UNIT 4

1. Weed detection

1.1 Introduction

The field distribution of weeds relies on the weed and crop genotype, ambient conditions and the applied crop management practices. Most of the times, weeds grow in the form of patches and their presence differentiates among different types of fields.

The different patterns of weed appearance with in the field, require subsequently customized crop management for targeted treatment application.

The patchy weed appearance implies that the field is partially weed free, so it has to be treated locally.

In terms of site-specific crop management, the weeds locations are obtained by employing various techniques including using GNSS tools while weed mapping is performed by portable instruments.

Weed control is mostly based on chemical application which leads to environmental degradation. For this reason, novel weed management solutions are high on demand.

Integrated Weed Management

(IWM) is the combination of various weed management methods depending on the weed appearance with respect to the crop life cycle.

Targeting the reduction of herbicide use, site-specific treatment aims on the targeted identification of plants for spraying application. To achieve individual target treatment, it is crucial to develop weed sensing for detection and machine learning for weed recognition.

Sensing equipment and AI are under development for real-time identification of weeds hence enabling site-specific treatment with high accuracy and the identification of the weed species from sensor signatures is crucial for determining the type of chemical and its exact dosage for spraying application. For applying the most appropriate dosage or treat mechanically the detected weeds, it is necessary to perform weed mapping prior to treatment application in order to access weed distribution and the appearance of weed patches.

The efficient combination of autonomous ground vehicles or unmanned aerial vehicles (UAVs) with multi-sensory systems have offered to the market novel solutions for weed mapping. More precisely, the employment of several Machine Learning techniques has substantially enhanced the automatic recognition of weeds during the last decade

Multispectral imagery enable the successful discrimination between weeds and crops with similar appearance like green grass versus rice or black grass versus winter wheat

A weed species classification approach based on hyperspectral signatures has been demonstrated employing a self-organizing map (SOM) which is aiming to optimize classification. The Self-Organizing Maps (SOMs) belong to the most prominent Artificial Neural Networks techniques .

1.2 Materials and methods

1.2.1 Defining hyperspectral versus multispectral imaging : Multispectral imaging can function as the basis for the development of hyperspectral imaging, which captures images at various wavebands in the electromagnetic spectrum and associating the spectral signatures with the chemical compounds that produce them, by absorbing the light frequencies that resonate with the chemical bonds.

The multispectral imaging usually concerns the acquisition of images in a few wavelengths usually up to six spectral bands between visible and near-infrared (NIR). Image acquisition in such a narrow wavelength range yields gaps in the spectrum, resulting in a loss of information and lack of exploitation of the spectral signature.

On the contrary hyperspectral imaging enables image acquisition in a wider spectral range including hundreds of 200 spectral bands between visible and NIR regions.

Hyperspectral imaging is considered an innovative method for assessing quality in agricultural industry, combining standard imaging, spectroscopy and radiometric principles. Radiometry is the estimation of the level of electromagnetic energy that resides in spectral range.

1.2.2 Advantages of hyperspectral imaging

Hyperspectral imaging is characterized as a pioneer tool for quality control in agri-products. Its main advantages regarding quality control are presented as follows:

1.No sample preparation is required.

2. It is a non-destructive method

3. By the time the model is formed, trained and tested, application of model is easy.

4. Eco friendly and cost effective technique, since no further inputs are needed for the model application.

5. The capability of storing a great amount of spectral information corresponding to every pixel enables more precise knowledge concerning the sample chemical composition.

6. The regions of interest are defined based on the number of spectral bands for each pixel, which runs through the hypercube as a column defined by a group of pixels.

7. Qualitative and quantitative estimations can be performed by using the same hyperspectral images.

8. Several substances can be analyzed simultaneously from the same hyperspectral images.

9. Additional analysis can reveal the chemical composition of the examined material and produce two dimensional map of chemical concentrations which is called chemical imaging.

1.2.3 Disadvantages of hyperspectral imaging

1. Hyperspectral imaging system require high expenditure compared to other image processing tools.

2. Due to the hyperspectral data volume, the requirements for data storage and speed of processing are very demanding.

3. The amount of the collected images covering the whole spectral region lead to longer acquisition times compared to traditional digital imaging devices.

4. They demand effective and accurate prediction algorithms to estimate the concentration of chemical components.

5. They are not appropriate for continuous measurement systems since the image acquisition and processing requires extended periods of time.

6. Imaging results are dependent on several ambient illumination factors caused by coverage, scattering angle of light incidence, shadows and cloudiness resulting in noisy images. The effect of the external factors can be mitigated by spectral transformations that alleviate the impact of these factors of image integrity

7. For an effective data processing, accurate pre-processing and predictive model generation is needed since row hyperspectral imaging offer only qualitative insights (ElMasry & Sun, 2010).

1.2.4 Hyperspectral imaging applications in agriculture

An initial attempt of applying hyperspectral imaging techniques has been made by Goetz et al. (1985) oriented to remote sensing. Further expansions of his study were oriented towards agriculture and mostly crop disease detection .

Bauriegel, Giebel, Geyer, Schmidt, and Herppich (2011) presented a hyperspectral imaging approach aiming to identify Fusarium infection at an early stage in wheat crops. A PCA method has been applied so as to discriminate infected from healthy plants. Both healthy and diseased plant were recognized reaching a accuracy level of 87% after the data have been subjected to the Spectral Angle Mapper image analysis method. Zhang, Paliwal, Jayas, and White (2007) utilized NIR hyperspectral imaging to recognize 3 different types of storage fungi infections in wheat kernels. The PCA was employed for dimensionality reduction. An SVM was used to build classifier which had a high performance reaching accuracies of 100%, 87.2%, 92.9% and 99.3% were achieved for the detection of healthy condition and the three different types of fungi, respectively.

