

REMOTELY SENSED VEGETATION INDICES: THEORY AND APPLICATIONS FOR CROP MANAGEMENT

INDICI DI VEGETAZIONE TELERILEVATI: TEORIA ED APPLICAZIONI PER LA GESTIONE AGRONOMICA DELLE COLTURE

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Abstract

Remote sensing of soil and crop can be an attractive alternative to the traditional methods of field scouting because of the capability of covering large areas rapidly and repeatedly providing spatial and temporal information necessary for a sustainable soil and crop management. The potential of remote sensing in agriculture is very high because it is able to infer about soil and vegetation amount as a non-destructive mean. Numerous spectral vegetation indices (VIs) have been developed to characterize vegetation canopies. Plant canopy reflectance factors and derived multispectral VIs are receiving increased attention in agricultural research as robust surrogates for traditional agronomic parameters. Spectral reflectance and thermal emittance properties of soils and crops have been used extensively to predict ecological variables, such as percent vegetation cover, plant biomass, green leaf area index and other biophysical characteristics. VIs are strongly modulated by interactions of solar radiation with photosynthetically active plant tissues and thus also are indicative of dynamic biophysical properties related to productivity and surface energy balance.

Recent advances on the resolution and availability of remote sensing imagery, coupled with a decrease in its associated costs, have allowed the collection of timely information on soil and crop variability by examining spatial and temporal patterns of vegetation indices. Precision agriculture applications rely on some form of VIs to quantify spatial variability within a field. The objective of this paper is to describe the biophysical principles of vegetation indices and to present a review of remote sensing applications for crop management. The paper first describes the techniques and capabilities of remote sensing then presents a series of novel and practical applications of different types of vegetation indices in agricultural research. The future challenges and opportunities section highlights the benefits and limitations of vegetation indices and remote sensing application in agriculture as well as the integration with decision support system and management-based crop simulation models.

Keywords: remote sensing, vegetation indices, crop management, spatial variability

Riassunto

Il telerilevamento viene utilizzato in agricoltura come mezzo non distruttivo per la stima delle condizioni delle colture nello spazio e nel tempo. Dallo studio della riflettanza spettrale della vegetazione sono state definite delle relazioni quantitative tra la fenologia della coltura ed i dati telerilevati elaborate in indici di vegetazione (IV). Numerosi studi condotti in questi ultimi anni hanno evidenziato la possibilità di utilizzare il telerilevamento per la stima di parametri agronomici tradizionali come ad esempio l'indice di area fogliare (LAI), la percentuale di copertura vegetale, la biomassa ed altri parametri biofisici. Gli IV risultano particolarmente sensibili a tre fattori esterni: l'effetto del sole; il background del suolo e gli effetti atmosferici. Il recente progresso scientifico e tecnologico associato ad una riduzione dei costi, consente di ottenere informazioni tempestive sulle colture mediante un'analisi spazio-temporale degli indici di vegetazione. L'uso degli indici di vegetazione rivesta un'importanza notevole nel contesto di applicazioni di agricoltura di precisione per la determinazione della variabilità spaziale delle produzioni.

Il presente lavoro descrive i principi biofisici degli indici di vegetazione e riporta una sostanziale rassegna bibliografica sulle applicazioni del telerilevamento per gestione ottimale del suolo e delle colture. L'articolo, prima analizza le tecniche e le potenzialità del telerilevamento, poi prosegue con la descrizione di una serie di approcci innovativi di indici di vegetazione in agricoltura. La sezione delle prospettive future evidenzia i benefici ed i limiti delle applicazioni degli indici di vegetazione e descrive l'integrazione del telerilevamento con i modelli di simulazione ed i sistemi di supporto alle decisioni.

Parole chiave: telerilevamento, indici di vegetazione, gestione agronomica, variabilità spaziale

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Introduction

Agricultural practices determine the level of food production and, to a great extent, the state of the global environment. Agriculture production strategies have changed significantly over the last few years because of economic decisions to reduce inputs and maximize profits and by environmental guidelines to achieve a better and safer and more efficient use of agricultural chemicals.

Current technologies available to farmers allow them to select the most profitable management strategy spanning from timing of planting (anticipated or delayed planting based on El Niño or La Niña years to cultivar selections (GMOs), from adopting conservation practices for selling carbon credits to industry to a variable rate applications through precision agriculture.

Agricultural production systems are inherently variable due to spatial variation in soil properties, topography, and climate are spatially variable. To achieve the ultimate goal of sustainable cropping systems, variability must be considered both in space and time because the factors influencing crop yield have different spatial and temporal behavior. Advances in technologies such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and remote sensing have created the possibility to assess the spatial variability present in the field and manage it with appropriate site-specific practices. Remote imagery, an old technology that has recently become widely available through small commercial vendors and advances in satellite capabilities, also confirms large differences in canopy development patterns that lead to yield variability. Thus, producers and researchers alike are inundated with evidence of yield variability. However, evidence of producers developing innovative management strategies that capitalize on variability has been limited.

The objective of this paper is to describe the biophysical principles of vegetation indices and to present a review of remote sensing applications for crop management. The paper first describes the techniques and capabilities of remote sensing then presents a series of novel and practical applications of different types of vegetation indices in agricultural research. The discussion highlights the benefits and limitation of vegetation indices and remote sensing application in agriculture as well as the integration with decision support system and simulation models.

Remote Sensing Techniques and Capabilities

Remote sensing is the science and art of obtaining information about an object through the analysis of data acquired by a device that is not in contact with the object (Lillesand and Keifer, 1994). Remotely sensed data can be of many forms, including variations in force distribution, acoustic wave distribution or electromagnetic energy distributions and can be obtained from a variety of platforms, including satellite, airplanes, remotely pilot vehicles, handheld radiometers or even bucket trucks. They may be gathered by different devices, including sensors, film camera, digital cameras, video recorders.

Our eyes acquire data on variations in electromagnetic radiations. Instruments capable of measuring electromagnetic radiation are called *sensors*. Sensors can be differentiated in :

Passive sensors: without their own source of radiation. They are sensitive only to radiation from a natural origin.

Active sensors: which have a built in source of radiation. Examples are Radar (Radio detection and ranging) and Lidar (Light detection and ranging).

This can be analogue (photography) or digital (multi-spectral scanning, thermography, radar). The elements of a digital image are called resolution cells (during the data acquisition) or pixels (after the image creation).

The implementation of remote sensing data by the user requires some knowledge about the technical capabilities of the various sensor systems. The technical capabilities of the sensor systems can be listed in three resolutions:

- **Spatial resolution:** concerns the size of the resolution cell on the ground in the direction of the flight and across. The size of the pixel determines the smallest detectable terrain feature.
- **Spectral resolution:** concerns the number, location in the electromagnetic spectrum and bandwidth of the specific wavelength bands or spectral bands. This resolution differs from sensor to sensor and largely determines the potential use of the sensor system.
- **Temporal resolution:** concerns the time lapse between two successive images of the same area. This primarily determined by the platform used, and secondly by the atmospheric conditions.

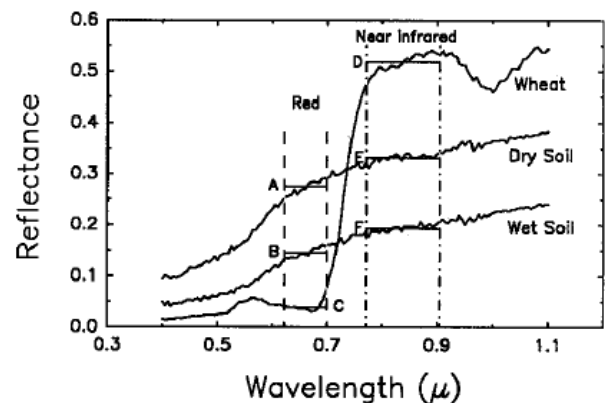


Fig. 1 - Spectral signature of soil (wet and dry) and wheat crop
Fig. 1 – Firma spettrale di un suolo (umido e asciutto) e di una coltura di frumento

Biophysical principles of remote sensing in agriculture

The potential of remote sensing in agriculture is very high because multispectral reflectance and temperatures of the crop canopies are related to two important physiological processes: photosynthesis and evapotranspiration. Much research has been carried out with the goal of inferring vegetation amount from remote sensing.

