touch, it has loose structure; without moisture impact
- soil is moderately moist, it's possible to make a form but low consistence, it gives the feeling of moisture in fingers
- soil is moist with good workability and possibility to make a fingerprint
- soil is fully saturated by water it sticks to fingers – it's muddy
- cannot be evaluated

2. How do you evaluate last 3 months according to water balance?

- extremely dry – precipitation deficit/intensive drought with significant impacts
- very dry – precipitation deficit with detectable negative drought impacts
- process is rather drier without visible impacts
- normal state
- process is rather moister, without negative manifestations
- very moist – with detectable negative impacts
- extremely moist – precipitation surplus with negative impacts

3. How do you evaluate last week in comparison with previous week according to water balance?

- dramatic decline – with negative impacts for crops
- significant decline – with potentially negative impacts for crops
- decline – without negative impacts on crops

- without change
- improvement – without crucial moisture recharge in the soil profile
- significant improvements – with crucial moisture recharge of the soil profile
- dramatic improvements – with significant recharge of soil moisture storage

4. Does our drought intensity estimation from this map *(link to regional map of given district)* correspond with reality in your area of interest?

- it exactly describes the current situation
- it corresponds with the current situation pretty well
- it basically corresponds with the current situation
- it rather does not correspond with observed state
- it does not correspond, it's useless

5. Estimate drought impacts on winter cereals for the yield of 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10% *
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30% *
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40% *
- vegetation extremely damaged by drought, yield loss bigger than 40% *
- cannot be evaluated

* in comparison with the average of last 3 years; before harvest, it's the qualified estimation based on vegetation condition (e.g. amount and strength of offshoots). After harvest, answers reflected the observed yield decreased by the effect of drought. *(Note: same explanation is repeating in all remaining questions and within this supplement will not be repeated anymore).*

6. Estimate drought impacts on winter rape for the yield of 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

7. Estimate drought impacts on spring cereals for the yield of 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

8. Estimate drought impacts on sugar beet for the yield of 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

9. Estimate drought impacts on potatoes for the yield of 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

10. Estimate drought impacts on maize for the yield 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

11. Estimate drought impacts on permanent grasslands for the yield 2017

- no effect of drought; vegetation is optimal
- no effect of drought but vegetation is worse for other reasons
- drought effected development of vegetation but considerable losses are not expected, yield loss will be to 10%
- middle level of damage, considerable decrease of yield is expected, yield loss will be to 10–30%
- hard damage of vegetation, yield on 10-year minimum, yield loss will be to 30–40%
- vegetation extremely damaged by drought, yield loss bigger than 40%
- cannot be evaluated

B: Results of coherence analysis of soil water content observed by reporters (SWC_{rep}) with other drought parameters (models and indices).
C: Results of coherence analysis of drought impacts on yield observed by reporters with other drought parameters (models and indices).

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