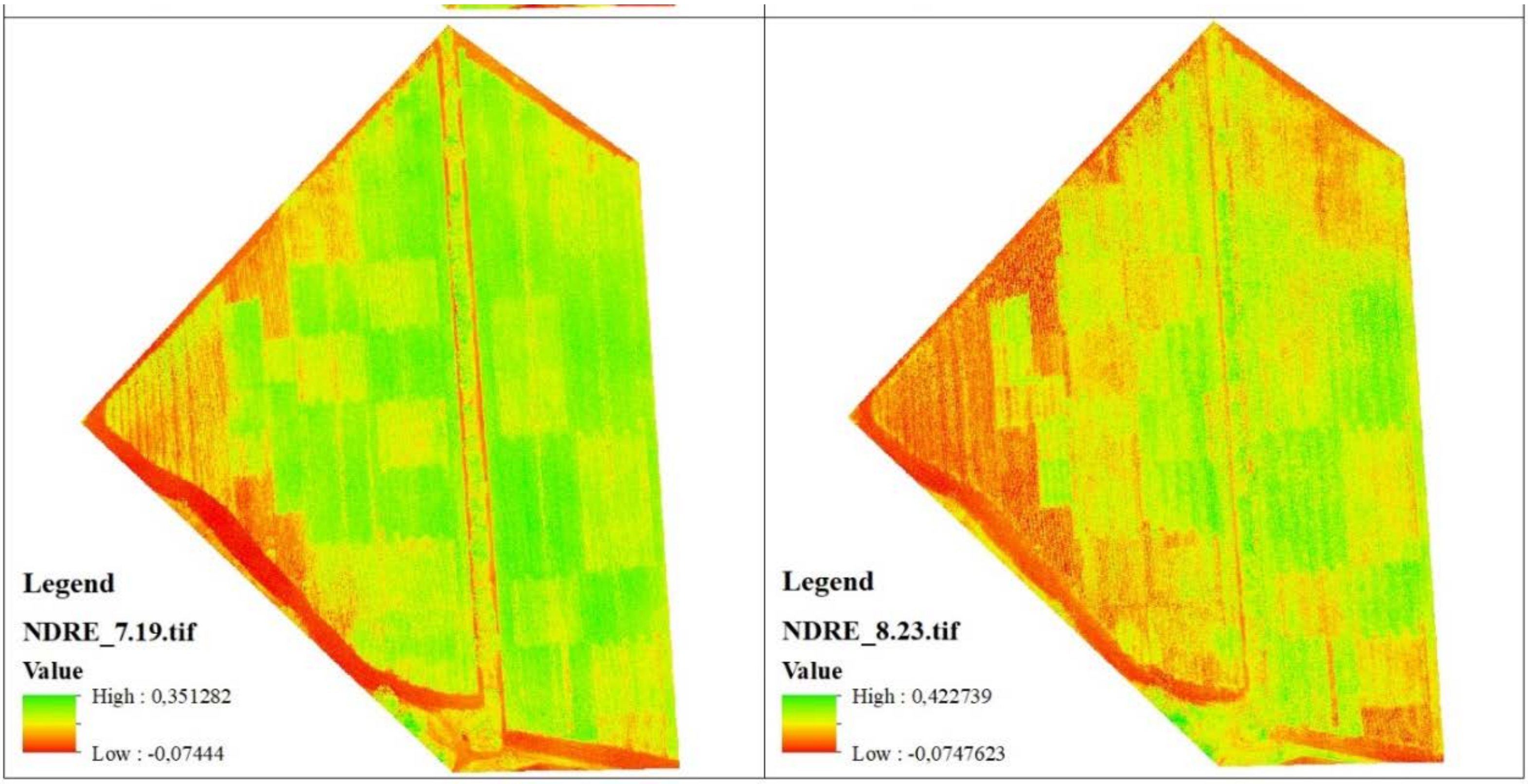
Remote sensing of drought stress and water balance modelling in agriculture



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Abstract

Remote sensing from satellites and drones can be used for irrigation scheduling in different ways. In the present report we outline some of these possibilities and present preliminary results from an irrigation experiment on potatoes conducted in 2017. Spectral indices can give information on drought stress directly either via detection of crop canopy temperature increases due to reduced transpiration, or by monitoring of changes in canopy reflective properties in the visible and near infrared spectrum. Another approach is to use measurements of canopy characteristics to complement current simulation model based irrigation scheduling to obtain higher accuracy and spatially distributed irrigation recommendations. While satellites can provide coverage of large areas and measurements at many wavelengths, drones can provide higher resolution and more frequent images, but at a higher cost. We have obtained satellite and drone imagery from an irrigation and N fertilization experiment on starch potatoes during 2017. We have shown clear patterns of different N-application rates on leaf area index and greenness of the crop, which may have influenced transpiration and soil water content pending further analyses. It is our plan to modify Vandregnskab to enable the model to use assimilated data obtained by remote sensing and investigate how much increase in precision can be obtained. From the drought stress perspective however, 2017 was less rewarding, as the potatoes were only irrigated twice relative early in the season. Nevertheless, during 2017, two 3-4 year duration projects for research on remote sensing for irrigation scheduling were applied for and granted, so that the activities can be continue until 2020.