Chlorophyll pigment absorbs mainly in the Blue and Red part of the electromagnetic spectrum and reflects the green (Chappelle *et al.*, 1992). Near-infrared (NIR) radiation is reflected from the structure of the spongy

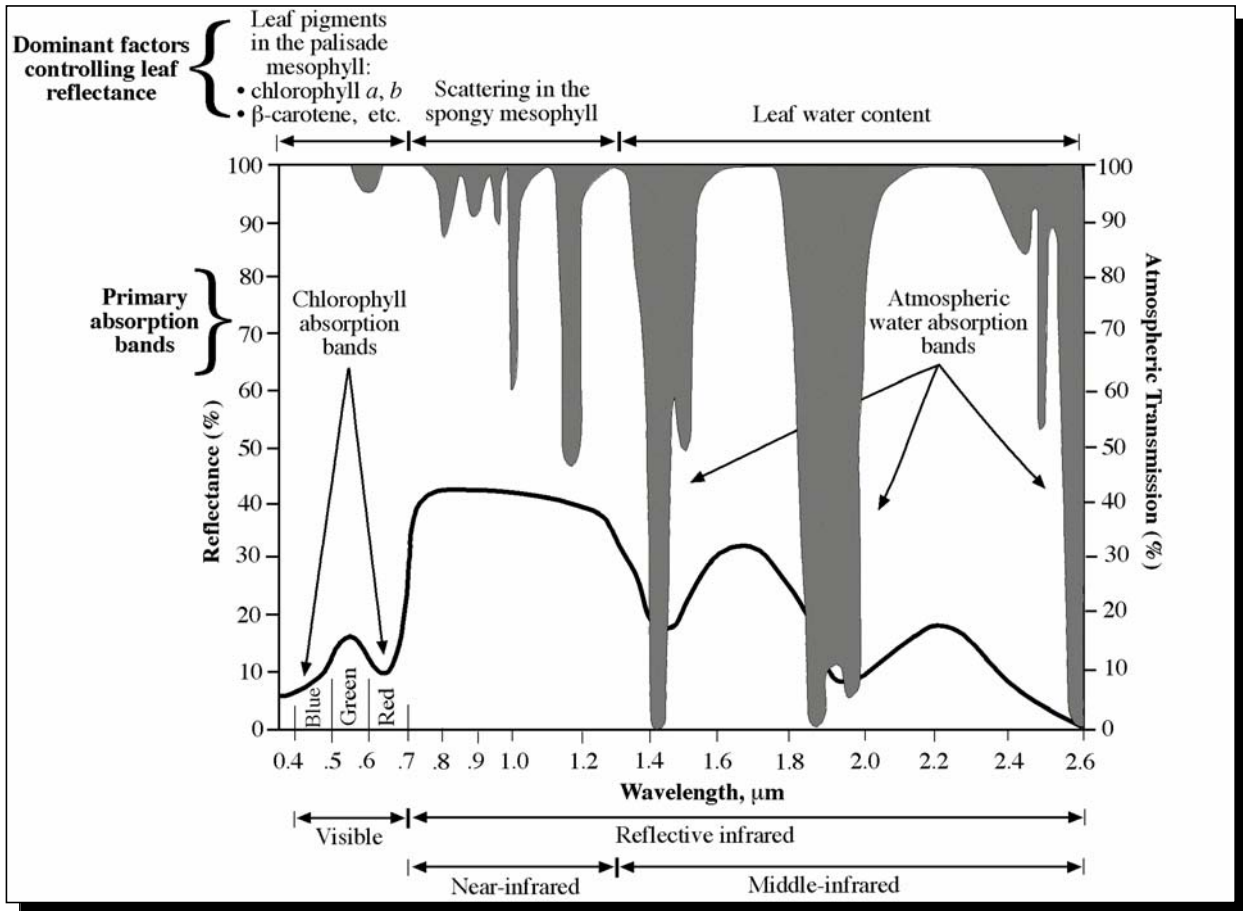


Fig. 3 - Primary absorption bands and factors responsible for changes in the spectral reflectance curve.
 Fig. 3 – Bande primarie di assorbimento e fattori responsabili dei cambi della curva di riflettanza spettrale

mesophyll tissue and cavities within the leaf. Therefore the percentage of radiation reflected from the leaf will be higher in the NIR than in the Green (Gausman *et al.*, 1969, Gausman, *et al.*, 1971). This spectral behaviour is useful to assess plant vigour and to separate canopy from bare soil (Fig.1, Fig.2 pag 48). Furthermore the discrimination of vegetation classes is possible using NIR reflectance due to the different NIR reflectance among plant species (Fig.3). The spectral behaviour of the leaf changes during senescence and in plants subjected to stress (e.g disease, pest, N shortage) by reflecting more Red light and absorbing more NIR. Opposite behaviour is shown in healthy plants with high values of reflectance in the NIR region and low values in Red portion (Gausman *et al.*, 1977a; Gausman, 1981; Pinter *et al.*, 2003). Soil reflects low in the blue, and its reflectance properties increase monotonically in the visible and NIR regions of the spectrum (Price, 1990; Rondeaux *et al.* 1996). Spectral properties of the soil, however, depends by *soil constituents* such as soil organic matter, iron oxides and soil water, and *soil roughness* such as particle and aggregate size (Rondeaux *et al.* 1996). High soil water and high organic matter contents show lower reflectance while soils with low water content and smooth surface

tend to be brighter (Daughtry, 2001). In the presence of iron oxides soil reflectance is higher in the red portion of the spectrum. Crop residues on soil surface also causes variation in reflectance compared to bare soil and partial canopy cover (Daughtry *et al.*, 1996; Nagler *et al.*, 2000; Barnes *et al.*, 2003).

For a given type of soil variability, the soil reflectance (ρ) at one wavelength is often functionally related to the reflectance in another wavelength (Jasinski and Eagleson, 1989; Rondeaux *et al.* 1996). So the relationship between two wavelength (λ_1, λ_2) can be expressed as follow:

$$\rho(\lambda_2) = a \rho(\lambda_1) + b \quad (1)$$

The slope a and intercept b are dependent on the both wavelength and the type of variability. The relationship shown above yield a line called *soil line*, defined as an hypothetical line in spectral space that describes the variation in the spectrum of bare soil in the image. Other lines that are important in the developed VIs are *Vegetation isoline* and *index isoline*. *Vegetation isoline* are formed by a set of reflectance points representing the same optical and structural properties of the canopy, so that have constant leaf reflectance, leaf transmittance,

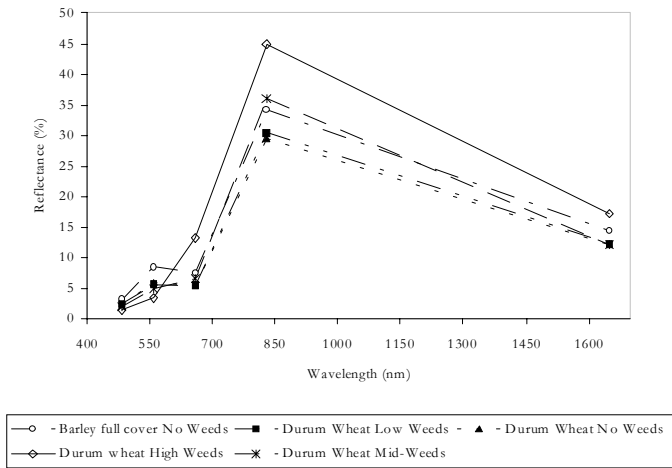


Fig. 5 – Spectral reflectance of barley, durum wheat and different level of pappy infestation in Puglia, Italy.

Fig.5 – Riflettanza spettrale di orzo, frumento duro e diversi livelli di infestazione di papavero

LAI and percentage of green cover, but different brightness conditions. An *index isoline*, shows any point on the line with the same index value (Yoshioka *et al.*, 2000). Huete and Jackson (1988) have studied the variation of VIs against variation in canopy background brightness. In fact if the noise effect is low the assessment of VIs will permit to improve estimation of vegetation parameters. Therefore Qi *et al.*, (1994) have used vegetation isoline to reduce noise effect. Yoshioka *et al.* (2000) noticed that the use of vegetation isolines is essential because VIs should yield constant values of all reflectance points on the same vegetation isoline, constant vegetation isoline with different backgrounds. Three important properties are useful in the use of vegetation isoline to design VIs:

- The intersection between soil line and vegetation isoline (as a function of LAI)
- The isoline slope
- The intercept (NIR-intercept)

Baret and Guyot (1991), Qi *et al.*(1994) and Huete (1990) pointed out that the slope of a vegetation isoline tends to increase exponentially with LAI; the intercept shows the inverse behaviour of the slope and the intersection between the two lines occur generally in the third quadrant and tend to reach the first quadrant as the LAI increase. Not all soils are alike. Different soils have different reflectance spectra. As discussed above, all of the vegetation indices assume that there is a soil line, where there is a single slope in Red-NIR space. Normally the assumption is that some VIs are obtained by the convergence of the two lines at the origin or that isoline and soil line are parallel. Soils show different Red-NIR slopes in a single image, thus the assumption proposed above is not exactly right and changes in soil conditions will give incorrect information in vegetation index. Soil noise is highly significant when vegetation cover is low.

