REVIEW

Earth Observation for agricultural drought monitoring in the Pannonian Basin (southeastern Europe): current state and future directions

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Abstract

The Pannonian Basin in southeastern Europe is heavily used for rain-fed agriculture. The region experienced several droughts in the last years, causing major yield losses. Ongoing climate change, characterised by increasing temperatures and potential evapotranspiration, and by changes in precipitation distribution will likely increase the frequency and intensity of drought episodes in the future. Hence, ongoing monitoring of droughts and estimation of their impact on agriculture is necessary to adapt agricultural practices to changing weather and climate extremes. Several regional initiatives, projects and online tools have been established to facilitate drought monitoring and management in the Pannonian Basin. However, reliable systems to forecast potential drought impacts on plant productivity and agricultural yields at monthly to seasonal scales are only in their infancy, as plant response to climatic extremes is still poorly understood. With the increasing availability of high-resolution and long-term Earth Observation (EO) data and recent progress in machine learning and artificial intelligence, further improvements in drought monitoring and impact prediction capacities are expected. Here we review the current state of drought monitoring in the Pannonian Basin, identify EO-based variables to potentially improve regional drought impact monitoring and outline future perspectives for seasonal forecasts of drought impacts on agriculture.

Keywords Pannonian Basin · Earth Observation · Agricultural drought · Machine learning

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Introduction

Drought mechanisms

Droughts are complex phenomena that can have an enormous impact on the environment, economy and society. Droughts are usually driven by a lack of precipitation and/or increased atmospheric water demand, which causes a shortage of water for plant growth, river runoff, inland ship trafficking or other use of water resources (Wilhite and Glantz 1985). Depending on the duration, effects and intensity, drought can be classified into four types: meteorological, agricultural, hydrological and socio-economic drought (Fig. 1). The first three types deal with the physical phenomenon, while the last one is associated with the impacts of drought on society. All types of drought are closely related. Therefore, oftentimes, it is difficult to distinguish between the different types as there is no definition or measurement of when one type of drought transforms into another. A meteorological drought is typically indicated by a period of precipitation deficit over a region of interest. In combination with increased atmospheric evaporative demand, e.g. by high temperatures, high solar radiation and wind, soil moisture levels may drop and cause agricultural drought, which is reflected in decreased photosynthesis and transpiration and, hence, decreased plant productivity. Ongoing depletion of soil and groundwater reserves may eventually lead to a hydrological drought, which is characterised by a reduced amount of water in streams, lakes, wetlands, reservoirs and groundwater tables. If these conditions lead to a failure of water resource systems to meet water demands, it is called a socio-economic drought (Mishra and Singh 2010).

Droughts often co-occur with other extremes like heat waves (Mazdiyasni and AghaKouchak 2015; Zscheischler et al. 2018) or atmospheric aridity (high vapour pressure deficit) (Zhou et al. 2019), which intensify the drought. These compound droughts have negative impacts on plants (e.g. stomatal closure, increase of respiration, reduction of net

assimilation) and ecosystems (e.g. reduction of evapotranspiration, gross and net primary productivity), and self-intensify via various positive feedbacks (e.g. reduction of evaporative cooling and decrease of precipitation and cloudiness) (Katul et al. 2012; Sippel et al. 2018; Miralles et al. 2019). Droughts and heat waves can also trigger the occurrence of other disturbances such as wildfires and insect outbreaks and lead to other environmental, economic and societal impacts (Zscheischler et al. 2018; Forkel et al. 2019).

Monitoring drought

Drought monitoring refers to the continuous collection and analysis of drought indicators that assist decision-makers by providing information regarding the onset and development of droughts (Wilhite 2000). The first, small-scale drought monitoring systems were based on in situ measurements of environmental variables such as precipitation, temperature, discharge and groundwater level. These variables were either used directly or indirectly, i.e. in the form of anomalies from the climatological mean conditions.

Large-scale drought monitoring began with the introduction of more complex indices such as the Palmer Drought Severity Index (Palmer 1965), Self-Calibrating Palmer Drought Severity Index (Wells et al. 2004), Surface Water Supply Index (Shafer and Dezman 1982), Standardized Precipitation Index (SPI) (McKee et al. 1993), and Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2009). These indices typically ingest gridded terrestrial meteorological datasets. Some of these indices are widely used by regional and national meteorological and hydrological institutions to observe meteorological drought. However, they do not resolve local surface characteristics or provide information regarding drought effects on vegetation, since the actual soil moisture available for plant growth is only represented indirectly. Moreover, the quality

Fig. 1 Types of drought: meteorological, agricultural, hydrological and socio-economic drought with their major triggers and impacts
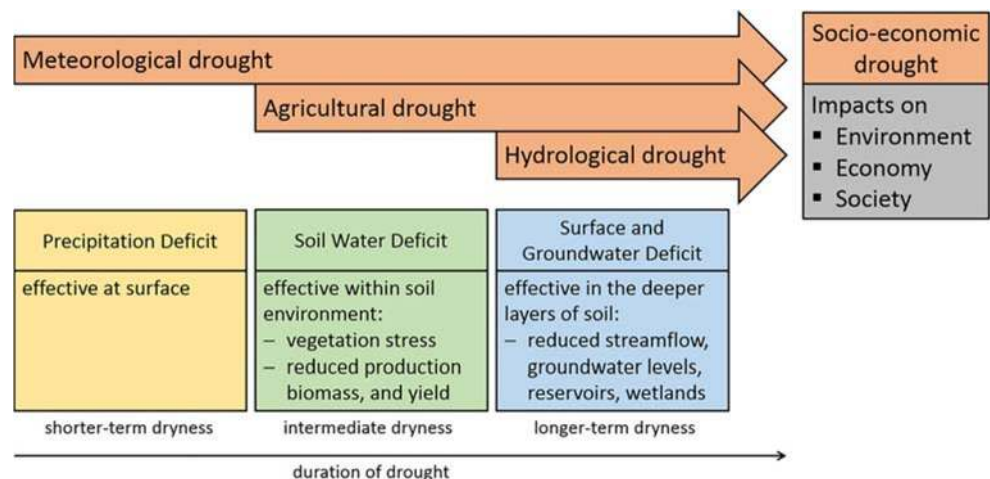
and spatial availability of the in situ measurements that are typically used to feed these indices strongly differ.

Advances in remote sensing technologies revolutionised the field of drought monitoring by enabling continuous observations of key drought-related variables over large spatial and temporal scales (West et al. 2019) (see the "Earth Observation–based drought monitoring" section). Remote sensing data have improved the ability to track drought, particularly in data-poor regions, by providing estimates of surface soil moisture, evapotranspiration or vegetation state (Anderson et al. 2007; Du et al. 2013; Enenkel et al. 2016). Several EO-based indicators have been incorporated into drought monitoring tools, serving policy and decision-makers with timely information on drought conditions.

One of the best-known drought monitoring systems is the US Drought Monitor (USDM),[1] which provides information about droughts in the USA since 1995 (Svoboda et al. 2002). The USDM has inspired several other regional drought monitoring systems, including the North American Drought Monitor[2] (Lawrimore et al. 2002) covering the USA, Canada and Mexico; the European Drought Observatory (EDO);[3] and the African Flood and Drought Monitor (Sheffield et al. 2013).

