Silver lining to a climate crisis: multiple prospects for alleviating crop waterlogging under future climates

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Abstract

Extreme weather events threaten food security, yet global assessments of crop waterlogging are rare. Here, we make three important contributions to the literature. First, we develop a paradigm that distils common stress patterns across environments, genotypes and climate horizons. Second, we embed improved process-based understanding into a contemporary farming systems model to discern changes in global crop waterlogging under future climates. Third, we elicit viable systems adaptations to waterlogging. Using projections from 27 global circulation models, we show that yield penalties caused by waterlogging increased from 3–11% historically to 10–20% by 2080. Altering sowing time and adopting waterlogging tolerant genotypes reduced yield penalties by up to 18%, while earlier sowing of winter genotypes alleviated waterlogging risk by 8%. We show that future stress patterns caused by waterlogging are likely to be similar to those occurring historically, suggesting that adaptations for future climates could be successfully designed using current stress patterns.

Main

Increasingly frequent and compound extreme weather events driven by intensification of the global water cycle threaten the sustainability and consistency of agri-food production[1, 2, 3]. Coupled with global population growth and a burgeoning demand for food, climate extremes are demanding the development of new knowledge, technologies and practices that enable scalable, sustainable intensification[4, 5].

Robust projections of climate impacts on crop growth underpinned by process-based models[6, 7] are fundamental in the quest to design effective and credible systems-based adaptations that minimise down-side risk associated with future climates[8, 9, 10]. Application of such models enables consideration of nonlinear and integrated crop responses to environmental, genetic and management conditions[7, 11], supporting the development of socially-acceptable and profitable climate change adaptation and/or greenhouse gas emissions mitigation strategies[12, 13, 14]. However, while the overwhelming majority of previous climate change assessments have used a lens that has been focused on either drought, heat or gradual climate change[1, 15, 16, 17], our knowledge of the impacts of soil waterlogging on crop growth is very much in its infancy[18, 19, 20].

Globally, around 27% of cultivated lands are impacted by flooding each year, with annual costs of flood damage over the last half century reaching a headline value of US$19 billion [21 22, 23, 24]. Intensification of the global water cycle driven by the climate crisis would appear to be driving a higher prevalence of waterlogging, placing pressure on use of economic, natural and social capital [20]. While genotype (G) × environment (E) × management (M) studies pertaining to climate change adaptation abound [25, 26, 27, 28 29, 30], such work is often not conducted in a way that facilitates scaling (to other regions) or transference (to other studies). Here, we develop a new approach for assimilating manifold results from crop models into common, discrete sets of groups. These groups - characterised by daily stress trajectories plotted over the crop lifecycle as a function of phenology – invoke plant stress, because perceived stress represents an integrated measure of biomass, canopy leaf area, cumulative water supply, vapor pressure deficit and several other factors interacting across an atmosphere-plant-soil continuum. As such, plant stress has long been a ubiquitous target for quantification and manipulation in molecular, breeding and agronomic studies [31, 32, 33].

While GxExM factorial studies are useful, attempts to interpret results using the association between management interventions and maturity biomass or yield[34] can make it difficult to derive functional, rationally-bounded[35] insights across all of the interventions deployed. In contrast, we suggest that crop stress patterns characterised as a function of phenology are limited in type; when grouped across an entire factorial analysis, such relationships can be aggregated into common groups and recurrence intervals, even though individual stress trajectories may appear unique. To standardize contrasts across treatments, we grouped waterlogging stress as a function of phenology. We focus on waterlogging stress and barley as case studies, but the principles could be generically applied to any crop or biological variable. A fundamental contribution of our approach is the ability to functionally categorize big datasets. Armed with knowledge of stress prevalence and typology using this method, decision-makers can more intuitively identify the most appropriate adaptation within their target stress pattern, but can also transfer adaptations across regions within any given stress type[33, 36].

Building on our insights from previous waterlogging experiments conducted using a range of genotypes and treatments in controlled environments[37], we enumerate effects of waterlogging on photosynthesis and phenology then use these insights to improve the capacity of the internationally-renowned model APSIM to simulate impacts of waterlogging on crop growth[38]. Although our new waterlogging algorithms reproduced effects of waterlogging stress on contemporary barley genotypes[38] with reasonable precision, the validity of our new algorithms across a broad array of global cropping environments remains unknown. To fill these knowledge gaps, we first calibrated and validated the waterlogging-enabled version of APSIM using measured field data from five countries. We then applied the waterlogging-enabled model and clustering paradigm in each of the major barley production zones across the world with the specific objectives of (1) quantifying effects of climate change on waterlogging, (2) characterising common waterlogging stress patterns and frequencies across environments, (3) determining the extent to which common stress patterns change under future climates, (4) quantifying the extent to which waterlogging tolerance genotypes, genotypic phenology and sowing time mitigate effects of waterlogging under future climates.

Conceptualising impacts of waterlogging on photosynthesis and phenology

Past work has shown that crop sensitivity to waterlogging stress is critically dependent on the developmental stage in which waterlogging occurs[30]. As such, we modelled waterlogging stress as a function of phenology, which is in itself a significant advance on the majority of previous studies, the latter assuming that waterlogging stress is primarily a function of water-filled pore space (e.g. Ref[38]). We developed new functions to account for measured effects of waterlogging on photosynthesis and phenology (*oxdef photo* and *oxdef pheno*, respectively; Fig. 1a)[38]. Each dimensionless function assumes multipliers ranging from nil to unity in the form of $y = f(x)$, where y is the stress factor and x is soil moisture. When x is at or below field capacity, $y = 0$; y linearly increases with increasing x until the point at which the soil is saturated ($y = 1$). These functions were incorporated into the APSIM software platform to enable improved simulation of crop responses to waterlogging as part of an integrated system. We calibrated the waterlogging-enabled framework using published data from field observations across five countries (Australia, Argentina, China, Canada and Ireland; Supplementary Table 4). Including the new waterlogging functions significantly improved the performance of APSIM in simulating biophysical impacts of waterlogging relative to the default version of the model, with the root mean square error (RMSE) for waterlogged yield loss predictions decreasing from 0.3 to 0.1 (Fig. 1b). The modified model adequately captured the variation in grain yield of multiple genotypes in response to a range of waterlogging treatments across environments (Fig. 1b), with simulations accounting for 70% of the variation in observed yield.

Impacts of a changing climate on global soil waterlogging and yield

Using downscaled projections from Assessment Report 6 (AR6[34]) from 27 global circulation models (GCMs; Supplementary Table 1), we quantified how current waterlogging frequencies may change under future climates. Following recent reports[39], we simulated crop growth and development using the most plausible greenhouse gas emissions scenario (ie. SSP585) for climate periods of 2030-2059 and 2070-2099 (hereafter respectively referred to as 2040 and 2080). To account for variable growing season durations under future climates, we examine crops sown relatively early and late at each site in factorial combination with shorter growing season genotypes (‘spring’) and longer growing season genotypes (‘winter’; Supplementary Table 2).

