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Monitoring drought and salinity stress in agriculture by remote sensing for a sustainable future

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Chapter 2

A review of remote sensing challenges for food security with respect to salinity and drought threats

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Abstract

Drought and salinity stress are considered to be the two main factors limiting crop productivity. With climate change, these stresses are projected to increase, further exacerbating the risks to global food security. Consequently, to tackle this problem, better agricultural management is required on the basis of improved drought and salinity stress monitoring capabilities. Remote sensing makes it possible to monitor crop health at various spatiotemporal scales and extents. However, remote sensing has not yet been used to monitor both drought and salinity stresses simultaneously. The aim of this paper is to review the current ability of remote sensing to detect the impact of these stresses on vegetation indices (VIs) and crop trait responses. We found that VIs are insufficiently accurate ($0.02 \leq R^2 \leq 0.80$) to characterize crop health under drought and salinity stress. In contrast, we found that plant functional traits have a high potential to monitor the impacts of such stresses on crop health, as they are more in line with the vegetation processes. However, we also found that further investigations are needed to achieve this potential. Specifically, we found that the spectral signals concerning drought and salinity stress were inconsistent for the various crop traits. This inconsistency was present (a) between studies utilizing similar crops and (b) between investigations studying different crops. Moreover, the response signals for joint drought and salinity stress overlapped spectrally, thereby significantly limiting the application of remote sensing to monitor these separately. Therefore, to consistently monitor crop responses to drought and salinity, we need to resolve the current indeterminacy of the relationships between crop traits and spectrum and evaluate multiple traits simultaneously. Using radiative transfer models (RTMs) and multi-sensor frameworks allows monitoring multiple crop traits and may constitute a way forward toward evaluating drought and salinity impacts.

2.1 Introduction

Food security is a serious problem around the world with a significantly large number of food production systems currently at risk (FAO 2011). It is predicted that by 2030, the population suffering from food insecurity will rise to more than 840 million. Meanwhile, it is projected that the ongoing COVID-19 could further worsen the number of undernourished people around the world (FAO 2020). Further exacerbating this food security problem, crop productivity itself also suffers great threats from stresses, such as drought stress, nutrient stress, and salinity stress, which reduce the yield at various locations by more than 50% (Anami et al. 2020). Moreover, crops frequently suffer from a combination of stress (Dresselhaus and Hückelhoven 2018), which further causes challenges for food production. In order to allow for sustainable agricultural production and mitigate the threat of global food shortages, the impact of these stressors needs to be monitored and alleviated.

Water stress, in the form of droughts, has been identified as the most serious threat for global agriculture, approximately affecting 40% of the world's land area (Dunn et al. 2020). Between 1980 and 2020, droughts have caused economic damages of around $6 billion per year in the United States, exceeding damages from other weather and climate disasters (Smith 2020). Likewise, in China, the average annual economic damage due to drought was $12.8 billion during 2006-2015 (Su et al. 2018). In addition to drought, salinity has emerged as a major factor limiting the productivity of crops. Southwest United States, southern Asia (including India and Pakistan), eastern Asia (Western China), eastern Australia, and northwest Africa are the most affected areas (FAO/IIASA/ISRIC/ISSCAS/JRC 2012; Ivushkin et al. 2019; Koohafkan 2012). The United Nations Food and Agriculture Organization (FAO) has estimated that 11% of the global irrigated area (34 Mha) is currently affected by different levels of salinity. Therein, China, the United States, Pakistan, and India hold more than 60% of the total area (21 Mha).

While presently, drought and salinity already pose tremendous challenges for food production, it has been forecasted that both stressors will increase both spatially and in severity. Climate change will increase the frequency and severity of drought events in numerous regions (Cook et al. 2015; Mosley 2015; Schwalm et al. 2017; Trenberth et al. 2013), leading to dramatic impacts on crop growth and productivity (Trenberth et al. 2013). Specifically, higher temperatures and lower humidity have been shown to lead to an increasing water demand (in the form of crop evapotranspiration) and a reduced water availability from effective precipitation, while simultaneously, a lower and infrequent effective precipitation significantly reduces water availability, thereby negatively affecting food production (Mimi and Jamous 2010). Similarly, it has been suggested that salinity will impact 50% of the cultivated land by 2050 (Butcher et al. 2016). Soil salinity levels have been shown to increase in arid lands because fresh water is not available to drain accumulated salts (Rozema and Flowers 2008), thus acting as a practically irreversible process. Moreover, soil salinization has been shown to increase with the expansion of agriculture to semi-arid and arid regions (Cramer et al. 2007; Oki and Kanae 2006; Rozema and Flowers 2008). Therefore, the increase in drought frequency and soil salinity under climate change further exacerbates the threat to crop production.

Drought and salinity cannot be seen independently of each other. As an aspect of water quality, salinity has been proven to increase during drought periods (Hrdinka et al. 2012; Mosley 2015; van Vliet and Zwolsman 2008). Specifically, it has been shown that due to lower river levels, hydrological drought significantly increases the salinity in rivers (Jones and van Vliet 2018; Mosley 2015). Consequently, increased drought frequency and severity will exacerbate the accumulation of salinization and adversely affect crop yield and sustainable agricultural development (Wang et al. 2013b). As such, there are already numerous areas in the world where both drought and salinity stress co-occur (Figure 2.1). Furthermore, due to sea level rise in the future, cultivated land (and in particular coastal lowlands) will have a higher probability to suffer from both drought and salinity stress (Corwin 2020; Gopalakrishnan et al. 2019; Katschnig et al. 2013; Pankova and Konyushkova 2014). Therefore, drought and salinity should not be viewed independently, and the impacts of joint drought and salinity stress on agricultural production should be investigated.

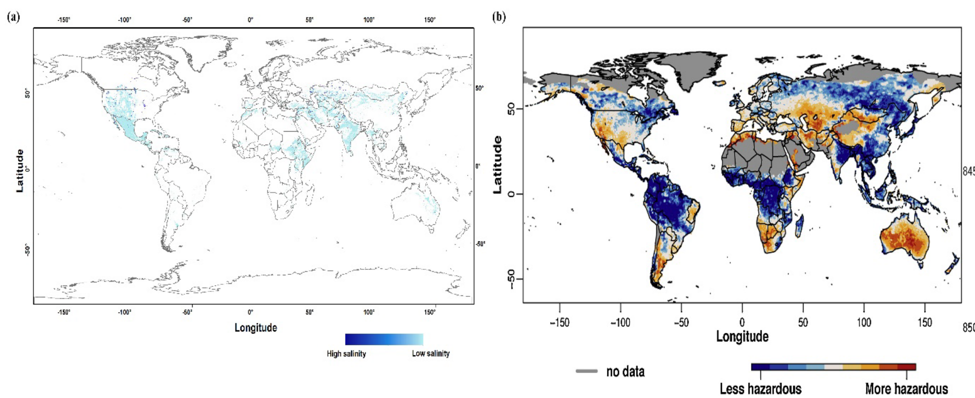


Figure 2.1 Global distribution of drought and salinity. In panel (a), the global map of soil salinity change is shown [10], while in panel (b) the global map of drought hazard (Carrão et al. 2016) is shown. Global soil salinity map was extracted from [10] and then transformed to the plate carrée projection by ArcGIS.

