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Remote Sensing

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Abstract: Remote sensing (RS) technologies provide a diagnostic tool that can serve as an early warning system, allowing the agricultural community to intervene early on to counter potential problems before they spread widely and negatively impact crop productivity. With the recent advancements in sensor technologies, data anagement and data analytics, currently, several RS options are available to the farm community

Key words: Remote sensing Gis, soil, Vegetation Indices

1. INTRODUCTION

The term sensor first appeared in the year (1960) and it constitutes a translation Remote sensing is known to the assembly-seeking aircraft here must be a presence in the whole picture And between the sensor also known as: the science, art and technology of obtaining body measurements After the shock? Cameras Shortwave devices, spectrophotometers and electronic scanners multilateral. The first remote sensing technology was imaging from aircraft, and after the invention of satellites, it developed to imaging from space, and then radar imaging. Electromagnetic rays are used in remote sensing. When this energy falls on an object, it interacts with it, part of it is absorbed and another part is reflected. The reflected energy is what is used to explore or survey the body, and it is received by remote sensors. Sometimes the body itself is a source of electromagnetic radiation, depending on its properties and temperature.

Remote sensing technologies

Remote sensing is defined as the science, art, and technique for obtaining measurements of a specific body It is a remote phenomenon, and without direct contact with it, cameras and short wave devices are consideredRadiometers, spectrophotometers, multispectral electronic scanners, as well as the eye human resources, systems for collecting information (acquisition data or collection data), and means for remote sensing. Remote sensing is often associated with measuring the reflected electromagnetic energy From 15.0 - 3.0 μm (Emitted) and Emitted (3.0 - 0.3 μm) (Reflected) Before objects that receive solar energy and reflect it back or re-radiate it to the sensor Muhammad Al-(Khuzamy Aziz ,2004) .Remote sensing (RS) is the process of inferring surface parameters from distant measurements of the upwelling emitted or reflected electromagnetic radiation from the land surface. The radiation reflected or emitted by soil varies according to a range of chemical and physical characteristics of the soil matrix (Schmugge *et al*., 2002; Barnes *et al.*, 2003; Anderson and Croft, 2009; Mulder *et al*., 2011;). Therefore, it is possible to discriminate between different soil surfaces and to infer soil properties based on the measured radiation (Dewitte *et al*., 2012). In this document, we use the term “remote sensing” (RS) for airborne and spaceborne acquisitions, whereas “proximal sensing” (PS) refers to ground-based laboratory and field measurements. Soil PS generally measures soil surface properties in a high spatial and spectral resolution from a short range. Depending on the source of energy utilized in the data acquisition**.** Remote sensing refers to various observation and exploration activities of the environment

involving humans and photoelectronic devices carried by satellites, spacecraft (including space shuttles), aircraft, near-space vehicles, and various terrestrial platforms. Artificial satellites that carry sensors to capture images of Earth's surface are referred to as remote sensing satellites. Satellites can successively observe the whole globe or an assigned part of it within a defined time period (Guo *et al*., 2016). Remote sensing is a measurement or acquisition of information of some property of an object or phenomena, by a recording device that is not in physical or intimate contact with the object or phenomena under study (Mladen Todorovic, 2016). Remote sensing technology remote sensing is a technique to observe the earth's surface or the atmosphere from out of space using satellites (space space-borne borne) or from the air using aircraft (airborne). Remote sensing uses a part or several parts of the electromagnetic spectrum. It records the electromagnetic energy reflected or emitted by the earth's surface. The amount of radiation from an object (called radiance) is influenced by both the properties of the object and the radiation hitting the object (irradiance). The human eyes register the solar light reflected by these objects and our brains interpret the colors, the grey tones, and intensity variations. In remote sensing, various kinds of tools and devices are used to make electromagnetic radiation outside this range from 400 to 700 nm visible to the human eye, especially the near-infrared, middle-infrared, thermal-infrared, and microwaves.
Remote sensing imagery has many applications in mapping land-use and cover, agriculture, soils mapping, forestry, city planning, archaeological investigations, military observation, and geomorphological surveying, land cover changes, deforestation, vegetation dynamics, water quality dynamics (Shefali Aggarwal ,2021)
Remote sensors can be classified depending on the power source into:
1-passive remote sensing
2- Active Remote Sensing
Active sensors produce
their own energy for sensing objects, whereas the passive satellite sensors depend on external energy sources (e.g., sun or earth)
Remote sensing plays an increasing role in near real-time soil, crop, and pest management in precision agriculture (Mulla, 2013). Remote sensing systems are divided into passive and active remote sensing. Passive remote sensing data are mainly optical imagery with a usually high spatial resolution and rich texture information. It helps to easily identify the type and status of the ground object through visual interpretation Jensen *et al.* (2008) Passive remote sensing sensors have a wide spectrum range, which can comprehensively observe ground features, however, optical images are easily affected by cloud conditions (Hosseini *et al.,* 2015; Gargiulo *et al.,* 2020) Active remote sensing sensor emits a certain form of electromagnetic waves to a target, and then the sensor receives and records the reflected waves, such as synthetic aperture radar (SAR) (Santi *et al*., 2017) and Light Detection and Ranging (LiDAR) (Shi *et al.* , 2020)
A number of applications related to Remote Sensing. Some of them are listed as follows:
• Forest monitoring and assessment of factors related to plants and animals Inglada *et al.*2015, Addabbo,2016, , Lippitt et al,2016
• Agriculture monitoring and assessment of soil quality, water quantity Lakhankar *et al*., 2009.Lakshmisudha,*et al*., 2016. Daponte *et al*., 2018. Fisher et al.,2018. Doshi, *et al* 2019.Kayad,*et al*.,2020, Ullo, and; Sinha,2020, Syrový, *et al*.,2020. Syrový.,2020,. Sishodia *et al*.,2020.
• Industrial monitoring. (Balogun, 2020).Syrovy *et al*., 2020n and Yekeen 2020
• Data monitoring (Lakhankar *et al*., 2009.Inglada *et al*., 2015.Koo *et al*., 2016; Shaf.*et al*., 2019; Di Napoli *et al*., 2020;; Corradini, *et al*., 2020).

