Remote Sensing for Drought Monitoring & Impact Assessment: Progress, Past Challenges and Future Opportunities

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Abstract

Drought is a common hydrometeorological phenomenon and a pervasive global hazard. As our climate changes, it is likely that drought events will become more intense and frequent. Effective drought monitoring is therefore critical, both to the research community in developing an understanding of drought, and to those responsible for drought management and mitigation. Over the past 50 years remote sensing has shifted the field away from reliance on traditional site-based measurements and enabled observations and estimates of key drought-related variables over larger spatial and temporal scales than was previously possible. This has proven especially important in data poor regions with limited in-situ monitoring stations. Available remotely sensed data products now represent almost all aspects of drought propagation and have contributed to our understanding of the phenomena. In this review we chart the rise of remote sensing for drought monitoring, examining key milestones and technologies for assessing meteorological, agricultural and hydrological drought events. We reflect on challenges the research community has faced to date, such as limitations associated with data record length and spatial, temporal and spectral resolution. This review then looks ahead to the future in terms of new technologies, such as the ESA Sentinel satellites, analytical platforms and approaches, such as Google EarthEngine, and the utility of existing data in new drought monitoring applications. We look forward to the continuation of 50 years of progress to provide effective, innovative and efficient drought monitoring solutions utilising remote sensing technology.

Keywords

Drought; Drought Monitoring; Meteorological Drought; Agricultural Drought; Hydrological Drought; Remote Sensing of Drought; Review Paper.

1.0 Introduction

Drought is a common hydrometeorological phenomenon (Hayes *et al.,* 2012), and a pervasive hazard, second only to flooding in its impact on social and economic security (Nagarajan, 2009). Since the turn of the century, several socio-economically significant regional droughts have occurred, for example in Australia (2000-2009), USA (2000-2016), Southern and Sub-Saharan Africa (2015-2017), China (2007-2012) and Europe (2007-2010) (Ummenhofer *et al.,* 2009; Ault *et al.,* 2016; Chao *et al.,* 2016; Cook *et al.,* 2016; Baudoin *et al.,* 2017). There is no universal definition of a drought (Lloyd-Hughes, 2014), but in its simplest form a drought event represents a deficit of water relative to normal conditions. Unlike floods which have a clear and sudden start and end (Wang *et al.,* 2016), droughts can be characterised by slow development and prolonged impacts. How spatio-temporally variable rainfall deficits propagate through the land surface to register deficits in soil moisture, runoff and recharge is complex and heterogeneous. While droughts can be ended by sudden extreme precipitation, how to precisely identify the termination point of a drought event is contested (Parry *et al.,* 2016). These attributes mean that drought is a phenomenon that is challenging to quantify and analyse. Impacts from recent droughts reveal high levels of exposure and vulnerability of both natural and human systems (Van Loon *et al.,* 2016). This is significant as with future climate change it is likely that many areas will start to experience more frequent and intense dry conditions, with irreversible impacts for people and ecosystems (IPCC, 2014). Consequently, drought monitoring and mitigation have become urgent scientific issues (Liu *et al*., 2016).

Historically drought monitoring approaches have focused on in-situ station-based measurements, for example the Palmer Drought Severity Index (PDSI) (Palmer, 1965). Towards the end of the 20th century a paradigm shift in drought monitoring approaches occurred, concurrent with advances in remote sensing and earth observation technologies such as the launch of the NASA Landsat series in 1972. In addition to providing meteorological data, remote sensing-based approaches also monitor conditions at the Earth's surface such as vegetation health and water levels, providing a rich mix of contextual data for drought monitoring. Remote sensing has consequently revolutionised the field, allowing observations and monitoring of key drought-related variables over larger temporal and spatial scales than was previously possible using conventional methods (Choi *et al.,* 2013; Sur *et al.,* 2015). The role of remote sensing technologies for effective water management has been highlighted as of particular importance in developing 'data-poor regions' (Sheffield *et al.,* 2018).

This paradigm shift in drought monitoring approaches is marked in the number of drought-related papers appearing in *Remote Sensing of Environment*; from less than 5 per year in 1982, to more than 70 per year since 2014 (Figure 1). Other journals (e.g. *Remote Sensing, International Journal of Applied Earth Observation and Geoinformation* and *International Journal of Remote Sensing*), have also seen a significant increase, and this is the case in hydrology and water management research journals too (Lettenmaier *et al.,* 2015).

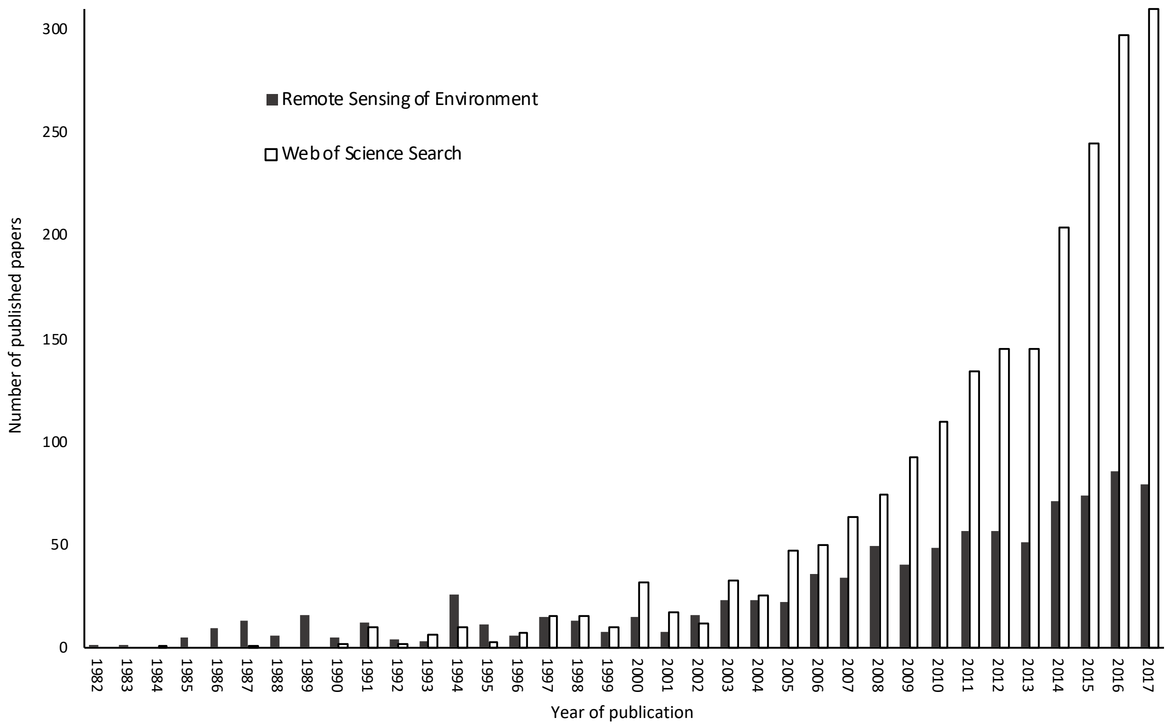

Figure 1: Number of papers relating to drought (in both paper titles and keywords) in *Remote Sensing of Environment* and *Web of Science* since 1982. Search terms included various versions of 'Drought' and 'Remote Sensing'.

Although droughts are complex phenomena which propagate in different ways with varied characteristics, they are commonly classified into one of four types, namely meteorological drought, agricultural drought, and hydrological drought (which represent the natural/environmental impacts), and socio-economic drought (which represents the impact on human population and society) (Van Loon, 2015; Liu *et al.,* 2016). These types are not independent but refer to different approaches of measurement and identification (Wilhite & Glantz, 1985) (Figure 2).

