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Review

Detection and Evaluation of Environmental Stress in Winter Wheat Using Remote and Proximal Sensing Methods and Vegetation Indices—A Review

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Abstract: Climate change has a significant impact on winter wheat (*Triticum aestivum* L.) cultivation due to the occurrence of various environmental stress parameters. It destabilizes wheat production mainly through abiotic stresses (heat waves, drought, floods, frost, salinity, and nutrient deficiency) and improved conditions for pest and disease development and infestation as biotic parameters. The impact of these parameters can be reduced by timely and appropriate management measures such as irrigation, fertilization, or pesticide application. However, this requires the early diagnosis and quantification of the various stressors. Since they induce specific physiological responses in plant cells, structures, and tissues, environmental stress parameters can be monitored by different sensing methods, taking into account that these responses affect the signal in different regions of the electromagnetic spectrum (EM), especially visible (VIS), near infrared (NIR), and shortwave infrared (SWIR). This study reviews recent findings in the application of remote and proximal sensing methods for early detection and evaluation of abiotic and biotic stress parameters in crops, with an emphasis on winter wheat. The study first provides an overview of climate-change-induced stress parameters in winter wheat and their physiological responses. Second, the most promising non-invasive remote sensing methods are presented, such as airborne and satellite multispectral (VIS and NIR) and hyperspectral imaging, as well as proximal sensing methods using VNIR-SWIR spectroscopy. Third, data analysis methods using vegetation indices (VI), chemometrics, and various machine learning techniques are presented, as well as the main application areas of sensor-based analysis, namely, decision-making processes in precision agriculture.

Keywords: climate change; environmental stress; winter wheat; remote sensing; proximal sensing

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1. Introduction

Wheat (*Triticum aestivum*, L.) is one of the most important crops and the essential source of calories and protein in the world [1]. Global wheat production averages 750 million tons per year [2] and was harvested from more than 218.5 million hectares in 2017. It is the largest cultivated area in the world [3]. Its importance for human nutrition and animal feed consumption makes it a critical factor for food security [1,2]. Food security depends on agricultural production providing the world's growing population with certain food that satisfies a growing number of consumers and has a composition that supports a healthy human population [4]. The stability of entire food systems may be threatened by climate change due to short-term fluctuations in supply [4,5]. However, at the regional scale, the potential impacts are less clear, but it is likely that climate change will exacerbate food insecurity in areas currently at risk of hunger and malnutrition [5]. In addition to climate change issues, we are currently experiencing the Russian invasion of Ukraine, a major wheat producer (accounting for about 12% of global wheat exports [6]). This has implications for agriculture and the food supply chain, especially for countries dependent on key food commodities such as wheat, sunflower oil, and corn. Food and fuel prices have also increased, as have the prices of agricultural inputs such as fertilizer [7], which can have immense consequences for crop yields and food security in general.

Modern scientific research and agricultural science focus on climate change in terms of increases in global temperature and atmospheric carbon dioxide (CO_2) concentrations, heat waves, floods, storms, droughts, and other extreme weather conditions [5,8]. Therefore, the above abiotic factors are receiving more attention in agricultural science because they negatively affect the development, morphological, cellular, and molecular processes of crops [8] and cause environmental stress that leads to yield losses of more than 50% on average for most crops [9]. Therefore, due to their long life span, crops are highly vulnerable to climate change, which makes it difficult for them to adapt to changing environmental conditions [10]. Predicted temperature changes over the next 40 to 70 years are expected to be in the range of 2–3 °C in different regions [11]. The intensity and duration of warming trends and heat wave events are projected to become more extreme in the future [11]. The climate changes exacerbate environmental stress in many crops, including wheat. A study by Warrick [12] for Western Europe, the United Kingdom, and the United States on the effects of global warming on wheat productivity shows catastrophic effects in terms of yield loss as higher temperatures accelerate the evapotranspiration process and cause drought stress. Recent analyses of cereal productivity in Europe confirm stagnation in yields due to the effects of climate change compared with the 1990s [13,14]. The temperature is the most important environmental variable affecting the growth and development, and thus the ultimate productivity, of agricultural grain crops [13]. Not only is a general increase in temperature expected, but short periods of extreme heat are also expected to occur more frequently, exacerbating heat stress in plants [15]. Precipitation patterns can be predicted with less certainty than temperature, although it is likely that the frequency of heavy precipitation (i.e., the proportion of heavy precipitation to total precipitation) will increase in many regions, leading to runoff and thus reducing water availability to crops [16]. At the same time, the frequency of drought stress is likely to increase in many regions. The combination of heat and drought stress is generally more damaging than any single stress [16,17]. Freshwater shortages are becoming a limiting factor for wheat production in many parts of the world [18], forcing farmers to use saline water for irrigation, which, combined with high soil salinity, can lead to salinity stress in wheat [19].

Climate change affects crop production mainly through abiotic stress factors but also by improving conditions for the development of biotic stress factors: diseases, weeds, and pests [20]. Changing climatic conditions are known to affect the occurrence, prevalence, and severity of plant diseases, playing a role in 44% of new disease emergence due to altered distribution and population size of plant pathogens [21]. The higher mean winter temperatures and decrease in number of frost days observed in many parts of the world, the shift in precipitation patterns, and the trend toward heavier rainfall favor infection by various pathogen species responsible for the increase in plant diseases [21]. Given the importance of temperature on the population dynamics of insect pests, global warming is expected to favor the expansion of their geographic range, increase the proportion of overwintering individuals, increase the number of generations, increase the risk of introducing invasive pests and vector-borne plant diseases, and alter interactions with host plants and natural enemies [20]. This leads to more crop damage and yield loss [20]. Climate change favors the emergence of weeds and the introduction of non-native species, which has significant ecological and agronomic implications [22]. If the incidence of insect pest, disease, and weed populations increases as a result of the climate change, this could lead to more frequent use of plant protection products [23].

Regarding the European Green Deal [24], whose main objective is to reduce the use of pesticides by 50% and the use of fertilizers by 20%, and the problem of non-existent irrigation systems in most wheat-producing European countries, the only solution is digital and precise agriculture [16]. It is necessary to monitor the occurrence of environmental stress in plants to detect it at an early stage so that timely and precise agricultural measures such as fertilization, irrigation, and pest management can be implemented. Remote and proximal sensing techniques can be used to identify hot spots in fields with stressed plants and focus interventions on that specific area.

The objective of this review was to understand the main physiological responses of winter wheat to environmental stress factors and to show how the combination of remote and proximal sensing techniques can help in the detection and evaluation of stress factors in winter wheat. Based on these techniques and data analysis using vegetation indices, chemometrics, and various machine learning techniques, decision-making processes in precision agriculture can be supported.

2. Physiological Response of Winter Wheat to Abiotic Stress Factors

Plants are very often exposed to stressful conditions, whether in nature or in agricultural production. Stress can occur within minutes (e.g., frost or heat) or over a period of several days, weeks (e.g., drought stress or waterlogging), or even months (e.g., nutrient deficiency or the presence of substances in toxic concentrations (e.g., salinity stress) [25,26]. Environmental stress factors severely limit agricultural production worldwide, cause large yield losses, and largely determine the distribution of certain plant species. Therefore, knowledge of the physiological mechanisms that occur under the influence of stress is crucial for agricultural production [25]. At the whole plant level, all abiotic stress factors trigger physiological and molecular conditions that in some cases lead to similar responses. Drought, salinity, and low-temperature stress can all be represented as physiological desiccation at the cellular level [26,27] (Figure 1). Wheat is subjected to a range of climatic and seasonal variations in the different phenophases, but it appears that stress has a more detrimental effect in the reproductive phenophases than in the vegetative [28]. The effects of stress on reproductive phenophases have a direct impact on grain formation, size, dry weight, and number of seeds [28]. More specifically, about 50% of all crop yield losses are due to abiotic factors such as high temperature (20%), low temperature (7%), salinity (10%), drought (9%), and other forms of stress (4%) [29].