Additionally, global drought monitoring systems exist, including the Global Drought Observatory[4] developed by the EDO team, the Global Integrated Drought Monitoring and Prediction System by Hao et al. (2014) and the well-known SPEI Global Drought Monitor[5] (Vicente-Serrano et al. 2012). The temporal resolutions of available drought monitoring systems typically range from daily to monthly observations, while the spatial resolutions range from kilometres to hundreds of kilometres. The frequency and resolution of national systems are generally higher than those operated at continental or global scales.

The available drought monitoring systems diagnose droughts in a given area in various ways. For example, the German Drought Monitor (Zink et al. 2016) relies on a hydrological model driven by meteorological observations to estimate daily soil moisture fields, which are then transformed into a soil moisture index, on the basis of which several drought severity classes are defined. Others use standard meteorological drought indices. The USDM uses the convergence of evidence approach, which combines weather- and satellite-based information with expert knowledge on drought impacts and selected key indicators into a single map.

In this review, we aim to provide an overview, assessment and analysis of the main scientific challenges, knowledge gaps and scientific problems with respect to drought monitoring in

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[1] droughtmonitor.unl.edu
[2] www.drought.gov/nadm/
[3] edo.jrc.ec.europa.eu
[4] edo.jrc.ec.europa.eu/gdo/
[5] spei.csic.es/map/maps.html

the Pannonian Basin. The Pannonian Basin is a region in southeastern Europe in which agriculture plays a significant role for the national economies, e.g. for Hungary, Serbia, Bulgaria and Romania. However, it is expected that this region will be most negatively affected by droughts and heat waves in the future in terms of crop production (Olesen et al. 2011). Hence, drought monitoring is essential to adapt agricultural practices to changing weather and climate extremes.

The "Drought events and impacts in the Pannonian Basin" section covers a more detailed description of the Pannonian Basin (see the "Pannonian Basin" section), its recent drought events (see the "Recent drought events" section), and agricultural drought impacts (see the "Agricultural drought impacts" section). The "Drought monitoring efforts in the Pannonian Basin" section gives a brief overview of drought monitoring efforts in the Pannonian Basin. First, we present regional stakeholders and initiatives (see the "Regional stakeholders and initiatives" section) and then we present the established drought monitoring systems (see the "Established drought monitoring systems" section). In the "Earth Observation–based drought monitoring" section, we discuss the role of satellite-based variables in agricultural drought monitoring. Finally, in the "Future perspectives—towards integrated agricultural drought impact forecasting" section, we aim to provide future perspectives on how information from EO satellites can be used in combination with novel machine learning methods to forecast drought impacts on vegetation state and crop production.

Drought events and impacts in the Pannonian Basin

Pannonian Basin

The Pannonian Basin is a lowland area in southeastern Europe. It largely covers the centre of the Danube River Basin and is confined by the Alps in the west; the Bohemian-Moravian Highlands in the northwest; the Carpathians in the north, east and southeast; and by the Dinaric Alps in the southwest (Balázs et al. 2016) (Fig. 2). The Pannonian Basin has a warm-temperate climate (mean annual temperature: 10.5 °C) with warm summers and relatively cold winters and receives relatively low levels of precipitation (around 550 mm per year, the spatial variability is fairly homogenous, based on E-OBS v19.0e data (Cornes et al. 2018) for the period 1950–2018). Most precipitation falls from May to July, whereas January, February and March are the months with the least precipitation (Fig. 2). The Pannonian Basin is one of the largest agricultural regions in Europe, with cropland covering around 71% of the basin (Fig. 2).

The Pannonian Basin is being increasingly confronted with heat waves and droughts (Croitoru et al. 2016; Spinoni et al. 2017; Ceglar et al. 2018). The frequency and intensity of both
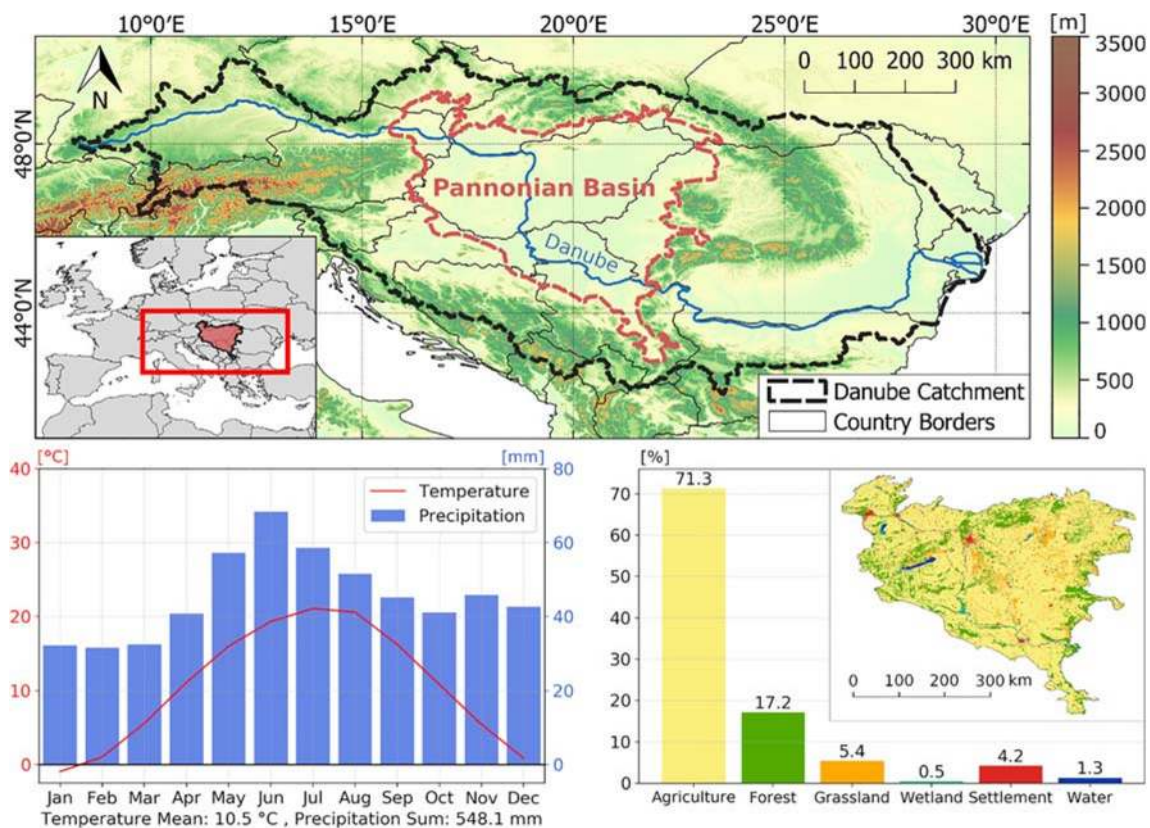
Fig. 2 Topography of the Danube Catchment and the Pannonian Basin. The boundaries of the Pannonian Basin are a combination of the definition of the biogeographical regions for Europe (2016) by the European Environment Agency (EEA 2016) and the definition of the European Environmental Stratification (Metzger 2018) (top). Climate of the Pannonian Basin for the period 1950–2018 based on E-OBS v19.0e data (Cornes et al. 2018) (bottom left). Percentage of land cover for the Pannonian Basin for the year 2015 based on the ESA CCI land cover map (version 2.0.7) (ESA 2017). The classes in the bar chart correspond to the Intergovernmental Panel on Climate Change (IPCC) land categories used for change detection (bottom right)

and their compound effects are expected to further increase due to climate change (Trnka et al. 2014, 2015; ICPDR 2015). Olesen et al. (2011) states that the Pannonian Basin is one of the regions that will be most severely affected in the future in terms of crop production, without possibilities for effectively shifting crop cultivation to other parts of the year. This is likely to have far-reaching impacts on agriculture, and thus on the regional economy.

