Review

Mechanisms and modelling approaches for excessive rainfall stress on cereals: Waterlogging, submergence, lodging, pests and diseases

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ABSTRACT

As the intensity and frequency of extreme weather events are projected to increase under climate change, assessing their impact on cropping systems and exploring feasible adaptation options is increasingly critical. Process-based crop models (PBCMs), which are widely used in climate change impact assessments, have improved in simulating the impacts of major extreme weather events such as heatwaves and droughts but still fail to reproduce low crop yields under wet conditions. Here, we provide an overview of yield-loss mechanisms of excessive rainfall in cereals (*i.e.,* waterlogging, submergence, lodging, pests and diseases) and associated modelling approaches with the aim of guiding PBCM improvements. Some PBCMs simulate waterlogging and ponding environments, but few capture aeration stresses on crop growth. Lodging is often neglected by PBCMs; however, some stand-alone mechanistic lodging models exist, which can potentially be incorporated into PBCMs. Some frameworks link process-based epidemic and crop models with consideration of different damage mechanisms. However, the lack of data to calibrate and evaluate these model functions limit the use of such frameworks. In order to generate data for model improvement and close knowledge gaps, targeted experiments on damage mechanisms of waterlogging, submergence, pests and diseases are required. However, consideration of all damage mechanisms in PBCM may result in excessively complex models with a large number of parameters, increasing model uncertainty. Modular frameworks could assist in selecting necessary mechanisms and lead to appropriate model structures and complexity that fit a specific research question. Lastly, there are potential synergies between PBCMs, statistical models, and remotely sensed data that could improve the prediction accuracy and understanding of current PBCMs' shortcomings.

1. Introduction

Extreme weather events such as heatwaves, droughts, and excessive rainfalls threaten crop production (Lesk et al., 2016; Rosenzweig et al., 2002). Leading to large impacts on crop yields, they are associated with crop price spikes, food insecurity, and civil unrest (Johnstone and Mazo, 2011; Kalkuhl et al., 2016; Nóia Júnior et al., 2022). Therefore, understanding and quantifying extreme weather impacts on crop yields are crucial for assessing climatic risks and establishing adaptation strategies to increase the resilience of food systems (Feng et al., 2021; Lorite et al.,

2023; Vogel et al., 2019). In recent decades, substantial efforts have been dedicated to improving PBCMs to simulate the impacts of heatwaves and droughts (Gabaldón-Leal et al., 2016; Liu et al., 2017; Maiorano et al., 2017; Webber et al., 2017) under the umbrella of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013), and the improved PBCMs were utilized to assess crop yield losses under hot and dry conditions (Ababaei and Chenu, 2020; Deryng et al., 2014; Webber et al., 2018; Xie et al., 2018).

On the contrary, there has been much less effort given to improving PBCMs' skill in capturing excessive rainfall events. Earlier evaluation

studies from the US (Rosenzweig et al., 2002) and Europe (van der Velde et al., 2012) already reported the inability of PBCMs to reproduce the adverse impacts of excessive rainfall on crop yields. Some recent PBCMs capture excessive rainfall stress (Vanuytrecht et al., 2014; de Wit et al., 2019), but their focus is limited to aeration stress caused by waterlogging on root growth, water uptake, carbon assimilation, and phenology (Liu et al., 2020). Furthermore, the processes of growth reduction due to oxygen shortage are poorly parametrized due to a lack of field data (de Wit et al., 2019). Accordingly, crop models still do not fully capture the excessive rainfall effects and overestimate crop yields under wet conditions (Li et al., 2019; Liu et al., 2022; Webber et al., 2020), probably due to the poor representations of other excessive rainfall stress mechanisms.

Excessive rainfall can reduce crop yield through several biophysical processes: waterlogging, submergence, lodging, pest and disease (Fig. 1). Yield loss related to waterlogging (*i.e.,* excessive soil moisture) is associated with delayed farm operations (Urban et al., 2015), poor crop establishment (Cannell et al., 1980), root damage reducing water and nutrient uptake (Herzog et al., 2016), impaired photosynthesis (Tian et al., 2019), and exacerbated nitrogen loss by leaching and denitrification (Kaur et al., 2017). Submergence (*i.e.,* roots and part or the full shoot are underwater) subjects crops to limited gas diffusion and reduced light in addition to the waterlogging stresses (Ito et al., 1999). Excessive rainfall accompanied by strong wind causes plant lodging, which results in reduced canopy photosynthesis by altered canopy architecture (Berry and Spink, 2012), reduced nutrient translocation due to bent or broken stems (Hitaka,1969), pre-harvest sprouting (Hwang et al., 2009), and harvest loss (Rajkumara, 2008), together reducing yield. Different types of crop pests and diseases benefit from excess water to infect and develop and cause, as a consequence, yield losses due to reduced plant biomass, impaired photosynthesis, and altered water dynamics in the soil-plant-atmosphere system (Boote et al., 1983; Savary et al., 2018).

This paper aims to review the state of the art on excessive rainfall stress mechanisms in cereal crops as basis for PBCM improvements. The focus is on three major cereal crops: wheat, maize, and rice covering, (1) yield-loss mechanisms of waterlogging, submergence, lodging, pests and diseases, (2) modelling approaches for each mechanism, and (3) required research for better representation of excessive rainfall effects.

2. Yield loss mechanisms

2.1. Waterlogging

Waterlogging refers to excessive soil moisture conditions. The mechanisms causing yield loss depend on when waterlogging occurs (Tian et al., 2021). If excessive soil moisture conditions occur before the growing season begins, planting dates are frequently delayed due to reduced soil workability with agricultural machinery (Schulte et al., 2012). Late planting beyond the optimum planting window is associated with crop yield loss (Urban et al., 2015). For example, in Ohio, excessive rainfall during the usual planting windows from April to May often forces farmers to plant their maize in June, and late planting leads to shorter growing seasons, harsher growing conditions (*i.e.*, hotter and drier) during reproductive stages, and eventually 12–22 % yield reduction compared to the yield of crops planted during the usual period (Lindsey et al., 2015). Similar yield loss patterns with delayed planting are reported for wheat (McDonald et al., 1983; Nleya and Rickertsen, 2014; Singh et al., 2021) and maize (Nóia Júnior and Sentelhas, 2019).