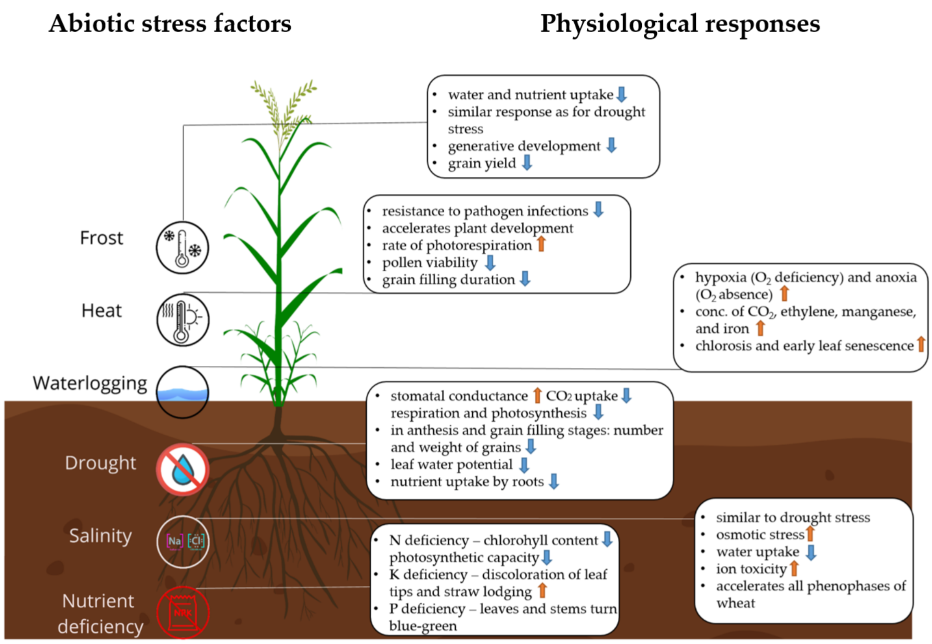

Figure 1. Abiotic stress factors (frost, heat, waterlogging, drought, salinity and nutrient deficiency) and corresponding physiological responses of winter wheat (↑ symbol represents increase and ↓ symbol represents decrease).

2.1. Drought Stress

Approximately 80–95% of the plant's fresh biomass is water, which plays a critical role in different physiological processes, including plant growth, development, and metabolism [30]. Therefore, many authors consider drought as the most important environmental stress for various plants, especially in drought-prone regions [30,31]. The extent of damage caused by drought cannot be accurately predicted because it depends on a number of factors, including rainfall patterns, the soil's ability to retain moisture, and crop water losses through evapotranspiration [32]. Drought results from an insufficient amount of precipitation and water in the soil during the growing season [33] and is the most limiting factor for wheat production worldwide [34]. The effects of drought stress on final wheat yield depend on the severity and duration of the stress, and the response varies depending on the phenophase of the crop [35,36]. Winter wheat crops are generally very resilient to mild and moderate drought stress prior jointing phenophase, and many adverse effects can be reversed after rewatering [37,38]. Furthermore, drought stress just before anthesis and during the grain filling phenophases is causing reduced number and weight of grains [39,40]. In addition, drought stress affected leaf area expansion, dry matter distribution, photosynthetic rate, and root growth [36]. Many plant functions and growth variables are affected by drought stress [41]. Under such conditions, CO_2 uptake is reduced due to stomatal closure, which affects respiration, photosynthesis, and overall plant development. As a result, the production of cell components such as carbohydrates, nucleic acids, lipids, and proteins is reduced [42]. Severe drought stress in wheat crops also significantly reduces the chlorophyll content in leaves and consequently leaf photosynthesis [39]. Drought stress can reduce the water potential of wheat leaves due to solute accumulation, resulting in a decrease in turgor [43,44]. The determination of leaf water potential is an efficient and reliable method to measure the response of plants to water deficits, which also affect various gas exchange traits such as stomatal conductance, net photosynthetic and transpiration rates, etc. Stomatal conductance and transpiration rates generally decrease when the water potential is reduced [42]. Drought-tolerant wheat genotypes maintain high turgor potential and relative water content, and the maintenance of leaf turgor is an important adaptive mechanism that plays an important role in regulating stomatal and photosynthetic activities under drought stress conditions [42,45]. Drought stress significantly impairs the efficiency of nutrient uptake and utilization by plants. Many important nutrients such as nitrogen, magnesium, calcium, etc. are taken up by roots along with water; drought restricts the movement of these nutrients by diffusion and mass, resulting in delayed plant growth [46]. Some of the adaptive mechanisms to water deficit in wheat are morphological in nature, such as avoidance of water deficit through deep rooting, reducing leaf area, early flowering, and alternation of leaf waxiness and trichome density [47,48]. These adaptive mechanisms can reduce water loss and protect against drought stress over longer periods [47,48].

2.2. Heat Stress

Drought and heat are two related but different constraints to grain production [49]. Temperatures that exceed the limit of adaptability result in heat stress, which significantly affects metabolism, plant viability, and possibly the ability of plants to resist attack by pathogens [50]. Temperature is an important factor affecting all phenophases of wheat plants, such as germination, tillering, stem elongation, booting, anthesis, and ripening [51]. Extreme heat has many influences, such as the typical acceleration of plant development at higher temperatures and the direct physiological effects of high temperatures on plant growth, reproduction, and final yield [36]. Considering global warming, Asseng et al. [52] estimated that global wheat production decreases by 6% for every 1 °C increase in temperature. Unusually high winter temperatures cause rapid plant growth and accelerate the growth rate [53]. Heat stress during the vegetative phenophases in winter wheat sown in November resulted in an earlier onset of stem elongation and a shortened tillering time [54]. During reproductive phenophases, the optimum temperature for wheat growth and development is 15–20 °C [55], and wheat is more sensitive during this period than during vegetative phenophases [56,57]. Heat stress during sensitive phenophases, such as anthesis, where heat has the most negative consequences and leads to the loss of pollen viability, causes significant yield losses due to the disturbance of the reproductive physiology [53,57]. Frequent short episodes of high-temperature stress can negatively affect seed number [58]. During grain filling (ripening), extreme heat can accelerate leaf senescence and affect final grain weight by shortening grain filling duration [50,59,60]. Hot periods during reproductive phenophases are often dry, so plants often suffer from heat and drought stress simultaneously [36,61], so it is important to consider both stressors together because their combined effect is greater than when considered separately [27]. Heat stress leads to a change in the water balance of plants [62]. In general, water loss under heat stress is higher during the day, mainly due to increased transpiration rate, which ultimately affects essential physiological processes in plants [32]. It also reduces the number, mass, and extension of roots, which limits the supply of water and nutrients to aboveground plant parts [63]. The relative water content and the amount of chlorophyll in leaves decrease rapidly, and the green parts turn yellow and reach harvest maturity much earlier [50,64]. It is well known that photosynthesis is an extremely heat-sensitive process [65]. It can be completely inhibited by high temperature, and a decrease in photosynthesis may be due to the inhibition of the activity of the photosystem II (PSII), which is the most temperature-unstable element of the photosynthetic electron transport chain [65,66]. In addition, high temperature damages the processes responsible for light collection and light energy conversion and increases the rate of photorespiration [50]. Kumar et al. [67] also found negative effects on soil microbial activity as a result of heat stress.

2.3. Salinity Stress

Among abiotic stresses, salinity stress has emerged as one of the most important threats to the sustainability of wheat production, especially in arid and semiarid regions of the world [68]. Globally, more than 800 million hectares of agricultural land are affected by salinity (including saline and sodic soils), representing more than 6% of the world's total land area [69]. Salinity stress produces many symptoms similar to those of drought stress [70]. The occurrence of salt in the soil reduces the plant's ability to absorb water, resulting in a reduction in growth rate. This is called the osmotic effect or water deficit due to salinity [70,71]. When excessive amounts of salt enter the plant through the transpiration stream, the cells of the transpiring leaves are damaged, which can lead to a further growth reduction, referred to as the salt-specific or ion-excessive effect of salt [71]. Including the effect of water deficit, salinity stress affects all major developmental processes of winter wheat such as germination, growth rates, photosynthesis and pigments, nutrient deficiency, and oxidative stress [72]. During seed germination, the plant responds most strongly to soil salinity by either exerting osmotic stress that impedes water uptake or causing ion toxicity. These consequences ultimately reduce the utilization of seed reserves [73]. It accelerates all phenophases of wheat; reduces the leaf number, leaf expansion rate, root–shoot ratio, number of fertile tillers, biomass production, spikelet number, and grain weight; and negatively affects the grain yield [74–78]. For example, yield losses of up to 45% have been observed in wheat grown under saline conditions [79]. The spatial variation in salinity arises from interactions between different edaphic factors (permeability, pH response, bulk density, geohydrology, topography, and groundwater depth and their salinity) [68,80]. Geographic factors, such as elevation, slope, and aspect, and agronomic practices, such as fertilization, irrigation, drainage, crop rotation, and tillage type, have immense effects on soil salinity [80]. Climatic parameters and the effects of global warming also affect the increase in soil salinity [68,80].

2.4. Nutrient Deficiency Stress

Although not directly related to climate change and environmental factors, nutrient deficiency is one of the most common stressors in wheat production. As sessile organisms, higher plants must cope with a spatially and temporally constantly fluctuating availability of soil nutrients [81]. The supply of all macronutrients (N, P, S, K, Mg, and Ca) can influence the distribution of dry matter between tillers and roots of higher plants.