The spectral signature of crop canopies in the field are more complex and often quite different from those of

single green leaves measured under controlled light conditions (Pinter *et al.*, 2003). Although the leaf reflectance signature may be the same during the season, the dynamic proportion of canopy/soil affects the final values of canopy spectral reflectance.

Estimation of Vegetation Properties

Use of remote sensing in agricultural management has been indirect for many years, beginning with mapping the soil resource on aerial photographs as early as 1929 (Bauer, 1975). Soils delineated according to landscape patterns shown on aerial photographs had properties that caused differences in productivity and agricultural inputs requirements. Aerial photographs filtered at critical wavelengths showed tone patterns related to stress in crop plants (Colwell 1974; Bauer, 1975). When the satellite technology became available, analysis of remotely sensed data was, and still is, the objective of many multidisciplinary research programs around the world. Examples of an airborne false color composite imagery is shown in Fig. 4 (pag.48) .

Vegetation monitoring is usually accomplished by simple regression approach, modeling approach using remote sensing data and by computing vegetation indices (VIs).

Simple Regression Approach

A simple regression approach can be applied because the reflectance in the red spectral region decreases while that in the near-infrared (NIR) region increases when the vegetation density (LAI) increases. The relation between LAI and spectral reflectance can be obtained by simply regress ground measured LAI and the surface reflectance. This approach has the advantage to be simple but has several limitations. The first limitation is that to get this relationship ground truth LAI measurements are necessary at the same site and time as the spectral reflectances are collected. The second limitation is that the relationship between LAI and spectral reflectance is crop type dependent. This approach is also vulnerable to noise from soil background, atmospheric effect, and especially bidirectional properties of the vegetation. Soil influences on incomplete canopy spectra are due to the soil background signal on the optical properties of the overlying canopy (Jackson *et al.*, 1980; Huete, 1988). Differences in Red and NIR flux transfers through a canopy result in a complex soil-vegetation interaction, which makes it difficult to subtract for soil background influences (Kimes *et al.*, 1985; Sellers, 1985; Choudhury, 1987). The influences are dependent on the reflectance properties of the soil. Soil background effect is considered significant at intermediate canopy covers (Huete *et al.*, 1985). A vegetated canopy will scatter and transmit NIR flux toward the soil as well as in between individual plants. The soil reflects part of the scattered and transmitted flux back to the sensor. The upper leaves absorb the red light, and the irradiance at the soil surface is only the one received directly from the sun and sky through canopy gaps.

Modeling Approach

This approach includes radiative transfer and empirical models. The empirical models have the advantage of being simple but when inverted they infer little information on the vegetation. The radiative transfer model approach characterizes light interaction with vegetation canopies and predicts the bidirectional reflectance distribution function (BRDF) as function of the observation geometry (Verhoef, 1984; Deering *et al.*, 1990; Pinty *et al.*, 1992; Strahler, 1994). Verhoef (1984) developed the SAIL (Scattering by Arbitrarily Inclined Leaves) model as function of solar position and sensor's viewing geometry. The SAIL model assumes that the leaves are randomly oriented and uniformly distributed in a single layer. The model requires reflectance of the soil underneath, LAI, leaf reflectance and leaf transmittance as inputs. Inverting the model with remote sensing data, LAI can be estimated. There are several other models more complicated due to parameters that are difficult or impossible to measure in the field.

The first two approaches to estimate vegetation with remote sensing have the advantage to be simple but the technology transfer behind these approaches is limited due to the ground truth measurements necessary, and for the sensitivity to bidirectional effect. The advantage of the modeling approach is that most radiative transfer models are based on the bidirectional properties of the natural land surface, therefore, by inverting them surface physical properties can be more objectively inferred (Qi *et al.*, 1995). The other advantage of the models is that the optical properties of leaves are characterized by parameters (leaf reflectance, transmittance, absorptance, LAI etc.) required by the model thus BRDF models can predict the bidirectional reflectance in different viewing directions and illumination conditions. This modeling approach has great potential for application with multidirectional measurements. One major limitation, though, is the limited availability of multidirectional measurements. They cannot be obtained from a single sensor and this consequently limits the direct application of the model for vegetation assessment. Qi *et al.*, 1995 applied a model-to-model approach to overcome this limitation. The approach consisted in using a series of models inverted to obtain the parameters required for the simulation of bidirectional reflectances. Remote sensing data were collected using a Modular Multi-band Radiometer (MMR). They found satisfactory results, but the accuracy of predicting LAI with this approach is dependent on the accuracy of the models and on the atmospheric corrections.

Vegetation indices

Several vegetation indices have been developed by linear combination or ratios of red, green and near-infrared spectral bands. Vegetation indices are more sensitive than individual bands to vegetation parameters (Baret and Guyot, 1991; Qi *et al.*, 1993). Plant canopy reflectance factors and derived multispectral VIs are receiving increased attention in agricultural research as robust surrogates for traditional agronomic parameters (e.g. leaf area index (LAI), fraction of green cover, fraction of absorbed photosynthetically active radiation (fAPAR) etc. Often viewed simply as measures of plant biomass or

green leaf area index, VIs are strongly modulated by interactions of solar radiation with photosynthetically active plant tissues and thus also are indicative of dynamic biophysical properties related to productivity and surface energy balance. Vegetation indices (VIs) have been designed to find a functional relationship between crop characteristics and remote spatial observation (Wiegand *et al.*, 1990). VIs tend to reach a saturation level asymptotically for values of LAI between 3 to 6, based on the type of index used and type of plant (Carlson, *et al.*, 1997; Aparicio *et al.*, 2000).

Another application is the use of VIs as a mapping device. In this case VIs are used in image classification, to separate vegetated from non-vegetated areas, to distinguish between different types and densities of vegetation, to monitor seasonal variations in vegetative vigor, abundance and distribution (Campbell, 1996; Barnes *et al.*, 2003).

VIs are influenced by external and internal factors (Yoshioka *et al.* 2000; Huete, 1989; Huete and Jackson, 1988; Baret and Guyot, 1998). External factors such as sensor calibration, sun and view angle and atmospheric condition, internal factors, instead, are variation in canopy and leaf optical properties and canopy background.

To understand how VIs are designed, it is essential to know some concepts related to influence of soil and the use of the soil line and vegetation isocline. At this point it is useful to introduce the different kind of VIs that have developed over the years. Some of the indices have developed considering that all vegetation isoclines converge at a single point. These indices are called "ratio-based" and measure the slope of the line between the point of convergence and the soil line. The indices are: Normalized Difference Vegetative Index (NDVI), Soil Adjusted Vegetative Index (SAVI) and Ratio Vegetative Index (RVI). When the vegetation isocline is considered parallel to soil line, and the distance is measured perpendicular to the soil line, the indices are called "perpendicular" vegetation indices. These indices are: Perpendicular Vegetative Index (PVI), Weighted Difference Vegetative Index (WDVI), Three Dimensional Greenness Index (GVI3) and Difference Vegetative Index (DVI).

Daughtry *et al.* (2000) classified VIs into two categories: *Intrinsic indices*, that include ratios of two or more bands in the visible and NIR wavelengths (NIR/Red; NIR/Green; NDVI; Green Normalized Difference Vegetative Index). These indices are sensitive to background reflectance properties and are often difficult to interpret at low LAI (Daughtry *et al.*, 2000; Rondeaux *et al.*, 1996); *Soil-line vegetation indices*, use the information of soil line in NIR-Red reflectance to reduce the effect of the soil on canopy reflectance (SAVI; Optimized Soil Adjusted Vegetative Index (OSAVI); Transformed Soil Adjusted Vegetative Index (TSAVI)).

Baret and Guyot (1991) have classified VIs into two categories: Indices characterized by "slope": RVI; NDVI; SAVI; TSAVI. Indices characterized by "distance": PVI; WDVI; GVI.

