Major Vegetation Indices in Precision Agriculture

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Vegetation indices have a crucial role in precision agriculture and crop monitoring by providing a straightforward and reliable assessment of the condition and health of crops. Depending on the vegetation index, information on various aspects of plant growth and development can be monitored, such as chlorophyll content, leaf area, canopy structure, and water status. This information can then be used to optimize prescription rates in precision agriculture, such as variable fertilizer application, irrigation, and pesticide application. This is generally performed by identifying intra-field zones that are underperforming or experiencing stress, and target inputs to those areas to improve crop productivity and yield. Vegetation indices also provide a cost-effective and non-destructive way of crop monitoring, ensuring a widely available and environmentally sustainable approach for assessing crop health. The development of remote-sensing sensors for crop monitoring in both broadband and narrowband bands opens immense possibilities for their combination into novel vegetation indices.

crop health | multispectral sensor | normalized difference vegetation index (NDVI) | remote sensing

1. Present and Future Vegetation-Index-Based Applications in Precision Agriculture Using Artificial Intelligence

Various vegetation indices are sensitive to different aspects of plant physiology, such as chlorophyll content, leaf area, and water stress, and can be used to identify areas of the field that require attention or treatment [1]. To efficiently manage large spectral data and vegetation indices, there has been a growing interest in research using artificial intelligence (AI) to extract valuable information about crop health and yield. While AI in precision agriculture encompasses a broad range of technologies, especially the Internet of Things (IoT) [2], the classification and regression using machine learning and deep learning are primary technologies for processing vegetation index data [3][4]. However, it is important to note that these techniques require significant data and computational resources, as well as careful calibration and validation to ensure accuracy and reliability [5]. As such, their use must be balanced with other tools and knowledge to make informed decisions about crop management in a dynamic and complex environment.

By determining the changes in vegetation indices based on multitemporal images, previous studies detected intra-field zones that are experiencing crop stress, caused by either water or nutrient deficiency [6]. On a larger scale, machine learning and deep learning algorithms were successfully adopted to classify different crops and identify areas of the field where crop rotation or intercropping may be beneficial [7][8]. Another frequent application of vegetation indices in recent research is crop-yield prediction, which is often based on machine-learning regression, using multitemporal vegetation indices as covariates [9]. This information can be used to make informed decisions about harvesting and marketing the crop, ensuring the optimization of agricultural inputs in future growing seasons. To determine low potential intra-field areas, it is possible to avoid low yield by adjusting input-use as a part of variable-rate technology (VRT), especially crop disease detection and management, enabling the development of algorithms to prevent the spread of disease and minimize crop loss [10]. Moreover, they are also being increasingly used for precision fertilization with the aim of determining the optimal amount and timing of fertilizer application [11]. This allows minimization of fertilizer use, which can be expensive and harmful to the environment, while maximizing crop yield. If a selected vegetation index indicates that a particular area of the field is experiencing a nutrient deficiency, the fertilizer specifically can be applied to that area to address the deficiency without overapplying fertilizer to other areas of the field.

2. Sensors Used for Calculating Vegetation Indices in Precision Agriculture

Available remote-sensing sensors have different spectral and spatial resolutions, as well as varying levels of atmospheric correction capabilities, which can affect the accuracy and reliability of vegetation-index calculations [12]. The sensors with higher spectral resolution can detect finer differences in plant reflectance, allowing for more accurate discrimination between different plant species and more precise measurement of vegetation parameters, such as chlorophyll content and leaf area [13]. On the other hand, sensors with higher spatial resolution can provide more detailed and accurate maps of vegetation patterns and distribution, allowing for finer-scale analysis of crop health and productivity [14]. The recent studies noted RGB, multispectral, hyperspectral, thermal, radar, and LiDAR sensors as the most frequently applied remote-sensing tools for determining crop properties [15][16].

While hyperspectral sensors offer the most advanced capabilities of sensing and calculating vegetation indices of the listed sensors, the high cost of commercial solutions for hyperspectral imaging presently restricts their widespread use [17]. Both RGB (red, green, blue) and multispectral sensors are more accessible and affordable for widespread vegetation-index calculation in precision agriculture, although they have different strengths and limitations [18]. RGB sensors, commonly found in low-cost consumer drones and cameras, can be used to visually inspect crop health and detect any obvious issues, such as pests or diseases, but they are limited in their ability to measure the subtler differences in plant reflectance that are indicative of changes in vegetation health and productivity [19]. Multispectral sensors, on the other hand, are designed to capture a wider range of wavelengths, including both visible and near-infrared light. This allows for the measurement of plant reflectance in different spectral bands, which can be used to calculate vegetation indices that provide more detailed information about vegetation health and productivity [20]. While RGB sensors can provide a quick visual assessment of crop health, multispectral sensors are typically better suited for vegetation-index calculation and more detailed analysis of vegetation health and productivity in precision agriculture [21].

