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Gaps and strategies for accurate simulation of waterlogging impacts on crop productivity

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With the changing climate, soil waterlogging is a growing threat to food security. Yet, contemporary approaches employed in crop models to simulate waterlogging are in their infancy. By analysing 21 crop models, we show that critical deficiencies persist in accurately simulating capillary rise, crop resistance to transient periods of waterlogging, crop recovery mechanisms, and the effects on soil nitrogen processes, phenology and yield components. This hinders the ability of such models to reliably simulate the impacts of excessive soil moisture. Advanced crop modelling analytics will enable scenario analysis and, with time, farming systems adaptation to climate change and increasing frequency of crop failure due to waterlogging.

Soil waterlogging, defined as prolonged root zone saturation causing oxygen deficit, inhibits the stability of crop and pasture productivity in many regions, threatening food security globally[1]. Extreme rainfall events can result in floods and subsequent waterlogging, impacting around 27% of cultivated lands globally each year[2]. For instance, waterlogging regularly affects 16% of the arable soils in the United States, 10% of the agricultural lands of Russia and 31% of the Argentine Pampas, as well as irrigated crop production areas of India, Pakistan, Bangladesh and China[3–7]. While heat stress remains the primary factor influencing yield anomalies worldwide, excess water plays a crucial role in explaining yield losses in key wheat-producing regions such as China and India[8]. In 2019, the US Midwest, a key global breadbasket, left more than 7.6 million hectares unplanted due to excessive waterlogged conditions[9]. Similarly, during the severe wheat yield decline in France in 2016, one of the most extreme in recent history, 26% of grain losses were attributed to soil anoxia[10]. Atypically large rainfall events are expected to increase in frequency and magnitude in many regions due to the intensification of the hydrological cycle by global warming[11], affecting both the world's dry and wet regions[12]. Intensified irrigated agriculture can also cause waterlogging and associated soil

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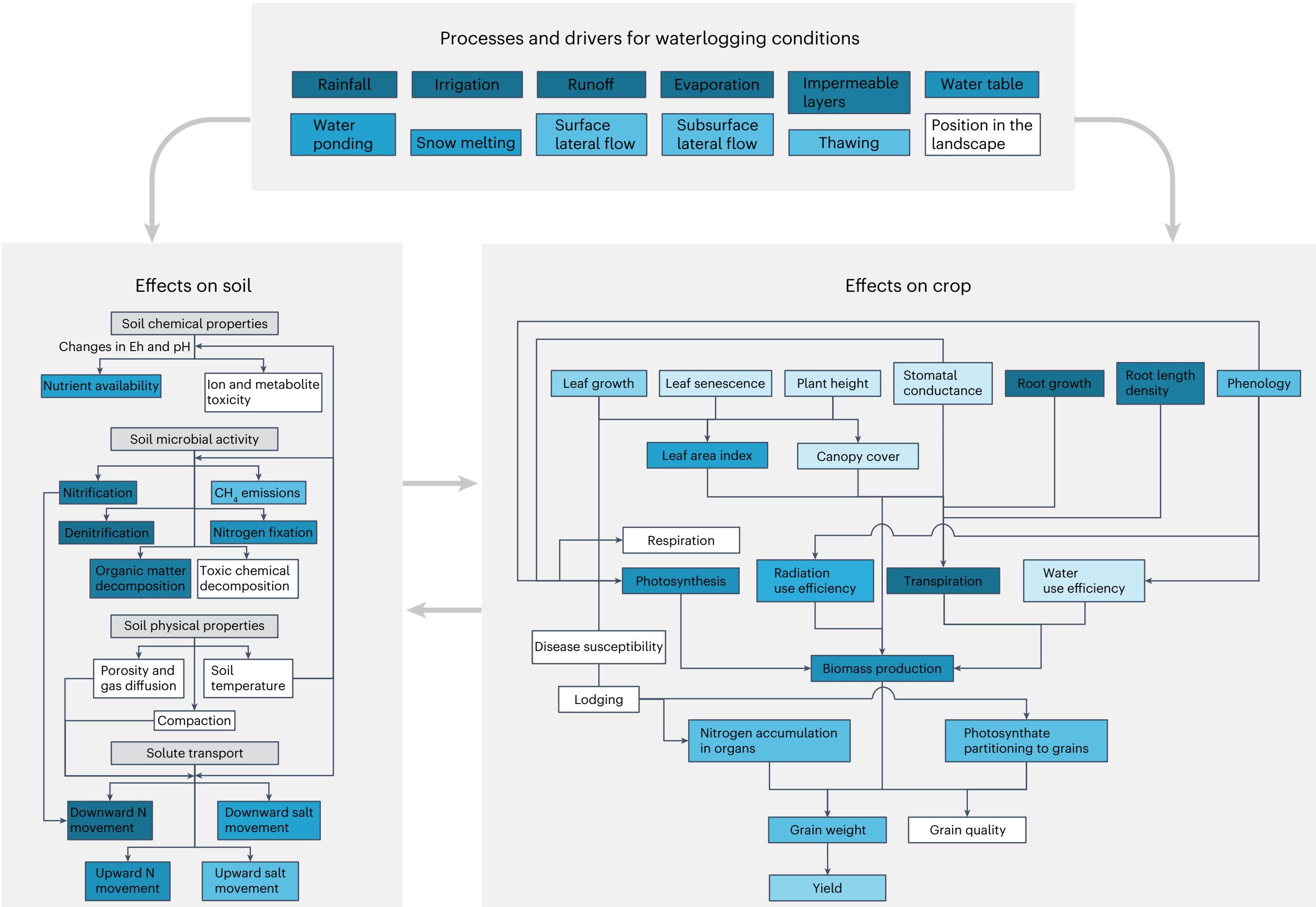