• Security and surveillance applications (Brown; 2018; Samaras *et al*., 20 19 Arias, *et al*., 2020. Elahi, *et al*.,2020

The applications employing smart sensors and dealing with the environment monitoring are described based on the evaluation of various factors, as discussed ahead

Its Uses In The Agricultural Field

In agriculture, some of the variables of interest include the characteristics of crops (e.g., morphological, biochemical, and physiological), soil properties (e.g., soil moisture, organic matter, pH, drainage), and topography (e.g., elevation, slope), and how they vary in space and time(Nock *et al*.,2016). Use of remote sensing is indispensable in the monitoring of agricultural field, crop & soil health, water management, and its quality, and atmospheric conditions with emphasis to yield. During the last two decades, remote sensing techniques are applied to explore agricultural applications such as crop.

discrimination, crop acreage estimation, crop condition assessment, soil moisture estimation, yield estimation, precision agriculture, soil survey, agriculture water management, agro-meteorological, and agro advisories. The application of remote sensing in agriculture, i.e. in crops and soils is extremely complex because of the highly dynamic and inherent complexity of biological materials and soils (Myers, 1983).In agriculture, some of the variables of interest include the characteristics of crops (e.g., morphological, biochemical, and physiological), soil properties (e.g., soil moisture, organic matter, pH, drainage), and topography (e.g., elevation, slope), and how they vary in space and time Nock *et al*. (2016). Since none of these traits can be measured directly through RS, they are often estimated by integrating spectral measurements with ground-truth data via empirical or mechanistic approaches or a combination of both Baker (2018). For example, nitrogen (N) stress in crops has been linked to RS observations through empirical approaches by comparing spectral signatures in a target field with a reference spectral signature in a well-fertilized plot representative of the target field (Bushong.,2016), or mechanistically by combining RS-based leaf area index and chlorophyll content with crop models Baret, F.; Houlès, V.; Guéri.,2007)Similarly, crop yield can be related to RS observations, but this involves the further consideration of other auxiliary variables such as weather (e.g., solar radiation, temperature, precipitation), vegetation conditions, and soil properties (Prasad, *et al.*, 2006). Remote Sensing and Vegetation Indices. Remote sensing of vegetation is mainly performed by obtaining the electromagnetic wave reflectance information from canopies using passive sensors. It is well known that the reflectance of light spectra from plants changes with plant type, water content within tissues, and other intrinsic factors (Chang and Liu, 2016). Yuan *et al*. (2017) used high spatial resolution (Worldview 2) and medium-spatial resolution (Landsat 8) satellite images to monitor the distribution of wheat disease and pest, achieving a monitoring accuracy of more than 71.0%.Remote sensing offers a non-destructive means of providing recurrent information from the local to the global scale in a systematic way, thereby enabling the characterization of spatiotemporal variability within a given area (Weiss *et al*., 2020). In this respect, satellite imagery has been used to monitor crops for a long time. Traditionally the Landsat constellation has been used both to determine land cover types and to keep track of agricultural production. At present, it is still used to determine the crop area adjustment policy in terms of the magnitude and direction of agricultural land-use change (Yang *et al*., 2019). Over the past decades, the Earth's surface has witnessed major changes in land use and land cover. These changes are likely to continue, driven by demographic pressure and by climate change. As part of the Earth's spheres, the pedosphere is responding and contributing to these environmental changes (Macías and Arbestain, 2010). Observed changes in the functioning of the pedosphere renewed the recognition that soil resources