Remote sensing (RS) is a key method for monitoring crop health due to its capability to monitor and detect effective changes of large areas at a relatively low cost, in comparison to traditional methods (Wu et al. 2015). For this purpose, several vegetation indices (VIs) such as the Normalized Difference Vegetation Index (NDVI) (Tucker 1979), the Perpendicular Vegetation Index (PVI) (Rondeaux et al. 1996), and the Soil Adjusted Vegetation Index (SAVI) (Huete 1988) have been developed in the past to monitor agricultural production. In addition, drought (impact) indicators have been developed that account for seasonality effects (based on long-term standardized observations), e.g., the Vegetation Condition Index (VCI) (Kogan 1995b), the Vegetation Health Index (VHI) (Kogan 1997), and the Normalized Difference Water Index (NDWI) anomalies (Gao 1996). However, each of these drought indicators has specific limitations that limit its applicability as early warning signals of drought (Liu et al. 2016). As a consequence, results vary among different indices, and most applications with these indicators focus on local scales and individual crop types. As such, no comprehensive vegetation index has been developed that can be applied globally to investigate drought impact consistently (Liu et al. 2016). Similar to drought monitoring, vegetation indices, used to monitor crop salinity stress, are also affected by limitations regarding noise, halophyte presence, and spatial resolution (Allbed and Kumar 2013; Metternicht and Zinck 2003). In response, a more comprehensive measurement of the reflectance spectrum representing crop traits is required to monitor crop growth and health as affected by stress. In this regard, it has been shown that hyperspectral data have a strong potential to detect biophysical and biochemical parameters (Serbin et al. 2015; Serbin et al. 2016). In addition, various studies highlighted that other (multi-spectral) RS methods (e.g., microwave, thermal infrared (TIR), hyperspectral) show great promise in characterizing vegetation stress (Gerhards et al. 2019; Vereecken et al. 2012). However, the number of studies focusing on this is limited, and only part of these investigations focused on agricultural RS applications (Homolova et al. 2013; Weiss et al. 2020), while studies on the relationship between crop traits and spectral properties in relation to under drought or salinity stress are even more limited. Therefore, an in-depth analysis of the reflectance spectrum of crop traits under stress is required to better identify plant drought and salinity stress by remote sensing.

The main objective of the study is to evaluate the current state and shortcomings in the RS monitoring of crops under drought and/or salinity stress. Based on a comprehensive analysis, we evaluate the potential of remote sensing to identify and assess agricultural ecosystems under drought and salinity stress through vegetation indices and plant traits.

2.2 Methodology

To evaluate the current state of monitoring drought and salinity stress by RS, we applied a thorough systematic review of recent scientific publications. For this, we

(a) collected a large representative set of scientific publications, and (b) analyzed their results to identify the response patterns in vegetation indices and plant traits. For the analysis of plant traits, we classified them according to underlying plant functions (relating to primary production, hydrological processes, and osmosis). This allows us to coherently investigate the potential of remote sensing for monitoring the salinity/drought impact on biological pathways/processes.

2.2.1 Creating representative database through a systematic review

In order to facilitate the analysis of a representative set of recent publications, we adopted an optimized systematic review approach (Berger et al. 2018). Specifically, we focused on scientific peer-reviewed papers published between 2005 and 2020 through the Web of Science (WOS) and Google Scholar (GS) (Figure 2.2). This approach first requires the definition of a representative set of keywords. For our study, these keywords were “remote sensing”, “drought”, “salinity”, “agriculture”, and “traits”, as well as their synonyms (such as RS, food security, etc.). Afterwards, publications were selected from WOS and GS according to the occurrence of combinations of these keywords in the title, abstract, author keywords, and keywords plus, to create a first selection of publications, leading to 1184 selected records. Then, this set of publications was screened to capture only papers that analyzed (a) the impact of drought/salinity stress on VIs/traits of crops by remote sensing, and (b) included information on the spectral wavelength on which the analysis was based. This resulted in 78 unique records. Next, through snowballing these records (to capture papers that were missed in the first step), an additional 49 publications were obtained. In total, 115 publications (Table S2-1) fitting these criteria were identified after removing 12 duplicates. More details on each step are provided in the supplementary information (Figure S2-1). Maps of co-authors and co-occurrences based on the results of the systematic review were created through VOSviewer (Figure S2-2).

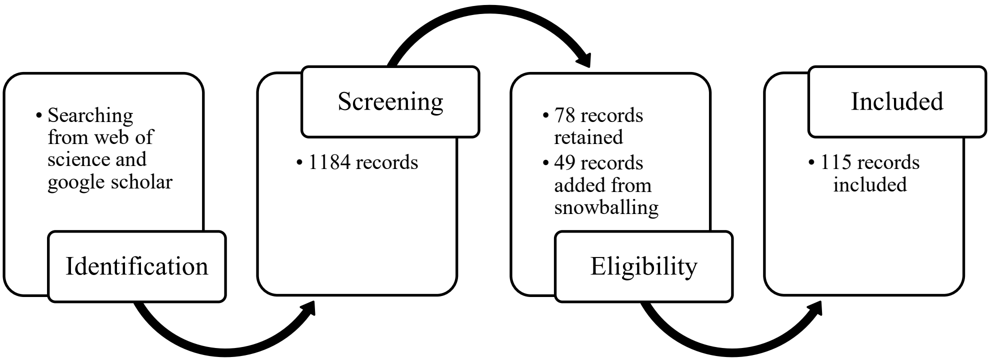


Figure 2.2 Flowchart of the systematic review.

2.2.2 Extraction of drought/salinity stress information

From the full set of publications on drought and salinity stress of agricultural crops, we extracted the correlation strengths between vegetation indices/crop traits responding to drought and salinity stress and spectral bands/wavelengths. Finally, 348 correlations were found, among which 102 traits were wavelength correlations, 171 were VIs-wavelength correlations, and 75 traits were VIs correlations. All 171 VIs-wavelength correlations that we found focused on drought, and no reviewed study provided correlations for salinity stress.

2.2.3 Classification of plant traits and vegetation indices

After the creation of our representative set of publications, we clustered the traits into four groups to relate the impact of drought/salinity stress on biological processes. Specifically, we classified the traits together on the basis of their definitions and the functional processes involved (Niinemets 2015; Pérez-Harguindeguy et al. 2013). This provided us with four clusters, namely biomass traits, photosynthesis traits, water traits, and osmosis traits. Afterwards, each cluster was further divided into RS (directly measurable by RS) and In-RS (indirectly derived by RS) (Table 2.1).

Table 2.1 Classification of plant traits included in this study.

Group	**RS methods**	**Traits**							
Biomass traits	RS	LMA	LAI	--	--	--	--	--	--
	In-RS	FS	SDW	BDW	BFW	--	--	--	--

Photosynthesis traits	RS	Chl	Chla/Chlb	--	--	--	--	--	--
	In-RS	A	Pn	ΔF/Fm	Chl*ΔF /Fm	--	--	--	--
Water traits	RS	LCT	CWC	RWC	EWT	CWM	--		
	In-RS	Gs	LOP	Ψp	LWP	Ψs	E	Tl - Tair	--
Osmosis traits	RS	--	--	--	--	--	--	--	--
	In-RS	Na^+	Cl^-	K^+	Ca^{2+}	K^+/Na^+	TSS	TA	TSS/ TA

Notes: leaf mass per unit area (LMA), leaf Area Index (LAI), fruit size (FS), shoot dry weight (SDW), biomass dry weight (BDW), biomass fresh weight (BFW), stomatal conductance (Gs), net gas exchange (A), leaf total chlorophyll (Chl), the quantum yield of photosystem II efficiency (ΔF/Fm), net photosynthesis rate (Pn), the difference between leaf and air temperature (Tl -Tair), transpiration rate (E), leaf water potential (LWP), stem water potential (Ψs), leaf osmotic potential (LOP), leaf canopy temperature (LCT), canopy water content (CWC), relative water content (RWC), leaf equivalent water thickness (EWT), pressure potential (Ψp), canopy water mass (CWM), Na^+ contents in leaf (Na^+), Cl^- contents in leaf (Cl^-), K^+ contents in leaf (K^+), Ca^{2+} contents in leaf (Ca^{2+}), total soluble solids (TSS), tritatable acidity (TA). RS methods: directly derived by remote sensing (RS), indirectly derived by remote sensing (In-RS).

In addition to individual plant functional traits, well-known RS vegetation indices have been related to the responses to drought and/or salinity stress. For consistency, we clustered the results of these studies on the basis of a functional classification, resulting in xanthophyll indices, water content indices, carotenoid indices and greenness indices (Table 2.2).

