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Using crop modeling to find solutions for wheat diseases: A review

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Plant diseases have caused serious challenges in the production of food globally. This has led to hunger and food insecurity. Different solutions for crop diseases have been introduced in the recent past that include cultural control using farm management methods, chemical control, resistant cultivars, and recently, biocontrol. Each of these solutions has varied weaknesses. Faced with the changes in climate and the recurrences of crop diseases, new strategies incorporating preventive measures would be important by reducing risks to crop production from crop diseases, thus alleviating food insecurity. Strategies for the prevention of these diseases and/or forecasting favorable environmental conditions for disease development have not been fully employed as preventive measures. The use of crop modeling has been used to advise farmers on planting procedures that would bring maximum yields using different management procedures at the farm level. Little is known about the use of crop models in crop disease control. In order to increase the use of crop models for these objectives, this review provides the current *status quo* and will help to stimulate more research in this regard.

KEYWORDS

climate change, crop model, crop yield, disease control, microbes, pathogens, disease forecasting

1 Introduction

Diseases of crops are known to be critical worldwide challenges to optimal food production. Different means are used to combat this menace and to reduce the impacts of pathogens and diseases in crop production (Ajilogba and Babalola, 2013).

Cultural control of crop diseases involves making the environment unfit for the growth and development of plant diseases and disease-causing factors by using local or international management procedures (Ajilogba and Babalola, 2013). In their study, Ajilogba and Babalola emphasized that the application of the working knowledge of environmental conditions aiding the growth of such pathogens and diseases would play an important role in mitigating the spread and impact of diseases. Some other cultural methods are used as part of the integrated control of pests and diseases (Ogle and Dale, 1997). These include mulching, crop rotation, and fallowing the land, while others that are seldom used include grafting of fruit trees (Ogle and Dale, 1997). Cultural control is always important as a support in farm management systems and can be used as additional support to the main preventive strategy.

In modern agriculture, chemical sprays are mostly used to control pest and diseases in a preventative fashion even before they are detected on the crop (Ajilogba and Babalola, 2013). Such chemicals can be called eradicants, which help to kill disease pathogens present in soils and plant parts. Protectants are chemicals that protect plants and stand as an interface between plants and pathogens while therapeutic chemicals are useful in situations where the disease is already progressing (Pelczar et al., 2020). One of the chemicals that is commonly used as a fumigant before planting to manage disease-causing microbes and weeds of plant diseases globally is methyl bromide (Mao et al., 2017).

The use of methyl bromide as a means of control of soil-borne crop diseases has been phased out although it is still used in a few cropping situations. It is normally used as a fumigant in the soil against nematodes of soil, parasites, and pathogenic inoculum. Because of environmental pollution and the risk of health hazards, it is now only used for critical situations (Mao et al., 2017). 1,3-Dichloropropene (1,3-D) and metam sodium (Sadrati et al., 2013) were observed to be as effective as using methyl bromide against soil nematodes. One of the critical challenges with the use of chemicals is an increase in the number of pathogens developing resistance to such chemicals. This makes suppression and elimination of such pathogens more burdensome (Leadbeater, 2015). Another challenge with the use of chemicals is the cost price in comparison to the final production obtained. This normally discourages some farmers from using chemical control methods.

Use of chemical applications is gradually being phased out, while the production of resistant cultivars and, recently, biocontrol methods are being increased (Ajilogba and Babalola, 2013).

Biological control is one of the integrated disease management practices of plant and animal diseases that reduce the yield loss by suppressing the disease and reducing the use of chemicals in order to promote sustainable crop production and human health (O'Brien, 2017; Thurman et al., 2017; Köhl et al., 2019b). It is the control of plant and animal diseases and pests by the application of biological agents to a host animal or plant that prevents the development of a disease by a pathogen (O'Brien, 2017). It can also include the use of microbial antagonists to suppress the disease (Heydari and Pessarakli, 2010; Ajilogba and Walker, 2020). These microbial antagonists can be bacterial, fungal, viral, or by nematodes, although bacterial and fungal antagonists are more common; recently, the use of bacteriophages, which are viruses that kill bacteria, have been reported to be effective (Jones et al., 2007; Buttimer et al., 2017). Sometimes, these microbial antagonists are used singly or as a consortium (O'Brien, 2017; Köhl et al., 2019b; Bradáčová et al., 2019). These microbial antagonists have different modes of operation which include hyperparasitism, phosphate solubilization, predation, antagonism, hydrogen cyanide production, and induced resistance (Jones et al., 2007; Ajilogba and Babalola, 2016). The mode of operation or action of a microbial or biological control agent (M/BCA) is dependent on different events happening in and around the M/BCA (Junaid et al., 2013; Köhl et al., 2019a). These range from how the M/BCA is able to establish itself, and its ability to produce and release metabolites and/or signaling compounds that can induce the defense mechanism of the plants and also how the pathogen in question will respond to the defense mechanism (Köhl et al., 2019b). Furthermore, other determining factors to ensure the effectiveness of the antagonist include the plant cultivar, mode of inoculation, time and duration of inoculation, available conditions for germination and infection of pathogens, physiology, and growing conditions of the plant (Junaid et al., 2013; Ajilogba and Walker, 2020). These growing conditions of pathogens, M/BCA, and plants are very important and form a trio impacted by environmental conditions.

Biological control and M/BCA will be affected by climate change both positively and negatively, as environmental conditions affect agricultural productivity. The biocontrol agents that are effective as a result of the positive impact of climate change might be ineffective in the future as the climate changes (Thurman et al., 2017). As the climate changes in terms of increases in temperature, decreases in precipitation and rainfall, and drought spells, the amount of water in the soil is reduced, which can impact the quality and quantity of soil microbes available depending on their various living conditions. This proceeds to change the incidence of pest and disease patterns and definitely the effectiveness, or lack of it, of M/BCA (Fuhrer, 2003; Jones and Thornton, 2003; Lin, 2011; Thornton et al., 2011).

Biocontrol has been effective against a host of wheat plant diseases including stem rust disease of wheat using a combination of *Trichoderma spp*. and arbuscular mycorrhizal (AM) fungi based on their efficiency and eco-safety (El-Sharkawy et al., 2018). The research by Larran et al. (2016) concluded that endophytes have potential in the biological control of the tan spot of wheat caused by *Drechslera tritici-repentis*, and particularly *Trichodema hamatum* and *Bacillus sp. Pseudomonas fluorescens* strains significantly improved the establishment and harvest yield of winter wheat infected by the *Microdochium nivale* causal agent of wheat-seedling blight (Amein et al., 2008). In different field trials, this led to an increase in the wheat yield and plant number by 26.5% and 48%, respectively. Suppression of the growth of wheat take-all disease caused *by Gaeumannomyces graminis* var. tritici (Ggt) was observed using a combination of Trichodema isolates (Zafari et al., 2008) and bacterial strains from wheat rhizosphere (Nasraoui et al., 2007). According to Bouanaka et al. (2021), *Trichoderma afroharzianum* is a promising biocontrol agent against *Fusarium culmorum*, which is responsible for fusarium head blight (FHB) and crown rot (FCR). Furthermore, *Lactobacillus plantarum* SLG17 and *Bacillus amyloliquefaciens* FLN13 were observed as biocontrol antagonists against FHB applied starting from the heading period until anthesis of wheat plants (Baffoni et al., 2015). Acceptance of the usage of these biocontrol agents has been slow. This is because farmers, due to different perceptions, including the learning process about new innovations, the ability to evaluate the relative advantages of a new innovation over previously used methods, and the ease of applying a new innovation (Cullen et al., 2010), have not accepted most biocontrol methods.