provide key ecosystem services and play a fundamental role in assuring Grunwald, 2011; Mulder, 2013). In this context, monitoring tools are needed for maintaining a sustainable ecological status and improving soil conservation. The implementation of sustainable agricultural, hydrological, and environmental management requires an improved understanding of the soil, at increasingly higher resolutions. Information on spatial and temporal variations in soil properties are required for use in conservations efforts, climate and ecosystem modelling, as well as engineering, agricultural, forestry applications, erosion and runoff simulations (King *et al*., 2005); Soils are a vital natural resource that provides multiple ecosystem services. Conventional soil sampling and laboratory analyses cannot efficiently provide the needed information, because these analyses are generally time-consuming, costly, and limited in retrieving the temporal and spatial variability. In this context, remote sensing (RS) is now in a strong position to provide meaningful spatial data for studying soil properties on various spatial scales using different parts of the electromagnetic spectrum. Digital soil mapping The advent of new technologies along with vast amounts of data and the need for effective soil characterization led to digital soil mapping (DSM). Digital soil mapping is defined as: the creation and population of spatial soil information by the use of field and laboratory Remote sensing communities have long used spectrum or spectral vegetation indices to estimate plant biochemical and morphological properties, which also presents huge potential in assessing the photosynthetic capacity of plants quickly and non-destructively at different scales (ground, airborne, and satellite) (Gamon *et al.* 2019). Razz *et al*. (2020) effectively utilized the high-resolution of Plant Scope imagery (3 m) to detect soybean sudden death syndrome and rice diseases, respectively Data for this study were collected from an ongoing soybean field experiment located at Iowa State University's Marsden Farm in Boone County, Iowa Food security and agriculture is probably not the first thing that comes to mind when you think about satellites being launched into space and orbiting planet Earth. You might even be surprised to learn that NASA, best known for its space exploration, actually has over a dozen satellite missions dedicated to monitoring food production, land changes, and vegetation. Truth be told, the data provided by these Earth-observing satellites provide critical information for analyzing the state of food production and food security around the world. From space, we can see things like the NDVI (namely, green light reflectance) of plants which is indicative of crop health, crop damage resulting from natural disasters (such as the 2020 Iowa derecho and even the amount of moisture stored deep within farmland soil. However, compiling these large satellite datasets into deep time series to monitor internal and within-season changes in vegetation requires a lot of skill, computational power, and time.
Agriculture:
crop classification
estimation of crop yield
determination of soil conditions
resource management υ monitoring of the EU Common Agricultural Policy quotas (SPOT)
wildlife habitat assessment (Mladen Todorović, 2016)

