

Spatio-temporal evolution of late spring frost and associated yield reduction risk for winter wheat in China

Kunhao Jiang^{a,b,c}, Min Su^{a,c}, Fangfang Liu^{b,d}, Xiaoqi Kang^{a,c}, Xinyi Fan^{a,c}, Bin Chen^{a,c}, Yingnan Wei^{a,c}, Linchao Li^e, Qiang Yu^a, Gang Zhao^{a,c,*}, Genghong Wu^{a,c,*} 

^a State Key Laboratory of Soil and Water Conservation and Desertification Control, College of Soil and Water Conservation Science and Engineering, Northwest A&F University, Yangling, Shaanxi, 712100, China

^b Institute of Hefei Artificial Intelligence Breeding Accelerator Co. Ltd, Hefei, Anhui, 230000, China

^c Institute of Soil and Water Conservation, Chinese Academy of Sciences and Ministry of Water Resources, Yangling, Shaanxi, 712100, China

^d Crop Research Institute, Anhui Academy of Agricultural Sciences, Hefei, 230001, China

^e College of Agronomy, Inner Mongolia Agricultural University, Hohhot, Inner Mongolia, 010019, China

ARTICLE INFO

Keywords:

Late spring frost
Winter wheat
Phenology shift
Yield reduction
Cultivar resistance
Climate change projection

ABSTRACT

Late spring frost remains a major threat to winter wheat even as the climate warms, because accelerated crop development can increase the overlap between frost-sensitive stages and episodic spring cold events. Yet large-scale yield risk remains difficult to quantify because this overlap changes over time and frost damage differs among cultivars. We developed a phenology-constrained, event-based framework that integrates controlled low-temperature experiments, phenology reconstruction constrained by agrometeorological observations, machine-learning-based yield-reduction modelling, and bias-corrected hourly temperature projections. We assessed three cultivar resistance groups across China's major winter wheat regions during 1980–2024 and under SSP2–4.5 and SSP5–8.5 during 2030–2100. Warming did not uniformly reduce frost damage but shifted its geographic center. For cold-sensitive cultivars, historical mean yield reduction was greatest in the Middle–Lower Reaches of the Yangtze River region (10.02%), whereas the Huang–Huai region became the principal future hotspot, reaching 6.49% under SSP5–8.5. This redistribution arose from phenological advancement and changes in the frequency and persistence of cold exposure during sensitive stages, while changes in minimum temperature were comparatively small. Counterfactual simulations using fixed historical phenology showed that dynamic phenological shifts increased future losses, mainly during jointing, the stage that dominated losses across both periods. Cold-tolerant cultivars reduced losses by approximately half in the most vulnerable regions. These findings show that warming reshapes rather than removes late spring frost risk by altering phenology–climate overlap, underscoring the need for phenology-aware monitoring and region-specific deployment of cold-tolerant cultivars.

1. Introduction

Climate change has substantially altered crop phenology and reshaped the exposure pathways of agricultural systems to extreme weather events (He et al., 2015). Late spring frost (LSF) remains a persistent agrometeorological threat to winter wheat production across major wheat-growing regions worldwide, including Australia (Stone et al., 1996; Zheng et al., 2015), the United States (Anandhi et al., 2013), Europe (Whaley et al., 2004; Trnka et al., 2014), and China (Xiao et al., 2018). Although rising mean temperatures are often

assumed to reduce frost occurrence (Ewert et al., 2015), warming does not necessarily lead to lower frost-related yield reductions (Eccel et al., 2009; Gu et al., 2008). A key reason is that warmer late winter and spring conditions can accelerate crop development and potentially shift frost-sensitive stages earlier into periods that remain susceptible to episodic cold events (Li et al., 2015a; Xiao et al., 2018; Zheng et al., 2018). This “warming–risk paradox” indicates that LSF risk cannot be adequately evaluated using temperature-based indices alone, but instead requires explicit consideration of crop phenology and stage-specific sensitivity. Evidence from South Korea shows that warm

* Corresponding authors at: State Key Laboratory of Soil and Water Conservation and Desertification Control, College of Soil and Water Conservation Science and Engineering, Northwest A&F University, Yangling, Shaanxi, 712100, China.

E-mail addresses: gang.zhao@nwfau.edu.cn (G. Zhao), wugh@nwfau.edu.cn (G. Wu).