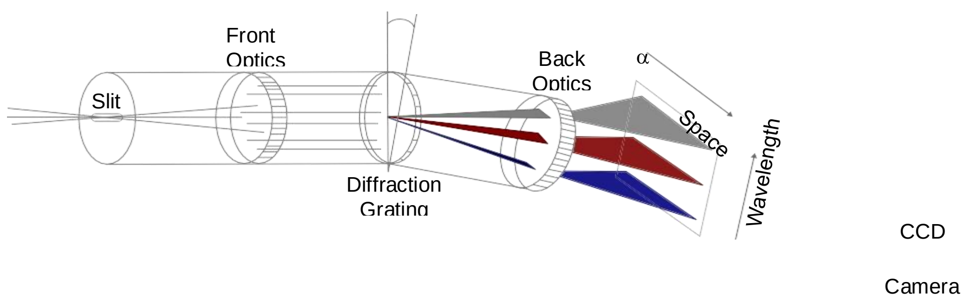

Fig. Illustrative depiction of a spectrograph operation (Moshou et al., 2002).

camera with two types of spectral axes: one spatial and one orthogonal. The hyperspectral camera system was manufactured and developed by Specim (Oulu, Finland). To overcome the illumination variability the reflected light was normalized by using the ambient light which was obtained by a 25% Spectralon panel. This kind of normalization is useful for maintaining the same relation between the magnitudes of the incident reflected light. By applying this technique, the spectral reflectance appears illumination invariant.

The device characteristics of the spectral camera included spectral resolution 1.5–5 nm, spectral range 435–855 nm, slit dimensions 80 μm × 8.8 mm, CCD specifications ½″ (4.8 × 6.4 mm) and the number of narrow band spectral bands was two hundred. The artificial lighting that was used as illumination source for the measurements included a halogen lamp (100 W) (Fig.).

Experimental trials in corn (*Zea mays*) plants were carried out greenhouse environment at Biologische Bundesanstalt, Bundessortenamt und Che- mische Industrie (BBCH) 12–14 (Meier, 2001). The main crop of the field was mixed in equal proportions with different weed species.

For the current case study, the spectral information was highly interrelated due to multiple peaks of chemical bonds. This led to redundant information that affected the computation time and the accuracy of estimation. A reduced number of wavelengths can lead to the same information

2. Disease detection with fusion techniques:

2.1 Introduction:

According to FAO (2009), the increasing demand for cereals is predicted to exceed approximately 3 billion tonnes before the year 2050, in comparison with the current production which is estimated at about 2.1 billion tonnes (FAO, 2009). Taking into consideration that this global demand is significantly higher than the relative supply; Therefore, the embracement of new policies targeting on adaptation of novel technologies is crucial, to cover this need.

An unpredictable enemy against this effort, several types of threats that poses significant challenge to the yield targets including climate change biotic stresses resulting from plant enemies (e.g. viruses, bacteria, fungi, pests, nutrient stress, lack of proper irrigation) responsible for the degradation of crop quality and possible yield losses. It is speculated that the absence of relevant prevention and treatment regarding the above mentioned plant enemies, would reach 18% for plant infections and 32% for weeds presence, independent of the applied crop management practices .

Biotic stress factors like weeds and microorganisms (viruses, fungi, bacteria) decrease both yield and the market potential of agricultural production and imposes negative impact on the cost in agriculture because of chemical applications.

Accurate diagnosis and monitoring of the possible infection presence are fundamental towards the application of effective management practices. Crop diseases usually appear in dispersed locations in the crop growing areas and they exhibit a dynamic pattern in terms of spatio-temporal variability. Effective techniques focusing on effective crop infections detection are vital. For this reason, several scientific studies are carried out aiming at analyzing the behavior of crop infections in various settings.

Precision agriculture is using information technology and sensor based monitoring solutions aiming to deal with timely effective identification and location of the invasion of crop diseases. It is characterized as a crop cultivation practice that uses spatio-temporal variations of crop and soil parameters for field management for providing efficient management decisions in real-time .

Keeping into consideration, that the crop infection appearance relies on several ambient conditions and they exhibit a heterogeneous appearance pattern, optical sensing is regarded as an efficient tool for detecting main invasion spots and access the disease severity pattern in the field. It can be combined effectively with different machine learning approaches, in order to aid decision for the application of sustainable pest management program. The precise and sensor driven pesticides applications complying to current crop protection practices lead to possible decrease concerning in pesticide application which can subsequently diminish the economic loss and ecological consequences in agricultural domain.

Currently phenotyping is related to non-contact imagery and sensor driven analytics of crop characteristics. Novel methods using standard monitoring systems like optical sensors are employed serving as useful and efficient tools for nondestructive crop infection identification. There is an ample variety of imaging and noncontact sensors ready to support crop infection detection

2.1.1 Optical sensing and their contribution to crop disease identification:

Plants exhibit a variety of phenotypic characters regarding their optical features, which can be assessed by eye, while various become explicit after applying special sensors. These sensory systems are proven helpful for detecting these optical features by measuring several light properties. A quality based assessment of the genomic expression for a given crop activity triggered by the environmental conditions is performed in a visual manner by human experts. This is the so-called phenotyping process. Phenotyping is the crop visual depiction and appreciation in a holistic way during crop growth (Fiorani & Schurr, 2013). The assessment concerns the growth rate, structure, tissue coloring, health condition, and establishment of abiotic and biotic stress manifestations and their related severity symptoms. Conventional visual crop infection level assessment has the tendency to false estimations due to plant-pathogen interactions involving cellular and leaf changes and the subjective character of the assessment by a human expert.