Theory of Vegetation Indices

RVI is the Ratio Vegetation Index (Jordan, 1969; Pearson and Miller, 1972). A common practice in remote sensing is the use of band ratios to eliminate various albedo effects. In this case the vegetation isoline converge at origin. Soil line has slope of 1 and passes through origin, it range from 0 to infinity. And it is calculated as follow:

$$RVI = \rho_{NIR} / \rho_{red} \quad (2)$$

NDVI is the Normalized Difference Vegetation Index (Kriegler, 1969; Rouse *et al.*, 1973) and it is the common vegetation index referring to. This index vary between -1 and 1. In this case vegetation isoline are considered to be convergent at origin and soil line slope is 1 and passed through origin. It is calculated as:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (3)$$

VI's assume that external noise (soil background, atmosphere, sun and view angle effect) is normalized, but this assumptions is not always true. The relative percentage of sunlit, shaded soil and plants components is highly dependent upon the view angle. Qi *et al.* (1995) studied the effect of multidirectional spectral measurements on the biophysical parameter estimation using a modeling approach. When the bidirectional effect is transformed from reflectance domain into vegetation index domain, it could be reduced (Jackson *et al.*, 1990; Huete *et al.*, 1992) or increased (Kimes *et al.*, 1985; Qi *et al.*, 1994b), depending on the vegetation types and solar zenith angles. Qi (1995) suggested that when bidirectional effect is a major concern ($NDVI/NDVI_0 > 1$) it is better to use NIR rather than NDVI, and that bidirectional effect on vegetation indices must be quantified before a quantitative VI-LAI relationship can be used.

The Green Normalized Vegetative Index (GNDVI) is a modification of the NDVI where the Red portion is substituted by the reflectance in the Green band (Gitelson *et al.*, 1996).

DVI is the Difference Vegetation Index, (Richardson and Everitt (1992), but appears as VI in Lillesand and Kiefer (1994). Vegetation isolines are parallel to soil line. Soil line has arbitrary slope, passes through origin, and index range is infinite.

$$DVI = \rho_{NIR} - \rho_{red} \quad (4)$$

PVI is the Perpendicular Vegetation Index (Crippen, 1990), and it is sensitive to atmospheric variation. In this case vegetation isolines are parallel to soil line. Soil line has arbitrary slope, passes through origin and the index range from -1 to 1.

$$PVI = \frac{1}{\sqrt{a^2 + 1}} (\rho_{NIR} - a\rho_{red} - b) \quad (5)$$

Where a and b are the coefficient derived from the soil line: $NIR_{soil} = a RED_{soil} + b$.

WDVI is the Weighted Different Vegetation Index (Clevers, 1988) and like PVI is sensitive to atmospheric variation (Qi *et al.*, 1994). Vegetation isolines are parallel to soil line. Soil line has arbitrary slope and passes through origin, vegetation index range is infinite.

$$WDVI = \rho_{NIR} - a\rho_{red} \quad (6)$$

Where a is the slope of the soil line.

Huete (1988) proposed a Soil Adjusted Vegetation Index (SAVI) to account for the optical soil properties on the plant canopy reflectance. SAVI involves a constant L to the NDVI equation. The index range is from -1 to +1.

$$SAVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red} + L} (1 + L) \quad (7)$$

The constant L is introduced in order to minimize soil-brightness influences and to produce vegetation isolines independent of the soil background (Baret and Guyot, 1991). This factor vary from 0 to infinity and the range depends on the canopy density. For $L=0$ SAVI is equal to NDVI, for L tends to infinity, SAVI is equal to PVI. However for intermediate density L was found equal to 0.5. Huete (1988) suggested that there maybe two or three optimal adjustment factor (L) depending on the vegetation density ($L=1$ for low vegetation; $L=0.5$ for intermediate vegetation densities; $L=0.25$ for higher density).

TSAVI is the Transformed Adjusted Vegetation Index (Baret *et al.*, 1989), and it is a measure of the angle between the soil line and the vegetation isoline. The soil line has arbitrary slope and intercept. The interception between soil line and vegetation isoline occur somewhere in the third quadrant. Baret and Guyot (1991) have proposed an improving of the initial equation as follow:

$$TSAVI = \frac{a(\rho_{NIR} - a\rho_{red} - b)}{[a\rho_{NIR} + \rho_{red} - a b + \chi(1 + a^2)]} \quad (8)$$

Where a and b are soil line parameters (slope and intercept of the soil line) and χ has been adjusted so as minimize background effect, and its value is 0.08. TSAVI values ranging from 0 for bare soil and is close to 0.70 for very dense canopies as reported from Baret and Guyot (1991).

At 40% green cover, the noise level of the NDVI is 4 times the WDVI and almost 10 times the SAVI, corresponding to a vegetation estimation error of +/- 23% for the NDVI, +/- 7% cover for the WDVI, and +/- 2.5% for the SAVI. Therefore the SAVI is a more representative vegetation indicator than the other Vis, but an optimization of the L factor will further increase his value (Qi *et al.*, 1994).

Qi *et al.* (1994) developed a Modified Soil Vegetation Index (MSAVI). This index provide a variable correction factor L. Geometrically vegetation isolines don't converge to a fixed point as SAVI, and soil line has not fixed slope and passes through origin. Correction factor is based on calculation of NDVI and WdVI as shown by equations 9 and 10:

$$MSAVI = \rho_{NIR} - \rho_{red} / (\rho_{NIR} + \rho_{red} + L) (1+L) \quad (9)$$

where L is calculated as follow:

$$L = 1 - 2 a * NDVI * WdVI \quad (10)$$

This term is computed to explain the variation of L among different types of soils, moreover L varies with canopy cover, and it's range varies from 0 for very sparse canopy to 1 for very dense canopy. To further minimize the soil effect Qi *et al.* (1994) use an L function with boundary condition of 0 and 1 ($L_n = 1 - MSAVI_{n-1}$) and an MSAVI equal to:

$$MSAVI_n = [(\rho_{NIR} - \rho_{red}) / \rho_{NIR} + \rho_{red} + 1 - MSAVI_{n-1}] * (2 - MSAVI_{n-1}) \quad (11)$$

The final solution for MSAVI is:

$$MSAVI = 2 \rho_{NIR} + 1 - [(2 \rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_{red})]^{0.5} / 2 \quad (12)$$

OSAVI is the Optimized Soil Adjusted Vegetation Index. This index has the same formulation of the SAVI family indices, but the value L or X as refered by Rondeaux *et al.* (1996) is the optimum value that minimizing the standard deviations over the full range of cover.

$$OSAVI = \rho_{NIR} - \rho_{red} / (\rho_{NIR} + \rho_{red} + 0.16) (1+0.16) \quad (13)$$

GESAVI is the Generalized Soil Adjusted Vegetation Index. This index is based on an angular distance between the soil line and the vegetation isolines. GESAVI is not normalized and vary from 0 to 1 (from bare soil to dense canopies). Vegetation isolines are neither parallel nor convergent at the origin. Vegetation isolines intercept the soil line at any point depending on the vegetation amount.

$$GESAVI = \rho_{NIR} - \rho_{red} b - a / \rho_{red} + Z \quad (14)$$

Z is the soil adjustment coefficient, and its based on the assumption that vegetation isolines intercept soil line at any point in the third quadrant. Z decrease when vegetation cover increase. However, practically, Z consider vegetation isolines convergent in a point. At least this hypotesis may be limited for dense canopies (Gilbert *et al.*, 2002). To normalize soil effects Z value is found at 0.35.

Indices that include the Mid-InfraRed Band (MIR) are:

Stress related Vegetation Index (STVI) (Gardener, 1983):

$$STVI = \rho_{MIR} * \rho_{red} / \rho_{NIR} \quad (15)$$

Cubed ratio index (CRVI) (Thenkabail *et al.*, 1994):

$$CRVI = (\rho_{NIR} / \rho_{MIR})^3 \quad (16)$$

The VIs that account for soil effect, do not consider atmospheric conditions, sensor viewing angle, solar illumination conditions. Kaufman and Tanré (1992) developed the Atmospherically Resistant Vegetation Index (ARVI) and the Soil and Atmospherically Resistant Vegetation Index (SARVI and SARVI2) where the reflectances are corrected for molecular scattering and ozone absorption. Liu and Huete (1995) incorporated a soil adjustment and atmospheric resistance concepts into a Modified Normalized Vegetation Index (MNDVI). SARVI2 as well as ARVI, SARVI are able to remove smoke effect and cirrus clouds from images (Huete *et al.*, 1996).

Remote sensing application for evapotranspiration estimation

All objects on the Earth's surface emit radiation in the thermal-infrared (TIR) part of the spectrum (~ 8 to 14 µm). This emitted energy has proven useful in assessing crop water stress because the temperature of most plant leaves are mediated by soil water availability and its effect on crop evaporation (Jackson, 1982; Hatfield *et al.*, 1983; Moran *et al.*, 1989b; Pinter *et al.*, 2003). In recent years, there has been much progress in the remote sensing of some of the parameters that can contribute to the estimation of evapotranspiration (ET). These include surface temperature, surface soil moisture, vegetative cover and incoming solar radiation. The surface temperature can be estimated from measurements at the thermal infrared wavelengths of the emitted radiant flux, that is the 10.5 and 12.5 µm. The microwave emission and reflection or backscatter from soil, primarily for wavelengths between 5 and 21 cm, are dependent on the dielectric properties of the soil, which are strong functions of the soil moisture content. Thus, measurements of these microwave properties can be used to obtain estimates of the surface soil moisture.