Use of resistant genes by genetic manipulation has been used to increase the growth of crops and crop yields. Certain genes have been inserted to combat infection by diseases (Dong and Ronald, 2019; Van Esse et al., 2020). This is because resistant genes are able to recognize an attack from a disease pathogen and resist such an attack. They have also been used to increase favorable traits in crops. Beyond this, genetics have also helped in improving genes resistant to pests and diseases and introducing them into other cultivars or crops (Gómez et al., 2009). For example, durable disease-resistant gene Lr34 (= Yr18/Sr57/Pm38) from bread wheat (*Triticum aestivum*) confers the resistance against multiple fungal diseases, namely leaf rust *(Puccinia triticina),* stripe rust (*Puccinia striiformis f.sp. tritici*), stem rust *(Puccinia graminis f.sp. tritici),* and powdery mildew (*Blumeria graminis f.sp. tritici)* (Bräunlich et al., 2021).

However, these different strategies are not short-term processes, and implementation can take decades; in order to forestall this, the projection of climate change effects on the severity and intensity of crop diseases and yield losses becomes imperative (Newbery et al., 2016).

Geocontrol is a coined term that means the use of geographical factors to control the incidences of plant diseases. It involves the use of

TABLE 1 Climate change and implication on plant disease susceptibility.

Plant disease	Class of causative pathogen	Sources of infection	Site affected	Impact on plants	Causative organism	Susceptibility to weather					References
						Location/ region	Temperature	Rainfall/ humidity/ precipitation	Solar radiation	Wind	
Wheat brown (leaf) rust	Fungal	Rust spores are wind-blown	Foliage, whole plant	Grain yield losses associated with plant rust are caused by flag leaf infection	*Puccinia triticina*	Warm, humid spells	Higher spring temperature/ optimum air temperatures ranged from 12°C to 15°C	Moisture-induced air triggers leaf wetness	Intensity of light can slow down or prevent disease		Junk et al. (2016); Spitters and Schapendonk (1990); Teferi (2015)
Wheat take all	Fungal	Soil-borne	Whole plant	The root tissue of upcoming plants is infected, conducive tissues are blocked, and water absorption is reduced. Tillering is reduced and premature maturation of plants with the seed heads bleached	*Gaeumannomyces graminis var. tritici*	Temperate climates	Optimum growth temperature is 20°C–25°C	High precipitation or irrigation/low precipitation	Light-textured soils with low fertility, and at alkaline pH		Kwak and Weller (2013)
Wheat *Fusarium* head blight	Fungal	Infested crop residue e.g. wheat straw/ rain-splash or wind dispersal during the winter	Head and spikes	As a result of contamination, the seed shrinks and wrinkles	*Fusarium graminearum (anamorph) Gibberella zeae (teleomorph)*	Warm and moist environment/ humid	Low temperatures (between 15°C and 30°C/59°F and 86°F)	High moisture or relative humidity (>90%)			Schmale and Bergstrom (2003)
Wheat yellow (stripe) rust	Fungal	Pst is capable of long-distance dispersal by wind movement and human-assisted transport	Foliage, whole plant	Pst infection in wheat causes losses in wheat yield because of the reduced number of kernels and lower kernels' values	*Puccinia striiformis f. sp. tritici (Pst)*	Low-temperature disease and frequently occurs in temperate areas with cool and moist weather conditions	Average temperature (range of 2–15°C)	High relative humidity	Low light intensities	Sensitive to air pollution	Chen et al. (2013)
Wheat septoria tritici blotch	Fungal	Airborne, rain-splash dispersal rubble from significantly infected stems and leaves persist in the soils for the next planting season	Foliage	Leaf and stem swellings lead to significantly lower yields and poor grain quality	*Mycosphaerella graminicola (asexual stage: Septoria tritici)*	Cool, wet weather/ Mediterranean-type climates (wet winters with temperate temperatures)		High humidity			Eyal, (1999); Fones and Gurr, (2015); Ponomarenko et al. (2011)

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TABLE 1 (*Continued*) Climate change and implication on plant disease susceptibility.

Plant disease	Class of causative pathogen	Sources of infection	Site affected	Impact on plants	Causative organism	Susceptibility to weather					References
						Location/ region	Temperature	Rainfall/ humidity/ precipitation	Solar radiation	Wind	
Wheat powdery mildew	Fungal	Wind and rain-dispersed, stubble borne and carried over on a green bridge	Foliage and the plant part above the ground	Photosynthesis is reduced while respiration and transpiration rates are increased in the host leaves leading to a loss of vigor, heading, and filling and death of leaves prematurely	*Blumeria graminis f. sp. tritici (syn. Erysiphe graminis)*	Summer storms and good autumn rainfall; humid, mild weather	Low temperature	High humidity			Martinez-Espinoza et al. (2014); Martinez-Espinoza (2014)
Wheat sharp eyespot	Fungal	Soil-borne, plant debris or in the soil	Base of tillers, crown, stem-base disease, and root tissues	Damping off before and after emergence and death of shoot in seedlings result in small wrinkled grains	*Rhizoctonia cerealis van der Hoeven (teleomorph: Ceratobasidium cereale D. Murray and L.L. Burpee)*	Temperate wheat-growing regions of the world			Cool autumn or spring	Neutral to slightly acid, dry and sandy soils	Lemańczyk and Kwaśna (2013)
Wheat crown/foot fusarium	Fungal	Seed-borne and soil-borne	Seed and whole tiller, crown, base of tiller	Loss of grain production, reduction in stands, and rottenness of the whole plant	*F. culmorum*	Humid/cooler semiarid		Heavy precipitation in Eastern Australia (>500 mm) and in the colder and higher Idaho/low rainfall years in the Pacific Northwest of the United States			Moya-Elizondo (2013); Xu et al. (2018)
					F. pseudograminearum	Slightly warmer					
					F. graminearum	Regions/warm and dry soil environment					
Wheat septoria nodorum blotch	Fungal	Seed-borne inoculum, Rain-splashed conidia or infected wheat debris ascospores	Foliage and all the parts that are above the soil	Death of leaves caused by coalescing of lesions on leaves and infected kernels leading to a reduction in grain quality and quantity due to glume contamination	*Parastagonospora nodorum*	Warm and moist weather/S. nodorum is more common in northern latitudes	High temperature	High relative humidity		High wind	Eyal (1999); Mehra et al. (2018)
Wheat spot blotch disease	Fungal	Seed-borne disease, surviving inoculum on crop residues, secondary hosts or soil conidia	Foliage, root, stem, and head tissues	Lesions on leaves lead to plant death causing significant yield loss	*Bipolaris sorokiniana*, which is an anamorph *(teleomorph Cochliobolus sativus)*	World's hottest wetlands, which includes Southeast Asia	Increase in temperature	High relative humidity			Gupta et al. (2018)

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TABLE 1 (***Continued***) **Climate change and implication on plant disease susceptibility.**

Plant disease	Class of causative pathogen	Sources of infection	Site affected	Impact on plants	Causative organism	Susceptibility to weather					References
						Location/ region	Temperature	Rainfall/ humidity/ precipitation	Solar radiation	Wind	
Bacterial leaf streak/black chaff on glume	Bacterial	Seed-borne infection, soil and crop debris	Foliage, culms, leaves, rachis, glumes, and awns	Sterility of wheat spikes as a result of infection leading to a reduction in grain weight	*Xanthomonas translucens pv. undulosa*	Sprinkler-irrigated fields in temperate climates, subtropical highlands with high precipitation, and hotter areas marked by cool nights or regular changes in the climate and unexpected fluctuations in temperature	High temperature	High relative humidity			Duveiller, (2002)
Bacterial leaf blight/leaf necrosis	Bacterial	Hail, wind, or mechanical damage	Flag leaves and other plant parts	Spots on leaves leading to plant death	*Pseudomonas syringae pv. syringae*	—	Temperatures between 60°F and 77°F favor disease development, along with	Cloudy, humid, and rainy weather			Duveiller, (2002)
Bacterial basal glume rot	Bacterial	It is disseminated by splashing rain or by insects and can be seed borne	The leaves, culms, and spikes of wheat and triticale can be infected, glumes	Water-soaked lesions leading to plant infections	*Pseudomonas syringae atrofaciens (McCulloch)*	Extraordinarily humid cool weather					Duveiller, (2002)
Wheat spindle streak mosaic (WSSMV)	Viral	It is intense in field areas that are extremely wet	Seedlings, and leaves	Reduction in stem, heads, and kernels leading to yield loss	*Polymyxa graminis*		High temperature		Moderate light	—	Zhang et al. (2005)
Soilborne wheat mosaic (SBWMV)	Viral	Humid soil conditions promote protozoa growth which transmit this viral disease	Leaves	Reduction in stem, heads, and kernels leading to yield loss	*Polymyxa graminis*	Weather is cool and moist in autumn	Temperature range of 10oC to 16°C	Cold weather			Altay and Bolat (2004)

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TABLE 1 (*Continued*) Climate change and implication on plant disease susceptibility.