Excessive soil moisture in the early growing season (*e.g.*, from sowing to seedling growth stage) can cause poor crop establishment, leading to decreases in plant population density (Cannell et al., 1980; von Haden et al., 2021). Under wet soil conditions, aerobic seeds, which require oxygen to germinate, may fail to germinate or may die soon after germination due to the inadequate aeration of the plant's root system, which restricts root growth and ability to absorb nutrients and water (Kanwar et al., 1988). The impact of poor crop establishment on final yield varies amongst crops. For example, in a study comparing the crop establishment and yield of maize and sorghum under early-season extreme rainfall conditions (von Haden et al., 2021), maize yield
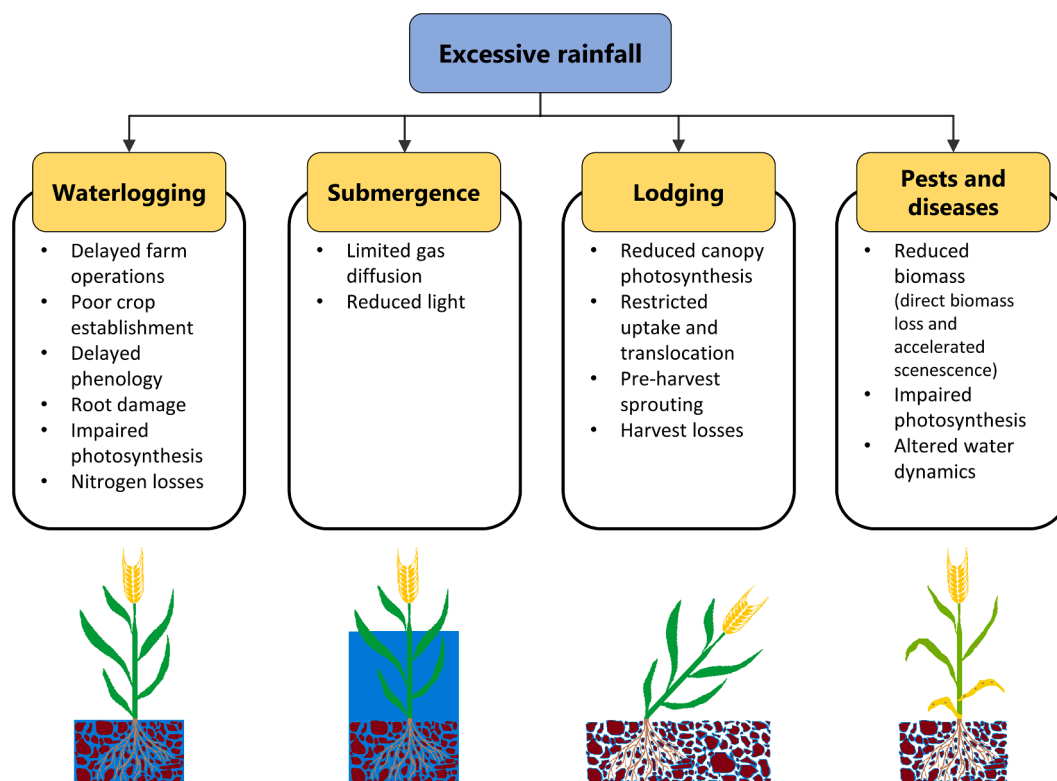

Fig. 1. Crop yield loss mechanisms due to excessive rainfall.

exhibited greater sensitivity to poor crop establishment, attributing to the lower phenotypic (*i.e.*, tillering and leaf area) plasticity compared to sorghum. Similar to sorghum, wheat can partially compensate for the poor establishment by vigorous growth (*i.e.*, more tillers and larger leaf area per plant) in the remainder of the growing season (Cannell et al., 1980).

Waterlogging during the vegetative growth stage can delay phenological development (de San Celedonio et al., 2016; Ren et al., 2014). If flowering is delayed beyond the optimum flowering period, reproductive processes are hampered by harsh environments, reducing grain yield (Flohr et al., 2017). The nutrient deficiency under waterlogged soil (see the following paragraphs) can be partially linked with the slowed-down phenology. Although controversial, some studies reported that nitrogen deficiency reduces leaf emergence rate and lengthens the time to flowering (Bennett et al., 1989; Uhart and Andrade, 1995). Furthermore, in some studies, waterlogging reduced soil temperature (Kaur et al., 2019), which is a main factor determining developmental rate during the early growth stage when meristem is underground (Stone et al., 1999).

Waterlogging throughout the growing seasons has detrimental impacts on roots (Herzog et al., 2016). Energy metabolism of O_2-deficient root tissues switches from aerobic respiration to anaerobic fermentation (low ATP-yielding), even though adventurous roots and aerenchyma, which facilitate O_2 diffusion from shoot to root, are developed in some upland crops such as maize and wheat under anoxic soil conditions (Hossain and Uddin, 2011; Liang et al., 2020). This energy shortage significantly limits root growth and causes the death of some roots, reducing active absorption area, hampering water and nutrients uptake, and eventually reducing aboveground growth and grain yield (Ren et al., 2016; Shao et al., 2013). In addition to the low O_2 stress, low redox potentials accumulate toxic elements (Fe^{2+} and Mn^{2+}) in soils and increase their concentration in wheat shoots grown on acidic soil (Mfarrej et al., 2022; Khabaz-Saberi et al., 2006; Setter et al., 2009). Meanwhile, Steffens et al. (2005) observed negligible waterlogging impacts on the Fe and Mn concentrations in wheat shoots and argued that a major mechanism of waterlogging stress is nutrient deficiency due to reduced uptake rather than nutrient toxicity.

Photosynthesis of wheat and maize decreases with waterlogging (Tian et al., 2019; Zheng et al., 2009). As root hydraulic conductivity and water uptake are reduced by waterlogging, stomatal conductance rapidly decreases, which results in decreased intercellular CO_2 concentration and photosynthetic rate (Hu et al., 2022; Zheng et al., 2009). This mechanism is valid for short-term but not long-term waterlogging in wheat (Herzog et al., 2016). When wheat is exposed to long-term waterlogging (*i.e.*, beyond six days), photosynthetic rate decreases and intercellular CO_2 concentration increases (Wu et al., 2014). This suggests that stomata play a limited role in the regulation of photosynthesis under long-term waterlogging (Herzog et al., 2016). The reduction in photosynthetic rate by long-term waterlogging could be due to the negative feedback from the accumulation of carbohydrates which could be a consequence of lowered sink activity, particularly reduced root growth (de San Celedonio et al., 2017). Furthermore, reduced nitrogen uptake results in reduced chlorophyll content, photosynthetic enzymes, photosystem II efficiency, and thus lower photosynthetic rates in wheat and maize (Malik et al., 2002; Ren et al., 2016; Wu et al., 2015).

Waterlogging also reduces soil nitrogen availability by enhancing denitrification and nitrate leaching (Kaur et al., 2020), which are associated not only with reduced crop growth but also greenhouse gas emission, groundwater contamination, and resulting negative impacts on aquatic ecosystems (Allen et al., 2010; Ascott et al., 2017; Fowler et al., 2013). Under anaerobic soil conditions, nitrate (NO_3^-) is reduced to gaseous forms (N_2O and N_2) by denitrifying bacteria, and soil surface N_2O emission increases (Butterbach-Bahl et al., 2013; Zurweller et al., 2015). Also, nitrate easily dissolves into soil water due to its high solubility and low adsorptivity to soil particles and quickly goes through soil profiles under excessive soil moisture conditions, particularly on coarse-textured soils (Salazar et al., 2014). Meanwhile, excessive rainfall on claypan soils enhances surface runoff and nitrogen losses from topsoil (Udawatta et al., 2006).