Nitrogen (N) fertilization is critical for wheat plant growth and development [82]. Nitrogen is a limiting factor for plant growth, as evidenced by lower plant productivity following N reduction [83]. Plants quickly perceive the stress of nitrogen deficiency and respond with a variety of physiological and metabolic processes. These include the degradation of proteins, the reduction of the corresponding enzyme activities, the accumulation of carbohydrates, especially starch, the initiation of oxidative stress through the formation of H_2O_2, and the causation of lipid peroxidation [84]. Among these events, the reduction of the photosynthetic capacity is one of the most important damages caused by N deficiency, which inhibits plant growth and development [84]. Under low-nitrogen conditions, the photosynthetic rate and the content of chlorophyll a and other pigments decreased after plants suffered from N deficiency [85]. The chlorophyll content of wheat leaves is closely related to leaf nitrogen since more than half of the nitrogen in a leaf is accounted for by the photosynthetic machinery, and it is already known that leaf chlorophyll content increases with nitrogen supply and is low under nitrogen deficiency [85–87]. Stem elongation is the most rapid stage of vegetative growth, during which the plant establishes a structure for the production of carbohydrates to fill the grain—the flag leaf accounts for about 75% of the effective leaf area contributing to grain filling [88]. This stage is also very sensitive to nitrogen deficiency and therefore provides a good basis for distinguishing plants with different nitrogen statuses using hyperspectral sensing in the field [88,89].

Potassium (K+) is a highly mobile element in the plant and is translocated from the older to the younger tissue. In the case of potassium deficiency, symptoms usually occur first on the lower leaves of the plant and progress toward the top as the severity of the deficiency increases [90]. Potassium deficiency in wheat causes discoloration of the leaf tips and margins, which turn yellow and brown during the rapid growth phase of the shoot [91]. As with other cereals, potassium deficiency in wheat often results in weakening of the straw, which can lead to lodging [91].

Phosphorus (P_2O_5) is present in the wheat plant in lower concentrations than nitrogen and potassium. However, as a component of adenosine di- (ADP) and tri-phosphates (ATP), phosphorus directly affects almost all energy-consuming biological processes in the plant, such as photosynthesis, respiration, synthesis of cellular components, and membrane transport [92]. In younger plants, phosphorus deficiency causes leaves and stems to turn blue-green and take on a strong purple color, while older leaves decline early. In the reproductive phenophases, the leaves turn purple bronze tones, and ears do not develop properly [91].

2.5. Frost Stress

Cold temperatures or frost cause tremendous losses in agriculture, especially in cereal crops in subtropical and temperate regions [93]. Wheat can be damaged by frost at all phenophases. Sensitivity to frost, however, increases as the crop develops. In contrast, the risk of frost damage decreases as spring advances [94,95], so it is important not to seed winter wheat too early or use rapidly developing varieties that carry a high risk of frost damage [95]. A short interval of freezing air has a devastating effect on the vegetative and reproductive growth of plants [96]. The freezing environment disrupts water uptake by the roots, and a lack of water in the stem leads to drought stress [97]. This drought stress due to the disturbed water ratio also reduces the root ion absorption rate and nutrient transport to other parts of the plant and ultimately leads to plant underdevelopment [40,98]. Wheat is reported to be the most susceptible to frost damage when the spike is emerged as ice crystals can form directly on the reproductive tissue when the spike is no longer protected by the stem and leaf sheath [95]. In addition, frost causes flower abortion, infertility, fertilization breakdown, and impaired seed filling, resulting in low grain set and ultimately low grain yield [93]. In the study by Fuller et al. [99], two wheat cultivars were placed in a freezing chamber for 2 h with various frost stress treatments. As a result, severe damage to flag leaves and spikes was observed, increasing with decreasing temperature. Partial to complete loss of grain yield was also observed in the wheat plants studied [99].

2.6. Waterlogging Stress

Inadequate soil aeration combined with excessive moisture usually has a negative effect on plant growth and leads to waterlogging. This phenomenon is becoming an obvious obstacle to agricultural production due to the increasing frequency of extremely heavy rainfall [100]. In addition to heavy rainfall, soil erosion and poor soil drainage can also be the cause. Waterlogging causes a number of physical, chemical, and biological changes in the soil that ultimately inhibit the growth of plants that cannot tolerate these conditions [101]. Thus, plants growing in waterlogged soils are exposed to unfavorable growth and negative development conditions, such as hypoxia (O_2 deficiency) or anoxia (O_2 deprivation), disruption of aerobic respiration, energy deficiency, and oxidative stress [102]. In waterlogged soils, CO_2, ethylene, manganese, and iron can accumulate to concentrations that can be lethal to plants [103]. The roots face the effects of waterlogging first, while the upper parts of the plant suffer. Many authors concluded decline of seminal roots in wheat [104]. Conversely, waterlogging stimulates aerial root development in wheat [101]. Poor soil aeration leads to chlorosis and early leaf senescence and also reduces grain weight and yield [103]. The extent of stress to wheat in waterlogged soils depends on the phenophase of the crop, duration of waterlogging, soil type, and growing conditions [103]. Wheat plants flooded with water for six days resulted in 39% and 47% reductions in grain yield on alkaline and sodic soils, respectively [105].

3. Physiological Response of Winter Wheat to Biotic Stress Factors

Biotic stress is an unfavorable condition in which the plant cannot maintain its normal growth due to interaction with harmful organisms such as plant pathogens (fungi, bacteria, and viruses), herbivorous insects, and undesirable plant species or weeds [106]. Economically, insects, weeds, and diseases regularly affect crop quality and yield and reduce agricultural profitability [107]. The consequences of biotic stress are poorly understood because physiological effects vary widely [108] (Figure 2). Pathogen inoculation and multiplication, herbivore detection and defoliation, and competition from weed species are highly variable and interact with the abiotic stress factors mentioned earlier [108]. Biotic factors cause environmental stress in plants, such as a reduction in net photosynthesis, which can be caused by insect feeding, foliar pathogens, or shading by weeds [107]. The occurrence and harmfulness of insect pests, weeds, and pathogens can be affected by changes in climate [20]. For example, rising temperatures are known to promote the spread of pathogens [109,110]. Climate change impacts may affect population dynamics of insect pests, with temperature increases favoring higher metabolic and developmental rates, reproduction, and survival [20]. Weeds are becoming more common in some cropping systems [22] and are likely to have greater resilience and better adaptability to changes in CO_2 concentration and rising temperatures due to their diverse gene pool and higher physiological plasticity when competing with crops [111]. Major crops growing in our future fields are therefore likely to be exposed to a wider range and number of abiotic and biotic conditions, as well as their combination. For example, both cold and heat stress have been found to reduce plant resistance to biotic stresses [112].

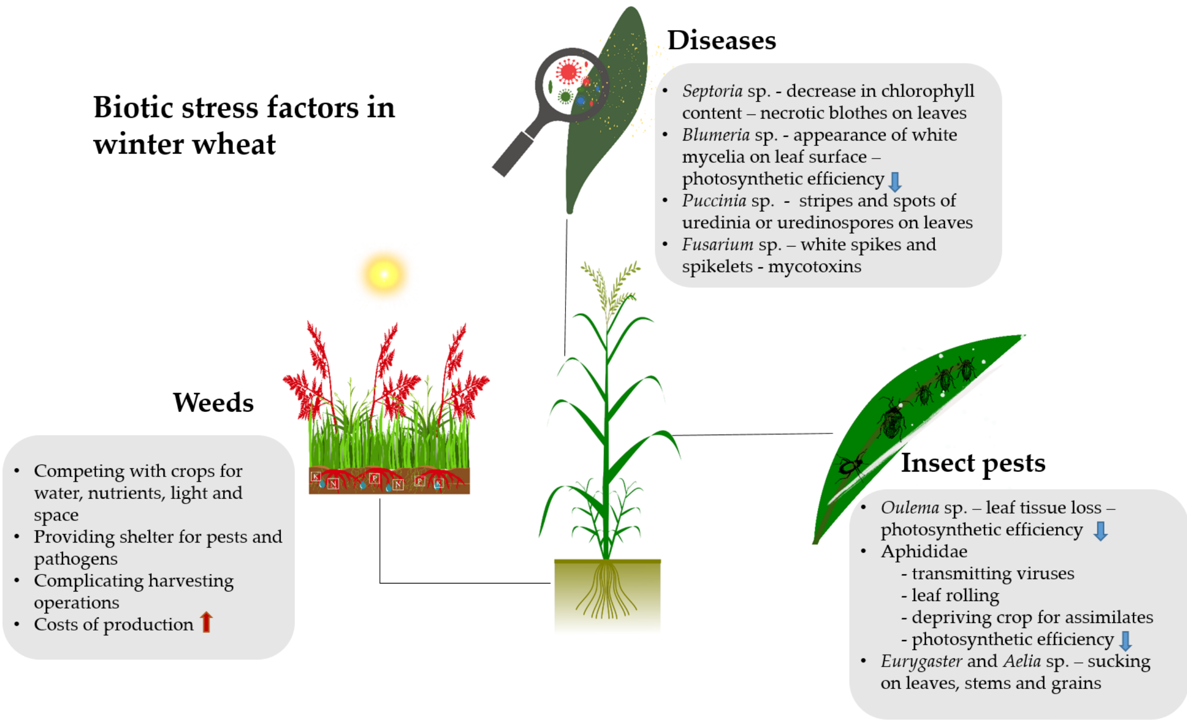

Figure 2. Biotic stress factors (diseases, weeds and insect pests) in winter wheat and their corresponding physiological responses of winter wheat (↑ symbol represents increase and ↓ symbol represents decrease).

