Unit - 3 Utilization of multisensors and data fusion in precision agriculture

3.1 The necessity of multisensors network utilization for agriculture monitoring and control:

Multisensory networks in agriculture are mostly designed aiming to serve different needs regarding event detection and timely intervention for site specific operations like monitoring and control.

Multisensory networks are deployed to gather information so as to give actionable insights that can enable timely intervention in case of preventing situations leading to yield loss or quality degradation.

Information fusion can be defined as the discipline that maximizes the information content of the combined data in order to reach improved inferences

Data fusion in precision agriculture comprises of the efficient and proper combination of numerous and heterogeneous data from different sensors aiming to provide actionable insights, which lead to decisions for most cost effective and sustainable crop management adaptation.

The necessity to offer a customized solution with the help of multisensory networks depends heavily on the application objectives. Inevitably, this affects the type of processing that needs to be applied as well as the delivery and assessment.

The effective combination of multisensory networking and several information fusion algorithms, are capable of reducing the amount of data traffic leading to bottlenecks avoidance due to extracting features or decisions deriving from the raw data.

3.1.1 Proximal sensing:

In contrast with remote sensing techniques, in proximal sensing the sensor's distance from the observed object is less than a defined threshold which is usually in the range of few meters .

For soil and plant sensing, proximal sensing can be realized as a handheld apparatus, or vehicle mounted (in this case the sensing is performed while a vehicle that carries the sensor, scans a field).

In spite of the fact that the handheld version is not difficult to utilize, it is laborious and ineffective from a data collection point of view. contrasted with those gathered by the on-line versions, which can end up collecting 1000 readings/hour

This is fundamental to investigate the inside field spatial variability at high resolution to ensure effective site specific administration of both soil and crop utilizing variable rate approaches.

3.1.2 Proximal crop sensors:

Recently, proximal crop sensing has become highly appreciated as a way to assess crop health status in natural, forestry and agricultural environments.

In situ strategies incorporate leaf-level to canopy level estimations from different devices including portable sensors, static equipment (e.g., tripods) and vehicles that carry the sensors in the field area. Furthermore, laboratory proximal sensors can assess the crop health status for the efficient agrarian administration.

A few proximal crop sensors are being utilized for serving research or business operations, through adapting optical, laser scanners and ultrasound sensing technologies.

The most utilized sensing techniques in proximal crop sensing are based on optical sensing principles.

Data obtained utilizing ordinary cameras are 2D projections of this present reality in a single frequency or multiple frequencies. RGB information usually concerns the red, green and blue wavebands, mimicking the human vision.

Information at other, non-perceptive frequencies captured by sensors, for example, a Color Infra-Red (CIR) camera, which gets multispectral information at certain VIS-NIR frequencies. The standard method to visualize these wavebands is utilizing separate dark white pictures or false shading pictures.

At the point when the leaf stomata shut during daytime, basic metabolic activities of the plant such as the circulation of CO2 and H2O within the plant, provoke an inner nursery impact in the leaf area. A worldwide increment in leaf temperature can be considered normal in the occasion that warm radiation is high (for example, due to sunlight or halogen illumination, and so on).

A common reaction of plants is the closure of their stomata when are subjected to water stress, subsequently this condition increases their temperature.

Thermal imaging employs a special lens that concentrates the infrared radiation (IR) radiated by plant canopy or different plants areas.

Nevertheless, plants have the tendency to shut their stomata when they are experiencing water stress and by this, their temperature increases.

Other ecological factors, for example, environmental temperature, daylight or wind speed can influence canopy or leaf temperature, thus limiting its functional activities (Mahlein, 2016).

3.1.2.1 Proximal sensors for crop biotic stresses:

Here we concern about the weed detection and crop infections.

Weed detection

Weed detection has demonstrated by implying proximal sensing with Weed seeker . The Weed seeker utilizes a functioning light sensor producing red (R) and NIR radiation, and finds alterations in reflectance from exposed ground versus weeds between crop rows lines. However, the Weed seeker is not capable of discriminating weeds from main crops or weed species from another.

Weedseeker has effectively demonstrated that herbicide application rates can be decreased by 90%, along these lines lessening herbicide expenses and environmental impact .

A subsequent way to deal with local weed detection is computer imaging, which depends on shape recognition. Weeds and plants have various shapes, and dependent on this distinction, weed detection is conceivably realistic though image processing techniques.

Weed detection incorporates two stages:

(a) recognize weeds that have attacked a field and separate them from the crops and

(b) identify the weed species, if different weed species have been set up in the field, so as to have the option to utilize the correct herbicide for application.

It is difficult to detect weeds, the recognition of their species is not a simple task because of a wide range of weed classes. Image processing has the efficiency of separating among weeds and crop plants.

Crop recognition is a complementary task with respect to weed identification. In specific circumstances, the assignment is less complicated as crops have a uniform outlook contrasted with the weeds.

