
Remote Sensing Applications in Agriculture

1.0 INTRODUCTION

1.1 What Is Remote Sensing

Remote Sensing is the acquisition or collection of due information about an object or phenomenon without making physical contact with the object and thus in contrast to on-site observation, especially the Earth.

Remote Sensing can also be said to be the art and science of acquiring information about the earth surface without having any physical contact with it. This is mainly done by observing and recording of reflected and emitted energy.

Generally Remote Sensing refers to the use of satellite- or aircraft-based sensor technologies to detect and classify objects on Earth, including on the surface and in the atmosphere and oceans, based on propagated signals (e.g. electromagnetic radiation). It may be split into "active" Remote Sensing (such as when a signal is emitted by a satellite or aircraft and its reflection by the object is detected by the sensor) and "passive" Remote Sensing (such as when the reflection of sunlight is detected by the sensor).

1.2 The Components of Remote Sensing;

1. Energy Source: The first requirement for Remote Sensing is an energy source which provides electromagnetic energy.
2. Radiation and the Atmosphere: As the energy travels from its source to the target, it will come in contact with and interact with the atmosphere it passes through. This interaction may take place a second time (active Remote Sensing) as the energy travels from the target to the sensor.
3. Interaction with the Target: once the energy makes its way to the target through the atmosphere, it interacts with the target depending on the properties of both the target and the radiation.
4. Recording of Energy by the Sensor: after the energy has been reflected by, or emitted from the target, we require a sensor (remote-not in contact with the target) to detect and record the electromagnetic radiation.
5. Transmission, Reception, and Processing: The energy recorded by the sensor has to be transmitted, often in electronic form, to a receiving and processing station where the data are processed into an image.

6. Interpretation and Analysis: The processed image is interpreted, visually or digitally, to extract information about the target.
7. Application: The final element of the Remote Sensing process is achieved when we apply the information we have been able to extract from the imagery about the target in order to better understand it, reveal some new information, or assist in solving a particular problem.

1.3 Principle of Remote Sensing

The basic principle of Remote Sensing is that different objects based on their structural, physical or chemical properties reflect or emit different amount of energy in different wavelength ranges of electro-magnetic spectrum. The sensors measure the amount of energy reflected from that object and represents it through an image.

The process of Remote Sensing involves an interaction between the incoming radiation and interest of target. This is done by using imaging and non-imaging system; however, the following steps are involved in the process

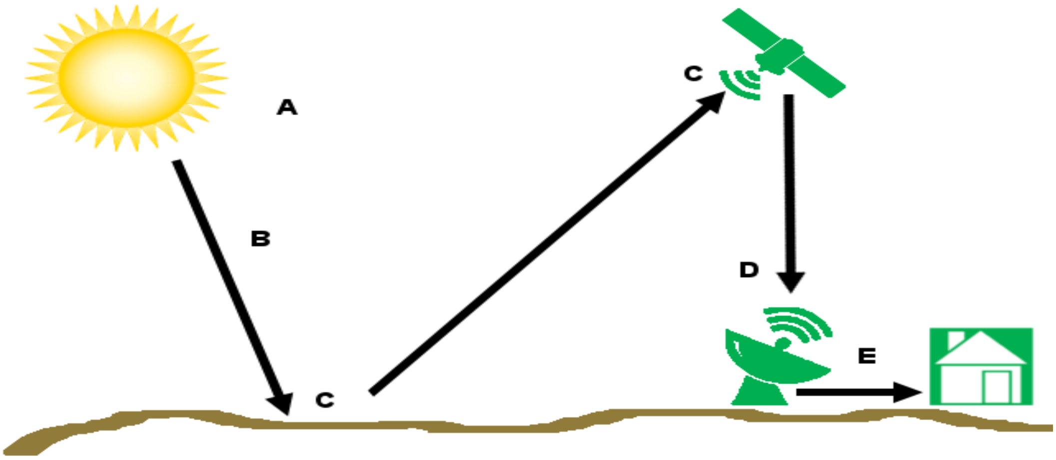

Fig 1.1

1.4 Types of Remote Sensing

1. ACTIVE REMOTE SENSING
2. PASSIVE REMOTE SENSING

Active Remote Sensing: when Remote Sensing work is carried out with a man made source of radiations which is used to illuminate a body and to detect the signal reflected form. Example. Radar and Lidar Remote Sensing.

Passive Remote Sensing: when Remote Sensing work is carried out with the help of electromagnetic radiations (signals) reflected by a natural body (sun and earth). Examples are: **Visible, NIR** and **Microwave Remote Sensing**.

Nowadays, Remote Sensing is employed in precision agriculture to manage and monitor farming practices at different levels. The data can be used to farm optimization and spatially-enable management of technical operations. The images can help determine the location and extent of crop stress and then can be used to develop and implement a spot treatment plan that optimizes the use of agricultural chemicals.

National governments can use Remote Sensing data, in order to make important decisions about the policies they will adopt, or how to tackle national issues regarding agriculture. Individual farmers can also receive useful information from Remote Sensing images, when dealing with their individual crops, about their health status and how to deal with any problems.

The main disadvantage of passive sensors is that they can collect or detect objects in the day time only because sun's illumination is not there at night, however they can record the naturally emitted energy like Thermal infrared.

On the other hand, Active sensor gives own energy for illumination so it enables to detect and record the images at any time. They are weather independent also; artificial microwaves can penetrate clouds, light and shadow. But Passive sensors are not weather independent. Radar signals can penetrate into vegetation and soil and even can give you the surface information at mm to m depth level at the same time major disadvantage is that radar signals do not contain any spectral characters while Passive Remote Sensing signals have spectral characters. Unlike active sensors passive sensor have the ability to produce fine resolution image. Active Remote sensors are cost intensive also when compared to passive sensor.