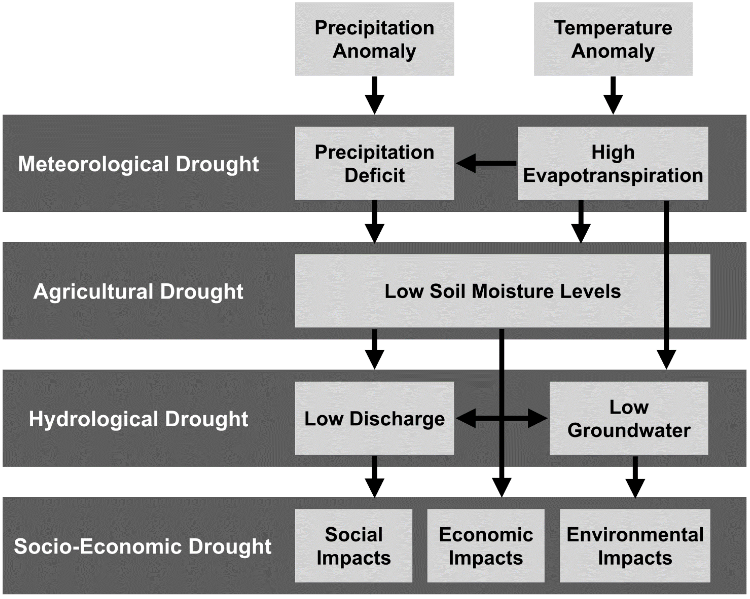

Figure 2: Different types of drought, their interactions and associated impacts (Adapted from Van Loon, 2015)

Drought propagation is the process whereby a precipitation deficit (i.e. below average rainfall) progresses through the hydrological cycle, starting with meteorological drought and developing into hydrological drought if conditions persist (Van Loon, 2015). Factors influencing the nature of drought propagation include regional climate and local catchment characteristics, such as geology, vegetation cover and type, soils, topography and human influence (Van Loon & Laaha, 2015; Baker *et al.,* 2016). Given the complex characteristics of drought, event heterogeneity, and various propagation pathways and influences, remote sensing can provide a valuable tool in the monitoring of a range of drought-related variables.

This review will focus on the remote sensing-based monitoring of ‘environmental drought’, that is events that can be classified as being either meteorological, agricultural or hydrological drought and the relationships between them. Since the start of remote sensing application in the field of drought monitoring active and passive sensors, recording measurements across the electromagnetic spectrum, have been used to improve understanding and inform environmental management decisions. Recent years have seen rapid evolution in remote sensing technologies which can be applied in drought monitoring, such as the launch of the ESA Sentinel satellites and the development of new indicators and analytical platforms. Given the rate of technological evolution it is important to continuously review and reflect upon historic and recent developments and look ahead to new opportunities.

2.0 Precipitation Monitoring

Meteorological drought typically results from the presence of continuously high atmospheric pressure over a region, representing a significant negative deviation from mean precipitation (Sheffield & Wood, 2011). Meteorological droughts tend to occur over relatively short time scales, usually days/weeks but possibly extending into months/seasons (Pal *et al.,* 2000), and the associated precipitation deficit is the propagation trigger for agricultural and hydrological drought. Unlike the other drought types, a meteorological drought will typically have few direct impacts (Sen, 2015). Nonetheless, given meteorological drought is often an early indicator of more impactful and significant dry events, effective monitoring is still critical.

Historically, site-based precipitation measurements were essential for meteorological drought monitoring, but the introduction of remote sensing precipitation products changed the efficiency and spatio-temporal coverage of rainfall mapping and drought monitoring (e.g. Islam & Uyeda, 2005; Islam & Uyda, 2007; Almazroui, 2011; Du *et al.,* 2013; Zhang *et* *al.,* 2017a). The first of these was the TRMM (Tropical Rainfall Measuring Mission), a joint collaboration between NASA and the Japan Aerospace Exploration Agency (JAXA). Launched in 1997 and decommissioned in 2015, TRMM measured tropical and subtropical rainfall (35°S - 35°N) and was the first satellite to carry a specific microwave precipitation radar (Kummerow *et al.,* 1998). Due to its restricted orbital cycle TRMM completed 16 cycles per day, with a measurement swath of 878km and spatial resolution of 0.25 degrees at the time of decommissioning. The 17-year legacy dataset represents a significant benchmark in global rainfall measurement and is still routinely used in assessing global rainfall patterns and atmospheric drivers of drought (e.g. Zhang & Jia, 2013; Sahoo *et al.,* 2015; Forootan *et al.,* 2016; Yan *et al.,* 2018). The successor to TRMM is the Global Precipitation Measurement (GPM) mission (Hou *et al.,* 2014). The GPM Core Observatory was launched in February 2014. This also operates in a non-polar, low inclination orbit completing 16 cycles per day, however with a wider coverage than TRMM (65°S - 65°N). Along with a constellation of other satellites this gives a revisit time for GPM products of 1-2 hours, with an improved spatial resolution (0.1-0.25 degrees). Studies have assessed the accuracy of GPM retrievals at various scales through correlation with in-situ gauged data and TRMM data (Tang *et al.,* 2016; Libertino *et al.,* 2016; Caracciolo *et al.,* 2018), with results suggesting high levels of agreement. Consequently, GPM and coupled TRMM/GPM datasets have become important products in drought monitoring research (e.g. Zhang *et al.,* 2017b; Alizadeh & Nikoo, 2018).

Studies have used a range of analytical approaches when employing remotely sensed precipitation in drought monitoring, including the calculation of long-term rainfall anomalies (e.g. Toté *et al.,* 2015; Bayissa *et al.,* 2017; Cattani *et al.,* 2018) and indices, such as the Precipitation Condition Index (PCI) (Zhang *et al.,* 2017a). One of the most commonly used indices that can be derived from remote sensing data is the Standardised Precipitation Index (SPI). Developed by McKee *et al.* (1993), the SPI is calculated using precipitation alone, which meant at the time it was far more data efficient than the PDSI for many applications. The main advantage of the SPI is that the values have the same probability of occurrence, no matter the time period, location, or scale, and equally represent both flood/wet and drought/dry events along a continuum. Until recently, its use has been limited in remote sensing studies, due to the need for a long-term precipitation record for calculation (traditionally ~30 years). However, with long-term records now becoming available it is possible to calculate SPI using remotely sensed data alone, enabling detection of meteorological droughts over large spatial scales (e.g. Sahoo *et al.,* 2015; Winkler *et al.,* 2017; Elhang & Zhang, 2018; Zhao *et al.,* 2018).

3.0 Evapotranspiration Monitoring

As discussed above, the onset of meteorological drought is often a key predictor of agricultural/hydrological drought. Consequently, it is common for research to attempt to integrate meteorological drought-related variables into studies which aim to assess and improve the monitoring of these other drought types. A key factor of both meteorological and agricultural drought is the increase in evapotranspiration rates (Figure 2). Reliable estimation of evapotranspiration is essential for effective drought monitoring and the development of hydrologic models (Fisher *et al.,* 2017). As with precipitation, a key benefit of using remotely sensed products is the ability to assess evaporation/evapotranspiration over large areas, and in the absence of in-situ monitoring stations. Calculation of evaporation/evapotranspiration requires additional variables relating to vegetation condition and type and/or soil properties (Narasimhan & Srinivasan, 2005) and these can be estimated through remote sensing. As such, various evapotranspiration remote sensing data products now exist - derived from observations from a range of satellite families, such as the MODIS and Landsat satellites.

The Global Land Evaporation Amsterdam Model (GLEAM) (Miralles *et al.,* 2011) is a set of algorithms for estimating terrestrial evaporation and soil moisture. The approach was revised in 2014 (Miralles *et al.,* 2014) and is currently on its third iteration (Martens *et al.,* 2017). The current GLEAM product consists of a series of microwave (C- and L-band) measurements of vegetation, soil moisture and precipitation and thermal observations of land surface temperature (LST), from sensors such as MODIS (Moderate Resolution Imaging Spectroradiometer) and the SMOS (Soil Moisture Ocean Salinity) mission (Martens *et al.,* 2017). The uniqueness of GLEAM is that it is the only global scale evaporation product designed to be driven by remotely sensed data alone (Miralles *et al.,* 2011). Given that GLEAM uses data from sensors which have a long operational history, Version 3.3 of the product is available for the period 1980-2018.

Many drought-related studies using remotely sensed precipitation or evapotranspiration products have been at global or continental scales (Sahoo *et al.,* 2015; Xia *et al.,* 2018), and necessarily at coarse spatial resolution (Huffman *et al.,* 1997; Martens *et al.,* 2017). This may be because many of the earlier earth observation satellites prioritised temporal over spatial resolution (Lettenmaier *et al.,* 2015). However, attempts have recently been made to increase the spatial resolution of meteorological remotely sensed data. For example, van Dijk *et al.* (2018) used MODIS observations of surface water extent, vegetation, and LST, assimilated into a landscape hydrological model, to derive a 5km resolution global scale dataset of secondary evaporation (i.e. evaporation from floodplain/wetland storage and irrigation systems).