<https://doi.org/10.1016/j.agrformet.2026.111487>

Received 8 April 2026; Received in revised form 25 August 2026; Accepted 15 September 2026

Available online 21 September 2026

0168-1923/© 2026 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

winters can advance winter wheat phenology and increase its exposure to subsequent spring frost, with future yield risks varying among regions (Kim et al., 2025).

For winter wheat, frost tolerance declines rapidly during spring deacclimation (Frederiks et al., 2012; Olsen et al., 2018), and yield impacts depend strongly on when cold exposure occurs relative to developmental stage. Among spring growth stages, jointing (stem elongation) and booting (reproductive development) represent two critical windows of frost sensitivity (Li et al., 2015b, 2015c). Frost during jointing can impair tiller survival, stem elongation, and spikelet differentiation, thereby reducing the formation of productive spikes and grains (Marcellos and Single, 1984; Zhong et al., 2008). Experimental evidence further shows that short-term exposure to temperatures of approximately -2 to -6 °C during this stage can reduce spike number and grain yield by 3.1–34.4% (Ji et al., 2025). By contrast, booting-stage frost more directly damages reproductive organs, especially the developing spike and flag leaf, and may cause severe yield reductions in extreme years (Liu et al., 2020). Convective freezing experiments indicate that visible injury may begin at approximately -3 °C and intensify rapidly with further cooling, with reported yield reductions ranging from about 10% to nearly complete crop failure under severe exposure conditions (Fuller et al., 2007). In addition, field observations suggest that prolonged low-temperature episodes lasting several days, even when minimum temperatures remain around 0–4 °C, can still reduce spikelet numbers by approximately 8–15% and lead to yield reductions of roughly 5–14% when they coincide with early reproductive development (Li et al., 2015c). Together, these findings show that frost damage is jointly governed by developmental timing, temperature intensity, and exposure duration, highlighting the need to move beyond generic frost indices when quantifying production risk.

Substantial varietal differences in tolerance to LSF have been documented in winter wheat (Sutka, 1994; Zheng et al., 2018; Nuttall et al., 2019), indicating that damage thresholds cannot be assumed uniform across cultivars. In China, field screening of 20 major wheat varieties identified three strongly resistant cultivars and five sensitive cultivars under natural late-spring cold events (Zhang et al., 2023). Controlled experiments with contrasting cultivars further showed that low-temperature stress during reproductive development caused consistently greater damage in sensitive genotypes than in tolerant ones: using Yannong19 and Xinmai26 as contrasting materials, low-temperature treatments during anther differentiation reduced photosynthetic performance by 26.8–42.2% in the tolerant cultivar but by 34.2–54.7% in the sensitive cultivar, and the associated yield reduction across treatments reached 24.1–64.1% (Xu et al., 2022). Similar patterns have also been reported at broader scales. In Australia, a multi-environment analysis from 2010 to 2019 phenotyped >557,000 spikes across 10,317 wheat experimental units and revealed strong genotype-by-environment interactions in frost susceptibility (Ferrante et al., 2021). Together, these findings indicate that cultivar resistance is agronomically meaningful and should be explicitly distinguished in large-scale assessments of LSF-induced yield reduction.

Existing LSF assessments generally rely on three main approaches: controlled low-temperature experiments, process-based crop models, and statistical analyses based on historical yield records. Controlled experiments provide mechanistic and quantitative relationships between cold-stress intensity/duration and yield components, yet direct one-to-one extrapolation can be challenging across heterogeneous climates, management practices, and cultivar backgrounds (Soualiou et al., 2022; Richetti et al., 2025). Process-based models can represent crop development and cold-stress interactions, but projected reductions are often sensitive to parameter choices and may incompletely capture rare, high-impact extremes (Barlow et al., 2015; Zheng et al., 2015). Statistical analyses based on historical yield records can reveal climate–yield associations, but purely correlation-driven relationships may be confounded by co-varying drivers and may become non-stationary as phenology shifts under warming, limiting confidence in forward

projections (Xiao et al., 2025). Together, these limitations leave substantial uncertainty in large-scale estimates of frost-induced yield reduction, especially in attributing risk changes to phenology-driven exposure shifts and in incorporating cultivar resistance into regional vulnerability assessments.