Crop stress, due to water deficiency, crop diseases, is often shown with a decrease in the transpiration rate of the crop. Several studies have been carried on estimating ET with remote sensing data (Reginato, 1985; Jackson *et al.*, 1987; Moran, *et al.*, 1992, 1994, 1995; Mas, 1992, 1993a, 1993b; Carlson *et al.*, 1995, Hunsaker *et al.*, 2003). A combination of remote sensing data and soil-plant-atmosphere models is commonly seen in the literature for ET estimation. The location of the "red edge" obtained with hyperspectral measurements shows potential for early detection of water stress (Shibayama *et al.*, 1993). "Stress-Degree-Day" (SDD; Idso *et al.*, 1977b), "Crop Water Stress Index" (CWSI; Idso *et al.*, 1981; Jackson *et al.*, 1981), "Non-water-stressed baseli-

ne (Idso *et al.*, 1982), "Thermal Kinetic Window" (TKW; Mahan and Upchurch, 1988), and "Water Deficit Index" (WDI, Moran *et al.*, 1994) are indices that measure plant stress induced by water stress. These indices have been used in research on more than 40 different crop species (Gardner *et al.*, 1992a; Gardner *et al.*, 1992b). Most studies have shown that the thermal infrared is more sensitive to water stress than is reflectance in visible or NIR. However, the reflective portion of the spectrum and VIs also respond to plant water stress status when the canopy changes architecture through the leaf rolling or wilting (Moran *et al.*, 1989a) or alters the senescence rate (Pinter *et al.*, 1981). Thermal plan water stress indices provide valuable information and adequate lead time to schedule irrigations.

Thermal indices can overestimate water stress when canopy cover is full and the sensors view a combination of cool plant and warm soil temperatures. The WDI a combination of VI and TIR (Moran *et al.*, 1994; Clarke, 1997 and Clarke *et al.*, 2001) seems to have overcome this problem since it accounts for the amount of plant cover through the VI part of the index

A cost benefit study by Moran (1994) shows that irrigation scheduling with thermal infrared sensors on aircraft is both practical and affordable if growers join together to purchase the images. Hatfield (1984c) found that spatial variation of surface temperature in wheat changed with the degree of water availability. One alternative tool for a spatially variable irrigation can be to mount infrared sensors on irrigation booms to provide the capability to vary irrigation amounts as the unit travels across the field.

VIs can be then used as surrogates for crop coefficients (K_{cb}). Crop coefficients are usually obtained from curves or tables and they lack flexibility to account for spatial and temporal crop water needs caused by uneven plant population, unusual weather patterns, non uniform water application, nutrient stress or pest pressures (Bausch and Neale, 1987; Choudhry *et al.*, 1994; Pinter *et al.*, 2003).

Soil Salinity

Remote sensing can also be used to map areas of soils that have been contaminated by salt. The principles behind this applications is that salt in the soil produces an unusually high surface reflectance. Salted areas can also be identified by detecting areas with reduces biomass or changes in spectral properties of plant growing in affected areas (Barnes *et al.*, 2003).

Leone *et al.* (2001) evaluated the impact of soil salinity induced through irrigation with saline water on plant characteristics and assessed the relationships between these characteristics and spectral indices. They showed that soil salinity had a clear impact on plant characteristics and significant relationships between chlorophyll content, biomass, NDVI and red edge peak.

Studies have also shown an increase in canopy temperature of plants exposed to excessive salts in irrigation water (Howell *et al.*, 1984a; Wang *et al.*, 2002b), suggesting the possibility of previsual detection of stress

which can manage with the appropriate measure of leaching or irrigation with good quality water.

Remote Sensing in Precision Agriculture

Direct Application

The past research efforts on remote sensing have provided a rich background of potential application to site-specific management of agricultural crops. In spite of the extensive scientific knowledge, there few examples of direct application of remote sensing techniques to precision agriculture in the literature. The reasons are mainly due to the difficulty and expense of acquisition of satellite images or aerial photography in timely fashion. With the progress in GPS and sensor technology direct application of remote sensed data is increasing. Now an image can be displayed on the computer screen with real-time position superimposed on it. This allows for navigation in the field to predetermined points of interest on the photograph. Blackmer *et al.* (1995) proposed a system for N application to corn based on photometric sensors mounted on the applicator machine. They showed that corn canopy reflectance changed with N rate within hybrids, and the yield was correlated with the reflected light. Aerial photographs were used to show areas across the field that did not have sufficient N. The machine reads canopy colors directly and applies the appropriate N rate based on the canopy color of the control (well fertilized) plots (Blackmer and Schepers, 1996; Schepers *et al.*, 1996).

Sensor technology has seen many innovations, but it is currently behind other technologies and their availability has been cited as the most critical factor preventing the wider implementation of precision agriculture.

Management zones can be extracted using VIs maps and with the use of a geographic information system (GIS) can be viewed over the a remotely sensed image. The computer monitor displayed the image along with the current position as the applicator machine moved on the field. When interfaced with variable rate sprayer equipment, real time canopy sensors could supply site-specific application requirements improving nutrient use efficiency and minimizing contamination of groundwater (Schepers and Francis, 1998).

Indirect Applications

The most common indirect use of remote sensing images is as a base map on which other information is layered in a GIS. Other indirect applications include use of remotely measured soil and plant parameters to improve soil sampling strategies, remote sensed vegetation parameters in crop simulation models, and use in understanding causes and location of crop stress such as weeds, insect, and diseases.

Satellite based images have limited use in precision agriculture due the cost related to the image acquisition and to the restricted spectral resolution, coarse spatial resolution and the inadequate temporal resolution of the images.

Moran *et al.* (1997) in their excellent review on opportunities and limitations for image-based remote sensing in

precision agriculture, classify the information required for site specific management in information on seasonally stable conditions, information on seasonally variable conditions, and information to find the causes for yield spatial variability and to develop a management strategy. The first class of information includes condition that do not vary during the season (soil properties) and only need to be determined at the beginning of the season. Seasonally variable conditions, instead, are those that are dynamic within the season (soil moisture, weeds or insect infestation, crop diseases) and thus need to be monitored throughout the entire season for proper management. The third category is comprehensive of the previous two to determine the causes of the variability. Remote sensing can be useful in all three types of information required for a successful precision agriculture implementation. Muller and James (1994) suggested a set of multitemporal images to overcome the uncertainty in mapping soil texture due to differences in soil moisture and soil roughness. Moran *et al.* (1997) also suggested that multispectral images of bare soil could be used to map soil types across a field.

Crop growth and intercepted radiation

Remote sensing techniques have also been applied to monitor seasonally variable soil and crop conditions. Knowledge of crop phenology is important for management strategies. Information on the stage of the crop could be detected with seasonal shifts in the “red edge” (Railyan and Korobov, 1993), bidirectional reflectance measurements (Zipoli and Grifoni, 1994), and temporal analysis of NDVI (Boissard *et al.*, 1993). Moreover Wiegand *et al.* (1991) consider them as a measure of vegetation density, LAI, biomass, photosynthetically active biomass, green leaf density, photosynthesis rate, amount of photosynthetically active tissue and photosynthetic size of canopies.

Aparicio *et al.* (2000) using three VIs (NDVI; Simple Ratio; Photochemical Reflectance Index) to estimate changes in biomass, green area and yield in durum wheat. Their results suggest that under adequate growing conditions, NDVI may be useful in the later crop stage, as grain filling, where LAI values are around 2. SR, under rainfed condition, correlated better with crop growth (total biomass or photosynthetic area) and grain yield than NDVI. This fact is supported by the nature of relationship between these two indices and LAI. SR and LAI show a linear relationship, compared to the exponential relationship between LAI and NDVI. However the utility of both indices, as suggested by the authors, for predicting green area and grain yield is limited to environments or crop stages in which the LAI values are < 3 . They found that in rainfed conditions, the VIs measured at any stage were positively correlated ($P < 0.05$) with LAI and yield. Under irrigation, correlations were only significant during the second half of the grain filling. The integration of either NDVI, SR, or PRI from heading to maturity explained 52, 59 and 39% of the variability in yield within twenty-five genotypes in rainfed conditions and 39, 28 and 26% under irrigation.