lts uses in the field of soil and land classification

Soil is one of the most important resources and vital components of the earth'ss critical zone. There are extraordinary pressures on soil due to urbanization, industrialization, or degradation; soils are reducing their quality that is unbalancing the agricultural practices and food production. Consequently, soil quality and its management with planning are essential to preserving the soil its quality for future generations (Rossel, *et al*., 2016).GIS and Remote Sensing technologies provide more efficient, economic, and rapid tools and techniques for soil salinity assessment and soil salinity mapping. As well, in Uzbekistan, the research institutes and projects, are responsible for soil salinity assessment using GIS tools in high level. Currently, two main organizations are doing soil salinity assessments in the study area. They are Soil composition and Repository, Quality analysis center" The State Unitary Company and Hydrologic ameliorative expedition of central Fergana valley. Both organizations are using GIS tools only for mapping and visualization of data. The methodology for soil salinity assessment has been developed by the State Scientific Research Institute of Soil Science and Agrochemistry. SSRISSAC is the main research institute for soil surveys in the Republic of Uzbekistan Isaev and Rakhmonov (2020) and (Nguyen, *et al*., 2020). Wang et al. (2020) analyzed the patterns of land degradation and restoration during 1990–2015 by using fine-resolution land cover data in Mongolia.Field exposure of salts can be well identified by using the multispectral satellite data due to the high reflectance of salts that depend on characteristics such as color, mineralogy, surface smoothness, and type of salts (Bannari *et al*., 2018; Al-Hemoud *et al*., 2020). Remote sensing data is the most common source for detection, quantification, and mapping of LULC patterns due to its repetitive data acquisition, suitability for processing, and accurate geo-referencing (Chen *et al*., 2005).As for the use of remote sensing in the study of land use, it is one of the tools Active in the process of studying the land cover and observing the changes in it during different periods, it is also an effective tool for decision makers- in countries. Satellite visuals have also become a means important used in land cover analysis at the local, regional, and international levels, thus Land use and land cover classifications can be made predicting the degradation process based on GIS technology allows not only to estimate soil loss, but also to predict the area of degradation distribution (Alikhanov *et al*., 2020) .GIS technologies play an important role in the identification and mapping of lands at high risk of degradation, as well as in the development of the necessary measures to prevent degradation (Vrieling, and Sterk, 2002) Studies conducted by the above scientists have proven that remote sensing of the Earth and GIS technology can be successfully used in accurate and high-quality mapping of land degradation processes M. (Abrams, 2003; Bayramin, 2006; Parlak 2007; Zhu, 2001). observational methods coupled with spatial and non-spatial soil inference systems (McBratney *et al*., 2003)(Lagacherie *et al*., 2007) (Carre *et al*., 2007). DSM relies on quantitative methods to integrate diverse soil observations from field, laboratory and remote sensing and proximal sensing data (Grunwald, 2010) for inferring spatial patterns of soils across various spatial and temporal scales. Using a broad range of data sources and methods, DSM aims to provide up-to-date and accurate soil maps to meet the current and future needs for soil information (Mulder, 2013)Such data help to interpret not only crop vitality (chlorophyll content) (Delegido *et al*., 2011; Clevers, 2013) and productivity (biomass) (Verrelst, 2012) but also soil properties, including physical (texture) (Ballabio,2016) chemical (pH value or nutrient contents) (Ballabio, 2019) and biological (soil organic carbon) (Yigini, 2016) properties.

Land use studies:

land use mapping

urban and suburban land use (urban growth)

categorization of land capability

land degradation and erosion

change of land use - map updating (Mladen Todorović, 2016)

Global environmental changes are currently altering key ecosystem services that soils provide. Therefore, it is necessary to have up to date soil information on local, regional and global scales to monitor the state of soils and ensure that these ecosystem services continue to be provided. In this context, digital soil mapping (DSM) aims to provide and advanced methods for data collection and analyses tailored towards detailed large-scale mapping and monitoring of soil properties. In particular, remote and proximal sensing methodologies hold considerable potential to facilitate soil mapping at larger temporal and spatial scales as feasible with conventional soil mapping methods (Mulder, 2013). Existing remote and proximal sensing methods support three main components in DSM: (1) Remote sensing data support the segmentation of the landscape into homogeneous soil-landscape units whose soil composition can be determined by sampling. (2) Remote and proximal sensing methods allow for inference of soil properties using physically-based and empirical methods. (3) Remote sensing data supports spatial interpolation of sparsely sampled soil property data as a primary or secondary data source (Mulder, 2013) Overall, remote and proximal sensed data are an important and essential source for DSM as they provide valuable data for soil mapping in a time and efficien-cost manner Detecting land use through remote sensing methods has already developed (Town *et al*. 2018

The importance of remote sensing in the study of soil

• Soil is divided and graded.
• Making climate maps of the soil
• Studying the possibility of soil conservation and improvement.
• Monitoring the drying up of lands and lakes

Land use and land cover are classified using remote sensing.

Is used in the agriculture sector is highlighted with the help of typical applications such as crop disease Marcuet al.2019 Sishodia et al.,2020 diagnosis, soil fertility analysis (Doshi, *et al*., 2019) erosion analysis, pesticide and fertilizer control (Doshi, J *et al*., 2019. Sishodia *et al*., 2020) crop quality assessment, optical irrigation (Ayaz, *et al*., 2019 ; Madushanki *et al*., 2019; Sishodia *et al.*, 2020; Lakhankar, *et al* 2009 Lakhankarm *et al.*, 2020) seed quality (1) and smart Io T-based alarm systems for the control of the agriculture production at various stages. All the results of image analyses were validated through field and laboratory studies. The study of laboratory spectra of evaporite minerals namely gypsum, anhydrite, and halite present in the salt crusts and gypsiferous soil flats showed their unique spectral absorptions in between 1.4–1.5 µm and 1.9–2.0 µm whereas, the calcite and dolomite minerals of the carbonate formations exhibited deep absorptions near 2.345 and 2.495 µm respectively (Rajendran *et al*., 2021)