3.1. Weeds

Weeds directly affect wheat productivity, including the cost of labor, machinery, herbicides, and other inputs. They also indirectly affect wheat production by competing with crops for resources, providing shelter for pests and pathogens, affecting water management, reducing grain yield and quality, and increasing processing costs [113,114]. Weeds not only reduce yield but also complicate harvesting operations [115]. Most importantly, weeds compete with crops for resources such as moisture, nutrients, light, and space, which puts crops at a disadvantage in obtaining these resources and can cause abiotic stress due to the lack of abiotic elements. In addition, weeds can grow much taller than many wheat varieties and partially shade wheat plants, causing them to droop due to their weak stems, which can result in severe yield losses [113–115]. Yield losses can range from 10% to 80%, depending on the occurrence of the weed and the phenophase in which the weed occurs [115].

3.2. Insect Pests

During the growing season, winter wheat crops are exposed to pests that can significantly reduce yields. According to Oerke [116], losses in total small grain production due to pest infestations are about 9% worldwide. Cereal leaf beetles, aphids, and sunn pest are the most important herbivores in European wheat production [117].

Cereal leaf beetles (*Oulema melanopus*, L., and *Oulema lichenis*, Voet.) are the main pests of winter wheat. They feed by chewing leaves, resulting in peeling of the epidermis and loss of tissue. The typical symptoms of both adults and larvae on the host plant are thin and long lines where the larvae peel away the epidermis of the leaf, while the adults chew completely through the leaf, resulting in narrow slits [117,118]. Under uncontrolled circumstances, this damage can worsen in several cases, although most photosynthetic surfaces can be affected [117,118]. In wheat, the reduction in grain yield per plant by one larva of the cereal leaf beetle was 9%, and the reduction by two larvae was 18% [119]. In their study, Lukasz et al. [120] indicated that tissue loss from *O. melanopus* chewing manifests itself in the decline of chlorophyll content, and the extent of photosynthetic tissue loss can be so pronounced that photosynthetic efficiency decreases.

While chewing insects cause extensive damage to plant tissue, aphids feed on the phloem sap of host plants by penetrating their spines and damage crops by depriving them of photoassimilates and transmitting numerous plant viruses [121]. The most wheat-damaging aphid species are the Russian wheat aphid (*Diuraphis noxia*, Mordvilko), the grain aphid (*Sitobion avenae*, Fabricius), and the bird cherry-oat aphid (*Rhopalosiphum padi*, L.) [122]. The persistent interactions of aphid stylet with plant cells result in plant responses to aphid infestations [121,123,124]. Probing by aphids can be affected by changes in the chemical content of the sieve sap or by physiological changes induced by the aphid saliva, which can trigger plant defense signals [121], as well as many of the stress symptoms, whose most characteristic symptom is white or purple longitudinal stripes on leaves and sometimes on the stem [125,126]. Leaf rolling can also be caused by feeding damage by aphids. For example, *D. noxia* feeds mainly on the upper leaf surface and causes leaf rolling in cereals resulting in a drastic reduction in chlorophyll content and decreased photosynthetic capacity, which combined with leaf curling resulted in a significant loss of effective leaf area in susceptible wheat plants [127]. In response to herbivore attacks, plants defend themselves with a range of defense strategies that include chemical and mechanical defense mechanisms, including the production of plant secondary metabolites [128,129] such as insecticidal phloem components, including toxic or growth-inhibiting alkaloids, proteins, and phenolics [121,130].

The sunn pest belongs to the genera *Eurygaster* and *Aelia* [131]. When overwintering adults invade wheat fields in spring, they damage wheat plants in the vegetative phenophases by sucking on the leaves and stems. The nymphs and the new generation of adult pests damage the spikes and grains of wheat plants in the reproductive phenophases. By sucking on the grains, the adults and the nymphs insert proteolytic and amylolytic enzymes that cause the destruction of gluten, which affects the favorable baking properties of the flour [132,133]. The infestation of as little as 2-3% of the grain may render the entire batch of grain unsuitable for baking due to poor flour quality [132,133]. It also causes lower starch content and grain weight [134,135], resulting in lower yield and seed viability [136].

Wheat crops are attacked by many pests, but not always with the same intensity. The decision to apply chemical pest control measures is based on data on the infestation intensity [117]. Integrated pest management is based on predicting the occurrence and spread of pests and involves the use of insecticides only when there are no other options to reduce the number of pests [137,138]. Many herbivorous pests are distributed in patches across fields, and because of this spatial heterogeneity, the appropriate scale of detection must be applied to determine the distribution pattern of pests within the field [139]. All of the above pests occur in heterogeneous areas of the field, which is important for monitoring and precise pest management.

3.3. Diseases

Pathogenic fungi, along with viruses and bacteria, represent a significant obstacle to wheat production [140]. An outbreak of these diseases can spread rapidly under favorable environmental conditions and result in significant yield and quality losses. Therefore, the development of technologies to accurately monitor and identify disease incidence is extremely important for agricultural management [141]. The most important diseases in winter wheat production are blotch diseases (*Septoria* sp.), powdery mildew (*Blumeria graminis* f. sp. *tritici*, Marchal), rust species (*Puccinia* sp.), and *Fusarium* head blight disease [140,142].

Septoria diseases of wheat include two important diseases, namely, *Septoria nodorum*, Berk., and *Septoria tritici*, Roberge in Desmaz. They are currently two of the most devastating foliar diseases of wheat worldwide and especially in northwestern Europe, causing yield losses every year [143,144]. The pathogen causes a decrease in chlorophyll content in leaf tissue. The destruction of the chloroplasts and shrinkage of the assimilative surface of the leaf lead to a decrease in photosynthetic activity and respiratory activity [144]. After a latent period, the pathogen enters the necrotrophic phase, and infected leaves become chlorotic and change to necrotic, irregularly shaped blotches in which asexual, fruiting sporulation forms (pycnidia) develop [145,146]. Yield losses occur mainly due to a decrease in grain content within individual spikes and a decrease in grain weight in general [147].

Powdery mildew is a well-known wheat disease that occurs worldwide [148]. Yield losses can be as high as 40%, and early infection can lead to seedling death. The characteristic symptoms of the disease are the appearance of white cotton-wool-like mycelia with spores that sometimes cover almost the entire leaf surface. The affected plants look weak and form shriveled grains [142]. Infection with wheat powdery mildew at the seedling stage can affect the growth and development of wheat plants and lead to a decline in grain filling and grain weight at the adult stage [149].

Rust diseases (*Puccinia* sp.) are the most widespread diseases in the world [148]. It is estimated that annual losses due to wheat rust pathogens are USD 4.3 to USD 5.0 billion worldwide [140]. There are three wheat rust diseases: stem rust (*P. graminis* subsp. *graminis* Pers.), stripe rust (*P. striiformis*, Westend.), and leaf rust (*P. triticina*, Eriks.) [150]. Symptoms of infection with stem rust typically appear as masses of red uredinospores on leaves, stems, glumes, and awns of susceptible cereals. Yield losses are associated with reduced grain size and stem lodging [142]. *P. striiformis* causes necrotic stripes or elongated spots that infect the green tissue of wheat plants, and chlorosis or necrosis occurs to varying degrees depending on plant resistance levels and temperature. The pathogen deprives the host plants of water and nutrients, which weakens the plants [151]. Leaf rust occurs more regularly and in more regions of the world than stem or stripe rust of wheat. Yield losses in wheat due to *P. triticina* infection are usually the result of a reduced number of kernels per head and lower kernel weight, preceded by foliar symptoms manifested by small uredinia surrounded by chlorosis or necrosis [152].

Fusarium head blight (known as scab) is an economically destructive wheat disease caused by *Fusarium graminearum*, Schwabe [153]. These fungal pathogens produce several mycotoxins, particularly deoxynivalenol (DON) and zearalenone (ZEA), which are poisonous to humans and animals [154]. Symptoms are detected at the time of spike emergence. The pathogen infects individual spikelets or the entire spike, which turns pale and almost white, and under moist conditions, pink spore masses are seen on or between spikelets. In early infections, the grains look pink and shriveled, while at harvest, black, hard structures (perithecia) are often seen on the infected spikes [142].

To determine the occurrence and spread of plant diseases and to assess the damage caused in a field, it is important to use crop monitoring programs to help with crop protection decision making to minimize crop losses. They are especially important for crops with large geographic distributions or for diseases that can quickly cause large economic losses [155].

