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FUSING SPECTRAL AND COMPUTATIONAL INTELLIGENCE: VEGETATION INDICES AND MACHINE LEARNING FOR CROP MONITORING

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ABSTRACT

This paper is focused on the in-depth review of relevant vegetation indices in crop analysis using remote sensing techniques, targeting the five major crops: cotton, maize, soybean, sugarcane, and wheat. Vegetation indices will help decipher several crop conditions concerning health, growth, and stress conditions. In the near future, these indices will be derived from the combination of particular wavebands related to biophysical characteristics, which will allow an estimate of the attribute of plants and the identification of the best crop management strategy to obtain the best possible productivity. Basically, it focuses on vegetation indices such as NDVI, EVI, GNDVI, and SAVI, which have been developed to capture the variability of vegetation canopies in density, leaf area, chlorophyll content, and other physiological activities or statuses of water stress, nitrogen status, and crop performance. These indices encapsulate the various plant responses influenced by soil, meteorological conditions, and management practices. The research contributes to our present knowledge of the wide range of vegetation indices required in crop analysis, improving monitoring and management strategies. The results will provide a better understanding in agricultural practices and decision-making by equipping researchers and practitioners with a complete package on vegetation indices to analyse crops. Further research in the validation field and optimization of their use are recommended for integration into decision support systems that promote sustainable crop production. In general, this paper improves our understanding of the diverse vegetation indices required for crop analysis, thereby fostering improved practices in crop monitoring and management.

KEYWORDS: Vegetation Indices (VI); NDVI; LAI; Precision Agriculture (PA)

1. INTRODUCTION

In the past few years, geospatial technology has been undergoing tremendous development and massive diffusion and is changing the very way of looking at and analysing our planet. Satellite imagery, sensing, geographic information systems, and location-based services are all constituents of geospatial technology that find application in many different kinds of fields, like agriculture, urban planning, disaster management, and environmental monitoring [1]. Another area in which geospatial technology has made a great impact is in precision agriculture. In the field of agriculture, researchers have utilized geospatial data for predicting crop yield and soil nutrient content, mapping health conditions of crops, and detecting anomalies [2]. The applications of geospatial technology have extended to optimizing irrigation, reduced fertilizer use, and increasing efficiency in agri-supply chains [3].

In urban planning, geospatial technology has been applied in population density, traffic pattern, and land-use analysis, with extensions to the planning and design of transportation systems, buildings, and public spaces [4] [5]. Geospatial technology has also been extended into use for disaster management, where it is applied in the mapping of the extent of damage from natural disasters and in relief efforts [6]. In the last couple of years, geospatial technology has turned out to be very potent in crop analysis by the simple fact that vast data is obtained by researchers to optimize the produce of crops and reduce waste. It provides useful insights into crop health, nutrient content, and yield potential through satellite imaging, remote sensing, and geographic information systems [7]. The other domain in which geospatial technology has contributed much to crop analysis is in developing techniques for precision agriculture. It has been used in predicting crop yield and soil nutrient content, observing crop health, and detecting any aberrations [8]. It has been applied to optimize irrigation, reduce fertilizer usage, and bring efficiency into agricultural supply chains [9].

Another important application of geospatial technology in crop analysis involves the monitoring and management of crops at different stages of growth. For instance, satellite imagery and remote sensing data have been applied in monitoring crop growth and detecting problems such as drought or insect invasion [10]. Here, geospatial technology can be applied to work out a crop's appropriate time of planting and harvesting, given the meteorological and other environment preconditions [11]. The recent past has seen geospatial technology advances usher in new tools and applications in crop analysis. For example, researchers have used machine learning algorithms in an automated classification of crops, including the identification of specific plant species from satellite images [12].

2. REMOTE SENSING AND VEGETATION INDICES FOR CROP ANALYSIS

Vegetation indices are mathematical algorithms that use the values of reflectance to retrieve information about the health and vigor of plants from remotely sensed data. They are computed by the ratio of the value of reflectance for two or more spectral bands that quantify biophysical parameters, including contents in chlorophyll, leaf area index, and biomass. VIs are important in crop analysis, for they give ability to monitoring plant health, identifying plant stress, detecting nutrient deficiency, and yield prediction [13]. Many research articles have validated the potential of remote sensing and VIs in crop analysis. For example, in the study, the author used remote sensing and VIs to access drought impacts on wheat crops in India. The authors found VIs efficient for the detection of drought stress in wheat crops, while among them, NDVI was most strongly correlated with yield [14]. Another study used remote sensing and VIs to monitor rice growth and yield. According to the writers, EVI was the best index in predicting rice yield with R2 = 0.76. Besides, it has been reported that VIs had the ability to detect nitrogen and phosphorus deficiency in rice crops [15]. In this paper, the author used remote sensing and VIs in monitoring wheat crops. The results showed that VIs were efficient in monitoring water stress and nitrogen deficiency of wheat crops, with NDVI presenting the best relationship with grain yield. Further, the authors established that VIs could be used to establish high yielding areas of wheat fields [16]. In general, remote sensing and vegetation indices are very useful for crop studies, and the information given by them enables farmers and researchers to monitor crops for stress or deficiencies and optimize management practices. With the ever-increasing population of the world, these technologies will have an important role in meeting food security [17].

3. VEGETATION INDICES

Vegetation indices are widely used in crop analysis through remote sensing because of the fact that they contain important information regarding the physiological and biophysical properties of plants. They are mathematical combinations of spectral bands that reflect different wavelengths of electromagnetic radiation reflected by vegetation [18]. These indices are useful in estimating the crop parameters such as vegetation cover, leaf area index (LAI), biomass and yield [19]. Commonly used vegetation indexes are Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Green Chlorophyll Index (GCI) and Chlorophyll Absorption Ratio Index (CARI). Each index has certain advantages and limitations and the index selection is dependent on the research objective and type of remote sensing data or sensor available [20].Following figure 1 specifies bands and their reflectance for dead, stressed and healthy leaf.