Recent drought events

The Pannonian Basin and its surrounding area have suffered from multiple drought events of varying severity over the last decades (Fig. 3) (Spinoni et al. 2015; Ceglar et al. 2018). Examples are the frequent drought events that affected Hungary, Romania and Serbia during the period from 1983 to 1995 (Spinoni et al. 2013) and the long drought period in Romania between 2000 and 2003 (Kozak et al. 2011).

Spinoni et al. (2013) performed a detailed study of drought events that occurred between the years 1961 and 2010 in the Carpathian Region. They compared four drought indicators, where one is typically associated with meteorological

droughts and three are typically associated with agricultural droughts. Four drought events occurred in the 2000s, three events were detected in the 60s, and two in the 1970s, 1980s and 1990s. Of the 13 observed droughts, three were considered exceptional: in 1990, 2000 and 2003. The 1990 drought was intense, especially in February, March and autumn. It was the longest drought event that occurred in this region in recent history. The drought in 2000 hit the entire Pannonian Basin and was the most intense one. The main driver was the rainfall deficit, but also the temperatures in the second half of 2000 were higher than the normal values (Spinoni et al. 2013). The event was particularly severe in Romania, where it was responsible for economic losses of over 500 million dollars (EM-DAT, the International Disasters Database). The year 2003 was extremely dry over the entire Europe. The lack of summer precipitation and extremely high temperatures were the main drivers for this exceptional drought which affected many sectors and caused enormous damage in agriculture, especially in Central and Eastern Europe (Rebetez et al. 2006).

The most recent agricultural drought events occurred in 2012 (Fiala et al. 2014; Zahradníček et al. 2015), 2015 (Van Lanen et al. 2016) and 2017 (Štěpánek et al. 2018). The 2012

Fig. 3 Recent drought events in the Pannonian Basin. Years of exceptionally strong droughts are highlighted (top). Monthly precipitation/temperature based on E-OBS v19.0e data (Cornes et al. 2018) averaged over the Pannonian Basin for the exceptionally strong drought years in contrast to the mean precipitation/temperature over the years 1950–2018 (bottom)
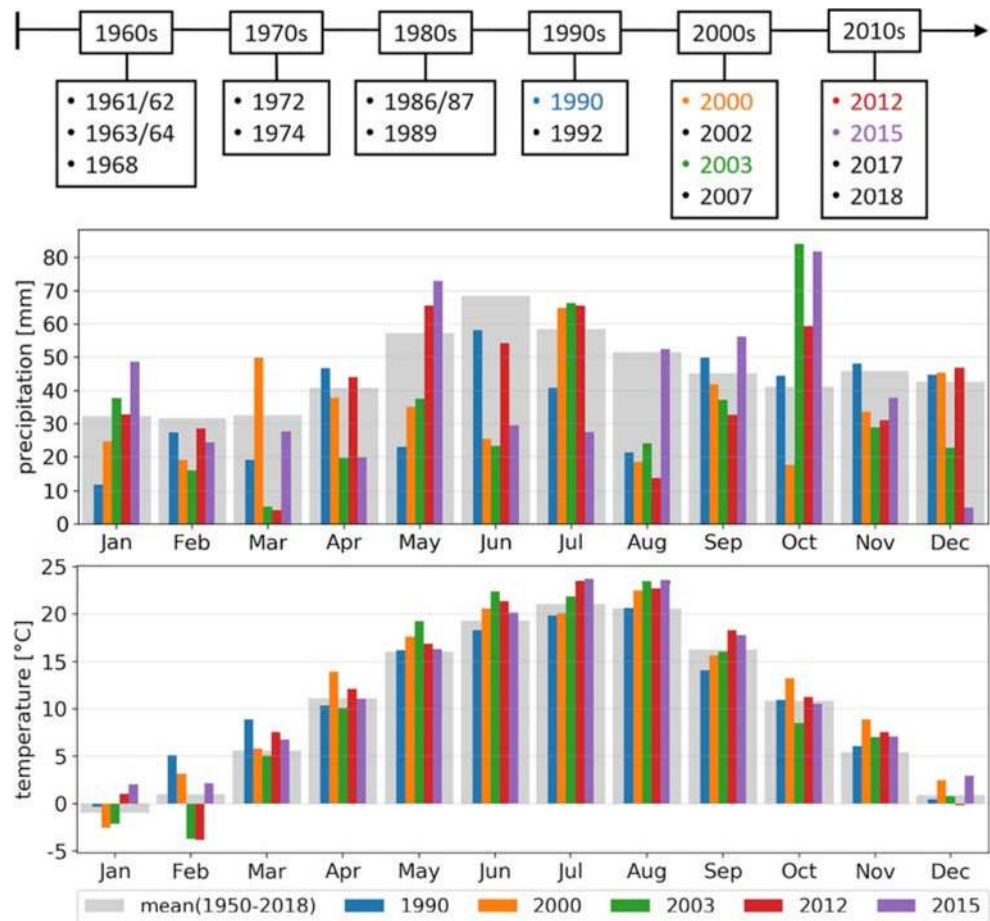
drought lasted from the beginning of June until the end of August (Govedarica et al. 2016). A lack of precipitation together with extremely high temperature in July and August were the main drivers of the severe drought. In 2015, a combination of rain shortages and very high temperatures led to major drought impacts across Austria, Bosnia and Herzegovina, Croatia, Czech Republic, Germany, Hungary, Moldova, Serbia, Slovakia, Slovenia and Ukraine (ICPDR 2015). The 2015 drought was severe particularly in Central and Eastern Europe (Van Lanen et al. 2016). In some regions, it was the driest (north of Slovakia) or second-driest (after the drought of 2003; Czech Republic and Poland) summer of the last 50 years. Severe droughts also affected most of the basins in 2017 and the northwest in 2018 (EDO 2018).

Agricultural drought impacts

According to the official agricultural yield statistics from Hungary, Romania, Slovakia and Serbia, in the years 2000, 2002, 2003, 2007 and 2012, droughts caused a loss in yield of 1 to 1.5 t/ha and 3 t/ha for wheat and maize, respectively, compared to the average yield of 2000–2015 (Nagy et al. 2018). This equates a yield loss of about 25–37.5% for winter wheat and over 40% for maize. According to Fiala et al.

(2014), maize is considered the most drought-sensitive crop cultivated in the Pannonian region, displaying a significant decrease of yield in dry years. The most significant drought-related decrease of maize yield in recent years was recorded in 2012, particularly in Hungary. In this year, maize yield was reduced by over 50% in the Csongrád county, while in the Bács-Kiskun county, it decreased by 44% compared to the average yield of the period 2000–2012 (based on data of the Hungarian Central Statistical Office). A similar situation occurred in Serbia with a 50% decrease of maize yield, a 40% decrease of potato yield and a 25% decrease of sugar beet yield in comparison to the average yield from 2004 to 2018 (based on data of the Statistical Office of the Republic of Serbia). Vegetation stress caused by the drought in 2015 led to lower crop yields in many countries in Central and Eastern Europe. Crop losses of sugar beet and potatoes up to 50% were reported in the Czech Republic and Slovakia. A significant impact was also recorded on livestock farming because of lower hay harvest (loss about 50% in the Czech Republic) and failing grass cuts (Slovakia), which led to substantial lower milk production in Slovakia and Romania (Van Lanen et al. 2016).