4. Application of Remote and Proximal Sensing Techniques for Environmental Stress Detection in Winter Wheat

Increasing understanding of how plants respond to abiotic and biotic stresses has led to the development of innovative sensing technologies that can estimate plant variables. Remote sensing technology allows for the non-contact acquisition of information and has been widely used in geoscience and engineering, shedding new light on plant phenotyping [156–158]. Remote sensing of vegetation is a non-destructive method suitable for rapid and accurate assessment of a plant's physiological status and objective evaluation of the plant's response to natural and anthropogenic environmental factors [159]. There are several types of remote sensing systems used in agriculture. Most of them are based on the information provided by visible and near-infrared radiation (VIS-NIR) reflected (or transmitted) from the plant [160]. The radiation reflected from the object (plant) is one of the most important properties in the field of remote sensing. It is measured as a function of wavelength and referred to as the spectral reflectance [161]. Therefore, the most useful wavelengths for remote sensing of vegetation changes include the visible (VIS; 400–700 nm), near-infrared (NIR; 700–1300 nm), and shortwave infrared (SWIR; 1300–2500 nm) regions of the electromagnetic spectrum [162]. Because solar energy is the largest component in the VIS, NIR, and SWIR bands, sensors using these bands can typically acquire data with a relatively high signal-to-noise ratio [162,163]. As a current and cost-effective technology, VIS-NIR-SWIR sensors are available on a variety of remote sensing platforms, including ground-based, airborne, and satellite-based systems [163]. Crop data that are sensed or collected “near” the crop are referred to as proximal sensing [160]. Proximal (remote) sensing methods include several approaches, the first of which is VIS-NIR-SWIR spectroradiometry (i.e., multispectral or hyperspectral sensor) (Figure 3), the second is infrared thermometry, and the third is RGB imaging cameras [160]. The quality of proximal and remote sensing data lies in their temporal, spatial, spectral, and radiometric resolution, which accounts for their advantages for plant phenotyping [156,158]. Since near and remote sensors differ in their sensitivities to different wavelengths and sizes of objects that can be detected, these differences are referred to as the spectral and spatial resolution. The spatial resolution defines the size of the pixels that cover the Earth’s surface and refers to the dimensions of the smallest object that can be detected on the ground [162]. The spectral resolution is the sensitivity of the sensor to different electromagnetic wavelengths of the spectrum, i.e., the number and width of wavelengths detected by the sensor (VIS-NIR-SWIR), distinguishing between multispectral, hyperspectral, and RGB sensors [164]. In recent decades, the number of studies on plant spectral reflectance has increased significantly as multispectral and hyperspectral cameras and field spectroradiometers have become increasingly capable of accurately measuring the entire electromagnetic spectrum (350–2500 nm), from which information for a range of plant traits can be obtained [165–167]. Multispectral and hyperspectral sensors measure the spectral reflectance of plants and enable the calculation of vegetation indices (VIs) as indicators of plant stress and yield predictions [168]. The VIs can be used for site-specific management in precision agriculture [169] and in in situ screening for a broad array of plant breeding objectives such as yield potential, adaptability to abiotic and biotic stresses, and plant quality [160].

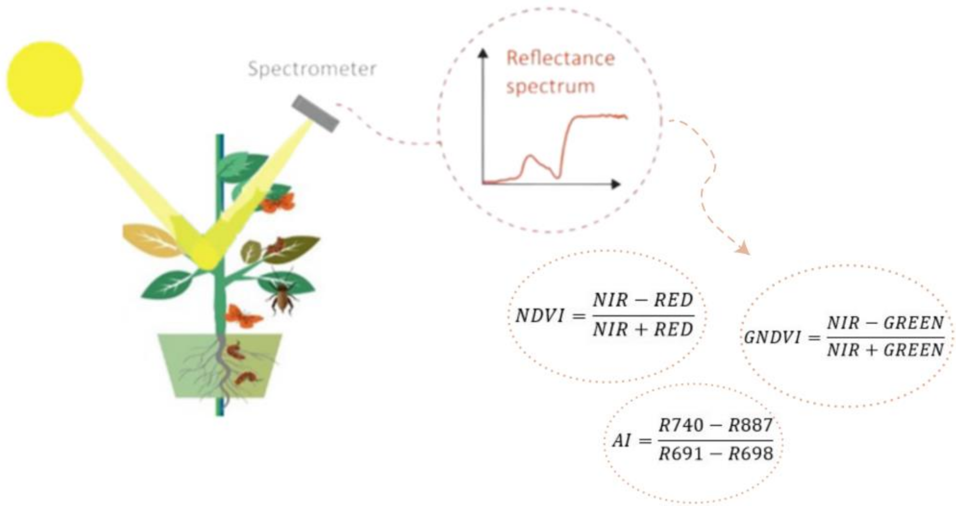

Figure 3. Method for obtaining spectral data from pest-infested plants using hyperspectral sensor (spectrometer). Vegetation indices (VI) such as NDVI, GNDVI and AI can be calculated from the reflectance spectral data.

4.1. Detection and Evaluation of Drought Stress in Winter Wheat

In wheat research, particular attention has been paid to drought stress because of its extremely negative effects on the growth, development, and final grain yield [170,171]. In addition to irrigation management, a rapid assessment of the water content in wheat plants would allow effective screening and identification of resistant cultivars in breeding programs [172]. Measuring the spectral characteristics of wheat plants represents a simple, rapid, practical, and economical technique for assessing various phenotyping criteria related to the drought resistance of plants, and high-throughput phenotyping data can be used for genomic selection to assess optimal wheat varieties under drought stress [158,173]. Several spectral ranges are considered useful for assessing drought stress. Based on the vegetation indices calculated from the ratios and differences between the reflectances of plant material in VIS, NIR, and SWIR, various agronomic plant traits related to drought can be estimated [174]. There is increasing evidence that the water content can be estimated remotely by using water absorption bands in the NIR to SWIR where there are strong water-absorbing features (970 nm, 1200 nm, 1450 nm, 1930 nm, and 2500 nm) [175]. Numerous spectral indices have been proposed to remotely estimate the water content of plant tissues to provide a measure of the water deficit stress [176,177], mostly based on these spectral bands [178]. To improve the extraction of the spectral information on water metrics in vegetation and soil, scientists have proposed several hyperspectral vegetation indices, including the water index (WI), normalized difference vegetation index (NDVI), simple ratio (SR), photochemical reflectance index (PRI), normalized difference water index (NDWI), water band index (WBI), brown pigment index (BPI), normalized difference infrared index (NDII), simple ratio water index (SRWI), moisture stress index (MSI), spectral ratio index in the NIR shoulder region (NSRI), soil adjusted index (SAVI), optimized soil adjusted vegetation index (OSAVI), deep water index (DWI), and red edge normalized difference vegetation index (Red edge NDVI) [18,60,179–185]. Besides the VIS-NIR-SWIR sensors, the most advanced proximal and remote sensing techniques to estimate plant water stress are thermal infrared (TIR) and solar-induced fluorescence (SIF) [186]. Many authors have related spectral characteristics of vegetation (along with derived VIs) and physiological parameters to assess the response to a water deficit in crops, including relative water content (RWC), canopy water content (CWC), leaf water content (LWC), and soil water content (SWC) [175,179,187]. The soil water content (SWC) or soil moisture (SM) is an important indicator of the photosynthetic rate and growth status of plants. Generally, the level of drought stress in winter wheat is evaluated by the soil water status [188,189]. Conventional methods for measuring the SWC rely on site-specific surveys, but these are often laborious and slow [185]. Some related parameters, such as red edge (the area where vegetation reflectance changes rapidly from the red component in VIS to the NIR region of EM) and spectral VIs have been used to determine the soil moisture of winter wheat [180,190]. In their study, Ren et al. [185] concluded that the spectral index based on the optimized index NSRI has good abilities to determine the SWC in the jointing, anthesis, and grain filling phenophases of winter wheat. The RWC can be determined with high accuracy by spectral remote sensing systems that analyze spectral data and provide simple and useful information [187,191]. Tian et al. [191] measured wheat leaves radiometrically to spectrally characterize water deficiency symptoms. The reflectance spectra of wheat leaves indicated that the water content dominated in the range of 1650–1850 nm, from which they concluded that with a decrease in the RWC of wheat leaves, the spectral absorption features at 1650–1850 nm were gradually more expressed. Liu et al. [192] found significant positive correlation coefficients between the plant water content (PWC) and spectral reflectance in the range of 740–930 nm at different growth stages of winter wheat, suggesting that spectral reflectance increases in the NIR and red edge region (680–740 nm) due to the effects of the PWC on the internal structure of the leaf. Peng et al. [190] investigated the relationship between the CWC and spectral reflectance under different water treatments during winter wheat vegetation and concluded that the CWC of winter wheat generally decreased as the growth and development progressed. Under the various water treatments in this study, CWC increased with increasing irrigation volume. In the VIS range, canopy reflectance decreased with irrigation volume. In contrast, the canopy reflectance in the NIR range increased with increasing irrigation amount. Using different VI, Sun et al. [179] accurately estimated the water status of winter wheat expressed as water metrics (LWC, PWC, and CWC) and observed a significant correlation between VIs (WI, WBI, MSI, NDWI, NDII, OSAVI, PRI, and Red Edge NDVI) and the water metrics, with Red Edge NDVI having the highest correlation coefficients with them.