Contents

1. Introduction

Water is essential to the life and growth of plants, being a major constituent of living green tissues and often comprising as much as 90-95 % of plants fresh weight (Vaadia et al., 2003). Plant stress due to lack of water (drought stress) occurs when the evaporative demand of the surrounding atmosphere exceeds the supply of water from the soil through the plant (Zarco-Tejada et al., 2012). Thus, many plant physiological processes are affected, e.g., protoplasmic hydration, osmotic effects, photosynthesis, plant assimilate and nutrient uptake (Vaadia et al., 2003). Finally, the plant will weaken and abscise. For agricultural crops, supplying water through irrigation is a solution but it is not a straightforward process because water is a limited resource and irrigation equipment is expensive. Agriculture is already the worlds' largest consumer of freshwater (Gilbert, 2012). Therefore, detecting and managing crops drought stress is important for food security and sustainable water resource management. In humid temperate climates, such as in Denmark, drought is intermittent and unpredictable, yet can be the major limitation to crop production throughout the growing season, especially for drought sensitive crops such as potato.

From 1960s onwards, remote sensing emerged for many applications, including crop production, drought stress detection and water management, due to its relative lower cost, easier operation and revisit capability compared to traditional methods (Homolová et al., 2013; Vadrevu, 2013). Plants have inherent spectral characteristics, such as they use only red and blue light in the visible spectrum (VIS, 400-700 nm) for photosynthesis, driven by the selective absorption of their pigments, leaving the reflected mid-VIS to give leaves their green visual color (Fig. 1). The most important chlorophyll-*a* (Chl-*a*) absorbs light at approximately 430 and 680 nm, whereas Chl-*b* uses 480 nm and 660 nm and *β*-carotene from 400 to 550 nm with two local maxima at 470 and 515 nm. The red edge (RE, 700-800 nm) is the region of rapid change in reflectance before the near infrared (NIR, 700-1300 nm). Maximum reflectance is reached in the NIR due to internal light scattering in the sponge mesophyll and due to external scattering within the canopy. In the shortwave infrared (SWIR, 1300-2500 nm), water dynamics and absorption is prominent, with absorption zones from 1450- 1530 nm and from 1900- 2000 nm. Yet, these spectral characteristics proved very similar, regardless of plant species and health status, which makes the spectral description of different plants and their eco-physiological status challenging for decades. Spectral indices (SIs), i.e. mathematical combinations and ratios of various bands, have proven useful in discriminating i.e. emphasizing differences.

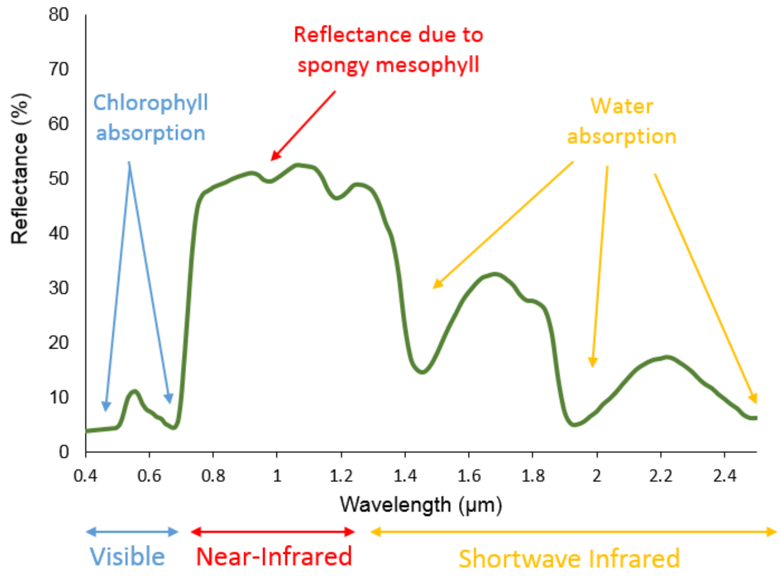

Fig. 1. Typical reflectance "signature" of vegetation (figure adapted from http://gsp.humboldt.edu/OLM/Courses/GSP_216_Online/lesson2-1/vegetation.html).