These challenges are particularly important in China, one of the world's largest winter wheat producers. Historical analyses reveal that the frequency of LSF in the 1990s was nearly double (1.88 times) that of the 1980s, coinciding with a twofold increase in the occurrence of warm winters (Yan et al., 2002). LSF is estimated to affect nearly 85% of China's winter wheat cultivation area (Yue et al., 2016), and high-risk frost stress regions have expanded southward, particularly toward southeastern provinces such as Anhui and Jiangsu (Xiao et al., 2018). Despite progress in characterizing the spatial distribution of LSF events, most regional-scale assessments still rely on fixed calendar windows or simple temperature thresholds, which fail to capture interannual and spatial variability in crop phenology and the nonlinear effects of temperature intensity and exposure duration. Moreover, cultivar resistance is rarely incorporated explicitly at large scales, despite its strong influence on damage likelihood and reduction magnitude during the jointing and booting stages (Ji et al., 2017). A key gap is a scalable approach that links regional exposure to experimentally constrained, stage-specific yield-reduction functions while explicitly distinguishing cultivar resistance groups.

To address these gaps, this study investigates several key questions regarding LSF risk in China's winter wheat systems. Specifically, we ask how experimentally derived, stage-specific relationships between LSF exposure and yield reduction can be integrated with phenological information to quantify frost-induced yield reduction at regional scales. We further examine what the historical spatio-temporal patterns and hotspots of LSF-related yield-reduction risk are during the jointing and booting stages across China's winter wheat belt. In addition, we explore how regional vulnerability to LSF may evolve under future climate change and to what extent cultivar resistance modifies the magnitude and distribution of projected yield-reduction risk. To address these questions, we combine experiment-derived yield-reduction response functions, phenology reconstruction from agrometeorological observations, hourly temperature-based event identification, and CMIP6 climate projections. We further account for cultivar resistance by differentiating cold-tolerant, moderately cold-tolerant, and cold-sensitive groups, thereby enabling large-scale risk estimates to be interpreted in a cultivar-targeted adaptation context. This phenology-informed and cultivar-explicit framework provides a basis for frost-risk mapping and adaptation planning to support the sustainability of winter wheat production under climate change.

2. Data and methods

2.1. Study area

This study focuses on China's main winter wheat belt, which contributes >85% of the country's total winter wheat production (National Bureau of Statistics of China, 2023). Following the regionalization of Jin (1996), the study area was divided into three subregions: the North Subregion (NS), the Huang–Huai Subregion (HHS), and the Middle–Lower Reaches of the Yangtze River Subregion (MYS) (Fig. 1a). The regional boundaries were defined independently of the winter wheat planting masks and were not adjusted to balance the number of retained wheat grid cells among subregions. Phenological observations from 130 agrometeorological stations distributed across the study area were used for model development and validation (Fig. 1b). Fig. 1c shows the spatial extent of winter wheat planting areas (resampled to 0.1°) and the locations of controlled freezing experiment sites.