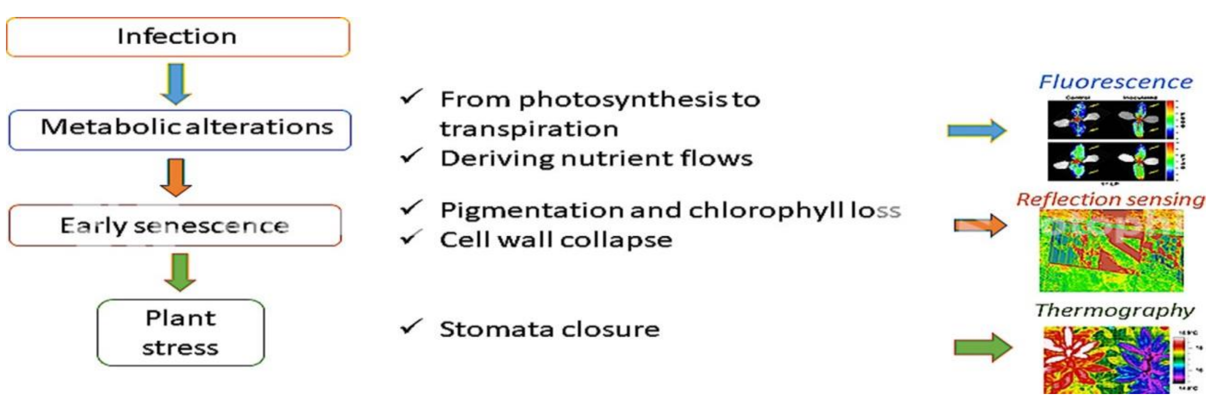
Image processing was utilized to apply a two-strategy approach, keypoint-based arrangement and Object Based Image Analysis examination (OBIA), to separate between sugar beets and different weeds.

Plant disease detection in field conditions:

The detection of plant disease under field conditions by proximal sensors has shown high evidence. The standard emerges from healthy crops and how they behave with respect to VIS and IR light in other spectral bands in comparison with contaminated crops.

Disease detection uses the range of spectral bands from crop, The reflected light has a unique signature as a spectral reflectance bend in the VIS range between (400–700 nm), the NIR area (700–1200 nm) .

Healthy leaves contain high water concentrations accordingly they carry emanating radiation at TIR band 10 µm proportionally to their temperature. Alterations of plant leaf reflectance are related with leaf structural changes. Diseases detection techniques can be performed dependent on light reflection for various wavelengths .



The overall leaf temperature changes quickly, in any case, and is intensely reliant on surrounding temperature, lighting and wind. In this manner, thermography may give poor outcomes utilizing proximal detecting stages in light of changing natural variables.

The strategies give increasingly solid outcomes if illnesses are fully developed and infections are high. Certain alterations in the spectral features of plants profoundly offer the possibility to utilize optical signals to distinguish the occurrences of diseases in crops.

Disease detection using light reflection:

Changes in reflectance of violet-blue and NIR wavebands (380–450 nm and 750–1200 nm) were utilized to identify early contaminations of cucumber leaves by the fungus called Colletotrichum orbiculare.

Diseased plants were described by decreased photosynthetic activity because of diminished stomatal conductance. VIS ,NIR reflectance changes can breakdown the leaf cell structure with the spread of the fungus in diseased plants .

Early detection of leafroll sickness can be distinguished even at a pre-symptomatic stage ,This was for the most part because of the negative impact of the virus infection on the plant physiology bringing about changes in metabolic activities and pigmentation.

The viability of the identification of infections relies upon the algorithms utilized for data processing. Hyperspectral imaging strategies can be utilized for each crop disease framework to improve and naturally identify diseases. This should be possible through simple ANN models.

The recognition of crop infections in an automated way at an initial stage of infection by utilizing a multipoint spectral camera and a multispectral camera.

The recognition between concurrent yellow rust contamination and N stress has been demonstrated by utilizing hyperspectral imaging and ANNs.

Smartphone apps for proximal sensing of biotic stresses

Crop exploring is upgraded by a wide selection of free and low cost, simple to utilize and user friendly applications for smartphones . Smartphones are ideally fit to help crop scouts as they stroll through fields, since they can take high resolution photos, which can be used to find known weed, insects or disease stresses. There are various smartphones versatile applications to identify biotic stresses.

There are IOS or Android OS applications, for example, ID Weeds which enables clients to look photographs for a particular weed or enter attributes of a weed so as to let the application distinguish it.

South Dakota State University in the USA built an application to distinguish diseases in soybeans. This application incorporates photographs of basic crop diseases and estimate the infection rate . More advanced applications like these have additionally been produced for use in developing countries.

Progressively complex applications include the harvest scout to take photographs of the weed, insects or diseased plants. These photographs are sent to a local specialist who at that point analyzes the assess the severity and disease type.

Proximal sensors to measure crop abiotic stresses:

The primary causes of abiotic stress are the absence of water, extremely high and low temperatures and insufficiency of crop nutrition (e.g., N, P and K). Plant reactions to abiotic stress are same as the reactions to biotic stress, for example discoloration of leaves such a yellowing and browning, loss of leaves, delayed growth, and diminished crop yield. The principle focal point of this segment is on photography and imaging and spectroscopy procedures for the estimation of abiotic stresses.

3.1.2.2 Basic principles of visible, near infrared and mid infrared spectroscopy:

VIS-NIR (400–2500 nm) and MIR (2500–25,000 nm) reflectance spectroscopy are techniques with low environmental impact ,they are used to know field soil conditions, particularly the VIS-NIR spectroscopy.

Since soils are a blend of mineral and Organic Matter (OM), When soil is exposed to a light source, some portion of the light is absorbed, and other part is reflected out of the soil. light diffusion and absorption that varies because of the physical and chemical Composition of the soil.

3.1.2.3 X-ray fluorescence (XRF) spectroscopy:

XRF spectrometry is one of the most effective proximal soil detecting strategies .The intensity of the fluorescence radiation in a given sample are utilized to perceive and decide their concentrations.

XRF has numerous advantages as it is quick, non-destructive, and compact, which is fundamental for in situ estimation. XRF has additionally a few impediments as it is volatile to matrix effects and moderately costly to run; in addition its investigation is slower contrasted with VIS-NIR and MIR spectroscopy.

portable XRF (PXRF) spectrometry has now turned out to be accessible, for on location, fast estimation of soil contaminants.