Plant disease	Class of causative pathogen	Sources of infection	Site affected	Impact on plants	Causative organism	Susceptibility to weather					References
						Location/ region	Temperature	Rainfall/ humidity/ precipitation	Solar radiation	Wind	
Wheat streak mosaic virus (WSMV)	Viral	The virus is sustained in the volunteer wheat and is transmitted by curl mites of wheat	Leaves	Death of mottled leaves leading to yield loss	*Wheat curl mite (Aceria tosichella)*	Warm (75°F–80°F, 24°C–27 °C), dry weather encourages diseases by stressing the crops and encouraging the increase in reproduction of the primary vector of the virus					Ellis et al. (2003)

climate data to forecast the activities of microbes in terms of their positive or negative responses to climatic factors including temperature, rainfall, solar radiation, and other factors (Plantegenest et al., 2007; Charaya et al., 2021). This is important because when the climatic factors affect the growth of pathogens by suppressing them, then disease incidence can also be suppressed, reduced, and/or, if possible, eliminated (Varma and Meena, 2020). Factors that can increase the growth of causative organisms are monitored and decreased and even removed where possible, while factors that will suppress growth are increased and encouraged. This leads to other preventive measures so that plant diseases are not initiated, crop losses are avoided, and invariably, crop yields are increased (Varma and Meena, 2020; Charaya et al., 2021).

It is important to note that changes in the climate affect both spatial and temporal distributions of diseases, pathogens, and pests affecting plants (Varma and Meena, 2020). Climate factors such as temperature, rainfall, and radiation are quite important in the growth and development of diseases in any given plant (Charaya et al., 2021; Skendžić et al., 2021). They affect all the different stages in the lifecycle of the pathogen and affect the disease process from the site of infection to sporulation and multiplication and survival of the pathogen in the system (Gautam et al., 2013; Skendžić et al., 2021). These environmental factors also affect the survival of the biocontrol agent in any system (Ahanger, 2013).

2 Climate change and its effect on wheat crop diseases

Climate change has been observed to affect the incidence of plant diseases and the growth of pathogens. In some cases, climatic conditions favored the spread of plant diseases (Juroszek and von Tiedemann, 2013; Seidel, 2014), while in other cases, climate had little to no impact on the progress of plant diseases (Chakraborty et al., 2000; Juroszek and von Tiedemann, 2013). The growth of wheat varies according to the altitude and different rainfall regions in South Africa, either in the summer or winter. The winter rainfall areas support the optimal growth of spring wheat cultivars while the high altitude summer rainfall areas support the growth of winter and intermediate wheat cultivars, and the warm western irrigation areas grow in mostly spring-type cultivars (Jordaan, 2002). The development of stem rust, stripe rust, and leaf rust disease of wheat caused by *Puccinia graminis* Pers. f. sp. tritici (Pgt), *P. striiformis* f. sp. tritici (Pst), and *P. triticina* Eriks (Pt), respectively, varies in their distribution across the wheat-growing regions (Pretorius et al., 2007). Thus, it is clear that environmental factors are very important in the establishment of diseases in plants (Table 1).

It has been observed that areas with high elevations had lower disease incidence in cereals compared with areas with lower altitude, probably due to variations in the temperature. This brings into perspective the classic disease triangle, which includes the interaction between the plant, deleterious microbe, and the ecosystem (including weather conditions) (Ghini et al., 2008). Humidity, heat, and wind are the three main climatic factors that increase the outbreaks of the wheat rusts diseases, even though in some wheat growing areas globally, an increase in temperature

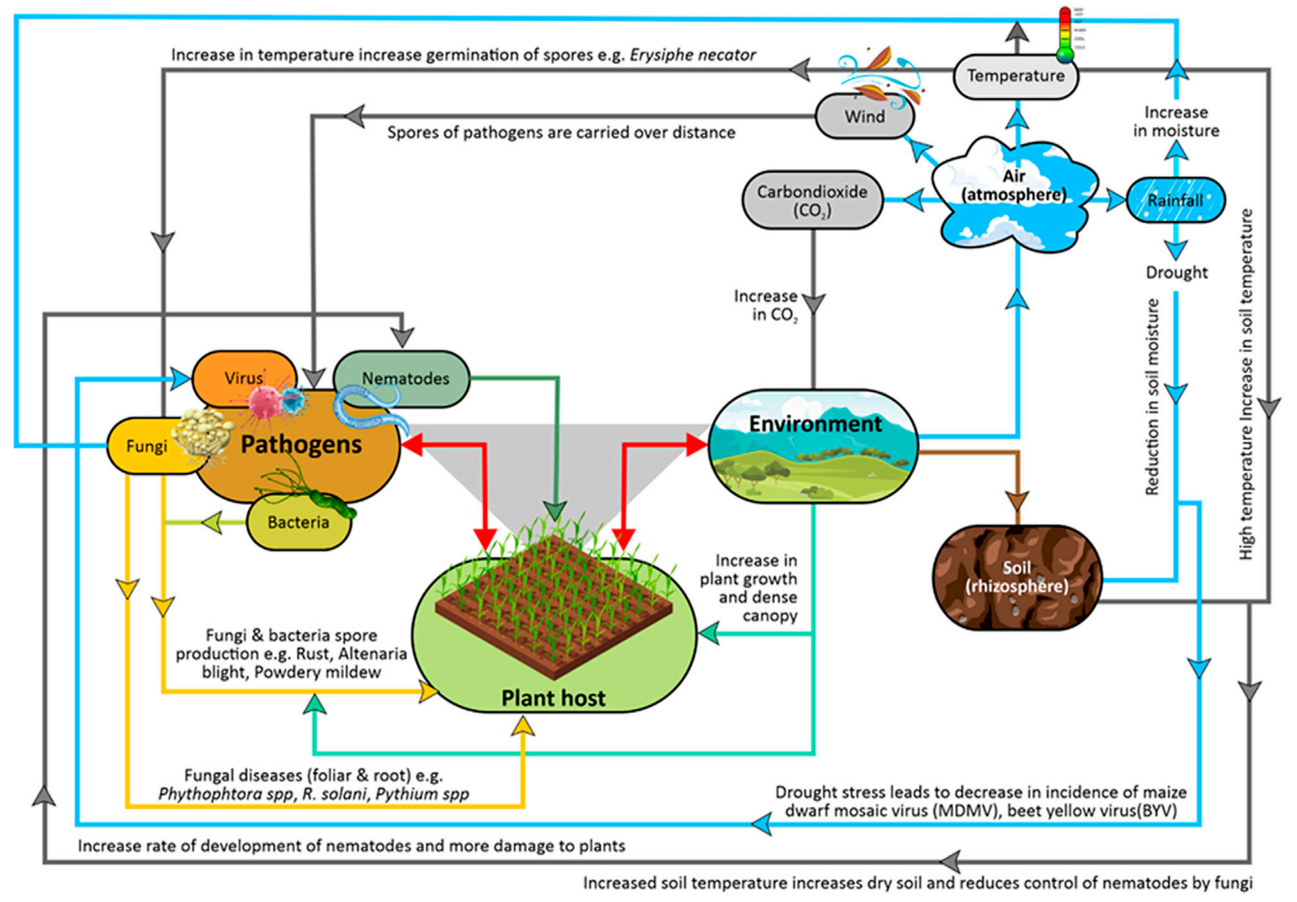

FIGURE 1
Schematic diagram of how climate affects the spread of plant diseases.

may decrease growth, development, and survival of some pathogens (Luck et al., 2011).