In the initial infection period, fluorescence is the most effective sensing principle because it assesses the health condition since it estimates photosynthetic efficiency, which is related to the health state.

After the early metabolic changes, the fungus disperses in a radial pattern outwards from the infection focus. Subsequently, the initial focus area demonstrates necroses symptoms including loss of pigmentation, the destruction photosynthetic apparatus and the cell walls breakdown. At this point of time, we have the first manifestation of the infection patterns. The characteristics of the reflected light can reveal specific patterns that are correlated to the incumbent infection contributing to the detectability of infections after this stage. Pathogen propagules are detectable in the visual part of the spectrum (detectability depends on the specific pathogen); chlorophyll downgrade in the region of visual and the red-edge (550 nm; 650–720 nm); senility in the VIS and NIR regions (680–800 nm) appears as browning while dryness is evident in SWIR area (1400–1600 nm and 1900–2100 nm). Finally, alterations in the structures of the canopy and the collapse of leaf area is evident in the NIR.

During the period that disease spreads across the whole plant, this manifests as a widespread stress, appearing through a general pause of stomata functioning. Aiming to water loss reduction. The altered transpiration leads to heat containment that can be sensed with the help of thermography. A difficulty that arises in recording a consistent indicator of stress through thermography is the dependency of thermal response to ambient factors like air temperature, lighting conditions and wind. Hence, thermography is not reliable if is used on ground vehicles as proximal sensor.

Changes of leaf reflectance are due to leaf compositional alterations resulting from an infection. Diseases can influence the optical leaf characteristics at multiple wavebands. Therefore, disease-sensing tools can possibly rely on recording spectral responses in a variety of wavebands or a fusing information from several wavebands. Induct plants have a green appearance because the green light (ca. 550 nm) is reflected at a high degree in comparison to the other colors like blue, yellow and red. The infected leaf areas are manifested through distinct leaf lesions, related to necrosis or chlorosis appearing in these regions, resulting in elevating reflectance in the visual band and more specifically, where the chlorophyll is absorbed. More specific, reflectance alterations at wavelengths circa 670 nm, result in the red edge shift to switch to lower wavelengths. Vice versa, the reduced biomass, correlated to senescence, signifies a lower growth and leaf loss resulting in a collapse of the canopy reflectance around the NIR region.

Optical sensing is predicted to be important factor in the forthcoming smart farming applications to enable sustainable farming thanks to efficient crop monitoring in precision agriculture. This operational model will become functional if multi-disciplinary expertise combining research, industrial and agronomic expertise collaborating to achieve a collective vision of functional methods.

2.1.2 Artificial intelligence approaches for crop disease monitoring:

A shortcoming of optical sensors concerns the volume and the complex character of the data that is accumulated. In order to apply optical sensor data in more effective way, efficient data analytics and machine learning methods are regarded crucial. The data analysis has to comply with several objectives including the crops early stage detection the discrimination between different types of infection, the discrimination between biotic and abiotic stresses, and the estimation of the disease severity level. These objectives have to be achieved at a least at the same level obtained with a standard technique and a shorter processing time.

Approach based on data mining and machine-learning methods are capable of minimizing the effort and achieving early detection of infections through hyperspectral imaging. Regarding machine learning techniques, unsupervised and supervised learning are employed for offering solutions to classification and clustering problems. On the other hand, unsupervised machine learning algorithms seek to discover data mining patterns automatically. To the contrary, for performing supervised learning there is a need for training data with labelled samples. Standard classifiers and clustering algorithms include k-means, SOMs, SVMs, and ANNs.

It is currently known that feature selection can affect positively the classification, the processing time. When multiple data sources are available an effective fusion method is necessary for combining the obtained features for

extracted from each source because the data from each source could be complementary. Feature concatenation is a basic technique to fuse the obtained features; therefore, the accuracy is not assured since weighted fusion is required.

A variety of techniques is available for performing feature fusion from different data or information sources. As an illustration, a feature fusion regression kernel was employed to assimilate features extracted from satellite imagery.Spectral, textural, and pattern similarity produced by every object to create a feature vector and then use the combined vector to improve object classification and improved generalization. In Sˇulc and Matas (2017)a kernel PCA (KPCA) was applied to perform normalization from hyperspectral images, positioning spatial and terrain (LiDAR) information, hence thus decreasing their dimensionality and denoising effectively to perform final fusion.

The acquisition of specific crop hyperspectral patterns would be very useful, for wide spread information extraction related to crop condition assessment. Moreover, this technique of data acquisition could become part of operational field monitoring for example growth monitoring maps, meteorological data and prediction models. This could lead to a development of an effective tool for functional early disease warning and precision farming for crop protection

2.1.3 Reference and advanced optical methods for plant disease detection:

Standard methods targeting on the identification and the discrimination of several plant infections involve visual crop disease severity assessment by human experts, morphology based identification of microscopic pathogens features, and molecular, serological, and microbiological methods (Bock et al., 2010). These methods are incorporated a main features of plant protection services for both research and industry purposes. In the recent years, DNA-based and serological techniques have triggered the targeted characterization and crop disease severity assessment (Martinelli et al., 2014).