Our simulations suggest that even though the risk of severe waterlogging will increase under future climates (2-10% increase across GCMs, sites and sowing dates; Supplementary Fig. 1), yields will also slightly increase due to CO_2 fertilization and mitigation of cold stress at high latitudes (Fig. 2a-d and Supplementary Fig. 1). It is likely that past estimates of yield that do not account for soil waterlogging may be overestimated: here we show that simulated future yields decreased by 8%-18% in 2040s and 17% to 26% in 2080s when physiological effects were embedded in the modelling framework (Fig. 2a, d). This modulating effect of waterlogging on yield was especially pronounced in winter genotypes regions (Fig. 2c), likely because such regions have longer growing seasons and greater annual rainfall. Globally, average yield penalty caused by waterlogging was 11% for historical baseline, 14% in 2040s and 20% in 2080s for winter barley [median yield penalty 130-591 kg ha^{-1}; Fig. 4d]; for spring barley yield penalties were 3% for the historical baseline, 6% in 2040s and 10% in 2080s [median yield penalty 50-91 kg ha^{-1}; Fig. 4a] across GCMs, sites and sowing dates.

Despite increased impacts of waterlogging, spring barley yields increased by 5% in 2040s and 13% in 2080s for early sowing (ES) and by 7% in 2040s and 18% in 2080s for late sowing (Supplementary Fig. 1). Future climate change had variable effects on spring barley yield, ranging from positive (e.g. Australia, Germany, Spain, France, United Kingdom, Ukraine and Russia) to antagonistic (Argentina, Canada, Central Ethiopia, Ukraine and United states; Supplementary Table 1). Averaged across sites and climate horizons, yields increased by 22% and 9% for early and late sown winter barley (Supplementary Fig. 1). For both future climate horizons, winter barley yields increased for most regions under early sowing, with greater gains expected in Europe (18%; Supplementary Table 1). These changes suggest that forward shifts in sowing time of long season genotypes may benefit yields, congruent with other recent work[40].

Distilling common stress patterns across diverse environments, genotypes and management approaches

Improved understanding of common waterlogging-stress seasonal patterns allows insight into the timing of waterlogging stress relative to crop phenology, which then governs cumulative effects on growth, tillering, floral development and yield[33, 38, 41]. When applied in the present study, these results help explain differences between yield penalty caused by waterlogging stress between winter and spring barley (Fig. 3 a-c, d-f). Using waterlogging stress outputs from the model computed as a function of historical climate, soil physics, atmospheric demand, plant biology and agronomy, we calculate stress indices for each day of crop growth.

We applied unsupervised *k*-means clustering to many thousand individual trajectories of discretised waterlogging stress as a function of phenological stage into four common clusters (Fig. 3, 4); within each stage the algorithm minimises within-cluster variances. The four clusters accounted for 71% of the variance for spring barley and 80% for winter barley (increasing to five clusters accounted for 74% and 85% of total variance for spring and winter barley and was deemed superfluous accuracy; Supplementary Fig. 9). While we showcase barley and waterlogging stress as exemplars, the principles shown here could be applied to any crop, region, stress type or biophysical model output.

Winter genotypes experienced substantially different patterns of seasonal waterlogging stress relative to spring genotypes at the global scale (cf. Fig. 3a-c, d-f); waterlogging primarily occurred in the juvenile phases of winter barley (WW3) cf. during reproductive development of spring types (SW2-3). While cereals are more likely to experience yield losses when exposed to waterlogging during their reproductive phases (yield formation of cereals being tightly coupled with kernel number and mass) we showed that winter genotypes exposed to waterlogging during their juvenile phases had lower yields than spring genotypes exposed to waterlogging during their productive phases, because the magnitude of waterlogging experienced by winter types was greater. Put another way, yield penalties caused by waterlogging reflected an important trade-off between the duration of waterlogging experienced within a given phase and the timing of waterlogging relative to crop stage; across simulations, yield penalties associated with winter barley were more severe than those of spring barley (Fig. 4a, d).

While recurrence frequencies for each of the four main waterlogging stress patterns for spring genotypes remained similar under future climates, frequencies of early severe (WW3) and mild (WW1) waterlogging during the juvenile phases of winter genotypes increased under future climates at the expense of seasons with minimal waterlogging. Stress pattern WW1 increased from 7% to 17% (under early sowing; Fig. 4e) while WW3 from 3% to 8% (under late sowing; Fig. 4f) compared with the baseline and 2080 periods (Fig. 3). Increased frequencies of severe waterlogging underpin the greater reductions in yields observed for winter genotypes compared with spring genotypes under future climates (Fig. 2a, c; 4d), primarily due to increased waterlogging in France, the UK, Russia and China (Supplementary Fig. 4).

Prospective pathways for adapting to waterlogging

Adaptation of agricultural systems to climate change has and will require cross-disciplinary action: new knowledge, practices and technologies that integrate agronomic, environmental, molecular, social and institutional dimensions will be required[5, 42, 43]. By 2080, early sowing of spring barley reduced occurrence of low waterlogging (SW0; Fig. 4b), while later sowing of spring barley increased the likelihood of low waterlogging occurrence (but did not affect the frequency of the most severe type of waterlogging SW3; Fig. 4c). In contrast, earlier sowing of winter barley diminished frequencies of both severe and low waterlogging stress (WW1 and WW3; Fig. 4e), while later sowing of winter types increased risk of early-onset severe and moderate waterlogging (WW1-WW3; Fig. 4f). Overall, we suggest that sowing time of spring barley in 2080 had relatively little effect on the magnitude of type of waterlogging stress, while later sowing of winter barley was likely to increase likelihood of exposure to waterlogging stress.

Altering sowing time coupled with adoption of superior genetics resulted in further gains in yield. Based on experimental observations, we developed *in silico* genotypes tolerant to soil hypoxia and anoxia typically experienced when soils become waterlogged[44]. After verifying the ability of the improved model to capture behavior of tolerant genotypes during and after waterlogging (Fig. 1b), we examined the long-term performance and yield benefit expected when waterlogging tolerant spring and winter genotypes were coupled with other prospective adaptations (altered sowing time and/or phenological duration). New genotypes with waterlogging tolerance demonstrably increased barley yield under wetter years (Fig. 5) and in general (Supplementary Fig. 7) under future climates. Across sites, the average yield benefit of waterlogging tolerant lines was 14% and 18% (s.d., 23% and 34%) for early- and later sowing in the 2040s compared with the baseline genotypes. Similar yield benefits were observed in 2080 (Supplementary Fig. 6). Mean yield benefits were greater for winter genotypes (480-620 kg ha^{-1}) than spring genotypes (194-213 kg ha^{-1}; Fig. 5). Importantly, yield benefits associated with waterlogging tolerance of new genotypes did not come at the expense of yield in drier years, and reduced downside risk associated with low yielding years (Supplementary Fig. 7).