An alert system for wheat rusts should be established as part of the preventive strategies for combating wheat stem rust. This will include the use of weather data to forecast and provide advisories dependent on different climate and weather conditions (Saunders et al., 2019).

3 Climatic change impact on the development process of wheat diseases

Some of the climatic factors that affect the development process of plant diseases include, temperature, water availability/rainfall/precipitation, and carbon dioxide concentration (Helfer, 2014). Because crop diseases are greatly impacted by environmental conditions, a plant host will not be affected by a disease pathogen even if it is virulent, especially in a situation where climatic conditions are not favorable for pathogen establishment and disease progression (Velásquez et al., 2018). With changes in the climate pattern, the ability of plant pathogens to adjust to the environmental changes keeps changing, which results in new bacterial infections. Plants, pathogens, and the environment form the disease triangle because for a disease to occur, there must be an interplay between these three factors (Figure 1) (Velásquez et al., 2018; Ajilogba and Walker, 2020).

As both plants and disease pathogens have optimal conditions under which they will grow and reproduce, environmental conditions then must be favorable for this to happen (Juroszek and von Tiedemann, 2013; Velásquez et al., 2018).

In recent times, when the temperature was warm during winter, wheat head blight thrived in China. The stripe rust's causative pathogen *Puccinia striiformis* was able to cause infection in the field experiment at a temperature range between 18°C and 30°C. This optimal temperature range helped the fungus to grow, establish, and be able to cause an infection (Velásquez et al., 2018). Furthermore, it is observed that warm winter temperatures also encouraged the infection rate of stem rust in wheat caused by the fungus *Puccinia graminis* f. sp. *tritici*. This is because, sometimes during the winter, wheat plants mature early and they are not able to withstand the accumulation of stem rust pathogen inoculum as was also observed in Germany in 2013 (Olivera Firpo et al., 2017; Saunders et al., 2019).

Furthermore, the geographical distribution of hosts and pathogens will alter as it is clear that the location where wheat is grown can impact the health of the crop as climate variability increases. For example, in the United Kingdom, there is a high probability that by the middle of this century, *Fusarium* head blight disease incidence will increase according to the analysis by Juroszek and von Tiedemann, 2013, while the opposite will be the case in France for *Septoria tritici*

TABLE 2 Overview of wheat crop models with the purpose of their development and documentation.

Wheat crop models	Purpose of development	Development based on the initial model	Type of model/documentation	Reference articles
ARCWHEAT1	Simulate the main temperature and solar radiation limitations to production	NA	Mechanistic	Porter (1984); Porter et al. (1993); Weir et al. (1984)
AFRCWHEAT2	to deal with water and nitrogen constraints	ARCWHEAT1	Mechanistic	Porter et al. (1993)
APSIM-Nwheat	Crop water demand routine, crop water stress calculation, root growth, carbon partitioning and respiration, carbon remobilization, waterlogging impacts, and grain protein routines	CERES-Wheat	Mechanistic http://www.apsim.info	Asseng et al. (1998); Asseng and Van Herwaarden (2003); Keating et al. (2003); McMaster et al. (2011)
APSIM-Wheat	Internationally recognized as an extremely advanced agricultural model simulator—it contains a series of modules that allow the simulation of systems covering a series of interactions between plants, animals, soil, climate, and management	NA	Mechanistic http://www.apsim.info/Wiki/	Keating et al. (2003); McMaster et al. (2011); Zheng et al. (2014)
AQUACROP	FAO crop model that is used to simulate multiple herbaceous crop water yield responses	NA	Statistical/mechanistic http://www.fao.org/nr/water/aquacrop.html	Farahani et al. (2009); Steduto et al. (2009); Vanuytrecht et al. (2014)
CENTURY	General plant–surface nutrient cycling model—used to predict carbon and nutrient cycles for various ecosystem types including wetlands, arable land, woodlands, and grasslands	NA	Process-based biogeochemical models https://www.nrel.colostate.edu/projects/century/index.php	Parton and Rasmussen (1994)
CropSyst	Multi-year multi-crop daily-time level simulation model that is user friendly, functionally straightforward yet robust	NA	http://www.bsyse.wsu.edu/CS_Suite/CropSyst/index.html	Stöckle et al. (2003)
COUP	Process-oriented, complex model representing water–heat–carbon (C) and nitrogen (N) flows in the soil–plant–atmosphere cycle as a climate process at different times and spatial scales; usually from a minute to day scale and from field to regional scale	NA	Process-based biogeochemical models http://www.coupmodel.com/sample-page	Conrad and Fohrer (2009); Jansson, (2004); Jansson (2012)
DailyDayCent	Regular biogeochemical template sequence used in agro-ecosystems to simulate carbon and nitrogen flows between the atmosphere, vegetation, and soil	CENTURY	Process-based biogeochemical models https://www.nrel.colostate.edu/projects/century/index.php	Del Grosso, (2012); Del Grosso, (2008); Del Grosso et al. (2005); Yeluripati et al. (2009)
DAISY	Daisy monitors rain, phosphorus, carbon, and contaminants in the biologically active region near the surface of the soil (around the top of the canopy to the bottom of the root system)	NA	Mechanistic http://daisy.ku.dk/	Hansen et al. (2012)
DSSAT-CERES-Wheat	Water and N constraint simulation	NA	Mechanistic http://www.icasa.net/dssat/	Hoogenboom and White, (2003); Jones et al. (2003); McMaster et al. (2011); Ritchie et al. (1987)
DSSAT-CROPSIM	Interconnected template in DSSAT v4.7, which simulates the production of wheat, growth, and phenotypic parameters based on specific crop, then transforms into the entire plant population	CERES-Wheat	Mechanistic http://www.icasa.net/dssat/	Hunt and Pararajasingham (1995); Jones et al. (2003); Hussain et al. (2018); McMaster et al. (2011)
EPIC-Wheat	Model of the plant systems developed to estimate the productivity of the soil affected by erosion as part of the 1980 review of the Soil and Water Resources Conservation Act	NA	Site-based process model http://epicapex.brc.tamus.edu/	Kiniry et al. (1995); Williams et al. (1989)
Expert-N—CERES	Application model with the goal of enhancing the process of understanding in the soil–plant–atmosphere cycle of the turnover and transport of matter and energy fluxes	NA	Process-based biogeochemical models http://www.helmholtz-muenchen.de/en/iboe/expertn/	Biernath et al. (2011); Klier et al. (2011); Priesack et al. (2006); Ritchie et al. (1987)
FASSET	Farm-wide integrated model used as a method to assess the impact of changes in policy, operations, values, and incentives on a variety of farm-level sustainability variables, such as farm	NA	Process-based biogeochemical models http://www.fasset.dk	Berntsen et al. (2003); Chatskikh et al. (2003); Chirinda et al. (2011); Olesen et al. (2002)

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TABLE 2 (*Continued*) Overview of wheat crop models with the purpose of their development and documentation.