Passive sensor derived datasets have also been re-analysed to represent evaporation/evapotranspiration. For example, the Landsat satellites have been used in the development of new, higher resolution, monitoring approaches (Wulder *et al.,* 2019). With the addition of the thermal band on Landsat 3 (launched in 1978), which was later enhanced on Landsat 4 (1982) onwards, high resolution (30m visible and 120m thermal) retrievals of land classifications and LST were made possible. These observations have led to the retrieval of relatively high-resolution estimates of evapotranspiration (Vinukollu *et al.,* 2011). Recent work has been undertaken using the Google EarthEngine (Gorelick *et al.,* 2017) to calculate key meteorological/hydrological variables using the thermal capabilities of space-borne sensors. EEFlux (EarthEngine Evapotranspiration Flux) was developed based on the METRIC (Mapping Evapotranspiration at High Resolution with Internalized Calibration) model (Allen *et al.,* 2007) and applies a series of algorithms to produce evapotranspiration estimates using Landsat 5 TM (1984-2013), Landsat 7 ETM+ (1999-Present) and Landsat 8 OLI-TIRS (2013-Present) imagery.

4.0 Vegetation & Soil Moisture Monitoring

Sustained meteorological drought over a region will begin to impact upon local hydrology and agriculture (Dutra *et al,* 2014). Agricultural drought (also referred to as soil moisture drought) represents a deficit in soil moisture available to vegetation driven by a precipitation deficit (meteorological drought) (Liu *et al.,* 2016). Agricultural droughts tend to occur over medium to long term time scales and associated impacts include crop yield reductions or failure, and eventually food demand/supply disequilibrium.

Remotely sensed agricultural drought monitoring can be via measurement of soil moisture content, usually through microwave radar (active) and radiometers (passive) such as SMOS or SMAP (Soil Moisture Active Passive) (e.g. Martínez-Fernández *et al*., 2016; Mishra *et al.,* 2017; Rajasekaran *et al.,* 2018), or through the assessment of vegetation using passive multispectral sensors such as Landsat or more recently Sentinel-2/-3 (e.g. Gu *et al.,* 2008: Zhang *et al.,* 2017a; Myoung-Jin *et al.,* 2018). The former represents a direct measurement of soil moisture, while the latter infer this by assessing vegetation condition or productivity.

4.1 Passive Multispectral Remote Sensing Approaches

In the late 20th and early 21st century various multispectral indices, applicable in drought monitoring, were developed. These include the Normalised Difference Vegetation Index (NDVI) (Tucker, 1979), the Normalised Difference Water Index (NDWI) (Gao, 1996), the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988), and the Vegetation Condition Index (VCI) (Kogan, 1995a) and the Temperature Condition Index (TCI) (Kogan, 1995b), which were later combined into the Vegetation Health Index (VHI) (Kogan, 1997).

Of these, the most well-established approach to agricultural drought monitoring is the NDVI. The NDVI's success derives from its exploitation of the 'red-edge' (the sharp increase in vegetation reflectance across the red and near-infrared regions of the electro-magnetic spectrum) to detect photosynthetically active plant material, from which plant stress can be inferred as the available moisture within the root zone is depleted (Wang *et al.,* 2007; Chen *et al.,* 2014; Ahmed *et al.,* 2017; West *et al.,* 2018). The NDVI is calculated using the near-infrared (NIR) and visible red bands of a multispectral sensor (Equation 1).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad \text{(Equation 1)}$$

The logic for the use of the NDVI for agricultural drought monitoring is that soil moisture plays a significant role in the sustained growth and healthiness of vegetation (Lavender & Lavender, 2016). Should soil moisture drop below a certain threshold vegetation will respond by wilting, lowering the NDVI due to a weakening of the leaf tissue structure and reduced chlorophyll content.

One of the first applications of NDVI based drought monitoring used the NOAA (National Oceanic & Atmospheric Administration) AVHRR (Advanced Very High-Resolution Radiometer). Launched in 1979, AVHRR enabled global scale vegetation mapping with a frequent revisit period (Tucker *et al.,* 1983). This was followed by numerous studies which aimed to refine the AVHRR NDVI products by accounting for atmospheric conditions, cloud masking, scale, temporal lags, amongst other variables (Holben & Fraser, 1984; Gatlin *et al.,* 1984; Townshend *et al.,* 1985; Holben, 1986; Loveland *et al.,* 1991; Gutman, 1991; Eastman & Fulk, 1993; Stone *et al.,* 1994).

As of September 2018, the combined search of NDVI and drought using Scopus returns 983 scientific journal articles published since 1979. In a literature review of drought-related papers, the NDVI is featured as a key index in more than 30% of the 300 agricultural drought related papers reviewed (Figure 3).

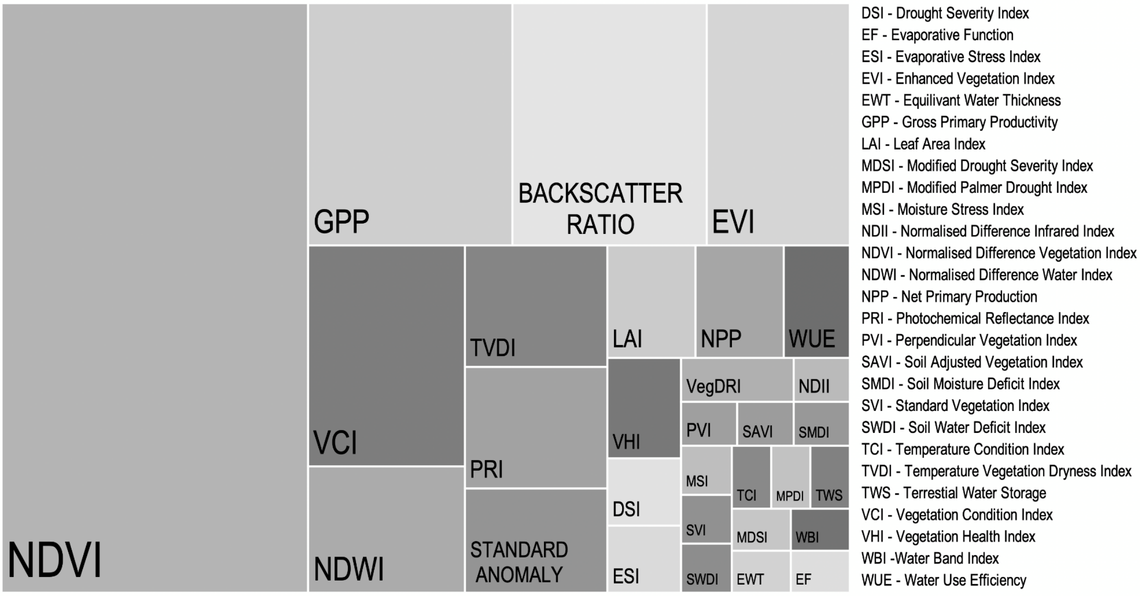

Figure 3: Treemap of monitoring approaches used in agricultural drought monitoring of the papers reviewed. Papers were sourced from a range of journals including *Remote Sensing of Environment, Remote Sensing, and the International Journal of Remote Sensing.*

NDVI-based drought monitoring has been conducted using a broad range of sensors over global, continental, regional and catchment scales (e.g. Park *et al.,* 2004; Bayarjargal *et al.,* 2006; Neigh *et al.,* 2008; Rojas *et al.,* 2011; Nicolai-Shaw *et al.,* 2017). Drought assessment and monitoring using NDVI has been undertaken across North America (e.g. Hwang *et al.,* 2017), South America (e.g. Sayago *et al.,* 2017), Europe (e.g. Zribi *et al.,* 2016), the Middle East (e.g. Pervez *et al.,* 2014), Australia (e.g. Chen *et al.,* 2014), Asia (e.g. Yu *et al.,* 2003) and Africa (e.g. Funk & Brown, 2006). Few studies using these sensors have successfully attempted to assess vegetation at finer more local scales, in particular when vegetation is highly heterogeneous or sparse, due to sensor spatial/spectral resolution limitations (e.g. Assal *et al.,* 2016).