Our results suggest that there would be more scope for and potential impact of waterlogging tolerant genotypes in environments with longer, cooler and more temperate growing seasons (e.g. the UK, France, Russia and China; Fig. 5, Supplementary Fig. 5), compared with shorter-growing season environments requiring fast-maturity genotypes. This result may reflect the fact that longer growing season environments have higher rainfall, more frequent soil saturation, and/or greater propensity for extreme rainfall events. In countries with higher annualised ratios of evapotranspiration to precipitation and lower risk of waterlogging (e.g. Australia), genotypes with waterlogging tolerance conferred relatively little benefit over the long-term.

Future crop waterlogging stress patterns remain similar to those occurring historically

We developed a new approach for clustering common stress patterns to facilitate functional insight into big data that would otherwise be outside the bounds of reasonable cognitive capacity. This characterisation of the timing of waterlogging stress as a function of phenology across diverse management, environments and climate types revealed two fundamental insights when assessed at the global scale. First, winter genotypes experience earlier seasonal patterns of waterlogging stress relative to spring genotypes (cf. Fig. 3a-c, d-f). Even though cereal crops are more sensitive to waterlogging during their reproductive phases, winter genotypes experienced greater yield penalty under early waterlogging (than spring genotypes under later waterlogging), because waterlogged durations experienced by winter genotypes were generally longer (Fig. 3, 4a, d). Second, even though future crop waterlogging events are likely to increase by 2-10% (Supplementary Fig. 8), we revealed the serendipitous outcome in which waterlogging stress patterns for each of winter and spring genotypes under present conditions are likely to be similar to those expected in future climates (Supplementary Fig. 3). Equipped with such knowledge, agronomists and crop breeders would likely to achieve more widespread impact if new spring genotypes were adapted to late-season waterlogging, while proposed development of new winter barley genotypes would likely achieve wider impact if designed with early waterlogging in mind. It should be noted that while situations with minimal waterlogging stress (SW0 and WW0) would predominate (Fig. 3c, f); this result does not guarantee that such environments will not experience waterlogging stress under future climates, rather that low waterlogging stress is more likely to emanate over the long-term[38, 45].

Similar frequencies of waterlogging under historical and future conditions is a fortuitous outcome, because it suggests that practitioners could effectively develop today's adaptations for the temporal waterlogging patterns of tomorrow. If future waterlogging-stress patterns were dissimilar to those occurring historically, then the design of effective adaptations to future conditions would be more hindered due to the need to establish controlled-stress environments[46] or create synthetic waterlogging stress patterns similar to those expected in future. However, similar historical and future waterlogging stress patterns suggest that beneficial adaptations within each waterlogging stress pattern – e.g. the early-onset severe pattern of winter barley – could be readily transferred between regions, production systems and time periods, provided that other factors remained unchanged (e.g. local-adaptation of genotypes for disease resistance). Clustering stress patterns into common groups allows us to move away from locally-specific factors causing the waterlogging stress (e.g. poor drainage, rising ground water, superfluous rainfall, sowing time, genotype, soil type etc.) to the stress pattern that would most likely be realised in a given environment as a function of crop phenology.

On the implications of regional climate change for waterlogging and yield

Our work has shown that mean yield penalty caused by waterlogging increased from 6-14% in 2040 to 10-20% by 2080 across GCMs, genotypes, management and sites. This result encompasses locally-specific findings for Europe (e.g. France, Germany, United Kingdom and Spain)[47] and China[41] under superfluous precipitation scenarios. In these regions, yields were higher under future climates due to elevated atmospheric CO_2 concentrations and moderate alleviation of cold stress when water was not limiting[48, 49, 50], analogous to yield gains seen in US dairy systems[16, 17]. Our findings also align with previous work which suggests that winter crop yields in Europe will rise by 2050[51] due to greater biomass production, grain number and grain weight associated with a fertilisation effect of atmospheric CO_2 and moderate warming[11]. In waterlogging-prone regions within Australia, we showed that yields are likely to increase under future climates due to lower incidence of waterlogging (Fig. 2). Less rainfall in regions with high precipitation (>600 mm/year) may reduce disease susceptibility (e.g. stripe rust), improve crop health and further raise yield under future climates, although it should be noted that biotic pressures were not accounted for in the modelling framework used here.

Climatic transition towards drier and hotter conditions by the end of 21st century is projected for many regions, often with increased likelihood of extreme weather events[39, 38, 48, 49, 50]. Even though future climates were conducive to 2-10% higher risk of severe waterlogging across the entire solution space (Supplementary Fig. 8), high variation between regions and genotypic lifecycles (Supplementary Figs. 3, 4) was offset by beneficial effects of climate change that collectively improved yield by 8-17% under future climates. As part of this, we found higher frequencies of early-onset severe waterlogging stress in Argentina, Ethiopia, China, the UK, France and Germany, in line with reports of increased flash flooding in some regions towards the end of the 21st century, particularly Asia and Africa[52]. We suggest that particular attention should be placed on the development of waterlogging mitigation approaches for smallholders and the rural poor in lower-latitude countries where increased flood frequency is projected and prevailing rainfall is already high; women, youth and marginalized groups need to be empowered for proposed adaptation approaches to be successful. To engender adoption, appropriate research, development, policy and extension packages will be required to ensure that proposed adaptations are cost-effective, demand-driven, socially-responsible and equitable[53, 54].

A requirement for contextualised adaptation to future climate change

The effectiveness of genotypic adaptation (i.e. introduction of crops with waterlogging tolerance genes) was higher in Ethiopia, China, Germany, France and UK. Across countries analysed, we showed that adoption of waterlogging tolerant genotypes could mitigate up to 18% yield penalty caused by waterlogging under future climates, suggesting further research and development of such genotypes would be a worthwhile investment. In other regions, converting from longer-season winter genotypes to short-season spring genotypes could help avoid waterlogging, but with regional specificity *viz.* long-season waterlogging tolerant genotypes were shown to be more effective in Ethiopia, while short-season waterlogging tolerant genotypes were more effective in Europe and China. Taken together, our results suggest that contextualised adaptation will be key: there is no panacea, and certainly no singular generic solution for all environments. Fruitful future research may include ‘stacking’ or combining of several beneficial adaptations to determine whether the benefit from individual adaptations is synergistic or antagonistic[5, 49].

As far as we are aware, the present study is the first experimental quantification of waterlogging expected under future climates in each of the major barley cropping zones of the world. To quantify waterlogging stress patterns, we develop and exemplify a simple, transferable approach for clustering crop stress patterns across regions, climates, management and genotypes. We show that even though frequencies of global waterlogging will become higher, these changes will be outweighed overall by reduced waterlogging in other regions together with elevated CO_2 and warmer growing season temperatures. Our clustering approach comprises a pathway in which diverse bio-climatic applications may be able to categorise big data outputs into functional and biologically-meaningful patterns. While we apply this method to waterlogging and barley, although the framework could be readily applied to any crop, production system, or temporal biological variable. With regards to adaptation, we show that waterlogging tolerance genetics will have benefit in Ethiopia, France and China, but particularly in regions were long-season 'winter' genotypes are commonplace. Shifting from relatively late to early sowing or from late to early maturity genotypes may alleviate waterlogging-induced yield penalties in some environments (Australia, Canada, Spain, Turkey and US). This pilot study only employs a single crop model and in view of large uncertainties associated with these models, follow-up work should corroborate our results based on additional models in the vein of multi-model assessments pioneered by AgMIP[55]. Successful implementation of these adaptations could only occur if coupled with appropriate socio-economic policies and extension programmes to enable awareness of waterlogging and uptake of context-specific genotype by management by environment adaptations.