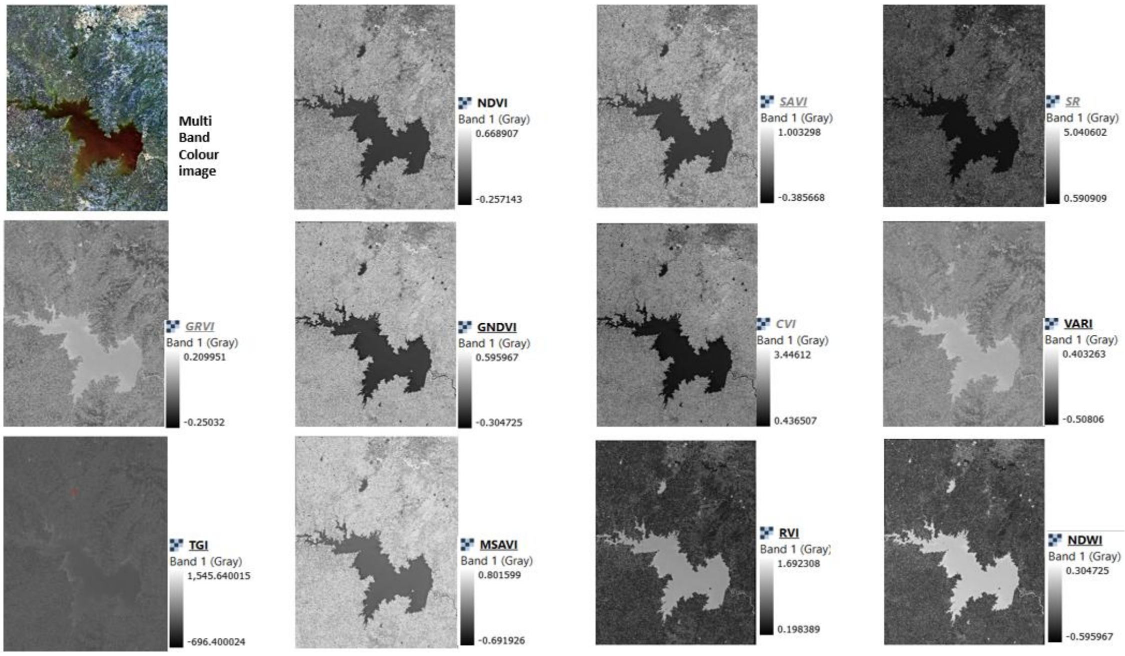

Figure 1: Different Vegetation Indices

In the studies, we have considered five crops specified in Table 1. These also include the usages of these indices for each crop underpinning their importance in crop management and precision agriculture.

Table 1: Vegetation Indices Based on Crops

Crop Name	Vegetation Indices	Use of Indices	References
Cotton	MTCI, TSAVI, EVI, GEMI, WDVI, S2REP, PVI, DVI, REIP, MSAVI, SAVI, IRECI, ARVI, MSAVI2, TNDVI, IPVI, NDVI, GNDVI, PSSRa, RVI, NDI45	Monitoring crop growth, yield estimation, and disease detection.	[21], [22]
Maize	Vi, RVI I, RVI II, MCARI/MTVI2, DCNI, MCARI, TCARI, TCARI/OSAVI, MTCI, , CCI, TGI, EXG, VARI, NDVI, NDRE, WDRVI	Monitoring crop growth, yield estimation, and water stress detection.	[23], [24]
Soybean	EVI, GNDVI, IV 790/550, IV 790/660, IV 790/735, InRE, MSAVI2, MTVI2, NDRE, NDVI, SAVI, SCCCI, IRVI	Monitoring crop growth, yield estimation, and nutrient management.	[25], [26]
Sugarcane	EVI, GDVI, GRVI, ARVI, DVI, GEMI, GNDVI, GARI, GVI, IPVI, LAI, MNLI, MSR, NLI, NDVI, OSAVI, RDVI, SAVI, VARI, TDVI, SIPI, ENDVI, NG, NR, NNIR, VI green, MSAVI2, NDWI	Monitoring crop growth, yield estimation, and water stress detection.	[27], [28]
Wheat	NDVI, NDRE, GNDVI, SR, SR re, EVI, CVI, TVI, MTVI2, RTVI core, MCARI, TCARI, GLI, CI-G, CI-RE, NGRDI, VARI, RENDVI, SAVI	Monitoring crop growth, yield estimation, and nitrogen management.	[29], [30]

Selecting the appropriate band combinations for crop analysis depends on the specific vegetation property to be estimated. Different vegetation indices are optimized for different applications, and the choice of bands is based on the spectral reflectance properties of vegetation that relate to those properties. [20] There are several VIs that are commonly used for crop analysis, each optimized for different applications. In this response, we will describe some of the most commonly used VIs for identifying biomass, leaf area index (LAI), and chlorophyll content in crops.

Table 2:

Vegetation Index	Equation	Significance	Range	Ref
Difference Vegetation Index (DVI)	$DVI = R_{NIR} - R_{red}$	DVI is used to monitor vegetation growth and stress in agricultural and natural ecosystems. It is particularly useful for detecting stress in vegetation caused by factors such as drought or nutrient deficiencies.	-1 to 1 Values close to 1 indicate dense, healthy vegetation, while values close to -1 indicate stressed or sparse vegetation. Values around 0 indicate moderate vegetation cover.	[20-21], [28],[31]
Ratio Vegetation Index (RVI)	$RVI = R_{RED}/R_{NIR}$	RVI is used to monitor vegetation growth and stress in agricultural and natural ecosystems. It is particularly useful for detecting stress in vegetation caused by factors such as drought or nutrient deficiencies.	0 to infinity Higher values indicate denser vegetation cover, while lower values indicate less dense or sparse vegetation.	[20-21], [32]
Enhanced Vegetation Index (EVI)	$EVI = 2.5(R_{NIR} - R_{RED})/(R_{NIR} + 6R_{RED} - 7.5R_{BLUE} + 1)$	EVI is used to monitor vegetation growth and stress in agricultural and natural ecosystems. It has been shown to be more sensitive than NDVI in areas with high biomass, such as forests.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[20-22], [29],[30-31], [33]
Global Environment Monitoring Index (GEMI)	$GEMI = \eta \times (1 - \eta \times 0.25) - [\frac{R_{RED} - 0.125}{1 - R_{RED}}]$ $\eta = (2 \times (R_{NIR}^2 - R_{RED}^2) + 1.5 \times R_{NIR} + 0.5 \times R_{RED})/(R_{NIR} + R_{RED} + 0.5)$	GEMI is used to monitor vegetation stress and productivity in agricultural and natural ecosystems. It is particularly useful for detecting stress in vegetation caused by factors such as drought or nutrient deficiencies.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[20-21], [28], [31-33]
Perpendicular Vegetation Index (PVI)	$PVI = (R_{NIR} - aR_{RED} - b)/(1 + a^2)^{1/2}$	PVI is used to estimate vegetation canopy structure, including leaf area index and vegetation height. It is particularly useful for monitoring vegetation growth and productivity in forested areas.	-1 to 1 Values close to 1 indicate dense, healthy vegetation, while values close to -1 indicate sparse, unhealthy vegetation. Values around 0 indicate moderate vegetation cover.	[20-21], [31-33]
Soil-Adjusted Vegetation Index (SAVI)	$SAVI = (R_{NIR} - R_{RED})(1 + L)/(R_{NIR} + R_{RED} + L)$	SAVI is used to correct for soil background effects in vegetation index calculations. It can be used to monitor vegetation growth and stress in agricultural and natural ecosystems.	-1 to 1 Values close to 1 indicate dense vegetation cover, while values close to -1 indicate sparse vegetation cover. Values around 0 indicate moderate vegetation cover.	[20-21], [27], [30-33]
Transformed Soil-Adjusted Vegetation Index (TSAVI)	$TSAVI = a(R_{NIR} - aR_{RED} - b)/(R_{RED} + aR_{NIR} - ab)$	TSAVI is used to correct for soil background effects in vegetation index calculations. It can be used to monitor vegetation growth and stress in agricultural and natural ecosystems.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[21], [31-33]
Modified Soil-Adjusted Vegetation Index (MSAVI)	$MSAVI = (2 \times (R_{NIR} + 1) - ((2 \times R_{NIR} + 1)^2 - 8 \times (R_{NIR} - R_{RED}))^{\frac{1}{2}})/2$	MSAVI is used to correct for soil background effects in vegetation index calculations. It can be used to monitor vegetation growth and stress in agricultural and natural ecosystems.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[20-21], [31-33]
Modified Soil-Adjusted Vegetation Index 2 (MSAVI2)	$MSAVI2 = ([2 \times R_{NIR} + 1 - \sqrt{((2 \times R_{NIR} + 1)^2 - 8 \times}$	MSAVI2 is used to correct for soil background effects in vegetation index calculations. It can be used to monitor vegetation growth and stress in agricultural and natural ecosystems.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[21], [28]

Normalized Difference Vegetation Index (NDVI)	$NDVI = (R_{NIR} - R_{RED}) - (R_{NIR} + R_{RED})$	NDVI is used to monitor vegetation growth and stress in agricultural and natural ecosystems. It is a widely used vegetation index that is sensitive to changes in vegetation biomass and productivity.	-1 to 1 Values close to 1 indicate high vegetation density, while values close to -1 indicate low vegetation density. Values around 0 indicate moderate vegetation density.	[20-29], [31-33]
Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = (R_{NIR} - R_{GREEN})/(R_{NIR} + R_{GREEN})$	GNDVI is used to estimate the vegetation cover and productivity of agricultural systems. It is particularly useful for monitoring crop growth and yield.	-1 to 1 Values close to 1 indicate healthy vegetation, while values close to -1 indicate little or no vegetation.	[20-22], [28-29], [30-33]
Texture-Adjusted Normalized Difference Vegetation Index (TNDVI)	$TNDVI = \sqrt{\frac{(R_{NIR} - R_{RED})}{(R_{NIR} + R_{RED})} + 0.5}$	TNDVI is used to estimate vegetation canopy structure and productivity. It is particularly useful for monitoring vegetation growth in forested areas.	-1 to 1 Values close to 1 indicate healthy vegetation, while values close to -1 indicate little or no vegetation.	[21], [32]
Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = (R_{NIR} - 2 \times R_{RED} - R_{BLUE})/(R_{NIR} + 2 \times R_{RED} - R_{BLUE})$	ARVI is used to correct for atmospheric effects in vegetation index calculations. It can be used to monitor vegetation growth and stress in agricultural and natural ecosystems.	-1 to 1 Values close to 1 indicate healthy vegetation, while values close to -1 indicate little or no vegetation.	[20-21], [31-32]
Infrared Percentage Vegetation Index (IPVI)	$IPVI = R_{NIR}/(R_{NIR} + R_{RED})$	IPVI is used to estimate the vegetation cover and productivity of agricultural systems. It can be used to monitor crop growth and yield.	0 to 1 Values close to 1 indicate healthy vegetation, while values close to 0 indicate little or no vegetation.	[21], [31], [32]
Weighted Difference Vegetation Index (WDVI)	$WDVI = R_{NIR} - m \times R_{RED}$	WDVI is used to monitor vegetation growth and stress in agricultural and natural ecosystems. It is particularly useful for detecting stress in vegetation caused by water deficits.	-1 to 1 Values close to 1 indicate healthy vegetation, while values close to -1 indicate little or no vegetation.	[21], [33]
MERIS Terrestrial Chlorophyll Index (MTCI)	$MTCI = (R_{NIR} - R_{RE})/(R_{RE} - R_{RED})$	MTCI is used to estimate the chlorophyll content of vegetation, which is an indicator of plant health and productivity. It is particularly useful for assessing the health and productivity of vegetation in areas with low chlorophyll concentrations, such as evergreen forests or grasslands.	-1 to 1 Values close to 1 indicate high chlorophyll content, while values close to -1 indicate low chlorophyll content.	[21], [32]
Sentinel-2 Red Edge Position (S2REP)	$S2REP = 705 + 35 \times [\left(\frac{\rho 783 + \rho 665}{2}\right) - \rho 705)]/(\rho 740 + \rho 705)$	S2REP is used to estimate the chlorophyll content and biomass of vegetation. It is particularly useful for monitoring vegetation growth in agricultural and natural ecosystems.	680 nm to 750 nm A measure of the position of the red edge in the reflectance spectrum of vegetation, which can be used to estimate chlorophyll content and plant stress.	[21], [32]
Red Edge Inflection Point (REIP)	$REIP = 700 + 40 \times (((R670 + R780)/2) - R700)/(R740 - R700)$	REIP is used to estimate the chlorophyll content and biomass of vegetation. It is particularly useful for monitoring vegetation growth and productivity in agricultural and natural ecosystems.	700 nm to 750 nm A measure of the inflection point on the red edge in the reflectance spectrum of vegetation, which can be used to estimate chlorophyll content and plant stress.	[21],[32]
Infrared-Red Edge Chlorophyll Index (IRECI)	$IRECI = \frac{(R_{NIR} - R_{RED})}{(R_{RE1}/R_{RE2})}$	IRECI is used in crop analysis to assess the chlorophyll content and overall health of vegetation.	-1 to 1 Values close to 1 indicate high chlorophyll content, while values close to -1 indicate low chlorophyll content.	[21],[32]
Plant Senescence Reflectance Ratio Index (PSSRa)	$PSSRa = \frac{R_{RE}}{R_{RED}}$	PSSRa is used to detect senescence or aging of plant tissues, which can be an indicator of plant health and productivity. It is particularly	0 to 1 Values close to 0 indicate healthy vegetation, while values close to 1 indicate senescence or aging of vegetation.	[21], [31], [32]