Wheat crop models	Purpose of development	Development based on the initial model	Type of model/documentation	Reference articles
	productivity, growth, loss of nitrogen, energy consumption, and greenhouse gas emissions			
GLAM	Simulates the effects of climate variability and plant change by using weather forecast data to determine crop growth and development, from planting to harvesting	NA	Process-based model https://environment.leeds.ac.uk/climate-change-impacts/doc/general-large-area-model-annual-crops	Challinor et al. (2004)
HERMES	Describes the growth of plants and the balance of water and nitrogen in the soil cycle	NA	http://www.zalf.de/en/forschung_lehre/software_downloads/pages/default.aspx	Kersebaum (2011); Kersebaum (2007)
INFOCROP	Standard crop model, simulates the environment, soil, agricultural management (planting, nitrogen, residues, and irrigation), and major pests on crop growth, yield, soil carbon, nitrogen and water emissions, and greenhouse gas emissions	NA	http://www.iari.res.in	Aggarwal et al. (2006)
LandscapeDNDC	Design framework for ecosystem scaling from site to national simulation domains	MoBiLE	http://ldndc.imk-ifu.kit.edu/	Grote et al. (2009); Haas et al. (2013); Kraus et al. (2015)
LINTUL	Simple standard plant growth simulation model—phenology component is a crop growth model capable of simulating crop growth under both potential and water-limited conditions (i.e., rain-fed)	NA	Process-based crop http://models.pps.wur.nl/models	Gourdji et al. (2013); Shibu et al. (2010); Spitters and Schapendonk (1990)
LPJmL	Designed to simulate the composition and distribution of vegetation and the exchange of carbon and water flows in the soil and atmosphere for both natural and agricultural ecosystems	MAgPIE and REMIND	Global ecosystem model http://www.pik-potsdam.de/research/projects/lpjweb	Beringer et al. (2011); Bondeau et al. (2007); Fader et al. (2010); Gerten et al. (2004); Müller et al. (2007); Rost et al. (2008)
MCWLA-Wheat	Models the effects on plant production over a large area of weather and climate variability. It is a general plant model based on processes	NA	Process-based http://www.scale-it.net/?tag = mcwla	Tao et al. (2009a); Tao and Zhang (2010); Tao and Zhang (2013); Tao et al. (2009b)
MODWht	Predict the canopy and resulting yield development and growth by using temperature	NA	Mechanistic	Rickman et al. (1996)
MONICA	Complex, process-based model framework explaining biomass, nitrogen, and water transport and biochemical transfer in agro-ecosystems	NA	One-dimensional, dynamic, process-based simulation model http://monica.agrosystem-models.com	Nendel et al. (2011)
OLEARY	Simulation model of a fallow-wheat system that includes nitrogen-related crops and alternative stubble and reduced tillage-management techniques	NA	Process-based crop model	Latta and O'Leary (2003); O'Leary et al. (1985); O'Leary and Connor (1996a); O'Leary and Connor (1996b)
QUEFTS	Addressing the primary nutrient interactions	NA	Mechanistic	Janssen et al. (1990); Kuang. (2012)
PhenologyMMS model	Simulation model detailing and measuring the growth sequence of different crops under different levels of water deficits, offering specific physiological data for each crop and is designed for use separately or integrated into established plant growth models	SHOOTGRO	Component-based https://www.ars.usda.gov/research/software/download/?softwareid=238	McMaster et al. (2011); McMaster et al. (2005)
SALUS	Designed to simulate the existing plant, soil, water, and nutrient conditions for multiple seasons under various management techniques	The CERES-Wheat	http://www.salusmodel.net	Basso et al. (2010); Senthilkumar et al. (2009)
SHOOTGRO	Phenology and metabolic processes (predict canopy development and growth and resulting yield through temperature utilization)	CERES-Wheat	Mechanistic https://data.nal.usda.gov/dataset/shootgro	McMaster et al. (2011); McMaster et al. (1992); Wilhelm et al. (1993); Žalud et al. (2003)
SIMPLACE	Compact modeling structure to help decisions to manage a wide variety of crops and habitats under the increasing availability of resources and climate conditions	NA	Mechanic http://www.simplace.net/	Angulo et al. (2013)

(Continued on following page)

TABLE 2 (*Continued*) **Overview of wheat crop models with the purpose of their development and documentation.**

Wheat crop models	Purpose of development	Development based on the initial model	Type of model/documentation	Reference articles
SIRIUS	Simulation of phenology, aggregation, and partitioning of biomass, plant nitrogen economy	Phenological sub-model of ARCWHEAT1	Mechanistic http://www.rothamsted.ac.uk/mas-models/sirius.php	Jamieson and Semenov (2000); Jamieson et al. (1998); Lawless et al. (2005); Semenov and Shewry (2011)
SiriusQuality	In response to plant–climate management, in the soil–plant–atmosphere environment of cereals and water, nitrogen and carbon flows, and phenology and canopy development is modeled	NA	Component based model http://www1.clermont.inra.fr/siriusquality/	Ferrise et al. (2010); He et al. (2010); Martre et al. (2006)
SSM-Wheat	Simulate the phenology, growth, and development of wheat	General (wheat) model	Process-based model https://sites.google.com/site/cropmodeling/-6-ssm-wheat	Amir and Sinclair (1991); Soltani and Sinclair, (2012); Soltani et al. (2013)
STICS	Models the routine soil–plant water carbon and nitrogen dynamics. Considers the effects of stress on crop growth and grain yield from water and nitrogen. A multidisciplinary simulation for model crops, projections of plot-level plant production across all agronomic criteria: climate, soil, and farming. Also, it is capable of modeling intercropping and crop rotation cycles	NA	Daily time-step crop model http://www.inra.fr/en/Scientists-Students/Agricultural-systems/All-reports/Modelling-and- agrosystems/STICS-an-agronomy-dynamo	Bergez et al. (2013); Brisson. (1998)
WHEATGROW	Simulates the response of the growth and production of wheat to climate and irrigation. Main model for future performance simulation	NA	Mechanistic	Cao et al. (2002); Cao and Moss (1997); Hu et al. (2004); Li et al. (2002); Pan et al. (2007); Pan et al. (2006); Yan et al. (2000)
WOFOST	Examines NPK macronutrients and uses QUEFTS performance	uses the output of QUEFTS	Mechanistic http://www.wofost.wur.nl	Boogaard and Kroes (1998); Kuang. (2012); Van Diepen et al. (1989)
Web InfoCrop	Forecast variables of daily plant growth, yield factors, soil moisture, and nitrogen dynamics, and global warming impact	InfoCrop	Web-based model http://InfoCrop.iari.res.in	Krishnan et al. (2016)

Source: Modified after Guarin and Asseng (2017).

blotch disease incidence, which will decrease. This means that, even though climate change is affecting plants negatively, there is hope that climatic change may also improve the health situation of wheat crops depending on the location. Using experimental observation data in China, the increase or decrease in wheat production was varied based on the regional climate, as wheat yields in Northern China rose by 1%–13%, while in Southern China, it reduced by 1%–10% (Wang et al., 2018).

As the level of atmospheric carbon dioxide (CO_2) increases, the disease severity in wheat (780 ppm) also increases (Váry et al., 2015). When the CO_2 level increases for the fungal pathogen *Fusarium graminearum*, the virulence of the causative agent of *Fusarium* wheat head blight increases, and different varieties of the wheat plant become highly susceptible. This is turn results in increased overall severity of the diseases (Váry et al., 2015). As temperature and carbon dioxide increases, there is also an increase in the fecundity of fungi (Chakraborty and Newton, 2011).

Thompson et al. (2014) suggested that the elevated and increasing temperature can increase the range of plant pathogens and thereby increase the range of plant infections and diseases. Furthermore, the spread of wheat diseases such stripe rust (*Puccinia striiformis*) is increased. It has been observed that migration of pathogenic rhizospheric nematodes would increase by over 160 km to the north as the temperature rises by 1°C (Dixon, 2012). In the United States, warmer and increased temperature has led to the increase in the emergence of *Puccinia striiformis* f. sp. *tritici* strains that are adapted to warmer temperatures. They are also resistant to wheat genes *Yr8* and *Yr9* (Gautam et al., 2013).

Disease development and severity is also increased because of rainfall, precipitation, high soil moisture, and air humidity for most plant bacterial and fungal infections (Pietraszko et al., 2018). The amount of time that water from rain, dew, and humidity stays on a leaf is also very critical for disease development from especially fungal pathogens. For example, for stripe rust infection caused by *Puccinia striiformis* to occur on a wheat plant, the leaf must have been wet for 5 h. In a situation where the sky is clear and it is not windy, the time needed for dew to accumulate on the leaf is longer. The opposite is the case when the temperature is higher; this will increase the amount of water vapor in the air and also increase the accumulation of dew which will invariably lead to an increased rate of disease infection (Rowlandson et al., 2015). Furthermore, for pathogenic rhizospheric microorganisms, soil moisture is very important in disease development, especially with wilting in plants (Velásquez et al., 2018).