Shanahan *et al.* (2001) use three different kinds of VIs (NDVI, TSAVI, GNDVI) to assess canopy variation and its resultant impact on corn (*Zea mays* L.) grain yield. Their results suggest that GNDVI values acquired during grain filling were highly correlated with grain yield, correlations were 0.7 in 1997 and 0.92 in 1998. Moreover they found that normalizing GNDVI and grain yield variability, within treatments of four hybrids and five N rates, improved the correlations in the two year of experiment (1997 and 1998). Correlation, however, increases with a net rate in 1997 from 0.7 to 0.82 rather than in 1998 (0.92 to 0.95). Therefore, the authors suggest that the use of GNDVI, especially acquiring measurements during grain filling is useful to produce relative yield maps that show the spatial variability in field, offering an alternative to use of combine yield monitor.

Raun *et al.* (2001) determined the capability of the prediction potential grain yield of winter wheat (*Triticum aestivum* L.) using in-season spectral measurements collected between January and March. NDVI was computed in January and March and the estimated yield was computed using the sum of the two postdormancy NDVI measurements divided by the Cumulative Growing Degree Days from the first to the second reading. Significant relationships were observed between grain yield and estimated yield, with $R^2 = 0.50$ and $P > 0.0001$ across two years experiment and different (nine) locations. In some sites the estimation of potential grain yield, made in March and measured grain yield made in mid-July differed due to some factors that affected yield.

The capability of VIs to estimate physiological parameters, as fAPAR, is studied on other crops, faba bean (*Vicia faba* L.) and semileafless pea (*Pisum sativum* L.) that grows under different water condition, as an experiment followed by Ridaou *et al.* (1998) where crops see above grew both under irrigated and rainfed conditions. They have computed several indices (RVI, NDVI, SAVI2, TSAVI, RDVI, PVI) and linear, exponential and power relationship between VI and fAPAR were constructed to assess fAPAR from VIs measurements. During the pre-LAI_{max} phase, in both species, all VIs correlated highly with fAPAR, however R^2 at this stage did not differ significantly between indices that consider soil line (SAVI2 and TSAVI) and those that did not consider it (NDVI, RVI, RDVI). In post-LAI_{max} phase the same behaviour was observed. All VIs are affected by the hour of measurement at solar angles greater than 45° . Authors conclude that simple indices as RVI and NDVI, can be used to accurately assess canopy development in both crops, allowing good and fast estimation of fAPAR and LAI.

Nutrient Management

Appropriate management of nutrients is one of the main challenges of agriculture productions and at the same environmental impact. Remote sensing is able to provide valuable diagnostic methods that allow for the detection

of nutrient deficiency and remedy it with the proper application.

Several studies have been carried out with the objective of using remote sensing and vegetation indices to determine crop nutrient requirements (Schepers *et al.*, 1992; Blackmer *et al.*, 1993; Blackmer *et al.*, 1994; Blackmer *et al.*, 1996a; Blackmer *et al.*, 1994b; Blackmer and Schepers 1996; Daughtry *et al.* (2000). Results from these studies concluded that remote sensing imagery can be a better and quicker method compared to traditional method for managing nitrogen efficiently.

Bausch and Duke (1996) developed a N reflectance index (NRI) from green and NIR reflectance of an irrigated corn crop. The NRI was highly correlated with an N sufficiency index calculated from SPAD chlorophyll meter data. Because the index is based on plant canopy as opposed to the individual leaf measurements obtained with SPAD readings, it has great potential for larger scale applications and direct input into a variable rate application of fertilizer.

Ma *et al.* (1996) studied the possibility to evaluate if canopy reflectance and greenness can measure changes in Maize yield response to N fertility. They have derived NDVI at three growing stage: preanthesis, anthesis and postanthesis. NDVI is well correlated with leaf area and greenness. At preanthesis NDVI showed high correlation with field greenness. At anthesis correlation coefficient of NDVI with the interaction between leaf area and chlorophyll content was not significant with yield. Ma *et al.* (1996) summarized that reflectance measurements taken prior to anthesis predict grain yield and may provide in-season indications of N deficiency.

Gitelson *et al.* (1996) pointed out that in some conditions, as variation in leaf chlorophyll concentration, GNDVI is more sensitive than NDVI. In particular is the green band, used in the computing GNDVI that is more sensitive than the red band used in NDVI. This changes occurs when some biophysical parameters as LAI or leaf chlorophyll concentration reach moderate to high values. Fertility levels, water stress and temperature can affect the rate of senescence during maturation of crops. In particular Adamsen *et al.* (1999) used three different methods to measure greenness during senescence on spring wheat (*Triticum aestivum* L.): digital camera, SPAD, hand-held radiometer. They derived G/R (green to red) from digital camera, NDVI from an hand-held radiometer and SPAD readings was obtained from randomly selected flag leaves. All three methods showed the similar temporal behaviour. Relationship between G/R and NDVI showed significant coefficient of determination and their relationship were described by a third order polynomial equation ($R^2 = 0.96$; $P < 0.001$). Relation is linear until $G/R > 1$, when canopy approach to maturity ($G/R < 1$) NDVI is still sensitive to the continued decline in senescence than did G/R. This fact suggest that the use of the visible band is limited in such conditions. However authors found that G/R is more sensitive than SPAD measurements.

Daughtry *et al.* (2000) have studied the wavelengths sensitive to leaf chlorophyll concentration in Maize (*Zea mays* L.). VIs as NIR/Red, NDVI, SAVI and OSAVI, have shown LAI as the main variable, accounting for >

98% of the variation. Chlorophyll, LAI, and their interaction accounted for > 93% of the variation in indices that compute the green band. Background effect accounted for less than 1% of the variation of each index, except for GNDVI, which was 2.5%.

Serrano *et al.* (2000) studied the relationship between VIs and canopy variables (aboveground biomass, LAI canopy chlorophyll A content and the fraction of intercepted photosynthetic active radiation (fIPAR) for a wheat crop growing under different N supplies. The VIs-LAI relationships varied among N treatments. The authors also showed that VI were robust indicators of fIPAR independently of N treatments and phenology.

Li *et al.* (2001) studied spectral and agronomic responses to irrigation and N fertilization on cotton (*Gossypium hirsutum* L.) to determine simple and cross correlation among cotton reflectance, plant growth, N uptake, lint yield, site elevation, soil water and texture. NIR reflectance was positively correlated with plant growth, N uptake. Red and middle-infrared reflectance increased with site elevation. Li *et al.* (2001) found that soil in depression areas contains more sand on the surface than on up-slope areas. This behaviour modified reflectance patterns. As a result, a dependence on sand content was shown by NDVI with higher values in the depression areas and lower values in areas where the soil had more clay. In addition cotton NIR reflectance, NDVI, soil water, N uptake and lint yield were significantly affected by irrigation ($P < 0.0012$). The N treatment had no effect on spectral parameters, and interaction between irrigation and N fertilizer was significant on NIR reflectance ($P < 0.0027$). Red and NIR reflectance and NDVI were cross-correlated with soil water, sand, clay and site elevation across a distance of 60 to 80 meters. Cross-correlation analysis of spectral reflectance, soil texture and site elevation could be useful for an in-season adjustment in water and N fertilizer application. Moreover authors pointed out on the possibility to use cross-correlation distance between NDVI and site elevation as a distance of variable N application over heterogeneous fields.

Wright (2003) investigated the spectral signatures of wheat under different N rates, and the response to a mid-season application at heading. VIs were computed (RVI, NDVI, DVI, GNDVI) and spectral data were compared with pre-anthesis tissue samples and post-harvest grain quality. The author found that imagery and tissue samples were significantly correlated with pre-anthesis tissue samples and post-harvest grain quality. The second application of N at heading improved protein only marginally. GNDVI was significantly correlated with nitrogen content of plants. VIs used in the study, whether from satellite or aircraft correlated well with pre-season N and plant tissue analysis, but had lower correlation with protein.

Osborne *et al.* (2002a; 2002b) demonstrated that hyperspectral data in distinguishing difference in N and P at the leaf and canopy level, but the relationship were not constant over all plant growth stages. Adams *et al.* (2000) have detected Fe, Mn, Zn and Cu deficiency in soybean using hyperspectral reflectance techniques and proposing a Yellowness Index (Adam *et al.*, 1999) that

evaluated leaf chlorosis based on the shape of the reflectance spectrum between 570 nm and 670 nm.

Pest Management

Remote sensing has also shown great potential for detecting and identifying crop diseases (Hatfield and Pinter, 1993) and weeds. Visible and NIR bands can be useful for detecting healthy plants versus infected plants because diseased plants react with changes in LAI, or canopy structure. Malthus and Madeira (1993) using hyperspectral information in visible and NIR bands, were able to detect changes in remotely sensed reflectance before disease symptoms were visible to the human eye.