2. Spectral Index-based study of drought stress

Under drought, plants optimise their water balance by closing leaves' stomata, thereby limiting the diffusion of gases. This also increases leaf temperature and affects Chl, i.e., particularly the thylakoid membranes, and results in a reduced Chl content and decreased light-absorbing efficiency in the photosystems. The Chl degradation is commonly observed under drought stress, while plants exposed to high temperatures exhibit reduced Chl biosynthesis. Thus, both canopy temperature and photosynthesis are indicators of drought stress. A wide range of SIs can be found in the literature in relation to describing drought stress in plants (Baluja et al., 2012; Gago et al., 2015). One of the best databases for SIs and their sensor-dependent formulation can be found online at https://www.indexdatabase.de/. Despite their sensitive to leaf and canopy properties under drought stress, SIs are confounded by many factors, such as plant cover, size and age, leaf angle, etc. (Kyratzis et al., 2017; Zhang et al., 2017). Therefore, index-based analysis essentially investigates whether, and if yes, which SIs, are able to discriminate plants with different status.

In the following, a short literature review of the most important/common SIs are presented and exemplified with recent studies.

2.1. Indices correlated to canopy temperature

Thermal remote sensing involves deriving thermal images (canopy temperature) and correlation with drought-sensitive plant response such as stomatal conductance (g_s) or leaf or stem water potential (Ψ_l , Ψ_s). Thermal indices can be derived from the thermal images to enhance differences in temperature between stressed and unstressed plants, and these have shown a great potential to determine field drought stress heterogeneity (Baluja et al., 2012). The Crop Water Stress Index (CWSI) has been long recognised and shown that plant temperature is a valuable qualitative index to detect plant and canopy water status. Well-irrigated crops can usually supply enough water to the leaves to satisfy transpiration demand and maintain a cool canopy temperature. Under water limitation, canopy temperatures is higher due to reduced transpiration and less associated evaporative cooling. Early work used canopy temperature (Tc) differential normalised by the non-stressed temperature differential that is a function of vapor pressure deficit to define the Canopy Water Stress Index (CWSI):

$$CWSI = (Tc - Ta) - (Tc - Ta)_{LL} / (Tc - Ta)_{UL} - (Tc - Ta)_{LL}$$

where Ta is air temperature, and LL and UL are, respectively, lower limit (canopy transpiring at its potential rate) and upper limit (a non-transpiring canopy), all in units ◦C. The determination of Ta under UL and LL in the above equation should be done with caution in order to avoid non-representative water stress index due to an inaccurate normalised span of CWSI (Park et al., 2017). Baluja et al. (2012) found strong relation between CWSI with g_s and Ψ_s measured for vineyard canopies in Spain. Gonzalez-Dugo et al. (2013) also used CWSI determined from thermal imagery to assess the variability in the water status of fruit trees within a commercial orchard in Spain. Both studies pointed that the CWSI relationships from thermal imagery and water status parameters are short-term responses, and other indices related to photosynthesis and change in plant pigments should accompany the thermal SIs as they may reflect better a cumulative water deficits, thus longer-term response. In addition, CWSI performs well in measuring drought stress in fully vegetated surfaces, but suffers from the inability to measure Tc under partially vegetated conditions (Clarke, 1997).

2.2. Indices correlated to photosynthesis

Under drought, the following effects can be expected in plants:

- Reduced Chl concentration (pigment degradation, reduced Chl biosynthesis).
- Changed Chl/carotenoid ratio (xanthophyll cycle).

- Reduced leaf/stem water content (prolonged, excessive transpiration).

Thus, suitable SIs for mapping site-specific crop drought stress levels should directly relate to these processes. From the SIs in relation to photosynthesis, majority of the studies use “greenness” indices such as the Normalised Difference Vegetation Index (NDVI= (NIR-Red)/(NIR+Red)), although these are also the least robust. NDVI relates more to plant vigor than the plant dynamic physiological status. Also, NDVI correlates well in crops where the biomass proportionally increases in parallel to photosynthesis, but for drought stress crops or evergreen crop results are often not so satisfactory (Gago et al., 2015; Zhao et al., 2016). As NDVI often fails to capture dynamic physiological processes, the Photochemical Reflectance Index (PRI) has been proposed as an indicator of the energy dissipation through the epoxidation state of the xanthophyll cycle pigments (Gamon et al., 1992). The epoxidation state of the xanthophylls pool is, what is the same, the proportion of violaxanthin that has been converted into zeaxanthin under stress conditions (Suárez et al., 2010). The PRI equation is:

$$\mathrm{PRI} = \frac{R_{550\ to\ 570} - R_{531}}{R_{550\ to\ 570} + R_{531}}$$

PRI is used to focus on the green part of the spectrum (Peguero-Pina et al., 2008) and it is very sensitive to indicate short-term variations in actual photosynthetic efficiency, especially in well-developed canopies where NDVI is the least sensitive (Gamon et al., 1992). PRI was proved to be sensible to canopy transpiration and to dynamic water stress in evergreen plants (Peguero-Pina et al., 2008), and even more sensitive than canopy temperature (Suárez et al., 2010).