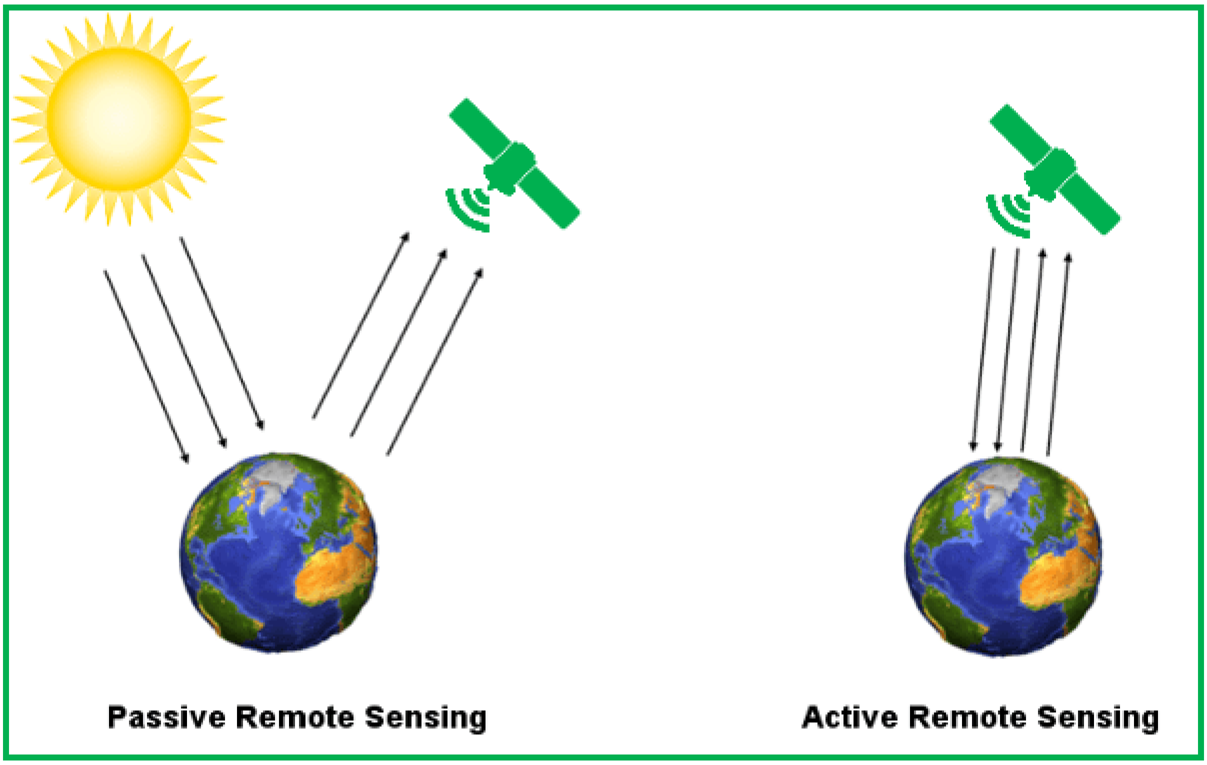

Fig 1.2

2.0 APPLICATIONS OF REMOTE SENSING IN AGRICULTURE

2.1 Crop Identification

The agricultural managers require information on the spatial distribution and area of cultivated crops for planning purposes. The can adequately plan the import and export of food products based on such information. Although some agricultural ministries annually commission their staff to map different crop types, these ground surveys are expensive and yet cover only a sample of farms. This serves the purpose of forecasting grain supplies (yield prediction), collecting crop production statistics, facilitating crop rotation records, mapping soil productivity, identification of factors influencing crop stress, assessment of crop damage due to storms and drought, and monitoring farming activity.

Key activities include identifying the crop types and delineating their extent (often measured in acres). Traditional methods of obtaining this information are census and ground surveying. In order to standardize measurements however, particularly for multinational agencies and consortiums, Remote Sensing can provide common data collection and information extraction strategies.

Remote Sensing offers an efficient and reliable means of collecting the information required, in order to map crop type and acreage. Besides providing a synoptic view, Remote Sensing can provide structure information about the health of the vegetation. The spectral reflection of a field will vary with respect to changes in the phenology (growth), stage type, and crop health, and thus can be measured and monitored by multispectral sensors. Radar is sensitive to the structure, alignment, and moisture content of the crop, and thus can provide complementary information to the optical data. Combining the information from these two types of sensors increases the information available for distinguishing each target class and its respective signature, and thus there is a better chance of performing a more accurate classification.

Interpretations from remotely sensed data can be input to a geographic information system (GIS) and crop rotation systems, and combined with ancillary data, to provide information of ownership, management practices etc.

A case study in Mali: For example in a study in Mali, the boundaries of 48 fields representing six dominant crops were mapped during an extensive field campaign, from which the temporal profiles of each crop were extracted. Figure 2.1 shows typical temporal profiles of dominant crops in Mali based on NDVI images for different crop types calculated from DigitalGlobe data. It shows the typical growth cycle of each crop during the cropping season (May – October).

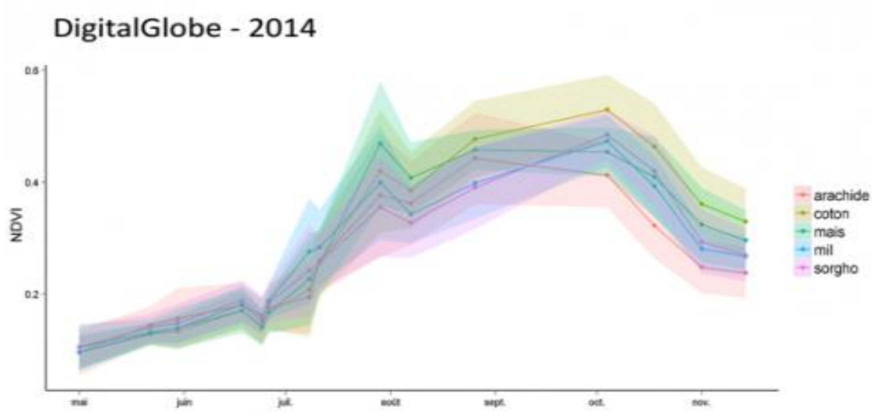

Figure 2.1 based spectral signatures of major crop types in Mali

Based on the potential uniqueness of these temporal profiles, UAV and satellite images can be classified to reveal the spatial distribution of crops in the area of interest. Apart from spectral information, several other information layers can be added to improve the accuracy with which different crops can be identified. An example is textural information (Haack and Bechdol, 2000; Sheoran and Haack, 2013).