		useful for monitoring crop growth and yield.		
Normalized Difference Infrared Index at 450 and 850 nm (NDI45)	$NDI45 = \frac{(R_{NIR} - R_{RED})}{(R_{NIR} + R_{RED})}$	NDI45 is used to estimate vegetation canopy structure and productivity. It is particularly useful for monitoring vegetation growth in forested areas.	-1 to 1 Values close to 1 indicate high water content in vegetation, while values close to -1 indicate low water content in vegetation.	[21], [32]
Vegetation Index (Vi)	$Vi = (R_{NIR}/R_{RED}) - 1$	Vi can be used to monitor changes in plant growth over time and to identify areas of the field that are experiencing stress.	-1 to 1 Values close to 1 indicate healthy vegetation, while values close to -1 indicate little or no vegetation.	[23]
Ratio Vegetation Index II (RVI II)	$RVI\ II = (R_{NIR}/R_{RED})^2$	RVI II is useful for estimating plant biomass and predicting crop yield potential.	-1 to 1 Negative values indicate background or soil, positive values indicate vegetation	[23]
Modified Chlorophyll Absorption Ratio Index (MCARI)	$MCARI = 1.2 \times (2.5 \times (R_{NIR} - R_{RED}) - 1.3 \times (R_{NIR} - R_{GREEN})$	MCARI is useful for detecting early signs of stress, such as nutrient deficiencies or disease.	0 to infinity Higher values indicate higher chlorophyll content in the vegetation	[20], [23], [29], [31-32]
Modified Chlorophyll Absorption Ratio Index II (MCARI 2)	$MCARI\ 2 = (1.2 \times (2.5 \times (R_{NIR} - R_{RED}) - 1.3 \times (R_{NIR} - R_{GREEN})) / (\sqrt{(2 \times R_{NIR} + 1)^2} - 6 \times (R_{NIR} - 5 \times R_{RED}) - 0.5$	MCARI is useful for detecting early signs of stress, such as nutrient deficiencies or disease and water shortages.	-1 to 1 Negative values indicate stressed vegetation, positive values indicate healthy vegetation	[20], [31-32]
Transformed Vegetation Index (TVI)	$TVI = (NDVI + 0.5)^{1/2}$	TVI is used to measure vegetation greenness and vigour.	-1 to 1 Negative values indicate bare soil, positive values indicate vegetation	[20], [29], [31], [33]
Modified Triangular Vegetation Index 2 (MTVI2)	$MTVI2 = 1.5 \times ((1.2 \times (R_{NIR} - R_{GREEN}) - 2.5 \times (R_{RED} - R_{GREEN})) / \sqrt{(2 \times R_{NIR} + 1)^2 - (6 \times}$	MTVI2 is useful for monitoring vegetation health and productivity, particularly in areas where soil reflectance is high.	-1 to 1 Negative values indicate stressed vegetation, positive values indicate healthy vegetation	[20], [23], [31]
Double-peak Canopy Nitrogen Index (DCNI)	$DCNI = (R_{GREEN} - R_{RED\ EDGE})/(R_{RED} - R_{RED\ EDGE})$	DCNI is useful for monitoring plant nitrogen content, which can be used as an indicator of plant health and productivity.	-1 to 1 Negative values indicate vegetation stress, positive values indicate healthy vegetation	[23]
Transformed Chlorophyll Absorption Ratio Index (TCARI)	$TCARI = 3 \times ((R_{RED\ EDGE\ 2} - R_{RED\ EDGE\ 1}) - 0.2 \times (R_{GREEN} - R_{BLUE}) \times (\frac{R_{RED\ EDGE\ 2}}{R_{RED\ EDGE\ 1}})$	TCARI is a vegetation index that is used to assess plant health and stress.	0 to infinity Higher values indicate higher chlorophyll content in the vegetation	[20], [23],[29], [31]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$OSAVI = (1 + 0.16) \times ((R_{NIR} - R_{RED})/(R_{NIR} + R_{RED} + 0.16)$	OSAVI is useful for estimating vegetation cover and vegetation vigour	-1 to 1 Negative values indicate background or soil, positive values indicate vegetation	[20], [23], [27], [28], [31]
Canopy Chlorophyll Content Index (CCI)	$CCI = R_{NIR}/R_{RED\ EDGE}$	CCI is used to estimate the amount of chlorophyll in plant leaves, which is useful for monitoring plant health and detecting nutrient deficiencies.	0 to infinity Higher values indicate higher chlorophyll content in the vegetation	[23]
Triangular Greenness Index (TGI)	$TGI = R_{GREEN} - 0.39 \times R_{RED} - 0.61 \times R_{BLUE}$	TGI is useful for identifying areas of the field with high plant productivity and yield potential.	-1 to 1 Negative values indicate stressed vegetation, positive values indicate healthy vegetation	[20], [24]