Fig. 1 | Overview of the processes and drivers leading to waterlogging and associated effects on soil and crop performance. Top: key processes and drivers that contribute to waterlogging. Bottom left: the effects of waterlogging on soil (specifically chemical properties, microbial activity, physical structure and solute transport) and their interconnections. Bottom right: the direct and indirect effects of waterlogging on crops, including interactions with soil-mediated processes. The arrows indicate the direction of influence, with bidirectional links where feedbacks occur. Processes more commonly represented in CMs are highlighted in darker blue and those often omitted are shown in white. Eh, redox potential.

salinization in arid and semiarid regions, impacting over one third of global irrigated land and thus endangering food security[13].

Despite its critical role in ensuring food security, climate change impact assessments in agriculture rarely cover waterlogging, with the majority of evaluations focusing on drought, heat or gradual climate change in localized contexts[2]. Assessments involving accurate analysis of risks brought by waterlogging are crucial for formulating production and investment strategies to enhance cropping systems resilience. Process-based crop models (CMs), simulating crop responses to environmental conditions, genetics and management scenarios, are at the core of these assessments[2,14–16]. Nevertheless, the complexity of processes affected by superfluous moisture poses a important limitation. Excessive soil moisture, as it transitions from aerobic to anaerobic conditions in the root zone, adversely affects crop growth, development and yield by altering soil physical, chemical, electrochemical and biological states, while simultaneously, the crop reciprocally influences waterlogging dynamics[17–20]. The severity of the waterlogging impacts varies substantially between crop species and depends on crop growth stage, stress duration, temperature, soil properties and the rhizosphere microbiome[19,21]. Moreover, crop species exhibit substantial variability in their adaptation mechanisms and recovery capacity from waterlogging[19,22]. Considering this complexity, it is justifiable to ask to what extent CMs can adequately reproduce these phenomena.

A decade ago, scientists highlighted the need for improvements in CMs to accurately simulate crop responses to waterlogged soils[23]. Since then, a few efforts have been made in improving the reliability of CMs in projecting how waterlogging affects global food security[24–28]. These improvements include an empirical three-stage representation of crop responses and adaptations[29] and a more accurate portrayal of effects on photosynthesis and phenology[25], nitrogen fixation[26] and other processes[27,28]. To assess and enhance the efficacy of current CMs, we conducted a global model intercomparison and improvement study with an international team as part of the Agricultural Model Intercomparison and Improvement Project[30]. To determine the effectiveness of existing approaches used to simulate waterlogging, it is first necessary to carefully review those processes used in CMs and subsequently determine the extent to which these processes capture the biological, biophysical and biochemical processes occurring in soils and plants (Fig. 1). While previous reviews have used a limited number of CMs[29,31], this study carries out an analysis of 21 contemporary wheat CMs used globally (Table 1) to contrast their capacity to predict waterlogging impacts on crop production. We address the gaps in process-based understanding and suggest a way forward for the crop modelling community to enhance the predictive capacity of CMs, thereby strengthening resilience and adaptation strategies.

Simulation of waterlogging conditions

While there is a general awareness of the need to enhance CM representation of responses induced in the soil and crops by anoxia and hypoxia, the same cannot be said for simulating soil hydrological processes

Table 1 | CMs reviewed

Model and version	Simulated crops	Reference
APSIM c./n.g. (classic and next generation)	Multiple	42
APSIM n.g. (next generation)	Multiple	66
APSIM v.7.9	Multiple	25
AquaCrop v.7.0	Multiple	51
ARMOSA v.4.2	Multiple	53
DSSAT CSM-CERES-Wheat v.4.8	Wheat	50
DSSAT CSM-NWheat v.4.7-mod.	Wheat	41
EPIC v.0810	Multiple	67,68
HERMES2Go	Multiple	36
LandscapeDNDC (ref. 20)	Multiple	48
MCWLA	Multiple	69,70
MONICA v.3.3.1	Multiple	71
SALUS	Multiple	49
SIMPLACE<LINTUL5,Hillflow1D> v.5.0	Multiple	72
SIMPLACE<LINTUL5,SlimWL> v.5.0	Multiple	72
SSM-iCrop	Multiple	37
STICS v.10	Multiple	73
SWAP v.4.2.0	Multiple	52
WheatGrow	Wheat	74
WheatSM	Wheat	75
WOFOST v.8.1	Multiple	43