Texture represents the degree of local spatial variations in an image. Different crop types, by virtue of their spatial arrangement, have different textural properties. Derivation and addition of textural measures to the spectral information can therefore improve classification accuracies.

Both texture and context are adding important information for the classification of image segments. Context refers to the relation between coarse and fine image segments. Texture serves as a valuable parameter in addition to spectral reflectance for characterizing the different segments. The texture parameters, which worked best, were GLCM (Grey Level Co-occurrence Matrix) and GLDV (gray-level difference vector) (Conrad et al., 2010; Novack et al., 2011).

Despite acquiring sufficient UAV/satellite and field data, crop classification can be very challenging and result in low accuracies. At the core of this difficulty is high variability in the spectral characteristics of the crops under study. In other words, the temporal profiles of the crops under study, are ideally unique for each crop, but this is often not the case.

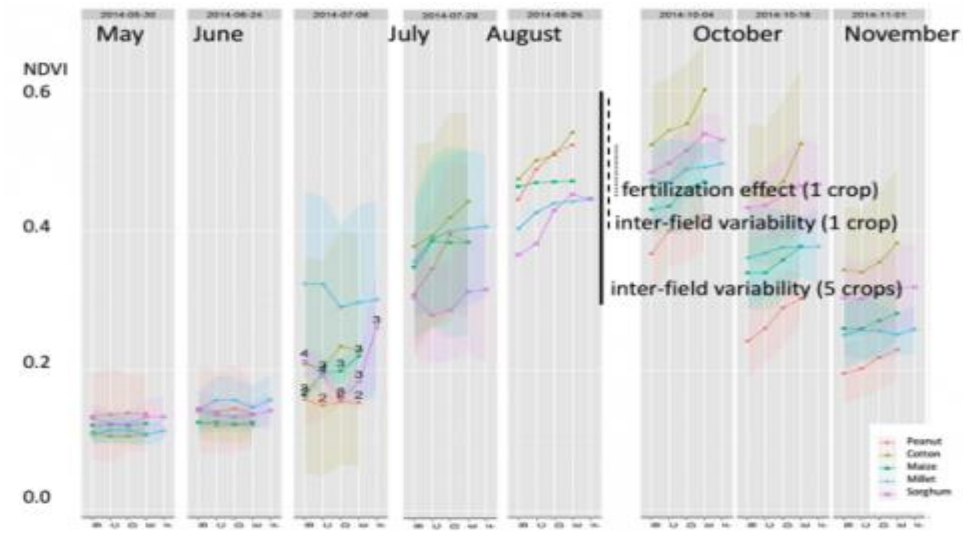

Figure 2.2 Monthly NDVI temporal profiles of major crop types in Mali (Source: STARS MALI TEAM).

Figure 2.2 (above), for example, shows the monthly temporal profiles of the dominant crops in our test site in Mali. Each column (labelled with a month name) depict the spectral patterns extracted from five quadrats within a field. The figure shows high similarity in the profiles, which could make crop identification and separation from satellite/UAV images quite challenging.

This high spectral and spatial variability can be attributed to a number of reasons. These include:

- Overlaps in cropping calendar, especially in rainfed dominated agricultural areas where different crop types are planted and harvested around the same time, leading to similarities in their temporal profiles.
- Differences in management practices (e.g. tillage, weeding, fertilization, etc.) between and within fields result in high spectral and spatial variability.
- Variations in soil type, depth and fertility
- Intercropping, i.e. cultivation of different crop types on the same land
- Proximity of natural/semi-natural vegetation to cultivated areas
- Occurrence of excessive trees on agricultural plots
- Water accumulation
- Occurrence of pest and diseases in some portions of a field

Figure 2.3: Un-weeded and weeded field in Njombe District, Tanzania (Source: AgriSense)

In order to reduce the effects of the above-mentioned factors on crop classification, a number of measures can be pursued: These include:

- Inclusion of additional RS data, e.g. Synthetic Aperture Radar (SAR) data (Forkuor et al., 2014; McNairn et al., 2009).
- Landscape stratification based on soil, topography, climate, etc.
- Performing object, instead of pixel-based, image analysis (Peña-Barragán et al., 2011).
- Testing different classification approaches such as the sequential masking classification algorithm (Forkuor et al., 2015; Van Niel and McVicar, 2004).

2.2 Soil Mapping

Soil is a fundamental natural resource, and it plays an essential role in the biophysical and biogeochemical functioning of the planet. Soil is a fundamental natural resource. Soil plays an essential role in the biophysical and biogeochemical functioning of the planet. Soil systems, like most natural systems, are dynamic in nature. Most changes are slow and imperceptible particularly when viewed in the time frame of human lifespan. However, catastrophic events such as high intensity storms can accelerate erosion processes resulting in measurable changes. The changes are mainly in the structure and composition of the material and such changes are referred to as structural changes (Manchanda et al., 2002). It is necessary to have an intimate knowledge of the kind of soils their spatial distribution for developing rational land use plan for agriculture, forestry, irrigation, drainage, etc. or for measuring the amount of soil erosion, desertification and damage caused by landslides, floods, etc. With the help of soil mapping of various properties of soil we gain an insight into the potentialities and limitation of soil for its effective exploitation. The soil systems, like most natural systems, are dynamic in nature. Most changes are slow and imperceptible particularly when viewed in the time frame of human lifespan. However, catastrophic events such as high intensity storms can accelerate erosion processes resulting in measurable changes. The changes are mainly in the structure and composition of the material and such changes are referred to as structural changes. It is necessary to have an intimate knowledge of the kind of soils their spatial distribution for developing rational land use plan for agriculture, forestry, irrigation, drainage, etc. or for measuring the amount of soil erosion, desertification and damage caused by landslides, floods, etc. With the help of soil mapping of various properties of soil, we gain an insight into the potentialities and limitation of soil for its effective exploitation.