Life cycles, growth stages, and development of pathogens and pests are also being affected by climate change, as host resistance and host–pathogen interactions are being modified (Chakraborty and Newton, 2011).

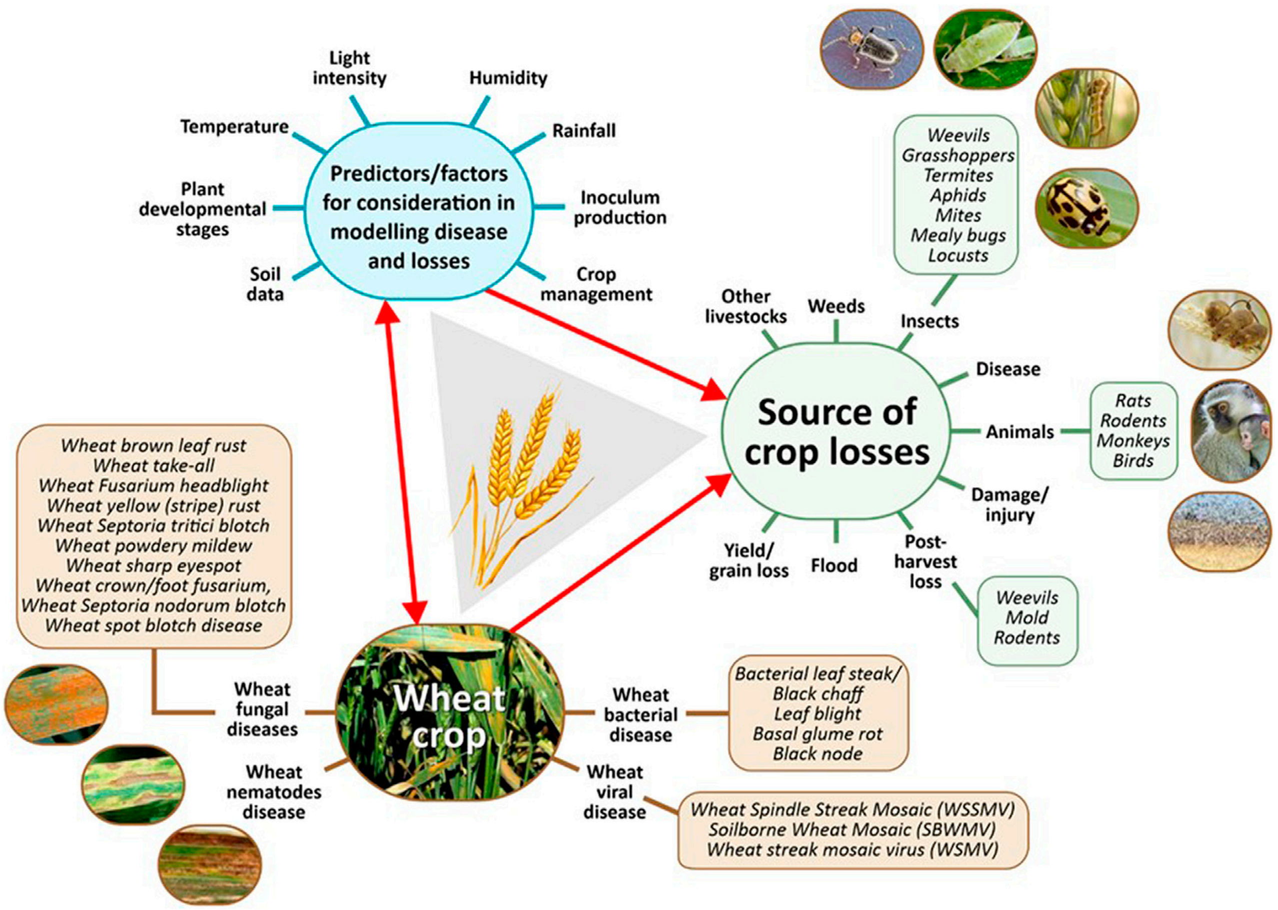

FIGURE 2
Factors involved in crop modeling of wheat disease.

3.1 Rust diseases of wheat

One of the leading reasons for crop yield loss and food insecurity is plant diseases. They are important hindrances to the production of food and the value of such production. They are a threat to food security, as they can cause up to 10% loss of global food production (Strange and Scott, 2005). Diseases such as rusts on wheat not only affect the quality of food production but also the safety of the food when it is consumed by animals and humans and is thus a big concern (Chakraborty and Newton, 2011). Wheat rusts are one of the major plant diseases that cause economic losses across the world and, in particular, in South Africa as a result of the biotic stress factors caused in wheat (Singh et al., 2006). Wheat rusts are plant diseases caused by fungi and include stem rust (black rust), leaf rust (brown rust), and stripe rust (yellow rust) and are all found in South Africa. Warm temperatures (>20°C) favor the spread of stem and leaf rust while cooler temperatures encourage the growth of stripe or yellow rust (<15°C) (Terefe et al., 2016). According to Singh et al. (2011), 90% of wheat varieties grown worldwide are prone to Ug99 variety of the stem rust. Ug99 is a different variety of wheat stem rust fungus that is extremely virulent with Sr31 wheat varieties and was discovered in 1999 in Uganda (Schumann and Leonard, 2000). Stem rust is likely to reduce grain yields of susceptible varieties by 10%–50% with higher losses, up to 90%, reported in rare but more severe cases (Beard et al., 2005). In 1726, for the first time, wheat stem rust was discovered around the wheat-growing areas located in the southwest of Western Cape according to Pretorius et al., 2007. As it gradually became an epidemic, it spread and affected the Free State summer rainfall regions and Western Cape winter rainfall regions (Figlan et al., 2014).

The causative agent of stem rust is *Puccinia graminis* f. sp. *tritici* (pgt). Stem rust is important as one of wheat's most devastating diseases globally, causing about 100% crop failure to the susceptible varieties under favorable climatic and soil characteristics (Leonard and Szabo, 2005). Of the three rust disease pathogens, pgt is highly aggressive and is a great concern for wheat farmers, breeders, and crop pathologists. This is because the disease pathogen can build up in the stem of the infected plant even a few weeks before harvest, and severely infected stems can prevent the flow of nutrients from the roots to the developing grain head, thereby leading to shriveled heads with little or no market value (Figlan et al., 2014).

4 Climate change, crop modeling, and their impact on wheat productivity

In order to mitigate the impact of pathogens and to develop models that will predict climate change, "plant disease models

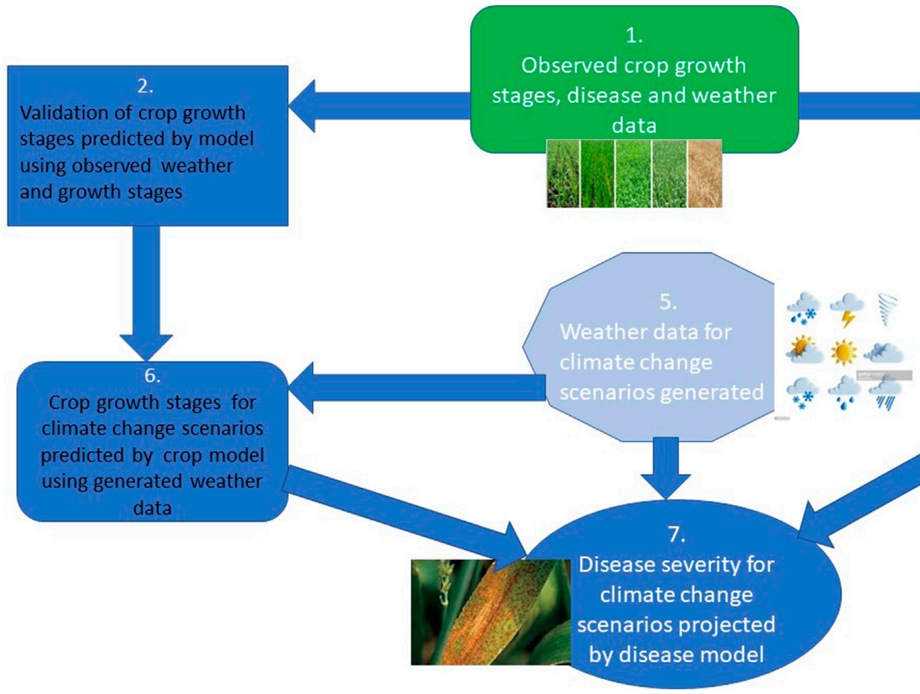

FIGURE 3
An illustration of how climate, crop growth, and disease models can be combined to produce projections of crop growth stages and disease incidence/severity for different climate change scenarios (Source: Modified after Newbery et al., 2016).

themselves must capture a thorough quantitative understanding of disease epidemiology and their reliability in disease forecasting must be proven through rigorous testing and validation" (Shaw, 2009). Furthermore, such models and management practices must include monitoring, forecasting, planning, and mitigation for diseases (Sturrock et al., 2011).