Vegetation Indices

Vegetation indexes are of important algorithms which are able to extract canopy conditions by means of remote sensing (Salas and Henebry, 2014). Or are mathematical expressions that combine measured reflectance in many spectral bands to produce value that helps assess crop growth, vigor, and several other vegetation properties such biomass and chlorophyll content (McKinnon, 2017)

1-VIs named Ratio Vegetation Index (RVI), which is based on the principle that leaves absorb relatively redder than infrared light; RVI can be expressed mathematically as

$RVI = R/ NIR$……………. (1)

where NIR is thenear-infraredd band reflectance and R is red band reflectance. According to the spectral characteristics of vegetation, bushy plants have low reflectance on the red band and have shown a high correlation with LAI, Leaf Dry Biomass Matter (LDBM), and chlorophyll content of leaves (Quan and Miao, 2011). The RVI is widely used for green biomass estimations and monitoring, specifically, at high-density vegetation coverage, since this index is very sensitive to vegetation and has a good correlation with plant biomass. However, when the vegetation cover is sparse (less than 50% cover), RVI is sensitive to atmospheric effects, and their representation of biomass is weak. VIs is widely used for agricultural applications including estimations of leaf area, canopy analysis, plant nutrients (nitrogen status), biomass estimations, crop yield, etc. Researchers have estimated agood relationship of VIs with measured plant nutrients (Walsh *et al*., 2018). Vegetation Indices (VIs) obtained from remote based-sensing canopies are quite simple and effective algorithms for quantitative and qualitative evaluations of vegetation cover, vigor, and growth dynamics, among other applications. These indices have been widely implemented within RS applications using different airborne and satellite platforms with recent advances using Unmanned Aerial Vehicles (UAV). Up to date, there is no unified mathematical expression that defines all VIs due to the complexity of different light spectra combinations, instrumentation, platforms, and resolutions used. Therefore, customized algorithms have been developed and tested against a variety of applications according to specific mathematical expressions that combine visible light radiation, mainly green spectra region, from vegetation, and nonvisible spectra to obtain proxy quantifications of the vegetation surface. In real-world applications, optimization VIs are usually tailored to the specific application requirements coupled with appropriate validation tools and methodologies in the ground. (Jinru Xue, Baofeng Su.,2017) .Vegetative Indices (VI) enable the acquisition of ecological information from satellite and drone data through the analysis of multi- or hyperspectral imagery bands. The reflectance of light changes with chlorophyll content, plant type, sugar content, water content within tissues and other factors. Due to this fact, the spectral reflectance responses captured by satellite imagery can reflect the interaction and coupling of carbon, nitrogen, and water cycles (Chang *et al*., 2016; Xue *et al*., 2017).

2- Difference Vegetation Index (DVI) was proposed
later (Richardson and Weigand.1977) and can be expressed as
DVI = NIR – R………….. (2)
The DVI is very sensitive to changes in soil background; it
can be applied to monitoring the vegetation ecological environment. Thus, DVI is also called Environmental Vegetation
Index (EVI).

Index	Explanation	Equation
DVI	The difference vegetation index is used to distinguish between soil and vegetation; however, it does not take into account the effect of atmosphere reflectance or shadows (Naji, 2018). The DVI index ranges from 1 to 0 for marine and non-vegetated areas and from 0 to 0.07 for unhealthy vegetation and from 0.07 to higher value (often 1) for areas with healthy plants (Vani, Mandla, 2017).	NIR-R

3- The Perpendicular Vegetation Index (PVI)
Richardson and Weigand.1977)is a simulation of the Green Vegetation Index (GVI) in R, NIR 2D data. In the NIR − R coordinate system, the spectral response from soil is presented as a slash (soil brighten line). The latter effect can be explained as the soil presents a high spectral response in the NIR and R bands. The distance between the point of reflectivity (R, NIR) and the soil line has been defined as the Perpendicular VI, which can be expressed as follows:

$$\mathrm{PVI} = \sqrt{\left(\rho_{\mathrm{soil}} - \rho_{\mathrm{veg}}\right)_R^2 - \left(\rho_{\mathrm{soil}} - \rho_{\mathrm{veg}}\right)_{\mathrm{NIR}}^2}, \qquad (3)$$

where ρsoil is the soil reflectance; ρveg is the vegetation reflectivity; PVI characterizes the vegetation biomass in ρred the soil background; the greater the distance, the greater the biomass.