related to waterlogging[2,29,31]. Most studies have focused on modelling crop responses to waterlogging[29,31–33], thus overlooking this crucial aspect. The first step in evaluating CMs' ability to simulate excess soil moisture impacts is to examine their capacity to reproduce waterlogging conditions, including extent (degree of saturation) and duration. Failure to accurately simulate soil water dynamics by CMs may lead to either over- or underestimation of yield loss from moisture excess. Waterlogging conditions in the root zone can arise from manifold avenues[34], influenced by factors such as weather, terrain topography, soil properties, and land and soil management, affecting water infiltration and fluxes inside the soil profile and over its boundaries[20] (Fig. 1). This complexity poses a challenge for the precise simulation of the relevant processes. For soil conditions with a shallow water table, we found that 24% of CMs are not able to simulate capillary rise (Fig. 2), most often replacing this process with an input parameter. Additionally, even with the presence of a water table, 33% of the CMs need a prescribed water table depth to compute capillary rise since they lack the capacity to simulate water table dynamics ('partial coverage', Fig. 2). Such limitations in simulating water flux due to capillary rise represent a notable constraint, as around 22–32% of the global land area is affected by a shallow water table, reaching the plant rooting zone in 7–17% of cases[35].

Water infiltration and runoff simulation also play an important role in enhancing CM accuracy since excessive rainfall is another major factor contributing to waterlogging. However, in 19% of the models, runoff estimation is limited due to the omission of the soil infiltration capacity ('partial coverage', Fig. 2) or even not computed at all, as in the case of HERMES2Go[36] (Fig. 2). Water infiltration is estimated in most models (57%) by applying a simple capacity model in which the maximum infiltration capacity is defined as the difference between the soil saturation water content and actual water content or a fraction thereof. However, following water infiltration, impermeable layers or soil compaction may disrupt water redistribution and drainage processes, often leading to waterlogging. The SSM-iCrop[37] and WheatSM[38] models face limitations in reproducing this phenomenon, as they are incapable of simulating impermeable layers or soil compaction (Fig. 2). This represents a major limitation, as soil compaction is a critical issue impacting soil productivity worldwide[4]. Additionally, upslope runoff can cause waterlogging in low-lying areas, especially in poorly drained soils. Even though simulating subsurface lateral flows is essential for replicating this waterlogging condition, most CMs (71%) do not incorporate this feature due to the complexity associated with reliable modelling in two dimensions. Furthermore, most CMs that do reproduce these flows limit them to lateral drainage processes ('partial coverage', Fig. 2), such as lateral outflows to drainage canals, leading to incomplete representation in the CM simulation.

Another cause of inadequately addressed waterlogging conditions in CMs is water ponding on the soil surface, with 43% of the CMs unable to simulate it. Similarly, 43% of the CMs reviewed do not account for snow accumulation and melting, which are among the primary causes of waterlogging in northern latitudes during springtime. In these regions, freezing and thawing soil is also prone to waterlogging, but these processes are considered by only five CMs (Fig. 2). The spatial variability associated with waterlogging is another added difficulty most CMs overlook. This limitation is particularly critical for their application in precision agriculture, where management decisions tailored to spatial variability are crucial for optimizing resource use efficiency, productivity, quality[39], profitability and the sustainability of agricultural production[40].

Simulation of aeration stress and recovery mechanisms

Accurately simulating the impacts of waterlogging on crops via CMs depends on the approaches that trigger aeration stress. Aeration stress coefficients vary considerably among CMs[31] but are mainly derived over a pressure-head or volumetric water content threshold (Fig. 3). However, for 14% of the CMs, aeration stress is triggered only when the water table is above a predefined soil depth, 0.3 m in the case of DSSAT CSM N-Wheat[41]. This constitutes an important limitation since a substantial portion of waterlogging in agricultural areas globally is caused by factors other than a shallow water table. Nevertheless, some CMs that use soil water content as a trigger have limitations considering a threshold restricted only to a particular soil depth. For instance, HERMES2Go[36] triggers aeration stress when the soil water content in the upper 0.3 m is above a specific threshold, without considering the entire rooting zone. Moreover, these thresholds should ideally be crop type and phenology specific. In this regard, SSM-iCrop[37] does not have a crop-specific threshold, and APSIM[25,26,42] and HERMES2Go[36] are the only CMs considering the sensitivity of phenological development stage.

Another aspect related to the trigger mechanisms of aeration stress is the duration of waterlogging. While crops are known to resist short periods of soil moisture excess, in most CMs (57%, Fig. 3), stress is triggered immediately once a waterlogging condition is detected. In only 33% of CMs, consecutive waterlogging days equal to or greater than three days are required to activate soil and crop responses. In HERMES2Go[36] and WOFOST[43], aeration stress builds up gradually over consecutive days under waterlogging. However, none of the CMs consider the interaction between the duration and frequency of waterlogging. Another usually neglected aspect is the crop recovery mechanisms after waterlogging. In all models except APSIM[25] and WOFOST[43], the aeration stress effects are assumed to disappear immediately after hypoxic/anoxic conditions cease. However, even brief periods of waterlogging can have negative long-term impacts on certain crops and can lead to crop failure and damage caused by rapid re-aeration[31]. These limitations suggest that trigger and recovery mechanisms of aeration stress in CMs deserve improvement, with a good example being the use of a multiplicative structure to calculate dry matter accumulation, which would include the after-effects of aeration stress[44].