Waterlogging at the end of a growing season can delay harvest by reducing the trafficability of machinery (Schulte et al., 2012). Furthermore, rainfall during the maturity period hampers the grain drying process and thus delays harvest maturity that is usually determined by grain moisture content (Bolland, 1984). Delayed harvest subjects plants to a longer period of weathering, increasing the risks of pests, diseases, pre-harvest sprouting, lodging, and thus yield loss (Edwards and Jennings, 2018; Yanagisawa et al., 2005; Thomison et al., 2011). For instance, wheat yield in Western Australia tended to decrease by up to 0.5 % per day of harvest delay (Bolland, 1984). For maize grown in Ohio, harvest delays after mid-November reduce maize yield by increasing stalk rot and lodging, particularly at higher plant populations (Thomison et al., 2011).

2.2. Submergence

Submergence occurs when a part or the full shoot is underwater. This is an important yield-reducing factor of rice production in South- and South-East Asia, where heavy monsoon rainfall induces complete submergence (Mittal et al., 2022). Submergence is also problematic in upland production in various regions where claypan restricts infiltration (Kaur et al., 2020) or degraded soil limits water-holding capacity (Mamadou et al., 2015). Submerged plants are subjected to the exhaustion of carbohydrate reserves and suffer from starvation due to limited gas diffusion and reduced light (Ito et al., 1999) in addition to the abovementioned waterlogging stresses since excessive soil moisture is often accompanied. Some rice varieties can sustain flash floods by temporarily halting growth and saving energy. Other varieties survive deepwater floods (*i.e.*, several meters) by rapidly elongating internodes and thus enabling upper leaves to be above the water surface (Hattori et al., 2011). However, these adapted varieties also cannot survive under extreme conditions such as long-term complete submergence or extreme deep water (Mittal et al., 2022). The following paragraphs provide detailed explanations of the mechanisms of rice yield loss under complete submergence.

Since gas diffusion in water is 10^4-fold slower than in air, O_2 and CO_2 exchanges between the plant shoot and the environment are severely impeded under completely submerged conditions (Armstrong, 1979), reducing plant photosynthesis and aerobic respiration (Voesenek et al., 2006). At night, as a result of respiration, O_2 concentration in floodwater decreases, and the amount of O_2 that diffuses from the floodwater to the leaves through stomata or cuticles, and from the leaves to the roots through aerenchyma, diminishes (Verboven et al., 2014; Winkel et al., 2013). As the roots are exposed to hypoxic conditions, root activity, leaf chlorophyll content, and photosynthetic rate are reduced (Bui et al., 2019; A. Winkel et al., 2014), which is similar to the abovementioned response of upland crops under waterlogging conditions. During daytime, photosynthesis depletes CO_2 accumulated during the night and produces O_2 for plant respiration; however, the photosynthetic rate in the late afternoon can be limited by low CO_2 entry to leaves and low light intensity (Winkel et al., 2013; A. 2014).

Light is another important stress factor in submergence as it limits underwater photosynthesis (Winkel et al., 2013). The proportion of light reaching plants reduces as turbidity and depth of floodwater increase (Ito et al., 1999; Das et al., 2009). For example, Gautam et al. (2015) observed that light intensities decreased throughout the floodwater profile and were 25, 48, and 70 % lower in turbid water than in clear water at 5, 50, and 75 cm water depth, respectively. These lowered light intensities in turbid water resulted in lower photosynthesis, dissolved oxygen, and plant survival compared to those in clear water. In addition to the reduction in light intensity, light quality is also altered by submergence: low blue light, particularly in turbid water, and high red: far-red ratio (Voesenek et al., 2006 and references therein), which

eventually affect plant development and growth (Kami et al., 2010).

2.3. Lodging

Lodging refers to the displacement of the shoots due to heavy rains and strong winds (Easson et al., 1993). Lodging causes significant yield losses for cereals in many parts of the world, especially where typhoons, hurricanes, cyclones, or tornados hit crop fields at reproductive stages (Baker et al., 2020; Hamidisepehr et al., 2020; Hitaka, 1969; Shah et al., 2017). Lodging could be classified as stem lodging (buckling of internodes) and root lodging (failure of root-soil anchorage) (Berry et al., 2004). Risk of root lodging increases under wet soil due to the reduced soil-root anchorage strength (Berry et al., 2004). A primary yield-loss mechanism of both types of lodging is reported to be reduced canopy photosynthesis (Berry and Spink, 2012), followed by limited nutrient uptake and translocation, enhanced pre-harvest sprouting, and increased harvest loss (Hitaka, 1969; Rajkumara, 2008).

Lodging reduces canopy photosynthesis by altering canopy architecture toward reduced light transmission through canopy layers (Berry and Spink, 2012). Modern cereal cultivars are bred to have erect top leaves, which enable more light to transmit into the lower parts of the canopy, leading to higher canopy photosynthesis and yield (Donald, 1968). However, as lodging compresses the canopy, erect top leaves become more horizontal, and the proportion of radiation transmitted into the low layer is reduced, which in turn, decreases the photosynthetic rate of the lower leaves significantly. Meanwhile, the horizontal top leaves receive more radiation, and their photosynthetic rates can be increased up to the rate at the light-saturation point. However, the increased photosynthesis at the horizontal top leaves cannot compensate for the decreased photosynthesis at the lower leaves, resulting in reduced canopy photosynthesis. For example, Setter et al. (1997) observed that 80 % of light is intercepted within the top 80 cm of non-lodged rice canopy; while, the same proportion of light is absorbed within the top 5 cm of a 75 % lodged rice canopy (*i.e.*, lodging treatment with reduced canopy height by 75 %). As a result, canopy photosynthesis is reduced by 60 to 80 %, leading to grain yield loss of 1 % per every 2 % of lodging (Setter et al., 1997).

Root anchorage failure from soil can restrict nutrient uptake, while stem buckling can impede nutrient translocation; both potentially leading to yield losses (Hitaka and Kobayashi, 1964). However, there is little published data to quantify the yield loss associated with this mechanism. Berry and Spink (2012) reported that about 70 % of wheat yield loss due to lodging could be explained solely by reduced canopy photosynthesis, indicating that limited nutrient uptake and translocation may play a minor role in physiological yield loss.