PVI can also be quantitatively expressed as

$$\mathrm{PVI} = \left(\mathrm{DN}_{\mathrm{NIR}} - b\right)\cos\theta - \mathrm{DN}_R * \sin\theta, \qquad (4)$$

where DNNIR and DNR are the radiation reflected luminance values from the NIR and R, respectively; b is the intercept of the soil baseline and the vertical axis of NIR reflectivity; and θ is the angle between the horizontal axis of R reflectivity and soil baseline. PVI filters out in this way the effects of soil background in an efficient manner; PVI also has less sensitivity to atmospheric effects and it is mainly used for the inversion of surface vegetation parameter (grass yield, chlorophyll content), the calculation of LAI, and vegetation identification and classification (Wenlong, 2009). However, PVI is sensitive to soil brightness and reflectivity, especially in the case of low vegetation coverage and needs to be adjusted for this effect (Major, 1990)

4- Normalized Difference Vegetation Index (NDVI)

The NDVI is one of the most common indices widely applied for monitoring dynamics at regional and global scales (Vrieling et al., 2013; Zhu et al., 2013). This index was introduced by Tucker (1979) and varies between − 1 and 1 in which the values less than zero during the growing season indicate no vegetation cover, such as desert, bare earth, cloud, snow, icepack, water body, and glacier; while values more than zero in the gowning season describe available vegetation cover. The NDVI was calculated using the following formula (Choubin *et al*., 2017b; Sajedi-Hosseini *et al*., 2018). NDVI was calculated based on the reflectance values in red (visible) and infrared-near ranges, where high values of NDVI indicate good soil quality and vice versa. NDVI is formulated as follows: NDVI=NIR−Red/NIR+Red
where NIR represents near-infrared reflectance and R represents visible red reflectance. Four dates of NDVI were determined to track the change of vegetative density, which included the initial growth stage, then vegetative growth, flowering stage, and maturity and harvest stage SPSS were used to analyze the statistical relationship between soil salinity and NDVI. The preprocessing of OLI images was conducted using the FLASH model according to (Felde *et al*. 2003). In addition, NDVI can also be an effective indicator of the vegetation moisture condition Ji,(2003). LST, in turn, mirrors soil moisture conditions, evapotranspiration, and vegetation water stress. Normalized Difference Vegetation Index (NDVI) is the most widely used as VI; it was proposed by Rouse Jr. et al. 1974 which can be expressed as

$$\mathrm{NDVI} = \frac{\left(\rho_{\mathrm{NIR}} - \rho_R\right)}{\rho_{\mathrm{NIR}}} + \rho_R. \qquad (5)$$

Since the index is calculated through a normalization procedure, the range of NDVI values is between 0 and 1, having a sensitive response to green vegetation even for low vegetation-covered areas. This index is often used in research related to regional and global vegetation assessments and was shown to be related not only to canopy structure and LAI but also to canopy photosynthesis Gamon *et al*., 1995However, NDVI is sensitive to the effects of soil brightness, soil color, atmosphere, cloud and cloud shadow, and leaf canopy shadow and requires remote sensing calibration. NDVI is used as a predictor of plant attributes, plant physiological status, yield predictions and crop distribution, and can also be used to detect and monitor aquatic vegetation (Pettorelli, 2013).

Index	Explanation	Equation
NDVI	The normalized difference index vegetation indicates how many green leaves exist. NDVI is calculated using the measured light intensity only at two wavelengths, e.g., near-infrared (NIR, 780-890 nm) and red (R, 650−680 nm) using (NIR+R)/(NIR-R) equation (Robinson et al. 2017). The NDVI index ranges for aquatic or non-vegetated areas (mountains or boulders) from –1 to 0, for areas with unhealthy or contaminated vegetation from 0 to 0.33, and for areas with healthy plants from 0.33 up to 1 (GIS Geography 2019). However, it should benoted that the magnitude of changes in this index for both healthy and unhealthy vegetation areas can be reduced by 0.1% in the cold season due to lower image contrast and in the hot season it should be increased by 0.1 due to higher image contrast.	(NIR-R)/ (NIR+R)

The main drawback of NDVI is that it is sensitive to the effects of soil (brightness and color), atmosphere (cloud cover and cloud shadow) and leaf canopy shadow (Xue et al., 2017).