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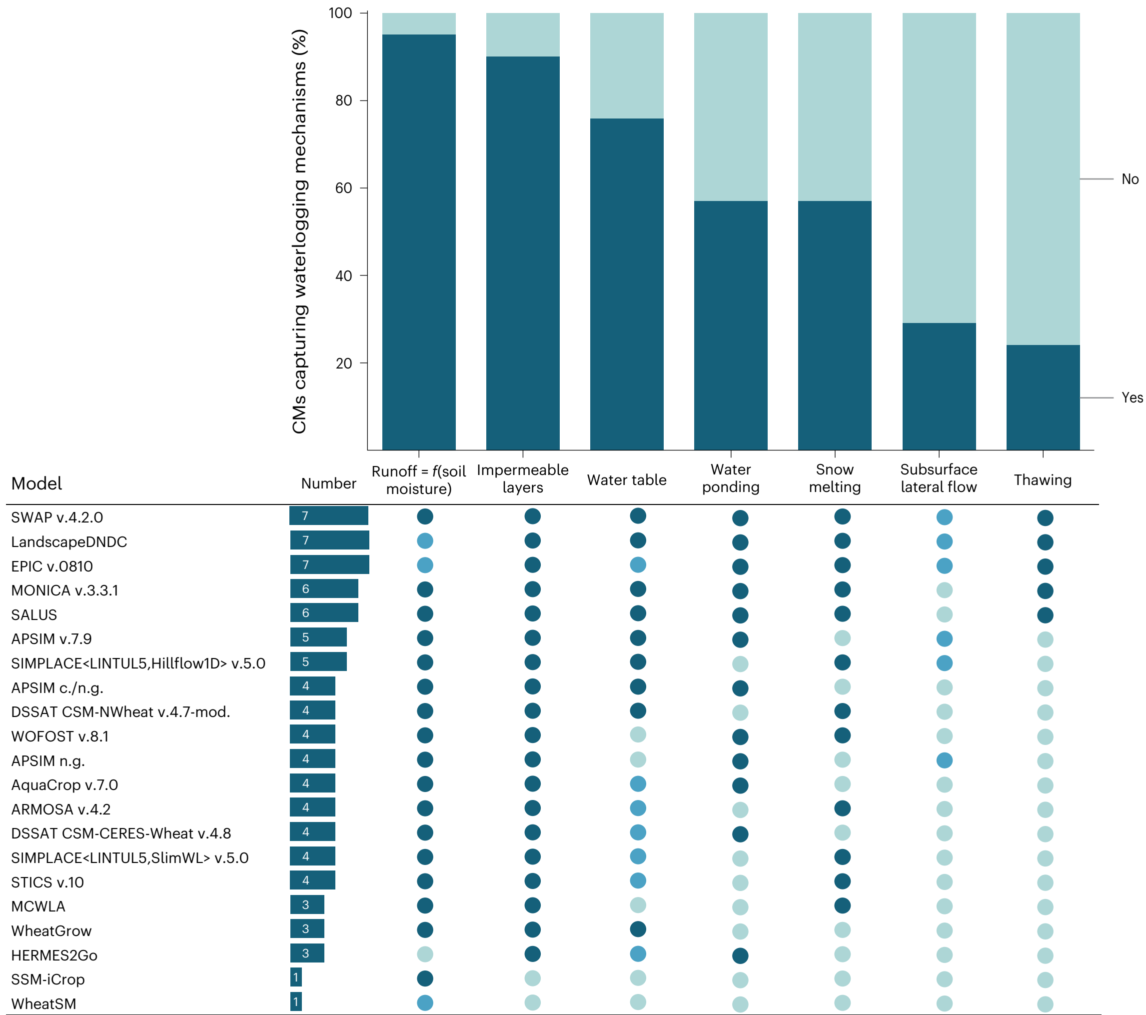

Fig. 2 | Processes in CMs involved in simulating waterlogging conditions. The bar chart shows the share of CMs considering the following processes: surface runoff as a function of soil moisture ('Runoff = *f*(soil moisture)'), effects of impermeable layers or soil compaction on redistribution and drainage processes ('Impermeable layers'), capillary rise ('Water table'), water ponding on the soil surface ('Water ponding'), snow accumulation and melting processes ('Snow melting'), subsurface water lateral flow ('Subsurface lateral flow') and soil freezing and thawing ('Thawing'). The processes considered in each model are shown in the table. Dark, medium and light blue circles indicate advanced, partial and nil coverage of the processes, respectively. 'Advanced coverage' indicates that the model includes functions that simulate the process with a higher level of detail and complexity, 'nil coverage' means that the process is not at all covered by the model and 'partial coverage' indicates that the process is either partially or indirectly represented. The 'Number' column denotes the total number of processes covered by each CM.