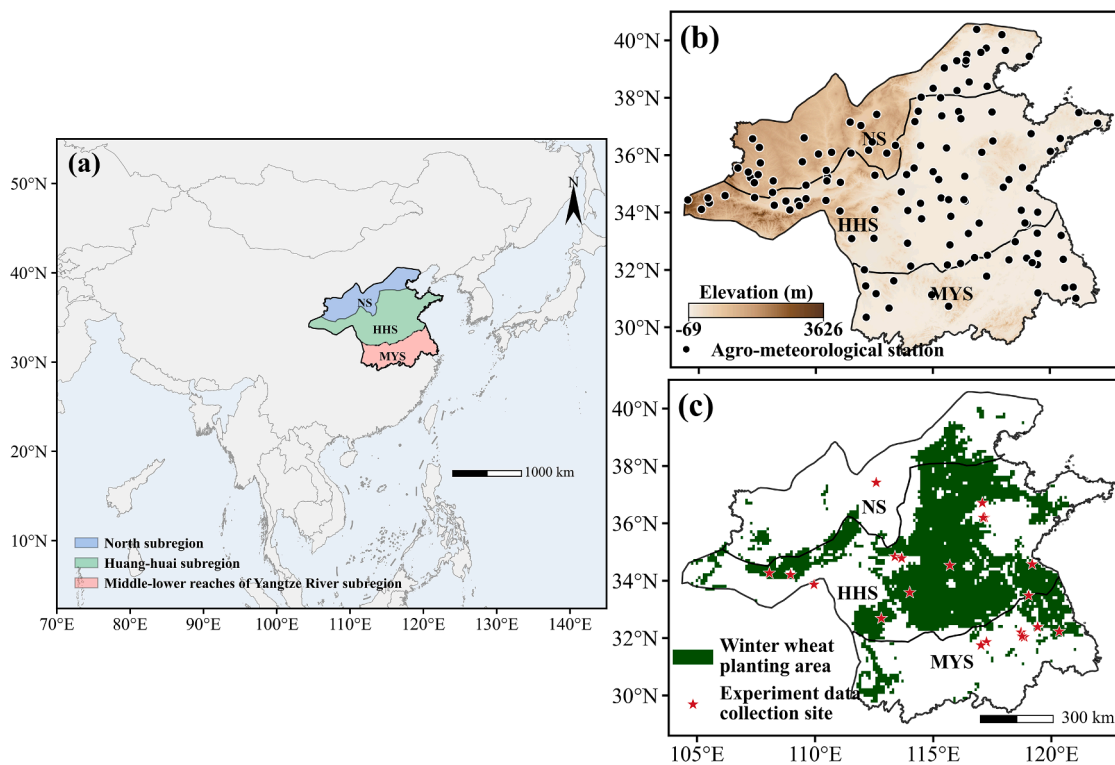


Fig. 1. Study area, agrometeorological stations, winter wheat distribution, and controlled low-temperature experiment sites. (a) Regional setting of the study area within East Asia and locations of the three winter wheat production subregions in China: the North Subregion (NS), Huang-Huai Subregion (HHS), and Middle-Lower Reaches of the Yangtze River Subregion (MYS). (b) Elevation and locations of the 130 agrometeorological stations within the study area. (c) Spatial distribution of winter wheat at $0.1^\circ \times 0.1^\circ$ resolution derived from the union of annual maps during 1980–2024 and locations of the controlled low-temperature experiment sites. Green grid cells represent winter wheat planting areas, and red stars mark experiment sites.

2.2. Data sources

2.2.1. Literature compilation of controlled low-temperature experiments

A literature database of controlled low-temperature experiments in winter wheat was compiled from Web of Science and China National Knowledge Infrastructure (CNKI), covering studies published up to October 2025. The search query was: TS = ((“winter wheat” OR “*Triticum aestivum*”) AND (“low temperature” OR “cold” OR “chilling” OR “freeze” OR “frost”) AND (“yield” OR “grain yield” OR “biomass” OR “spike number” OR “kernel number” OR “thousand kernel weight” OR “harvest index”) AND (“treat” OR “experiment” OR “growth chamber” OR “phytotron” OR “controlled environment”)).

The search yielded 843 records from Web of Science and 225 from CNKI, together with two additional book chapters. Studies were retained if they met four criteria: (1) a clearly defined non-stress control was included, and yield data allowing calculation of yield reduction were reported for both control and treatment conditions; (2) both low-temperature intensity and duration were explicitly reported; (3) the developmental stage at which the treatment was applied was clearly specified; and (4) cultivar information was documented. Because most controlled low-temperature studies focused on the jointing and booting stages, and because these two stages are widely recognized as the major spring frost-sensitive windows in winter wheat, subsequent analyses were restricted to these stages.

After screening, 782 eligible experimental records (treatment $\times$ cultivar $\times$ stage) were retained, including 331 observations at jointing and 451 at booting, covering 131 winter wheat cultivars. Growth habit (spring, weak-spring, semi-winter) was extracted from the original sources when reported and otherwise assigned according to established classification schemes. For each record, the compiled variables included cultivar identity (i.e., the cultivar name or identifier reported in the original study), growth habit, treatment temperature ($^\circ\text{C}$), treatment

duration (h), development stage, and yield reduction (%). Yield reduction was calculated relative to the corresponding non-stress control as:

$$\text{Yield reduction}(\%) = \frac{(Y_{\text{control}} - Y_{\text{treatment}})}{Y_{\text{control}}} \times 100 \quad (1)$$

where Y_{control} and $Y_{\text{treatment}}$ denote yield under control and low-temperature treatment conditions, respectively.