Based on numerous studies of water stress in plants and applications of remote sensing, there are a large number of accurate, reproducible methods that can be applied under a wide range of climatic, soil, and growing conditions. Future improvements in water use efficiency, and thus high yields in cereal crops, are needed to adapt field practices and irrigation schedules [179,187].

4.2. Detection and Evaluation of Heat Stress in Winter Wheat

Early detection of heat stress could help mitigate its detrimental effects on grain production, which can be assessed using remote sensing technology to help markets and governments prepare for grain shortages and organize insurance and recovery management [193–196]. While the use of remote and proximal sensing to detect drought has attracted considerable scientific interest, heat stress in cereals has not been nearly as well studied. Many studies have shown that photosynthetic parameters (i.e., net photosynthetic rate (Pn), maximum and potential efficiency of PSII (Fv/Fm and Fv/Fo), stomatal conductance (Gs), and leaf chlorophyll content (LCC)) can serve as indicators of heat stress conditions due to their effects on photosynthetic decline [32,36,197,198]. Because VIs provide the ability to non-destructively observe photosynthetic parameters, they can potentially be used as estimators of heat stress in plants [195]. Cao et al. [195] selected potential VIs for heat stress detection that were most strongly associated with photosynthetic parameters. The PRI was the most sensitive VI for heat stress among the 17 spectral indices mentioned, and this sensitivity was due to the relationship between PRI and photosynthetic activity, with PRI showing a positive correlation with the chlorophyll/carotenoid ratio, which normally decreases under heat stress in plants [196,199]. With respect to the LCC, chlorophyll index-red edge (CI red edge) had the highest coefficient of determination (R^2), and the normalized difference red edge index (NDRE) had the highest R^2 with respect to Pn; these two indices result from the fact that they are closely related to chlorophyll content in plants. These results are consistent with those of Ryu et al. [200], who concluded that the PRI is the most useful vegetation index under physiological stress caused by heat stress in paddy rice. Unlike other VIs, the PRI decreased under the extreme heat stress even before rice entered the heading stage. Considering that drought stress and heat stress usually occur simultaneously in winter wheat, it is necessary to distinguish the symptoms of these two types of stress and thus differentiate the spectral characteristics depending on the type of stress.

4.3. Detection and Evaluation of Salinity Stress in Winter Wheat

Remote detection of salinity stress can provide a robust approach for monitoring crop condition, evaluating the economic impact of using poor-quality water, and optimizing crop productivity [201]. Many studies have derived soil salinity directly from the spectra of salinized soil surfaces, but this method is not an option for a salinized soil surface with vegetation cover [202–205]. Identifying and developing salt-tolerant genotypes is one of the promising methods to improve the productivity of salt-stressed soils, and hyperspectral proximal and remote sensing could be a reliable and rapid method [206]. In their study, Elmetwalli et al. [201] compared the spectral responses of wheat and corn canopies grown under different salinity and drought stress conditions and showed how the spectral curves differed with respect to the stress parameters. Using PCA and PLDA, they found that it was possible to distinguish between low and high levels of salinity- and moisture-related stress in corn but not in wheat. Remotely sensed VIs of crops are also promising indicators of the soil salinity [207]. In their study, Zhu et al. [207] measured the hyperspectral reflectance of winter wheat during the grain filling phenophases. The VIs derived from the collected hyperspectral data of winter wheat were compared with the salinity at four soil depths. The results showed that the VIs, which include blue, red edge, and near-infrared wavebands, best estimate the soil salinity. The study shows that the spectral reflectances of winter wheat illustrate well the physiological changes of plants under salt stress and that it is possible to detect the soil salinity from the spectral response of plants.

4.4. Detection and Evaluation of Nutrient Deficiency Stress in Winter Wheat

Intensive cultivation and unbalanced fertilization practices have left soils depleted of macronutrients such as N, P, and K. Deficiencies in these essential elements can drastically affect the growth, development, and yield of wheat [208]. By the time the symptoms of nutrient deficiency become clearly visible in the plant, a number of biophysical processes have already been disrupted by nutrient deficiency stress, so it is critical to detect stress early [209]. Traditional methods for monitoring nutrients in plants require sampling and expensive chemical laboratory analysis, which is time consuming and sometimes economically and environmentally unacceptable [210]. Ground-, air-, and satellite-based remote sensing systems have been successfully used to determine plant nutrient requirements [162]. The principle of remote sensing to determine nutrient stress in plants is to change the photosynthetic activity and cell structure, stretch, and overtones of chemical bonds such as the N–H bond, which alters the spectral reflectance of plants [210,211]. However, most studies monitoring nutrient deficiencies are related to N deficiency. N is a critical element required for biomass formation in agricultural crops. The proportion of chlorophyll in the leaf and the corresponding N content are indicators of the N requirement of wheat plants [89]. Since the leaf N concentration is related to the chlorophyll amount, many remote sensing studies have focused on estimating the chlorophyll concentration in leaves to estimate the N status in an indirect way, which is a simpler method than the classical laboratory analyses to estimate the N content in the plant [212]. A good correlation between canopy reflectance and N accumulation in leaves was found by Zhu et al. [213] in a study on rice and wheat, with the best results obtained when a ratio of reflectance at 810 nm to reflectance at 660 nm and a ratio of reflectance at 870 nm to reflectance at 660 nm were used. Similar results were presented by Jia et al. [214], who showed that reflectance at NIR, red, and green wavelengths and vegetation indices NDVI, GNDVI (Green normalized difference vegetation index), RVI (Ratio vegetation index), and OSAVI were well correlated with the N content of wheat plants using high-resolution satellite imagery. N deficiency usually leads to a significant increase in the reflectance of the red component in the VIS region and a decrease in the NIR region, so this change in spectral reflectance is considered key to detecting insufficient N supply to the plant [89,215]. Li et al. [216] demonstrated a positive linear relationship between index RVI and N uptake in winter wheat using a portable radiometer capable of measuring in the 325–1075 nm range. Many authors have identified significant wavelengths within the electromagnetic spectrum (515, 520, 525, 550, 575, 743, 1116, 2173, and 2359 nm) that correlate with nitrogen content in plants [217]. Some studies have shown a correlation between indices based on the red edge spectral region and nitrogen content in plants. The DCNI (Double Peak Canopy Nitrogen Index) is an example of an index based on the red edge using wavelengths of 720, 700, and 670 nm [218]. In addition to the DCNI index, the following indices are most commonly used in the literature for this purpose: NDVI, CCI (Chlorophyl content index), GNDVI, SAVI, OSAVI, and RVI [89,219–221]. Since potassium (K) and phosphorus (P), along with nitrogen (N), are of paramount importance to crops, monitoring their status through remote sensing systems would be prominent. Previous studies have shown that hyperspectral remote sensing can be used to accurately estimate K content in crops, which could be used for optimal K fertilization [91,210]. The same authors indicated that the 1450 nm wavelength in the SWIR range was significantly correlated with the K content in wheat leaves. Pimstein et al. [91] proposed a spectral index based on the ratio 1645–1715, which can be used to determine the K concentration in wheat plants. Another study by Yang et al. [222], which examined the relationships between spectral reflectance, determined spectroradiometrically, and K content in wheat, found a strong correlation with the leaf K content for wavelengths in the 1900–2300 nm range. According to previous studies by Pimstein et al. [91] and Mahajan et al. [210], a strong correlation between the P concentration and spectral reflectance was found in wheat at 1400–1500 and

1900–2100 nm and 1650–1710 nm [91,210], so these regions of the EM spectrum could be a potential area for developing VIs for P monitoring. In addition, Osborne et al. [223] found that linear models that included 730 and 930 nm were able to predict the P concentration at the V6 growth stage of corn, while for later stages, prediction of the P content was possible in the blue region of the spectrum (440 and 445 nm), implying that very specific models are needed for different stages, depending on the different effects of P concentrations on the plant.