Table 2.2 Classification, explanation, and equations of different vegetation indices (VIs) included in this study.

VIs	Meaning	Equation	Reference
Xanthophyll Indices			
PRI570	Photochemical reflectance index	(R531 - R570) / (R531 +R570)	(Gamon et al. 1992)
PRI515	Photochemical reflectance index	(R531 - R515) / (R531 +R515)	(Hernández-Clemente et al. 2011)
PRI586	Photochemical reflectance index	(R531 – R586) / (R531 + R586)	(Panigada et al. 2014)
PRI600	Photochemical reflectance index	(R531-R602) / (R531 + R602)	(Hernández-Clemente et al. 2011)
PRI670	Photochemical reflectance index	(R531-R668) / (R531 + R668)	(Hernández-Clemente et al. 2011)
Water Content Indices			
WI	Water index	R900 / R970	(Peñuelas et al. 1993)
CWSI	Crop Water Stress Index	CWSI = (Tleaf - Twet) / (Tdry - Twet)	(Idso et al. 1981)
Carotenoid Indices			
R520/R500	Carotenoid concentration		(Zarco-Tejada et al. 2012)
R515/R570	Carotenoid concentration		(Zarco-Tejada et al. 2012)
Greenness Indices			

OSAVI	Optimized Soil-Adjusted Vegetation Index	(R800 −R670) / (R800 + R670 + 0.16)	(Rondeaux et al. 1996)
TCARI	The Transformed Chlorophyll Absorption in Reflectance Index	TCARI = 3 · [(R700 − R670) − 0.2 · (R700 − R550) · (R700/R670)]	(Haboudane et al. 2002)
TCARI/OSAVI	Normalized by OSAVI to obtain	TCARI/OSAVI = [3 · [(R700 − R670) − 0.2 · (R700 − R550) · (R700/R670)]]/ [(1 + 0.16) · (R800 − R670) / (R800 + R670 + 0.16)]	(Haboudane et al. 2002)
CIgreen	Green chlorophyll index	(R750 / R550)–1	(Gitelson et al. 2005)
CIred edge	Red edge chlorophyll index	(R750 / R710)–1	(Gitelson et al. 2005)
SR	Simple ratio	R800 / R670	(Asrar et al. 1985)
Red edge ratio index		R700 / R670	(Zarco-Tejada et al. 2013b)
VOG1	The chlorophyll a +b index	R740 / R720	(Vogelmann et al. 1993)
ZM	The chlorophyll a +b index	R750 / R710	(Zarco-Tejada et al. 2001)

Notes: R means the reflectance of the band and T means temperature. While NDVI has been used frequently for drought monitoring at a regional scale, we did not include it in this review. The reasoning for this is that NDVI is considered as a greenness index related to chlorophyll instead of the water status of the vegetation. In support of this interpretation, NDVI has not been found to respond to rainfall or major precipitation events during the crop growth period (Rahimzadeh-Bajgiran et al. 2012; Rahimzadeh Bajgiran et al. 2008). Therefore, NDVI was not included in the review.

2.2.4 Analyses of Vegetation Responses

After all functional clusters were defined, we aggregated the results from the different papers for each functional cluster (of VIs and plant traits) and proceeded to analyze their correlations. We first analyzed the spectral signatures of VIs under drought and their strengths. Afterwards, the distribution of spectral signatures of each functional traits cluster was investigated in the range of 400–2800 nm. Finally, we analyzed the correlations of different clusters of VIs and plant traits.

2.3 Results

2.3.1 Spectral signatures of vis under drought stress

We found a wide range of correlations for the four clusters of VIs (defined within the spectral range of 500–1050 nm) under drought stress, as highlighted in Figure 2.3. Specifically, xanthophyll indices showed their highest R^2 at 531 nm (R^2max = 0.80) and 570–600 nm (R^2max = 0.80), while greenness indices showed their highest R^2 at 550 nm (R^2max = 0.70), 670 nm (R^2max = 0.76), 700–750 nm (R^2max = 0.78), and 800 nm (R^2max = 0.76), and water indices showed their highest R^2 at 900 nm (R^2max = 0.72) and 970 nm (R^2max = 0.72). For carotenoid indices, no such region could be identified due to mostly low correlations ($0.20 \leq R^2 \leq 0.49$).

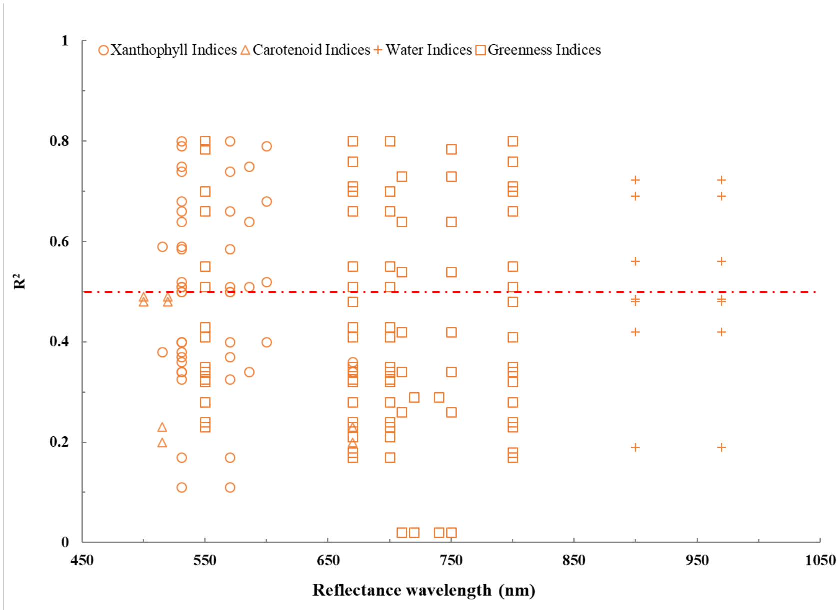


Figure 2.3 Relationships between R^2 and wavelength of different VIs clusters under drought stress. The red line indicates that $R^2 > 0.50$.

While we could identify specific regions where individual VIs provided a maximum sensitivity, we also found variation in this sensitivity. Although we identified studies that highlighted the potential of specific VIs for drought monitoring, we also found other studies reporting low R^2 ($R^2 < 0.50$) for the same VIs and wavelengths. Thus, there are undeniable limitations to identifying vegetation health using VIs under drought stress.

2.3.2 Spectral signatures of plant traits under drought and salinity stress

The reviewed studies focusing on plant trait signals showed that these crop responses were not constrained to specific wavelengths. Biomass, photosynthesis, water, and osmosis clusters of traits were identified across the full spectral range. These clusters showed few spectral patterns, even for those trait clusters that were supposedly directly measurable by RS (Figure 2.4). The only recognizable trends concern the osmosis traits cluster (with a significant response to salinity stress), with a slight tendency to occur more frequently at 550–750 nm, and the biomass traits and water traits occurring at 1400–1850 nm. As far as the few observations for drought do allow, those patterns did not seem to deviate much from those for salinity (Figure 2.4).

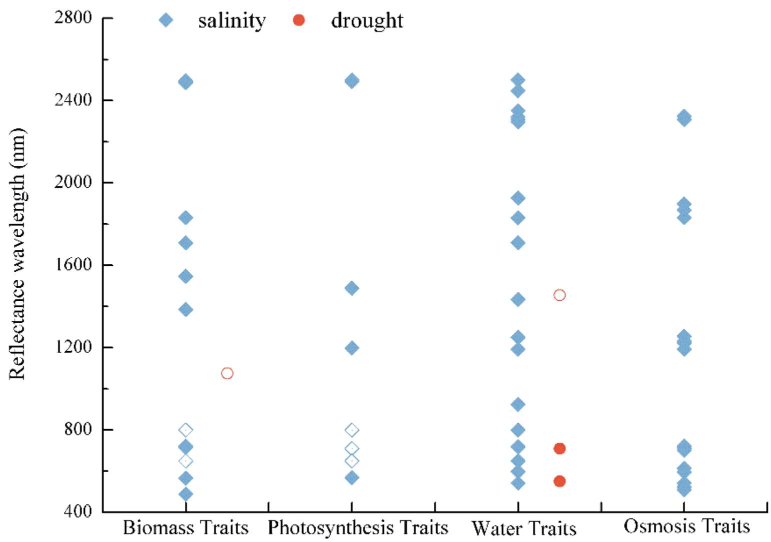


Figure 2.4 Drought and salinity stress responses of different trait clusters across the reflectance spectrum based on relationships with $R^2 > 0$. Solid symbols indicate traits directly measured by RS; empty symbols are related to traits indirectly measured by RS.