Excess Green Index (EXG)	$EXG = (2 * GREEN - RED - BLUE)$	The EXG is useful for predicting crop yield potential and identifying areas of the field with high biomass.	-1 to 1 Negative values indicate stressed vegetation, positive values indicate healthy vegetation	[20], [24], [31]
Visible Atmospherically Resistant Index (VARI)	$VARI = (GREEN - RED)/(GREEN + RED - BLUE)$	VARI is useful for detecting early signs of plant stress, such as nutrient deficiencies or disease.	-1 to 1 Negative values indicate vegetation while positive values indicate soil and bare areas	[20], [24], [27], [29],[31], [33]
Normalized Difference Red Edge (NDRE)	$NDRE = (R_{NIR} - R_{RED\ EDGE})/(R_{NIR} + R_{RED\ EDGE})$	NDRE is useful for detecting early signs of plant stress and predicting yield potential.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [24], [29], [31], [33]
Wide Dynamic Range Vegetation Index (WDRVI)	$WDRVI = (\propto R_{NIR} - R_{RED})/(\propto R_{NIR} + R_{RED})$	WDRVI is a vegetation index that is used to assess plant growth and productivity.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[24], [31], [33]
Simplified Canopy Chlorophyll Content Index (SCCCI)	$SCCCI = NDRE/NDVI$	SCCCI is used to estimate the chlorophyll content of vegetation, which is a key indicator of plant health and productivity.	0 to 1 Higher values indicate higher chlorophyll content	[25]
Green Difference Vegetation Index (GDVI)	$GDVI = R_{NIR} - R_{GREEN}$	GDVI is used for assessing plant vigour, crop growth and stress detection	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[27], [31]
Green Ratio Vegetation Index (GRVI)	$GRVI = R_{NIR}/R_{GREEN}$	GRVI is a vegetation index used to evaluate the vegetation greenness, and it is particularly useful for analyzing crops.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [27], [31]
Atmospherically Resistant Vegetation Index (ARVI)	$ARVI = (R_{NIR} - (R_{RED} - \gamma(R_{BLUE} - R_{RED})))/(R_{NIR} + (R_{RED} - \gamma(R_{BLUE} - R_{RED})))$	ARVI is used to correct for atmospheric interference in satellite imagery, enabling more accurate analysis of vegetation cover, density, health, and growth patterns.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [27], [31], [32]
Greenness Vegetation Index (GVI)	$GVI = (-0.2848 \times TM_1) + (-0.2435 \times TM_2) + (-0.5436 \times TM_3) + (0.7243 \times TM_4) + (0.0840 \times TM_5) + (-0.18 \times TM_7)$	GVI is used in measuring vegetation biomass and monitoring plant growth	0 to 1 Higher values indicate higher greenness	[27], [31]
Modified Non-Linear Index (MNLI)	$MNLI = [(R_{NIR}^2 - R_{RED})(1 + L)]/(R_{NIR}^2 + R_{RED} + L)$	MNLI is used to estimate vegetation chlorophyll content and assess plant health, making it useful for crop management and monitoring crop growth and yield.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [27], [31]
Modified Simple Ratio (MSR)	$MSR = ((\frac{R_{NIR}}{R_{RED}}) - 1)/\sqrt{(\frac{R_{NIR}}{R_{RED}}) + 1}$	MSR is used in assessing vegetation stress and monitoring plant water status	0 to infinity Higher values indicate higher vegetation	[20], [27], [31]
Non-Linear Index (NLI)	$NLI = (R_{NIR}^2 - R_{RED})/(R_{NIR}^2 + R_{RED})$	NLI is a vegetation index used to estimate vegetation chlorophyll content and evaluate plant health.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [27], [31]
Renormalized Difference Vegetation Index (RDVI)	$RDVI = (R_{NIR} - R_{RED})/\sqrt{(R_{NIR} + R_{RED}}$	RDVI can be used for a variety of applications, including crop yield estimation, vegetation monitoring, and land cover mapping.	-1 to 1 Positive values indicate vegetation while negative values indicate soil and bare areas	[20], [27], [31]
Structurally Independent Pigment Index (SIPI)	$SIPI = (R_{NIR} - R_{BLUE})/(R_{NIR} + R_{RED})$	The SIPI index provides a measure of the ratio of chlorophyll to carotenoid pigments in plant leaves.	-1 to 1 Values closer to 1 indicate a high concentration of photosynthetic pigments, while values closer to -	[20], [27], [31]