Pre-harvest sprouting or grain germination on mother plants before harvest, is another crucial damage mechanism of lodging (Hwang et al., 2009). Pre-harvest sprouting occurs when natural dormancy breaks down and is enhanced under wet conditions (Tai et al., 2021). When plants are lodged, ears or panicles are exposed to high humidity conditions due to poor aeration inside the canopy or submergence, increasing pre-harvest sprouting (Fischer and Stapper, 1987). Pre-harvest sprouting affects both yield and the quality of cereal crops. For example, Kim et al. (2008) reported that the 1000-grain weight of milled rice was lowered by around 5 % (1.2–1.7 g) in pre-sprouted grains compared to that of normal grains. At the same time, head rice percentage, the most important criteria of milled rice quality, was reduced by 9–10 % in pre-sprouted grains due to an increase in broken or chalky grains. The cooking characteristics of rice, such as peak viscosity and hardness, were deteriorated. Similarly, pre-harvest sprouting reduced wheat yield by reducing grain weight and quality by elevating early alpha-amylase activity (*i.e.*, lower falling number), endoprotease activity, protein degradation, and free asparagine concentration (Simsek et al., 2014; Thomason et al., 2019).

Lodging increases harvest losses and reduces harvest efficiency during harvesting (Berry et al., 2004). Ears of lodged maize plants sometimes fall to the ground due to their large mass or are shifted to lower than the effective working height of the corn header and are not collected by harvesters (Bruns and Abbas, 2005; Fu et al., 2022). For example, when lodging occurred at late growth stages (V17–R1), maize grain yield was 13–31 % lower for mechanically harvested plots than for hand-harvested plots (Carter and Hudelson, 1988). In addition, the mechanical harvesting speed decreases exponentially as the maize lodging rate increase (Xue et al., 2018), increasing production costs (Corbin et al., 2016). Similar results are reported for rice that lodged plants often get jammed in combine harvesters (Masuda et al., 2013), which increases yield losses (Bunna et al., 2019) and harvest time. The efficiency of combine harvesters was 38 % lower in lodged rice (2.16 ha per day) compared to that in non-lodged rice (3.49 ha per day) (Xangsayasane et al., 2019).

2.4. Pests and diseases

Pests and diseases spread widely under high humidity conditions due to promoted germination and proliferation of fungi, bacteria, nematodes, etc. and are a major cause of global crop yield losses (Savary et al., 2019). Pests and diseases can damage crop growth by reducing plant biomass, impairing photosynthesis, and altering water dynamics in the soil-plant-atmosphere system. According to Boote et al. (1983), pests can be further classified into seven categories according to their damage mechanisms: stand reducer, tissue consumer, assimilate sapper, leaf senescence accelerator, photosynthetic rate reducer, light stealer, and turgor reducer. However, a single pest can have more than one damage mechanism.

Crop biomass can be reduced by stand reducers, tissue consumers, assimilate sappers, and leaf senescence accelerator. Stand reducers decrease plant number and plant biomass per unit area. For example, damping-off pathogens, such as *Fusarium* species, decay seeds or seedlings, and thereby reduce plant population (Lamichhane et al., 2017). Some insects directly consume plant tissues or assimilates. In maize, chewing insects, such as Acrididae, Chrysomelidae, Curculionidae, and Noctuidae families, consume shoot tissues; while piercing-sucking insects, such as Aphididae and Cicadidae families, extract plant sap (Contreras-Cornejo et al., 2021). Some other insects, such as the brown planthopper, accelerate leaf senescence (Sogawa, 1994). In the reproductive phase, leaf chlorosis by brown planthopper progresses upwards, and when chlorosis occurs in the flag leaf, grain filling terminates, and grain yield reduces.

The assimilation rate can be reduced by light stealers, photosynthetic rate reducers, and the pests that reduce leaf area as mentioned above. Light stealers develop leaf lesions that are not photosynthetically functional but intercept radiation (Carretero et al., 2010). Leaf rust and *Septoria tritici* blotch are major light stealers causing yield loss in wheat. Robert et al. (2004) reported that the reduction of green leaf area by lesions could explain 70 % of the reduction in plant growth by leaf rust and *Septoria tritici* blotch, which can cause more than 50 % of reductions in plant growth after flowering and final yield. Photosynthetic rate reducers directly limit carbon uptake by reducing chloroplast concentration, causing structural damage to the chloroplast, and altering the electron transport chain (Boote et al., 1983). The wheat blast caused by *Pyricularia oryzae* reduces both net carbon assimilation rate and stomatal conductance; however, the reduced assimilation rate is mainly associated with non-stomatal processes, *e.g.*, reduced Rubisco activity (Debona et al., 2014).

Pests alter plant turgor eventually affecting cell expansion, stomata conductance, photosynthesis, and plant growth. Nematodes, which feed on roots, can damage lateral roots and root hairs, reduce root growth, cause the death of distal root tissue, and result in weak and shallow root systems, eventually reducing water and nutrient uptake ability and lowering turgor (Fosu-Nyarko and Jones, 2016). Vascular wilt pathogens, such as *Fusarium oxysporum*, generally infect through the roots, enter xylem vessels, proliferate, and obstruct the transportation of water

and minerals (Aoki et al., 2014; Yadeta and Thomma, 2013). Finally, some pathogens cause malfunctions of guard cells (Grimmer et al., 2012): *Puccinia triticina* impairs the stomatal opening of wheat in the light, reducing CO_2 exchange and photosynthesis (Prats et al., 2007), while Powdery mildew (*Erysiphe graminis)* impairs the stomatal closure of barley in the dark, increasing night transpiration (Ayres and Zadoks, 1979).

3. Modelling approaches

3.1. Waterlogging

3.1.1. Modelling water dynamics in crop fields

Waterlogged soil should be simulated in time and intensity as the basis for including effects on crop growth and development in a PBCM. This requires an accurate and precise simulation of soil moisture through water balance. Modelling approaches for the water balance of crop fields were extensively reviewed by Tenreiro et al. (2020). After comparing seven PBCMs and five hydrologic models, the authors asserted that PBCMs rely largely on discrete and empirical approaches and lack water processes relevant to spatial variability (*i.e.*, subsurface lateral flows). As modelling approaches for simulating a water balance have been extensively reviewed recently (Tenreiro et al., 2020), in the following text we summarize general simulation methods for processes relevant to waterlogging: infiltration, runoff, drainage, capillary rise from groundwater, evaporation, and transpiration.

The amount of soil surface water available for infiltration can be expressed as a sum of rainfall and irrigation. Some PBCMs, such as STICS, consider water interception by canopy or mulching (Brisson et al., 2003). The fraction of water infiltrated into the soil can be calculated using a maximum infiltration capacity defined as the difference between soil saturation water content and actual water content. Alternatively, empirical parameters, such as the USDA curve number, can be used to estimate the infiltration fraction (Allen, 1991). The remaining fraction after infiltration is partitioned into runoff or, in some models, ponding.