Remote Sensing techniques have significantly contributed to speeding up conventional soil surveys by reducing field work to a considerable extent. Remote Sensing is the acquisition of information about an object or phenomenon without making physical contact with the object. In India, initially aerial photographs were used in deriving information on degraded lands (Kamphorst and Iyer, 1972). The application of remotely sensed data in mapping degraded lands space borne sensors started with the launch of the first Earth Resources Technology Satellite ERTS-1 /Landsat-1. However, the satellites Landsat-TM, SPOT and Indian Remote Sensing Satellites with better spatial and spectral resolution, enabled to map and monitor degraded lands more efficiently (Tagore et al., 2012). The use of digital image processing for soil survey and mapping was initiated in India with the establishment of National Remote Sensing Agency and Regional Remote Sensing Service Centres. The works carried out by Venkatratnam (1980), Kudrat et al. (1990), Karale (1992), etc. demonstrated the potential of digital image processing techniques for soil survey. Following this, a number of modeling studies were carried out to develop a variety of soil maps, e.g. land evaluation, land productivity, soil erosion and hydrologic budget (Kudrat et al., 1990; Saha et al., 1991; Kudrat 1996; Kudrat et al., 1995; Kudrat et al., 1997) to derive information about the various phenomenon of soil.

2.2.1 Methods of Soil Mapping

There are different types of soils on the Earth. Hence, mapping of various properties of soil is essential. Soil mapping provides us an insight of the various properties of soil which are required to analyse the various potentialities and limitations of soil. There are various methods of soil mapping. Remote Sensing has proved to be an important part of soil survey and mapping. Various properties of soil can be mapped with the help of Remote Sensing. **Optical Remote Sensing** helps in the mapping of properties like land cover, land type, vegetation and soil moisture. **Thermal Infrared Remote Sensing** is commonly used to estimate moisture and salinity. **Visual Image interpretation** technique helps in the identification and mapping of soil elements like land type, vegetation, land use, slope and relief. **Microwave Remote Sensing** is a new and effective technique for mapping of soil moisture and salinity which is being commonly used today. **Hyperspectral Remote Sensing** is another recent method which is applied in soil salinity mapping as well as identification and mapping of minerals in the soil.

I. **Optical Remote Sensing**: This has been used to monitoring of various properties of soil like land cover, land type, vegetation and even soil moisture. Optical Remote Sensing provides a quantitative measure of surface reflectance, that is, the reflected radiation of the sun from the Earth's surface, which is related to some soil properties. Organic matter, particle size and moisture content influence soil reflectance primarily through a NES Geo-Congress 2013 62 change in average surface reflectance, and produce only broad spectral expression (Irons et al., 1989). Optical Remote Sensing is the most commonly used for soil moisture estimation. Lobell and Asner (2002) developed a physical model to explain the soil reflectance variations due to moisture change based on their analysis of the reflectance for four different soils at various moisture contents. Liu et al. (2003) analyzed 18 different soils that represent a large range of permanent soil characteristics and investigated the potential of estimating soil moisture from reflectance measurements in the solar domain.

II. **Thermal Infrared Remote Sensing:** The thermal infrared Remote Sensing is commonly used to estimate moisture and salinity. Thermal infrared Remote Sensing measures the thermal emission of the Earth with an electromagnetic wavelength region between 3.5 and 14µm (Curran, 1985). The moisture content is mainly measured by the thermal inertia method and the temperature/vegetation index method (Wang and Qu, 2009). Thermal infrared Remote Sensing is also commonly used to detect salt-affected areas from the relationship between crop water stress and temperatures of the crop canopy (Metternicht and Zinck, 2003). Although thermal infrared Remote Sensing has many scopes, the potential use of thermal systems for soil monitoring appears to be little investigated.

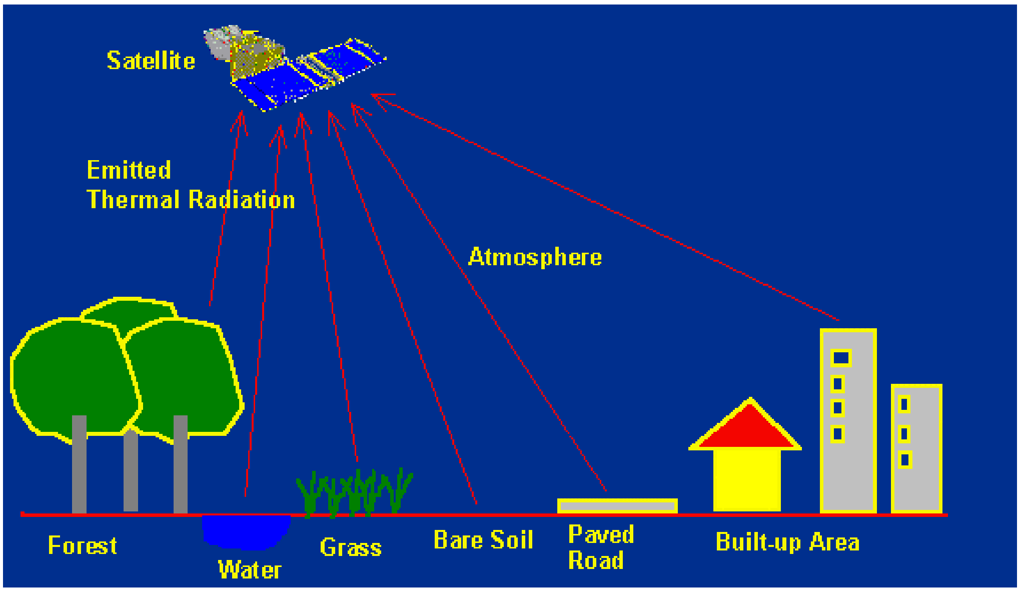

Fig 2.4

Infrared Remote Sensing makes use of infrared sensors to detect infrared radiation emitted from the Earth's surface. The middle-wave infrared (MWIR) and long-wave infrared (LWIR) are within the thermal infrared region. These radiations are emitted from warm objects such as the Earth's surface. They are used in satellite Remote Sensing for measurements of the earth's land and sea surface temperature. Thermal infrared Remote Sensing is also often used for detection of forest fires.