			1 indicate low pigment concentrations	
Transformed Difference Vegetation Index (TDVI)	$TDVI = \sqrt{0.5 + [\frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}}]}$	TDVI is a vegetation index that is used to measure the greenness and biomass of vegetation.	-1 to 1 Values closer to 1 indicate healthy vegetation, while values closer to -1 indicate stressed vegetation	[27], [31]
Enhanced Normalized Difference Vegetation Index (ENDVI)	$ENDVI = \frac{(R_{NIR} + R_{GREEN}) - (2 \times}{(R_{NIR} + R_{GREEN}) + (2 \times}$	ENDVI is a vegetation index that is used to estimate vegetation cover and monitor plant growth and health.	-1 to 1 Values closer to 1 indicate healthy vegetation, while values closer to -1 indicate stressed vegetation	[27]
Simple Ratio (SR)	$SR = \frac{R_{NIR}}{R_{RED}}$	SR is a basic vegetation index used to estimate vegetation biomass and health.	0 to infinity Values greater than 1 indicate healthy vegetation	[20],[29], [31]
Simple Ratio Red-Edge (SRRE)	$SR = \frac{R_{NIR}}{R_{RED\ EDGE}}$	The SRRE vegetation index is commonly used in remote sensing and precision agriculture applications, where it can be used to monitor crop health and productivity.	0 to infinity Values greater than 1 indicate healthy vegetation	[29], [31]
Chlorophyll Vegetation Index (CVI)	$CVI = R_{NIR}(R_{RED}/R_{GREEN})^2$	CVI is a vegetation index used to estimate the chlorophyll content of vegetation.	-1 to 1 Values closer to 1 indicate high chlorophyll content, while values closer to -1 indicate low chlorophyll content	[29]
Green Leaf Index (GLI)	$GLI = \frac{(2 \times R_{GREEN} - R_{RED} - R}{(2 \times R_{GREEN} + R_{RED} + R}$	GLI is a vegetation index that estimates the amount of green leaf area in vegetation.	0 to 1 Values closer to 1 indicate healthy vegetation	[20], [29], [31]
Chlorophyll Index-Green (CI-G)	$\mathrm{CI} - \mathrm{G} = \frac{R_{NIR}}{R_{GREEN}} - 1$	CI-G is a vegetation index used to monitor crop health and estimate chlorophyll content in vegetation.	-1 to 1 Values closer to 1 indicate high chlorophyll content, while values closer to -1 indicate low chlorophyll content	[29]
Chlorophyll Index-Red Edge (CI-RE)	$\mathrm{CI} - \mathrm{RE} = \frac{R_{NIR}}{R_{RED\ EDGE}} - 1$	CI-RE used to monitor crop health and estimate chlorophyll content in vegetation.	-1 to 1 Values closer to 1 indicate high chlorophyll content, while values closer to -1 indicate low chlorophyll content	[29]
Normalized Green-Red Difference Index (NGRDI)	$NGRDI = \frac{R_{GREEN} - R_{RED}}{R_{GREEN} + R_{RED}}$	NGRDI is a vegetation index used to detect vegetation stress and chlorophyll content in vegetation.	-1 to 1 Values closer to 1 indicate high chlorophyll content, while values closer to -1 indicate low chlorophyll content	[20], [29], [31]
Red Edge Normalized Difference Vegetation Index (RENDVI)	$RENDVI = \frac{R_{NIR} - R_{RED\ EDGE}}{R_{NIR} + R_{RED\ EDGE}}$	Red Edge Normalized Difference Vegetation Index (RENDVI) is used to monitor crop health and estimate chlorophyll content in vegetation.	-1 to 1 Values closer to 1 indicate healthy vegetation, while values closer to -1 indicate stressed vegetation	[30], [31]
Normalized Difference Water Index (NDWI)	$NDWI = \frac{R_{GREEN} - R_{NIR}}{R_{GREEN} + R_{NIR}}$	Normalized Difference Water Index (NDWI) is used to identify and monitor water bodies and changes in water content in vegetation.	-1 to 1 Values closer to 1 indicate high moisture content, while values closer to -1 indicate low moisture content	[20], [28], [31], [33]

3.1. Standard Deviation

Statistical analysis of vegetation indices (VIs) contributes to an understanding of the nature and the variability of the crop conditions. Basic statistic parameters such as mean, median, standard deviation, minimum and maximum are widely used to analyse vegetation index data. The mean is an average value of the level of vegetation in a crop field, but the median gives a central value that is less influenced by extreme values. Standard deviation (SD) is a measure of the spread of the vegetation index values from the average and gives a measure of variability within the crop area. Minimum and maximum values describe the range of index values and assist in interpreting spatial differences in the crop health and vigor [34]. In one study, Tetracam multi-spectral data was used in the analysis of vineyard crops and tomato crops using vegetation indices such as NDVI, GNDVI, and SAVI. Statistical analysis of index maps was done based on mean and standard deviation values to validate qualitative observations of crop vigor [35]. Another study estimated maize yield using SOPT-6 aerial data where the crop yield was modelled as a function of NDVI and Leaf Area Index (LAI). Ground data collected from 15 plots revealed LAI mean values of 3.96 (SD = 0.3) and NDVI mean values of 0.41 (SD = 0.03). Yield prediction using NDVI showed 97% accuracy while the LAI model over-predicted the yield by ~14% [33].

3.2. Skewness and Kurtosis

Skewness and kurtosis are statistical measures that are used to describe the distribution pattern of the values of the vegetation index. Skewness is a measure of asymmetry of a distribution. A positively skewed distribution has a longer tail towards the higher end of the distribution and a negatively skewed distribution has a longer tail towards the lower end. Kurtosis explains the peakedness of the distribution as well as the existence of extreme values. In one study with LISS-IV imagery, texture features such as mean, variance, skewness and kurtosis were calculated to aid in crop classification [36]. These texture measures were combined with vegetation indices to create decision tree models to classify land cover. Training samples were collected from field observations and the Google Earth data. The results showed that classification based on vegetation indices only resulted in 81.08% overall accuracy with a Kappa value of 0.79, whereas the combination of vegetation indices with texture features gave the accuracy up to 89.42% with a Kappa value of 0.87 [36].