Drainage is simulated using the simple tipping-bucket approach (Van Keulen, 1975) in most PBCMs such as APSIM-SoilWAT, AquaCrop, DSSAT, MONICA, STICS, and WOFOST. The tipping-bucket approach assumes that if water content at a given layer exceeds its field capacity, a fraction of the excess water is drained into the below layer for a specified time step. If the fraction is set close to zero, the layer becomes nearly impermeable, as in claypan, and the perched water table begins to form from the layer. Due to the low prediction accuracy under high soil water content above field capacity (Uzoma et al., 2015) and the lack of continuous representation of water movements (Emerman, 1995) of the tipping bucket approach, some PBCMs, such as APSIM-SWIM, EPIC-Rich-vGM, and SIMPLACE-HillFlow, recently incorporated more mechanistic soil water models based on the Richards (Huth et al., 2012; Longo et al., 2021) or Darcy equation (Nguyen et al., 2020).

Capillary rise from groundwater is reported to considerably affect crop growth under shallow groundwater tables (Kroes et al., 2018). However, it is often neglected or considered a predefined amount in most PBCMs. AquaCrop, a model focusing more on water dynamics than other PBCMs (Raes et al., 2022a), estimates capillary rise considering the soil type and its hydraulic characteristics but does not update the groundwater table (Raes et al., 2022b). To better represent crop growth under waterlogged areas, recently, Deng et al. (2021) coupled a processed-based agroecosystem model (DayCent) and a 3D groundwater model (MODFLOW) on a daily basis: whenever the water table from MODFLOW is within the soil profile, DayCent water processes are constrained by the water table from MODFLOW.

Potential evapotranspiration is computed based on the energy balance methods such as a Penman-Monteith equation (Allen et al., 1998; Monteith and Unsworth, 1990) or alternative methods such as Priestley-Taylor (Priestley and Taylor, 1972) and Hargreaves equations

(Hargreaves and Samani, 1982). Potential evapotranspiration can be partitioned into potential evaporation and transpiration in several ways (Kool et al., 2014). One of the most common methods is the FAO-56 dual crop coefficient approach (Allen, 2000), which splits the crop coefficient (K_c) into a basal crop coefficient (K_{cb}) for transpiration and soil evaporation coefficient (K_e). For each crop type and growth stage, there are recommended values of K_{cb}, which are further modified by wind speed, relative humidity, and plant height. Actual transpiration can be computed by applying a reduction factor due to soil water stress (K_s). K_e is computed as the maximum value of K_c (K_{cmax}) minus K_{cb}, which is further modified by a reduction factor based on soil water availability (K_r) to calculate actual evaporation. The value of K_e should be less than a multiplication of the fraction of the soil that is both exposed and wetted (f_{ew}) and the maximum value of crop K_c.

3.1.2. Modelling crop response to waterlogging

Recently, modelling approaches for crop responses to waterlogging have been reviewed by Liu et al. (2020). According to the authors, many PBCMs now simulate aeration stresses on root growth, water uptake, photosynthesis, transpiration, and hence biomass accumulation and yield at various degrees of detail. For example, many models simulate reduced root water uptake under waterlogging conditions using empirical functions such as the Feddes reduction function (Feddes et al., 1978), which assumes a linear reduction of root water uptake between two constant pressure heads. However, using the fixed anaerobiosis point of the Feddes function for all environmental conditions is reported to be inappropriate because pressure heads do not provide direct information about the soil aeration status (Feddes et al., 1978). To overcome this shortcoming, Bartholomeus et al. (2008) proposed a process-based method, considering both plant physiological and soil physical processes relevant to the reduced water uptake by aeration stress, and this method is implemented in the SWAP/WOFOST model. The review by Liu et al. (2020) also underscores that genetic tolerance parameters, such as phenology of stress onset and root hydraulic conductance, have yet to be incorporated. However, modelling approaches for other mechanisms, such as crop establishment failure and harvest losses due to delayed harvesting, were rarely discussed and are not implemented in PBCMs.

A good crop establishment is the first process for successful yields (Finch-Savage and Bassel, 2016), which consists of emergence time and density of emerged plants. The effects of soil water on the duration from sowing to germination/emergence are simulated by most PBCMs; however, their focuses are mainly on drought stress. In APSIM, germination occurs a day after sowing if soil water is sufficient (Zheng et al., 2014), which captures the drought stress on seed imbibition but not the waterlogging stress. After the germination, the duration to emergence is generally determined by sowing depth and thermal time. Also, PBCMs do not consider the waterlogging impacts on the density of emerged plants, although some PBCMs take drought stress into account. In STICS, emergence density is reduced according to the length of the germination–emergence period, which is controlled by soil temperature and water status (HUMIRAC); however, HUMIRAC does not take waterlogging stress into account (Brisson et al., 2009; Tribouillois et al., 2018). Since there are existing equations to simulate the duration from sowing to emergence and emergence density with consideration of drought stress, the inclusion of aeration deficit factors in these equations can be a first conceptual attempt to consider waterlogging impacts on crop establishment. The threshold parameters for waterlogging stress (*e. g.*, the critical soil water contents for oxygen deficiency on germination and coleoptile elongation) should be introduced and calibrated with proper experimental data for each crop. As mentioned earlier, using a fixed threshold value to simulate aeration stress might be problematic since sometimes soil retains enough oxygen for seed germination even though soil water content is above the threshold. Thus, applying a more process-based approach similar to the method from Bartholomeus et al. (2008) would be required, although it may significantly increase the

parameter number and model's uncertainty.

Yield loss by delayed planting and harvesting due to waterlogging can be simulated by first postponing the dates and relating it to crop growth. Some PBCMs automatically delay the farm operation dates based on soil moisture conditions (Brisson et al., 2009). Even for the PBCMs that do not consider the waterlogging impacts on the crop calendar, these impacts can be captured by calculating the input dates based on weather and soil conditions (Iizumi et al., 2019). All PBCMs can capture the impact of delayed planting on yield since they simulate crop growth and development processes from sowing to physiological maturity (Anapalli et al., 2005). On the other hand, yield loss due to delayed harvesting is determined by the interaction between crop physiological characteristics (*e.g.*, grain moisture, shattering resistance, and degree of lodging) and machinery properties (*e.g.*, harvester type and its operating parameters). Since PBCMs do not consider any of the abovementioned physiological characteristics or machinery properties, they can't simulate harvest losses. Including machinery properties in PBCMs might be unnecessary since PBCMs are developed for simulating crop growth and development, not the operation efficiency of agricultural machinery. However, the simulation of the harvest loss due to heavy rainfall around harvest is important not only for improving model skills but also for supporting farmers' decisions on when to harvest. PBCMs may have a role in simulating the physiological characteristics, and the simulated characteristics may be used as inputs for existing empirical harvest loss models, which estimate dry matter loss or mechanical loss as a function of the number of delayed harvest days, grain moisture content, forward speed, and cutter height of combine harvester (Chaab et al., 2020; Patel and Varshney, 2014; Philips and O'Callaghan, 1974). To do so, the modules for estimating the physiological characteristics, particularly grain moisture content, must be developed first since most PBCMs simulate plant growth on a dry matter basis.

