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Current state and usage limitations of vegetation indices in precision agriculture

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Abstract

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The current state of development and interpretation of vegetation indices makes them relatively difficult for practical use in farming. In this review, we briefly describe the key bottlenecks, together with discussing possible solutions to overcoming some of them. Based on our own experience with developing working precision agriculture solutions for field crops we propose an integrated approach to working towards building systems that can prove easily understandable outputs with low management requirements for the farmers that plan to use them.

Keywords: precision agriculture; vegetation indices; NDVI

Approaches to Data Collection

Agricultural machinery, pesticides and fertilizers, improved cultivars, and other technologies have improved farm production and productivity over the last century. However, further advancements in agricultural production are essential to meet growing food and fiber demands of the global community and maintain sustainable agricultural production (Liaghat & Balasundram, 2010). Traditional farming practices have difficulties meeting this goal and technological advancements and automation should be scaled up to achieve sustainable global agricultural production (Ennouri et al., 2021). Optimized crop management requires a good understanding and close follow-up of crops' development. To improve the efficiency of field production one of the main pre-requisites is to greatly increase the amount of data collected. Expanding both the volume of data collected at each point in time and the overall timespan of data collection can contribute to better understanding of crop/pest interactions simultaneously with more insights into the effects exerted by abiotic stresses. Advances in acquired basic knowledge of these multiple interactions should ultimately provide for better crop management practices with optimized water, fertilizer, and plant protection products applications thus contributing to a more sustainable production.

Unlike research settings farm-scale crop management cannot rely on individual plant/soil measurements because of their high labor intenseness (Bienkowski et al., 2019). Therefore, farm data is usually remotely collected by implementing multiple (i.e. ground-, air-, and space-based) sensor positioning while collection itself is done at varying frequencies. Remote sensing allows analysis of the spectral images with different bands, which helps to provide information on vegetation distribution, soil moisture, occurrence of stress, etc. It can also be used in crop growth monitoring, land use pattern and land cover changes, water resources mapping and water status under field condition, monitoring of diseases and pest infestation, forecasting of harvest date and yield estimation, precision farming and weather forecasting purposes along with field observations (Shanmugapriya, 2019). This enables timely identification of abiotic and biotic plant stresses, and making practical decisions to maximize agricultural yield. Along with the multi-spectral image analysis of the remote sensing approach, the introduction of artificial intelligence helps to identify and anticipate various factors that can play in the final yield outcome of crop cultivation.

Currently, what particular set of data is collected and what combination of sensor positioning is used at each farm very often depends on the advice of specific technology providers that the farmer is used to working with. This situation has little effect on balancing the benefits and limitations of just the sensor positioning, let alone other aspects of optimizing the volume and frequency of data collection. Satellites, for example, are collecting data with relatively low resolution (on the multi-meter scale), thus providing a general overview of large areas (Ahamed et al., 2011). Even with the latest improvements in the resolution achieved it still is in the meter-decameter range (Sousa et al., 2017). While very useful at regional/state scale the usability of space-based observation for on-farm applications is further limited by the fixed intervals at which data is collected. Yet another usability restriction for satellite-based data acquisition is that in many cases it can be compromised by the presence of cloud coverage over particular areas, therefore expanding data collection gaps for them. Finally, when working with data collected by satellites, it is important to pay attention to the varying characteristics of the spectrum bands used by different satellites for calculating the identically named indices. Whether these differences in band distribution and sensor sensitivities result in significantly different values for the same vegetation index calculated from data from different satellites is a question that needs to be taken for consideration each time data provider is changed.

Ground-based data acquisition, on the other hand, can provide high precision (in the centimeter range) by attaching sensors to GPS-guided agricultural machinery, or by directly integrating GPS data modules in hand-held or permanently positioned data collection appliances. These limit either the number of passes for data collection or the areas over which it can be done, or both.