Weed management represents an important agronomic practice to growers. Weeds compete for water, nutrient, light and often reduce crop yield and quality. Decisions concerning their control must be made early in the crop growth cycle. Inappropriate herbicide application can also have the undesirable effect on the environment and a side effect to the crop. With the advent of precision agriculture, there has been a chance from uniform application to the adoption of herbicide-ready crop and to apply herbicide only when and where needed. This kind of approach is economically efficient and environmentally sound but site-specific herbicide management requires spatial information on the weeds. The discrimination between crops and weeds is usually accomplished based on the differences in the visible/NIR spectral signatures of crops and specific weeds (Gausman *et al.*, 1981; Brown *et al.*, 1994) or by acquiring images when weed coloring is particularly distinctive. Richardson *et al.* (1985) demonstrated that multispectral aerial video images could be used to distinguish uniform plots of Johnsongrass and pigweed from sorghum, cotton and cantaloupe plots. Several other authors have utilized spectral imagery to separate crops from weeds based on spectral signatures of species and bare soil (Hanks and Beck, 1998) or based on the leaf shape determined by the machine vision technology (Franz *et al.*, 1995; Tian *et al.*, 1999).

Basso *et al.* 2004 (unpublished data) used the handheld radiometer CropScan to determine if a wheat field with various levels of pappy (*Papever Rhoëas*) infestation could be detected by the multispectral radiometer. The study showed that the reflectance in the Red and NIR of the highly infested areas with pappy of the durum wheat field was significantly different from the no infestations of lower levels of weed presence (Figure 5).

Remote sensing can also be used to determine herbicide injury to the crop for insurance purposes (Hickman *et al.*, 1991; Donald, 1998a, Donald 1999b). To improve application efficiency of herbicides, Sudduth and Hummel (1993) developed a portable NIR spectrophotometer for use in estimating soil organic matter as part of the estimation procedure for the amount of herbicide to be sprayed.

Several studies have also been carried out using remote sensing for identifying and managing insects, mite and nematode populations. Such studies have been able to demonstrate that remote sensing is able to detect actual

changes in plant pigments caused by pest presence, damages by pest and to identify areas susceptible to infestation. Riedell and Blackmer (1999) infested wheat seedlings with aphids and after 3 weeks they measured the reflectance properties of individual leaves. The leaves of the infected plants had lower chlorophyll concentration and displayed significant changes in reflectance spectra at certain wavelengths (500 to 525, 625 to 635 and 680 to 695 nm). This study in combination with others (Cook *et al.*, 1999; Elliot *et al.*, 1999; Willers *et al.*, 1999) suggests the potential usefulness of canopy spectra for identifying outbreaks in actual field situations and to guide field scouts to specific areas for directed sampling. Site specific pesticide application can reduce the impact of toxic chemicals on the environment by 40 percent (Dupont *et al.*, 2000).

Roots may sense difficult conditions in the soil and thence send inhibitory signals to the shoots which harden the plants against the consequences of a deteriorating or restriction environment, especially if the water supply is at risk. TIR can provide early, sometimes previsual, detection of diseases that interfere with flow of water from the soil through the plant to the atmosphere. Pinter *et al.* (1979) found that a cotton plant whose roots were infected with the soil-borne fungus *Pythium* displayed sunlit leaf temperatures that were 3 to 5°C warmer than adjacent healthy plants. TIR was also used for detecting root diseases in red clover under irrigated conditions (Oliveira *et al.*, 1994).

Plant Population

Plant population is an important variable that influences the final yield (Ritchie and Wei, 2000). Plant stands are affected by soil parameters, weather, field slope, aspect, seedling diseases, tillage etc. Remote sensing imagery taken after emergence at the proper spatial resolutions can be used to determine plant populations. Basso *et al.* (2001) through NDVI were able to identify 3 management zones where plant population of soybean was highly different due to the different position in the landscape. Moran *et al.* (2003) stated that development of new sensitive sensors that remove soil background is on the way and accurate assessment of plant density should improve.

Selection of growth traits

The use of morphological and physiological traits as indirect selection criteria for grain yield is an alternative to breeding approach. Future wheat yield improvements may be gained by increasing total dry matter production (TDM). VIs have been proposed as an appropriate and nondestructive method to assess total dry matter and LAI. Aparacio *et al.*, (2000) and (2002) investigated whether VIs could accurately identify TDM and LAI in durum wheat and serve as indirect selection criteria in breeding programs. They found that the best growth stages for growth traits appraisal were stages 65 and 75 of the Zadock scale. VIs accurately tracked changes in LAI when data were analyzed across a broad range of different growth stages, environment and genotypes. Since

VIs lack of predictive ability for specific environment/growth stages combinations, their value as indirect genotypes selection criteria for TDM or LAI was limited. Ma *et al.*, (2001) showed that canopy reflectance measured between R4 and R5 stages in soybean adequately discriminates high from low yielding genotypes and providing a reliable and fast indicator for screening and ranking soybean genotypes based on the relationship between NDVI and grain yield.

Yield Estimation

Remote sensing can provide valuable information of yield assessment and show spatial variation across the field. There are two approaches for yield estimation, the first is a direct method in which predictions are derived directly from remote sensing measurements (Figure 6). The second method is an indirect one, where remotely sensed data are incorporated into simulation model for crop growth and development either as within season calibration checks of model output (LAI, biomass) or in a feedback loop used to adjust model starting conditions (Maas, 1988).

The direct method for prediction yield using remote sensing can be based on reflectance or thermal-based. Both methods have been applied with case of successes on various crops like corn, soybean, wheat, alfalfa (Tucker *et al.*, 1979; Tucker *et al.*, 1981; Idso *et al.*, 1977; Pinter *et al.*, 1981). Hatfield (1981) in his survey of 82 different varieties of wheat was not able to find a consistent relationship between spectral indices and yield.

Hatfield (1983b) coupled frequent spectral reflectance and thermal observation in a more physiological method to predict yields in wheat and sorghum. This method requires TIR daily measurements during grain filling period to estimate crop stress.

Shanahan *et al.* (2001) demonstrated that the time of corn pollination was not a good growth stage to estimate yield because of the various that can cause tassel emergence dates to vary. Yang *et al.* (2000) found similar results, concluding that images from images taken at grain filling can provide good relationships between VIs and yield. Reliability of imagery for use in yield estimation decreases as the time before harvest increases because there is more opportunities for factors like various nature of stresses to influence yield.

Aase and Siddoway (1981) had cautioned that the relationships of spectral indices to yield were dependent upon normal grain-filling conditions for the crop. Similar results were found by Basso *et al.* (2004) (personal communication, unpublished data) where the NDVI images on a rainfed durum wheat field showed different correlation to yield depending on the time of the image selected (Fig.7). In this specific case, spatial variability of soil texture and soil water uptake by plants affected by drought varied at anthesis presenting different scenarios from the one predicted by the NDVI estimation.

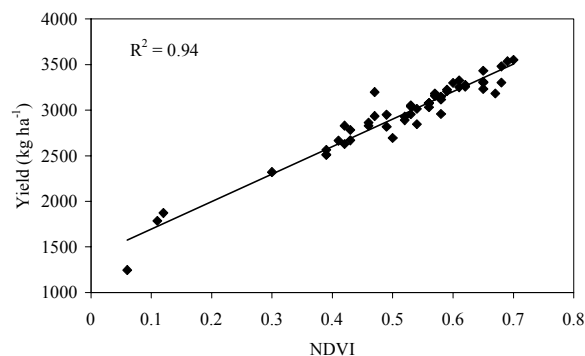


Fig. 6 – Correlation between NDVI derived from an image taken at flowering and yield for a soybean crop in Michigan USA.