Methods

Data for model development and validation. Measured data from five two-year experiments (Exp1, Exp2, Exp3, Exp4, Exp5) conducted in five countries (Australia, Argentina, Canada, China and Ireland) were used for model development and validation. Exp1 was conducted under controlled conditions (Mt Pleasant Laboratories, Launceston, Tasmania, Australia) with four waterlogging treatments using six contemporary Australian barley genotypes differing in their waterlogging tolerance from 2019 to 2020 (see ref.[37, 38]). For Exp2 barley yields were measured under five waterlogging treatments in the greenhouse and field conditions at the School of Agronomy, University of Buenos Aires, Argentina during 2010 (see ref.[56]). In Exp3, barley genotypes were evaluated for waterlogging tolerance in controlled field conditions at Brandon Research and Development Centre, Brandon, Manitoba, Canada from 2016 to 2017. Waterlogging treatments were initiated at the tillering stage by adding the water to heights of 0.5–1 cm above the soil surface (see ref.[57]). In Exp4, barley yields were measured in field conditions carried out at Oak Park, Carlow, Ireland from 2017 to 2018. Waterlogging treatments were initiated at the tillering stage using a boom irrigator (see ref.[58]). In Exp5, field experiments were conducted in 2003-2004 and 2005-2006 at Zhejiang University, Hangzhou, China. Waterlogging treatments were imposed at tillering (see ref.[59, 60]). All experiments were carefully managed to provide adequate nutrition and control of biotic pressures.

Impact of waterlogging tolerance genes on barley growth and development. The waterlogging gene evaluated enables barley plants to tolerate saturated soils by accelerating aerenchyma formation and increasing root porosity following a waterlogging event. To account for this, we propose three stages of plant response and adaptation (Supplementary Fig. 11). Stage one is the immediate plant response upon waterlogging at which time water supply to the plant is unlimited and with soil strength lowered, root growth has little physical impediment. With this situation the expectation is that biological functioning is not limited by oxygen or water availability, and hence growth processes are not affected. During the second stage, soil water pores become fully saturated and oxygen dependent bioprocesses (e.g. photosynthesis; 1 = no stress, 0 = full stress) are negatively influenced. The third stage encompasses adaptation responses, the net result of which is a variable level of adaptation depending on waterlogging tolerance genetics. After the adaptation stage, genotypes that are tolerant to waterlogging may exhibit similar or increased function compared with before the waterlogging event, analogous to plants that grow aerenchyma after waterlogging[37]. Barley genotypes that are sensitive to waterlogging and devoid of genetics conducive to aerenchyma formation exhibit decreased growth and capacity to recover after waterlogging events; depending on waterlogging duration and timing this may penalise grain filling and yield. We embed these concepts within the source code of APSIM; the executable containing the modified source code and XML files are available from the authors upon reasonable request. Genotypic parameters describing waterlogging tolerance were calibrated and validated in our previous study[38].

Study sites. Simulations were conducted using data from thirteen countries based on national barley production and planting area. In each country, simulated sites were prioritised based on dominant soil types in cropping zones from the Digital Soil Map of the World[61]. These representative sites (see Supplementary Table 2 and Supplementary Figure 9) where barley is grown[62] have sites with documented reports of waterlogging[63].

Historical and future weather data. Historical daily climate data for maximum and minimum temperature, rainfall and solar radiation for 1985-2016 at each location were obtained from the National Aeronautics and Space Administration/Prediction of Worldwide Energy Resources (NASA/POWER). NASA/POWER presents a global coverage of complete climate data at horizontal resolution of 1° latitude-longitude. The yearly atmospheric [CO_2] for future periods were calculated using empirical equations that were obtained by nonlinear least-squares regression, based on the Shared Socio-economic Pathway 585 (SSP585), a business-as-usual (high) emission scenario. This scenario most closely represents the climate trajectory to date[39]. For SSP585, representative annual atmospheric CO_2 concentrations were estimated for each year (see Supplementary Methods).

To generate climate scenarios for 2040 and 2080, monthly temperature, rainfall and radiation projected from 27 GCMs (Supplementary Table 1) are available from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Here we used the statistical downscaling model NWAI-WG, developed by Liu and Zuo[64] to downscale GCM monthly gridded data to daily climate data for each of study sites. Spatial downscaling used inverse distance-weighted (IDW) interpolation as described in our previous study[65] then applied bias correction, resulting in bias-corrected monthly data using a relationship derived from observations and GCM data for the historical training period of 1985-2016. Bias-corrected and downscaled GCM trends were then transcribed into time series of daily maximum and minimum temperature, rainfall and radiation using a modified stochastic weather generator. The major advantage of this statistical downscaling method, particularly in comparison with more computationally demanding dynamical downscaling, is that it can be easily applied to any location for which a long-term daily historical climate record is available.

Model calibration and validation. A recent review[53] revealed that APSIM is one of the most appropriate extant farming systems models for simulating waterlogging phenomena. In APSIM-Barley (version 7.9)[66], phenology is described in terms of thermal time accumulation using 11 crop stages and 10 phases (time between stages). Further model details, including phenology and growth are detailed[66, 67]. Site-specific genotype selection, crop management (e.g. sowing date) were based on local expert advice and experimental records (Supplementary Table 2). We created site-specific genotypes to match the thermal time between emergence and maturity for each site by adjusting phenological parameters in APSIM barley for vernalisation (*vern_sens*), photoperiod (*photop_sens*) and the thermal time between emergence and the end of the juvenile phase (*tt_end_of_juvenile*). The purpose of this was to identify and create appropriate genotypes (representative synthetic genotypes) that suited local context, with lifecycles developed in line with sowing, flowering and maturity times observed in practice.

In the APSIM source code, effects of waterlogging on photosynthesis and phenology in the APSIM source code were represented by the new functions oxdef_photo and oxdef_pheno, respectively. Each dimensionless function assumes multipliers ranging from nil to unity in the form of $y = f(x)$, where y represents the stress factor and x is soil moisture. When x is equal to or below field capacity, $y = 0$; y increases linearly with increasing x until $y = 1$ when the soil is saturated.