Moreover, while plant traits are more directly related to plant functioning and thus to stress, the correlations between the plant traits and the (drought and salinity) stress were not necessarily stronger (Figure 2.5). Biomass traits showed to have high R^2 value to salinity stress at around 720 nm (R^2max = 0.74), 1300–1800 nm (R^2max = 0.88), and around 2500 nm (R^2max = 0.88). Photosynthesis traits had high R^2 values at 710 nm (R^2max = 0.97), 800 nm (R^2max = 0.89), 1200 nm, and around 2500 nm (R^2max = 0.75). Interestingly, for both biomass and photosynthesis traits, the indirectly derived plant traits had generally higher R^2 values than the directly measurable RS traits. For water traits, we found different patterns from biomass traits and photosynthesis traits, with high R^2 widely distributed between 500 and 2500 nm (R^2max = 0.78). While high R^2 peaked in the 600–800 nm range, they were also highly variable ($0.02 \leq R^2 \leq 0.78$). In contrast, osmosis traits (only indirectly retrievable) showed a very promising performance (all with $R^2 > 0.50$) across the entire region of 500-2300 nm. Thus, it seemed that osmosis traits were most directly related to salinity stress responses. For drought stress, the number of studies that presented the wavelengths they used was too limited to draw clear conclusions. In general though, neither the range of R^2 values nor the wavelengths at which traits responded to drought stress deviated much from those for salinity stress.

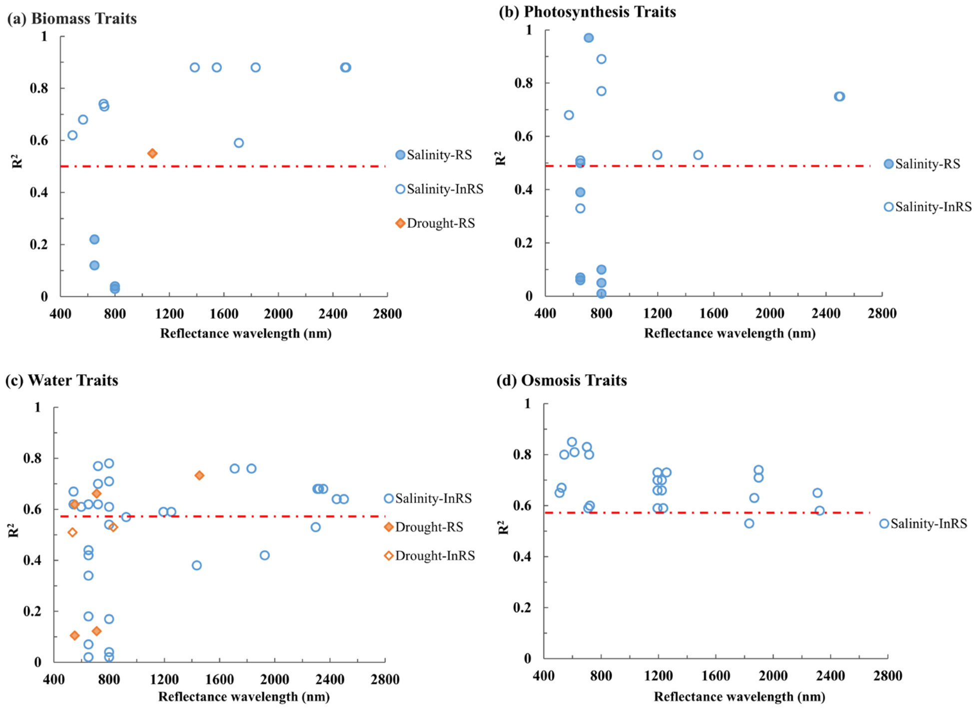


Figure 2.5 Relationship between R^2 and wavelength of different trait clusters under drought/salinity stress. RS identifies traits that can be directly measured by RS; InRS identifies traits that can be indirectly measured by RS. The red line indicates $R^2 > 0.50$.

2.3.3 The relationship between vis and plant traits

Vegetation indices have been shown to strongly correlate with individual plant traits (e.g., LAI and Chl), but the linkage between VIs, spectral reflectance, and crop traits remains inadequately understood. Thus, we analyzed the relationship between VIs and plant traits, and the results are shown in Table 2.3. For biomass traits, LAI showed high correlations with xanthophyll indices (R^2max = 0.66) and greenness indices (R^2max = 0.71) (particularly for OSAVI). Photosynthesis traits were also highly correlated with xanthophyll indices (R^2max = 0.68) and greenness indices (R^2max = 0.70). Especially, ΔF/Fm was highly correlated with TCARI/OSAVI (R^2max = 0.70). Water traits showed a wide range of correlations ($0.02 \leq R^2 \leq 0.80$) with VIs. Therein, Tl − Tair was highly correlated with PRI570 ($R^2 = 0.74$), PRI600 ($R^2 = 0.79$), and TCARI/OSAVI ($R^2 = 0.80$). CWC was highly correlated to three VIs, including WI ($R^2 = 0.72$), CIgreen ($R^2 = 0.78$), and CIred edge ($R^2 = 0.73$). EWTcanopy was highly correlated to PRI586 ($R^2 = 0.75$) and OSAVI ($R^2 = 0.76$). LWP was highly correlated to CWSI ($R^2 = 0.78$) and Gs was highly correlated with CWSI ($R^2 = 0.77$). Osmosis traits were mainly highly correlated with PRI570 (R^2max = 0.50). Thus, in general, the four trait clusters were highly correlated with xanthophyll indices ($0.50 \leq R^2max \leq 0.79$), while they showed lower correlations with carotenoid indices ($0.20 \leq R^2 \leq 0.49$). Furthermore, water traits were correlated stronger with water indices ($0.42 \leq R^2 \leq 0.78$) than with the other three trait groups ($0.19 \leq R^2 \leq 0.49$). Greenness indices showed high correlations with biomass traits ($R^2max = 0.71$), photosynthesis traits ($R^2max = 0.70$), and water traits ($R^2max = 0.80$) but not with osmosis traits ($R^2max = 0.35$). However, despite these general patterns, Table 2.3 also shows that variability in the relationships is high.