Modification i.e. normalisation of PRI (PRI_{norm} = PRI/[RDVI·R700/R670] showed an improved capacity for water stress detection (correlated with g_s and Ψ_l) in comparison with other greenness and structural indices (commonly are more insensitive to dynamic changes in vegetation).

Other indices include transformed Chl absorption in reflectance index (TCARI) based on the modified chlorophyll absorption in reflectance (MCARI), normalised by the optimised soil-adjusted vegetation index (OSAVI) to obtain TCARI/OSAVI:

TCARI = 3[(R700 - R670)−0.2(R700 −R550)∗(R700 -R670)]

OSAVI = [(1+0.16)(R800 −R670)] / (R800 ∗R670 +0.16)

Berni et al. (2009) successfully linked NDVI, PRI and TCARI/OSAVI to LAI and Chl *a+b* concentrations for maize in the USA. Zhou et al. (2016) used green normalized difference vegetation index (GNDVI = (NIR−[540:570])/(NIR+[540:570])) and was able to significantly discriminate crops with different irrigation treatment. These authors also emphasised the importance of coupling spectral data collected at various scales, i.e., handheld and aerial to improve results.

Sensing of drought stress by the use of SIs has the potential to improve current irrigation scheduling methods due to their ability to cover large areas with good resolution depending on the platform used. The widely used methods for irrigation scheduling that are employed today are based on simulation modelling of soil water content e.g. the Danish Vandregnskab. Such models presume that a large range of crop characteristics and their interaction with the environment can be described based on a limited number of input data. Furthermore, a whole field is usually presumed to be a uniform unit. As fields are becoming larger, it is more a rule than an exception with quite some differences in textural and other water balance and crop growth influencing properties across fields. A particular under-researched area is the dependence of root depth on soils' physical properties. As the available water capacity of a soil is directly proportional to the effective rooting depth, it is obvious that SIs capable of detection of drought stress would allow for a much more differentiated irrigation scheduling in time and space.

2.3. Indices correlated to leaf area index and light interception

Despite the shortcomings of current field water-balance models, they will be the method of choice for irrigation scheduling for the near future due to their ability to predict soil water deficits when coupled to weather forecast and thus allow planning of irrigation scheduling. Drought stress detection by remote sensing may be too late due to intervals of satellite observation and sensitivity issues. However, combinations of the methods should allow significant progress. Apart from the direct sensing of drought stress that may allow stratification in space of model variables, SI can be used as input to the water balance models. While NDVI may be less suitable to detect drought stress directly, it has been demonstrated in many research papers that SIs based on ratios between red and near-infrared reflectances such as NDVI and RVI are good predictors of light interception by green leaves and green leaf area index e.g. Christensen and Goudriaan (1983). Assimilation of such data into current models would therefore allow for a more precise and spatially distributed modelling of water balance e.g. Battude et al. (2017). For instance, it would be relative easy to modify the Vandregnskab model to use light interception data derived from RVI measurements in its calculation of transpiration from green leaf area to replace the current modelling of green leaf area index and subsequent calculation of light interception and transpiration.

3. Platforms for studying drought stress and water balance

Reflectance data necessary for remote sensing analysis such as index-based analysis can be derivied from sensors at various scales, from field (handheld) to space (airborne). Lately, many advanced platforms carrying the sensors have emerged with the raising demand for improved spatial and temporal resolution, such as aircrafts, unmanned aerial vehicles (UAVs), and terrestrial/hand-held techniques. Each platform has its own advantages disadvantages (Fig. 2). The choice of platforms, and thus of data resolution, depends on the study objective, but synergies are ongoing and expected to further enhance the results.