4.5. Detection and Evaluation of Frost Stress in Winter Wheat

Frost damage is a common disaster for winter wheat, and monitoring frost damage is of great economic importance [224]. The advantages of remote sensing have led to a number of studies on monitoring the effects of spring frost on crops. One of the first reports on the remote sensing of frost in wheat was by Jurgens [225], who proposed the modified normalized difference vegetation index (mNDVI) as a qualitative spectral indicator of frost damage based on the fact that frost-damaged plants reflect radiation differently from dehydrated plants, possibly due to damage in the cell structure. Gu et al. [226] found that the effects of spring frost on plant development could be seen in the reduced NDVI values after the frost event. The mechanism behind the frost-induced decrease in VI values has been described in several studies [224,226–228]. During freezing and after thawing, pigment degradation is greater than composition, resulting in a significant decrease in leaf chlorophyll content [229]. It is reported that the reflectance in the NIR region decreases due to the changing cell structure, while the water absorption band in the SWIR region becomes weaker due to the reduction of the water content in the leaf. Consequently, the increasing reflectance in the red region and decreasing reflectance in the NIR region lead to a decrease in NDVI and EVI values under low-temperature stress [229]. Therefore, Wang et al. [229] proposed to use the spring frost damage index (SFDI) and the normalized difference phenology index (NDPI), the calculation of which includes the weighted sum of the reflectance of the red and SWIR bands.

4.6. Detection and Evaluation of Waterlogging Stress in Winter Wheat

Waterlogging is becoming a limiting condition for crop production as extremely heavy rainfall becomes more frequent worldwide, and its early detection is essential for accurately managing production inputs and reducing the risks associated with crop production [100,230]. Using various machine learning models, Yang et al. [230] found that waterlogging can be well detected in the specific sublevels of the wavebands in the red spectral region (640–680 nm), red edge region (670–737 nm), and NIR region (700–900 nm). There are a few studies on the degree of waterlogging based on remote sensing, which mainly focus on monitoring the occurrence of waterlogging and distinguishing between different types of environmental stress [100,231,232]. Jiang et al. [233] found that spectral VIs, which are based on wavelengths of 800, 550, and 680 nm, are optimal for detecting waterlogging stress. Yang et al. [100] conducted a pot experiment in which they exposed winter wheat to different levels of waterlogging and collected hyperspectral leaf data and LWC values. They concluded that waterlogging leads to a decrease in LWC. The NDVI, DVI, RVI, and LWC were also calculated. Using the BPNN model with the original and first derivative spectrum, red edge, RVI, NDVI, and modified NDVI as independent variables, they were able to invert the LWC and estimate waterlogging stress in winter wheat. Using high-spatial-resolution satellite data, Liu et al. [234] mapped the waterlogging damage in winter wheat fields based on VIs (NDVI, GNDVI, and EVI), LAI, and biomass.

4.7. Detection and Assessment of Biotic Stress Due to Weed Occurrence

Weeds cause notorious yield losses in crops and are usually more economically important than other biotic stresses [235]. It is difficult to estimate the magnitude of crop stress caused by weeds at large spatial and temporal scales because yield reductions caused by weeds cannot be separated from variation caused by climatic and edaphic conditions or geographic areas and from other biotic stress parameters [236]. However, there are a number of scientific data on the incorporation of remote sensing techniques into the decision-making process that is fundamental to site-specific crop protection against weeds [237–240]. More recently, various multispectral or hyperspectral sensors are capable of providing high-resolution data on crop canopy conditions that can form the basis for early detection and identification of weed species [239]. Numerous machine learning methods (ML) have been used in precision agriculture, where weed detection in the field is based on specific shape, color, and texture descriptors (i.e., the morphological characteristics of weed leaves as features for further classification) [241]. In their study, López-Granados et al. [242] used spectral reflectance data in the 400 to 900 nm range to classify monocotyledonous weeds from wheat plants in a field study. They concluded that real-time analysis of high-spectral-resolution images was sufficient to map weed patches in wheat. Eddy et al. [243] tested an artificial neural network (ANN) for classifying weeds (wild oats species and redroot pigweed) and crops (spring wheat, canola, and field pea) using hyperspectral images and achieved an overall accuracy of 94%. In their work, Shapira et al. [244] used general discriminant analysis (GDA) to detect grasses and broadleaf weeds in cereals and broadleaf crops. Using spectral reflectance values obtained by field spectroscopy, the total spectral classification of canopies by GDA for specific narrow bands was 95 $\pm$ 4.19% for wheat and 94 $\pm$ 5.13% for chickpea. The results of the study by de Castro et al. [245] showed that multispectral aerial imagery can be successfully used to map the area of cruciferous weed patches in wheat and legume stands for site-specific treatment mapping. Creating images to classify cruciferous weeds based on multispectral sensors is possible when plants are in the vegetative (green) phenophases, while cruciferous weeds are in the early or full flowering phenophase, when they have an intense yellow color. Martın et al. [246] investigated the potential of hyperspectral data to discriminate between two weed species (*Lolium rigidum*, Gaudin, and *Avena sterilis*, L.) in winter wheat and barley crops. They found that the far SWIR range (1900–2500 nm) was particularly important for distinguishing *A. sterilis* in the phenophases of stem elongation and grain filling. In contrast, for *L. rigidum*, the best results were obtained with the early SWIR range (1300–1900 nm) in the phenophases of late tillering and stem elongation. These authors also chose the red edge part of the EM spectrum (680–780 nm), which is as sensitive for weed discrimination.

4.8. Detection and Assessment of Biotic Stress Due to Insect Pest Infestations

Remote sensing of insects is challenging due to the cryptic nature of many taxa and the limitations imposed by spectral data resolution. Insects are often orders of magnitude smaller than the spatial resolution or pixel size of many remote sensing systems, so their monitoring and detection can be easily overlooked [247]. Insect-caused damage, such as defoliation and stress symptoms on plants, is often easily observed with remote sensing systems and has long been used for indirect insect detection [247,248], which is an important component of crop protection strategies and site-specific pest management [163]. Several studies have shown that insect herbivory affects photosynthesis through defoliation and chlorophyll loss [120,127,137]. As a result, the spectral reflectance of leaves changes accordingly due to lower light absorption by leaf pigments [249]. Many authors have noted that differences in spectral reflectance can be seen in several wavelength ranges, including a band at 450–500 nm corresponding to the green color in the VIS range, a chlorophyll absorption band at 625–675 nm, and an NIR band [250,251]. The above bands are commonly provided in satellite-based multispectral sensors such as Landsat, Sentinel-2, SPOT, etc. and in a variety of airborne multispectral sensors [252,253]. In their work, Luo et al. [254] showed significant differences between the spectral signatures of a leaf infested with the wheat aphid *S. avenae* and a non-infested leaf, as well as in the values of the vegetation indices NDVI and GNDVI, the red edge vegetation stress index (RVSI), and the aphid index (AI). The reflectance of the infested leaf was higher in the VIS and SWIR regions and lower in the NIR region of the EM spectrum. Elliot et al. [255] used aerial multispectral imaging to investigate the damage caused by *D. noxia* to wheat crops, and the authors were able to relate vegetation indices to the amount of infested plants. In their study, Mirik et al. [256] found that *D. noxia* significantly increased reflectance in the VIS range and decreased reflectance in the NIR range at the canopy level compared with uninfested plants. This statement provided evidence that *D. noxia* feeding degrades photosynthetic pigments and alters the leaf morphology in wheat canopies. Since the leaf morphology has a strong influence on the spectral signatures of leaves [256,257], its alteration by *D. noxia* feeding resulted in optical differences between infested and uninfested plants. Genc et al. [258] investigated the potential of spectroradiometrically determined vegetation indices (NDVI and structure insensitive pigment index, SIPI) as indicators of damage by sunn pest (*Eurygaster integriceps*, Put.) under field conditions. They concluded that spectral measurements detect the different sunn pest stages on wheat and also the sunn pest densities in controlled trials, with higher numbers of individuals resulting in lower reflectance in the NIR range. Higher reflectance values in the VIS region and lower reflectance values in the NIR region indicate that lower chlorophyll concentration leads to lower photosynthetic rate of wheat [258].

The basic requirement for hyperspectral remote sensing to identify insect pests is to detect changes in leaf reflectance caused by insect infestation and damage. However, as mentioned earlier in this study, leaf damage can be caused not only by insect infestation but also by other biotic and abiotic stress factors, making it important to accurately determine the cause of the plant stress and damage. In this context, Backoulou et al. [259] showed that spatial data from multispectral images can be used to identify spatial patterns of insect damage to plants. They also applied this strategy to quantify the extent of stress caused by *D. noxia* in wheat fields and to distinguish this damage from that caused by unfavorable agronomic conditions and drought [249]. In their study, Yuan et al. [260] demonstrated the potential use of hyperspectral data to discriminate between wheat diseases (yellow rust and powdery mildew) and *S. avenae* infestations in winter wheat.