Jakubínský et al. (2019) created a comprehensive drought impact database for the Danube river catchment for the period

Fig. 4 Number of reported drought impacts on agriculture (AGR), forestry (FOR), soil system (SOI), water resources (HYD) and impacts in the form of wildfires (WFR) for each year for all the available NUTS3 regions being part of the Pannonian Basin. The data were obtained from the drought impact database by Jakubínský et al. (2019)
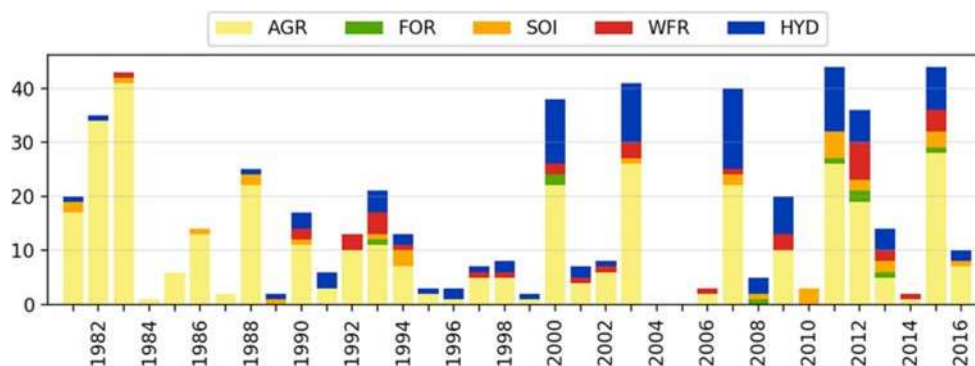
1981–2016 based on assessments of local newspapers and journal articles that reported drought impacts by regional drought experts. The individual drought impact reports were classified into five categories, depending on the sector in which the impacts of the drought episode were the most apparent: agriculture, forestry, soil system, wildfires and hydrology. In case of drought reports occurring in multiple categories over the same region and period, only one drought event is listed in the category of its highest impact. Whenever possible, the spatial distribution of the phenomena was categorised in Nomenclature of Units for Territorial Statistics level 3 (NUTS3) regions of the Member States of the European Union. In non-EU countries, national divisions were used with the area of each region roughly equivalent to the size of NUTS3 regions. Impacts affecting more than one NUTS3 region were counted separately for each region (Jakubínský et al. 2019).

Although the quality of the drought impact database is influenced by several factors, e.g. the different human perception of a drought event in different countries and inhomogeneous data sources, to date, this is the most complete and accurate database of reported drought events in the region.

The number of reported drought impacts from the drought impact database by Jakubínský et al. (2019) for the period from 1981 to 2016 is shown in Fig. 4. The drought impacts were summed up for all the NUTS3 regions being part of the Pannonian Basin where the data was available at the NUTS3 level (i.e. Croatia, Czech Republic, Hungary, Romania, Slovakia, Slovenia). It can be seen that there were numerous agricultural drought impacts in the years 1982, 1983, 1988, 2000, 2003, 2007, 2011, 2012 and 2015. Here, it must be mentioned that the high number of agricultural impacts (26) and hydrological impacts (12) in the year 2011 are mainly reported by Croatia (23 agricultural impacts and 8 hydrological impacts), (see Cindrić et al. (2016) for more details about the 2011 drought). However, since only a small part of Croatia belongs to the Pannonian Basin, literature investigating the Pannonian Basin often does not list this year as an extraordinary drought year.

Drought monitoring efforts in the Pannonian Basin

Regional stakeholders and initiatives

Several cooperative initiatives have been established to manage drought-related risks in the Pannonian Basin. The Drought Management Centre for South Eastern Europe (DMCSEE)[6] was established in 2006 by the hydrometeorological services of 14 countries in cooperation with the United Nations Convention to Combat Desertification and the World Meteorological Organisation (WMO). The mission of the DMCSEE is to coordinate and facilitate the development, assessment and application of drought risk management tools and policies in southeastern Europe with the goal of improving drought preparedness and reducing drought impacts. The Centre provides information on the drought situation in the region through monthly drought bulletins that are based on numerical weather prediction model simulations, SPI index calculations and remote sensing data.

The Integrated Drought Management Programme for Central and Eastern Europe (IDMP CEE) was launched by the WMO and the Global Water Partnership in February 2013. In Central and Eastern Europe, the programme involves more than 40 organisations representing ten countries, nine of which are from the Danube region. The IDMP CEE provides monitoring and early warning for droughts, assessments of vulnerabilities and drought impacts, and strategies for drought mitigation and preparedness (IDMP 2018).

The Pannonian Basin Experiment (PannEx), which is part of the Global Energy and Water Exchanges activity (Ceglar et al. 2018), reconciles user needs and state-of-the-art scientific knowledge in order to identify gaps in our hydro-climatological knowledge of the region. The main research priorities address current challenges in agriculture, air quality, sustainable development, water management and education (Ceglar et al. 2018). The European Space Agency (ESA) contributes to PannEx with its EO programme by initiating a

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[6] www.dmcsee.org

regional initiative for the Black Sea and Danube region. One of the priorities of this initiative is EO-based environmental monitoring, including drought characterisation for the Danube Basin.

Established drought monitoring systems

A regional high-resolution evidence-based monitoring and early warning system called Drought Watch[7] was recently developed for the Pannonian Basin (Bucur et al. 2018). This system includes remotely sensed drought indicators of soil moisture and vegetation conditions. National reporting networks, consisting of farmers and other agricultural experts, have been set up to compile weekly drought impact maps. These maps provide information on how drought influences expected crop yield or forest growth at a specific location.

One of the most advanced drought monitoring systems for the region is the drought monitoring system for the Czech Republic and Slovakia called InterSucho,[8] which is based on several independent approaches (Trnka et al. 2020). The system simulates the soil water balance with the SoilClim model (Hlavinka et al. 2011; Štěpánek et al. 2018) and covers the entire area of the Czech Republic and Slovakia with a spatial resolution of 500 m. In addition, InterSucho reports soil moisture, evaporation and vegetation conditions from satellite observations for Central Europe and provides information on drought impacts. Moreover, the system provides a drought forecast based on numerical weather prediction for the upcoming 9 days and a weekly drought outlook for the upcoming 2 months based on statistical likelihood of drought with respect to the current state and typical weather pattern.

Earth Observation–based drought monitoring

The following subchapters are not restricted to the Pannonian Basin only but apply worldwide for agricultural drought monitoring.

Satellite-based variables and their use in drought monitoring

Many state-of-the-art drought monitoring systems (see the "Drought mechanisms" and "Established drought monitoring systems" sections) make use of satellite-based indicators, with demonstrable improvements in drought monitoring capabilities. Satellites can detect variables of meteorological drought such as precipitation and land surface temperature, of

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7 droughtwatch.eu
8 intersucho.cz

agricultural drought such as soil moisture, vegetation state, land surface temperature and evapotranspiration, and of hydrological drought such lake extent, lake and river levels and terrestrial water storage (AghaKouchak et al. 2015; Zhang et al. 2016; West et al. 2019).