Air-borne data collection can fit in-between the above two approaches. Most unmanned aerial platforms allow the operation height to be very low (e.g. less than 30 m), enabling low-altitude aerial photography (LAAP) (Verhoeven, 2009) to acquire image data that can resolve the finest details. The quick deployment and the ability to fly for extended times, unobstructed by the cloud coverage, are two of the main benefits of using this approach. It has its limitations, with some of the most relevant to agricultural settings including the requirement for a levelled landing strip and the difficulties of precise positioning when side- and gusty winds are occurring during the flight. Furthermore, high shutter speeds are needed to combat the blurring effect of relative ground speed that occurs at lower altitudes in the case of an airplane (Verhoeven, 2009).

Multi-rotor UAVs (MRUAV) are propeller-lifted (or “copter”) drones that do not require any specific take-off/landing path preparation and they generally require less pilot training to operate (Hatton et al., 2019). Our experience shows that they are also better at dealing with gusty winds and have lower relative ground speed, thus providing for a more precise following of the pre-defined observation path (Bojinov et al., 2018). As a consequence, they meet the critical requirements of optimum resolution, which makes them ideally suited for identifying within-field variations in vegetation health resulting from non-optimal growing conditions (Houborg et al., 2015).

The enhanced cm-scale spatial detail that MRUAVs provide allows for the separation of soil, weed, and crop canopy and reducing obfuscating effects of soil background, structure, and shadow (i.e., by isolating pure vegetation signals), providing an improved capacity to remotely sense and model vegetation traits and function (Houborg et al., 2015). This can be ensured by one of the unique assets of UAVs – the capacity to employ several sensors at the same time – as in many research areas (e.g., nutrient level assessment, disease, and drought stress detection) thermal information was complementary with multispectral or hyperspectral information (Maes & Steppe, 2019).

Remote sensing will be best used by providing accurate, site-specific data that can be converted into information used by decision support systems (Shaw, 2005). Despite its great potential to monitor events at different temporal and spatial resolutions the majority of the studies are exploratory investigations, tested at a local scale with a high dependence on ground data, involving one remote sensing sensor at a time, and are constrained by local knowledge and conditions (Bégué et al., 2018). The main difficulty in obtaining remote sensing derived products at a regional scale with a high accuracy is the spectral and temporal variability of the vegetation cover which is multi-factorial. In the case of the MRUAVs, major advantages include the ability to operate close to the ground and using these devices for photographic situations where low amounts of reflected radiation need to be recorded (Verhoeven, 2009). By providing both higher resolution and longer daytime operational duration than other air- and satellite-based systems, MRUAVs provide two other crucial data streams for the decision support. The first one is the capacity to produce 3-dimensional field topography maps in the centimeter range (Mancini et al., 2013), thus providing a possibility for erosion prediction and prevention. The second one is the near real-time measurement of the biomass accumulation in the crops (Ahamed et al., 2011; Dunford et al., 2009; Sousa et al., 2017).

Vegetation Indices Currently in Use

Plants have a very low response in the red band wavelength region as they absorb incident radiation by chlorophyll pigments. In contrast, they have a high response rate for Near-InfraRed bands (NIR) due to the high reflection of this type of radiation. The vegetation conditions can be evaluated by developing different indices based on various multi-spectral bands and the related plant response (Xue & Su, 2017). Normalized difference vegetation index (NDVI) is the main one currently used in remote data collection for evaluating crop condition. It is usually calculated according to Rouse (Rouse, Jr. et al., 1973a; Rouse, Jr. et al., 1973b), as further developed by Tucker (Tucker, 1979) and Panda (Panda et al., 2010). The use of this index is based on the assumption that its relatedness to the presence of actively functioning chlorophyll complexes can be used as an indicator of presence/absence of (various levels of) stress in plants. It is calculated as:

$$NDVI = \frac{\lambda 1 - \lambda 2}{\lambda 1 + \lambda 2} \qquad (1)$$

where λ1 and λ2 are specific wavelengths collected by the sensor.