3.2. Submergence

3.2.1. Modelling ponded water

For modelling submergence stresses on crops, standing water at the soil surface must first be simulated. The modelling works on ponding environments were primarily done in rice models, such as APSIM-Oryza (Gaydon et al., 2012) and its parent model ORYZA2000 (Yu and Cui, 2022). In APSIM, when daily irrigation or rainfall exceeds the infiltration rate, the exceeding amount is added to the pond pool (Gaydon et al., 2012). For each soil layer, the maximum drainage rate of the water above saturation can be specified by setting the parameter KS (water amount allowed to drain from the layer when the soil water is above saturation). Otherwise, impermeable layers can be specified by setting the parameter MWCON to around 0. The drainage rate of saturated water (between saturated water content and drained upper limit) is determined by SWCON (the fraction of saturated water that can drain in one day). When both KS/MWCON and SWCON prevent the downward water movement, the water begins to back up and generates a perched water table, and when the table reaches the soil surface, ponding appears. When ponding depth exceeds max_pond (the maximum available surface water storage), an exceeding amount is allocated to the runoff pool. AgroIBIS VSF, an agroecosystem model that simulates the growth of several upland crops including wheat and maize, simulates ponded water similarly to APSIM-Oryza (Edmonds et al., 2021). Furthermore, AgroIBIS VSF incorporates an empirical module to capture the varying ponding depth in response to topographical features such as potholes (Edmonds et al., 2021) which cause heterogeneity of flood risks within a field (Nahkala et al., 2022).

3.2.2. Modelling crop response to submergence

Although rice models simulate ponding environments, their primary focus is on capturing water and nutrient dynamics under anaerobic conditions, not the submergence stress on crop growth and development. To our knowledge, the only attempt in PBCMs to capture submergence impacts on crop was a version of APSIM-Oryza by Gaydon et al. (2017). The authors tried to mimic the quiescence strategy of rice, suppressing shoot elongation to preserve carbohydrates under flash-flood conditions (Nishiuchi et al., 2012). Rice development and biomass accumulation were held constant during the complete submergence (*i.e.*, pond depth $\geq$ crop height $\times$ 0.9). Until now, there have been no process-based attempts to capture yield loss mechanisms, such as limited gas diffusion and reduced light. Alternative to process-based models, empirical flood damage functions, which use flooding duration, inundation depth, and crop growth stages, are widely used to estimate rice yield losses by submergence (Kotera and Nawata, 2007; Nguyen et al., 2021; Shrestha et al., 2021). For example, Shrestha et al. (2021) estimated yield loss as the linear regression equation of flood duration multiplied by the difference between inundation depth and the minimum damageable inundation depth. The linear regression coefficients of flood duration (*i.e.*, intercept and slope) were estimated for different growth stages: vegetative, reproductive, and maturity stages.

3.3. Lodging

3.3.1. Modelling lodging

The first step for simulating lodging impacts on crops is to estimate the timing and extent of lodging under specific weather and soil environments. Mechanistic modelling approaches for lodging timing and extent were considered in a series of papers since the 1990s (Baker, 1995; Baker et al., 1998; C.J. 2014; Berry et al., 2003, 2021). The basic concept of these lodging models is that stem and root lodging occur when the base bending moment of the shoot exceeds the failure moments of the stem base and anchorage system, respectively (Berry et al., 2003). The base bending moment is estimated as a function of the wind speed upon the ear, the area and drag of the ear, the height of the centre of mass (which increases as grains fill), the shoot's natural frequency and damping ratio. Stem failure moment is calculated from the stem radius, wall width, and failure yield stress. Anchorage failure moment is computed with the root plate's spread and the surrounding soil's shear strength, which is calculated as a function of rainfall, clay content, and bulk density. This approach is applied to wheat (Berry et al., 2003) and maize (Berry et al., 2021) but not to rice.

3.3.2. Modelling crop response to lodging

A mechanistic model for wheat yield loss caused by lodging is proposed by Berry and Spink (2012), with a strong assumption that the reduced photosynthesis by altered canopy structure drives most yield losses. The model adapted the canopy photosynthesis model from Campbell and Norman (1998), which calculates gross canopy photosynthesis by multiplying the photosynthetic rates by the areas of sunlit and shaded leaf areas. This yield loss model for lodging assumes that the horizontalized leaves due to lodging increase the light extinction coefficient of the canopy and reduce the green area index (*i.e.,* GAI; the ratio of green leaf and stem area to the area of ground) exposed to direct or diffuse radiation. GAI exposed to direct or diffuse radiation of lodged canopy at a lodging angle of θ ($L_{ds\theta}$) is calculated as Eq. (1):

$$L_{ds\theta} = L_{ds} - ((1 - cos\theta) \times (L_{ds} - L_{ds90})) \tag{1}$$

where L_{ds} is the GAI for a none lodged crop, and L_{ds90} is the GAI exposed to direct or diffuse radiation for fully lodged (*i.e.*, 90° from the vertical) crop. L_{ds90} is computed as Eq. (2) with the assumptions of the extinction coefficient of fully lodged crop as one and the amount of PAR transmitted through leaves as zero.

$$L_{ds90} = 1 - e^{-L_{ds}} \tag{2}$$

Similar to the approach from Berry and Spink (2012), GECROS (Yin and van Laar, 2005), a detailed PBCM to analyse genotype-environment interaction, can capture the effect of lodging on canopy photosynthesis by using the lodging severity as an input parameter.

For the pre-harvest sprouting, no mechanistic models exist; however, there are some empirical attempts to estimate the pre-harvest sprouting of cereals as a function of rainfall and temperature during grain ripening (Mares, 1993). There are no quantitative modelling studies on lodging-induced harvest loss; however, it may be possible to introduce this mechanism into the empirical harvest loss functions mentioned in the waterlogging modelling approaches by including the ear height and comparing it with the cutter height.