Our previous studies have shown that waterlogging affects both photosynthesis and phenology to varying degrees depending on the timing and duration of waterlogging[37]. We thus modelled the impacts of waterlogging as a function of water-filled pore space and crop stage (oxdef_photo), which is a significant advance on the majority of previous studies that assume that waterlogging stress depends only on water-filled pore space. In light of this, we applied a stage dependency on the functions such that the plant's response to waterlogging stress is different across growth stage (e.g. more extreme during the reproductive stages). The stage dependency component provided the model with more flexibility with which to fit experimental observations and perform scenario analysis regarding the susceptibility of cultivars to waterlogging stress. The crop stage at which the plant is more sensitive to excess water is a user defined parameter. Similarly, our experimental work has shown that waterlogging delays crop development, and in some cases induces premature senescence. The phenology function we added to APSIM (oxdef_pheno) was derived using information from environment-controlled experiments[37]. In general, it follows the principles used in the oxdef_photo function.

Experimental data described above were used to parameterise and validate. As barley phenology datasets were only recorded in Exp1 and yield datasets were measured in all experiments, here we only parameterised and validated yield datasets. We first initialised APSIM for the (non-waterlogged) control using APSIM's SWIM3 (soil water infiltration and movement) Module (Supplementary Fig. 12), then later tested the new functions using data measured in the waterlogging treatments. To examine the extent to which the new processes added to APSIM-Barley improved the ability to simulate crop growth and development under waterlogging, we also run a default (unimproved) version of APSIM-Barley with waterlogging. Simultaneous multi-objective optimisation (Harrison et al 2019) of oxdef_photo for each genotype was performed for waterlogging treatments by minimising the sum of squared residuals across datasets.

Factorial simulations. Barley was sown at 180 plants m^2 using a depth of 20 mm and row spacing of 200 mm. Nitrogen was applied as NO_3^- and maintained above 200 kg ha^{-1} in the top 300 mm throughout the season to ensure that nitrogen supply did not limit growth. Other nutrients were also assumed unlimiting. Simulations were continuous from one year to the next. To ensure successful crop establishment, initial plant available water at sowing was set 15 mm to ensure consistency of emergence across sites and sowing dates. Soil parameters and management settings were prescribed constant values for all climate horizons. Soil parameters (soil texture, bulk density, pH, and organic carbon content etc) were obtained from the International Soil Reference and Information Centre[68]. Global groundwater table depths used in model initialisation were obtained from Aquaknow[69].

Advancing the process basis of APSIM-Barley for simulation of waterlogging. Using detailed data from several waterlogging treatments conducted in controlled environments[37], we embedded recent physiological results into APSIM-Barley, improving the ability of the model to simulate waterlogging[38]. Upon realisation of appropriate verification statistics, this work substantiated the performance of APSIM-Barley in simulating impacts of waterlogging on phenology and photosynthesis. Details of the waterlogging algorithms and their implementation within the APSIM source code are provided[38] and are available from the corresponding author on reasonable request. Waterlogging tolerance (or susceptibility) of genotypes used in the present study were parameterised and validated in previous studies[37, 38, 33].

Novel approach for clustering seasonal waterlogging-stress typologies. To categorise waterlogging stress patterns, we output seasonal time-courses of waterlogging-stress days relative to phenology (APSIM output variable *oxdef_photo*). These stresses were clustered across simulation years, sites, genotypes and management. For each environment, waterlogged days (i.e. days with *oxdef_photo* lower than 1) were cumulated for each of six discrete growth stages (i.e. early juvenile (JV1, 10<=APSIM growth stage<21); late juvenile (JV2, 21<=APSIM growth stage<32); floral initiation to heading (FIN, 32<=APSIM growth stage<65); flowering to grain filling (FIN, 65<=APSIM growth stage<71); early grain filling (GF1, 71<=APSIM growth stage<80); late grain filling (GF2, 80<=APSIM growth stage<87). *oxdef_photo* was averaged for each growth stage across simulation years, sites, genotypes and management. Prevailing seasonal waterlogging patterns were realised by applying unsupervised *k*-means clustering to all seasonal trajectories of *oxdef_photo* against phenology. Clustering was applied using R statistical package (R Development Core Team, 2013), with clusters being defined such that total within-cluster variation was minimised (partitioning *n* observations into *k* clusters (the value of K is assigned as four) where each observation belongs to the cluster with the nearest mean, i.e. the cluster centroid).

Impacts of extreme waterlogging events on yield. The impact of waterlogging stress on crop yield for a given location was quantified by comparing the yield difference of each year simulated by default version of APSIM and improved APSIM with waterlogging algorithms. The yield difference caused by waterlogging (Yield percentage$_{WL}$) was calculated in Equation 1.

$$\text{Yield percentage}_{WL} = (\text{Yield}_y - \text{Yield}_{Y,WL})/\text{Yield}_y \times 100\% \quad (1)$$

Where Yield$_y$ was the simulated yield (kg ha^{-1}) obtained by default APSIM version from 1985-2100 (Y = 1985, 1986, ..., 2100) and yield$_{WL,y}$ was the simulated yield (kg ha^{-1}) obtained by the modified version of APSIM with waterlogging algorithms for the said year.

Data availability

Data and parameters are available in Supplementary Table 2. Downscaled climate data and simulated yield data are available from the corresponding author upon reasonable request.

Code availability

The R code containing the clustering algorithm and APSIM executable containing the improved waterlogging algorithms are available from the corresponding author upon reasonable request.

Declarations

Acknowledgements

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Author Contributions

K.L. and M.T.H conceived the study. K.L., H.L.Y and D.L.L conducted the crop model simulations and downscaled global climate models. K.L., M.T.H. and S.A coded the waterlogging functions into APSIM source code. K.L., M.T.H. and H.L.Y created and analysed the results. K.L and M.T.H wrote the paper. All authors edited and revised the paper.

Competing Interests

All authors declare no competing interests.