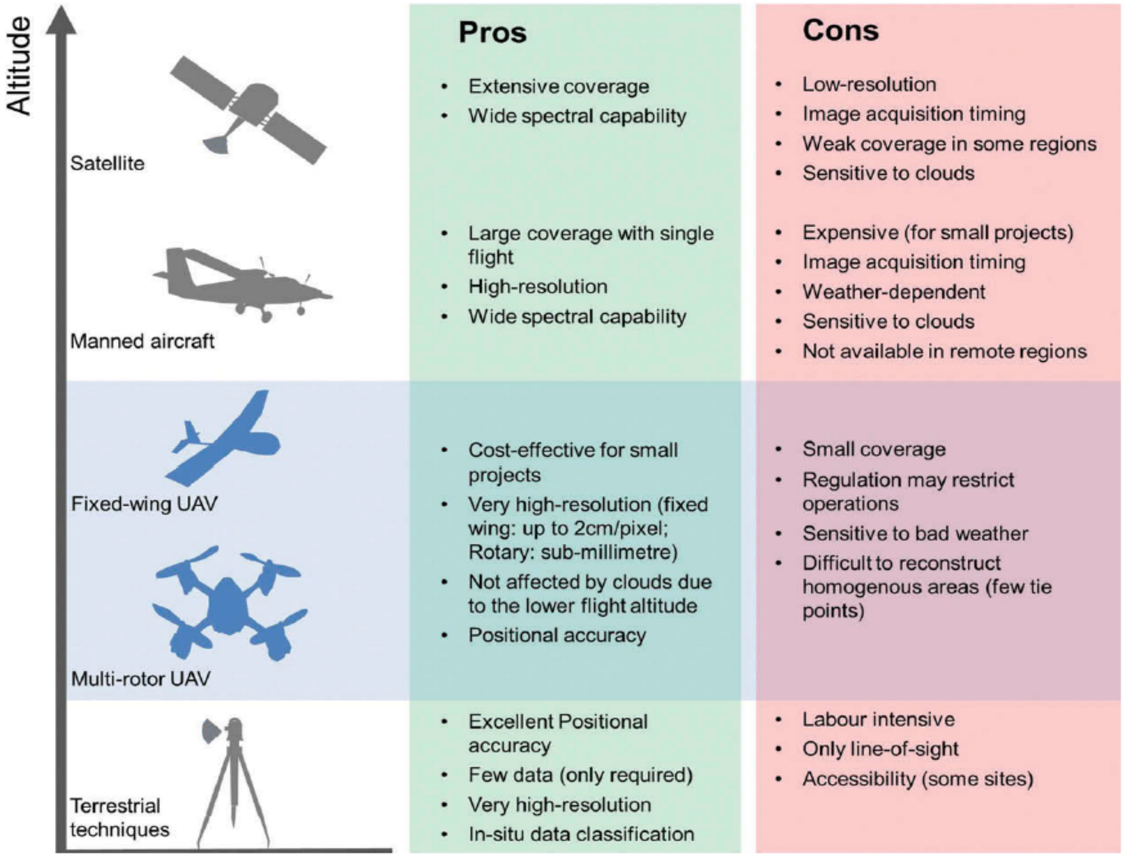

Fig 2. An overview of different remote sensing platforms with associated advantages and disadvantages. Figure adapted from Pádua et al. (2017).

3.1. Satellites

3.1.1. Landsat

With the launch of Landsat-1 in 1972, satellites proved as a valuable and necessary data source for agriculture, geology, forestry, regional planning, education, mapping, and global change research.

There is an extensive literature describing the use of Landsat data in agricultural drought monitoring on large scale (Zhang et al., 2017), tracking seasonal drought effects for various ecosystem properties (e.g., Goerner et al., 2009). Landsat satellites were launched by NASA and so far there are eight, the last (Landsat 8) enabling processing and analysis of multispectral and thermal data at 30 and 100 m spatial resolution, respectively (Ding et al., 2014). Jackson et al. (2004) and Anderson et al. (2004) calculated Normalised Difference Water Index (NDWI= (R860-R1240)/(R860+R1240)) from Landsat 5 and 7 and correlated it well with vegetation water content. Other Landsat application include the use of Normalized Difference Infrared Index (NDII) to remotely sense Equivalent Water Thickness (EWT) of leaves and canopies in fields (Yilmaz et al., 2008), or integrated temperature vegetation dryness index (TVDI) based on a synergistic with the aid of Landsat TM/ETM data (Gao et al., 2011).

Apart from Landsat, MODIS data (500-1000 m spatial resolution) have also been used extensively in relation to large-scale drought stress investigation (Goerner et al., 2009; Huete et al., 2002; Wang et al., 2018). However, because of the coarse spatial resolution of Landsat and MODIS, it is difficult to apply the data on smaller scale without coupling with finer-scale data.

3.1.2. Sentinel-2

Sentinel-2 is a multispectral sensor with 13 bands from 443 to 2190 nm (Table 1) and a 10 day repeat cycle. The three red edge bands seem especially attractive, as this part of the spectrum is known to contain certain information about fine differences in plant pigments; higher Chl content can indicate higher canopy density or complex community structure, or higher N content in plant tissue (Alvarez-Añorve, Quesada, & De la Barrera, 2008). Laurin et al. (2016) showed high potential for ecological monitoring using simulated Sentinel-2 data for tropical rainforests in West Africa. Despite its potential in terms of good spectral and spatial resolution, studies with actual use of Sentinel-2 for agro-environmental investigations are very limited as the satellite started providing data in late 2015, thus research yet have to investigate the actual potential of Sentinel 2 for drought stress detection and management.