Table 2.3 The relationship between traits and VIs under drought stress

VIs	Biomass Traits		Photosynthesis Traits			Water Traits							Osmosis Traits		
	LAI*	FS	Chl*	ΔF/Fm	Chl×ΔF/Fm	Tl - Tair	CWC*	RWC*	EWT*	EWTcanopy*	LWP	Gs	TSS	TA	TSS/TA
Xanthophyll Indices															
PRI570	0.66	0.11	--	--	0.40	0.74	--	0.51	--	--	0.37	0.59	0.17	0.50	0.50
PRI515	--	--	--	--	--	--	--	--	--	--	0.38	0.59	--	--	--
PRI586	0.64	--	--	0.51	0.34	--	--	--	--	0.75	--	--	--	--	--
PRI600	0.40	--	--	0.68	--	0.79	--	0.52	--	--	--	--	--	--	--
PRI670	--	--	--	0.34	0.36	--	--	--	--	--	--	--	--	--	--
Carotenoid Indices															
R520/R500	--	--	--	--	--	--	--	--	--	--	0.48	0.49	--	--	--
R515/R670	--	--	--	--	--	--	--	--	--	--	0.20	0.23	--	--	--
Water Content Indices															
WI	0.49	--	--	0.48	0.19	0.69	0.72	0.42	--	0.56	--	--	--	--	--
CWSI	--	--	--	--	--	--	--	--	--	--	0.78	0.77	--	--	--
Greenness Indices															
OSAVI	0.71	--	--	0.48	0.32	--	--	--	--	0.76	--	--	--	--	--
TCARI	--	--	0.43	--	--	--	--	--	--	--	0.325	0.32	--	--	--
TCARI/OSAVI	0.34	0.32	0.66	0.70	0.51	0.80	--	0.41	0.55	--	0.28	0.23	0.24	0.35	0.28
CIgreen	--	--	--	--	--	--	0.78	--	--	--	--	--	--	--	--
CIred edge	0.64	--	--	0.42	--	0.54	0.73	0.34	--	--	--	--	--	--	--
SR	--	0.18	--	--	--	--	--	--	--	--	--	--	0.28	0.34	0.17
Red edge ratio index	--	--	--	--	--	--	--	--	--	--	--	0.21	--	--	--
VOG1	--	--	--	--	--	--	--	--	--	--	0.02	0.29	--	--	--
ZM	--	--	--	--	--	--	--	--	--	--	0.02	0.26	--	--	--

Note: bold numbers indicate that R^2 >0.50. * means the traits could be directly measured by RS.

2.4 Discussion

In this study, we systematically evaluated the usefulness of current monitoring approaches (i.e., vegetation indices and plant traits) for evaluating vegetation responses to drought and salinity stress. Vegetation indices have been developed to monitor vegetation health conditions since the 1980s (Rahimzadeh-Bajgiran et al. 2012), and a review of drought indices can be found in (Zargar et al. 2011). In contrast, only over the past two decades, remote sensing techniques have advanced enough to retrieve plant traits, increasingly leading to remote sensing applications to monitor plant traits to characterize both natural vegetation and crop functioning (Moreno-Martínez et al. 2018). However, a systematic review on the extent to which these metrics can pick up drought and salinity stress has so far been missing.

Our study reveals that most VIs reviewed are not accurate and consistent enough to detect changes in crop temporal and spatial responses under stress. This finding coincides with previous studies (Liu et al. 2016) that showed that simple VIs were hardly able to detect the impact of drought on crops. A possible explanation for this is that most VIs do not directly reflect the mechanism of crop responses to stress. While many VIs are related to (normalized) features of e.g., greenness, carotenoid, or xanthophyll concentrations, it seems that these features do not only vary because of the actual drought and salinity stress but also under the influence of various other local conditions. This may explain the wide range of R^2 values in relation to drought or salinity stress. In order to comprehensively monitor stress, we should therefore focus on exploring the spectral characteristics of crop tolerance and stress response mechanisms to truly reflect the crop health condition under stress.

Plant traits might provide an approach to measure these stress mechanisms, given that traits have proven to be indicators of plant and ecosystem functioning. While previous studies showed that RS could potentially address plant traits, in particular traits related to photosynthetic process, canopy structure, and leaf biochemistry (Homolova et al. 2013; Weiss et al. 2020), there are a few plant traits studies that focus on drought and salinity stress. More specifically, the number of drought and salinity studies evaluating plant traits is much lower than those using VIs. Irrespective of this dichotomy, our systematic review shows that neither the wavelengths at which traits are detected nor the strength of the relationship to drought and salinity stress is consistent within or between traits of different crops. In fact, a wide range of wavelengths used to detect plant traits was found (Homolova et al. 2013), which suggests that most relationships to spectral signatures are indirect at best. These indirect relationships, and thus the potential for confounding factors, may provide a partial explanation for the large variance we found in R^2 values and the generally low explained variance. One of those confounding factors concerns that crop (biomass and water) responses to salinity are to some extent similar to those to drought. This confounding factor leads to confusion in some results and has hitherto not been accounted for in previous studies. Furthermore, the relationship between traits and stress is further complicated by the fact the drought and salinity tolerance mechanisms of crops are complicated and multivariate.

An exception to the low and varied R^2 values is the osmotic traits as detected (indirectly) by remote sensing. In all evaluated studies, osmotic traits were strongly related to salinity stress. This phenomenon is linked to crop response mechanisms and is -in contrast to biomass and water responses- unique to salinity stress. Salinity stress inflicts damage to plants due to (a) the disruption of the ionic equilibrium, (b) an osmotic imbalance, and thereby (c) a decreased photosynthesis due to the toxicity of Na^+. Likewise, evidence shows that an increased expression of K^+, Ca^{2+}, Salt Overly Sensitive (SOS) pathways, and glycine betaine are related to salinity stress tolerance (Mahajan and Tuteja 2005; Niu et al. 1995; Yeo 1998). Both drought and salinity stress cause osmotic stress and decrease cytosolic as well as vacuolar volumes. In the case of drought, this osmotic stress is the result of a displacement of membrane proteins and disruptions in cellular metabolism (Mahajan and Tuteja 2005). In addition, reactive oxygen species are produced, which have adverse effects on cellular structures and metabolism (Bartels and Sunkar 2005). Therefore, the responses of plants to drought and salinity are identical at the early stage. Consequently, osmotic traits show a high potential as a suitable indicator for drought and salinity stress RS monitoring. In particular, promising results have been found for detecting ionic concentrations of sodium, potassium, and chloride (El-Hendawy et al. 2019b; Zhang et al. 2017). Unfortunately, though, it seems that our understanding at which wavelengths the osmotic traits are expressed is still limited.

As highlighted in the previous paragraph, plant functioning under stress is affected by various pathways. From that perspective, instead of focusing on individual VIs or traits, an alternative approach to monitoring drought and salinity stress is the consideration of multiple trait responses simultaneously. Although stresses have been investigated using many aspects, previous studies rarely utilized multiple variables to assess these pathways. Radiative transfer models (RTMs) may be particularly useful to retrieve such multiple variables from remote sensing observations. RTMs have been developed to study the relationship between vegetation biochemical and biophysical properties, and hyperspectral reflectance (Bayat et al. 2016; Botha et al. 2006). In the forward mode, RTMs simulate the vegetation spectrum based on known spectral signatures of vegetation biochemical and biophysical properties. Likewise, RTMs can retrieve vegetation properties from reflectance data in the inverse mode (Jacquemoud 2000; Lu et al. 2020a; Timmermans et al. 2009). Indeed, RTM inversion has been successfully applied to monitor the changes in plant traits and reflectance upon drought (Bayat et al. 2016). By monitoring multiple traits simultaneously, through the inversion of RTMs, it will become possible to evaluate how multiple traits in concert are affected by drought and/or salinity stress. This may also provide additional insights into the plant strategies to deal with drought and/or salinity stress. Unfortunately, though, the ill-posedness of the inversion problem commonly puts major constraints on the generic applicability of RTMs for crop monitoring. Another major constraint, in the context of this review, is that osmosis traits are difficult to measure directly by remote sensing. Dissolved salts such as Na^+, Cl^-, $K^{+,}$ and Ca^{2+} are not directly tractable, although NaCl has a clearly defined spectrum in the infrared spectrum. This strongly limits its incorporation within RTMs, which indeed only focus on a limited number of vegetation traits such as LAI, Chl, and CWC. More research will be needed to evaluate the prospects of physical modeling of radiative transfer under the influence of known stress response mechanisms. Traditional multi- or high-spectral field sensors to investigate the impacts of drought and salinity on crops in relation to in situ observed traits related to these stresses will be the way forward here.