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Figures

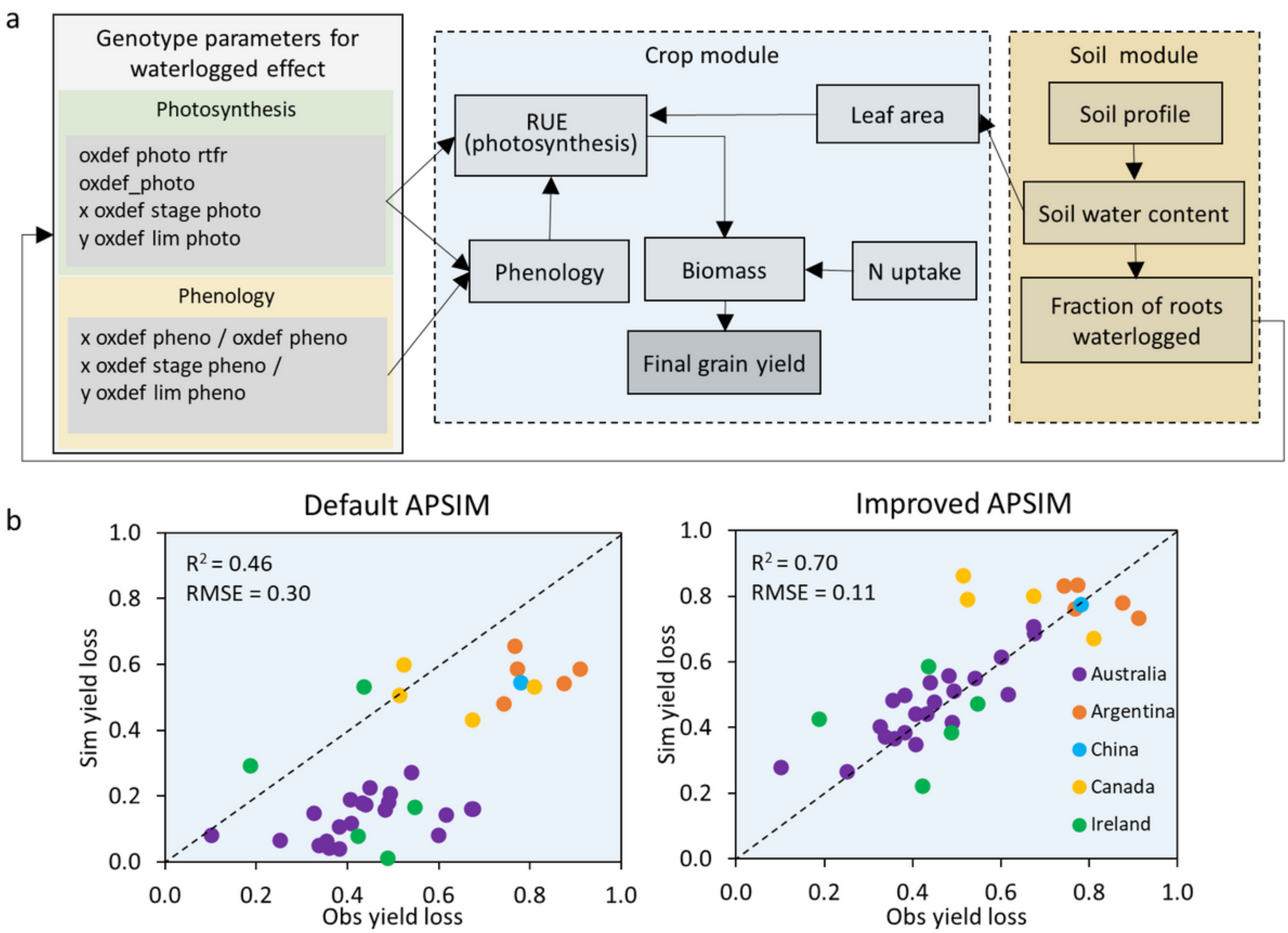

Figure 1

Framework for modelling the effects of waterlogging (WL) stress, including conceptual design of crop physiological responses to waterlogging and model evaluation. a, schematic of genotypic traits influenced by waterlogging and linkage with existing soil and water sub-models in APSIM **b,** Comparison of observed (Obs) and simulated (Sim) waterlogged yield loss compared with controls across environments simulated by improved and default versions of APSIM. Data in (b) represent contemporary barley genotypes with varying waterlogging tolerance (n=36). Details of each parameter are provided in Supplementary Table 4.

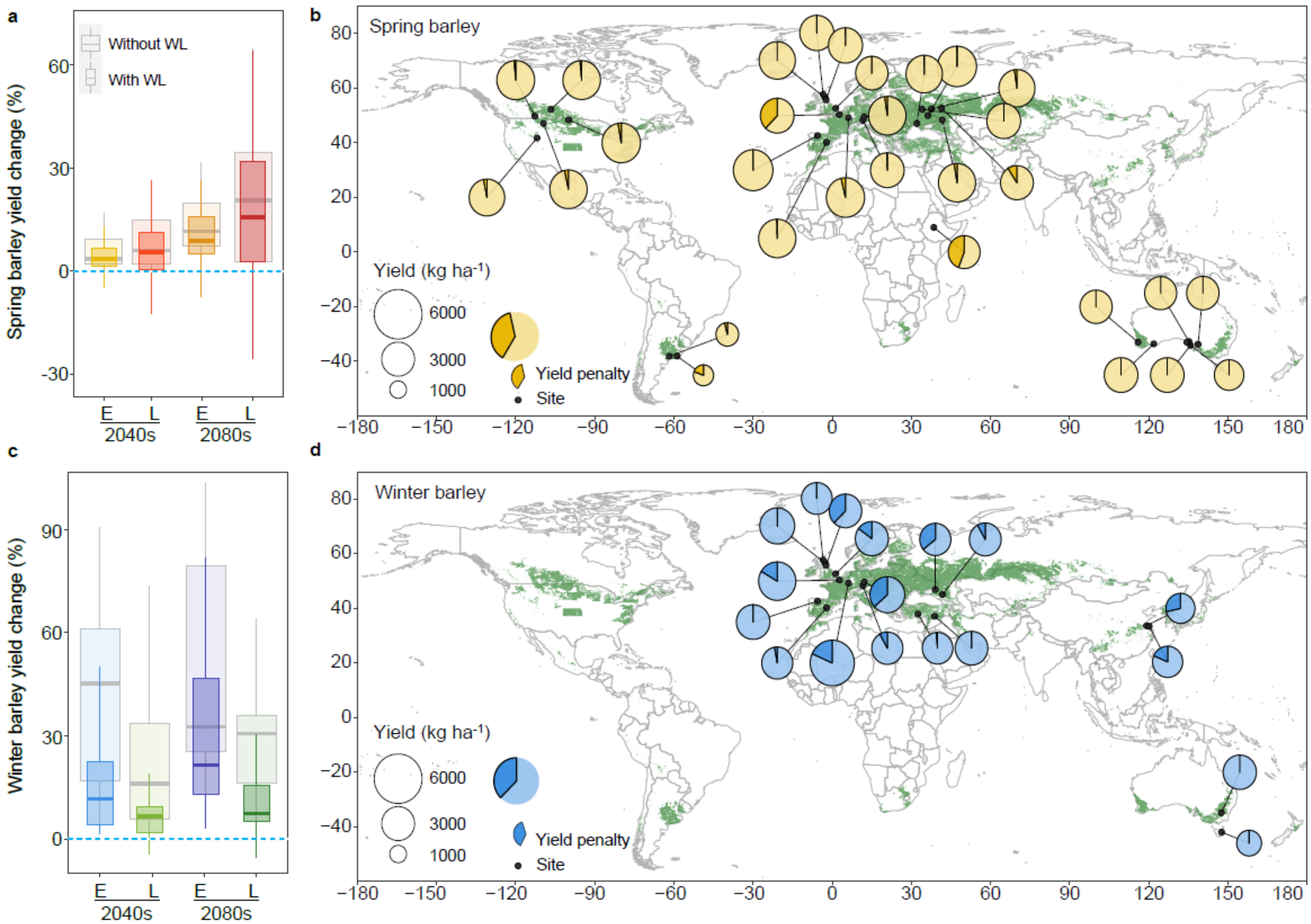

Figure 2

Impacts of waterlogging on yield under future climate (2040, 2080) relative to the historical baseline (1985-2016) for early and late sowing (E, L). a, c, Simulated yield differences under future climate with and without waterlogging (WL) for genotypes with early- (spring) or late maturity (winter). **b, d,** simulated yields (pie charts; dark segments denote yield penalty) under late sowing for spring barley and early sowing for winter barley in 2040 (results for early or late sowing in 2040 and 2080 can be found in supplementary Fig. 2). Yields were simulated with APSIM using downscaled projections from 27 GCMs. Boxplots indicate simulated yield change across sites and GCMs; box boundaries indicate 25th and 75th percentiles, whiskers below and above each box denote the 10th and 90th percentiles, respectively. Green regions in the maps define predominant barley cropping areas.