When employing molecular and serological techniques, different types of pathogen strains can be classified according to their virulence level or are invulnerable to specific fungicides. The diseases severity is not directly correlated to the infestation level of the pathogen, since the disease manifestation does not follow a linear correlation with the pathogen biomass.

Traditionally, disease infection symptoms such as blight, tumors, rots, cankers, etc., or observable pathogen symptoms such as mycelium are utilized as indicators for detecting infections. Visual crop disease assessment has become capable of providing better and trustworthy estimations thanks to the meticulous protocols and standardization of the assessment process (Bock et al., 2010). However, the drawback concerning visual assessment lays on the temporal variability of the assessor experience, which brings often-significant credibility issues regarding the repeatability of the assessment (Bock et al., 2010). On the whole, these methods are characterized as time-consuming and also require experts with high levels of experience in the field of disease evaluation which leaves open the possibility of human bias.

Recently, novel sensory-based approaches have been introduced aiming to the detection, identification, and crop disease severity assessment (West et al., 2010). The current methods are capable of estimating the optical crop features from different spectral bands, by using spectral bands from the nonvisible range. They take into account possible alterations affecting the crop status due to a possible infection that modifies the textural, structural and optical leaf properties negatively (West et al., 2010). The most efficient methods are considered sensory systems capable of measuring optical and thermal crop properties. Most of them were initially developed for military applications, earth remote sensing, satellite and aerial sensing and in certain manufacturing applications.

The early multispectral remote sensing systems were developed in 1964. Hyperspectral imagery appeared during the 1980s. In agricultural engineering, remote sensing is a technique for attaining plant features in a non-destructive manner. The idea has been extended through proximal and limited-scale sensing concerning crop status .The sensory systems have been incorporated to several platforms including agro-machinery and other aerial, space and ground vehicles and are listed as follows:

1.RGB-imaging :

Visual imaging is used in the field of plant pathology for monitoring crop health status. Digital cameras produce images in RGB format (red, green, and blue) for crop monitoring and infection severity assessment. Regarding the technical features of these easy to use, portable devices, including the dynamic range of the imaging chip, spatial accuracy, or lens characteristics have evolved through the years. Nowadays, the wide spread use of high quality imaging sensors is common due to their availability in mobile devices so that phytopathology experts and farmers can utilize them when needed. There are also other common ways for crop monitoring through video sensors which are capable of obtaining frames from various plant parts, ranging from the lower parts such as roots to the higher ones like the clusters of flowers. The RGB cameras utilize the red, green, and blue channels on different resolutions for identifying possible crop biotic stresses during the growing period (Bock et al., 2010,). In addition, there are other morphological features and textural characteristics that can be correlated to the presence and identity of various plant infection symptoms .

The targeted selection of correlated features from preprocessing the RGB images tend to improve the classification performance .The digital image analysis is a commonly used technique for assessing different types of crop infections. ASSESS 2.0 and "Leaf Doctor," are the most known software based on digital image analysis. There is also the possibility of custom-made modules. In ASSESS 2.0 software, the RGB characteristics of the images is visualized in histogram form, which are used to define threshold for further processing. The user through a user-friendly interface provides the parametrization needed to fine-tune the discrimination between healthy and diseased areas. Regarding the severity symptoms assessment, an extraction of the pixels classified as infection symptom pixels or they appear as an area after thresholding the image so that a mask is created that deletes the background around of the region of interest. Therefore, ASSESS 2.0 requires single leaves or well-defined background in order to isolate the leaf areas. Moreover, further constraints such as homogeneous focus, detail, and ambient lighting affect the overall performance and reliability for automatic image analysis. The image analysis seems to be affected by the several natural conditions including the acquisition angle, the pixel size as defined by the distance between the leaf and the camera. In the event of heterogeneous environmental settings and low image analysis the infection symptoms areas are hard to identify. The most critical condition for repeatability is a credible image acquisition protocol that produces consistent results.

2.Multi- and hyperspectral reflectance sensors :

Spectral sensing devices are characterized from their spectral resolution, their spatial coverage, and the detection principle used by the sensor. Multispectral sensing systems appeared earlier than the other spectral approaches. These sensors usually gather the spectral response of targets in a few wide wavebands. The introduction of modern The hyperspectral sensory systems elevated the complexity of the recorded images by having a spectrum defined between 350 and 2500 nm and by some case carrying a very high spectral resolution that can be lower than 1 nm.

Unlike the non-imaging devices, which contain the average spectral response from specific area, hyperspectral imaging devices are capable of providing the spectral and spatial features of the target object. Hyperspectral information is appended by three-dimensional matrices (x, y, z). The spatial resolution affects strongly the detectability of the crop infections. Airborne devices are capable of identifying infected field patches by soil propagated pathogens or in later infected filed areas .Sensory of approximately 1m spatial resolution are not able to discriminate isolated infection symptoms or infected leaves and crops. For this application, sensors that are mounted on proximal platforms are considered more appropriate (Oerke et al., 2014).

The reflection of the electromagnetic waves from plants is a complicated process, which emerges from a cascade of interactions, which are biophysical, and biochemical in nature. The visual region of the spectrum (from 400 to 700 nm) is correlated by the pigment concentration of the leaf. The near infrared region, from 700 to 1100 nm is highly related to the leaf architecture, structural interference with light scattering and dependence on leaf water concentration. The short-wave region from 1100 to 2500 nm is affected by the chemical components and water content.