Due to the current relevance of wheat for food safety, various crop models were designed to model the growth and development of wheat crops. Some of these crop models include the Decision Support System for Agrotechnology Transfer (DSSAT) - CERES-Wheat, Nwheat, DSSAT-CROPSIM-Wheat, and the Agricultural Production Systems Simulator (APSIM)-Wheat model. According to Hussain et al. (2018), only the APSIM model had poor accuracy of the simulated performance of days to maturity of wheat compared to the other models (Asseng, 2015). A detailed list of wheat crop models and the purpose of their development and documentation are given in Table 2.

Using the CropSyst model to assess crop growth and yield of 14 wheat varieties in the study by Sommer et al. (2013), elevated temperature resulted in early and fast growth of wheat. Simulations also revealed that higher temperature during flowering could increase the risk of flower sterility and thus crop yield would be reduced. Zhao et al. (2017) found that temperature increase decreased the global wheat yield by 6.0%, rice by 3.2%, maize by 7.4%, and soybean by 3.1% using multi-method analysis. The impacts of climate change have been studied on different wheat models based on different underlying factors such as management, nitrogen availability (Abeledo et al., 2008), rainfall or irrigation impact, differences in cultivar/genetic coefficient, water-use efficiency, and canopy level. In the study carried out by Valizadeh et al., 2014, it was observed that in Iran, using the CERES-Wheat model of DSSAT to simulate wheat growth in the future, wheat production was affected by climate change, possibly because of an increase in temperature and wheat growth rate. This means that different strategies to mitigate this climate change impact should be considered in order to manage the situation so that wheat can be properly adapted. It is also very interesting to note that climate change with an increase in temperature can also bring an increase in the yield based on location and topography, such as that which was observed in the simulation using the CERES-WHEAT model in Mexico from 1988 to 2002 (Janjua et al., 2010). In a mechanistic wheat model in northwestern Turkey, at a stable climatic condition, increased atmospheric CO2 led to an increase in wheat yield. But when the climate varied with temperature and precipitation, the winter wheat yield declined (between 5% and 35%) depending on the GCM inputs used (Özdoğan, 2011).

In China, several studies based on experimental observations have also shown that an increase in temperature increased wheat productivity. For the past 20 years, the impact of climate change has been positive in wheat production in North-Central China (Zhang and Huang, 2013; Zhai et al., 2017). It was also observed that wheat production increased in northern China but decreased in southern China by .9%–12.9% and 1.2%–10.2%, respectively, because of the climate change in temperature, precipitation, and solar radiation. This was also true for simulated future climate scenarios in the northern China plain using a new process-based model to capture the crop–weather relationship over a large area (MCWLA) and a new super ensemble-based probabilistic projection system (SuperEPPS) (Tao and Zhang, 2013; Tao et al., 2014; Zhai et al., 2017).

4.1 Crop modeling of wheat diseases

Use of crop modeling techniques as found in DSSAT (Jones and Thornton, 2003) and APSIM (Keating et al., 2003) can increase the diversity in the agricultural system in terms of control of plant diseases by increasing the resilience of the system to variability in the climate (Lin, 2011). This ultimately leads to increasing and maintaining of high yields in crop production (Lin, 2011). In the study by Savary and Willocquet, 2014, an applied simulation model was proposed for the estimation of disease risk using the DSSAT model and/or the APSIM model. The GENEPEST is a good example of the simulation of crop growth, yield including yield losses. This was done by incorporating the presence/absence of damage/destructions caused by pests into the crop growth model GENECROP. (Savary and Willocquet, 2014). Using the DYMEX-APSIM crop disease model to simulate the rust disease of wheat, it was showed that the model was able to predict the disease proportion in some of the years examined and was able to change the development of the wheat plant to the rust population that was growing (Whish et al., 2015). This invariably translates to improved crop growth and yield.

In order to reduce the usage of chemicals such as fungicides and to increase the crop yield in the midst of plant disease epidemics, two risk models were used to collect decisions on the control of leaf blotch disease in wheat (caused by *Zymoseptoria tritici, Parastagonospora nodorum,* and *Pyrenophora tritici-repentis*) (Jørgensen et al., 2020). The two risk models, Crop Protection Online (CPO) and humidity model (HM), both use precipitation and relative humidity to determine the need for fungicide application. Using the models forecasted, very few treatments thereby reduced the amount of chemicals applied before disease inception, leading to 95% correctness in prediction during the 2018 trials (Jørgensen et al., 2020).

A site-specific model (coffee leaf rust model) and hhh4 model (spatial) were evaluated in predicting wheat stripe (yellow) rust caused by (*Puccinia striiformis* f.sp. *tritici*) in Alberta, Canada. These two models were effective in reproducing the observed pattern of the disease, with the hhh4 model having the highest forecast accuracy. This disease prediction is important as a preventive measure to forestall crop disease epidemics and thereby reducing crop losses to diseases (Newlands, 2018).

Optimal weather conditions are important for the development of wheat rust diseases with temperature and moisture as the major environmental factors that increase disease severity and limit regional production and the yield of wheat species. So, in order to control these lethal wheat diseases, in-depth knowledge of the requirements of the host plant, the disease cycles of the pathogen, and the environmental factors influencing the cycle are required (Rodríguez-Moreno et al., 2020). Using two weather-based models and lassification and regression trees (CARTs) for data analysis, Rodríguez-Moreno et al. (2020) were able to predictively forecast the presence of leaf rust (LR) and stripe rust (SR) on wheat in Mexico. These predictions are important as early warning systems to enhance informed strategies to reduce yield losses due to the rust diseases.

The forecasting of the pattern of spread of wheat diseases is a preventive measure that can be used to give governments, authorities, and farmers enough time to act in order to prevent crop losses using satellite imagery, machine learning, and forecasting models in Europe based on the study by Patil et al. (2018).

4.2 Impact of crop modeling on wheat rust/crop disease control

It is now very clear that the effect of change in climate on plant diseases leading to yield loss is enormous, and weather forecasts and projections are being used by researchers to combat this challenge (Collins, 2013; Morley and Lewis, 2014; Newlands, 2018). Since climate variability affects the biology of pathogens both directly and indirectly, this interaction and the impact on crop yield is made available by the inclusion of crop models in such assessments (Sparks et al., 2014; Zhang et al., 2014; Duku et al., 2016) (Figure 2).

According to Madgwick et al. (2011), a wheat growth model and a weather-based model were used for forecasting the dates of wheat anthesis and *Fusarium* ear blight incidences, respectively, in a research carried out in the United Kingdom. The projections showed that the anthesis date will be earlier while disease incidence will be more severe. Such relationships and predictions are very important to improve the control of disease incidence and formulation of adaptive measures to ensure food security. The average annual wheat losses to diseases in Australia were estimated at 913 million dollars or $76.64 per hectare (Murray and Brennan, 2009).