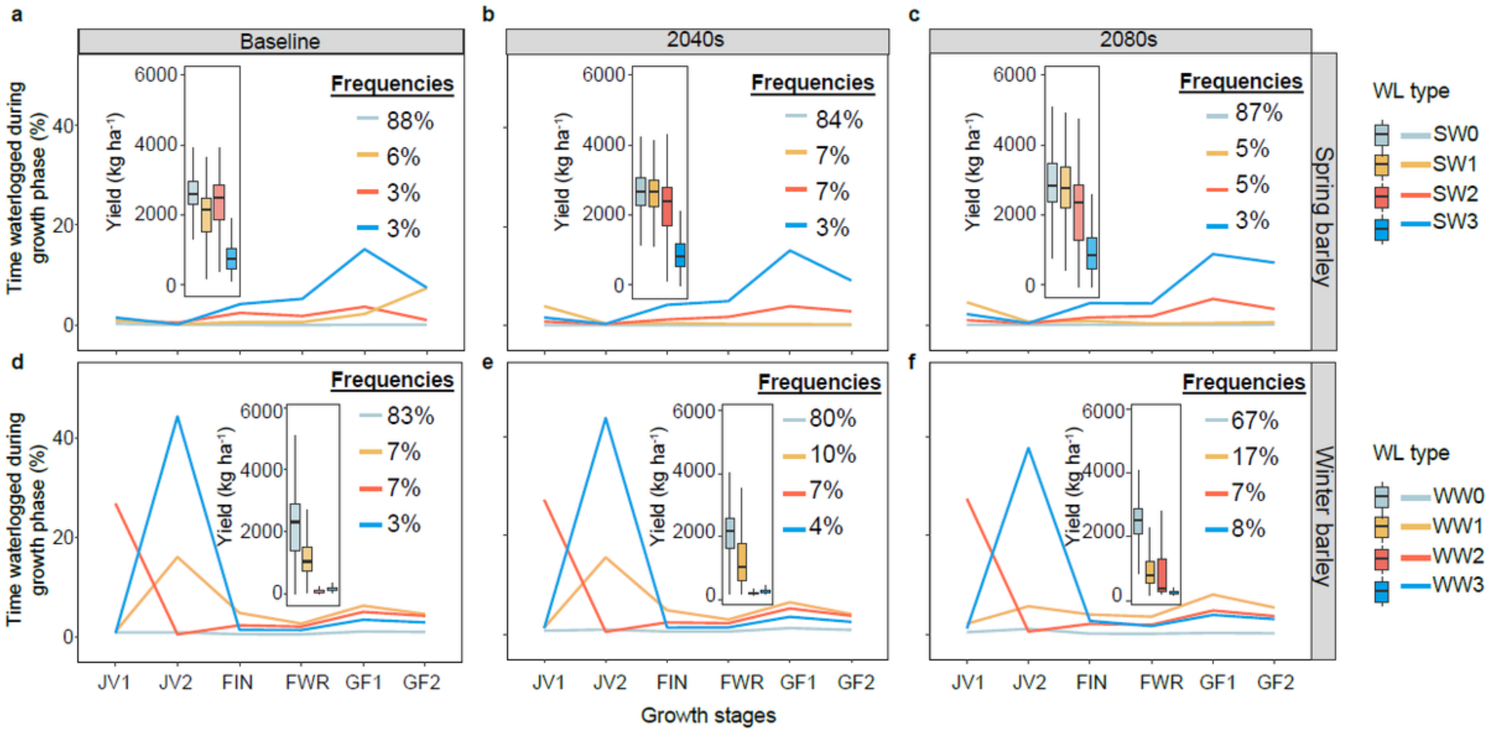

Figure 3

Waterlogging stress patterns and frequencies and grain yields for the baseline (1985-2016), 2040 (2030-2059) and 2080 (2070-2099). Data shown for spring (**a-c**) and winter barley (**d-f**) across sites, sowing times and genotypes. Four key waterlogging stress patterns across sites and genotypes are depicted: stress patterns for spring barley include SW0 (minimal waterlogging); SW1 (low moderate-late waterlogging); SW2 (late-onset moderate waterlogging); SW3 (late-onset severe waterlogging) and winter barley WW0 (minimal waterlogging); WW1 (low early-onset waterlogging relieved later); WW2 (moderate early-onset waterlogging); WW3 (severe early-onset waterlogging). Boxplots indicate yield for spring and winter barley across sites and GCMs; box boundaries indicate the 25th and 75th percentiles across 27 GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. Growth stages include the early juvenile phase (JV1, 10<=APSIM growth stage<21; late juvenile phase (JV2, 21<=APSIM growth stage<32); floral initiation to heading (FIN, 32<=APSIM growth stage<65); flowering to grain filling (FIN, 65<=APSIM growth stage<71; early grain filling (GF1, 71<=APSIM growth stage<80) and late grain filling (GF2, 80<=APSIM growth stage<87).