As NDVI is only a mathematical representation of the crop reflectance under specific conditions it can vary by the crop/crop development stages. This means it is usually not its absolute value that is taken into account. This is apparent form the varying approaches to calculating this index that may vary both as dependent on the exact wavelength`s diapasons taken onto account (Table 1) and the overall intensity of the electromagnetic emissions collected (Kalichkin, 2011). Sudden changes in NDVIs (within 2-3 days from the previous observation) are the ones that could serve as indicators of pest/disease/weed or water/nutrition stress development. In practice (under current usage systems) detected changes in NDVI trigger emergency consultations (Aravind et al., 2019) and/or visits of specialists to the crop site. Upon determination of the specific causative agent for the NDVI fluctuation, appropriate plant protection/nutrition/irrigation treatments are then applied. However, this shuffling between remote and on-site data collection and analysis largely compromises the whole idea of efficient digitization of agriculture. Furthermore, the plant protection products then have to be applied discriminately to the areas with modified NDVI with inverse logic – increased where lower NDVI indicates pest/disease development and reduced in case lower NDVI indicates lower weed infestation. Only under these conditions can both machinery and plant protection / plant nutrition products' uses be optimized, thus reducing also the number of machinery passages, soil compaction and the number of working hours needed to assure high productivity.

At present, the application of the main index used (NDVI) poses several difficulties, since the interpretation of its values is problematic due to their dependence on both qualitative and quantitative components (Bourgeon et al., 2017). As the index can be calculated from various NIR sub-spectra (Table 1) its values will inevitably vary as dependent on the NIR/visible light filter used. Therefore, it is often necessary to apply specific interpretations of NDVI obtained which is further compounded by the differences of phenophases of both cultivated (Bourgeon et al., 2017) and weed plants.

Table 1. Variations in wavelengths collected by some satellites for NDVI calculation

Satellite	Band No.	Band range, μm
Sentinel 2	4	0.650 – 0.680
	8	0.785 – 0.900
Landsat 5 and 7	3	0.630 – 0.690
	4	0.750 – 0.900
Landsat 8	4	0.630 – 0.680
	5	0.845 – 0.885

As vegetation indices are vague in quantitative biophysical meaning, and most of them were formulated to minimize the effect of non-vegetation factors on spectral data (Baret & Guyot, 1991) this capacity is of crucial importance for identifying exact crop condition. Several propositions exist to tackle the abovementioned points. One of the proposed solutions is to use an optimized set of color calibration patches to improve phenological comparisons (Sunoj et al., 2018). Another one (Daughtry et al., 2000) tries to more precisely dissect chlorophyll absorption:

$$MCARI = ((\lambda 700 - \lambda 670) - 0.2(\lambda 700 - \lambda 550))\frac{\lambda 700}{\lambda 670} \qquad (2)$$

A further modification (Haboudane et al., 2008) of equation (2) leads to

$$MCARI1 = 1.2(2.5(\lambda 800 - \lambda 670) - 1.3(\lambda 800 - \lambda 550)) \qquad (3)$$

A different approach is to develop new and complementary indices. As NDVI targets mostly the chlorophyll complex, one complementary solution is to detect changes in other stress response molecules, such as anthocyanins. This is achieved by probing wavelengths at which these compounds specifically emit:

$$ANT1 = \frac{1}{\lambda 550} - \frac{1}{\lambda 700} \quad (4)$$

Similarly, carotenoids can be probed by

$$CRT1 = \frac{1}{\lambda 510} - \frac{1}{\lambda 550} \quad (5)$$

or

$$CRT2 = \frac{1}{\lambda 510} - \frac{1}{\lambda 700} \quad (6)$$

Finally, plant water status can be determined using a Normalized Difference Water Index (NDWI) (Gao, 1996) although its calculation requires taking into account the measured radiance, the solar zenith angle, and the solar irradiance above the earth atmosphere, which makes it quite difficult to use.