3. Major Vegetation Indices in Precision Agriculture Based on Multispectral Sensors

According to the number of scientific papers indexed in WoSCC since 2000 with the topic of “precision agriculture” and vegetation indices based on multispectral sensors, the normalized difference vegetation index (NDVI) was dominantly the most frequently used vegetation index in precision agriculture with a total of 2200 studies. Like most vegetation indices based on multispectral sensors, NDVI is calculated using the reflectance values of red and near-infrared light, and it provides a measure of the greenness or photosynthetic activity of vegetation [22]. China (553 papers) and the United States (484 papers) accounted for 47.1% of these papers. With the additional query of “yield” in the topic search, 1046 papers were identified, as well as 382 papers for “biomass” and 140 papers for “fertilization”. The majority of these studies were based on satellite mission data (925 papers), as opposed to unmanned aerial vehicle (UAV) images (303 papers), out of which 162 papers were indexed from 2020 to 2022. The research of NDVI for the prediction of crop traits, especially yield and biomass, of various crops was proven successful, while the exact effect of remote-sensing platforms on prediction accuracy is still unclear.

Despite the immense popularity of NDVI in scientific studies of precision agriculture in the past decade, several indices were developed to improve its drawbacks, potentially providing more effective crop monitoring and assessment depending on the field and crop conditions. Among them, EVI improves NDVI by minimizing the effects of soil background and atmospheric influences [23]. Enhanced vegetation index (EVI) takes into account the non-linear relationship between reflectance and vegetation coverage, and it includes the blue reflectance in addition to the red and near-infrared bands used in NDVI [24]. This makes EVI a more robust index for analyzing vegetation health and vigor, especially in areas with high soil background or atmospheric interference [25]. By replacing the red band with green in NDVI formula, GNDVI is potentially more suitable in areas with high soil background or atmospheric interference [26]. GNDVI may also be more effective than NDVI at detecting changes in vegetation caused by environmental factors such as water stress, disease, or nutrient deficiencies [27].

4. Major Vegetation Indices in Precision Agriculture Based on RGB Sensors

Similar to the case of major vegetation indices based on multispectral sensors, the normalized green–red difference index (NGRDI) has been the predominantly used index of the available indices based on RGB sensors during the past decade, based on the scientific papers indexed in WoSCC with the topic of “precision agriculture” and vegetation indices based on RGB sensors. The NGRDI provides a low-cost solution to replace NDVI using the RGB sensors, allowing a similar degree of sensitivity to changes in chlorophyll content in plants by replacing near-infrared with green reflectance [28]. While the NGRDI can be a useful index for detecting early signs of crop stress or disease [29], the NDVI provides a more comprehensive assessment of vegetation health and productivity. Since NGRDI is primarily sensitive to chlorophyll content in plants [30], while the NDVI is sensitive to the amount of vegetation present, including leaves, stems, and branches, its application in precision agriculture is less obstructed than areas with more heterogeneous vegetation, such as forestry [31].

ExG and ExR indices follow NGRDI as the cost-effective solutions for the assessment of vegetation health and vigor and are mutually complementary. The ExG is sensitive to chlorophyll content of crops, with its higher values indicating healthier and more vigorous vegetation, while lower values indicate stressed or damaged vegetation [32]. The ExR is more sensitive to density and crop distribution than ExG, complementing the crop health assessment by ExG by providing the indirect information about the crop biomass [33]. The VARI is based on a similar formula to that of NGRDI, with the addition of blue reflectance in the denominator, which improves resistance to atmospheric effects such as haze, clouds, and shadows [34]. It is particularly useful in areas with high atmospheric interference, such as urban environments or areas with frequent cloud cover, where other vegetation indices may be less reliable [35]. It is also useful for monitoring vegetation health in areas with mixed land use or variable soil conditions, where the vegetation signal may be mixed with non-vegetation signals [36].

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