Different reflectance alterations caused by possible infections result from damages in the leaf assembly and its chemical components during infection that is characteristic. This alteration flow specific pattern like the evolution from chlorotic to necrotic symptoms or the occurrence of fungal colonies. In the case of biotrophic fungi an example of which is different types of powdery mildew and rust they influence leaf integrity and chlorophyll content in negligible at an early stage of infection. On the other hand, perthotrophic pathogens activity in crops often brings leaf degradation caused by the emitted toxins or enzymes to the infected crop area, which are characteristic for each pathogen, leading finally to necrotic lesions.

The aforementioned leaf infection manifestations facilitate the spectral detection of leaf infection. Mahlein et al. (2013) has presented the identification of leaf infections in sugar beet plants attained from leaf spectral signatures. In ground sensing, hyperspectral camera approaches are regarded an efficient and trustworthy method for the detection of fungi that emit mycotoxins in Zea mays plants .

3.Thermal sensors:

Infrared thermography (IRT) detects plant temperature as a parameter to differentiate the water content of plants, the crop microclimate, and with transpiration related symptoms resulting from the establishment of an infection .The infrared emissions in the spectral regions between 8 and 12mm are detectable by thermal infrared sensors and is visualized in a raster format, where each pixel is assigned the level of the temperature reading from the observed target. In precision agriculture, thermal cameras are applied in various different settings ranging from aerial to microscopic thermal acquisition tasks. Nevertheless, the functionality of thermal cameras is compromised by ambient disturbances like variations in temperature, precipitation, sunlight, or wind interference. The temperature on the leaf is directly affected by the transpiration of the plant, which is resulting as an impact from the invasive activity of different pathogens. While several pathogens, like rust infection, cause localized foci, damage by root infection or systemic diseases like Fusarium spp. induces an impact on plant transpiration and affects the water circulation globally in the plant.

In the case of apple infection by fungus, thermal imaging achieved a visual mapping of the fungus invasion area that was not possible with a visible light camera on apple crops, while fungal organs could be detected only with the help of a microscope .

4.Fluorescence imaging :

A variety of chlorophyll fluorescence factors have proven useful regarding the assessment of changes in the photosystems of plants due to biotic and abiotic stresses. Chlorophyll fluorescence cameras are usually sensors with a light excitation source for sensing the emission light from electron di-excitation which is interpreted as a signature of the specific stress factor. Interpreting fluorescence imaging with signal processing algorithms has enabled the detection and severity assessment of fungal infections .

A drawback of chlorophyll fluorescence cameras concerns the conditioning of the plants which has to comply to a specific protocol, which prevents its use in field circumstances. Hence, alternatives have been oriented towards the sunlight as an excitation source for obtaining the fluorescence factors in field conditions, thus enabling crop infection monitoring in ambient conditions (Rossini et al., 2014).

2.1.4 Combination of optical sensing with data mining algorithms

In precision farming, several applications have emerged that employ hyperspectral sensing for identifying the crop status. Lorente et al. (2013) have utilized hyperspectral camera in order to identify citrus decay infection by employing a wavelength pruning approach with a receiver operating characteristic curve (ROC) which was fed as input to a neural network algorithm. Ahmed, Al-Mamun, Bari, Hossain, and Kwan (2012) have used digital imaging for classifying crops and weeds by SVM algorithms. Liu, Zhang, Wang, and Wang (2013) combined effectively an SVM algorithm with a self-adaptive mutation particle swarm optimization (SAMPSO) algorithm aiming to label land use/cover.

Water stress in plants signifies the response of the plant to water scarcity. When this happens, the water deficiency starts affecting the plant’s physiological activities. Water existence to plants is quantified as water potential. This potential is estimated using measurements of leaf water before dawn.It has been estimated that the value of 0.8MPa notifying a threshold for plant stress detection.

Spectral indices were defined as indicators of plant water content as detectors of crop water stress. The correlation of the spectral indices to the plant water content is defined by the leaf structure. This explains the fact that only some specific spectral indices are more sensitive to the water stress appearance (Eitel et al., 2011). A couple of spectral indices that have been utilized are the normalized difference water index (Gao, 1995) while an additional one is the water band index .The water band index results from the division of reflectance that appears at 900 nm to that of 970 nm .This index is affected by the plant water concentration in both the leaf and the canopy but it is more sensitive to variations in leaf water. This fact offers an advantage in the case of agriculture because drought affects the leaf water content at an earlier stage compared to the rest parts of the plant .

A crucial feature of plant growth concerns the accurate assessment of crop productivity with the use of non-destructive approaches. Important breakthroughs in the sensing devices used for chlorophyll fluorescence acquisition and advances in the comprehension of the relation between the plant fluorescence features and the physiological status have made the use of fluorescence very popular in crop physiology research. Rumpf et al. (2010) investigated the use of hyperspectral sensing for the automated detection of crop infections and severity assessment with SVM in which the chlorophyll concentration and other physiological factors were used as indicators for the infection severity level assessment.