5-Atmospherically Resistant Veg etation Index (ARVI).

proposed the Atmospherically Resistant Vegetation Index (ARVI). This index is based on the knowledge that the atmosphere affects significantly compared to the NIR. Thus, Kaufman and Tanré modified the radiation value of by the difference between the blue (B) and(R) . Therefore, ARVI can effectively reduce the dependence of this VI on atmospheric effects, which can be expressed as

ARVI = (NIR $- RB$)/ (NIR + RB)

, $\rho* rb = \rho* \tau - \gamma (\rho* b - \rho*)$, (6)

Where is the difference between and, is the reflectivity related to the molecular scattering and gaseous absorption for ozone corrections, and represents the air conditioning parameters? The ARVI is commonly used to eliminate the effects of atmospheric aerosols. The aerosols and ozone effects in the atmosphere still need to be eliminated by the 5S atmospheric transport model.(Tanre *et al*.,1990).

6-Soil-Adjusted Vegetation Index (SAVI),

Simões et al. (2005) studied the patterns of SAVI and other vegetation indices in sugarcane.

Index	Explanation	Equation
SAVI	The soil-adjusted vegetation index is one of the most common indices that is only slightly different from the NDVI index. The difference lies in a factor that can be used to moderate the effect of background soil. The NDVI index is affected by soil reflectance in some areas.It overshadows the recorded reflectance for vegetation. SAVI index solves this problem in the NDVI index. This index uses a factor called L to moderate the effect of background soil. The value of this parameter is a function of the amount of vegetation available in the area and prior knowledge the user has of the vegetation density status in the area and is calculated using (1+L){(NIR-R)(NIR+R+L) equation (Garcia, Perez 2016). The amplitude of changes in the SAVI index for aquatic and non-vegetated areas is the same as for the NDVI index from 1 to 0, for areas with unhealthy vegetation from 0 to 0.15 and for areas with healthy vegetation from 0.15 to 1; by the way, L factor is set at 0.5 (Vani, Mandla 2017). This parameter reduces the field-effect index and reflects a lower plant cover percentage.	(R+L)/(NIR-)/ NIR+R+L)

Masoud and Koike (2006) used SAVI indicator to prepare a vegetation cover map of the Siwa Region of Egypt, paying attention to the desertification of area, this was done by reducing the afterward influence of soil and assuming a value of the soil coefficient of 0.5. SAVI contains a constant “L”, which has the function of minimizing the soil effect on the vegetation signal, especially in less dense areas (Santos *et al*., 2014). The L factor varies according to the vegetation density and the reflectance characteristic of the soil. The value of L = 1 is suggested for use in low density vegetation areas, L = 0.5 for intermediate vegetation and L = 0.25 for large density vegetation areas. After considerations made by Huete (1988), the L constant was estimated and included in the experimental measurements using the reflectance values in the red and near infrared bands (PONZONI *et al*., 2012) The Soil-Adjusted Vegetation Index (SAVI) is a vegetation index that attempts to minimize soil brightness influences using a soil-brightness correction factor. This is often used in arid regions where vegetative cover is low.

SAVI = ((NIR - Red) / (NIR + Red + L)) x (1 + L)

NIR = pixel values from the near-infrared band

Red = pixel values from the near red band

L = amount of green vegetation cover

NIR and Red refer to the brands associated with those wavelengths. The L value varies depending on the amount of green vegetative cover. Generally, in areas with no green vegetation cover, L=1; in areas of moderate green vegetative cover, L=0.5; and in areas with very high vegetation cover, L=0 (which is equivalent to the NDVI method). This index outputs values between -1.0 and 1.0.

7- Soil-Adjusted Vegetation Index (OSAVI)

Index	Explanation	Equation
Optimized soil adjusted vegetation index (OSAVI)	Disease [153]; crop yield [159]; biomass, N-uptake [28,142]; soil moisture [148]; water stress [158]	1.16(*RNIR*-*RRed*) *RNIR*+*RRed*+0.16