III. **Visual Image Interpretation:** Visual interpretation is based on shape, size, tone, shadow, texture, pattern, site and association. This has the advantage of being relatively simple and inexpensive. Soils are surveyed and mapped, following a three tier approach, comprising interpretation of Remote Sensing imagery and/or aerial photograph (Mulder, 1987), field survey (including laboratory analysis of soil samples) and cartography (Sehgal et al., 1989). This technique helps in the identification and mapping of soil elements like land type, vegetation, land use, slope and relief. Interpretation of aerial photographs have also been used in soil salinity mapping, especially colour-infrared photographs in which barren saline soils (in white) and saltstressed crops (in reddish brown) can be easily discriminated from other soil surface and vegetation features (Rao and Venkataratnam, 1991; Wiegand, Rhoades, et al., 1994).

IV. **Microwave Remote Sensing:** Microwave Remote Sensing is an effective technique for mapping of soil moisture and salinity, with advantages for all-weather observations and solid physics. It presents advantages in special soil conditions, such as salt-affected areas (Taylor et al., 1996), sandy coastal and desert zones, waterlogged areas, and places with irregular micro-topography such as puffy crusts and cloddy surfaces (Metternicht, 1998; Singh and Srivastav, 1990). There are two methods of microwave sensing - active microwave sensing and passive microwave sensing. Great progress has been made in mapping regional soil moisture with active microwave sensors. In active microwave methods, a microwave pulse is sent and received. The power of the received signal is compared with which was sent to determine the backscattering coefficient of the surface, which has been shown to be sensitive to soil moisture (Wang and Qu, 2009). The most common imaging active microwave configuration is Application of Remote Sensing in Soil Mapping: A Review ` 63 the synthetic aperture radar (SAR), which transmits a series of pulses as the radar antenna traverses the scene (Moran et al., 2004). Active sensors, although having the capability to provide high spatial resolution in the order of tens of meters, have a poor resolution in time with repeat time excess of 1 month. On the other hand, the space borne passive systems can provide spatial resolutions only in the order of tens of kilometres but with a higher temporal resolution. Passive microwave remote sensors can be used to monitor surface soil moisture over land surfaces (Eagleman and Lin, 1976; Ulaby et al., 1986; Schmugge and Jackson, 1994; Jackson et al., 1995; Wigneron et al., 2004). These sensors measure the intensity of microwave emission from the soil, which is proportional to the brightness temperature, a product of the surface temperature and emissivity (Wang and Qu, 2009). Because of the differential behaviour of the real and imaginary parts of the dielectric constant of soil, microwaves also are efficient in detecting soil salinity. While the real part is independent of soil salinity and alkalinity, the imaginary part is highly sensitive to variations in soil electrical conductivity, but with no bearing on variations in alkalinity. This allows the separation of saline soils from others (Sreenivas, Venkataratnam and Rao, 1995).

V. **Hyperspectral Remote Sensing:** Recent developments in hyperspectral Remote Sensing offer the potential of significantly improving data input to predictive soil models. The key characteristic of hyperspectral imagery data is the high spectral resolution that is provided over a large and continuous wavelength region. Each pixel in a hyperspectral image is associated with hundreds of data points that represent the spectral signature of the materials within the spatial area of the pixel. The result is a three-dimensional data set that has two axes of spatial information and one axis of spectral information (Rogers and Luna, 2004). The high resolution of hyperspectral imagery makes it possible to uniquely identify different materials at the earth's surface. The large number of spectral bands permits direct identification of minerals in surface soils. Clark and Swayze (1996) mapped over 30 minerals using hyperspectral sensor, Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) at Cuprites, Nevada. AVIRIS measures a contiguous spectrum in the visible and near-infrared, and thereby better characterize atmospheric and surface properties (Goetz et al., 1985). The capabilities of hyperspectral imagery for soil salinity mapping have been recently investigated by Ben-Dor, Patkin, Banin, and Karnieli (2002) and Taylor and Dehaan (2000).

2.3 Crop-Type Classification

Using remote sensing data to identify crop types is common, since these data cover large areas in various temporal and spatial scales. The classification of different crop types is based on their varying reflectance characteristics in the course of the year and hence considers nearly always the temporal component. Previous studies on crop-type classification differ concerning the applied method, the number and type of data sets, the study area and thus the crop types to differentiate, as well as the availability of field and training data. There is consequently no consistent crop-type classification approach due to multiple regional conditions and characteristics.

Since the early 1980s, crop types were distinguished using temporal and spectral characteristics (Badhwar 1984; Odenweller and Johnson 1984). Time periods with highest differences between crop types are often previously identified (Bargiel 2017; Blaes et al. 2005; Conrad et al. 2014; Foerster et al. 2012; Waldhoff et al. 2017). Also, hierarchical classification approaches are already effectively used for crop-type mapping (De Wit and Clevers 2004; Forkuor et al. 2015; Villa et al. 2015; Wardlow and

Egbert 2008) as well as the integration of expert knowledge to establish classification rules. For instance, Waldhoff et al. (2017) classified crop types in a similar study area in Germany and applied a knowledge-based approach in combination with supervised methods such as maximum likelihood and support vector machines. The classification of crop types in the early season has been examined in fewer studies (Conrad et al. 2013; Inglada et al. 2016; Osman et al. 2015).