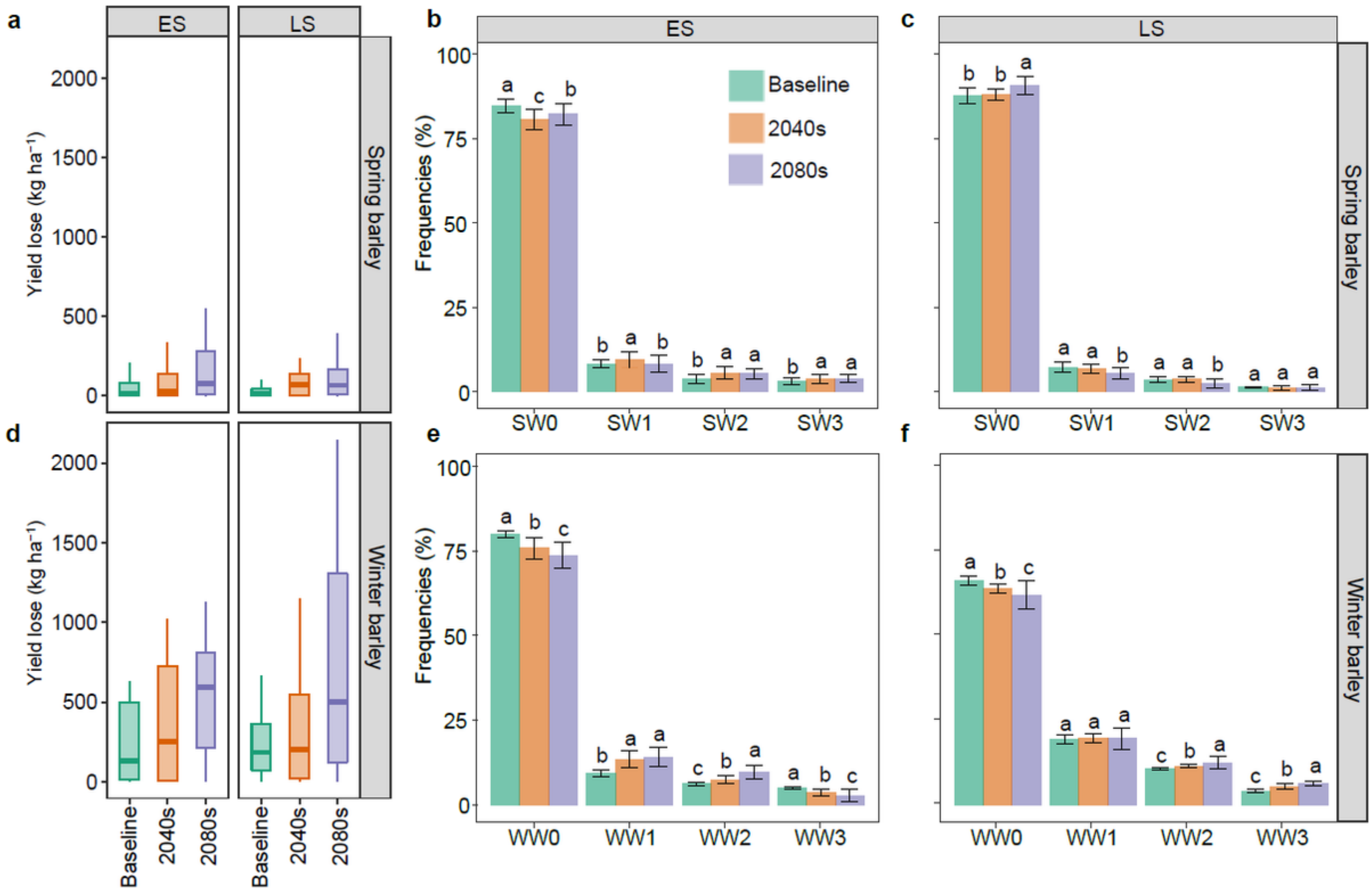

Figure 4

Yield penalty and prevailing waterlogging stress patterns for the baseline (1985-2016), 2040 (2030-2059) and 2080 (2070-2099). Yield penalties are shown for spring (**a**) and winter (**d**) barley across sites and genotypes for relatively early or late sowing (ES, LS) at each site. Waterlogging stress patterns for spring barley include SW0 (minimal waterlogging); SW1 (low moderate-late waterlogging); SW2 (late-onset moderate waterlogging); SW3 (late-onset severe waterlogging) and winter barley, WW0 (minimal waterlogging); WW1 (low early-onset waterlogging relieved later); WW2 (moderate early-onset waterlogging); WW3 (severe early-onset waterlogging). Different letters in (b), (c), (e) and (f) indicate significant difference(s) in frequency of stress patterns between climate periods within waterlogging stress patterns. Boxplots indicate yield penalty for spring and winter barley across sites and GCMs; box boundaries indicate 25th and 75th percentiles, whiskers below and above the box indicate the 10th and 90th percentiles, respectively.

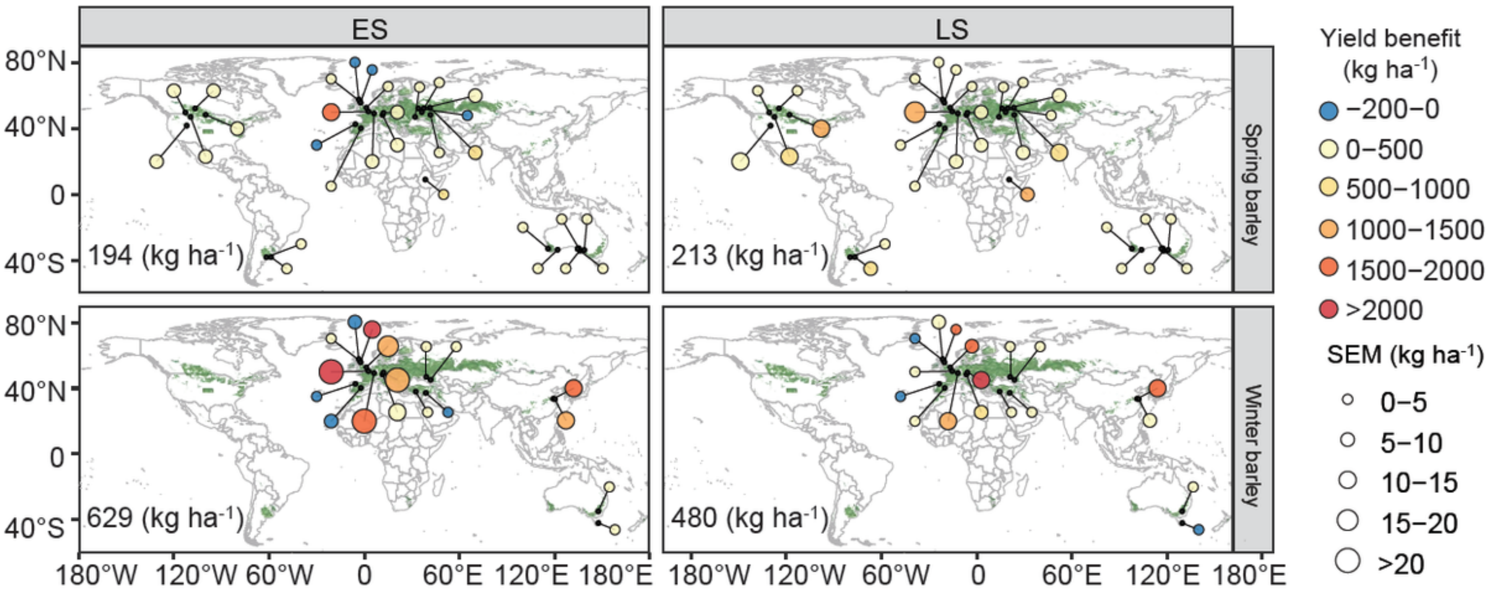

Figure 5

Mean and standard error of the mean (SEM) of yield benefit associated with waterlogging tolerant genotypes relative to waterlogging-susceptible genotypes for 2040 (2030-2059). Values were computed across years and 27 GCMs in which barley growing season rainfall was higher than the 90th percentile; numerical values shown in each panel represent mean yield benefit across sites, years and GCMs.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Liuetal2022Supplementaryinformation16July2022submitted.docx