The most important EO technologies for agricultural drought monitoring, including frequently used satellite systems, derived surface variables and their advantages and limitation are listed in Table 1. In the following subchapters, we will give an overview of the key EO observables for agricultural drought monitoring, explain why they are important for agricultural drought monitoring, how they can be measured via remote sensing and how they are used in drought monitoring.

Often these variables are not used directly. Instead, anomalies are derived from the variables as drought indicators or they serve as input for drought indices. It must be noted that in literature, often there is no distinction between the terms "drought indicator" and "drought indices" and both terms are used interchangeably. In this work, the term "drought indicator" is used when referring to a physical characteristic of a specific variable (e.g. soil moisture anomalies), while the term "drought index" is used when referring to a numerical representation of a drought's severity or magnitude (e.g. Soil Water Deficit Index (SWDI) (Martínez-Fernández et al. 2015)).

Soil moisture

Reliable, accurate and timely information about the actual and historic water content of soils is crucial to establishing an effective drought monitoring and prediction system. Soil moisture (SM) anomalies are a good indicator to detect agricultural drought events and several drought indices use SM as their input (Sridhar et al. 2008; Martínez-Fernández et al. 2015; Sohrabi et al. 2015; Sánchez et al. 2016; Carrão et al. 2016; Yang et al. 2017; Xu et al. 2018).

Based on the wavelength of the observed electromagnetic radiation, three different general approaches for retrieving SM from satellite data exist: optical, thermal infrared and microwave remote sensing. Optical and thermal infrared remote sensing methods have some limitations concerning the retrieval of soil moisture, e.g. due to the limited penetration of sunlight through the vegetation canopy or variation across time and land cover types due to a strong dependence on local meteorological conditions (e.g. high cloud cover). The most effective technique for space-borne SM estimation is microwave remote sensing (Wardlow et al. 2012). Several operational global products are generated from active as well as passive microwave data. Operational satellite SM products are derived from the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al. 2010), the Soil Moisture Ocean Salinity (SMOS) mission (Kerr et al. 2010), the Advanced Scatterometer (ASCAT) (Bartalis et al. 2007), or the

Table 1 Summary of EO technologies and derived variables used for agricultural drought monitoring

Remote sensing technology (wavelength)	Land surface variables	Satellite systems (examples)	Advantages	Limitations	Application in the Pannonian Basin and surrounding areas
Visible and near to shortwave infrared remote sensing (400–2500 nm)	Vegetation indices (e.g. NDVI) Crop types Leaf and canopy biophysical properties (e.g. LAI, FAPAR) or biochemical properties (e.g. chlorophyll, water, nitrogen content) Estimation of GPP, NPP	High resolution (< 30 m): Landsat-8 OLI Sentinel-2 MSI Medium resolution (>250 m): AVHRR MODIS Sentinel-3 OLCI	High spatial resolution Close relation with vegetation Well-developed understanding of measurement principles Large number of spectral bands High revisit time Large spatial coverage Long time series	Low revisit times Short time series Low spatial resolution	(Immizer et al. 2016; Heidler and Fietzke 2019) (Govedarica et al. 2016; Nagy et al. 2018; Kern et al. 2018; Albergel et al. 2019)
Thermal infrared remote sensing (5.6–14 μm)	Land surface temperature Evapotranspiration Soil moisture	Landsat-8 TIRS MODIS Sentinel-3 SLSTR	Physical relations with energy balance, plant stress, soil moisture	Low spatial resolution	(Anderson et al. 2016; Cammalleri et al. 2017)
Passive microwave remote sensing (1 mm–1 m)	Soil moisture Vegetation optical depth, vegetation water content, biomass	AMSR2 SMOS SMAP	Long time series High revisit times Physical relations with soil moisture	Very low spatial resolution Weak understanding of vegetation signals	(Owe et al. 2001; Cammalleri et al. 2017; Moesinger et al. 2019a)
Active microwave remote sensing (0.75 cm–1 m)	Soil moisture Vegetation optical depth Vegetation water content, biomass	Scatterometers: ASCAT Synthetic aperture radars: Sentinel-1	High revisit times Physical relations with soil moisture	Very low spatial resolution Weak understanding of vegetation signals Complex data processing	(Bartalis et al. 2007; Vreugdenhil et al. 2016; Pfeil et al. 2020) (Bauer-Marschallinger et al. 2018; Vreugdenhil et al. 2018)

Advanced Microwave Scanning Radiometer 2 (AMSR2) (Jackson et al. 2010), as well as the ESA Climate Change Initiative (CCI) and Copernicus Climate Change Service (C3S) SM products (Gruber et al. 2017, 2019; Dorigo et al. 2017). However, these products have a spatial resolution that is rather coarse (9–40 km), which limits their usability for small-scale drought monitoring. However, novel methods to downscale the existing SM estimates to finer resolutions make them increasingly interesting for regional drought monitoring, e.g. in the Pannonian Basin. The SCATSAR Soil Water Index (SWI) product distributed through the Copernicus Global Land Service (CGLS) is one example combining high-resolution Sentinel-1 data with long-term but coarse resolution ASCAT data to provide estimates of the soil water content at an unprecedented combination of spatial (1 km) and temporal (1 day) resolution (Bauer-Marschallinger et al. 2018).

Satellite SM products have great potential for agricultural drought monitoring. Cammalleri et al. (2017) found that remote sensing datasets are particularly suitable for drought monitoring, especially, over dry areas and sparsely monitored areas. In the studies by Martínez-Fernández et al. (2016, 2017), data from the SMOS and the CCI SM product were used to derive the SWDI, while Mishra et al. (2017) and Zhu et al. (2019) used SMAP data to derive the SWDI.

Vegetation state

In most cases, agricultural drought affects vegetation in terms of decreased production, increased plant mortality, poor vegetation health and lower yields. Vegetation variables and vegetation indices (spectral transformations of two or more bands designed to enhance the vegetation signal) (Huete et al. 2002) obtained via remote sensing can be valuable for identifying plant stress due to drought and can be used in crop management to maximise production (Dorigo et al. 2007). Seasonal integrals of vegetation indicators are good proxies for the total Gross Primary Productivity (GPP) or Net Primary Productivity (NPP) that together with a harvest index can be related to the potential yield (Johnson 2016; He et al. 2018) and are, therefore, important measures for yield estimation.

Traditionally, remote sensing of vegetation state measures electromagnetic wave reflectance information from canopies in the wavelength range between 400 and 2500 nm (Xue and Su 2017). The reflectance in these bands provides information among others on greenness, relative density, chlorophyll content, leaf water content and health of vegetation. Well-known vegetation variables that can be derived from these observations are the fraction of absorbed photosynthetically active radiation (fAPAR), Leaf Area Index (LAI) and Gross Primary Productivity (GPP), while examples of vegetation indices are the Normalized Difference Vegetation Index (NDVI) (Tucker 1979) or the two-band Enhanced Vegetation Index (EVI2) (Jiang et al. 2008). Newer

approaches of vegetation remote sensing make use of high spectral-resolution observations in the red/near-infrared domain to derive Sun-Induced chlorophyll Fluorescence (SIF) or of space-borne microwave observations to derive Vegetation Optical Depth (VOD). SIF is a measure for photosynthetic activity that provides an estimate for the amount of carbon that is taken up by plants based on the re-emission of sunlight (Mohammed et al. 2019). VOD is an indicator for vegetation density, biomass and water content (Konings et al. 2019) and is also related to GPP (Teubner et al. 2019).