Table 1. General spectral characteristics of Sentinel 2 satellite and band comparison with RapidScan field hand held spectrometer.

Sentinel-2 Bands	Central wavelength (nm)	Min (nm)	Max (nm)	Resolution (m)	Rapidscan bands (nm)
1 – Coastal aerosol	443	430	457	60	
2 – Blue	490	448	546	10	
3 – Green	560	538	583	10	
4 – Red	665	646	684	10	670
5 – Vegetation Red Edge	705	694	713	20	
6 – Vegetation Red Edge	740	731	749	20	730
7 – Vegetation Red Edge	783	769	797	20	780
8 – NIR	842	763	908	10	
8A – Narrow NIR	865	848	881	20	
9 – Water vapor	945	932	958	60	
10 – SWIR – Cirrus	1375	1336	1411	60	
11 – SWIR	1610	1542	1685	20	
12 – SWIR	2190	2081	2323	20	

3.2. Unmanned aerial vehicles

UAVs greatest advantage over satellites and other airborne platforms is the reduced altitude of their flight, which greatly decreases costs and improves the data resolution, allowing for higher monitoring frequencies (Fig. 2). Also, the thickness off the atmosphere is much smaller compared to space borne platforms, thus atmospheric effects are less. However, their disadvantage is that they require more flights to cover large areas due to their reduced flight time (Gago et al., 2015). As for other data, a possible solution is coupling UAV data with field data.

The use of UAV data in remote sensing of drought stress is rather recent and it develops rapidly Gago et al. (2015). Studies successfully employing UAV data include thermal remote sensing of drought stress (e.g., Berni et al., 2009; Gonzalez-Dugo et al., 2013), as well various photosynthesis correlated SIs (Kyratzis et al., 2017; Park et al., 2017).

4. Preliminary results from the POTENTIAL potato project

Field experiments with potato crop (table potatoes) under various irrigation (and nitrogen fertilisation) treatments were established in 2017 on coarse sandy soil in Havris site, Denmark (Fig. 3). UAV flights for remote sensing data collection were conducted at two occasions, 19/07 and 23/08. The camera is multispectral with green, red, red edge and near infrared bands. These were used to investigate preliminary SIs for drought assessment, to test whether SIs are correlated with ground based variables such as soil water content and leaf area index (LAI). The collected drone images were georectified, geometrically and radiometrically corrected to ground reflectance and used to calculated SIs:

$$\text{NDVI} = \frac{NIR - RED}{NIR + RED}$$

$$\text{GNDVI} = \frac{NIR - GREEN}{NIR + GREEN}$$

$$\text{NDRE} = \frac{NIR - RED\ EDGE}{NIR + RED\ EDGE}$$

where NDVI is normalized difference vegetation index, GNDVI is green normalized difference vegetation index, and NDRE is normalized difference red edge index. The resulting SIs maps are presented on Fig. 4.