Disparities in coverage of waterlogging effects on soil and crops

While extreme moisture excess events disrupt crop growth and development, limitations persist in our understanding of how waterlogging conditions may impact soil physical, chemical and microbial properties[45], as well as above- and belowground linkages[17]. This gap extends to CMs, with 33% of the models overlooking any effect of aeration stress on soil properties (Fig. 4a). Soil nitrogen, a crucial yield-limiting nutrient, is markedly influenced by waterlogging[20] through processes such as decreased redox potential, suppressed nitrification and enhanced denitrification[46]. The ammonia-oxidizing microbial communities in the soil are affected by waterlogging with a potential nitrification rate decrease[47], which is simulated by only 43% of the CMs. Similarly, its impact on nitrogen fixation by limiting associations with rhizobacteria and nitrogenase activity[17] is represented in only 38% of the CMs, and the inhibition of soil organic matter decomposition under waterlogging conditions is represented in 48% of the CMs. On the contrary, 67% of CMs consider the positive correlation between soil surface N_2O emissions and water-filled pore space[20] as a consequence of increasing denitrification with aeration stress. Additionally, alterations in the availability of nitrogen and other nutrients can be induced by pH changes (pH increases in acidic soils and pH decreases in alkaline soils) occurring in waterlogged soils[20]; APSIM[25], LandscapeDNDC[48] and SALUS[49] are the only CMs covering this. LandscapeDNDC[48] and DSSAT CMS-CERES-Wheat[50] are the only models reviewed that recognize that waterlogged soil becomes a source of CH_4 emissions. Furthermore, none of the CMs address the increase of ions (such as iron and manganese) and metabolites (such as phenolics and fatty acids) to toxic levels in waterlogged soils, which is driven by changes in oxidation potential and pH[18]. Concerning the effects on physical soil properties, none of the CMs consider that waterlogged soils have a low structural cohesion, with soil management more likely to lead to irreversible soil compaction. Compaction, in turn, often exacerbates waterlogging and its adverse effects by further limiting water movement within the soil profile, affecting infiltration and drainage.

Beyond aeration stress, other stresses related to solute transport also contribute to the overall effect on crop production. Excessive rainfall can lead to soil nitrogen losses through nitrate leaching, contributing up to 11% of the total nitrate load in groundwater[20]. Additionally, nitrogen can move upwards to the rooting zone from a shallow

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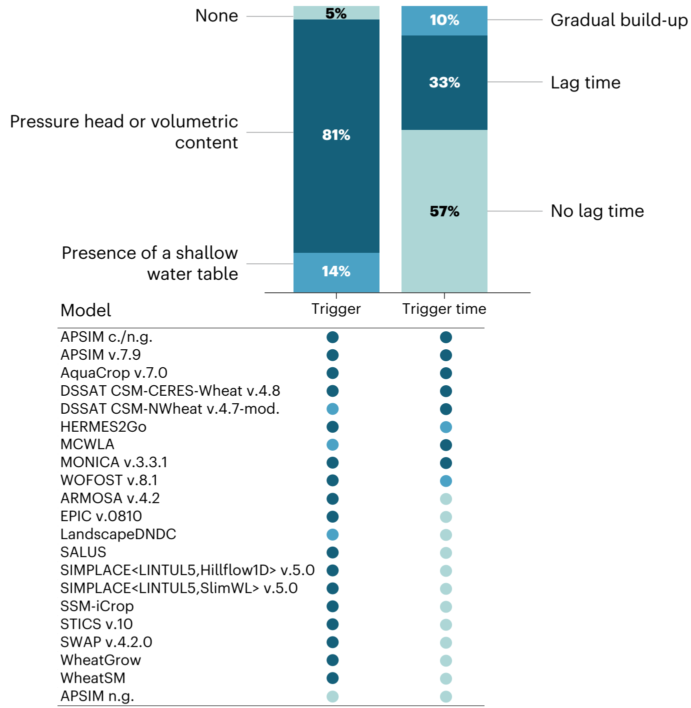

Fig. 3 | Mechanisms required to initiate waterlogging stress in CMs. The bar chart shows the share of CMs using each trigger mechanism of aeration stress and each trigger time approach. 'No lag time' stress is triggered immediately once a waterlogging condition is detected, 'Lag time' indicates that stress is triggered after some consecutive waterlogging days and 'Gradual build-up' indicates a gradual build-up of stress over consecutive days under waterlogging conditions. In the table, dark, medium and light blue circles indicate the trigger mechanism and trigger time approach adopted by each CM following the colour guide of the bar chart.

water table through capillary rise, thus becoming a nutrient source. While downward nitrogen movement is simulated by the 86% of the CMs, only 29% consider upward movement (Fig. 4b). CMs also exhibit limited coverage regarding salt transport despite the frequent simultaneous occurrence of waterlogging and soil salinization[13]. Among the CMs, only APSIM[25,42] models, AquaCrop[51] and SWAP[52] can simulate downward salt movement, while AquaCrop[51] and SWAP[52] account for upward transport (Fig. 4b). These findings highlight the insufficient attention to the effects of waterlogging in the soil despite its notable impact on crop production[20]. Inadequate coverage of the impacts of waterlogging on soil nutrient availability, the accumulation of toxic elements and physical properties can lead to an underestimation of its effects on crop productivity. This may result in the development of inappropriate management strategies, such as suboptimal fertilization plans, which negatively impact both farm economy and environment.