3.3. Time Series Analysis

Time series analysis is known to be widely used to study temporal patterns in vegetation indices and understanding the dynamics of crop growth. It allows, for example, to know the stages of development, the seasons and the anomalies of the vegetation. Trend analysis is useful in determining the direction and magnitude of long-term variation in crop conditions. In one study, time series vegetation index data was used to derive crop phenological metrics and analyse crop growth patterns over time [37]. Another study was conducted comparing the citrus orchard inventories using LISS-III and LISS-IV satellite imageries acquired during summer and winter seasons. NDVI values were calculated and ground truth data was collected from field surveys and CHAMAN app. Both unsupervised classification (ISODATA) and supervised classification (maximum likelihood classifier) were used. Temporal NDVIs spectral profiles were produced for the discrimination of crops. Results showed that with LISS-III data the classification accuracy increased from 55% to 77% using LISS-IV data [38].

3.4. The Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is used to analyze spatial patterns in the values of the vegetation index, and to identify clusters of similar crop conditions. This approach can be used to detect areas where vegetation is vigorous or observed to be weak, which in turn can be targeted for agricultural management practices. Spatial autocorrelation can usually be measured by using Moran's I statistic. Positive spatial autocorrelation is a sign of clustering of similar values of the vegetation index and negative autocorrelation is a sign of spatial outliers. In one study, spatial autocorrelation analysis using Global Moran's I and Local Moran's I were used on vegetation indices such as NDVI, SAVI, CSI and NBR in order to analyze aridity and potential land-fire risks. The results showed positive spatial autocorrelation implying the existence of strong spatial relationship among the studied regions [39]. Another study used Landsat-8 imagery to identify white molds disease in soybean fields. Vegetation indices like NDVI, SAVI, and EVI and Support Vector Machine (SVM) classifier were used. The results were tested with the help of Local Moran's I spatial autocorrelation index and ground truth data. The SVM model successfully detected white-mold-affected areas with a success rate of about 70% and spatial autocorrelation analysis largely showed clustering patterns [36].

3.5. Correlation Analysis

Correlation analysis is used to identify the relationships between the vegetation indices and the crop parameters like yield, biomass, soil properties and environmental conditions. A positive correlation means that both variables go up together while a negative correlation means there is an inverse relationship between the two variables. Correlation strength is generally expressed in terms of Pearson's correlation coefficient or Spearman's rank correlation coefficient [40].In one study, the MA crop area and green biomass from maize were estimated using Landsat 8 and Sentinel 2 imagery. Nine vegetation indices were derived and compared to photosynthetic vegetation fraction (fPV) derived from spectral mixture analysis. The performance of indices was assessed by Pearson correlation, RMSE and Willmott's index of agreement. Results showed that the best correlation (0.99) was found between EVI and biomass estimation followed by SAVI and OSAVI [41].

3.6. Regression Analysis

Regression analysis is widely used to model relationships between vegetation indices and crop parameters e.g. yield, biomass, or nutrient content. It aids in quantifying the strength and direction of relations and predictive modeling for crop monitoring and decision making [42]. In one study, the hyperspectral data from the UAV imagery were used to estimate the biomass of the barley. Combination of five vegetation indices with plant height crop surface model (PHCSM) data. Both linear and exponential regression models were tested, followed by multiple nonlinear regression model composed of vegetation indices and plant height: Results showed that the combination of vegetation indices and plant height improved biomass prediction compared with vegetation indices only models [43].

3.7. Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) are used to compare whether values of vegetation index are significantly different among the different treatments or varieties of crops or environmental conditions. Using the group means, the effect of the factors on crop growth and spectral response can be discovered with the help of the analysis of variance (ANOVA) [44]. In research on field grown cultivars of olive, 14 vegetable indexes calculated, two-way completely randomized analysis of variance (ANOVA) and principal component analysis (PCA) and linear discrimination analysis (LDA). The results revealed that some of the vegetation indices such as NGRDI, NDVI, GRVI, GNDVI, SR, RVI, and GRNDVI had significant discriminating power in identifying scion types [45].

3.8. Principle Component Analysis (PCA)

Principal Component Analysis (PCA) is a multivariate statistical technique which is applied to vegetation index groups to minimize the dimensionality of the data by converting correlated variables into a smaller number of uncorrelated components. PCA assists in identifying the most influential vegetation indices that influence crop growth and crop condition [46]. In a study on sweet corn, hyperspectral reflectance data were analysed by PCA to find out the most significant wavelengths. Stepwise algorithms and multiple linear regression were then applied to select the best vegetation indices for monitoring crop yield and crop physiological conditions under varying water and nitrogen levels. Results showed that the red edge spectral indices were good predictors of yield and crop physiological parameters [47].

3.9. Classification Methods

Classification techniques are used for classification of vegetation indexes into categories for crop monitoring, crop type identification and detection of crop stress. There are several machine learning algorithms that are widely used in vegetation index classification.

3.9.1. Support Vector Machine (SVM)

SVM is a supervised classification method that is based on the theory of statistical learning. It finds the best hyperplane to separate the samples of data into different classes by maximizing the margin between training data. In one paper, SVM was applied to the classification of cotton crops using five vegetation indices obtained by LISS-III satellite data. Training samples have been created using a training library that was developed from satellite imagery and field data. Results showed that the Simple Ratio (SR) vegetation index gave higher classification accuracy than other indices [48].

3.9.2. Decision Tree

A decision tree is a supervised learning algorithm that uses a hierarchy of rules to classify data. It divides the data according to some features like vegetation indices to make some predictions or classifications. In one study, Sentinel-2 multispectral images, as well as vegetation indices such as NDVI, PSRI, GNDVI, RVI, and red-edge NDVI variants were used for the classication of fruit trees. The optimization model of classification obtained accuracy values in the range of 0.89-0.91 on the training datasets [49].

3.9.3. Random Forest (RF)

Random Forest is an ensemble learning algorithm, which is a combination of multiple decision trees to enhance the accuracy of classification and decrease overfitting. It has the capability to deal with noisy data and it also estimates the importance of features. In a study to predict maize yield, 33 vegetation indices were analysed with Random Forest model. The most influential indices were NDVI, NDRE and GNDVI, which made a significant contribution to the enhancement of yield prediction accuracy [50].