More recently, studies using hyper-spatial/-spectral imagery (captured using very high spatial and spectral resolution satellites, aircraft, or ground-based/tram sensors) have also applied the NDVI to examine agricultural drought. For example, the Quickbird and RapidEye satellite sensors have shown great potential for high spatial resolution (~1m) assessment of drought impacts on vegetation (Garrity *et al.,* 2013; Krofcheck *et al.,* 2014), with results suggesting that vegetation dynamics closely reflect precipitation deficits at the field scale (Laliberte *et al.,* 2004). The majority of this high-/hyper-resolution research has been based in North America and Europe (e.g. Calaudio *et al.,* 2006; Mänd *et al.,* 2010; Coates *et al.,* 2015), most likely due to the expense of obtaining such imagery, or the instalment of ground-based sensor systems, which cannot as easily be met in less developed regions.

NDVI based approaches do however have limitations. For example the NDVI only represents conditions on one specific date and does not show condition relative to longer term change, is easily influenced by soil brightness in areas of low-density vegetation (Huete, 1988; Jasinski, 1990), and, at the other end of the spectrum, is limited in its sensitivity in high density biomass environments (Mutanga *et al.,* 2012; Galidaki *et al.,* 2016). The Vegetation Health Index (VHI) (Kogan, 1997) was seen to offer notable improvements over standalone NDVI-based monitoring as it provides a representation of vegetation condition relative to long term change. The VHI is a weighted average of two sub-indices: the VCI (Kogan, 1995a) and the TCI (Kogan, 1995b)

$$VCI = \frac{(NDVI - NDVI_{min})\ x\ 100}{NDVI_{max} - NDVI_{min}} \quad \text{(Equation 2)}$$

$$TCI = \frac{100\ (BT_{max} - BT)}{BT_{max} - BT_{min}} \quad \text{(Equation 3)}$$

$$VHI = \alpha \, x \, VCI + (1 - \alpha) \, x \, TCI \quad \text{(Equation 4)}$$

Where max/min represent the maximum and minimum values of that variable over the study period and BT is Brightness Temperature recorded from a thermal sensor. The VCI pixel-based normalisation minimises any spurious or short-term signals in the data and amplifies the long-term trend (Anyamba & Tucker, 2012). Studies assessing the VCI have found that both NDVI anomalies and the VCI are correlated with rainfall deficits, but the VCI offers a more robust comparison of seasonal drought conditions (Liu & Kogan, 1996). The VCI is commonly used, with results suggesting the index is effective in monitoring vegetation change and agricultural drought at continental scales (Jiao *et al.,* 2016; Winkler *et al.,* 2017).

The TCI makes use of thermal remote sensing technologies and measurements of LST. LST computed from thermal infrared bands, from sensors such as AVHRR and Landsat (Landsat 3 onwards), has been found to provide valuable information on surface moisture conditions (Gutman, 1990). As a result, efforts have been made to merge multispectral vegetation indices with measurements from thermal-equipped sensors, such as the Temperature Vegetation Drought Index (TVDI) (Sandholt *et al.,* 2002) or the Vegetation Supply Water Index (VSWI) (Haboudane *et al.,* 2004). Compared to NIR-based vegetation indices alone, temperature/brightness indices have been found to be more sensitive to soil water stress (Wang *et al.,* 2004).

By the time of its publication (1997) the VHI had successfully been used in research in parts of Asia, Europe, North America and Africa (Kogan, 1994a; 1994b; 1995a; 1995b). The VHI has been used in applications of drought management (e.g. San Miguel-Ayanz *et al.,* 2000;

Qu *et al.,* 2019), in the development of more complex remote sensing monitoring approaches (e.g. Brown *et al.,* 2008), and in vegetation health and crop studies (e.g. Rahman *et al.,* 2009). The VCI/VHI have also been used in combination with other indices such as the NDWI and Enhanced Vegetation Index (EVI) (Huete *et al.,* 2002). The value of a multi-index approach is that different indices have been found to have differing sensitivities to factors including vegetation type/density/biomass and soil brightness (Prabhakara *et al.,* 2015).

Given the main socio-economic impact of agricultural drought is the potential disequilibrium between the demand and supply of food/crops, being able to accurately monitor crop growth and productivity is of particular importance. A commonly used method to assess vegetation growth and productivity is to calculate gross primary productivity (GPP) (Figure 3). GPP represents the rate at which vegetation converts light into energy via photosynthesis (Gilabert *et al.,* 2015). New sensors and analytical approaches have meant that traditional hydrological methods of calculating GPP have been revisited (Rossini *et al.,* 2012). Many approaches now use satellite data in combination with models and other datasets (Song *et al.,* 2013; Anav *et al.,* 2015; Joiner *et al.,* 2018). In the papers reviewed it was common for GPP to be based on the light-use efficiency (LUE) method of Monteith (1972) (Equation 5).

$$\mathrm{GPP} = \mathrm{LUE}\ x\ FAPAR_{chl}\ x\ PAR_{in} \text{ (Equation 5)}$$

Where PAR_{in} is top of canopy photosynthetically-active radiation and $FAPAR_{chl}$ is the fraction of PAR_{in} absorbed by chlorophyll. The inclusion of remotely sensed data has largely been to provide a value for $FAPAR_{chl}$. The NDVI is one of the most commonly used proxies of

$FAPAR_{chl}$ (e.g. Zhang *et al.,* 2009; Rossini *et al.,* 2012; Joiner *et al.,* 2018). Therefore, a revision to Equation 5 would be:

$$\text{GPP} = S\ x\ VI\ x\ PAR_{in} \quad \text{(Equation 6)}$$

Where VI is the selected vegetation index to represent $FAPAR_{chl}$ and S is a constant representing LUE (Sims *et al.,* 2008). A range of satellites and sensors have been used to calculate the VI element of Equation 6 (Nightingale *et al.,* 2007; Zhang *et al.,* 2014; Dong *et al.,* 2015; Bayat *et al.,* 2018). This includes some hyper-resolution sensors (Krofcheck *et al.,* 2014; Gitelson *et al.,* 2018). Findings suggest that GPP is an important variable for monitoring drought and is more sensitive to non-typical dry conditions than traditional VIs such as the NDVI and EVI (Wagle *et al.,* 2014). Sims *et al.* (2008) also note the non-linear relationship between GPP and LST under extreme drought conditions (compared to a linear relationship under normal conditions). This is likely due to the low values and highly variable nature of VIs under drought conditions (owing to poor quality/stressed vegetation or sparse coverage). GPP has also proved useful in the detection of irrigated/non-irrigated fields in droughty southern USA (Peng *et al.,* 2013; Doughty *et al.,* 2018).

Beyond calculation of GPP, some drought monitoring studies have further calculated the Water Use Efficiency (WUE) of crops (e.g. Lu & Zhang, 2010; Ahmadi *et al.,* 2019). WUE is defined as the ratio of leaf carbon uptake to water loss (Morison & Morecroft, 2006). WUE can be calculated using Equation 7

$$WUE = \frac{Volume\ of\ water\ used\ productively}{Volume\ of\ water\ potentually\ available} \quad \text{(Equation 7)}$$

The volume of water used productively is taken as GPP, and the volume of water available as evapotranspiration (Huang *et al.,* 2015; Yang *et al.,* 2016). MODIS GPP and evapotranspiration products have been used to calculate WUE with results showing similar patterns to GPP under drought conditions. For example, Lu & Zhuang (2010) show non-linear trends between WUE and drought intensity; with WUE increasing under moderate conditions but decreasing sharply under severe drought.