The way aeration stress directly impacts crops varies considerably among CMs, reflecting the diversity in their simulation approaches. In some cases, waterlogging can directly impact the biomass production process (29% of the CMs; Fig. 5). Conversely, other processes leading up to dry matter accumulation, such as crop transpiration and photosynthesis, may be the focus in other CMs. These two processes, as well as limited root growth and root length density, are the main direct effects simulated. In any case, CMs have limited representation of plant physiological responses under waterlogged conditions, reflecting limited knowledge available[1]. A recent meta-analysis assessing the overall impact of waterlogging on crop yield[21] revealed that, on average, crop yield decreased by 39%, attributed to a diminished net photosynthetic rate, and by 23% due to a reduced leaf area index. However, the effect of aeration stress is not covered in 48% of the CMs for photosynthesis and 29% for leaf area index or canopy cover. Only 24% of the CMs account for photosynthate partitioning and grain weight, even though waterlogging-related lower grain weight causes a 14% reduction in yield[21]. The mentioned meta-analysis found that waterlogging during the reproductive growth phase caused a slightly larger yield reduction (42%) than during the vegetative growth phase (35%)[21]. Thus, there is a need to further improve the ability of CMs to simulate late-season waterlogging[25]. Additionally, the effect of surplus water on phenology is considered by only APSIM[25,42] and ARMOSA[53] (Fig. 5) by delaying flowering and reducing the grain filling duration[2]. However, properly simulating the flowering window is crucial for yield determination[25]. Furthermore, sensitivities of different growth stages and crop varieties to aeration stress are also important but are limitedly addressed in the CMs[31]. This limits the ability of CMs to assist in designing waterlogging-tolerant genotypes[54], a promising approach for crop production in regions with longer temperate growing seasons[2]. Concerning the adaption and acclimation crop response[20], only APSIM v.7.9 (ref. 25) represents these mechanisms after three days of soil moisture excess. Additionally, CMs do not capture the unique response to concurrent stresses, such as waterlogging, nutrients and temperature[31]. Not incorporating the adaptation and acclimation mechanisms may lead to an accurate crop yield estimation, but it is raised from the wrong factors.

Pathways for improving model simulation of waterlogging and agricultural adaptation

CMs are widely used to assess the potential impacts of climate change on crop production and to identify adaptation strategies and priority regions for targeted interventions. However, as evidenced here, approaches used in wheat CMs for simulating both waterlogging conditions and coupled soil and crop processes are still largely underdeveloped and variable. There is no single CM that fully addresses all processes, perhaps because no model has been explicitly derived for the simulation of crop growth and production under regular waterlogging. While models with a hydrological focus, such as SWAP[52], perform well for simulating waterlogging conditions and their effects on solute movement, models such as APSIM[25,42] are more suitable for capturing the mechanisms that induce waterlogging stress and its impacts on soil and crop growth and development.

Persistent limitations in accurately simulating crop resistance to transient waterlogging, crop recovery mechanisms and effects on soil processes, phenology and harvest index or yield components hinder CMs' ability to reliably predict both the immediate and long-term impacts of excessive soil moisture. Addressing these limitations is crucial for using CMs to evaluate the feasibility of investing in drainage systems, devise nutrient management strategies[18], support breeding programmes for waterlogging-tolerant genotypes or optimize planting dates[2]. Given the notable role played in crop growth processes by soil hydrology, there is a pressing need for more comprehensive representation of capillary rise, water ponding and lateral flows, avoiding unnecessary empiricism[55]. Enhancing the depiction of soil water dynamics in CMs will substantially improve their utility in identifying effective site-specific adaptation strategies. For instance, CMs may be employed to assess the economic viability of integrating cover crops or other soil-structure-enhancing crops[56], the use of raised beds[57], or the implementation of precision agriculture practices[58] or farming by stability zones[59]. Improved CMs will also facilitate their application as a nature-based solution for aquifer recharge in agricultural regions with stressed water resources through the controlled flooding of crop fields[60].

Nonetheless, the integration and improvement of waterlogging-related processes are still largely constrained by the limited understanding of these interlinked processes, the adequate representation of soil properties[61], the spatial connectivity of soil hydrological dynamics and the availability of adequate and representative experimental data[1]. We are therefore far from accurately predicting the