Overall, the compiled experiments covered a wide range of exposure conditions, with treatment durations of up to 72 h and minimum temperatures as low as -10°C (Fig. 2). Yield reduction ranged from 0.15% to 100% at jointing and from 0.6% to 99.26% at booting, with median losses of 36.85% and 39.34%, respectively. Larger losses generally occurred under colder and longer exposures, and booting records more frequently showed high losses than jointing records under comparable conditions (P90: 82.72% vs. 73.15%). These patterns support stage-resolved parameterization of the yield-reduction response.

2.2.2. Agrometeorological phenology observations

Historical phenological observations were obtained from the China Meteorological Administration (CMA) (<http://data.cma.cn>) for the period 1980–2020. The dataset included observed day of year (DOY) for the onset of jointing and heading at 130 agrometeorological stations distributed across the study area (Fig. 1b), together with station longitude and latitude. After quality control, the final dataset comprises 1507 observations each for the jointing and heading stages (Fig. S1). Valid observations were available mainly during 1993–2013, although record length varied among stations and missing years occurred at some sites. Station elevation was derived from the 90 m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) provided by the National Cryosphere Desert Data Center (<http://westdc.westgis.ac.cn/>). The observed phenology showed a clear south–north gradient, with MYS

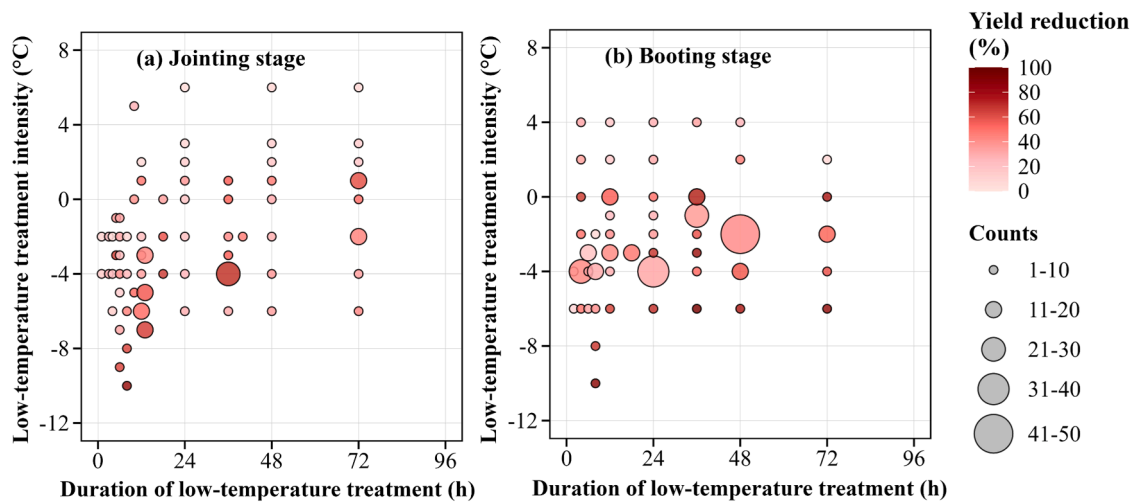


Fig. 2. Distribution of literature-derived controlled low-temperature experimental records in the intensity–duration space for winter wheat at the (a) jointing stage and (b) booting stage. The x-axis indicates treatment duration (h), and the y-axis indicates treatment temperature (°C; negative values denote sub-zero/freezing exposure). Bubble size represents the number of records falling into each unique intensity–duration combination, and color shading denotes the mean yield reduction (%) for that combination.

generally earliest, NS latest, and HHS intermediate; mean jointing dates ranged from DOY 56 to 116 and mean heading dates from DOY 86 to 143 (Fig. S2). Phenological trends were dominated by advancement overall, although regional differences were evident.

2.2.3. Meteorological datasets

Historical meteorological data were obtained from the ERA5-Land reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). Hourly 2 m air temperature data were extracted for 1980–2024 at $0.1^\circ \times 0.1^\circ$ resolution. Air temperature values were converted from Kelvin (K) to degrees Celsius (°C), and timestamps were converted from Coordinated Universal Time (UTC) to Beijing Time (UTC+8).