Swanhart et al. (2013) utilized PXRF to assess salinity of soils attained from coastal areas in USA utilizing chlorine (Cl) as an intermediary, detailing strong connections between PXRF Cl and saturated paste electrical conductivity and between PXRF Cl, S, K, Ca and saturated paste electrical conductivity .

Sharma, Weindorf, Man, Aldabaa, and Chakraborty (2014) assessed the possibility of utilizing PXRF for pH determination utilizing elemental data as a proxy for soil pH.

Generally, PXRF instruments are found in the market with ready calibrations for various soil properties. But, like within the VIS NIR or MIR spectroscopic analysis, mentioned before, XRF spectra are often employed to develop customer-built calibration, using statistics or machine learning tools.

3.1.3 Remote sensing:

Remote detecting is the estimation of soil or yield attributes, by UAVs or satellites from distances running from several meters, to numerous kilometers from the objective.

Remote sensing in farming depends on the collaboration of electromagnetic radiation with soil or plant material. remote sensing includes the estimation of reflected radiation versus retained radiation.

Remote sensing includes the estimations of radiation reflected or produced from horticultural fields .The utilization of remote sensing resources is useful for crop classification, which incorporates crop development demonstrated as Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), biomass, crop thickness, yield potential estimation, recognition of insects, weed ,water pressure, N, P, K.

The Utilization of remote sensing for gathering information on soil is confined to 2–3 mm of the soil.

UAVs acquires information from 2 m to 100 m distance though satellite sensing attains information from a several hundreds kilometers over the crop .The imaging sensors cover VIS, IR, thermal and microwave spectral range. They are intended to procure single band pictures, like thermal or microwave multispectral pictures with a few bands in the VIS NIR, or hyperspectral pictures with hundreds of bands in the VIS-NIR.

Inside the electromagnetic range, the most well-known wavelengths that are utilized for crop monitoring applications are green, red and NIR. Plant pigments overwhelm the reflectance of vegetation in the VIS wavelengths. Chlorophyll absorbs red and blue energy and reflects green. Leaves cell structure and canopy structure overwhelm the reflectance of NIR, with healthier vegetation producing high reflectance. Hypothetically, NIR and red reflected energy could be evaluated to gauge plants development improvement, the quantity of vegetation biomass, or even their health status.

The fundamental standard of LiDAR functioning is the estimation of the distance between the sensor and the object, through deciding the passed time between a laser beam outflow and the arrival to the sensors' receiver. Increasing this time with the speed of light and dividing by two to represent the doubled distance voyaged, gives an exact gauge of the distance between the sensor and the object. At the point when the sensor is loaded on an airborne vehicle, it gives a transect of detailed data acquisitions concerning the canopy and ground, where gaps appear.

Preparing these estimations creates an exact depiction of the canopy stature, an Digital Surface model (DSM). An issue identified with canopy stature estimations utilizing LiDAR incorporate the powerlessness to decide the ground surface height in thick or complex canopies or the highest point of the canopy in sparse vegetation. An elective strategy for evaluating an DSM from UAV picture stereopairs is utilizing the structure from movement (SfM) calculation, which is a photogrammetric method that was at first produced for archeological locations .

SfM is for the most part recommended when pictures were procured by value for money cameras on board UAVs, as opposed to costly metric cameras, which follow photogrammetric strategies and require high ability.

3.1.3.1 Remote earth observation for crop diseases identification:

Crop biotic stresses can emerge from weeds, insects or infections. Biotic stress cause serious monetary harm to crops when limits for occurrence of the stress are exceeded. Early recognition of biotic stress is basic for control through practices that incorporate tilling, spraying, or IPM. In any case, early discovery of biotic stresses is demanding (Pinter Jr et al., 2003). At the initial stage of infection, weeds are small and hard to recognize from crops. Insects and sicknesses may cause no discernible marks of crop damage at beginning periods of invasion. At later phases of expansion a crop harm can show up as spots or stripes of varying hues (e.g., yellow, dark, or white). Also, leaves can twist or shrivel and crop biomass can be decreased. In regular agribusiness, crop exploring is utilized to survey the rate and occurrence of the biotic stresses. Domain specialists regularly scout fields for biotic stresses at fixed growth crop stages dependent on historical records of developing degree days, wind and moistness patterns that are known to advance development of weeds, insects or diseases. Exploring happens in constrained zones of the field, ordinarily along edges and in w or z patterns that can be effectively crossed by strolling. Subsequently, exploring may miss viewing clusters of a biotic stress in remote zones from these pathways. These bunches of pressure can quickly grow if not identified, causing expansive crop harm. Remote detecting offers the likelihood of quickly studying huge regions of a field for biotic stresses dependent on images gathered by utilizing satellites, planes, or UAVs. Every one of these platforms has clear pros and cons (Mulla, 2013). Be that as it may, recognition of biotic stresses at beginning periods of occurrence, makes an especially significant requirement for high resolution imagery. Indeed, even with high resolution imagery, biotic stress detection has demonstrated considerably more difficult than abiotic stress detection, as biotic stress indicators may not be identified at the leaf area or canopy until seriousness of disease raises beyond the threshold levels

3.1.3.2 Weed detection:

Early identification of weeds utilizing remote detecting regularly depends on segmentation of images to separate weeds from soil or from growing crops. Segmentation of weeds from crops has proven to be feasible utilizing high goals remote sensing imagery .Segmentation attempts to initially distinguish the area of harvest columns dependent on the assumption that crop lines are linear. As a subsequent advance, green vegetation varying in area from crop lines is delegated a weed. Segmentation alone can’t separate between various weed species. Precision of weed segmentation techniques varies, relying upon the degree of shadows in crop rows and overlap between leaves of crop and weeds. Weeds patches inside a crop row or in crops that are not cultivated in columns like the little grain crops, can’t be separated from crops through employing segmentations techniques.