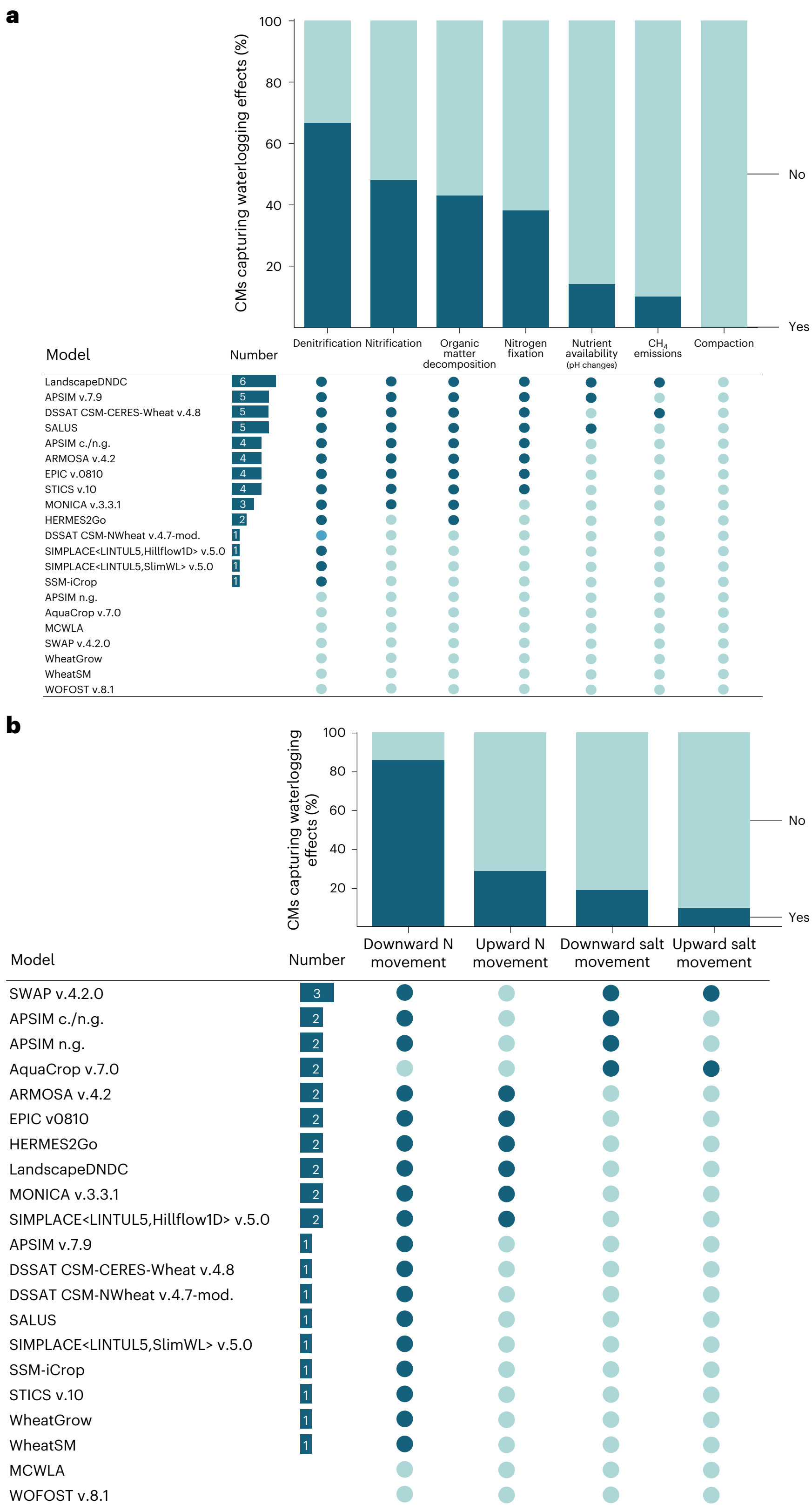

Fig. 4 | Effects of waterlogging on soil properties and solute transport processes in CMs. a, Effects of waterlogging on soil physical, chemical and microbial processes and properties in CMs. The bar chart shows the share of CMs considering each effect. The processes considered in each model are shown in the table. Dark, medium and light blue circles indicate advanced, partial and nil coverage of the process, respectively. 'Advanced coverage' indicates that the model includes functions that simulate the process at an advanced level of coverage, 'nil coverage' means the process is not at all covered by the model and 'partial coverage' indicates that the process is either partially or indirectly represented. The 'Number' column denotes the total number of processes covered by each analysed CM. **b**, Solute transport processes in CMs. The bar chart shows the share of CMs considering nitrogen (N) and salt movement. The processes considered in each model are shown in the table. Dark and light blue circles indicate inclusion or exclusion of the process, respectively. The 'Number' column denotes the total number of solute transport processes covered by each CM.

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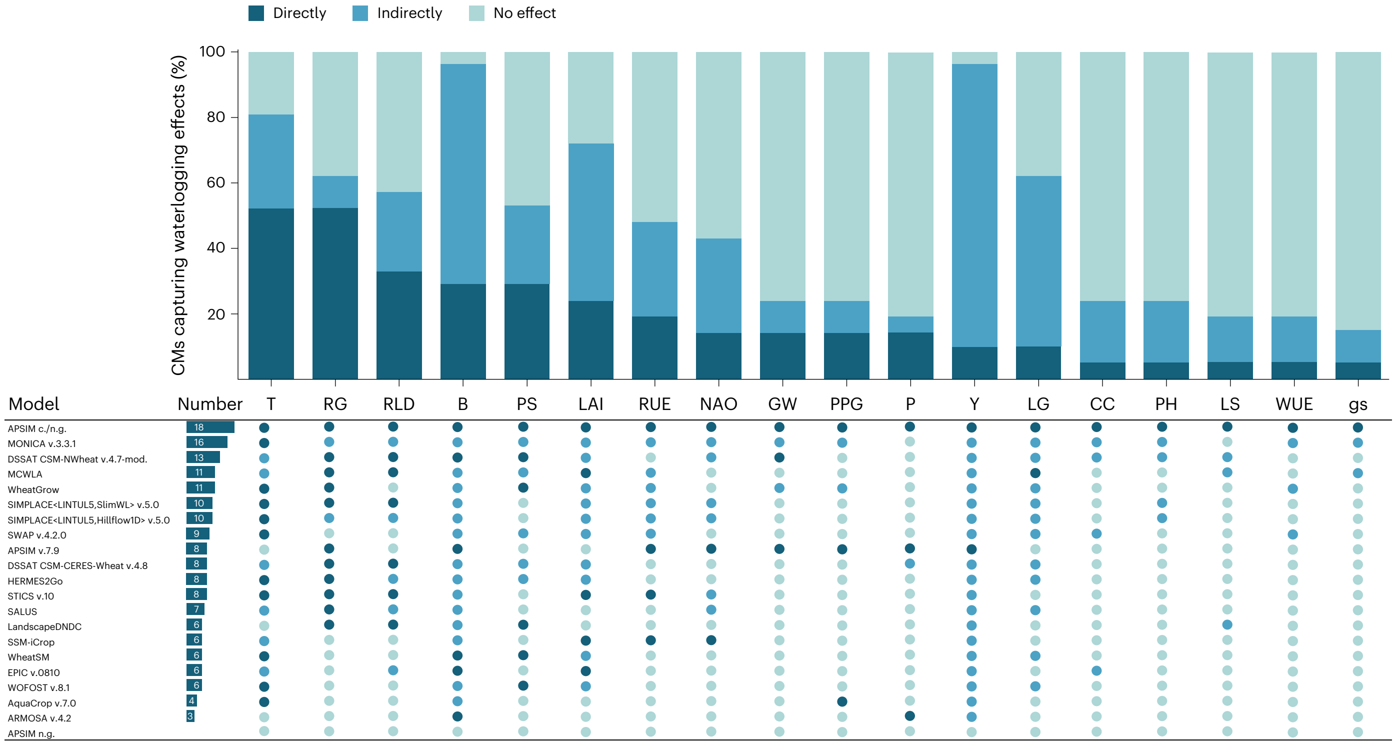