For future projections (2030–2100), hourly 2 m air-temperature data were taken from the CMIP6 Geophysical Fluid Dynamics Laboratory Earth System Model version 4 (GFDL-ESM4) under two scenarios: SSP2–4.5 (intermediate emissions; 4.5 W m^{-2} by 2100) and SSP5–8.5 (high emissions; 8.5 W m^{-2} by 2100) (O'Neill et al., 2016; Riahi et al., 2017). GFDL-ESM4 was selected based on its demonstrated performance in representing temperature variability over East Asia (Bai et al., 2022). The model has a native atmospheric horizontal resolution of approximately 1° . Model outputs were converted to degrees Celsius and Beijing Time and were regridded to 0.1° and bias-corrected prior to LSF identification (Section 2.7).

2.2.4. Winter wheat distribution map

Three crop-domain datasets were considered (Table S1): a 30 m annual winter wheat distribution product covering 2001–2024 (Fu et al., 2026), a 1 km annual product covering 2001–2020 (Wen et al., 2026), and annual 4 km wheat-presence layers covering 1982–2020 from the GlobalWheatYield4km workflow (Zhang et al., 2024). For the 4 km dataset, grid cells with valid wheat-yield estimates were treated as wheat-presence cells, and the underlying wheat-mapping procedure followed Luo et al. (2022). The 30 m product was used in the main analysis because it directly maps winter wheat at finer spatial resolution, retains greater spatial detail in fragmented planting areas, and provides a longer annual record than the 1 km product. The 1 km and 4 km datasets were used for sensitivity analyses of crop-domain uncertainty.

All three datasets were aggregated to 0.1° by calculating the proportion of underlying pixels classified as winter wheat, with grid cells containing $>30\%$ wheat retained. Within each dataset's original temporal coverage, the corresponding annual layers were used; outside that

period, the nearest available boundary-year layer was held fixed. Thus, the 2001 and 2024 maps were used to extend the 30 m product backward and forward, respectively, while the corresponding boundary years for the 1 km product were 2001 and 2020. After aggregation, the retained 0.1° masks derived from the annual 4 km layers were identical across 1982–2020, so their common mask was used for all periods in the sensitivity analysis. The temporal treatments of the three datasets are summarized in Table S1.

The union of the historical annual 30 m masks contained 3777 retained 0.1° grid cells, including 349 in NS, 3001 in HHS, and 427 in MYS (Table S2). This imbalance reflects the extensive and continuous winter wheat belt in HHS, the smaller wheat extent in NS, and the more fragmented planting pattern in MYS. The resulting annual grid-cell counts differed among the three datasets, particularly in MYS, although HHS consistently had the greatest coverage (Fig. S3). Yield-reduction simulations were repeated using the alternative datasets with all other model inputs, parameters, and settings held constant.

2.3. Overview of research framework

We developed an integrated phenology–exposure–damage workflow to quantify LSF risk and associated yield reductions across China's winter wheat belt (Fig. 3). The workflow consisted of two coupled modules: (i) an experiment-anchored yield-reduction response module that linked yield reduction to cold-stress intensity and duration while accounting for developmental stage and cultivar traits, and (ii) a phenology reconstruction module that estimated the timing of key developmental stages and defined spatially and temporally varying frost-sensitive windows for jointing and booting. These two modules were driven by hourly temperature series to identify LSF events within the dynamically defined jointing and booting windows, using a winter wheat planting mask to restrict analyses to cultivated grid cells. For each identified event, fluctuating temperature exposure was summarized into comparable intensity–duration metrics and was translated into event-level yield reduction using the yield-reduction response model; losses were then aggregated to stage-level yield reduction within jointing and booting, and were further combined into annual cumulative yield reduction metrics across the two sensitive windows. The same procedure was applied to historical (ERA5-Land) and future (bias-corrected CMIP6) temperature series, producing gridded maps and time series of stage-specific and aggregated yield-reduction risk for regional comparison and cultivar-targeted interpretation.