Crop row detection through utilizing segmentation regularly depends on analytical strategies, for example, the basic Hough transform (Montalvo et al., 2012). The Hough transform requires that panchromatic pictures be changed over into grayscale ones, which are then renamed into binary classes, one corresponding to vegetation and the other to soil. Straightforward Hough transforms depend on iteratively assessing the angle and the distance from origin of all lines going through a plant in a crop row, and repeating this procedure with every other plant. The line that goes through most of part the plants in the column is assigned as the line. Clearly, this methodology works best for straight columns.

Recognition of bended columns is conceivable utilizing a Generalized Hough Transform (Mukhopadhyay & Chaudhuri, 2015). The Hough transforms and their variations are generally used to recognize crop rows in PA because of their sturdiness to planting skips and failed development. Be that as it may, Hough transform, regularly do not manage to precisely recognize crop rows in the events of high weed weight, where overlapping between weeds and crop occur.

Pen˜a, Torres-Sa´nchez, de Castro, Kelly, and Lo´pez-Granados (2013) utilized a UAV equipped with a multispectral TetraCam with 2 cm spatial resolution to label different growth stages (V4-V6) at a spanish maize field into areas with high (>20%), medium (5–20%) and low (0.2 and object oriented order were utilized to detect yield and weeds from soil, and after that to recognize weeds from crop. Weed inclusion was then mapped in pixels of measurement of 1m0.7m.

Brilliant understanding (R2 ¼ 0.89) was gotten between ground truth observations and UAV based estimations of weed occurrence Tellaeche, Pajares, Burgos-Artizzu, and Ribeiro (2011) utilized segmentation and SVM calculations to effectively recognize regions with over the top abundant wilds oat weed presence in a small field of cereal. SVM method is an administered grouping approach for separating data that possess two conditions (e.g., weed inclusion and weed weight) just as a binary decision label (e.g., spray weeds or don't spray weeds) into two classes having the best separation across a hyperplane separating the two classes from each other.

Maximum Likelihood classification produced from spectral signatures was precise at recognizing leafy spurge from green vegetation at the principal study site, however it failed at recognizing leafy spurge from different weeds and forage crops at the second study field. Ikonos images was not capable of recognizing areas at either study field that included leafy spurge patches that of 200 m2 size or with a weed spread less than 30%. Higher goals satellite images, for example, images attained through employing the GeoEye-1 (with a spatial resolution of 1.84 m) or WorldView-2 (with a spatial resolution of 0.46 m) satellites would hypothetically permit weed patches having a size of 16 m2 or larger to be identified (LopezGranados, 2011)

3.1.3.3 Detection of insects:

Biotic stress caused by insects or disease presence utilizing spectral indices got from remote sensing images has to a great extent not been economically reasonable. The main reason behind this is side effects of insects or disease occurrence are ordinarily not detected by remote sensing images at the beginning of presence. At beginning periods of populace development, insects may dwell on the lower sides of leaves or in crop roots, where they are not noticeable utilizing remote sensing imaging. A wide scope of remote detecting methodologies have been utilized to identify insects and diseases at later phases of pervasion under wisely controlled conditions when just one kind of insect or infection harm appears (Pinter Jr et al., 2003).

Insects and diseases harms in these cases can be recognized through utilizing different spectral indices dependent on VIS-NIR reflectance, combined with Partial Least Squares Regression (PLSR) analysis or AI models. Insects and diseases presence normally cause higher reflectance, most of the times due to lower absorption at blue and red wavelengths because of lower concentrations of chlorophyll pigments, and lower reflectance at NIR wavelengths because of lower biomass. Green and red-edge wavelengthslikewise may react to an assortment of biotic crop stresses. Generally utilized spectral indices for biotic stress involve NDVI, Green NDVI, Red Edge NDVI, and Soil Adjusted VI (SAVI). In any case, these spectral indices are not indicative of a particular insect or disease presence, and frequently react similarly also to other biotic or abiotic stresses, including nitrogen (N) insufficiency.

Some examinations employing satellite remote sensing have been carried out aimg to recognize insect harm in crops . Satellite remote sensing of insects presence is fundamentally used to recognize the area and greatness of woodland extent .Normally, changes in NDVI values from consecutive satellite pictures gathered crosswise over enormous forested regions at moderate to low spatial resolution are utilized to find the trees defoliation due to insects presence. UAVs have the capability of insect effect recognition compared to satellites due to their spatial resolution, less effect because of cloud cover and an expanded capacity to get images at basic phases of insects invasion and development.

Hunt and Rondon (2017) demonstrated that harms to potato crops from Colorado potato beetles could be distinguished with UAV images inside one day of an expansion in invasion. Recognition of harm depended on changes in crop height from one day to another, utilizing potato canopy cover remaking with Structure from Motion (SfM) and Object Based Image Analysis (OBIA). Identification of insects invasion was more exact with this method than with one that is dependent on recognizing when UAV based vegetation indices lowered under a basic limit esteem.