2.3.1 The Study Area: The study area, located around the town Demmin in the federal state Mecklenburg-West Pomerania in Northeast Germany, is intensely used for agriculture. As part of the North German Plain, it was formed by three glacial periods and periglacial processes. The contemporary young drift morainic landscape is composed of numerous lakes, bogs and water systems as well as of characteristic glacial landscape elements such as flat, extensive sand regions, hills and sinks (Ratzke and Mohr 2005). The streams Peene, Tollense and Trebel with their up to 1.5 km broad valleys are used as grasslands and traverse the study area in ancient glacial valleys. Besides agricultural lands and pastures, pine and deciduous forests as well as wetlands spread over the area. The soils are mainly sandy and loamy (Ratzke and Mohr 2005).

With a mean annual ground temperature of 8.8^{0}C and a total annual precipitation of about 600 mm, the region is located at the transition zone between continental and maritime climate (Deutscher Wetterdienst 2017). In the course of the climate change, a lower summer precipitation with the risk of droughts as well as increasing temperatures is expected (Zacharias et al. 2011).
Out of the 1.34 million hectares of agricultural land, which is 57% of the total area of Mecklenburg-West Pomerania, 80 and 20% are used as cropland and grassland, respectively (Ministerium für Landwirtschaft 2015). The main cultivated crop type is winter grain (winter wheat, winter barley and winter rye), which is cultivated on 52.3% of the cropland. Also, rapeseed (22.7%) and corn (around 8%) grow on large areas. Root crops like potatoes and sugar beets are cultivated on around 10% of the cropland (Ministerium für Landwirtschaft 2015). Since 2017, DEMMIN is an official German test site of the Joint Experiment of Crop Assessment and Monitoring (JECAM), which is an initiative developed in the framework of GEO Global Agricultural Monitoring (Emmerich 2017). The test site covers an area of over 1200 km22.

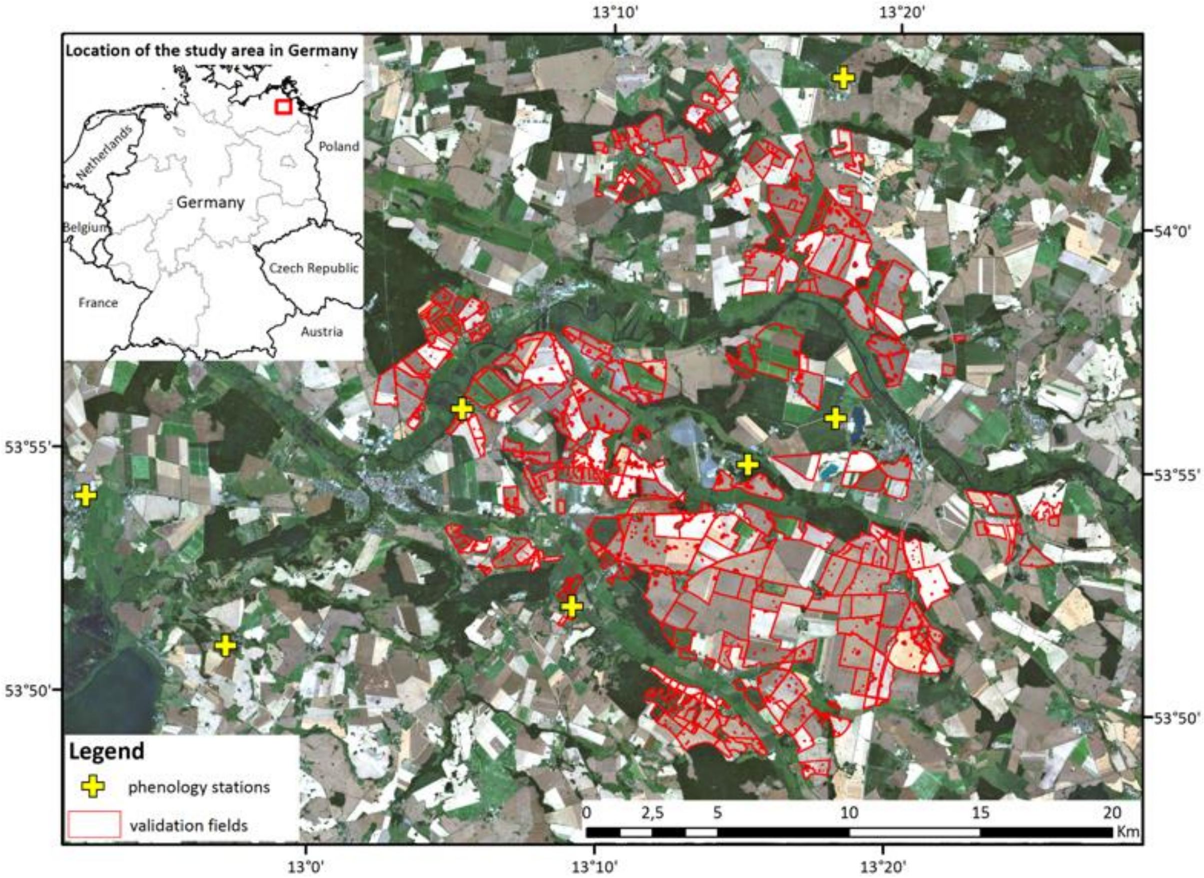

Fig 2.5: Study area DEMMIN with validation fields and phenology stations

Most studies are obligatory dependent on ground reference data to calibrate the classification. Furthermore, crop types are often classified at the end of the growing season, thus classification results are not available before summer. We present a progressive algorithm to classify crop types from the beginning of the growing season in early spring. It was developed in the growing season 2015 and tested in the growing seasons 2015 and 2016. Instead of classifying all fields backwards, the classification results are updated when a new satellite image is available. Current crop-type classifications with additional information about reliability and stability are processed and iteratively improved and updated during the course of the year. Seven different crop types are to be distinguished based on fuzzy c-means clustering.

2.3.2 Remote Sensing Data: Satellite imagery of four different multispectral sensors were used for the crop-type classification. The NASA satellites Landsat-7 and Landsat-8 provide images every 16 days with a spatial resolution of 30 m. They are available free of charge.