Fig. 6 – Correlazione tra NDVI in fioritura e produzione per una coltura di soia nello stato del Michigan, USA

Combining remote sensing with crop modeling

Crop models provide the ability to simulate different management options under different weather conditions, while remote sensing allows for identification of spatial patterns. Remote sensing data can directly be used for within season model calibration (Maas, 1993), model validation (Fisher, 1994). Once information on stable and dynamic variable are collected, remote sensing in combination with crop growth model can be used to quantify the spatial and temporal crop variability (Fig. 7 pag. 48). Clearly, the goal of crop simulation is to explain the spatial variability of crop performance mapped with grain yield monitoring systems and to help guide in management decisions related to the site-specific management of crop inputs. It is also clear that crop simulations cannot be performed everywhere given that the cost and the availability of detailed inputs would be prohibitive. A more balanced approach to spatial application of crop simulation models would be to delineate zones within the field representing areas of similar crop performance. One approach may be to obtain vegetation indexes derived from remote sensed imagery during critical times during the growing season, classify the images for target sampling, delineate spatial patterns and use the results of the target sampling as inputs for the models. Model validation can then be performed at selected sites within these delineated management zones. Such an approach would facilitate the challenge of using crop models in precision farming by obtaining spatial inputs to simulate variations of crop yields across the field, as well as to decide where to use field averages for some factors along with spatially variable inputs for others. Basso *et al.* (2001) conducted a study to examine a new procedure for spatial validation of crop models for use in precision farming. This procedure used the CROPGRO-Soybean model to validate management zones across the field that were delineated using a NDVI classification procedure. Airborne false color composite images in the blue, red, green and NIR portion of the spectrum were taken at selected time during the season at

1 meter pixel resolution. The images provided spatial information about the condition of the crop throughout the season. Each image was used to generate NDVI maps of the field and to identify spatial patterns across the field. The false color composite image taken on July 18 was selected for quantifying areas with similar reflectance by grouping areas into classes of similar NDVI values using supervised classification technique. Pixels of similar reflectance were queried across the field after trying various ranges of values able to reproduce the spatial patterns visible in the original false-color composite image. The reclassified NDVI map from 18 July image clearly showed spatial variability in soybean performance. Classification of the NDVI image indicated three classes of importance in this field. The model performance indicated that the NDVI reclassification procedure was appropriate and with multi-year simulation should allow for the characterization of management zones for this field. The use of site specific model inputs obtained with the NDVI-reclassification procedure has a major advantage since the power and application of simulation models in precision farming has been limited by data requirements at the sub-field scale. The site-specific inputs approach is scale-independent because the scale is controlled by the observed variation in the field and that is the scale at which the model is applied.

Future challenges and Opportunities

VIs are often used as synonymous of plant vigour. This is not necessarily correct because broad wave band VIs do not have the capability for identifying the factor responsible for a specific type of stress. Narrow band indices such as the Photochemical Reflectance Index (PRI), Water Band Index (WBI), and the Normalized Pigment Chlorophyll Ratio Index (NPCl) are examples of reflectance indices correlated with physiological stresses such as nutrient and water deficits (Peñuelas *et al.*, 1994). A step forward was taken by the Environmental and Plant Dynamic Unit of Soil and Water Conservation Laboratory of the USDA-ARS in Phoenix Az, with the work conducted by Clarke *et al.*, (2001), Pinter *et al.*, (2003) Moran *et al.*, (2003) on the Canopy Chlorophyll Content Index (CCCI) based on a VI plus the reflectance in a narrow red edge band (~720 nm) to distinguish nutrient stress from other causes of reduced green biomass in cotton.

Yield monitor and remote sensing images at harvest should display similar pattern but in many cases due to errors in yield monitor system this match does not occur. Shanahan *et al.* (2001) and Pinter *et al.* (2003) suggested that VIs can be used as an alternative to yield monitor systems. New ideas for commercialization are the combinations of pre-harvest remote sensing image and yield map to display the actual and realistic spatial variability of yield across the field.

A major research challenge is to develop stress detection algorithms that are universal and perform well over space, throughout the seasons and between years. Remote sensing technology will improve as spatial, spectral and

temporal resolution imagery will increase. Remote sensing application in precision agriculture can be direct, but most likely, is indirect. Rapid response is required to provide information about the condition of the current crop in time to make management input corrections to accomplish maximum yield. Images only show the spatial variability of plant condition, thus suggestions can only be made if the causes of the variability are understood. The current limitation for image-based applications is due to sensors attributes. Crop spatial variability is usually observed at a scale that only is too fine for the sensors currently available on the orbiting satellites. Airborne images are already limiting this problem but the temporal and spectral aspects still need to be improved. The success of remote sensing in agriculture will be measured by the type of information that is provided to the farmer, how quickly the information is delivered and the fee that is charged for the information. Because the potential market for remote sensing is great, competition in farming business should help make the success a reality. The future brings tremendous prospects for remote sensing applications especially if integrated with crop simulation models.

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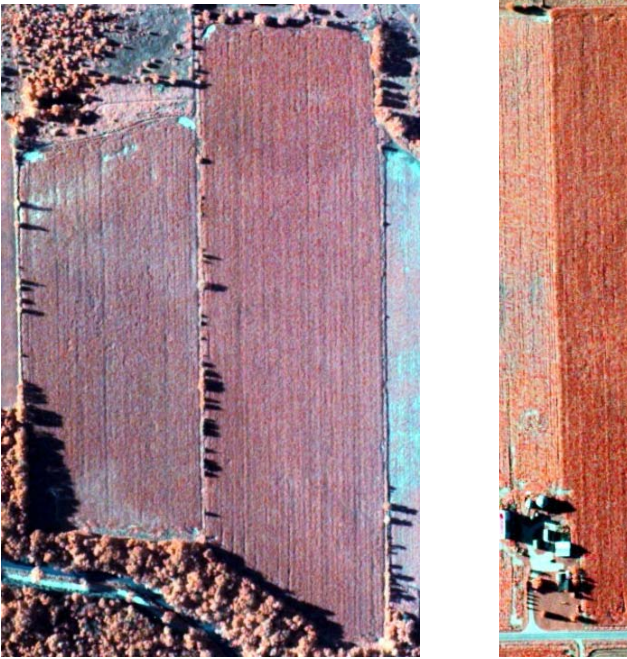


Fig. 2 - Example of false color composite images of a corn crop in Michigan USA.

Fig. 2 – Esempio di immagini a colori falsi composti di un campo di mais nello stato del Michigan USA

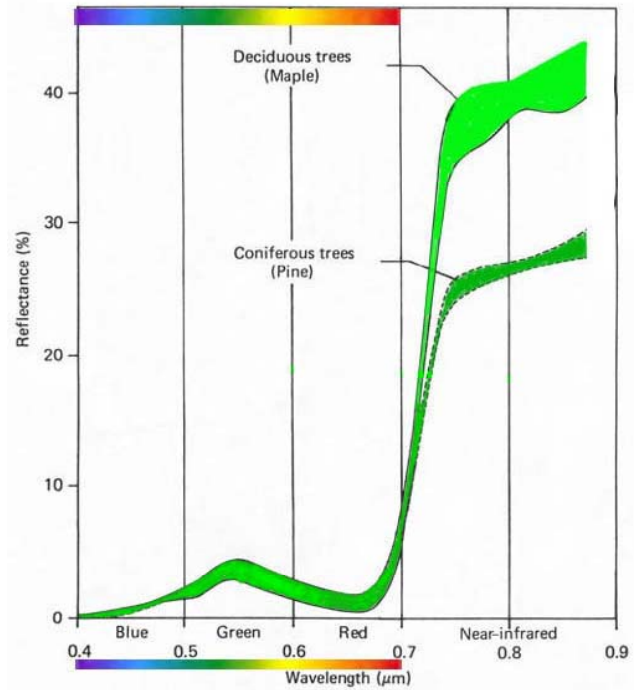


Fig. 4 – Spectral reflectance envelopes for deciduous (broad-leaved) and coniferous (needle-bearing) trees (Adopted by Kalensky and Wilson, 1975).

Fig. 4 – Curva di riflettanza spettrale di alberi cedui (a foglia larga) e conifere (ad aghi). (Da Kalensky e Wilson, 1975)

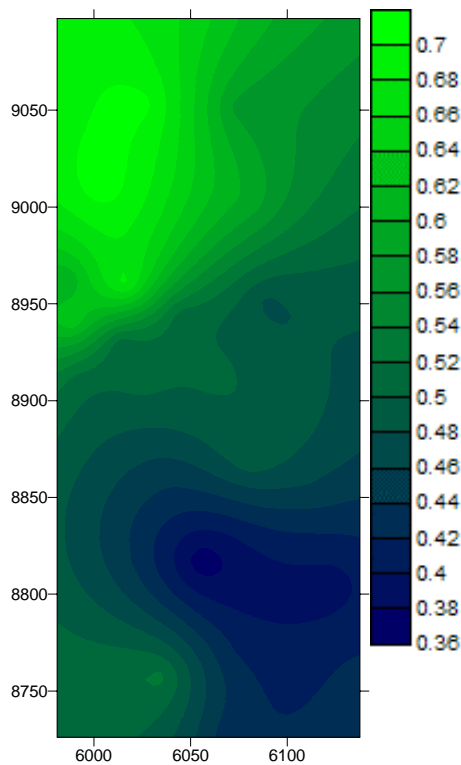


Fig. 7 – Examples of a NDVI map of a durum wheat crop in Puglia, Italy, to illustrate spatial variability within the field as affected by landscape position and soil properties.

Fig. 7 – Esempio di una mappa di NDVI di frumento duro per illustrare la variabilità spaziale in funzione della topografia e proprietà del suolo.