Photosynthetic activity level is considered as a possible stress indicator and the plant adaptation is quantified by the chlorophyll fluorescence behavior. Due to alterations in the chlorophyll fluorescence showing up at an early stage preceding other manifestations of tissue degradation, leading to the early detection of many stress types before any symptoms of destruction. The division FV/FM, which results from the variable fluorescence (FV) after division with the maximal fluorescence (FM), defines the estimation of the photochemical efficiency of Photosystem II (PSII). Intact H plants demonstrate FV/FM ratio approaching 0.8. In studies that concern the practical use of chlorophyll fluorescence, the FV/FM ratio is associated with the presence of water stress.

Performing fusion of data that emanate from sensors mounted on vehicle or they are installed on ground platforms facilitates a practical implementation of automated systems for recognizing different types of infections or nutrient efficiencies (Moshou et al., 2011). The PCA approach was effectively employed for observing the evolution of infection in wheat crops by F. graminearum (Bauriegel, Giebel, Geyer, Schmidt, & Herppich, 2011). Various studies have indicated that the spectral range between 350 and 2.500 nm did not manage to detect the infection from fungus under field conditions due to the reason that the narrow spectral wavelengths demonstrate a high correlation between them

Mahlein et al. (2013) proposed a method for obtaining specific hyperspectral wavebands that were correlated to disease presence in the leaves of sugar beet. The specification provided by the hyperspectral-imaging sensor can form the basis of designing new low cost instruments, which will be based off the shelf optics like LEDs and C-MOS chips, resulting in devices that can be used by the wider public for crop monitoring .

In the last decades, novel approaches utilizing machine learning architectures have been introduced. Wahabzada et al. (2015a) presented a data based and automatic approach using hyperspectral camera images depicting infected barley leaf areas. The spectral signatures were extracted in order to monitor the evolution of the symptoms during the infection development (Mahlein, 2016).

In the current case study, the fusion of features derived from multispectral sensors and hyperspectral cameras was employed to discriminate induct from infected wheat aiming to further utilize it as a detector for crop biotic stress. Spectral reflection has been employed in order to discriminate water stress from symptoms of Septoria appearance by the use of a hyperspectral camera. At the same time, the crop health status was evaluated through fluorescence kinetics measurements with the help of a Plant Efficiency Analyser (PEA) fluorimeter .A data fusion approach was combined with LSSVM approach aiming to discriminate water stress from infected wheat plants. The LSSVM is evaluated against various classifiers including the MLP and QDA for detecting and separating water stress plants from the diseased ones.

2.2 Optical instrumentation:

Hyperspectral signatures have been measured by a monochrome V10 Specim hyperspectral camera by Specim. The sensor creates a reflectance spectrum per single point from on a narrow line on the object that is targeted (Herrala et al., 1994). Three modules including a lens, a grated prism, and a Digital Video Camera (DVC) compose the hyperspectral imager. The spectral pixel was 7 nm in the spectral region between 460 and 900 nm.

llumination was produced with the help of incandescent lamps within the greenhouse area. A couple of halogen lamps of 500W each provided complementary lighting. The spectral signatures from wheat leaves were collected and preprocessed so that the spectral magnitudes were invariant to ambient lighting. The spatial footprint of each pixel was equal to 0.65mm and the acquisition was performed from an angle of 45°. There was no particular tension to the plant to the plant positioning with respect to ambient conditions and the averaged data values were considered for the whole scene.

The fluorescence measurement were carried out by using the PEA fluorimeter by Hansatech Instruments Ltd., UK. The excitation light for the fluorescence measurement was realized by ultra-bright light LEDs that had a peak waveband at 650 nm. Chlorophyll fluorescence signatures were obtained by a photocell after being filtered by a high pass filter of 50% transmission in the region of 720 nm. For achieving a recording of the transient fluorescence signal the acquisition period for the fluorescence signal was 1 s with a period of 10μs during at the first 2ms and then with a duration of 1ms. The ambient light was blocked with the help of a leaf clip. Dark adaptation was imposed on the plants for a minimum time of 20min. The clip was applied on the topmost side of the leaf in the central area of the leaf, for 1 s duration with the PEA. The Septoria infected leaves were measured on those leaves that carried early symptoms of the infection.

2.3 Fusion of optical sensing data:

Multi-sensing fusion systems augment signals emanating from various sensing platforms to produce decisions that would be infeasible to reach by a stand-alone sensor. Areas of deployment (target recognition, risks identification), earth observation applications (minerals mapping), human health status assessment, predictive maintenance of machines, navigation of robots and multi-sensor control of industry machines.

Table 2.13 Symbolism of the four investigated crop health status

s-w-	s+w-	s-w+	s+w+
Control treatment	inoculated with *Septoria tririci*	deficient water supply	inoculated treatment, deficient water supply

Data fusion is a simulation of the continuous functioning of human neural systems that try to combine signals from the human senses to produce decisions regarding the status of the environment that the human entity lives in. For fusing various types of sensors, spectral signatures were augmented with transient fluorescence signal parameters. In Moshou et al. (2014) a quartet of differing treatments were applied aiming to create specific stress status that needed to be accessed. The applied treatments are presented in the Table 2.13 as follows: Spectral signatures were composed of 21 signatures. Every signature corresponded to 21 nm wavebands throughout all the spectral bands of the spectrograph (which had region of 460–900 nm). The fluorescence signatures comprised of a couple of parameters given as follows: the F0 denoting the fluorescence at 0.05ms and the FV/FM ratio which corresponds to the efficiency ratio of the primary photochemical system while FM denotes the peak of the fluorescence transient

3 Disease and nutrient stress detection

3.1 Introduction:

Precision agriculture methodologies concerning the synergy of various tools including sensory systems, decision support and farm management software are capable of achieving sustainability targets regarding the minimization of environmental and financial impact .It is estimated that 40% of the global yield potential is lost due to various pests presence .The occurrence of weed and disease establishment is based on the environmental factors and demonstrates a variable pattern within the field. Thus, the early detection of significant pest infected patches as well as defining management zones with variable infection severity is of high importance. Pest monitoring and the decision procedure are fundamental for site-specific treatment of pests . To achieve a level of precision in crop management a prerequisite is a high resolution of spatio-temporal data availability.