Except for the specific compounds, overall plant phenology can also be probed by developing so called plant phenology index (PPI) that is derived from radiative transfer equations (Jin & Eklundh, 2014). PPI is approximately linear to the green leaf area index (LAI) and has the same unit as LAI ($m^2 \cdot m^{-2}$). The authors of this index argue that, as LAI is the most dynamic visible canopy variable during the phenological cycle, linearity with green LAI is a fundamental property of a phenology vegetation index. It is for this reason that the index can be used for representing canopy green foliage dynamics for any green terrestrial vegetation. Although integral, this index still gives an idea of changes late after the stress onset – only when these changes are so advanced that the leaf growth has become substantially affected and the opportunity of taking action most efficiently is already missed.

In an attempt to find a workaround Corti et al. (2019) have developed a low-cost system with a high spatial resolution for estimating the nitrogen state of maize by combining blue- and green-normalized NDVIs. The system however has very limited applicability, as maize is one of the few crops that respond with such quick and significant biomass accumulation to the increase of nitrogen application.

Other authors also tried to reduce the costs of data acquisition with various degrees of success (Berra et al., 2017; Deng et al., 2018). Their studies, however, have little to contribute to the main limitation of the proposed systems – discrimination capacity for different causative agents of crop stress – as the proposed uses are in experimental conditions where the causative agent is strictly controlled. One promising exception might be the approach to find the ratio between specific, narrow band sub-spectra, related to the nitrogen status of maize (Zhao et al., 2018). Calculation of this index (N nutrition index – NNI) is done as

$$NNI = 0.95\frac{\lambda 512 - \lambda 710}{\lambda 512 + \lambda 710} + 0.14 \quad (7)$$

Before adopting it for wider use, however, their work still needs verification in other crops and under more diverse field conditions. This is especially important in the context of findings that the interaction between leaf properties and canopy structure confounds the estimation of foliar nitrogen (Wang et al., 2017) and that the combination of various indices is better at estimating maize nitrogen condition that the use of single index (Kogan et al., 2018).

Several other vegetation indices (VIs) were also proposed (Baret & Guyot, 1991; Fern et al., 2018; Houborg et al., 2015; Jin & Eklundh, 2014; Liu et al., 2018; Mingzhao et al., 2017; Zhang et al., 2019) as well as ways to incorporate them into crop growth models (Du & Noguchi, 2016; Hassan et al., 2019; Machwitz et al., 2014; Su et al., 2019; Zhang & Zhou, 2017) and yield prediction neural networks (Panda et al., 2010). Within that context it has been suggested that the determination of phenolic concentration may also contribute to the assessment of plant stress and discrimination of plant species (Houborg et al., 2015). Since the determination of phenolic concentration is possible by measuring changes in the unique absorption characteristic near 1.66 μ in the spectrum of leaves and plants (Kokaly & Skidmore, 2015), it can be used as one of a series of indicators (Ramdani et al., 2019) necessary to achieve reliable distinction between crops and weeds. This demonstrates how data acquired in one context can be used in other contexts to enrich crop characterization and achieve better crop/weed discrimination.

Although several other vegetation indices have been proposed so far (Maes & Steppe, 2019; Oliveira et al., 2017; Su et al., 2019), their applicability is as limited as it is often debatable, especially as regards their discriminatory capacity.

Unfortunately, no adequate system based on any of the above indicators has been developed to allow reliable discrimination of weeds from cultivated plant species. While reports on some progress are available (Knoll et al., 2019; LÓPez-Granados, 2011) the complexity of algorithms used and the computer power needed to achieve farm-level relevance are still far from practicality.

Apparently, no vegetation index can be used alone for resolving the complex structure of plant-environment interactions. Therefore using the information provided by different vegetation indices seems like a reasonable solution.

Remote data collection cannot achieve complete plant/environment interaction characterization without assessing soil conditions. This can be done by directly measuring soil conductance and reflection (Dunford et al., 2009; Ivushkin et al., 2019; Křížová et al., 2018; Mancini et al., 2013; Panciera et al., 2009) or by inference of soil characteristics from plant responses (Rango et al., 2009; Yin et al., 2012). Currently available sensors however are not capable of discriminating main nutritional ions at an affordable cost. Therefore the models used tend to be developed for a specific soil type and sub-type, and specific water and salinization regimes, thus again being of limited applicability to the large-scale agricultural practices where all of the above could vary significantly even within a single field.