All these variables and indices have already been used for drought monitoring and to identify losses in the agricultural sector. A study by Nagy et al. (2018) tested MODIS NDVI for estimating wheat and maize yield losses affected by drought in the Tisza river catchment. Rossi et al. (2008) showed that fAPAR is able to capture droughts by evaluating its performance by correlating fAPAR anomalies with the anomalies of independent other drought indicators, i.e. the SPI, soil moisture anomalies and surface temperature anomalies. Chen et al. (2019) explored the potential of satellite-borne SIF in drought detection and crop production assessment and demonstrated that SIF is reliable for drought monitoring.

Land surface temperature

Land surface temperature (LST) is a fundamental parameter in the physics of surface energy and water balance. It serves as proxy for assessing evapotranspiration, vegetation water stress, soil moisture and thermal inertia (Karnieli et al. 2010). LST is derived from thermal infrared or microwave satellite observations (Holmes et al. 2015), where thermal radiance from the land surface is converted to a radiometric temperature associated with the Earth's skin (Hulley et al. 2019). Since high LSTs can be associated with moisture deficit in soil and vegetation, LST is recognised as a drought indicator either on its own or in combination with a vegetation indicator like NDVI (Kogan 1995, 2000; Orhan et al. 2014).

LST and NDVI are typically strongly negatively correlated (Goward et al. 1985; Hope and McDowell 1992). Many studies make use of this relationship with respect to drought monitoring (Karnieli et al. 2010). McVicar and Bierwirth (2001) assessed drought by computing the ratio of LST and NDVI. A study by Hu et al. (2019) computed the vegetation temperature condition index for agricultural drought monitoring, based on LST and radiance products of Sentinel-3A SLSTR (sea and land surface temperature radiometer).

Evapotranspiration

Evapotranspiration (ET) is a key variable of the landscape water balance. It describes the exchange of water between the land surface including plants and the atmosphere and is,

therefore, a measure of water loss. The controls on ET include temperature, radiation, wind speed and relative humidity (McVicar et al. 2012; Seneviratne 2012). All these drivers affect the conductance of stomata, canopy and the surface and are represented in physical-based evapotranspiration models such as the Penman-Monteith formulation (Allen et al. 1998). ET can be used to describe the water availability, but also the water consumption rate of plants and is, therefore, a viable indicator of vegetation health and a useful variable for drought monitoring (Zhang et al. 2019).

ET can be modelled or estimated indirectly through satellite remote sensing (Zhang et al. 2016). Examples of the latter are the MODIS Global Terrestrial Evapotranspiration Product (Mu et al. 2013) and the Global Land Evaporation Amsterdam Model (GLEAM) (Miralles et al. 2011, 2014; Martens et al. 2017). GLEAM uses a set of algorithms to estimate the different components of evaporation from remotely sensed input variables (e.g. precipitation, radiance, vegetation optical depth). Other EO methods for determining ET are generally either based on an empirical relationship between ET, crop coefficient (or surface resistance) and some vegetation metric or use an energy balance approach (Anderson et al. 1997; Allen et al. 2011). As an example of the latter, the Atmosphere-Land Exchange Inverse (ALEXI) model (Anderson et al. 1997, 2007) combines the two-source energy balance method, where the fluxes from soil and vegetation are treated separately (Norman et al. 1995), with a simple atmospheric boundary layer model. This diagnostic model is based on satellite retrievals of LST combined with additional data of meteorological conditions including solar radiation and information about the surface properties such as LAI or canopy height. The basic principle of the ALEXI model is to quantify how much water loss is required to keep the soil and vegetation at the observed temperatures under given known radiative energy inputs.

Several drought indices use ET as input (Mu et al. 2012; Kim and Rhee 2016; Hobbins et al. 2016; Zhang et al. 2019). One example is the Evaporative Stress Index (ESI) (Anderson et al. 2011, 2013), which is based on ALEXI. The ESI represents the ratio of actual to reference ET standardised anomaly and is available with a weekly temporal resolution in the form of two composites with 0.05° spatial resolution: a 4-week composite with the ability to capture flash drought events and a 12-week composite with a potential to indicate agricultural as well as hydrological drought. The ESI is routinely used in the InterSucho portal alongside the SWI to assess water stress across Central Europe. Anderson et al. (2016) investigated the relationship between ESI and winter wheat and spring barley yields in the Czech Republic. Drought years characteristic of large yield losses were captured by negative anomalies in the ESI.

Comparison of drought indicators and drought indices over the Pannonian Basin

Several commonly used remote sensing–based drought indicators and drought indices for the Pannonian Basin are shown in Figs. 5 and 6. Several studies showed that these indicators and indices can be used for agricultural drought monitoring and yield prediction (Anderson et al. 2016; Mathieu and Aires 2018a, b; Chaparro et al. 2018; Nagy et al. 2018; Chen et al. 2019). The temporal variability is visualised with Hovmöller diagrams. Water-related drought indicators/indices are shown in Fig. 5: SPEI is based on precipitation and temperature data and can be computed at different time scales. The ESI can detect water stress based on ET, while the SWI provides an estimate of the moisture content in the soil profile.

Vegetation-based drought indicators such as NDVI, VOD and SIF anomalies are shown in Fig. 6.

Comparing the patterns in these two plots, we see strong correspondence between soil moisture and vegetation indicators/indices as well as the drought events discussed in the "Recent drought events" section and drought impacts discussed in the "Agricultural drought impacts" section. The right-hand column in Figs. 5 and 6 depict the spatial distribution of indicators/indices associated with a severe drought event during September 2012. When comparing the maps of Figs. 5 and 6, it is obvious that the negative anomalies of water-related drought indicators/indices correlate with the negative anomalies of vegetation-based drought indicators.

Future perspectives—towards integrated agricultural drought impact forecasting

A key interest of the agricultural sector is to receive information on how drought impacts soil moisture conditions, plant productivity, biomass production and hence agricultural yields. Such information will potentially help to adapt irrigation and land management strategies and hence to mitigate drought impacts, not only in the Pannonian Basin but also worldwide. As discussed in the "Earth Observation–based drought monitoring" section, satellite-based variables are increasingly used for drought monitoring and yield impact prediction due to their advantage of being globally available. More and more studies using new machine learning methods to predict yields and drought impacts are being carried out, but they are still in their infancy.

Complementarity of information sources

Due to the increasing availability of sophisticated, operational EO data, meteorological forecasts and (agro-)ecosystem model improvements, significant progress has been made towards the assessment of drought impacts on agro-ecosystem functioning and yield forecasting. However, the combination of these data sources remains nearly untouched, despite their complementary potential. The new fleet of Sentinel and commercial EO satellites provides systematic updates on soil moisture and vegetation conditions every few days at high spatial resolutions down to a few meters. Meanwhile, new long-term climate data records provide a systematic and consistent baseline of past land surface conditions over the last 40 years but at lower spatial resolutions (Dorigo et al. 2017). These new products are complemented with new observables of ecosystem functioning, e.g. SIF, GPP or vegetation water content (Sun et al. 2018; Moesinger et al. 2019a; Teubner et al. 2019).