Puig, Gonzalez, Hamilton, and Grundy (2015) utilized K-means grouping of high resolution RGB imaging acquired though utilizing a UAV in order to characterize white grub harm in a 6 ha Australian field, cultivated with sorghum. Groundtruth perceptions were utilized to distinguish regions of the field with heavy, moderate and no insect harm. Before K-means clustering, images was smoothed for high frequency noise utilizing a Gaussian convolution kernel applied to the red, green and blue parts of images separately. K-means clustering effectively classified insects invasion in the field, heavy on 1.7 ha, moderate on 1.1 ha and no insect harmed on 3.2 ha. It ought to be noticed that there were no yield stresses other than white grubs in the investigated field area. In this manner, it is vague whether the methodology introduced by Puig et al. (2015) could be spreadable to different fields where changes in crop biomass occur because of stressors other than white grubs

3.1.3.4 Remote sensing for crop abiotic stresses:

The role of remote sensing information in the field of PA is to survey crop condition in the field, to trace homogeneous zones, and describe and examine them to create recommendation maps for variable rate application (VRA) of inputs, like fertilizer, pesticide and water.

Remote sensing data information regarding crop variability, plant health status and yield constraining factors that can have a positive impact on the crop productivity. While mapping crop variations requires basic remote sensing information at several times in a season, basic decision making requires increasingly advanced remote sensing at high temporal and spatial resolutions

3.1.3.5 Remote sensing for prediction of yield productivity:

Yield and biomass prediction

One of the primary targets of PA is the precise and effective expectation of crop development and yield. This practice is mainly followed by farmers and leaders to agricultural consultants during the crop growth season. Notwithstanding accessibility of soil supplements, crop genotype and farming management practices, crop improvement is a function of meteorological conditions, for example, temperature, daylight and precipitation. Harvest crop growth models recreate these connections to anticipate the expected yield and biomass improvement. It is basic to take note of that crop yield prediction or yield potential will be profitable to farmers for raising the expected yield.

Crop models are arranged in two principle classes, in view of their structure; to be specific, powerful models and observational models. Dynamic models, likewise called procedure based models, which recreate the improvement of the yield utilizing differential conditions (Rauff & Bello, 2015). These models require countless info parameters to assimilate the natural conditions (Lobell & Burke, 2010). Empirical models, otherwise called measurable models, are presented as relapse conditions with one or couple of parameters. These models require less information than dynamic models. Empirical models are helpful to gauge harvest yield in specific situations to give valuable information to policymakers. A constraint of experimental models is that they can't gauge crop yield without historical data and they can't be generalize to different areas than to those that have been initially used for calibration. Contingent upon the kind of model and the application, dynamic crop models may require a lot of information, which at times may confine their usability. Each crop model requires at least soil data, climate conditions, initial conditions and the management practices.

Since the early advancement of crop models, agrarian researchers have exploited the accessible remote sensing images to improve models' performance, screen crop biomass, phenology and crop yield at scales ranging from field or sub-field level to territorial and national. The primary benefit of fusing remote sensing information with crop models are the accurate depiction of the crop's condition during the growing season and the augmentation of the missing spatial data. Among all the accessible remotely detected parameters, LAI, NDVI and portion of ingested photosynthetically dynamic radiation (fAPAR) are the most ordinarily utilized for assessing crop yield.

AI is likewise utilized for yield prediction, while fusing remote sensing information. The arised models created through these architectures permit the investigation of variables that influence crop growth in an unsupervised manner (Elavarasan, Vincent, Sharma, Zomaya, & Srinivasan, 2018). They give a viable technique to look at the huge datasets and to extract insights from the acquired data so as to give a progressively significant understanding into the procedures impacting crop yield. Pantazi et al. (2016) employed three SOMs for wheat yield prediction utilizing NDVI information obtained from the Disaster Monitoring Constellation for International Imaging (DMCii) satellite pictures, just as VIS-NIR spectra were obtained from an on-line soil scanner (Mouazen, 2006). The performance of the employed SOM models exceeded 90% of accuracy, demonstrating that the models potential of predicting wheat yield and of labeling correctly the management zones.

3.1.4 Spectral and thermal properties of plants in a nutshell:

The VIS-NIR range (400–2500 nm): Green vegetation has very prominent spectral features in the VIS spectral portion: two chlorophyll pigment absorptions in the blue (450 nm) and red (680 nm) regions that bound a reflection in the green region (550 nm).

This explanation behind the ability of the human eye seeing healthy vegetation as green. At the point when the plant is stressed that subsequently blocks ordinary growth and chlorophyll generation, there is less absorption in the red and blue bands and the measure of appearance in the red waveband raises. These bands were generally used to screen N content. The spectral reflectance signature in the VIS-NIR range implies an elevation in the reflection for healthy vegetation at about 700 nm. In the NIR range between 750 and 1300 nm, a plant leaf normally reflects between 40% and 80%, of the incident radiation; the rest is transmitted, with just about 5% being absorbed. For correlation, the reflectance in the green range reaches 15–20% of the incident radiation.

Far or Thermal Infrared (TIR) Range (3–14µ), plants assimilate efficiently the far infrared radiation at wavelengths greater than 2500 nm (2.5 µ) (Gates, Keegan, Schleter, & Weidner, 1965). Leaf temperature can be detected by estimating the far-infrared or thermal infrared (8–14 µm) radiation they transmit. Evapotranspiration is the procedure where water buffered in the soil or vegetation is converted over from the fluid into the vapor stage and is released to the air (Maes & Steppe, 2012). Water evaporation is an energy requesting process, elevates evapotranspiration rates, lowering consequently the surface temperature of leaves and plants. As plant stomata close, evapotranspiration rate diminishes; the energy heat balance between the vegetation and its status alters and leaf temperature rises. First approaches concerning the employment of canopy temperature for characterizing the plant water status and plant health condition, were developed in the 1960s (Fuchs & Tanner, 1966). The accessibility of thermal cameras provoked a critical advancement of the thermal remote sensing during 2000s .