For maintainable increase of crop production, fertilizers and pesticides have to be administered according to environmental compliance requirements. Pesticides are applied in a uniform way, while disease invasions form distinct foci. The patches occurrence can be decreased effectively by employing site-specific approaches avoiding spraying healthy areas and targeting solely on the infected ones aiming to minimize the environmental impact and maximize the financial gain. Regarding fertilizer dosage applications, these are customized according to the site-specific nutritional crop requirements. The intercorrelation of the spectral crop signatures corresponding to different types and levels of stresses, can function as the main components for an optical device that is capable of recognizing several disease foci and crop nutritional requirements. On the other hand, sensory systems including multispectral, hyperspectral imaging and chlorophyll fluorescence can provide detailed and high precision data concerning different crop health conditions.

Progress in sensor devices together with advances in information technology and earth observation systems introduces innovative tools for precision agriculture, by enabling the early detection of several types of pests (Rumpf et al., 2010).

The volume and the fitness of the acquired data by sensory systems has substantially increased, but since those systems are highly correlated to several biological variations, cannot lead to trustworthy conclusions. Considering also the inability of those systems quantifying crop physiological factors in a direct way, and their capability of measuring a spectrum of reflectance components associated to several crop signatures and the corresponding ambient conditions ,it is concluded that introduction of applications employing advanced data mining methods is crucial.

Lu, Ehsani, Shi, Castro, and Wang (2018) used a hand-held spectroradiometer to recognize various tomato leaf diseases by constructing a set with halogen lamps and black background in order extract the leaf area. The diseases that were investigated were late blight and bacterial spots, discriminated from healthy tomato leaves, yielding a high accuracy reaching 100%. The employed classification method was KNN combined with PCA. He, Li, Qiao, and Jiang (2018) used a hyperspectral spectroradiometer applying a regression approach by extracting wavelet coefficients on hyperspectral data to recognize stripe rust occurrence on winter wheat leaves. The authors conclude that the detection of strip rust is possible by using hyperspectral sensing to correlate the disease severity with a decrease in chlorophyll content. The employed multivariate linear model that utilized wavelet transform features achieved an R2 of 0.905.

3.1.1 Yellow rust disease detection:

Wheat is regarded as significant grain crop worldwide and is associated with food security in many countries. A variety of wheat infections have imposed great threats affecting the sustainability of wheat yield in global basis. Yellow rust belongs to the family of fungal diseases and more specifically is caused by the pathogen called Puccinia striiformis f. sp. tritici (Pst). It is considered as one of the most devastating diseases in wheat ,mostly due to their frequent occurrence and their potential to spread as an epidemic, causing significant crop losses while at the same time decreasing the quality of the produced wheat. The current practice, involved observation of visual symptoms that are connected to the presence of the infection, but also damaging the environment due to the heavy use of fungicides .Yellow rust has the propensity to appear sporadically in a location. Hence, it is needed to use a different way that is more applicable for assessing the locations in which the disease has established its presence.

It is commonly established that leaf water content, pigment concentrations, and the inner crop structure may deteriorate when an infection occurs, and their relevant physiological and biochemical alterations are depicted in its spectral response, for example different changing in spectral features and the deviation in reflectance value. A variety of research works have suggested the use of relevant wave bands or vegetation indexes (VIs) that are capable of detecting and observing crop infections at leaf and canopy level. a photochemical reflectance index (PRI) was suggested by Huang et al. (2007, 2014) for yellow rust identification at crop .

Plant disease and stress mapping could be accomplished with the help of air-borne systems. Unfortunately, the currently used satellite sensor cannot provide practical disease recognition (even if the gathered data belong to relevant wavebands) due to inappropriate spatial resolution. In the best case, satellite imagery are useful tools for aiding the spotting of extended areas of disease or stress occurrence in crop as an early warning that can be examined by the farmer. Moreover, in frequent observations and variable visibility due to intermittent cloud appearance, lead to the conclusion that satellites are not reliable source of information when required. To the contrary, airborne sensing platforms overcome these constraints because their access to the acquisition object can be controlled by manipulating the positioning of the platform.

Nitrogen (N) is regarded globally as one of the most important nutrients closely linked to plant growth due to its crucial role to the photosynthetic procedure. Simultaneously, N widely known for its impact to both environment and economy. Consequently, the optimal administration of N based fertilizer application in different crops has been the case study of many spectroscopy studies .

Additionally, to the nitrogen content, the distribution of color alterations in canopy might be attributed to certain interconnected factors, including nutrients, dehydration and infections. This lead to the need for collecting information about crop which can be used to aid the recognition of the type of stress situations that the crop is facing and lead to actionable insights and associated managements inductions.