Seasonal meteorological forecasts have improved and are able to provide skilful estimates of the key drivers of drought up to several months ahead (Johnson et al. 2019), which in turn can be used to compute classical drought indices like SPI or SPEI, or to drive land surface models that simulate soil moisture anomalies and vegetation impacts.

Despite their lower actual spatial resolution than current EO data (e.g. because of the absence of forcing and ancillary data at these scales), process-based (agro-)ecosystem models allow for a better mechanistic understanding of the impact of droughts on crop development and provide seamless estimates in space and time. Hence, they can be used in predictive mode by including seasonal forecasts of meteorological variables.
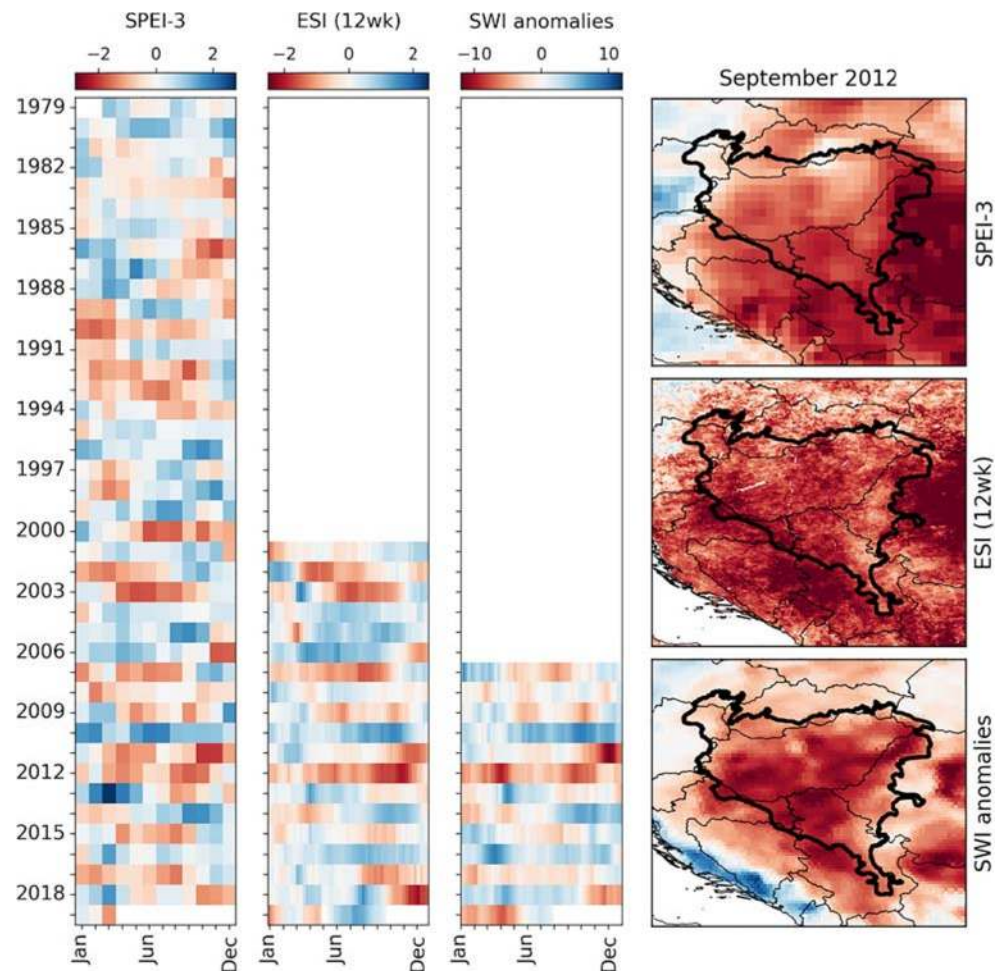
Integrating multiple data streams

Integrating the various data sources and approaches for improved drought impact forecasting can evolve along various pathways and at various stages in the drought information system. The approaches to do so can roughly be categorised into machine learning approaches and model-data integration techniques (Fig. 7).

Machine Learning (ML) can be used to:

- *Establish the most suitable drought impact diagnostic*: ML allows identifying the observable diagnostics that are most sensitive to climate anomalies and indicative for yield anomalies. These diagnostics can then be targeted for by drought (impact) forecast models.
- *Identify the key drivers of agricultural drought and their impacts on yield*: ML is able to simultaneously assess the importance of multiple, co-varying drivers. Actually, thousands of features can be ingested simultaneously in ML models (Papagiannopoulou et al. 2017) or emergent features can be obtained from deep learning models (Reichstein et al. 2019).
- *Predict drought diagnostics*: Based on current and past observed states, e.g. of soil moisture, precipitation, or vegetation conditions and their cumulative memory effects, ML can be used to predict future states of these variables.

Fig. 5 Temporal variability of three drought indicators/indices averaged over the Pannonian Basin: SPEI-3 computed at the time scale of 3 months from the ERA5 reanalysis; the 12-week composite of ESI; and the SWI anomalies (T value = 40) based on the 0.1° product distributed through the CGLS. The right-hand side shows the spatial distribution of these variables for a drought in September 2012 throughout the Pannonian Basin. The colours of the maps are equivalent to the colours of the corresponding Hovmöller diagram


These predicted states can then be used alone or in combination with process-based forecasts to drive process-based crop and yield models.

Integration of EO with land surface models can be used to combine multiple data streams, e.g. by:

- *Benchmarking model physics*: The emergent relationships between meteorological drivers, droughts and drought impacts identified by ML from the observational data cubes may be insufficiently accounted for by the land surface and vegetation models used for prediction. Hence, observation-based relationships provide a unique opportunity to identify and improve the model processes (Forkel et al. 2019).

- *Calibrating model parameters*: Constraining land surface model states like soil moisture by observed values allows to optimise model parameters, e.g. those controlling the response of evapotranspiration and photosynthesis to drought. Particularly the increasing availability of novel EO data sets allows initial calibration of global land surface models to local and regional conditions (Drüke et al.

2019). A proper model calibration should assess the change in performance of the agro-ecosystem model, in particular with respect to extreme events (droughts) (Huang et al. 2019). In addition, novel climate ensembles allow estimating probabilities and recurrence times of drought impacts on ecosystems (Sippel et al. 2017).

- *Updating initial and intermediate conditions* in land surface, vegetation and yield models (i.e. data assimilation) with observed values continuously improves the predicted vegetation and yield anomalies (Albergel et al. 2019).
- *Optimally combining data-driven and process-based forecasts* of drought and drought impact variables by generating weighted averages of the multiple datasets based on their respective error characteristics.
- *Hybrid approaches* combining model forecasts with observations. For example, one could use the best surface soil moisture forecast, based on a combined meteorological/land surface model forecast, with the best ML approach for linking surface soil moisture to yield.