The semi-commercial RapidEye satellite constellation provides images with high spatial (6.5 m) and temporal resolution. Images of the ESA satellite Sentinel-2A are available since late 2015. With a high spatial resolution of up to 10 m and a very high temporal resolution of 5 days, these data are notably useful for crop-type classification and are available at no charge (Immitzer et al. 2016).

In total, 36 satellite images were available from March till end of August 2015, including 22 RapidEye images, ten Landsat-8 images and four Landsat-7 images. In 2016, 47 satellite images from March till August were used for the crop-type classification. Among them, 8 images were acquired by Landsat-7, 4 images by Landsat-8, 19 by RapidEye and 16 by Sentinel-2A. Not every image covers the entire area; furthermore, some images are disturbed by clouds.

The use of data from different sensors is appropriate for crop analysis since the data availability is restricted in terms of atmospheric effects like clouds and shadows as well as of the repetition rate of the satellites over the study area. Since the vegetation appearance changes quickly in the course of the phenological cycle, a high observation density particularly in key phenological stages may be promising to optimize the separation of crop types.

2.3.3 Field and Cultivation Data: The crop-type classification is object based; therefore, polygons representing field borders are required. Borders of large field units are provided by the ministry for agriculture, environment and consumer protection of the federal state Mecklenburg-West Pomerania. These polygons represent connected agricultural areas with nearly stable outer borders, which are cultivated with one or more crop types by one or more farmers. However, the locations of single cultivated crop types within these field units can change between different years.

To validate the classification results, actual cultivation data are needed. They are provided for selected fields by local farmers. Additionally, they provide current field borders within field blocks for the appropriate year. The average field size in the study area is around 45 ha. In 2015, 295 validation fields were available. They cover an area of over 150 km22. The classification for 2016 was performed using the manually adjusted field borders of 2015, whereas only 57 fields of around 35 km22 were available for validation in 2016.

2.4 Climate Change Monitoring

Climate can be defined as the average weather condition of a place. Its factors include: humidity, degree of temperature patterns, wind, seasons, precipitation, etc. The natural ecosystem of a place is greatly affected by its climatic patterns/condition. Thus, the consistent increase in temperature, flooding, tornados, hurricane, drought, etc. that has been observed overtime, and has been predicted to continue, has been ascribed to climate change and the general consensus in the scientific community is that human activities accelerates the rate climate change.

Monitoring of the causes and effects of climate change has proven to be difficult because of its very nature, as a result of the fact that it takes place over a long period of time and over a large geographic area. Although measurements can be taken on site, however, because of its global and remote nature, climate change monitoring is done remotely through Remote Sensing networks and satellite sensors. The information gathered is used in evaluating and predicting the present and future effects of climate change.

For the purpose of this discussion, we will be looking at the effect of climate change on agriculture and how Remote Sensing is used to mitigate this effect. The following are some of the effects of climate change:

- Rapid growth in the intensity and frequency of natural disasters such as drought, flood, etc.
- Unpredictable rainfall patterns.
- Distortions in the timing of seasons.

However, as a result of the application of Remote Sensing, changes in climatic conditions can be earlier detected so that adequate measures can be put in place to mitigate its effect.

The following is an image showing Ice Age maps for spring 1989 And 2009 Showing large changes in age coverage

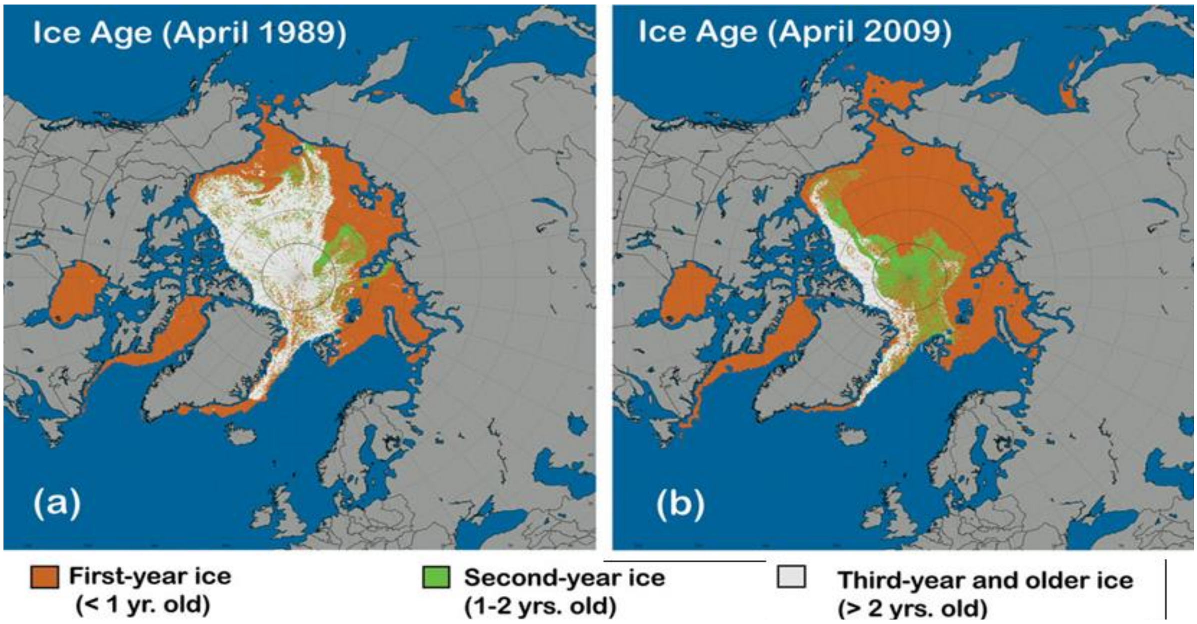

Fig 2.5 From J. Maslanik, C. Fowler, Univ. Colorado. NASA MEASURES Project.