4.9. Detection and Assessment of Biotic Stress Due to Diseases

Remote sensing techniques using RGB cameras and multispectral and hyperspectral sensors have been used to detect various plant diseases [261]. Fungal pathogen infection causes various biochemical, physiological, and morphological changes in leaves and can be detected using spectral reflectance data in the VIS and NIR regions of the EM spectrum [144]. Remote sensing and mapping methods have been proposed as innovative tools to improve plant disease management [262–264]. This idea is based on precision agriculture approaches where site-specific fungicides are applied based on remote sensing data and GIS [265]. Using hyperspectral imaging, leaf diseases can be detected at an early stage prior to the appearance of visible symptoms, which has proven to be a useful tool for detecting and differentiating fungal diseases in wheat [144,265–267]. Some foliar diseases can cause chlorophyll loss, while others can lead to leaf water deficits [260]. Consequently, infected plants may have different characteristics in the chlorophyll and/or water absorption regions of their spectral reflectance curves, in contrast to healthy plants [264]. Yu et al. [264] investigated the potential of different spectral traits to robustly estimate the severity of *Septoria* infection at the canopy level in wheat genotypes. They demonstrated that the canopy reflectance and the selected VIs were promising for disease quantification, with the NDWI index performing better compared with other VIs. The study by Anderegg et al. [268] demonstrates the potential of time-resolved canopy reflectance data for assessing foliar disease in the context of breeding for resistance to *Septoria* blotch. In particular, the temporal dynamics of the green leaf area index, in conjunction with the dynamics of physiological senescence, is an important indicator of the presence of *Septoria* infection and its severity. Therefore, the values of VIs (modified chlorophyll absorption ratio index 2-MCARI2 and SIPI) could allow the evaluation of these traits with very high throughput. Bravo et al. [269] used hyperspectral imaging for the early detection of yellow rust disease (*P. striiformis*) in winter wheat in the spectral range between 463 and 895 nm. They found that infected plants had higher reflectance in the VIS region and higher absorbance in the NIR region, which was due to lower chlorophyll activity, mainly due to degradation of the internal leaf structure. Huang et al. [270] investigated the relationship between *P. striiformis* infection and PRI index in wheat, finding that PRI detects yellow color changes with a correlation coefficient of ($R^2 > 0.9$). Ashourloo et al. [265] detected leaf rust (*P. triticina*) in wheat in a controlled environment using the VIs (NDVI, PRI, Greenness Index-GI, and RVSI) with accuracy greater than 60%. Cao et al. [266] studied 17 VIs for predicting powdery mildew in wheat and reported that the difference vegetation index (DVI), triangle vegetation index (TVI), and red edge peak area were highly correlated with disease severity under field conditions. Lorenzen and Jensen [271] found a change in reflectance in the visible spectrum of barley leaves infected with powdery mildew. Graeff et al. [272] found that the most sensitive reflectance response to leaf damage from wheat powdery mildew infection was in the 490–780 nm range.

Bauriegel et al. [273] analyzed wheat plants with a hyperspectral imaging system under laboratory conditions and applied principal component analysis (PCA) to distinguish spectral reflectance data from *Fusarium* diseased and healthy wheat spike tissues in the wavelength ranges of 500–533 nm, 560–675 nm, 682–733 nm, and 927–931 nm. *Fusarium* infections in spikes were successfully detected at BBCH stages from 71 (watery ripe stage) to 85 (soft dough stage). However, it was found that the optimal time for disease detection was at the beginning of medium milk stage (BBCH 75).

5. Data Analysis in Proximal and Remote Measurements of Environmental Stress

There are two main areas to consider when applying remote and close sensing techniques to precision agriculture: data acquisition and data analysis methods. Multispectral and hyperspectral imagery and sensor data collected by various platforms provide a wealth of information about vegetation characteristics [274]. Using remote sensing data, scientists can characterize specific environmental stresses by calculating and developing spectral vegetation indices, multivariate models, and machine learning methods in modeling the spectral and imaging measurements [256,275,276].

5.1. Vegetation Indices

The VI, calculated from the absorption and reflectance properties of vegetation (e.g., in the red and NIR regions), is commonly used to monitor vegetation vigor and indicate plant growth status [277,278]. A remote sensing time series VI can reflect the status of winter wheat throughout the growth and development cycle from sowing to harvest [279]. Table 1 shows a summary of the most commonly used VI of environmental stress in winter wheat that are listed in this paper. The timely detection of crop stress enables rapid coordination and adjustment of planned agrotechnical measures and avoidance of negative effects on yield, which is one of the postulates of precision agriculture. Precision agriculture, a management approach based on observing, measuring, and responding to crop variability within a field, includes data collection to characterize spatial field variability, mapping, and in-field decision making and implementation [169]. The development of remote sensing influenced a greater number of precision agriculture applications and enabled the development of vegetation indices as indicators of crop stress and yield predictions [168]. Today, vegetation indices are used in wheat crops to assess abiotic and biotic stress. In addition to stress assessment, vegetation indices play an irreplaceable role in predicting the biomass and final grain yield [280].

Table 1. Vegetation indices used for environmental stress detection and evaluation in winter wheat crops.

Index	**Name**	**Calculation**	**Application**	**Source**
NDVI	Normalized difference vegetation index	$\text{NDVI} = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}}$	Drought stress Nutrient deficiency Pest detection Disease detection	[179,214,254,266]
PRI	Photochemical Reflectance Index	$\text{PRI} = \frac{\text{R530}-\text{R570}}{\text{R530}+\text{R570}}$	Heat stress Disease detection	[200,270]
GNDVI	Green normalized difference vegetation index	$\text{GNDVI} = \frac{\text{NIR}-\text{GREEN}}{\text{NIR}+\text{GREEN}}$	Nutrient deficiency Waterlogging stress Pest detection	[214,234,254]
SAVI	Soil adjusted vegetation index	$\text{SAVI} = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}+\text{L}} x(1+L)$	Nutrient deficiency	[210]
OSAVI	Optimized soil-adjusted vegetation index	$\text{OSAVI} = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}+\text{L}}$ L = 0.16	Drought stress Nutrient deficiency	[179,214]
AI	Aphid index	$\text{AI} = \frac{\text{R740}-\text{R887}}{\text{R691}-\text{R698}}$	Assessment and early detection of aphid infestation	[254,256]
WI	Water index	$\text{WI} = \frac{\text{R900}}{\text{R970}}$	Drought stress	[179]
NDWI	Normalized difference water index	$\text{NDWI} = \frac{\text{R860}-\text{R1240}}{\text{R860}+\text{R1240}}$	Disease detection Drought stress	[18,264]

5.2. Multivariate (Chemometric) Models and Machine Learning Methods

To obtain more comprehensive information on the state of crops, it is essential to examine the entire EM spectrum. The use of multivariate regression techniques and machine learning methods, such as artificial neural networks (ANNs), can utilize the full spectrum to detect crop stress [281]. Valuable examples of chemometric and statistical techniques for estimating vegetation biophysical variables from spectral measurement data are partial least squares regression (PLSR), principal component regression (PCR), and stepwise multiple linear regression (SMLR) [282]. Since chlorophyll content in plants is a biophysical variable representative of canopy photosynthetic activity and its level is influenced by numerous stress factors, Atzberger et al. [282] investigated the predictive power and noise sensitivity of SMLR and "full spectrum" methods PCR and PLSR in their work. In [282], PLSR showed the lowest cross-validated RMSE while being relatively insensitive to artificial noise in given dataset. The large volume and accuracy of the proximal and remote sensing data acquired by various platforms pose a "Big Data" problem. Data acquired from these platforms must be properly archived and retrieved for further analysis. ML is used when large datasets are available that relate inputs (e.g., imagery or spectral data) to desired outcomes (e.g., stress detection). The advantage of using ML is the ability to search large datasets to discover patterns and guide discovery by simultaneously observing a combination of factors rather than analyzing each feature individually [283]. ML methods such as support vector machines (SVM), artificial neural networks (ANNs), and kernel methods have been used to detect various stress factors. The SVM method has been successfully used in a variety of scenarios for stress detection in plants [283]. Recently, the combination of linear models such as PCA or PLSR with ML methods, especially nonlinear models such as ANN, has gained great popularity [206].

6. Conclusions

This report discusses the current state of the art and capabilities of remote and proximal sensing technologies that have been used in precision agriculture over the past few decades with various applications to detect, evaluate, and monitor environmental stressors in winter wheat. Among abiotic factors, the most important plant stressors include drought, heat stress, salinity, nutrient deficiency, frost, and waterlogging, while biotic stressors include weeds, pests, and diseases. As climate change significantly impacts winter wheat production due to more frequent occurrences of various abiotic stress parameters as well as improved conditions for weed, pest, and disease development, the need for these technologies can only increase in the future. For sustainable agricultural management, all factors affecting crop production must be analyzed on a spatiotemporal basis. The future perspective concerns stress detection algorithms that operate reliably in space and time and are able to distinguish, for example, water-, disease-, or pest-related stress signals from "noise" caused by soil and other non-photosynthetically active plant material. Distinguishing stress factors from multispectral and hyperspectral data is also important for making appropriate and accurate crop management decisions, but advanced statistical, chemometric, and especially machine learning models are making this goal increasingly achievable.

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