While the development of multispectral and thermal indices from passive sensors has been of interest to the research community for some time, Kogan (1997) noted that while technology was advancing indices such as the NDVI and VHI, at the time, had not yet been ground-truthed or validated against traditional monitoring techniques. To an extent this is still true today, with issues around accuracy and uncertainty in remotely sensed data still a challenge (Liu *et al.,* 2016). However, as demand has grown for continuous and reliable data, studies have examined the relationship between traditional approaches/ground measurements and remote sensing observations. Wang *et al.* (2007) found that MODIS derived NDVI at 16km spatial resolution produced statistically significant correlations between NDVI and measured soil moisture. Gu *et al.* (2008) conducted similar analysis also using MODIS derived NDVI, finding that correlation between NDVI and measured soil moisture was dependent on landcover heterogeneity and soil type. Areas with homogenous vegetation cover and silt loams produced the highest correlations, while areas with heterogenous vegetation cover and loam soils produced the lowest correlations. The correlation between remote sensing and traditional meteorological/ground-based indices and data is significant in the field of remote sensing-based drought monitoring. Remote sensing indices offer a multi-scaled approach, and do not rely on site-based climatic datasets which are sparse in many parts of the world (Choi *et al.,* 2013; Sur *et al.,* 2015). As satellites are able to observe areas of the Earth where such ground-based datasets do not exist, effective drought monitoring and management can still take place.

4.2 Microwave Remote Sensing Approaches

Both active and passive sensors which record measurements in the microwave segment of the EMS have been applied in agricultural drought monitoring research. Active microwave sensors (radar/scatterometers) use backscatter strength to determine moisture conditions. Retrievals of soil moisture content from active microwave sensors can characterise key drought variables, including the intensity, frequency and spatial extent of soil moisture deficit. A key benefit of microwave sensors is they can provide continuous coverage over large geographic extents, and do not suffer the same limitations associated with light availability and cloud coverage as their multispectral counterparts.

However, active microwave sensors are limited in their ability to penetrate deep soil horizons. Typically, sensors can monitor moisture at a depth equal to about 1/10th to half of the sensor's wavelength. Longer wavelengths result in deeper penetration, with L-band sensors (around 1.4GHz) offering the deepest measurements at around 1-5cm. Microwave sensors tend to have coarse spatial resolution (often kilometres, rather than metres) resulting in studies having a global or continental scale; unlike passive sensors which have much finer spatial resolution allowing analysis to be undertaken at more local scales. This is often due to a trade-off between antenna size (affecting wavelength size and spatial resolution) and orbital geometry (which affects satellite revisit time) (Pan *et al.,* 2017). In comparison to multispectral sensors, the number of microwave sensors in orbit is smaller, as the former usually have a broader range of applications. Nonetheless, global coverage, long-term records and often short revisit times (daily/weekly) make microwave sensor derived soil moisture estimates valuable for drought monitoring and impact assessment over global, continental and regional scales.

The SMAP (Soil Moisture Active Passive) mission launched in 2015 was well positioned to revolutionise soil moisture remote sensing (Entekhabi *et al.,* 2010). The goal was a product which merged high spatial resolution active radar and coarse-resolution, but highly sensitive, passive radiometer observations (Entekhabi *et al.,* 2010; Das *et al.,* 2014), to produce relatively high spatial (3km, 9km and 36km) and temporal resolution (2-3 days) data products. Early SMAP data was assessed for accuracy and validity and satisfied all standards (Colliander *et al.,* 2017). However, only 9 months into the mission the on-board radar equipment failed and was deemed unrepairable. However, there have been successful attempts to downscale and produce higher spatial resolution datasets using in-situ field observations and available active-passive algorithms (Das *et al.,* 2018; Wei *et al.,* 2019. There have also been attempts to compare and merge available SMAP products with observations from other active microwave sensors such as ASCAT (Advanced SCATterometer) (Kim *et al.,* 2018), SMOS (Al-Yaari *et al.,* 2017) and Sentinel-1 SAR data (Das *et al.,* 2016) with varying results depending on local conditions. Despite the loss of the on-board radar, recent studies suggest SMAP products have potential for large scale agricultural drought monitoring. Eswar *et al.* (2018) compared SMAP estimates of soil moisture with modelled USDM (US Drought Monitor) and SPI data. Results indicated that SMAP data over 13-26 week intervals was able to accurately capture changing drought intensity levels. Bai *et al.* (2018) used SMAP estimates to calculate the Soil Water Deficit Index (SWDI) for mainland China and concluded that SMAP derived SWDI has good overall performance under drought conditions.

Launched in 2009, SMOS was the first mission to provide global measurements of L-band brightness temperature. Its microwave radiometer allows for remotely sensed estimation of soil moisture (and ocean salinity) with a spatial resolution of approximately 43-50km and a revisit time of less than three days (Kerr *et al.,* 2010). Like SMAP, studies using SMOS soil moisture retrievals suggest that the satellite is well suited to support the monitoring of agricultural drought, through both direct sensor observations or the data product's utility in calculating agricultural drought indices (e.g. Sánchez *et al.,* 2016; Pablos *et al.,* 2017; Tagesson *et al.,* 2018). The SMOS mission is reported to be in excellent technical condition (Mecklenburg *et al.,* 2016), so it is likely that the sensors role in agricultural drought monitoring will continue to grow.

The AMSR-E (Advanced Microwave Scanning Radiometer - Earth Observing System), also equipped with a passive microwave radiometer, has shown similar potential for effective drought monitoring (e.g. Rao *et al.,* 2019). The AMSR-E observation record is made up of daily 25km (resampled) soil moisture products from 2002-2011. AMSR-E historic products have been reanalysed to calculate various agricultural drought indices and results show that the data record has good potential for the representation of long-term drought events over large spatial scales (Champagne *et al.,* 2011; Abelen *et al.,* 2015; Draper & Reichle, 2015; Zhang *et al.,* 2017a; Liu *et al.,* 2017). As with multispectral sensors, a range of active and passive microwave sensors, including those discussed above, have been evaluated against in-situ measurements with generally positive results, although this is dependent on analytical procedures and local characteristics (Al-Yaari *et al.,* 2019; Zhang *et al.,* 2019).

5.0 Integrated Approaches to Drought Monitoring

Zhang *et al.* (2017a) highlight the importance of a multi-/integrated index approach to drought monitoring. Many studies use various remote sensing products to simultaneously explore multiple drought types. Nicolai-Shaw *et al.* (2017) used GLEAM data as an additional factor for agricultural drought monitoring, by exploiting the link between evaporation and vegetation condition. The delay in the response of vegetation to peaks in evapotranspiration was of particular interest; which the authors attribute to a potential limitation of GLEAM data - the underestimation of water availability in deeper soil horizons which supports plant growth. In a similar study, Orth & Destouni (2018) used various remote sensing data products to assess water balance disequilibrium during droughts across mainland Europe. In particular, they focused on the relationship between various hydrological cycle stages, such as precipitation, evapotranspiration (GLEAM), vegetation condition (vegetation index based), and runoff. GLEAM data was incorporated to reveal patterns in evapotranspiration, which lagged significantly behind variations in runoff following drought onset in southern Europe, suggesting that agricultural drought reduces runoff faster than it reduces evapotranspiration.

Remotely sensed data products have also been used to calculate new integrated monitoring indices designed to monitor various drought types. For example, Du *et al.* (2013) propose the Synthesized Drought Index (SDI) – a principal components product combining the Vegetation Condition Index (VCI) (Kogan 1995a), the Temperature Condition Index (TCI)

(Kogan 1995b) and the PCI. The uniqueness of the SDI is the integration of remote sensing data products derived from MODIS and TRMM, allowing an integrated assessment of precipitation deficit, soil moisture depletion and vegetation stress as drought propagates. The integration of indices and different remote sensing derived data products is an important development in effective drought monitoring across multiple drought 'types'. This is highlighted by Zhang *et al.* (2017a) who found that shorter-term dry events are not fully represented in many agricultural or hydrological drought indices; which are better suited for longer-term drought monitoring. Therefore, there is a need to use some form of meteorological index alongside these measures to fully examine drought propagation and short-term meteorological droughts.

Even when monitoring a small number of drought-related variables it is important to consider a range of comparable datasets from different sensor types (Hao *et al.,* 2015). For agricultural drought monitoring, Zhang *et al.* (2017a) show how different soil moisture datasets and indices are correlated with different length accumulation periods of SPI data (which represent different drought severity levels). Passive microwave remotely sensed data from AMSR-E, in the form of the Soil Moisture Condition Index (SMCI) (Zhang & Jia, 2013), correlated well with short-term SPI in regions with low vegetation cover, while multispectral indices, such as the VCI and TCI, were better correlated with 3-month SPI. The use of multiple remotely sensed soil moisture products is clearly valuable in agricultural drought monitoring as different indices and sensors have particular strengths and weaknesses. However, the relationship will be highly dependent on the characteristics of the land surface variables under observation, for example some vegetation parameters may respond more slowly to drought onset than soil moisture at the same location due to resilient vegetation biophysical characteristics. Other local land surface characteristics will also affect this relationship such as terrain and landcover (Zhang *et al.,* 2017a).