According to Newlands (2018), in a study on the wheat stripe rust disease, crop modeling had the ability to provide advice about implementing some measure of control of crop diseases in fields or on farms in record time such that it is an effective and preventive measure using an integrated forecasting approach. It is also important in helping reduce crop losses while reducing financial costs and the effect on the environment. The study concluded that crop modeling using a forecasting approach and data from the satellite monitoring of disease inoculum in the air when used by farmers could be a preventive approach against multiple disease threats while protecting crops.

4.3 Crop growth models' gaps, challenges, and possible interventions

The purpose of a model or what the model aims to achieve determines the data to be collected (Harou et al., 2021). A constant challenge to crop model simulation, especially for future crop performance projections and impact studies under varied conditions, is the unavailability of reliable historical data for model calibrations (Kephe et al., 2021). The historical data available are also not consistent for different locations and crops, and the same inconsistency is observed with the parameters collected and the units in which they were collected. That means that the amount of available input data may not be sufficient, and the type of input data to drive the crop models may also not be available (Lüke and Hack, 2017). For example, apart from the fact that data units may be different from what the modeler is used to, the modeler may not be able to do the conversion from one unit to another. Furthermore, using climate data as another example, if the climate data available are coded in a programming language unfamiliar to the modeler, then the data will be available but of no use to the modeler.

It is also clear that one model cannot solve all agricultural challenges even though it has been a challenge as modelers sometimes are tempted to use a one-size-fit-all approach in modeling. Therefore, to face the diversity in modeling, modelers will certainly have to adopt some approaches that will be able to inculcate these challenges, maybe not in one model but in several models interconnected together (Boote et al., 1996; Gary et al., 1998). The use of a particular model should depend on whether the complexity of the model is able to answer the research question and whether the model has been tested in diverse environments. As a result of this, there should be need for both complex and simple models, and depending on the research question, either complex or simple models could be used or both could be coupled and integrated (Ewert et al., 2015).

However, integration of models also has its own pros and cons. Ewert et al. (2015) emphasized that crop models must link with other sub-models by providing information and responding to information needed by those sub-models in such a way that there is a feedback mechanism between models. This could be done in such a way that the output from a model is the input for another model and there must be compatibility in terms of units and scales.

Furthermore, parameters should be in place and be agreed upon to determine what makes a model simple or complex. This is because, in some cases, simple models are not appropriate, as they are not programmed to address the particular phenomenon in question, which means they were programmed for other phenomena. However, in other cases, complex models are not appropriate because they may require more input data that are not feasible to obtain in a field situation and so cannot be used to run the simulation (Boote et al., 1996). It is also important that modelers inform themselves on the capabilities of models, what the models can do, what they cannot do, and the assumptions under which the models can run. Even though minimum data are advocated for crop models, these minimum data are also not available and not accessible (Kasampalis et al., 2018).

Even though the study by Zinyengere et al. (2015) in South Africa with minimum data was able to simulate crop yield in specific locations using DSSAT, studies by Gaiser et al. (2010) using EPIC and Raes et al. (2017) using Aquacrop observed that use of limited data impacted the result from these models thereby assumed to be a challenge for crop modeling.

It is also important to note that some public and private companies, institutions, and organizations have done thorough investigations, experiments, and data collection about several crops; these data, if available to the public, can be used to resolve the issues of qualitative and quantitative data in specific locations and for specific crops. The use of databases is also important, and acknowledgement of the use for the data from the original depositor should be encouraged, especially with private establishments (Kephe et al., 2021).

Furthermore, the use of spatial data over regions may also be another solution even though it is thought to be an arduous task, and there are different limitations to coupling it with crop models, which include the low spatial resolution of satellites and missing information from the collected data because of the frequency of using remote sensing. Spatial data can be used where, due to poor growth conditions, plant models are not able to identify a solution (Kumari, 2020).

It is worth noting that because weather data are not available in every location where crops are grown, the Geographical Information System (GIS) approach has opened a whole field of crop modeling applications at the spatial scale—from the field level for site-specific management to the regional level for productivity analysis and food security (Hoogenboom, 2000; Murthy, 2004; Resop et al., 2012).

Furthermore, using the examples of models such as APSIM (Al-Azri et al., 2015) and DSSAT with examples of crop disease simulations underway, there should be more disease models for different crop diseases which can then be coupled with any of the wheat growth models having numerical weather forecasting. These disease models should consider seasonalities as well as the climate suitability for such wheat diseases.

Using the example of wheat blast, a new wheat model has been created in DSSAT which is under validation in Brazil and Bangladesh, and can predict the yield in the presence or absence of the wheat blast disease (Krupnik, 2019; Molero Milan et al., 2019).

4.4 Future perspective using crop disease models

The use of a decision support system has been ongoing to predict future crop yield and agricultural productivity in the face of environmental factors that can enhance the onset of crop disease. To forestall the wastage of resources and prevent disease progression, disease forecasting and integration of decision support systems for managing plant diseases are important (Figure 3).

Crop disease modeling and forecasting involve predicting the occurrence of a plant disease in a specified area, location, or region ahead of time, so that suitable preventive and control measures can be undertaken in advance to avoid losses (Martinelli et al., 2015; Charaya et al., 2021).

Because of advancements in computer technology, it is now possible to create computer programs that simulate outbreaks of plant diseases. Some of the crop disease models that have been developed and used previously include BLITECAST (for late blight of potato), TOM-CAST (for tomato early blight), PLASMO (for downy mildew of grapes), EPIBLAST (for rice blast), and "Indian Stem Rust Rules", JHULSACAST (Charaya et al., 2021).

Other computer simulation models that were created that have helped to produce an immense understanding of mechanisms affecting disease epidemics include EPIDEM (early blight of tomato and potato), CERCOS (*Cercospora* blight of celery), MYCOS (*Mycosphaerella* blight of chrysanthemum), EPICORN (Southern corn leaf blight), and EPIVEN (apple scab). These models were all created to fit into different locations to prevent an outbreak of plant diseases (Charaya et al., 2021).

Some of the crop disease models that have been developed for wheat are black stem rust of wheat, brown rust of wheat in India, and EPIDEMIC for stripe rust of wheat. It is worth noting that crop disease modeling is location-specific based on the environmental and climatic factors in such areas (Newbery et al., 2016; Donatelli et al., 2017). Even though there are no such models for wheat diseases in South Africa yet, with data collection of pathogen, plants, and environment, the emergence of new information and communication technologies (ICT) such as Internet of Things (IoT), remote sensing, Geographic Information Systems (GIS), and Global Positioning Systems (GPS), which have revolutionized precision farming in the last few decades, can be a new research area in precision agriculture in South Africa.

5 Conclusion

The use of crop modeling to forecast crop diseases is a new and upcoming field of research that should be embraced, as it will work on the principle of "prevention is better than cure." This is because this concept will help predict the impact and effect of the different climatic factors on the different growth stages, with application to wheat production as a pilot, then later to other crops in general. Furthermore, it will help predict which favorable conditions for microbe growth and development have been activated as a result of the climatic factors.

Under the current advances in technology and modeling expertise, it is now possible to incorporate the template of a calibrated crop and disease model to use the current weather forecast as an input to the combined models, following an update to the current time position in the growing season so as to provide an outlook for possible disease infestations in the following 10–14 days for a current weather forecast, etc. This combination will also make it possible for other modules to be incorporated, such as a module on the effect of weather conditions on pesticide and fungicide spray activities. This will be possible when parameters such as heat, wind, and humidity are available in the model to give advice for when and when not to spray the field.

Ultimately, farmers and stakeholders can be advised on the impacts of this chain reaction on crop yield and crop productivity. They can also be advised on the timing of management practices that can reduce the creation of favorable conditions for pathogenic microbial growth, development, and spread.

Furthermore, data collection for crop disease modeling can be carried out systematically, considering the use of artificial intelligence (AI) techniques, machine learning (ML), and deep learning (DL) techniques, as they are playing a pivotal role in the analysis of big data in order to confer useful findings that can help chart the way forward in crop disease modeling.

Author contributions

CA and SW conceived the project, CA carried out the project, and SW supervised the project. Both wrote the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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