A final limitation to monitoring plant traits in response to drought and salinity stress is the spatiotemporal and spectral resolution of current satellites. Low spatiotemporal resolution and revisit periods are two main restraints for current satellite sensor applications in crop management (Berni et al. 2009), although this has strongly improved with the launch of the Sentinels satellites. The spectral resolution is currently probably more limiting. The inconsistency across multiple sensors of different satellites does not allow combining them in one retrieval (Liu et al. 2016). Hyperspectral missions, such as those foreseen in EnMAP, may provide such information. This may be particularly interesting if combined with Light Detection and Ranging (LiDAR) information (e.g., from Global Ecosystem Dynamics Investigation (GEDI)) or high-resolution information on temperature (e.g., the Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS)). However, also, for a fruitful incorporation of such information sources, it will be essential to first characterize the spectral properties of traits directly related to the plant responses to drought and salinity stress. This will reduce the impacts of confounding factors that currently seem to dominate the patterns obtained, as seems apparent from Figures 2.3-2.5.

2.5 Conclusions

Based on a systematic review, we conclude that a significant number of challenges remain before RS can be used to monitor drought and salinity stress on crop health. Specifically, we found that VIs are insufficiently accurate to consistently estimate these effects. For plant traits, we found some positive correlations for individual cases, confirming that plant traits indeed reflect stress response mechanisms. However, these cases were too few to accurately monitor the pathways for drought and salinity stress. Furthermore, we found that both spectral wavelengths and the strength of the relationship to drought and salinity stress varied strongly. Osmosis traits appear to be the exception to this and consequently have the potential to be used for monitoring the pathways along which drought and salinity impact crops. However, osmosis traits cannot be directly measured by RS. In order to fully capture the biophysical/biochemical pathways of drought/salinity stress on crop health, future research should focus on (1) advancing our capability to simultaneously monitor (through multi-sensor frameworks) the suite of crop traits that are connected to the different pathways affected by drought and salinity, and (2) expanding our characterization of the spectral properties of osmotic traits (through optimized RTMs).

2.6 Author contributions

Conceptualization, J.T., P.M.v.B., and W.W.; methodology, J.T., W.W., and P.M.v.B.; investigation, W.W.; writing—original draft preparation, W.W.; writing—review and editing, P.M.v.B., J.T. and Q.C.; supervision, P.M.v.B. and J.T. All authors have read and agreed to the published version of the manuscript.

2.7 Supporting information

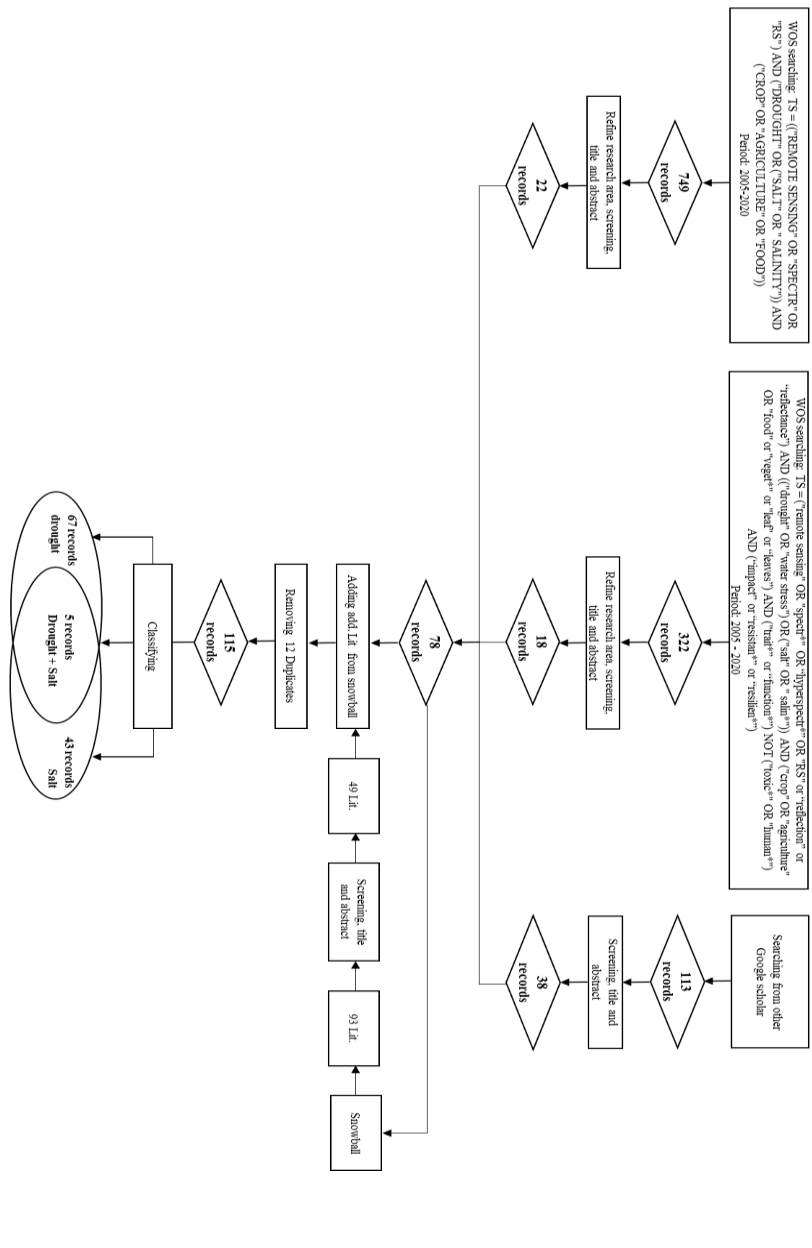
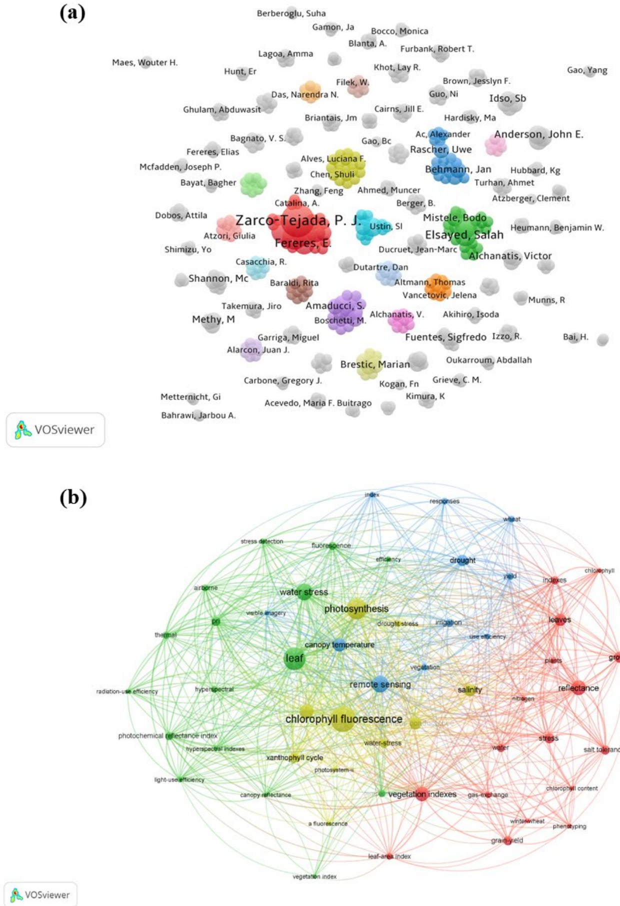


Figure S2-1 The flowchart of the systematic review

(a)



(b)

Figure S2-2 Maps of co-authors and co-occurrences from the results of the systematic review. A bubble and a tag constitute an element. The size of an element depends on the number of nodes, the strength of the line, and the number of citations. The color of an element represents the cluster to which it belongs, and different clusters are represented by different colors. In the co-author map, it shows the network of co-authorship links between 115 publications from the systematic review. The "bubbles" represent authors. The size of an author bubble represents the number of publications. Colors represent authors groups that are clustered by co-authorship links (Perianes-Rodriguez et al. 2016; Van Eck and Waltman 2011, 2014).