Fig. 5 | Processes relating to waterlogging that are captured in CMs. The bar chart shows the share of CMs considering the following effects of aeration stress on crops: crop transpiration (T), root growth (RG), root length density (RLD), biomass production (B), photosynthesis (PS), leaf area index (LAI), radiation use efficiency (RUE), nitrogen accumulation in organs (NAO), grain weight (GW), photosynthate partitioning to grains (PPG), phenology (P), yield (Y), leaf growth (LG), canopy cover (CC), plant height (PH), leaf senescence (LS), water use efficiency (WUE) and stomatal conductance (gs). The processes considered in each model are shown in the table. Dark, medium and light blue circles indicate the processes captured by each CM following the colour guide of the column charts.

impacts of waterlogging on crop production. This calls for a strategic pathway to enhance CMs' capabilities by bringing together different scientific disciplines (such as plant physiology, hydrology, soil physics, soil ecology and biogeochemistry) and collaborative efforts of modeller groups. A useful first step is to promote the establishment of soil water, crop and field observation networks to bridge knowledge gaps relating to the effects of excessive soil moisture on crop productivity, using advances in proximal and remote sensing technologies to generate valuable databases. Building on these data, the improvement of CMs to address waterlogging issues must be driven by the requirements of field management at the farm scale and water management at the catchment scale, making CMs more effective for practical management purposes. In this regard, the coupling of CMs with large-scale hydrological models[62,63] or leveraging machine learning algorithms[64,65] could markedly enhance their performance and effectiveness at these scales. The integration of biogeochemical cycles, as well as vadose-zone transport models to better simulate soil water and heat dynamics and their effect on water content and temperature fluctuations (including soil freezing and thawing), should also be further explored.

We propose guiding model improvements by the following questions: Is it more important to improve the simulation of waterlogging conditions than to enhance the representation of soil and crop responses to excessive moisture? What is the optimal level of detail in process descriptions for each of the involved processes and their interactions so that the impacts of waterlogging on crop yields can be reliably estimated under different scenarios? What is the extent of uncertainty in evaluating the impacts of waterlogging on crop yield? CM intercomparison assessments against observed data and sensitivity analysis are essential for addressing these questions, with the Agricultural Model Intercomparison and Improvement Project network[30] potentially playing a crucial role. This work lays the foundation for these investigations, providing key information for their design and result interpretation.

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M.G.-V., M.d.S.V., T.P., M.T.H., K.L., R.d.S.N.-J., T.K.D.W. and J.Z. conceived of the study. M.G.-V., M.d.S.V. and T.P. designed and coordinated the study. M.G.-V., M.d.S.V., M.T.H., K.L., R.d.S.N.-J., T.K.D.W., J.Z., M.A., S. Archontoulis, S. Asseng, P.A., J.B., B.B., X.C., Y.C., Q.d.J.v.L., M.D., A.d.W., B.D., R.F., C.F., M.G., T.G., A.G., G.H., K.C.K., Y.-U.K., D.K., B.L., L.M., K.M., C.N., G.P., A.P., D.M.S., C.S., V. Shelia, V. Stocca, F.T., E.W., H.W., Z.Z., Y.Z. and T.P. provided crop model information and discussed the results. M.G.-V. performed the formal analysis, produced the figures and wrote the initial paper. M.d.S.V., T.P., M.T.H., K.L., R.d.S.N.-J., T.K.D.W. and J.Z. contributed to the discussion, reviewed the paper and provided critical feedback. All authors contributed to editing the final paper.

Competing interests

The authors declare no competing interests.

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