2.5 Pest and Disease Control

Pests and diseases cause serious economic losses in yield and quality of cultivated plants. As a result, detecting and assessing their symptoms is very paramount and of utmost importance in commercial agriculture and that's where remote sensing comes in.

In time past, disease and pest damage assessment in plant populations is being done by visual approach, i.e. relying upon the human eye and brain to assess the incidence of disease or pest in crops. However, the problem with the traditional approaches is that they are often time-consuming and labour intensive.

Therefore, there is a need to develop different approaches that can enhance or supplement traditional techniques. Remote sensing has been used in agriculture for many decades. One of its earliest applications was on crop disease assessment. Reflectance data was found to be capable of detecting changes in the biophysical properties of plant leaf and canopy associated with pathogens and insect pests. Additionally, remote sensing may provide a better means to objectively quantify disease stress than visual assessment methods, and it can be used to repeatedly collect sample measurements non-destructively and non-invasively.

Studies on the use of remote sensing for crop disease assessment started long time ago. For example, in the late 1920s, aerial photography was used in detecting cotton root rot.

The use of infrared photographs was first reported in determining the prevalence of certain cereal crop diseases. In the early 1980s, aerial colour infrared photography was used to detect root rot of cotton and wheat stem rust. In these studies, airborne cameras were used to record the reflected electromagnetic energy on analogue films covering broad spectral bands. Since then, remote sensing technology has changed significantly. Satellite based imaging sensors, equipped with improved spatial, spectral and radiometric resolutions, offer enhanced capabilities over those of previous systems.

Pathogens and pests can induce physiological stresses and physical changes in plants, such as chlorosis or yellowing (reduction in plant pigment), necrosis (damage on cells), abnormal growth, wilting, stunting, leaf curling, etc. Incidentally, these changes can alter the reflectance properties of plants. In the visible portion of the electromagnetic spectrum (approx. 400nm to 700nm), the reflectance of green healthy vegetation is relatively low due
to strong absorption by pigments (e.g. chlorophyll) in plant leaves. If there is a reduction in pigments due to pests or diseases, the reflectance in this spectral region will increase. found that reflectance in the red wavelengths (e.g. 675–685nm) contributed the most in the detection of ‘sclerotinia’ stem rot infection in soybeans.

At about 700nm to 1300nm (i.e. the Near-Infrared Portion (NIR), the reflection of healthy vegetation is significantly high. With a disease or pest that damaged the leaves (e.g. cell collapse), the overall reflectance in the NIR region is expected to be lower. On stress in tomatoes, induced by late blight disease, it was found that the near-infrared region, was much more valuable than the visible range to detect disease in a different spectral region of the shortwave infrared (SWIR) range (1300nm to 2500µm), the spectral properties of vegetation are dominated by water absorption bands. Less water on leaves and canopies will increase reflectance in this region. noted the key role of the SWIR narrow bands in the spectral discrimination of healthy and diseased (orange rust) sugarcane crops.
Hyperspectral remote sensing increases our ability to accurately map vegetation attributes.

Images acquired simultaneously in narrow spectral bands may allow the capture of specific plant attributes (e.g. foliar biochemical contents) previously not viable with broadband sensors. Although the broadband multispectral sensors may be helpful in discriminating diseased and healthy crops, the best results for identifying diseases were obtained with hyperspectral information. Thus, there are indications that the use of hyperspectral sensing can be valuable to disease/pest detection and crop damage assessment. Our present study aspired contribute to the body of knowledge of how spectral data can be utilised to enhance crop disease and pest assessment.

A Case Study On the Use of Remote Sensing in Pest And Disease Control

The study area is located near Toowoomba, Queensland, Australia. With sub-tropical climate, the site is part of a smallscale (approx. 0.25 ha) organic, pesticide-free garden of various vegetable crops. The tomato crops were affected by a fungal "early blight" disease (*Alternaria solani*), with symptoms characterised by a yellowing senescence (chlorosis)
and drying-off of the affected leaves. Conversely, the eggplants exhibited skeletal interveinal damage on mostly older leaves that created irregularly shaped "holes"
These symptoms were characteristic of leaf damage caused by the 28-spotted ladybird (*Epilachna vigintioctopunctata*).

The research was carried out using a handheld ASD *FieldSpec Pro FR* spectrometer operating in the 350nm to 2500nm range, sample measurements of diseased/infested and non-diseased/non-infested leaves were collected separately from the tomato and eggplant crops. Following the sampling procedures and considerations provided in the User's Guide, each sample corresponded to a field of view of about 1.5 cm diameter, collected between 1030 to 1200 hr on 10th February 2005. While there was no ordinal measurement scale used to categorise disease severity, the "diseased" or "insect-infested" samples were taken from leaves where symptoms are visually obvious.
NB; Further details of this research was withheld due to the nature of this article. The following conclusion was drawn up from the research;

This study demonstrated that it is feasible to detect the effects of insect pest and disease in vegetable crops using hyperspectral measurements (Remote sensing). Different sets of pest and disease symptoms provided different sets of diagnostic spectral regions.

The most significant spectral bands for the tomato disease prediction corresponded to the reflectance red-edge, as well as the visible region and part of near-infrared wavelengths. For the eggplant's insect infestation, the near infrared region was identified by the regression model to be as equally significant as the red-edge in the prediction.

However, the inclusion of the shortwave infrared bands as significant variables has indicated the effect of other contributing factors. It was recognised that the use of a portable field spectrometer can provide a means for rapid observation and digital recording of hundreds of plant samples in a few hours of scouting through the fields.

Combined with Global Positioning Systems (GPS) location data collected simultaneously, field level maps can be created by spatial interpolation among the sampling points. By creating spectral libraries of specific crops comprising a wide range of healthy and diseased crop spectra, such site-specific crop data can be used routinely with various spectral-matching type algorithms for automated detection of disease spots. More work is being done to test other analytical techniques (e.g. SIMCA) to substantiate the results obtained in this study, as well as to analyse the data collected from other vegetable crops with disease severity ratings.

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