The development of integrated indices combining traditional meteorological datasets and remote sensing approaches has been of interest in drought monitoring research more recently (Liu *et al.,* 2016). The integration of local field measurements, such as those from soil moisture probes, potentially offers a significant improvement over using remotely sensed data alone. Even with recent advances in remote sensing, it is only possible to measure the soil moisture content of the surface material (1-5cm). This is problematic given that crop roots are usually 10-20cm deep, and consequently root zone soil moisture deficits cannot be determined directly. This could be resolved by incorporating in-situ measurements at deeper depths into drought monitoring techniques, alongside satellite observations. The benefit of such approaches is that the spatial and temporal benefits of the remote sensing approaches are retained, while localised data for soil moisture, precipitation and other variables are also incorporated.

Brown *et al.* (2008) developed one of the first and most widely applied integrated drought monitoring indices – VegDRI (Vegetation Drought Response Index). VegDRI was developed to exploit the strengths of both remote sensing and climate-based drought monitoring techniques. The remote sensing component provides spatial information about the distribution and general condition of vegetation from NDVI data. VegDRI produces drought-related vegetation stress/condition data at 1km resolution which is updated weekly (Brown *et al.,* 2008). Initially VegDRI was compared against the USDM model and results suggested that VegDRI offered significant advancements. As of 2015, VegDRI features as a part of the new USDM model to enhance the spatial resolution of modelled drought patterns (Hao & Singh, 2015). Since its development VegDRI has been used in the development of new models (e.g. Tadesse *et al.,* 2010) and to contribute to drought assessment at a national scale (e.g. Wu *et al.,* 2013). As new sensors are launched, and datasets developed, it is likely that remotely sensed data will be incorporated into national scale models and early warning systems in a similar way (Roy *et al.,* 2014).

While the benefits of integrating field measurements and traditional meteorological indices with remote sensing techniques are clear, many studies are still focusing on developing solely remote sensing-based approaches. Since VegDRI (Brown *et al.,* 2008) was published, many remote sensing only based techniques have been proposed, such as the Temperature-Vegetation-Soil Moisture Dryness Index (TVMDI) which utilises LST, soil moisture and NDVI observations (Amani *et al.,* 2017). This is likely due to newer and more advanced satellites and sensors having been launched in the interim, such as Sentinel-2 and SMAP. As a result, recent research has been characterised by the parallel development of both remote sensing and integrated approaches (Figure 4).

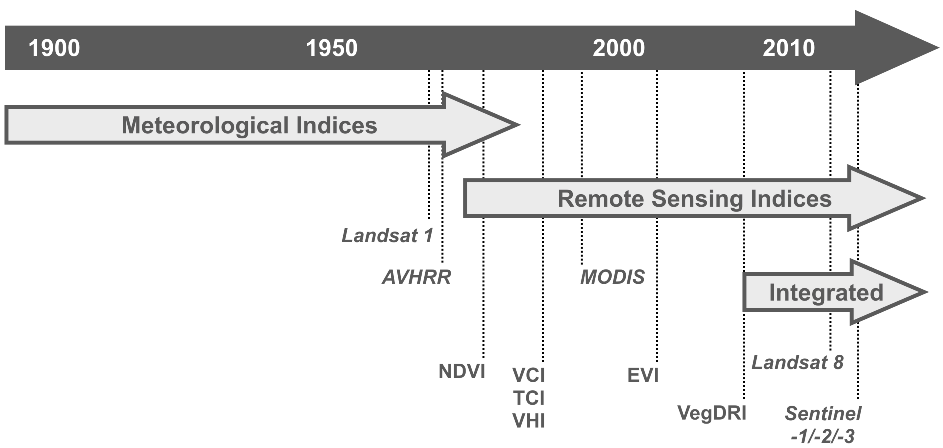

Figure 4: Key milestones and a chronological view of the development of agricultural drought monitoring indices

As evidenced previously, a review of the remote sensing literature relating to agricultural drought monitoring found that the NDVI is by far the most commonly applied monitoring method. This is significant given that since its development, many more sophisticated and potentially more representative indices have been developed, including pure remote sensing approaches, and integrative remote sensing and field-based indices. In relation to sensor type, passive sensors/approaches outnumber active in the papers reviewed. This is likely due to a number of factors relating to data availability/resolution/timeliness, ease of application and interpretation, awareness of methods, and what is perceived as 'standard practice' (Bachmair *et al.,* 2016).

6.0 Streamflow Monitoring

Agricultural droughts can trigger positive feedback loops in the hydrologic cycle (Teuling *et al.,* 2005). Soil moisture will continue to be lost during a drought via evapotranspiration, which will be enhanced due to increased radiation and temperature (Van Loon, 2015). This loss will not be offset with precipitation, reducing the percolation and throughflow of water to recharge groundwater and streamflow (Ivanov *et al.,* 2008). This triggers a hydrological drought, characterised by a deficit in the supply of surface and subsurface water (Sheffield & Wood, 2011). Hydrological drought is often quantified by reduced streamflow/groundwater and low levels in lakes and reservoirs (Tallaksen & Van Lanen, 2004). Hydrological droughts occur over long time scales and socio-economic impacts can be severe (Figure 2) (Isaak *et al.,* 2012).

In comparison with meteorological and agricultural drought, the development of remote sensing-based approaches to hydrological drought has been more limited. In particular, research into the role of remote sensing in providing estimates of river discharge has been minimal due to the lack of sensors/satellites dedicated to this purpose (Lettenmaier *et al.,* 2015). Some studies have used basic fluvial geomorphological theory and supplementary in-situ data (river flow gauges) to estimate discharge via remote sensing. Landsat and SAR datasets have been used in this context to provide estimates of channel width to calculate hydraulic geometry relationships (e.g. Smith *et al.,* 1996; Gleason & Smith, 2014; Gleason *et al.,* 2014). However, there are no studies to date which apply this within the context of hydrological drought.

Through remote sensing technologies it has been possible however to monitor change in Earth's total water storage in association with hydrological/groundwater drought. The Gravity Recovery & Climate Experiment (GRACE) (Tapley *et al.,* 2004) mission launched in 2002 was operated by NASA and the German Aerospace Center. The mission originally had a lifespan of 5 years, however due to its successes, the mission was extended until 2017. The GRACE mission consisted of two satellites in tandem orbit. On-board instruments measured the distance between the satellites, which fluctuated at around 200km as a result of Earth's changing gravitational field. These measurements were used to produce monthly representations of changes in the Earth's gravity field. The main drivers being the shifting oceanic/atmospheric/terrestrial distribution of water within the hydrological cycle. GRACE therefore observed terrestrial water storage (TWS) variations in all water storage locations (soil moisture, surface water, and groundwater). GRACE was unique in its non-dependence on surface conditions and being able to provide measurements below the first five centimetres of the surface.

GRACE data has been successfully applied in numerous hydrological drought monitoring studies, for example in the analysis of drought event signatures and propagation (Hirschi *et al.,* 2006; Yirdsaw *et al.,* 2008; Thomas *et al.,* 2014; Ma *et al.,* 2017), examining regional differences in drought severity (Xavier *et al.,* 2010; Frappart *et al.,* 2013), and monitoring groundwater depletion (Rodell *et al.,* 2009; Zhong *et al.,* 2018). GRACE has also been used to calculate indices which can be applied in large scale hydrological drought monitoring, such as the Drought Severity Index (DSI) (Zhao *et al.,* 2017), the Total Storage Deficit Index (TSDI) (Narasimhan & Srinivasan, 2005; Yirdaw *et al.,* 2008) and the Multivariate Standardised Drought Index (MSDI) (Forootan *et al.,* 2019); most being applied in order to show spatio-temporal changes in drought severity (e.g. Voss *et al.,* 2013; Zhao *et al.,* 2015; Forootan *et al.,* 2016). Recent work has also sought to incorporate GRACE data into complex hydrological and groundwater models (e.g. Schumacher *et al.,* 2018) and in the USDM, GRACE was used to monitor hydrological/groundwater drought.