It was noticed that very few people are focusing on the topic of using remote sensing to monitor crop response to drought and salt stress. Also, the connections among most authors were rather weak. Also, there was a very limited number of studies focusing on monitoring crop traits responses to drought and salinity using remote sensing techniques as the co-occurrence map showed that the connection of plant traits and spectra was rather weak. Therefore, we conclude that these topics need further investigation.

Table S2-1 115 publications identified from the systematic review

No.	Title	Reference
1	Detection of early plant stress responses in hyperspectral images	(Behmann et al. 2014)
2	A crop-specific drought index for corn: I. Model development and validation	(Meyer et al. 1993)
3	A field experiment on spectrometry of crop response to soil salinity	(Leone et al. 2007)
4	A PRI-based water stress index combining structural and chlorophyll effects: Assessment using diurnal narrow-band airborne imagery and the CWSI thermal index	(Zarco-Tejada et al. 2013b)
5	Advanced phenotyping offers opportunities for improved breeding of forage and turf species	(Walter et al. 2012)
6	Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs	(Atzberger 2013)
7	Aerial canopy temperature differences between fast- and slow-wilting soya bean genotypes	(Bai and Purcell 2018)
8	Agricultural drought monitoring: Progress, challenges, and prospects	(Liu et al. 2016)
9	Anatomy of a local-scale drought: Application of assimilated remote sensing products, crop model, and statistical methods to an agricultural drought study	(Mishra et al. 2015)
10	Application of vegetation index and brightness temperature for drought detection	(Kogan 1995a)
11	Application of visible and near-infrared spectrophotometry for detecting salinity effects on wheat leaves (*Triticum aestivum* L.)	(Mokhtari M. H. et al. 2014)
12	Applying hyperspectral imaging to explore natural plant diversity towards improving salt stress tolerance	(Sytar et al. 2017)
13	Assessing canopy PRI for water stress detection with diurnal airborne imagery	(Suarez et al. 2008)
14	Assessing canopy PRI from airborne imagery to map water stress in maize	(Rossini et al. 2013)
15	Assessment of Photochemical Reflectance Index as a Tool for Evaluation of Chlorophyll Fluorescence Parameters in Cotton and Peanut Cultivars Under Water Stress Condition	(Yoshizumi et al. 2010)
16	Assessment of the water status of mandarin and peach canopies using visible multispectral imagery	(Kriston-Vizi et al. 2008)
17	Associated changes in physiological parameters and spectral reflectance indices in olive (*Olea europaea* L.) leaves in response to different levels of water stress	(Sun et al. 2008)
18	Biophysical properties and biomass production of elephant grass under saline conditions	(Wang et al. 2002a)
19	Broadband Spectral Reflectance Models of Turfgrass Species and Cultivars to Drought Stress	(Jiang and Carrow 2007)
20	Can chlorophyll-a fluorescence parameters be used as bio-indicators to distinguish between drought and salinity stress in *Tilia cordata Mill*	(Kalaji et al. 2018)
21	Canopy temperature as a crop water stress indicator	(Jackson et al. 1981)

22	Characterization of Crop Canopies and Water Stress Related Phenomena using Microwave Remote Sensing Methods: A Review	(Vereecken et al. 2012)
23	Chlorophyll fluorescence performance of sweet almond [Prunus dulcis (Miller) D. Webb] in response to salinity stress induced by NaCl	(Ranjbarfordoei et al. 2006)
24	Chlorophyll, anthocyanin, and gas exchange changes assessed by spectroradiometry in *Fragaria chiloensis* under salt stress.	(Garriga et al. 2014)
25	Comparative evaluation of the Vegetation Dryness Index (VDI), the Temperature Vegetation Dryness Index (TVDI) and the improved TVDI (iTVDI) for water stress detection in semi-arid regions of Iran	(Rahimzadeh-Bajgiran et al. 2012)
26	Computational water stress indices obtained from thermal image analysis of grapevine canopies	(Fuentes et al. 2012)
27	Crop yield prediction under soil salinity using satellite derived vegetation indices	(Satir and Berberoglu 2016)
28	Data fusion of spectral, thermal and canopy height parameters for improved yield prediction of drought stressed spring barley	(Rischbeck et al. 2016)
29	Detecting salinity stress in tall fescue based on single leaf spectrum	(Gao and Li 2012)
30	Detecting water stress effects on fruit quality in orchards with time-series PRI airborne imagery	(Suárez et al. 2010)
31	Detection of water stress in an olive orchard with thermal remote sensing imagery	(Sepulcre-Canto et al. 2006)
32	Detection of water stress in orchard trees with a high-resolution spectrometer through chlorophyll fluorescence In-Filling of the O2-A band	(Pérez-Priego et al. 2005)
33	Determining the Canopy Water Stress for Spring Wheat Using Canopy Hyperspectral Reflectance Data in Loess Plateau Semiarid Regions	(Wang et al. 2015)
34	Drought and Salinity Impacts on Bread Wheat in a Hydroponic Culture: A Physiological Comparison	(Movahhedi Dehnavi et al. 2017)
35	Drought stress effects on photosystem I content and photosystem II thermotolerance analyzed using Chl a fluorescence kinetics in barley varieties differing in their drought tolerance	(Oukarroum et al. 2009)
36	Early drought stress detection in cereals: Simplex Volume Maximization for hyperspectral image analysis	(Römer et al. 2012)
37	Effect of different concentrations of diluted seawater on yield and quality of lettuce	(Turhan et al. 2014)
38	Effects of four types of sodium salt stress on plant growth and photosynthetic apparatus in sorghum leaves	(Zhang et al. 2018)
39	Effects of saline reclaimed waters and deficit irrigation on Citrus physiology assessed by UAV remote sensing	(Romero-Trigueros et al. 2017)
40	Effects of salinity on physiological responses and the photochemical reflectance index in two co-occurring coastal shrubs	(Zinnert et al. 2012)
41	Estimating crop water stress with ETM+ NIR and SWIR data	(Ghulam et al. 2008)
42	Estimating growth and photosynthetic properties of wheat grown in simulated saline field conditions using hyperspectral	(El-Hendawy et al. 2019a)

	reflectance sensing and multivariate analysis	
43	Estimating Yields of Salt- and Water-Stressed Forages with Remote Sensing in the Visible and Near Infrared	(Poss et al. 2006)
44	Estimation of Canopy Water Content by Means of Hyperspectral Indices Based on Drought Stress Gradient Experiments of Maize in the North Plain	(Zhang and Zhou 2015)
45	Estimation of Water Stress in Grapevines Using Proximal and Remote Sensing Methods	(Matese et al. 2018)
46	Evaluation of agronomic traits and spectral reflectance in Pacific Northwest winter wheat under rain-fed and irrigated conditions	(Gizaw et al. 2016)
47	Evaluation of Hyperspectral Reflectance Parameters to Assess the Leaf Water Content in Soybean	(Kovar et al. 2019)
48	Evaluation of wavelengths and spectral reflectance indices for high-throughput assessment of growth, water relations and ion contents of wheat irrigated with saline water	(El-Hendawy et al. 2019b)
49	Fluorescence excitation spectra of drought resistant and sensitive genotypes of triticale and maize	(Grzesiak et al. 2007)
50	Fluorescence Spectroscopy to Detect Water Stress in Orange Trees	(Lins et al. 2005)
51	Fluorescence, PRI and canopy temperature for water stress detection in cereal crops	(Panigada et al. 2014)
52	Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera	(Zarco-Tejada et al. 2012)
53	Fluorescence-based sensing of drought-induced stress in the vegetative phase of four contrasting wheat genotypes	(Bürling et al. 2013)
54	Genes and salt tolerance: bringing them together	(Munns 2005)
55	Ground-based canopy sensing for detecting effects of water stress in cotton	(Stamatiadis et al. 2010)
56	High-throughput field phenotyping in dry bean using small unmanned aerial vehicle based multispectral imagery	(Sankaran et al. 2018)
57	Hyperspectral Reflectance Response of Freshwater Macrophytes to Salinity in a Brackish Subtropical Marsh	(Tilley et al. 2007)
58	Hyperspectral remote sensing of salinity stress on red (*Rhizophora mangle*) and white (*Laguncularia racemosa*) mangroves on Galapagos Islands	(Song et al. 2011)
59	Hyperspectral remote sensing to assess the water status, biomass, and yield of maize cultivars under salinity and water stress	(Elsayed and Darwish 2017)
60	Identifying leaf traits that signal stress in TIR spectra	(Acevedo et al. 2017)
61	Image-Derived Traits Related to Mid-Season Growth Performance of Maize Under Nitrogen and Water Stress	(Dodig et al. 2019)
62	Imaging chlorophyll fluorescence with an airborne narrow-band multispectral camera for vegetation stress detection	(Zarco-Tejada et al. 2009)
63	Integrating satellite optical and thermal infrared observations for improving daily ecosystem functioning estimations during a drought episode	(Bayat et al. 2018)
64	Interpretation of salinity and irrigation effects on soybean	(Wang et al. 2002b)