3.1.4.1 Spectral analysis methods to estimate N and water status in crop:

Spectral information in the VIS-NIR-short wavelength infrared (SWIR) range, split into multispectral and hyperspectral information. Multispectral imagery for the most part corresponds from 3 to 5 bands, which have a width of 20–100 nm. Hyperspectral imaging comprises of much smaller bands (1–5 nm), having hundreds of bands. As of late, the term super-spectral images was introduced, referring to satellites pictures that give more than 10–15 bands, some generally limited groups, particularly in the red-edge and water absorption areas. Basically, there are three fundamental strategies for spectral investigation: (a) spectralfiles, (b) band selection, and (c) linear and nonlinear multivariate statistics and data mining. The primary strategy is generally utilized for each of the three image types while the other two are for the most part used to break down hyperspectral pictures to address dimensionality complexity. An extensive amount of reference material was composed on spectral image investigation (Thenkabail, Lyon, & Huete, 2019), and the reader has the opportunity to get introduced to further information.

3.1.4.2 Nitrogen crop status:

Nitrogen deficiency belongs to one of the most significant crop abiotic stress to be identified, since it influences directly the yield profitability. An extra reason that makes the recognition of N deficiency significant is the way that N leaches below the root zone in the occasion that irrigation system or water administration is not proper, yielding conditions that are problematic for crop development. Numerous VIs have been created to gauge crop N status at leaf and canopy levels. A list of indices can be found in different works, for instance, in Tian et al. (2011). Most of the indices depend on surrogate markers generally of chlorophyll content, which is demonstrated to be physiologically connected to N concentration. Best-performing VIs incorporate common ratios in the red edge area, in the blue band and in the SWIR bands (1200–2500 nm), especially the 1510 nm band (Herrmann, Karnieli, Bonfil, Cohen, & Alchanatis, 2010).

The abilities of the VIs to foresee N content are influenced by different components such as crop type, growth stage, site, year, and spectral, spatial and temporal resolutions of the sensor. This fluctuation prompted the improvement of many indices, and numerous investigations appear to rehash a similar scenario: looking at all indices created until this point, one next to the other upcoming combinations of 2–3 bands that performed some way or another better with the new data sets gathered in the new feed campaign. Along these lines, new indices are continually created. The accompanying sequence of recent studies quickly shows that apparently endless improvement or fitting of indices. The Medium Resolution Imaging Spectrometer (MERIS) terrestrial chlorophyll index (MTCI) (Dash & Curran, 2004) is regarded as the best spectral index to be utilized for variable rate N supplementations in two fields cultivated with potato (USA) (Nigon et al., 2015). In an examination in some fields, cultivated with rice coming from various locations in China during four seasons the MTCI performed essentially more poor than another 3-band spectral index presented by Tian et al. (2011). The new index performed well utilizing ground spectra just as utilizing collected Hyperion satellite cube.

Moharana and Dutta (2016) investigated the spatial fluctuation of N content of rice from Hyperion cube in India, has presumed that in spite of the fact that the 3-band index proposed, gave great N estimation abilities, pursuing a totally different relationship. Along these lines, the new adjusted connections were better for mapping the spatial fluctuation of N content than the connections demonstrated by Tian et al. (2011). This succession of studies, demonstrated the significant impacts of crop type and sites.

3.1.4.3 Canopy/leaf relative water content (CRWC/LRWC):

Spectral features of water can be utilized to evaluate the leaf and canopy relative water content (LRWC/CRWC). For wavelengths easily affected to water retention, leaf reflectance diminishes as water content increases. Various examinations have demonstrated the capacity of spectral indices to define LWC, for instance, the early work of Hunt and Rock (1989), the investigation of Ceccato, Gobron, Flasse, Pinty, and Tarantola (2002), and later examinations for crops (Zhang & Zhou, 2015). While a different scope of vegetation indices have prior been produced for the remote estimation of CRWC. The majority of them are characterized for specific crop types and zones, making them less generally relevant (Pasqualotto et al., 2018). In a couple of studies, endeavors to utilize indices as derivations of reflectance values for individual wavelengths did not yield huge correlations regarding the canopy level It is particularly valid for early phenological stages, described by low fractional vegetation cover. However, strategies that utilize the entire range performed superior to commonly utilized water index indicators. An ongoing report proposed an index that depends on a spectral area difference that was appropriate for a wide assortment of crop types, having a R2 equal to 0.8, got utilizing an exponential regression algorithm, contrasted with less performing CRWC spectral indices.

3.1.4.4 Thermal image processing to predict water content in crops:

Thermal cameras gives multispectral pictures in the an area of 3–14 µm. However, the extensive research for assessing crop status in agribusiness was led with panchromatic images, which means there is no spectral dimensionality associated with the investigation of thermal pictures. Thus, the center of the thermal image processing is to change over the surface temperature to horticulturally important yield water status indices.

Leaf Water Potential (LWP) in crops and Stem Water Potential (SWP) in plantations are significant biophysical parameters that demonstrate the capacity of the crop to move water from soil to the environment by the leaf (Jarvis, 1976). The parameters LWP and SWP are utilized for water supply administration, since the water content isn't an indicator on whether the plant is capable of utilizing the available water. Literature provides constrained knowledge regarding to their remote estimation through applying hyperspectral sensing in the VIS-NIR area because they express the affection of water in the plant tissue. A recent investigation acquired average relationships between spectral indices features in the VIS-NIR area and SWP in vineyards. For this reason, they took advantage of the daily revisit time of the Planet-Labs satellites and high volume data corresponding to seasonal SWP estimations from dozens of vineyard fields.