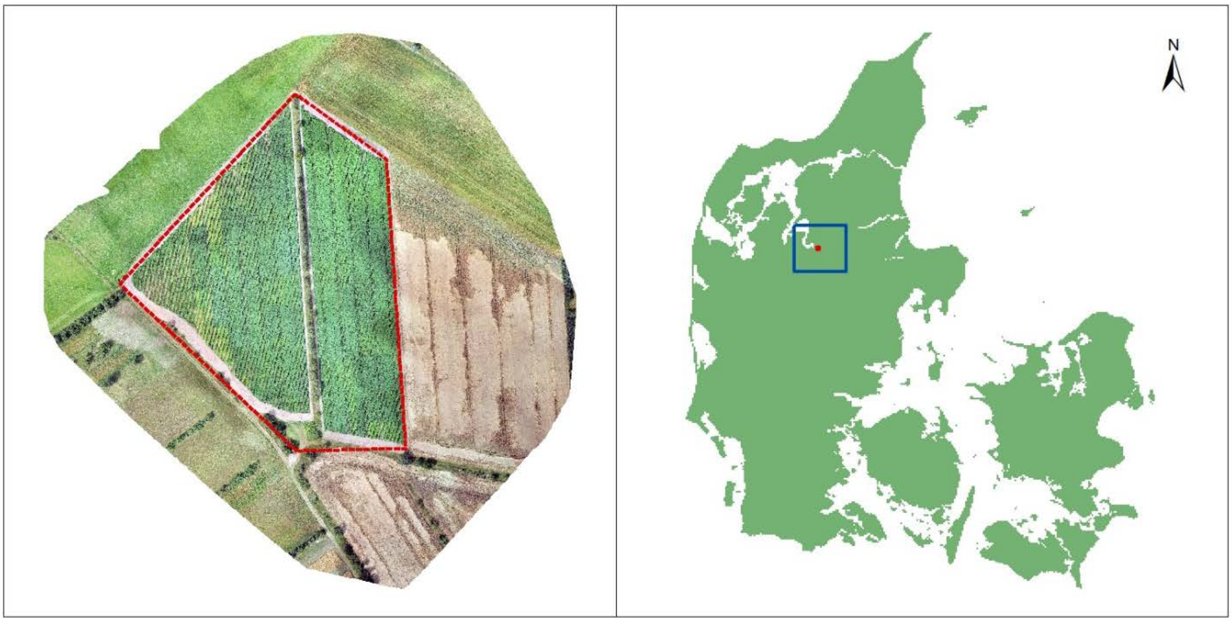

Fig. 3. Location of the experimental fields at Havris site (left) and of the study location on coarse sand soil in Denmark (right). Left image in left is true-color RGB from UAV data from 26/07-2017.

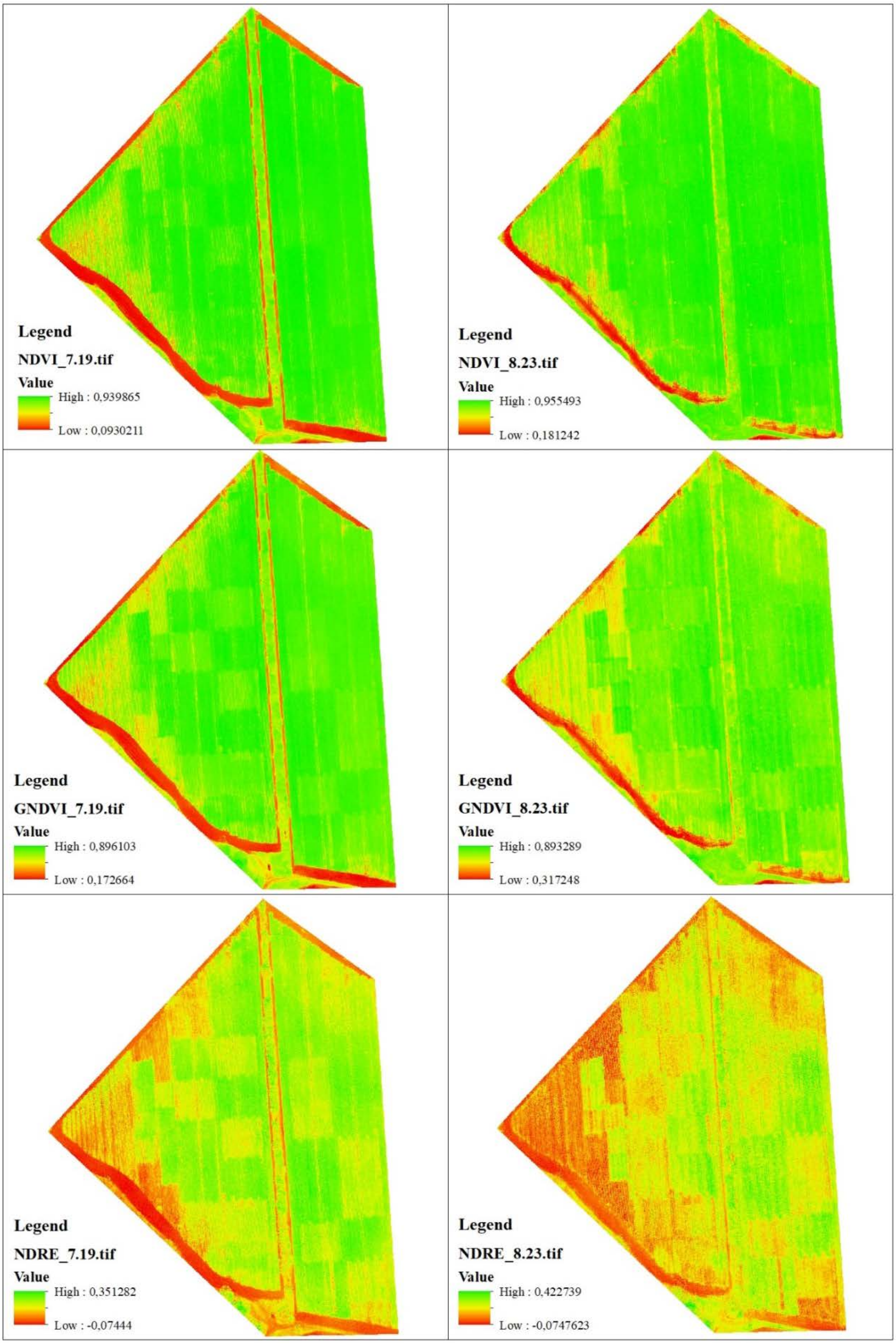

Fig. 4. Vegetation indices maps for the potato experimental fields at two dates: 19/7 (left) and 23/8 (right) at Havris coarse sand soil site in Denmark.