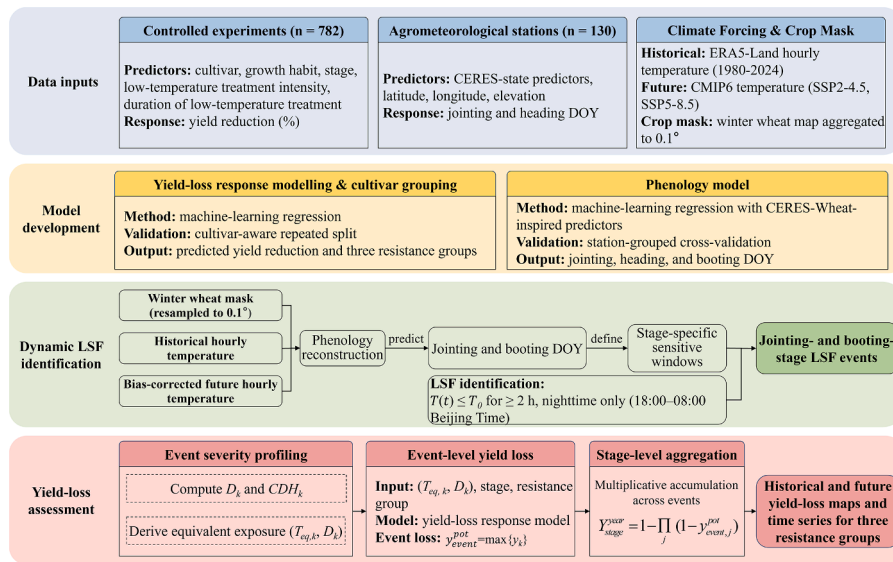


Fig. 3. The overall workflow of this study.

2.4. Yield-reduction response modelling and cultivar resistance grouping

2.4.1. Yield-reduction response model

We modelled yield reduction (%) under controlled low-temperature treatments using a supervised regression approach. Predictors included two continuous variables describing cold-stress exposure—treatment temperature (°C) and exposure duration (h)—and three categorical variables capturing biological context: developmental stage (jointing or booting), growth habit (spring, weak-spring, semi-winter), and cultivar identity. Categorical variables were one-hot encoded prior to model training.

We compared several commonly used regression families (Table S3), including tree-based ensembles—gradient boosting decision tree (GBDT), extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), random forest (RF), and extremely randomized trees (ExtraTrees)—as well as kernel-based support vector regression (SVR) and linear/regularized linear models (least absolute shrinkage and selection operator, Lasso, and ordinary linear regression, LR). Hyperparameters were tuned via randomized search using cross-validation on the training data. To evaluate model generalization while reducing cultivar-specific memorization, we adopted a cultivar-aware repeated random subsampling strategy with 20 repetitions and an 80/20 train-test split. Cultivars represented by a single observation were assigned to the training set only, whereas cultivars with multiple observations were stratified across training and testing subsets. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE), and the final yield-reduction response model was selected based on predictive accuracy and stability across repetitions (Alsafadi et al., 2024; Hauduc et al., 2015).

To interpret the fitted yield-reduction model, we used Shapley Additive exPlanations (SHAP) to quantify the relative contribution and directional effects of individual predictors on yield-reduction predictions (Han et al., 2022; Lundberg et al., 2020; Xie et al., 2025). For the selected tree-based model, SHAP values were computed using TreeSHAP to summarize global feature importance and to visualize non-linear effects and interactions among exposure variables and categorical factors.

2.4.2. Cultivar resistance grouping

Direct comparison of observed yield reduction among cultivars is confounded by large heterogeneity in treatment temperature and duration across experiments. To isolate cultivar-related resistance

signals from exposure severity, we implemented a residual-based grouping procedure.

First, we trained a baseline yield-reduction model using exposure and developmental predictors only (treatment temperature, duration, stage, and growth habit), excluding cultivar identity. For each observation i , the residual was computed as

$$\varepsilon_i = Y_{obs,i} - Y_{pred,base,i} \quad (2)$$

where negative (positive) residuals indicate lower (higher) loss than expected under the same exposure conditions. To ensure robustness, only cultivars with at least four independent observations ($N_{var} \geq 4$) were retained. Within each growth-habit group (spring, weak-spring, semi-winter), cultivars were ranked by their mean residual $\bar{\varepsilon}_{var}$. The spring growth-habit group was excluded because cultivar replication was insufficient to support stable resistance grouping. Resistance grouping was therefore performed only for the weak-spring and semi-winter groups. Within each of these two growth habit groups, three resistance groups were defined using a fixed-number selection: the five cultivars with the lowest $\bar{\varepsilon}_{var}$ were classified as cold-tolerant, the five with the highest $\bar{\varepsilon}_{var}$ as cold-sensitive, and the five closest to the median as moderately cold-tolerant. This yielded 30 representative cultivars in total (2 growth-habit groups $\times$ 3 resistance groups $\times$ 5 cultivars). In subsequent spatiotemporal simulations, yield-reduction estimates for each resistance group were computed as the ensemble mean across the five representative cultivars within that group.