Under drought conditions GRACE data has been used alongside in-situ measurements and other sensors (Forootan *et al.,* 2016), and assessed against climate models (Xia *et al.,* 2016) and established hydrological drought indices. Results suggest that GRACE significantly improved our ability to monitor hydrological/groundwater drought over large spatial and temporal scales (Long *et al.,* 2014; Thomas *et al.,* 2017; Sun *et al.,* 2017). For example, Forootan *et al.* (2019) used GRACE TWS data to assess the global distribution of hydrological drought events and their relationship with atmospheric/oceanic teleconnections. They found that droughts in the Middle East, America and South Asia have increased in intensity in recent years, and that in Asia and Australia hydrological drought events are largely associated with the El Niño Southern Oscillation (Forootan *et al.,* 2019).

7.0 Snow Monitoring

Accurate monitoring of snow cover and depth is important for the characterization of hydrological droughts due to snow's role in ensuring constant water supply in many parts of the world (Shaban, 2009; Kumar *et al.,* 2014). A lower than normal winter snowfall could lead to a hydrological drought through reduced streamflow supply later in the water year (AghaKouchak *et al.,* 2015). As with other drought variables, long records and current observations of spatio-temporal consistent snow cover measurements, especially in mountainous upland areas, are not always readily available. Therefore, remote sensing plays an important role in providing these measurements.

Multispectral based snow monitoring approaches rely on snow's strong spectral reflectance/signature and discernibility from surrounding landcovers (Pepe *et al.,* 2005; Dozier *et al.,* 2009). Satellites and sensors such as AVHRR, MODIS and ENVISAT have been routinely used in multispectral-based snow cover assessments (Romanov *et al.,* 2000; Pepe *et al.,* 2005) and indices such as the Normalised Difference Snow Index (NDSI) have been proposed (Hall *et al.,* 2002). Validation of multispectral snow cover datasets against in-situ measurements suggests high levels of accuracy, although this is heavily influenced by underlying and neighbouring landcovers (Hall & Riggs, 2007; Simic *et al.,* 2004). A significant limitation however of multispectral snow monitoring is the potential spectral signature confusion between snow cover and clouds, which can lead to notable snow cover overestimation (Wang *et al.,* 2005). Alternatively microwave sensors, which are not limited by cloud cover, can provide estimates of both snow cover and depth (Durand *et al.,* 2008). However, the longer microwave wavelengths, and associated antenna size required to achieve high spatial resolution data (or at least data comparable to that observed by multispectral sensors), has been a technological limitation (Kongoli *et al.,* 2012).

In specific relation to drought monitoring, studies have used remotely sensed snow cover/depth estimates in numerous land surface/hydrological models in order to improve streamflow estimates, and therefore monitor hydrological drought events (e.g. Dong *et al.,* 2007). Multispectral snow cover estimates have also been used alongside ancillary datasets, such as soil moisture, in more general agricultural and hydrological drought monitoring (Kumar *et al.,* 2012)

8.0 Past Challenges & Future Opportunities

The key challenge in the remote sensing of drought in the past has revolved around resolution (spatial, spectral and temporal). Kogan (1997) noted that AVHRR data was used in many of the index development studies that took place at the close of the 20th Century. AVHRR allowed for the development of drought monitoring indices based on a 1-month data publication period. A month, however, could be considered too long a period to assess variation in vegetation condition during a drought, as the water deficit related change in leaf structure occurs between 3 and 7 days (Anyamba & Tucker, 2012). Additionally, weather patterns typically change at an even faster rate which can significantly affect the creeping nature of drought onset and recession (Sen, 2015). Kogan (1997) therefore suggests that one of the key limitations of remote sensing approaches at the time was that the monthly publication interval of data was inadequate. Studies conducted using MODIS and Landsat have also encountered temporal resolution limitations.

As well as challenges associated with temporal resolution, a recurring limitation of many remote sensing approaches has been the spatial and spectral resolution of sensors. In agricultural drought monitoring, for example, datasets derived using both active and passive sensors have encountered limitations associated with resolution (Becker, 2006; Davies *et al.,* 2008; Rao *et al.,* 2019). Often researchers have had to trade-off spatial and spectral resolution when selecting data products (Lavender & Lavender, 2016; West *et al.,* 2018). For example, when using multispectral sensors, it is common for either the spatial resolution not to be high enough to observe low density/dispersed vegetation, or the spectral resolution to be limited in its sensitivity to change in NIR reflection. These technological issues have limited the potential detection of changes in key environmental variables under drought conditions. Davies *et al.* (2016) attempted to use Landsat 8 derived NDVI (at 30m spatial resolution) to assess soil moisture recharge in semi-arid Rajasthan, India. While the results of this study were statistically inconclusive, they add to the body of evidence suggesting a role for remotely sensed NDVI products in providing proxy information for changes in moisture condition when sensors have appropriate spatial and spectral resolutions.

Following more recent technological advancements and the launch of new satellites/sensors there is renewed potential to address the limitations of previous studies with regard to resolution. The launch of the ESA (European Space Agency) Sentinel-2 multispectral imaging mission has provided a significant improvement in the spatial, spectral and temporal resolution of global coverage freely available multispectral imagery (Drusch *et al.,* 2012). Sentinel-2A was launched in June 2015 and Sentinel-2B in March 2017. From June 2017 both satellites have been fully operational giving a revisit time of around 10 days at the equator and 2-3 days towards the poles (with the number of available images for analysis depending on latitude and cloud cover). Each Sentinel-2 satellite is equipped with a single MultiSpectral Instrument (MSI) with a ground-tracked swath of 290km and 13 spectral bands (ranging from 10-60m spatial resolution), including four high spectral resolution bands positioned at the red-edge region of the EMS designed to provide spectrally precise measurements of vegetation condition and leaf chlorophyll content (Gitelson *et al.,* 2005; Delegido *et al.,* 2011; Clevers & Gitelson, 2013; Frampton *et al.,* 2013). Because of its enhanced resolution, initial studies have suggested that the mission has potential for considerable advances in the remote sensing of vegetation (Hill, 2013; Korhonen *et al.* 2017; Sadeghi *et al.,* 2017; Clevers *et al.,* 2017; Lambert *et al.,* 2018; Vanino *et al.,* 2018), which may in turn provide improvements in agricultural drought monitoring.

West *et al.* (2018) correlated NDVI derived from each NIR band from Sentinel-2 and the standard NIR band from Landsat 8, against ground measured soil moisture in extreme drought conditions and sparse vegetation. While Sentinel-2 NDVI produced significant correlations (variation was found across the different NIR bands and spatial resolution), no significant results were found with NDVI derived from Landsat 8. The spatial dispersion of vegetation may well explain the lack of significant results with Landsat 8 data due to the 30m resolution being too coarse too detect the vegetation signal (West *et al.,* 2018). The improved temporal resolution of Sentinel-2 was also noted in this study. As well as NDVI, GPP estimates derived from Sentinel-2 have been explored with promising results

(Sakowska *et al.,* 2016). Most research suggests a key role for Sentinel-2 in future drought monitoring. A key research challenge remains however in assessing the relative importance of spatial and spectral resolution in drought monitoring (Dotzler *et al.,* 2015; Lepine *et al.,* 2016; Chemura *et al.,* 2017).

As well as comparative studies, recent research has also sought to combine datasets from Sentinel-2 and Landsat 8. The MSI on-board Sentinel-2 and the OLI (Operational Land Imager) of Landsat 8 have partially overlapping spectral characteristics, and their differing spatial resolutions can be addressed through resampling (e.g. Li *et al.,* 2017). Therefore, there is potential for data from the two to be integrated through data fusion or transformation (e.g. Zhang *et al.,* 2018). Data fusion of Sentinel-2 and Sentinel-3 has also been explored (Korosov & Pozdnyakov, 2016). Given that key drought-related variables such as LST and NDVI can be derived from Sentinel-3's OCLI (Ocean Land and Colour Instrument) and SLSTR (Sea and Land Surface Temperature Radiometer) sensors (Donlon *et al.,* 2012), there may also be significant drought monitoring opportunities using combined Sentinel-2 and Sentinel-3 data that have yet to be fully explored (Guzinski & Nieto, 2019).