All of the indices range from +1.0 to -1.0, and areas dominated by soil have low values, whereas vegetated areas have high values. As each index reflects different part of the spectrum where plants respond differently (Fig. 1), some indices discriminated better the treatment responses than other. From the figure, it can be seen that NDVI is not sensitive, at least for the dates of image acquisition, probably because the potato canopy was well developed for all treatments and this index becomes saturated under too green canopy plants and the sharp difference between the reflectance of near infra red and red. Similarly, GNDVI also resulted in relatively low response, though better than NDVI, probably because the high green values. NDRE was the most promising of the three tested indices, because of notable difference between the RE and NIR used in this index. The different plots were clearly distinguished although differences were probably induced by nitrogen fertilization differences. Linear regression modelling was also applied to test whether the indices are correlated with ground variables, i.e. soil water content and LAI, and if yes, how much of their variation they explain. The result (Table 2) showed that only NDVI is significantly related to soil water content ($p<0.01$), essentially translating to higher soil water content inducing higher NDVI, but only 13% of soil water content variation could be explained. For the LAI, all indices were significantly correlated ($p<0.01$) but they also explained very little part of the LAI variation observed on the field.

Table 2. The results of the linear regression analysis of the indices with soil water content

Index	Sope	Intercept	R^2	P
Soil water content				
NDVI	48.46	-30.98	0.1295	0.001901
GNDVI	-3.96	15.80	0.0013	0.7617
NDRE	1.03	12.47	0.0001	0.9261
Leaf Area Index				
NDVI	16.88	-11.37	0.18	0.0002
GNDVI	12.84	-6.46	0.16	0.0005
NDRE	14.56	1.5	0.28	0.000002

From the above, it can be concluded that more SIs need to be tested in order to explain the variation in soil water content and LAI between irrigation treatments better. This is, however, limited due to the small number of bands in the recorded multispectral data. In addition, during the experimental period of summer 2017, Sentinel-2 images will also be examined and included in the analysis for not only detecting drought stress, but also if it is possible to support the estimation of water balance (Zhang et al., 2016).

5. Perspectives

Remote sensing for detection of drought stress and input to water balance models for irrigation scheduling has a significant potential to improve the economic outcome and possibly reduce water use in agriculture. However, significant methodological challenges exist as well as to devise swift and efficient procedures to process the large amounts of data produced by the Sentinel program and those obtainable from unmanned aerial vehicles imagery. For efficient irrigation scheduling the output of these procedures has to be ready preferably within 24 hours from the time the data were acquired. Furthermore, the irrigation scheduling software and hardware has to be able to utilize spatially distributed information. Based on the current project, our group has obtained funding for two research projects within the subject of remote sensing for irrigation scheduling – both starting from 2018.

The first research project called "Potential" is a cooperation between Belgian, Dutch, German and Danish researchers and farmers as well as the irrigation industry represented by the Danish company Fasterholt. This project aims to use both satellite, drone and ground-based remote sensing to model water balance using acquired information on soil and crop heterogeneity for precision irrigation. Fasterholt will deliver a variable rate irrigation gun for the field experiments to be conducted during 2017-2020. Furthermore, it is investigated how drought stress and nitrogen deficiencies can be distinguished by use of both thermal and multispectral information from UAVs. Both thermal and multispectral cameras have been purchased for this purpose. The investigation is done in order to develop guidelines for split-N fertilization in combination with irrigation allowing for less N-leaching and adjustment of the total N-dose according to soil mineralization (Zhou et al., 2017; Zhou et al., 2018).

The second research project called "MOIST" or "Managing and Optimizing Irrigation by Satellite Tools" is a cooperation between a number of Danish partners: DTU-Space, AU-Agro, SEGES, Cowi, AgroSens and Sandholt consulting as well as partners from Italy and Spain. In this project a more ambitious approach to precision irrigation scheduling is taken, which is envisaged to be based entirely on information from satellite data obtained with a broader range of the Sentinel sensors including thermal bands and SAR for soil moisture sensing. A two source energy Balance (TSEB) land surface scheme (Norman et al., 1995) will be used to estimate ET as it contains a level of complexity which makes it robust for many different landscapes (Kustas et al., 2016). Field experiments will be conducted during 2017-2019.

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