OSAVI ‹ OSAVI - Optimized Soil Adjusted Vegetation Index
OSAVI = (1 + L) * (NIR - RED) / (NIR + RED + L)
where L = 0.16
OSAVI has the same formula as SAVI but has a fixed L factor value
of 0.16. Inputs should have reflectance values between 0 and 1.
8-the amount of vegetation present to obtain the optimal adjustment for the soil effect. Thus, a modified SAVI (MSAVI)
MSAVI2 - Modified Soil Adjusted Vegetation Index
MSAVI2 = [2*NIR + 1 - sqrt((2*NIR+1)2 - 8*(NIR - RED))] / 2
This is a modified version of SAVI with parameter values derived by iterative analysis of images over a range of L factor values and soil line slopes/intercepts in near-infrared versus red scatterplots. MSAVI2 is the simplified version of the MSAVI algorithm. It was created to deal with the soil brightness problem, which is one of NDVI's largest limitations. Whenever MSAVI is used, it is almost always the MSAVI2 version, which does not require a soil line (slope). It is mainly used in the analysis of plant growth, desertification research, grassland yield estimation, LAI assessment, analysis of soil organic matter, drought monitoring, and the analysis of soil erosion (Xue *et al*., 2017). In comparison to SAVI and TSAVI (below), the resulting equation does not require an estimate of soil cover percentage or a determination of the soil line slope and intercept values. Inputs should have reflectance values between 0 and 1. Reference: (Qi *et al*., 1994).

Index	Explanation	Equation
Modified soil adjusted vegetation index (MSAVI)	Biomass [153]; crop yield [159]; N-uptake [142]; chlorophyll content [112,160]	2*RNIR*+1- q(2*RNIR*+1)2- 8(*RNIR*-*Rred*) 2

6- The Bare soil Index (BI):

The Bare Soil index (BI) enhances the identification of bare soil areas and fallow lands. The Thermal Index (TI) is the calibrated values of the thermal band and increases as the vegetation quantity increases. It is lower inside the canopy of a forest due to blocking and absorption of the sun's rays and because of the cooling effect of evaporation from leaves. The TI is therefore used to further differentiate bare soil from grassland and forest. The below figure demonstrates the interaction of the four different indices in the FCD model (Azizia et al., 2008; Rikimaru et al., 2002; Baynes, 2004).

$$BI = \frac{(B4 + B2) - B3}{(B4 + B2) + B3}$$

The Transformed Soil Adjusted Vegetation Index (TSAVI) is a vegetation index that attempts to minimize soil brightness influences by assuming the soil line has an arbitrary slope and intercept.
TSAVI=(s(NIR-s*Red-a))/(a*NIR+Red-

a*s+X*(1+s2))
NIR = pixel values from the near-infrared band
R = pixel values from the red band
s = the soil line slope
a = the soil line intercept
X = an adjustment factor that is set to minimize soil noise
where XSAVI is the soil adjustment factor of SAVI. Reference: Baret, F. and G. Guyot, 1991, "Potentials and limits of vegetation indices for LAI and APAR assessment," Remote Sensing of Environment, Vol. 35, 161–173." (ESRI, 2018).
TSAVI is defined as:
TSAVI = a · (N − a · R − b) a · N + R − a · b + XTSAVI · (1 + a 2) (3) where a and b are the slope and interception of the soil line, respectively. Here these two parameters were set as the constant value of 1.2 and 0.04, respectively, which are considered global soil line parameters Baret, *et al*.1991XTSAVI is the soil adjustment factor of TSAVI, recommended to be equal to 0.08 in the original paper (Baret, *et al*.1991). The Enhanced Vegetation Index (EVI) is the most common alternative vegetation index which addresses some of the issues with NDVI (soil and atmosphere limitations).(Brecht,2018)

8- simple ratio SR

SRI is mainly relating with crop physiology (Wan *et al*., 2018).

Index	Explanation	Equation
SR	The solar reflectivity is composed of a simple ratio between two bands, one with the highest and the other with the lowest reflectance concerning vegetation. This index is calculated using the (NIR/R) equation (Melillos, Hadjimitsis 2020). The range of SR index variations for aquatic and non-vegetated zones is from 1 to 1, for regions with unhealthy vegetation from 1 to 2.2 and for regions with healthy plants from 2.2 to higher values (Robinson et al. 2017)	(NIR/R)

plant health index PHI

Index	Explanation	Equation
PHI	The plant health instructor index is also used to determine the health condition of the plants in some regions and can be calculated using the equation 1.4 × LN(DVI) + 1.298. This index is mostly used to identify the health status and the regions of water without vegetation. The amplitude of changes in the PHI index for aquatic and vegetation-free regions is pixel-free. It is shown as NaN, for the unhealthy vegetation from -n to -18 and for the regions with healthy vegetation from –8 to –0 (Asadi et al. 2016).	1.4 × LN(DVI) + +1.298

The objective of the study of remote sensing: to enable the collection of
Information, analysis, classification, provision of services and provision of services This information, including
Prepare files for images, various satellite images, and images, and present
Economical box

2.REFERENCE:

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