Issues around spatial/spectral resolution may also be addressed with the continued rise in number of hyper-spatial/-spectral sensors being launched in the coming years. For example, the planned NASA HyspIRI (Hyperspectral InfraRed Imager), which will be equipped with 10nm bands from the visible to short wave infrared segments of the EMS (see Lee *et al.,* 2015), should be able to provide valuable measurements for agricultural drought-related monitoring.

Beyond resolution-related limitations, a key challenge historically has been the shorter-term availability of remotely sensed data for inclusion in drought monitoring practices when compared to traditional in-situ measurements (Liu *et al.,* 2016). For example, the SPI has a conventional requirement of a long-term precipitation record for calculation (Sen, 2015), which until fairly recently has not been available solely from remotely sensed data (e.g. the CHIRPS rainfall dataset). The availability of a long data record is what gives the Landsat series satellites and sensors a particular advantage over newer missions; having a 40-year record comprised of observations from 7 satellites (Roy *et al.,* 2014). With the launch of Landsat 9 (currently scheduled for late 2020) this record will continue to expand allowing new opportunities for long term agricultural drought monitoring practices. The continuation of the Landsat record may also help in tackling limitations associated with Landsat 8's frequency of observation (e.g. West *et al.* 2018). Given the success of the GRACE mission, in hydrological drought monitoring and beyond, the remote sensing community also awaits measurements from the GRACE-FO (Follow On) mission which was successfully launched in May 2018 and will extend the data record of its predecessor.

As noted above, accurate estimate of river discharge from solely remotely sensed data is still a major ambition (Lettenmaier *et al.,* 2015). The proposed 2020 launch of the ESA SWOT (Surface Water Ocean Topography) mission may well achieve this goal. SWOT is expected to provide estimates of water surface slope, elevation and width for large river systems globally (i.e. those with a minimum width of 100m). Research using synthetic SWOT observations of channel slope and elevation suggest great potential of the mission to reliably estimate river discharge (Andreadis *et al.,* 2007; Biancamaria *et al.,* 2011). While no research has been conducted relating SWOT to hydrological drought monitoring, the above studies suggest the sensor may have potential in this field.

As well as new sensors, opportunities for effective drought monitoring will continue to expand with new approaches to 'blend' data products, such as the fusion of Landsat, Sentinel-2 and Sentinel-3 discussed above. A key example of a sensor blended data product is the ESA CCI (Climate Change Initiative) SM (Soil Moisture) dataset. The CCI SM dataset combines various active and passive soil moisture datasets into three products: a merged ACTIVE and merged PASSIVE, and a COMBINED active and passive product (Dorigo *et al.,* 2017). The current version of the dataset covers the period 1978-2016. The CCI SM dataset has been used in agricultural drought-related research (e.g. Chen *et al.,* 2014; Sawada, 2018), with the authors noting the value of the long CCI SM data record. As the data continues to expand temporally and improve in accuracy, it is expected that its utility in the field of drought monitoring will be core to examining long term soil moisture trends. Recent comparisons of CCI SM data and GLDAS (Global Land Data Assimilation) simulated soil moisture show that the two are significantly correlated; showing similar severity and spatial extents of drought events. However, the research concluded that the ESA CCI SM dataset is more effective in drought monitoring, except in highly vegetated areas (Liu *et al.,* 2019); further demonstrating the high potential of this dataset.

As well as new sensors and data products, new applications of existing datasets and analytical platforms are becoming available as technology continues to advance. For example, recent work has seen SMAP data used to improve estimates of evapotranspiration (Purdy *et al.,* 2018). The utility of the Google EarthEngine in rapidly calculating evaporation/evapotranspiration for meteorological drought monitoring has already been highlighted in this review. The platform allows for analysis of key remote sensing data products, including the full Landsat record from Landsat 4 onwards, Sentinel-2A, MODIS (including VI's, GPP estimates and thermal anomalies), and TRMM and GPM precipitation estimates (Gorelick *et al.,* 2017). However, the platform has still yet to be fully utilised for wider/integrated drought monitoring approaches at a global scale.

With increased research on the effects of climate change and human activities, the role of anthropogenic influences on drought event propagation and termination is now becoming ever more apparent, suggesting that drought is not only a phenomenon induced by solely natural processes (Van Loon & Van Lanen, 2013; Van Loon *et al.,* 2016). Various methods to assess the role of human activity on drought have been proposed (Rangecroft *et al.,* 2019; Van Loon *et al.,* 2019), however no such research has yet considered the role of remote sensing and earth observation in assessing anthropogenic activity and the association with drought propagation/termination.

9.0 Summary

Since, 1970 there has been a fundamental shift in how we approach drought monitoring; moving away from traditional site-based measurements which are often limited in temporal and spatial resolution to the deployment of remote sensing technologies. In 2005 Wilhite & Pulwarty noted four key issues in drought monitoring. These challenges are still relevant today; however we suggest that the application of remote sensing has, and will continue to, help the research community address these:

1. Spatial resolution and coverage: Remote sensing has significantly improved the coverage and spatial resolution of drought-related variables and has allowed for effective water management in data-poor regions (Sheffield *et al.,* 2018). Sensors have large swaths and high temporal resolution, giving frequent global scale coverage. While in the past there have been limitations around spatial resolution (Brown *et al.,* 2008; Davies *et al.,* 2016), as technology advances this will become less of an issue in drought monitoring, particularly as advances are made in the development and deployment of hyper-resolution sensors.
2. Temporal frequency of observations: Due to the complex nature of drought events, in both their development and termination (Parry *et al.,* 2016), regular observations of key variables are required. Through remote sensing a range of daily to weekly observations are available, such as (sub-)daily rainfall from GPM and weekly/bi-weekly vegetation condition indices from MODIS, Landsat and now Sentinel-2. Frequent observation, in combination with enhanced spatial coverage, of drought-related variables has provided data in what were traditionally data-sparse regions, particularly in the developing world.
3. A need for a range of drought indicators: There are a large number of remote sensing data products covering almost all phases of drought propagation, the exception being accurate and frequent observations of river discharge. The combined uses of these datasets to calculate drought monitoring indices has allowed for integrated studies monitoring drought propagation to be undertaken at scales previously unavailable to researchers (e.g. Nicolai-Shaw *et al.,* 2017; Orth & Destouni, 2018).

4. A lack of understanding of extreme events: Wilhite & Pulwarty (2005) noted this challenge in relation to the monitoring of both floods and droughts. Remote sensing technologies, through the wide range of sensors and data products, have allowed for greater understanding and better-informed decision making across a range of scales. For example, remote sensing is now commonly used to monitor irrigation systems in many very droughty and dry regions, allowing for scarce water resources to be effectively and efficiently managed to support crop growth (e.g. Vanino *et al.,* 2018)

In the field of drought monitoring the increasing detail, reliability and accuracy of remote sensing data products will enhance our capacity to forecast and monitor all forms of drought and its impacts at a range of spatial and temporal scales. As we move into the future and technology advances, we must extend the use of remote sensing in drought monitoring (Andela *et al.,* 2013). This may be through the launch of new satellites/sensors or developing new approaches and methodologies to reanalyse existing data. We conclude this paper by thanking *Remote Sensing of Environment* for its role as a key platform for dissemination, and the research community for the advances in the field over the last 50 years, and now look forward to the continued application of remote sensing for effective, innovative and efficient drought monitoring solutions.

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Figure Captions

Figure 1: Number of papers relating to drought (in both paper titles and keywords) in *Remote Sensing of Environment* and *Web of Science* since 1982. Search terms included various versions of 'Drought' and 'Remote Sensing'.

Figure 2: Different types of drought, their interactions and associated impacts (Adapted from Van Loon, 2015)

Figure 3: Treemap of monitoring approaches used in agricultural drought monitoring of the papers reviewed. Papers were sourced from a range of journals including *Remote Sensing of Environment, Remote Sensing, and the International Journal of Remote Sensing.*

Figure 4: Key milestones and a chronological view of the development of agricultural drought monitoring indices