	canopy reflectance in visible and near-infrared spectrum domain	
65	Landsat images and crop model for evaluating water stress of rainfed soybean	(Sayago et al. 2017)
66	Leaf chlorophyll fluorescence, reflectance, and physiological response to freshwater and saltwater flooding in the evergreen shrub, *Myrica cerifera*	(Naumann et al. 2008b)
67	Leaf-rolling in maize crops: from leaf scoring to canopy-level measurements for phenotyping	(Baret et al. 2018)
68	Linking leaf chlorophyll fluorescence properties to physiological responses for detection of salt and drought stress in coastal plant species	(Naumann et al. 2007)
69	Linking physiological responses, chlorophyll fluorescence and hyperspectral imagery to detect salinity stress using the physiological reflectance index in the coastal shrub, *Myrica cerifera*	(Naumann et al. 2008a)
70	Measurement of leaf relative water content by infrared reflectance	(Hunt Jr et al. 1987)
71	Melon crops (*Cucumis melo* L., cv. Tendral) grown in a mediterranean environment under saline-sodic conditions: Part I. Yield and quality	(Tedeschi et al. 2011)
72	Meta-analysis assessing potential of steady-state chlorophyll fluorescence for remote sensing detection of plant water, temperature and nitrogen stress	(Alexander et al. 2015)
73	Modelling PRI for water stress detection using radiative transfer models	(Suarez et al. 2009)
74	Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data	(Rhee et al. 2010)
75	Monitoring stomatal conductance of *Jatropha curcas* seedlings under different levels of water shortage with infrared thermography	(Maes et al. 2011)
76	Monitoring water stress and fruit quality in an orange orchard under regulated deficit irrigation using narrow-band structural and physiological remote sensing indices	(Stagakis et al. 2012)
77	Monitoring yield and fruit quality parameters in open-canopy tree crops under water stress. Implications for ASTER	(Sepulcre-Canto et al. 2007)
78	Natural selection and neutral evolutionary processes contribute to genetic divergence in leaf traits across a precipitation gradient in the tropical oak *Quercus oleoides*	(Ramírez‐Valiente et al. 2018)
79	NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space	(Gao 1996)
80	New phenotyping methods for screening wheat and barley for beneficial responses to water deficit	(Munns et al. 2010)
81	Normalizing the stress-degree-day parameter for environmental variability	(Idso et al. 1981)
82	Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture	(Maes and Steppe 2019)
83	Phenotyping for Abiotic Stress Tolerance in Maize	(Masuka et al. 2012)
84	Photochemical reflectance index as a mean of monitoring early water stress	(Sarlikioti et al. 2010)

85	Photochemistry, remotely sensed physiological reflectance index and de-epoxidation state of the xanthophyll cycle in *Quercus coccifera* under intense drought	(Peguero-Pina et al. 2008)
86	Photosynthetic gas exchange, chlorophyll fluorescence and some associated metabolic changes in cowpea (*Vigna unguiculata*) during water stress and recovery	(Souza et al. 2004)
87	Potential and constraints of different seawater and freshwater blends as growing media for three vegetable crops	(Atzori et al. 2016)
88	Radiation use efficiency, chlorophyll fluorescence, and reflectance indices associated with ontogenic changes in water limited Chenopodium quinoa leaves	(Winkel et al. 2002)
89	Recovery responses of photosynthesis, transpiration, and stomatal conductance in kidney bean following drought stress	(Miyashita et al. 2005)
90	Relationships between net photosynthesis and steady-state chlorophyll fluorescence retrieved from airborne hyperspectral imagery	(Zarco-Tejada et al. 2013a)
91	Relationships between stomatal behavior, spectral traits and water use and productivity of green peas (*Pisum sativum* L.) in dry seasons	(Nemeskéri et al. 2015)
92	Remote sensing of soil salinity: potentials and constraints	(Metternicht and Zinck 2003)
93	Risk identification of agricultural drought for sustainable Agroecosystems	(Dalezios et al. 2014)
94	Salinity tolerance and the decoupling of resource axis plant traits	(Eallonardo Jr et al. 2013)
95	Seasonal and drought-related changes in leaf area profiles depend on height and light environment in an Amazon forest	(Smith et al. 2019)
96	Seasonal patterns of reflectance indices, carotenoid pigments and photosynthesis of evergreen chaparral species	(Stylinski et al. 2002)
97	Simple reflectance indices track heat and water stress-induced changes in steady-state chlorophyll fluorescence at the canopy scale	(Dobrowski et al. 2005)
98	Soil salinity mapping and hydrological drought indices assessment in arid environments based on remote sensing techniques	(Elhag and Bahrawi 2017)
99	Spatial–spectral processing strategies for detection of salinity effects in cauliflower, aubergine and kohlrabi	(Rud et al. 2013)
100	Spectral assessments of wheat plants grown in pots and containers under saline conditions	(Hackl et al. 2013)
101	Spectral indicators for salinity effects in crops: a comparison of a new green-indigo ratio with existing indices	(Rud et al. 2011)
102	Spectral indices for the detection of salinity effects in melon plants	(Hernández et al. 2014)
103	Spectral Reflectance for Indirect Selection and Genome-Wide Association Analyses of Grain Yield and Drought Tolerance in North American Spring Wheat	(Gizaw et al. 2018)
104	Steady-State and Maximum Chlorophyll Fluorescence Responses to Water Stress in Grapevine Leaves: A New Remote Sensing System	(Flexas et al. 2000)
105	The influence of diluted seawater and ripening stage on the	(Sgherri et al. 2007)

	content of antioxidants in fruits of different tomato genotypes	
106	The influence of soil salinity, growth form, and leaf moisture on the spectral radiance o	(Klemas and Smart 1983)
107	The Photochemical Reflectance Index (PRI) as a water-stress index	(Thenot et al. 2002)
108	The relationships between electrical conductivity of soil and reflectance of canopy, grain, and leaf of rice in northeastern Thailand	(Touch et al. 2015)
109	The use of infrared thermal imaging as a non-destructive screening tool for identifying drought-tolerant lentil genotypes	(Biju et al. 2018)
110	The Vegetation Drought Response Index (*VegDRI*): A New Drought Monitoring Approach for Vegetation	(Wardlow et al. 2008)
111	Thermal and Narrowband Multispectral Remote Sensing for Vegetation Monitoring From an Unmanned Aerial Vehicle	(Berni et al. 2009)
112	Use of thermal and visible imagery for estimating crop water status of irrigated grapevine	(Möller et al. 2007)
113	Using paired thermal and hyperspectral aerial imagery to quantify land surface temperature variability and assess crop stress within California	(Shivers et al. 2019)
114	Utilization of a high-throughput shoot imaging system to examine the dynamic phenotypic responses of a C-4 cereal crop plant to nitrogen and water deficiency over time	(Neilson et al. 2015)
115	Water stress detection in potato plants using leaf temperature, emissivity, and reflectance	(Gerhards et al. 2016)