With the wealth of new EO datasets and advances in using ML for EO, a solid foundation is being laid for improving

Fig. 6 Temporal variability of three drought indicators averaged over the Pannonian Basin: NDVI anomalies based on the 1-km product distributed through the CGLS; SIF anomalies based on retrievals from GOME-2 on MetOp-A (Joiner et al. 2013, 2014, 2016); and VOD anomalies based on the VODCA X-Band product (Moesinger et al. 2019b). The right-hand side shows the spatial distribution of these variables for a drought in September 2012 throughout the Pannonian Basin. The colours of the maps are equivalent to the colours of the corresponding Hovmöller diagram
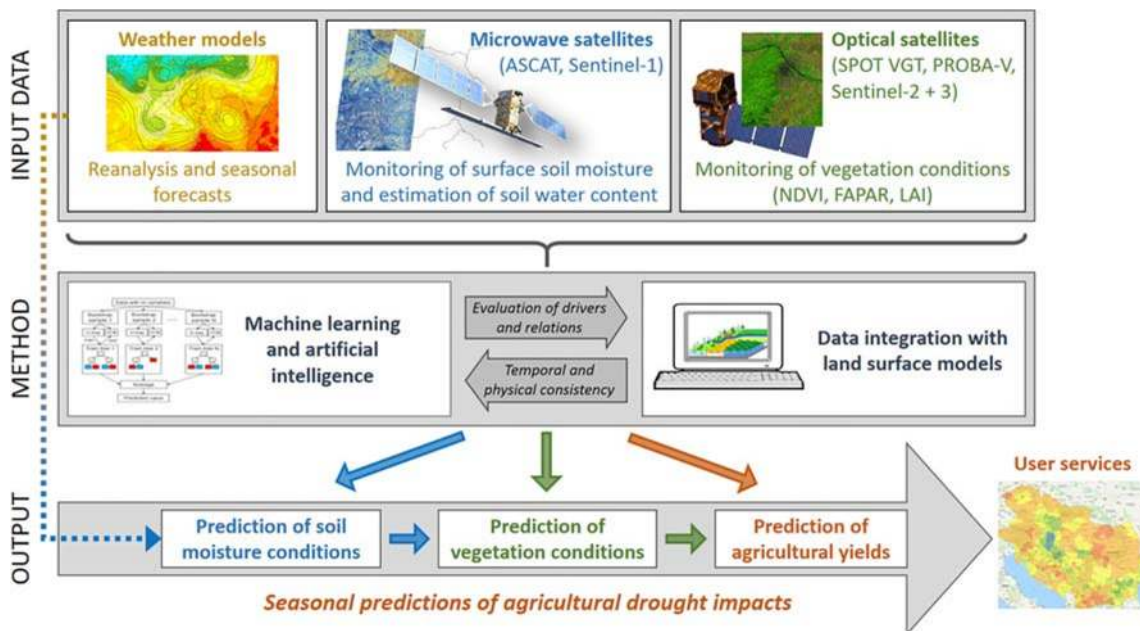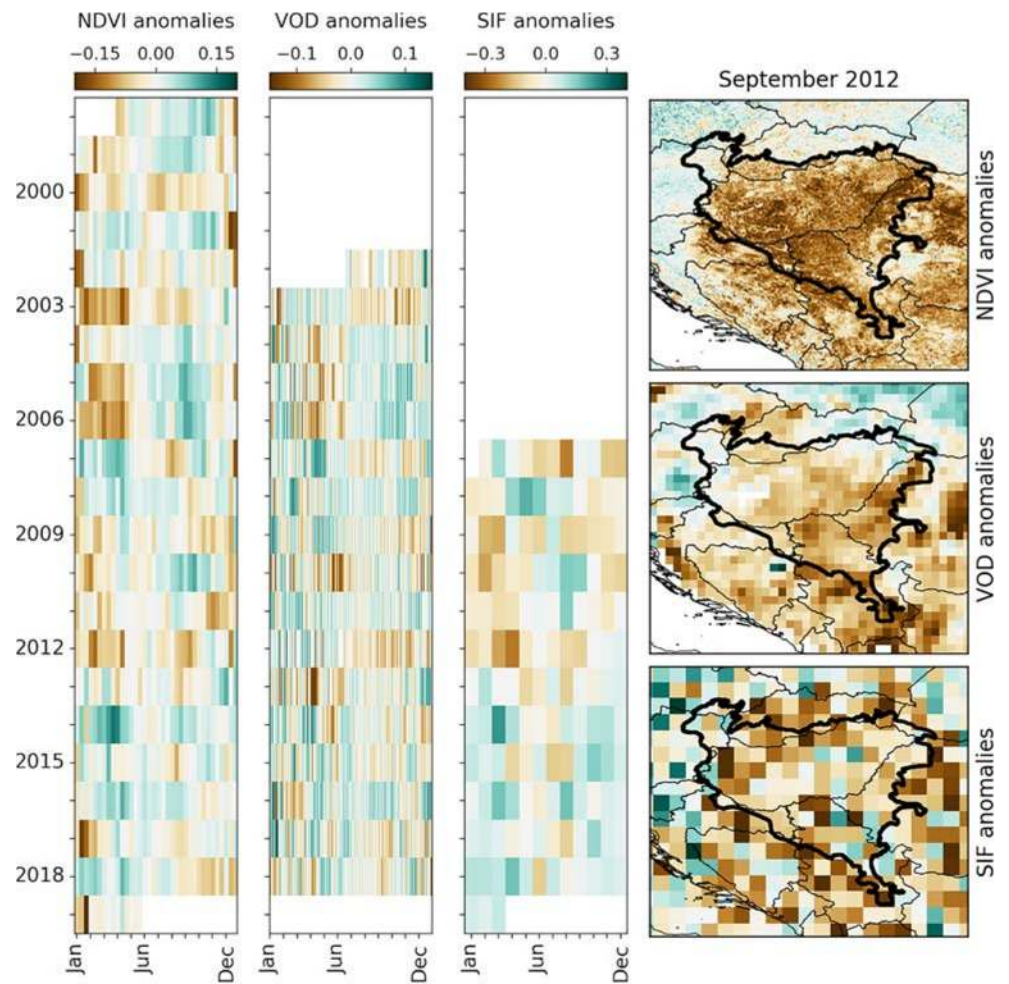
Fig. 7 Conceptual outline to integrate meteorological reanalysis and seasonal forecasts with optical and microwave satellite observations within machine learning approaches and land surface models to enable seasonal predictions of agricultural drought

drought monitoring and (impact) forecasting systems. ESA's upcoming Earth Explorer - Fluorescence Explorer mission, scheduled to be launched in mid-2024, will provide global measurements of vegetation fluorescence to quantify photosynthetic activity, plant health and stress. The mission will help to understand how photosynthesis affects the carbon and water cycle. This information is valuable since understanding plant health and productivity is essential to predict drought impacts on vegetation.

Conclusions

Recent drought events in the Pannonian Basin have created an urgent need for advanced monitoring of drought (impacts) on agriculture by international programmes and regional practitioners. In addition to meteorological reanalysis and forecast data, EO estimates of surface soil moisture, evapotranspiration and vegetation conditions are already included in operational drought monitoring portals such as droughtwatch.eu and intersucho.cz that provide up-to-date information on drought conditions in the Pannonian Basin and neighbouring regions. However, forecasts of drought impacts on vegetation and agricultural productivity, including an umbrella of methods from classical crop growth and land surface modelling, statistical correlation and regression analyses, machine learning and artificial intelligence are still in their infancy. A systematic assessment of the predictive performance of forecasting approaches using different EO variables and methods is still lacking. For the Pannonian Basin area, user-oriented drought monitoring portals are already in place and capable of providing forecasts of drought impacts to practitioners, but the scientific development and assessment for such forecasts is missing.

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