3.10. Wavelet Transform

The Wavelet Transform (WT) refers to a mathematical technique used to analyze vegetation index data of the time series data at different frequency scales. It makes it possible to detect seasonal behaviour, anomalies and vegetation dynamics in crop growth. In one study, wavelet transform was used to analyse non stationary NDVI time series data in Tunisia. Using multi-resolution wavelet analysis (MRA-WT), whose effectiveness has been demonstrated in the analysis of climate time series, as well as statistical tests and weather data, researchers managed to determine vegetation trends in agricultural and forest areas. The mother wavelet function was found to be useful in temporal vegetation pattern extraction [51].

4. RESULTS AND DISCUSSION

Several studies measured the effectiveness of vegetation indices (VIs) to monitor the crop situation with different statistical and machine learning methods. One study compared the variability of soybean using canopy sensors and three vegetation indices, NDVI, NDRE, and IRVI. Saturation detection indexes and control charts were used to determine the stages of soybean development that are suitable for sensor readings. NDVI exhibited greater tendencies of saturation and control charts were useful to identify points of saturation during crop growth [14].

Another study used standard deviation and linear regression methods to assess the vegetation index for monitoring sugarcane conditions near oil and gas fields. Vegetation indices with greater than 0.8 coefficient of determination (R2) were chosen, resulting in 6 effective vegetation indices including NDVI, ENDVI, GDVI, LAI and SIPI. The study concluded that synthesis of various statistical methods helps to increase the crop condition assessment reliability [40]. In order to investigate the nitrogen uptake of wheat, 17 vegetation indices from RapidEye imagery were processed. Regression analysis was used to identify the best indices of nitrogen uptake at harvest. Model performance was assessed by using R2 and Root Mean Square Error (RMSE) which showed successful use of spectral indices for precision agriculture applications [44]. Sentinel-2 imagery had also been used to examine sugarcane vulnerability to biochemical factors. Correlation analysis revealed that several vegetation indices were very sensitive to biochemical variables of crops, indicating their usefulness for crop monitoring [49]. Similarly, Support Vector Machine (SVM) classification along with vegetation indices like NDVI, SAVI and EVI were used to detect white mold affected soybean fields with detection accuracy of about 70% [52]. Another study used decision tree classification of the LISS-IV satellite data using 11 vegetation indices. The model reached an overall classification accuracy of 81.08% and 0.79 was the kappa coefficient. When texture features such as mean, variance, skewness, and kurtosis together with vegetation indexes were combined, the classification accuracy was increased up to 89.42% with a kappa coefficient of 0.87, showing the improved performances of the integrated approaches [53]. Additional studies were dedicated to the estimation of leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) using different vegetation indices. Multiple modeling techniques including curve fitting, least squares support vector regression (LS-SVR), and random forest regression (RFR) were used to develop the predictive models [52]. Regression analysis between vegetation indices and ground-measured chlorophyll content also revealed strong relationships with high R2 values and low RMSE which confirmed the reliability of vegetation indices in crop monitoring [54]. In another study carried out in the Indus Basin, regression models using Landsat-8 and MODIS data provided good correlations between vegetation indices and wheat production. SAVI was highly correlated with yield with R2 values of up to 0.74 and Pearson correlation values of up to 0.88 showing that SAVI can be used for mapping in crop applications [55]. Statistical analysis using Python tools have also been used to assess chlorophyll content for different plant species based on vegetation indexes and standard statistical measures such as mean and standard deviation [56].

5. VEGETATION INDEX FUTURE OUTLOOK

Vegetation indices play an important role in the monitoring of crops for major crops such as cotton, maize, soybean, sugarcane, and wheat. Different indices are useful for evaluation of specific crop characteristics. For example, EVI, GEMI and SAVI are widely used for monitoring the cotton canopy density and the vegetation health, while indices like MCARI, OSAVI and VARI are good for maize biomass and chlorophyll estimation. For soybean monitoring, indices such as GNDVI, MSAVI2 and NDRE are commonly used while NDVI, LAI, DVI and NDWI are important for sugarcane analysis. In the case of wheat monitoring, there are indices like RENDVI, TVI and CVI which help to look at vegetation vigor and canopy structure. Common vegetation indices such as NDVI, EVI, GNDVI, and SAVI are used extensively in various crops because they deliver useful information about vegetation health, concentration of chlorophyll, and growing conditions in crops. In future, research is expected to incorporate some of the latest technologies including machine learning, artificial intelligence, cloud computing, Internet of Things (IoT) and big data analytics for better analysis of vegetation index datasets. Vegetation indices have several advantages such as being sensitive to vegetation change, can be computed easily and applied in large geographical areas using satellite, UAV or ground-based sensors. However, they also have limitations like sensitivity to the soil background, atmospheric conditions and sensor characteristics. Additionally, vegetation indices can suffer from saturation effects in areas of dense vegetation which can limit their sensitivity in highly vegetated areas.

6. CONCLUSION

Vegetation indices obtained from remote sensing data are playing a vital role in the modern agriculture sector with some of the applications being crop monitoring, yield prediction, disease detection, and precision farming. These indices give valuable information about crop characteristics such as biomass, leaf area index (LAI), chlorophyll content, canopy structure, photosynthetic activity and plant stress level. Statistical and analytical techniques such as descriptive statistics, correlation analysis, regression modeling, time-series analysis, spatial autocorrelation, and machine learning classification methods (e.g., Random Forest, SVM and Decision Trees) are common methods for the analysis of vegetation index data. Higher values of R2 and higher correlation coefficient values indicate reliable relationships between vegetation indices and crop parameters, and lower RMSE values indicate higher prediction accuracy. This study reviewed vegetation indices useful for crop analysis for five major crops, which are cotton, maize, soybean, sugarcane, and wheat. The results show that vegetation indices are good tools for monitoring crop health, better yield prediction and data-driven agricultural decision making. However, various parameters such as atmospheric conditions, sensor characteristics, background effects, etc., should be considered in the interpretation of vegetation index results. Therefore, vegetation indices should be used in conjunction with other sources of data and analysis methods, to achieve a complete understanding of the crop conditions.

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