L/SWP do influence the leaves' stomata condition, which are responsible for the evapotranspiration procedure and influence leaf temperature. A significant result of the stomatal closure, happening when plants are exposed to water stress is that energy scattering is lowered, so leaf temperature will in general ascent. The utilization of canopy temperature as a marker of plant water status was advanced by Idso and associates. Since canopy temperature is influenced by both plant water status and natural conditions, water stress indices that align the ecological conditions were created. The crop water pressure index (CWSI) in view of canopy temperature has turned into an efficient index to delineate field fluctuation of crop water condition utilizing thermal images.

3.1.4.5 Decision support for fertilization and irrigation regimes based on augmentation on remote sensed data:

Studies have demonstrated that actual N treatment is not really effective and the planning and rate of N application with the N crop needs during various growth stages may expand N Use Efficiency (NUE)

N content can be observed from multispectral and hyperspectral satellite images , N content can be supported by the utilization of the high spatial resolution of images.

Irrigation system basic decision support likewise profits by utilizing devices that screen water crop needs all through the season. Regarding irrigation system, the crop coefficient (Kc) strategy is a pragmatic and solid procedure for assessing evapotranspiration coefficient (ETc) (Allen, Pereira, Raes, & Smith, 1998), and has been employed by the farmers in different rural districts globally. Keeping that in mind, digital devices are accessible for farmer that keep (or help with storing) accumulated water needed for irrigation as directed by the crops type, growth stage and climate conditions.

From the abovementioned, it is inferred that for remotely-sensing supported uniform or VRN fertilizer application, the NSI is proposed to be applied through utilizing multi-otherworldly satellite imagery. Hyperspectral sensing can conceivably give extra data over multispectral sensing. Nonetheless, because of the absence of hyperspectral satellite frameworks with high spatial and temporal resolution, these tools are not yet utilized in currently followed cultivating practices (Hank et al., 2019).

Improvement of the spatial resolution of the airborne thermal images can likewise be accomplished by utilizing resolution that take advantage of the extensive overlap between consecutive pictures.

3.2 Data fusion background:

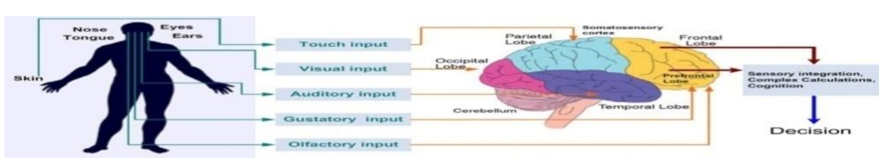
The human brain is incredibly proficient at learning from numerous sources. data flows from a variety of sensors are fused and organized by complex processing stages utilizing biochemical energy at the cerebrum.

For instance, someone in the assembly hall is hearing to a speech, the most significant data originates from the visual and hearing related sensory systems.

The cerebrum is accepting contributions from different senses (e.g., the temperature, the smell, the taste), it flawlessly suppresses these less applicable senses and keeps the focus on the most significant data.

The multiple senses of both humans and animals have contributed to the improvement of their survival capability. For instance, in fact the sense of vision is not reliable regarding the edibility of food but it has to be integrated with other senses like touch, smell, and taste.

Multisensor data fusion techniques have been applied extensively for several purposes. Primarily, they have been used in Department of Defence (DoD) applications for example automated threat assessment, vehicles and generally early defense systems.



Data fusion techniques have been further expanded so as to offer solutions to non military cases, including health monitoring, complex machinery management, safety and operations, crop monitoring, remote sensing and medical applications

Hall and Llinas (1997) defined data fusion as a combination of data derived from multiple sources including sensors and correlated information from various of relevant data streams. These data streams include Internet of Things and social networks that are used in order to reach more reliable .

3.2.1 Taxonomy of fusion architectures:

Sensor data can be fused, in many ways starting from sensor output to a processed level as state vector of features or fusion of decisions from each sensor.

The fusion levels are described as follows:

1. **Raw sensor data fusion** concerns data that can be directly combined and is feasible only in the case that the sensor data originate from the same physical manifestations of a natural phenomenon, for example data from a number of cameras or some sensors . Most of the raw sensor data fusion algorithms are based on classic detection and estimation principles

2. **Feature-level data fusion** concerns the production of relevant characteristics from raw sensor data that are correlated to the observed phenomenon. This method is employed often by specialists like artists aiming to bring easily to mind well-known figures. To perform feature-level fusion, the features are produced by processing several raw sensor data streams, and assimilated in a vector format by direct concatenation of feature values to produce one combined state vector that feeds into machine learning algorithms like neural networks either supervised or unsupervised to produce the fusion decision.

3. **The decision level fusion** concerns the augmentation of sensor based decisions, following the process of determining the identity and other semantic or categorical data about the observed phenomenon. Here we use Bayesian augmentation.

Taxonomies based on the semantic information level which are presented below:

1. **The centralised architectures** comprised of plain algorithms which cannot follow possible sensor alterations.

2. **The hierarchical architectures** are based on cooperative processing of sensor data and require bidirectional communication.

3. **The decentralized architectures** are characterized by robustness to sensor faults and operational alterations but a significant drawback of them is that require complex algorithms to function properly

3.2.2 Data fusion advantages:

The advantages of data fusion compared to classical algorithms include:

1. Increased confidence that is a consequence of the complementary nature of the antecedent sources of information;

2. Reliable navigation information regarding position and state estimation in noisy and rapidly changing environments (limited visibility, overlapping objects);

3. Elevated spatial and temporal covering of important regions of interest and effective tackling of the dimensionality of the input space;

4. Improved separability when comparing hypotheses thanks to fuller and more relevant information availability;

5. Increased system resilience with self-healing capability regarding operation in the event that one or more sensors are in a fault condition;

6. An effective solution for handling the big data that become available from sensor information and other sources like social media, remote sensing and open data repositories. The main criterion that concerns the optimization of fusion function is the minimal error of identification of the fusion decision compared to actual situation.