3.4. Pests and diseases

3.4.1. Modelling pests and diseases

The yield loss by pests and diseases can be modelled by first simulating botanical epidemics with consideration of the interactions amongst pathogen, host, and environment, and then simulating the impacts of epidemics on crop growth and yield (Savary et al., 2018; Teng, 1985). A large number of mechanistic epidemic models, which represent the dynamics of pest and disease populations, have been developed to understand, predict, and manage crop diseases and pests (De Wolf and Isard, 2007; Madden, 2006) after the first introduction by Van der Plank (1963). Many epidemic models follow the SEIR concept (susceptible, exposed, infected, and removed) described by Zadoks (1971), which divides the host population into four sites according to disease status: healthy, latent, infectious, and removed (Cunniffe et al., 2012; Savary et al., 2012, 2015). Infection rate, computed as a function of basic infection rate, temperature, wetness, and crop age, is used to derive the transition from healthy to latent site. Durations for latent and infectious periods are generally provided as input. Host (crop) growths are simulated relatively simply using relative growth rate and senescence rate, and the senescence rate is computed as a sum of age-induced senescence and disease-induced senescence (i.e., transition rate from infectious to removed sites). One of the most practical outputs from these models is the area under the disease progress curve (AUDPC), which quantitatively summarize disease intensity over time.

3.4.2. Modelling crop responses to pests and diseases

Several methods for simulating crop loss by pests and diseases have been developed. One of the simplest methods is directly relating AUDPC to crop yield (Bhathal et al., 2003). However, this method does not consider various damage mechanisms by pests and diseases, meaning that the methods could not be generalized and is limited to the production situation where the model was developed. To overcome this shortcoming, more mechanistic and generic crop loss models, such as GENEPEST (Savary and Willocquet, 2014), RICEPEST (Willocquet et al., 2002), and WHEATPEST (Willocquet et al., 2008), were developed. GENEPEST simulates biomass growth by multiplying radiation intercepted by canopy and radiation use efficiency (RUE) and then partitions the biomass into different plant organs depending on phenological stages. A large difference from other PBCMs is that multiple damage mechanisms caused by pests and diseases are reflected in different processes, such as radiation interception and RUE. Radiation intercepted by the canopy is reduced by light stealers, leaf senescence accelerators, and tissue consumers. On the other hand, RUE is limited by photosynthetic rate reducers and assimilate sappers. However, this model still needs to be dynamically linked to epidemic models. Although there are several other modelling frameworks for integrating process-based epidemic and crop models (Bregaglio et al., 2021; Donatelli et al., 2017), they are rarely used in modelling studies compared to either the process-based epidemic or crop models.

4. Shortcomings of current PBCMs and future perspectives

Current PBCMs do not consider many yield loss mechanisms by excessive rainfall, such as crop establishment failure and harvest loss due to waterlogging, limited gas diffusion and reduced light under submerged conditions, reduced photosynthesis and harvest loss due to

lodging, and damage mechanisms of pests and diseases (Table 1). Such lack of representations is mainly due to insufficient experimental data to develop and calibrate the modules and knowledge gaps on the yield-loss mechanisms (Fig. 2). For example, crop experiments with objectives other than evaluating the impacts of excess water, when affected by an unexpected waterlogging, are often considered unsuccessfully and terminated without any measurements. However, these field data could be essential for testing new algorithms to consider the damage mechanisms. In the case of pests and diseases, one of the most critical bottlenecks is the lack of experimental data that can be used to calibrate and evaluate both process based epidemic and crop models (Donatelli et al., 2017). Rötter et al. (2018) showed that although there were several empirical studies on the effects of excessive rainfall events on major cereal crops, including wheat, maize, and rice, almost none of the studies aimed to utilize empirical data sets for model improvements. The discrepancy between the number of two study types (i.e., experimental and modelling) may be partially due to the failure to meet minimum data requirements for model improvement, such as input data (e.g., weather, soil, management, and initial values) and state or flux variables (e.g., phenology, LAI, water flux) (Kersebaum et al., 2015). Thus, there is an urgent need to plan and conduct targeted experiments for generating new data to close knowledge gaps and improve model skills in simulating excessive rainfall stresses. In the meantime, for the mechanisms in which stand-alone mechanistic models already exist (e.g., lodging), adding them to PBCMs may improve model performance, particularly under production situations prone to the mechanisms.

However, adding complexity to models with more equations and parameters can increase parametric uncertainty without guaranteeing better model skill (Passioura, 1996). For regional or global scale studies, where observed data for calibration and evaluation are often limited and data inputs are aggregated over large areas, using overly complex models is not recommended (Ramirez-Villegas et al., 2017). On the contrary, for local studies with complex farming systems, recent PBCMs still lack describing potential stressors such as submergence, weeds, pests, and diseases (Gaydon et al., 2017; Huet et al., 2022), decreasing the reliability and potentially usefulness of simulation results. Therefore, the degree of model complexity should correspond to the specific research objective with the rules of "getting the right answers for the right reasons" and "keeping models as simple as possible but no simpler" (Keating, 2020 and references therein; the latter remark attributed to Albert Einstein). However, creating a model for each study takes time. Furthermore, as the number of application studies increased, users

Table 1
Summary of the current capability of simulating excessive rainfall stresses on crops.

| Yield reduction factor	Current capability
Waterlogging	1 Process-based crop models (PBCMs) simulate waterlogging environments with varying degrees of detail on soil water balance.
	2 Aeration stresses on root growth, water uptake, transpiration, photosynthesis, and aboveground growth are captured with varying degrees of detail by PBCMs but not other mechanisms such as crop establishment failure and harvest loss.
Submergence	1 Rice models simulate ponding environments.
	2 Stand-alone empirical yield-loss models exist, but no process-based model exists for limited gas diffusion and reduced light.
Lodging	1 Stand-alone process-based lodging models and a yield-loss model based on reduced canopy photosynthesis exist.
Pests and diseases	1 Process-based epidemic models exist.
	2 PBCMs that incorporate pest and disease damage mechanisms and simple yield loss simulation methods using areas under the disease progression curve (AUDPC) exist.
	3 Some frameworks try to link process based epidemic and crop models but rarely tested.
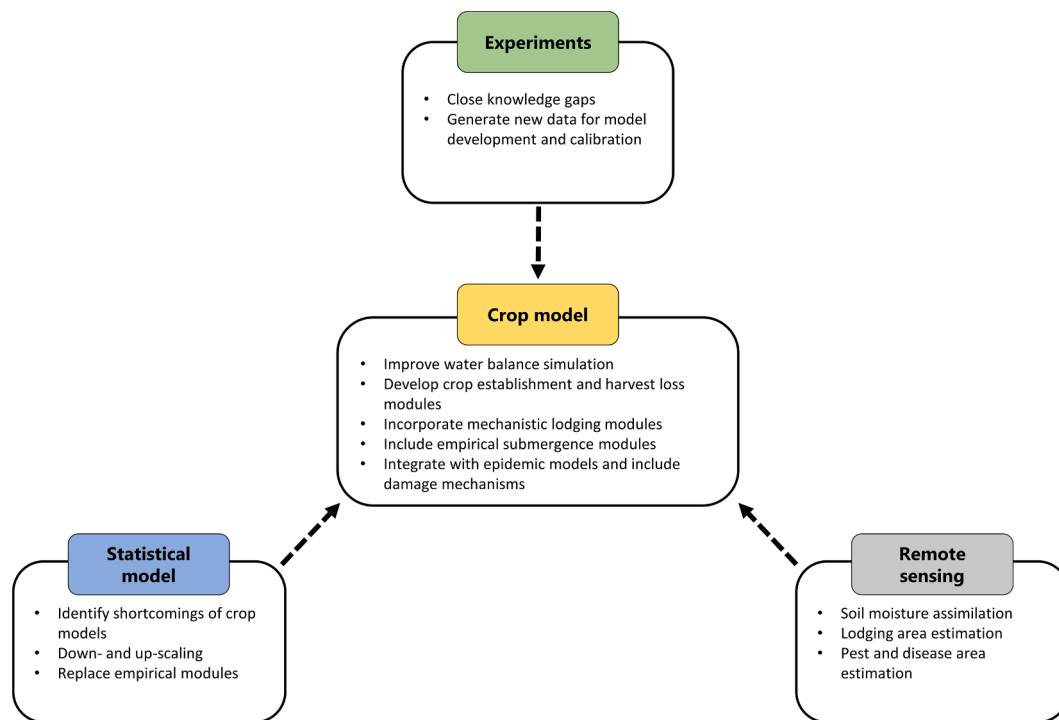
Fig. 2. Proposed framework to better capture excessive rainfall stress on cereals.