The determination of the plant N content can be categorized into two categories: destructive and non-destructive. The most frequently used technique of destructive evaluation is a laboratory analysis based on the Kjeldahl technique requires a lot of effort, is time consuming and of high cost. Regarding the nondestructive approach, it is mainly dependent on canopy reflection in the visible–NIR spectral region (400–900 nm) aiming to offer an optical remote sensing technique for assessing the of the N crop status. The acquisition is carried out locally, decreasing the amount of field samples that are needed and thus shortening the time and the expense of field acquisition, preprocessing and lab evaluation. A large amount of work research has been allocated to non-destructive evaluation of the N condition, determination plants by remote sensing technologies and spectral indices closely associated to the N crop content have been extracted from hyperspectral signatures.

Crop yield prediction and N content determination are handled simultaneously due to the direct connection with fertilizer administration strategies. Crop yield targets are commonly utilized for estimating the crops N needs, both at the pre-season and in-season period. For deriving precision fertilization schedules for N fertilization, especially during season, an evaluation of both is required.

3.1.2 Machine learning in crop status recognition

The main objective of PA is to aid decision making though acquisition of information that can lead to improved decisions concerning crop interventions in a spatial and temporal dimension. More specific, changes in crop condition, have to be followed by the discrimination between biotic and abiotic stress in a way that can lead to enable the appropriate decision regarding treatment.

In the last decade, the crop protection technology has started adopting different tool that are based on various Machine Learning architectures .The efficiency of these architectures relies on their ability of finding associations and intercorrelations between data for aiding the detection of reason that leads to crop stress. Mehra, Cowger, Gross, and Ojiambo (2016) applied ML methods including ANNs, categorical and regression trees and Random Forests (RFs) for preplanting risk prediction of Stagonospora nodorum blotch that affects winter wheat crop. The proposed models for risk assessment have been proven efficient of applying suitable disease treatments before planting the winter wheat crop.

Machine learning methods combined with hyperspectral imagery are capable of exploring the physiological and structural crop behavior and sense possible alterations in the crop physiology due to different ambient conditions.Goldstein et al. (2017) has proven that field parameters including as soil moisture content, ambient conditions, irrigation practices, and the expected yield are fused successfully by employing ML models aiming to form an automated irrigation schedule. Gutierrez, Diago, Ferna´ndez-Novales, and Tardaguila (2018) have applied thermal imaging by employing two ML models including Rotation Forests and Decision Trees, in order to assess water status in wine crops for irrigation purposes.

Spectral vegetation indices (VIs) are special designed to capture the functional links between the crop features and observations from spectral sensors. Apart from the Normalized Difference Vegetation Index (NDVI). a various vegetation indices have been introduced, such as the two-band Enhanced Vegetation Index (EVI2) and Normalized Difference Water Index (NDWI).

Yuan, Lin, and Wang (2015) extracted the most appropriate bands aiming to lower the data dimension without any loss of information. They introduced an unsupervised selection band selection framework, which progressively eliminated the redundant bands. Trials on hyperspectral classification and color visualization have been carried out, demonstrating that the applied technique is more accurate compared to traditional pointwise art selection techniques.

The need for active learning in order to recognize disease is dictated by the drawbacks of the usual approach which is based on one crop measurement which is not sufficient for identifying the factor that causes the crop stress. The current case study aims to realize a functional pest/nutrient crop protection system. The investigated system proposes a One Class Classifier that is capable of identifying type of stress that occurs, relying on unforeseen spectra by having been trained with spectra from asymptomatic plants. The realized Active Learning classifier is able to learn iteratively in order to identify various malignant conditions by appending new classes of new stresses by using an One Class Classifier against the previously identified target class. This is accomplished through a repeatable way, One Class Classification class augmentation of the already identified class

Moreover, for the current case study, a second approach has been employed based on different Self Organizing Maps. This technique utilized a supervised learning method for classifying spectral signatures aiming to estimate the health condition in winter wheat. Three different crop health conditions corresponding asymptomatic, nitrogen stressed and yellow rust infected plants were validated. Cross-validation has been applied for assessing the validity of the results in a relation to the capacity of the networks and their relevant generalization ability. Finally, the ability of the employed self-organizing models in visualizing the spectral features topology, was evaluated.

3.2 Materials and methods:

Yellow rust patches were formed in 6 areas of winter wheat, and surrounded by guradrows with a 3m width. The control of non-target diseases was achieved by using fungicides in those areas that was regarded as necessary. Spectral signatures corresponding to asymptomatic, infected and nutrient deficient winter wheat crops were attained through hyperspectral imagery, consisting of a V10 Spectrograph (Specim, Oulou, Finland). The plant spectra were acquired at a range from 400 to 1000 nm. In the nutrient deficient crops, there was no fertilization applied for approximately one week. Optical sensor measurements were carried out in the most distinct three patches of Yellow Rust diseased plants. Then, the observations of these measurements were contrasted with those acquired from three induct plots and a substantial area that was not received any type of fertilization. The spectral measurements were attained at six plots of the field, randomly chosen. For calibrating the employed classifiers, feature vectors were formed by using the mean values of the 21 spectral bands of the spectrograph. Light intensity normalization was performed to eliminate the high spectral variability due to canopy structure and various illumination levels. Discrimination was enhanced by applying a spatial average window, which was wide as one plant. Using five wavebands with a width of 20 nm, the precise detection of the different crop stress conditions and of the asymptomatic crops was performed. Three wavebands, including 725, 680, and 475 nm +/ 10 nm achieved high performance when using normalized features and a window of 300 pixels for the calculation of averages. Another two extra wavebands, corresponding to 750 and 630 nm .