3.3 Data fusion applications in precision agriculture:

Precision Agriculture depends on a variety of sensors in order to assess the spatial variability in crop and soil characteristics that are needed for site specific management.

The different sensors carry complementary information regarding the crops, soil and the combination of sensor information in order to estimate accurately the crop and soil parameters. This combination of sensor information is the so-called sensor fusion.

The approach used by novel fusion methods involves high-level fusion refers to feature based fusion or decision level fusion.

Features combination enhance the precision of image classification and information acquisition. The algorithms of high-level fusion techniques include the Bayesian theory, fuzzy logic, artificial neural networks etc. high-level fusion techniques from different sensors were employed to classify land use and more precisely vegetation monitoring.

Sankey et al. (2018) combined an octocopter UAV with an embedded lidar scanner and hyperspectral imager, yielding a big dataset with augmentation potential for vegetation mapping. The additional advantage of the fusion with respect to the hyperspectral data alone, proves that the lidar fusion and hyperspectral data increase by more than 30% the species identification.

The fusion method reached an accuracy of 84–89% concerning vegetation classification. On the other hand, the acquired hyperspectral features contributed to an accuracy of 72–76%.

3.3.1 Fusion of optical images and synthetic aperture radar (SAR) approaches:

SAR-based approaches are the effective research tool for assessing spatial variation and monitoring a crop-planting area. radar reflection complexity is increased due to variability of canopy, its geometric characteristics and the soil properties and surface texture.

SAR data features can provide useful information for dryland crops recognition. However, in the case of individual crops, reflection complexity patterns demonstrate reflection variability.

The fusion of optical data derived from RapidEye and TerraSAR-X radar data used to recognize maize.

UAV approaches provide optical observations without any interruptions compared to satellite optical remote sensing. Due to the fact that they are susceptible to common weather phenomena (rain, snow, clouds) that reduce visibility. This results into the limitation of availability of optical remote sensing data in certain periods during crop growth.

In the case of SAR, the visibility is independent of cloud existence and lighting. Consequently, SAR data offer several advantages for crop variation assessment

3.3.2 Fusion of light detection and ranging (LiDAR) data and images:

LiDAR is an active sensor that is used for modeling the structure of crops and terrain mapping. Digital Elevation Models (DEM) resulting from LiDAR and Canopy Height Models (CHM) are possible to be produced with higher accuracy due to the resolution of UAV sensors.

The combination of LiDAR data and camera produced imaging data has been widely applied in many cases including Digital Surface Model (DSM)/Digital Elevation Model (DEM) production, 3D object detection and simulation to land use identification.

Park et al. (2001) combined LiDAR data and RGB images for land cover identification. The augmentation results have led to the conclusions that different types of imaging sensors provide synergistic content which can increase precision of recognition and lead to a more consistent identification of land cover categories.

3.3.3 Fusion of optical images and GIS data:

GIS spatial data, including topographic features, land use and demographic data, can be fused with data acquired from remote sensing to enhance precision of image categorization, object identification.

The combination of remote sensor and GIS data has contributed to geospatial visualization. fusion of data from various applications requires the consideration of the deviation of the fusion object representation and the object's category.

Remote sensing images are formed by a matrix of pixels denoting the color levels in the RGB-domain, while GIS data encloses regions with label metadata, which carry semantic information concerning the region of the objects.

The object recognition and alteration detection technique represents a way of fusing these two heterogeneous data sources in an effortless way because a default feature of this technique is the image pixels augmentation to label semantic polygons to allow overlay and further analysis with vectorized GIS data.

3.3.4 Data fusion of satellite, aerial and close-range images:

Unmanned aerial vehicles (UAVs) represent a novel way for acquiring high resolution and detailed mapping and forming a spatial database with low cost and minimal risk.

Recent progress led to elevated use of UAVs in sensor technology ,Current UAV sensors can acquire image with a precision of 1 cm at hourly intervals. Their high temporal and spatial resolution capability at a range between 1 and 100 hectares.

UAV-obtained information have shown potential in biodiversity monitoring and alterations detection concerning land use, precision agriculture, water management and biotic and abiotic stress detection.

The vehicle mounted sensor data are acquired with a mounted calibrated camera, differential Global Positioning System (GPS) and laser scanner.

Hence, the fusion of multiple sensors can achieve the discrimination of stresses based on their type either biotic or abiotic stresses.

3.3.5 Optical and fluorescence imaging:

Fluorescence is regarded as the most reliable approach for fungal disease detection at an early stage, since it assesses the health condition regarding how efficient the phytosynthesis process, the leaf pigments absorb partially the incident visible light as a driver of photosynthetic activity and another part is redirected to the production of fluorescence.

Fluorescence by itself is not able to reach a conclusion regarding plant stress detection, reaching an average certainty of detection, due to light level sensitivity. At an early stage of infection, metabolic alterations take place, while the fungus activity extends around the infection area.

The credibility of disease detection is relies on the utilized algorithms. Every case of crop and disease, spectral imaging techniques are available to make user friendly and automate infection assessment, by employing Data mining algorithms like ANNs and Machine Learning, or other AI techniques.

Consequently as the disease spreads on the entire plant, a general closure of the stomata occurs aiming to prevent further water losses. This stage can be detected and monitored by thermal infra-red imaging sensors.

Fluorescence is regarded as a useful technique for Early stage disease identification even before leaf alterations take place. However, is not capable of identifying the type of stress factor and the level of infection providing an average detection accuracy.