Perspectives

The current state of development of the various vegetation indices clearly shows that this scientific field is still evolving at a rapid pace and thus poses a great challenge for practical application. Although some developments aimed at answering specific questions in plant physiology (mainly as options for monitoring the effectiveness of basic processes such as photosynthesis) have emerged (Haboudane et al., 2008; Parry et al., 2014) they are still in the early stages of development as even the recently published indices can be influenced by erective plant structure, low N fertilizer application density, no water application, and early sowing dates of crops (Cui et al., 2019). Therefore, they can serve rather as detectors of general changes in plants than being capable to characterize accurately the balance of factors responsible for the particular degree of change in the fundamental processes. This means that the proper evaluation of the feasibility of many different indicators and indices is still a pressing need. Combining this with other remote data collection capabilities to better characterize crops/pests/abiotic elements of the environment remains an underexplored field.

An integral approach for possible overcoming of the limitations of current indices is to use multiple sensors/filters at once for characterizing the crop condition (Bai et al., 2016; Rischbeck et al., 2016; Wang et al., 2014). This however significantly complicates the use of underlying technology as both temporal and spatial synchronization becomes exponentially more complex with increasing the number of sensors used simultaneously (Su et al., 2019).

To overcome the shortcomings of the solutions offered so far, it will be necessary to combine knowledge and experience in several different fields, whose points of contact have not been effectively explored so far. A multidisciplinary approach is therefore needed to achieve a new level of knowledge on both the basic biological processes that determine the optimal development of plant organisms and the factors beyond the narrow range of agro-technical solutions that lead to increased efficiency from the use of any technology. As a result of integrating data from different soil and air quality sensors with collecting data from various bands of the electromagnetic spectrum collected directly from plants, specific relationships between them can be identified. This should allow for the adequate prognosis of the development and remote identification of the particular causes of the respective stress states in the plants – those caused by insects, diseases (Knoll et al., 2019), competition from weed species, temperature, nutritional or water stress, etc. Most of the current digitization systems in agriculture are only able to detect the presence of stress in plant species, but the identification of its specific cause is still too uncertain (Maes & Steppe, 2019). This is mainly due to the inability to differentiate clearly between individual plant species in dynamic agroecosystems, as well as due to insufficient knowledge of the subtle nuances in the manifestations of stresses induced by various possible causative agents. In this regard, there is still an insufficient accumulation of basic knowledge in the scientific literature, which significantly compounds the development of applied algorithms.

Our experience shows that the accumulation of significant volumes of data allows for a more detailed characterization of the conditions and processes that determine the quality of agricultural products under the specific conditions of respective farms. At present achieving higher causative agent resolution and predictive capacity relies mostly on educating the algorithms applied by feeding perennial data on a per-field basis. As this essentially involves parameters such as specific plant varieties, water, fertilizer, and pesticide application rates, it, in turn, can have as a side effect providing better traceability of origins and quality for the agricultural products concerned.

Conclusions

Both technical and processing challenges in data collection and fusion from historical yield maps, soil analyzes, and other measurements need to be resolved before remotely collected data can be efficiently included in the decision-making process With the quick developments in satellite, aerial, and ground-based remote sensing systems they have to be regularly compared and decisions made based on site-specific management goals. Here we presented the main limitations that the current state of vegetation indices' development faces and propose possible avenues for their overcoming. Our view is that currently the development of more specific indices is needed and it could rely on finer splitting the observation spectrum in drone-based sensors, together with developing and applying advanced ground-based sensors, specifically tuned for agricultural uses. The magnitude of the data collected and, consequently, the degree of detail achieved will be directly dependent on what characteristics of the output the end-user (be it farmer or consumer) would regard as essential/sufficient for meeting production management/production traceability requirements.

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