without experience in developing process-based models increased; thus, in many cases, it would be almost impossible for individual researchers to build whole processes across soil-plant-atmosphere systems by themselves. Module-based modelling frameworks allow users to build a model that fits their aim by enabling various configurations with different levels of detail (Jones et al., 2003; Wang et al., 2002). Users can create their own models without the inclusion of unnecessary mechanisms by following the protocol by Adam et al. (2012): (i) select modules and build a model with a clear objective, (ii) calibrate and evaluate the model with appropriate data, and (iii) if needed, users can develop their own module and add them to the framework with developers' help, and then re-calibrate and re-evaluate.

Hybrid modelling, combining statistical models and PBCMs, has gained much attention for its better prediction accuracy and ability to identify climatic drivers of crop yield losses (Shahhosseini et al., 2021; Webber et al., 2020). Zhang et al. (2023) provided three different structures of the hybrid model: parallel, serial, and modular structures. In parallel structures, both models use the same input variables. However, a machine learning model is used to predict the residual between experimental data and PBCM outputs. In this way, prediction accuracy can be increased by considering the mechanisms that PBCMs miss, and it provides ideas on which parts of PBCMs need improvements. In serial structure, a PBCM is run prior to a machine learning model or *vice versa*. This approach is particularly useful in down- or up-scaling the outputs of PBCMs. For example, Folberth et al. (2019) showed that machine learning techniques, such as extreme gradient boosting and random forests, could be robust downscaling tools for global gridded crop model outputs, including grain yield, evapotranspiration, and crop available water. On the other hand, Kaneko et al. (2022) used an artificial neural network to upscale the simulated leaf-level photosynthesis to canopy photosynthesis. This hybrid model has an advantage over an artificial neural network in that this model can accurately simulate canopy photosynthesis even when training and test datasets were obtained under different weather conditions. In modular structure, some modules in PBCMs are substituted by machine learning models. For example, Jeong et al. (2022) replaced a LAI module, which has long been a bottleneck for PBCM performance (Wolf et al., 1996; Yin et al., 2021),

with deep neural network and machine learning models that were trained based on remotely sensed LAI.

Remote sensing with satellites and unmanned aerial vehicles has the potential to provide timely and ubiquitous observations on agricultural fields at a range of spatial scales and can be used to improve PBCM prediction accuracy (Huang et al., 2019; Launay and Guerif, 2005). Remotely sensed crop canopy state variables and soil properties can be used to calibrate model parameters and replace or update state variables (Jin et al., 2018). The most common method to improve grain yield estimation is assimilating remotely sensed LAI into PBCMs (Fang et al., 2011; Huang et al., 2015; Ma et al., 2013; Mokhtari et al., 2018). However, this method does not distinguish the yield-loss mechanisms since LAI is the end-product of various stressors such as light, temperature, water, nutrient, pests, and diseases. On the other hand, remotely sensed surface soil moisture or root zone moisture derived from sophisticated models (Martens et al., 2017) can help PBCMs to reproduce drought and waterlogging conditions and their impacts on grain yield (de Wit and van Diepen, 2007; Fahad et al., 2019). Remote sensing-based crop lodging assessment is gaining much attention from farmers, agronomists, and insurance loss adjusters for its rapid quantification without extensive parameterizations, which is required for mechanistic lodging models (Chauhan et al., 2019). Remote sensing can also detect damages from pests and diseases, such as reduced biomass and LAI, canopy surface lesions, pigment systems' destructions, and plant wilting (Zhang et al., 2019).

5. Conclusion

Under climate change conditions, where crop yield loss by weather extremes such as excessive rainfall, drought, and heatwave is expected to increase, the role of PBCMs that can consider multiple stressors will grow in assessing yield level and stability and identifying feasible adaptation and mitigation strategies. There has been considerable progress in heat and drought stress modelling, but substantial improvement is still needed in representing excessive rainfall stresses. Regarding waterlogging, some current PBCMs capture aeration stresses in various degrees of detail, while some damage mechanisms, such as

crop establishment failure, are not considered. Rice models can reproduce ponding conditions but not the submergence stress on crop growth due to reduced gas diffusion and light. Lodging is currently neglected by PBCMs, however, some stand-alone mechanistic lodging models exist, which can be used to simulate lodging areas and relate the areas to yield loss by computing the reduced canopy photosynthesis of the lodged canopy. The coupling of process based epidemic and crop models is in progress. However, the lack of data to calibrate and evaluate both model types limits the use of such coupled models. Further field experiments are required to close knowledge gaps for the yield loss mechanisms and generate data for model improvement. Including unnecessary mechanisms in a model will lead to a complex model with too many parameters resulting in considerable model uncertainty. Modular approaches can help select necessary mechanisms and build the appropriate model structure that fits a specific goal. Furthermore, machine learning models or remotely sensed data can improve prediction accuracy of PBCMs, particularly for mechanisms where mechanistic models are not yet available. In addition, hybrid models can help explore the drawbacks of current PBCMs.

CRediT authorship contribution statement

Yean-Uk Kim: Conceptualization, Writing – original draft. **Heidi Webber:** Conceptualization, Supervision, Writing – review & editing, Project administration, Funding acquisition. **Samuel G.K. Adiku:** Writing – review & editing. **Rogério de S. Nóia Júnior:** Writing – review & editing. **Jean-Charles Deswarte:** Writing – review & editing. **Senthold Asseng:** Writing – review & editing. **Frank Ewert:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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