2.5. Phenology prediction model construction

We developed a phenology prediction model to reconstruct the onset DOY of winter wheat. Observed jointing and heading dates from agrometeorological stations were used as the response variables. Predictors combined geographic descriptors (latitude, longitude, elevation, and subregion) with a CERES-Wheat-inspired daily development framework, in which development accumulation began at sowing rather than at a fixed calendar date. Following the accumulated thermal development unit concept of the CSM-CERES framework, the daily thermal development unit (DTDU) was calculated as:

$$DTDU = DTT \times DF \times VF \quad (3)$$

where DTT is daily thermal time, and DF and VF are the photoperiod factor and vernalization factor, respectively, both constrained between 0 and 1. Daily thermal time was calculated:

$$DTT = \begin{cases} 0 & , T_{mean} < T_{base} \text{ or } T_{mean} \geq T_{max} \\ \frac{T_{mean}}{T_{ol}} \times T_{mean} & , T_{base} \leq T_{mean} < T_{ol} \\ T_{mean} & , T_{ol} \leq T_{mean} < T_{ou} \\ \frac{T_{max} - T_{mean}}{T_{max} - T_{ou}} \times T_{mean} & , T_{ou} \leq T_{mean} < T_{max} \end{cases} \quad (4)$$

where T_{mean} is daily mean air temperature, T_{base} is the base temperature, T_{ol} and T_{ou} are the lower and upper optimum temperatures, respectively, and T_{max} is the upper temperature limit for development. The photoperiod and vernalization factors were calculated as:

$$DF = 1 - \frac{PID}{10000} \times (20 - DL)^2 \quad (5)$$

$$VF = VF_0 + \frac{CUMVD}{P1V} \quad (6)$$

$$VF_0 = 1 - \frac{P1V}{50} \quad (7)$$

where PID and $P1V$ are the photoperiod- and vernalization-sensitivity coefficients, respectively; DL is day length calculated from latitude and DOY; and $CUMVD$ is accumulated vernalization days calculated following McMaster et al. (2008) and Tao et al. (2012). Region-specific parameter values were obtained from Tao et al. (2012, 2022) and are provided in Table S4. The accumulated thermal development unit $ATDU$ from sowing to day (t) was calculated as:

$$ATDU_t = \sum_{d=\text{sowing}}^t DTDU_d \quad (8)$$

Because sowing dates were not available for all grid cells and simulation years, regional mean sowing dates calculated from the available station observations were used: September 29 for the NS, October 13 for the HHS, and October 30 for the MYS (Fig. S4). These dates were held constant across grid cells and simulation years within each subregion. Daily developmental variables were summarized over consecutive 15-day intervals after sowing. For each interval, cumulative DTT and $DTDU$, end-of-window $ATDU$, and mean VF and DF were calculated. For model development, ERA5-Land hourly temperature at each station was used to construct the predictors, while the corresponding observed phenological dates provided the responses. The same predictor-construction procedure was subsequently applied to the gridded historical and future temperature data. Before model fitting, one member of each pair of numerical predictors with an absolute Pearson correlation coefficient greater than 0.95 was removed.

To preserve biological consistency between stages, we adopted a dual-target strategy by predicting (i) jointing onset DOY and (ii) the jointing-to-heading interval, from which heading onset DOY was derived. Model generalizability was evaluated using station-grouped cross-validation to approximate prediction at unseen locations. In each repetition, 20% of stations were withheld as an independent test set, and all observations from a given station were assigned exclusively to either training or testing. We compared several commonly used regression families, including tree-based ensembles (GBDT, XGBoost, LightGBM, RF, and ExtraTrees), and kernel-based SVR (Table S3). Model performance was evaluated using R^2 and RMSE, and the final model was selected based on predictive accuracy and stability across validation repetitions.

An empirically informed prediction constraint of 20 days was imposed on the predicted jointing-to-heading interval. This value was used as a prediction constraint rather than as a fixed phenological duration or a universal biological minimum. For the paired observations presented in Fig. S5, the mean jointing-to-heading intervals were 24.5,

26.4, and 31.1 days in NS, HHS, and MYS, respectively, with a pooled mean of 26.7 days. The 20-day value was therefore below all regional means and positioned near the lower end of the displayed distribution. It was applied only to prevent unrealistically short or reversed predicted intervals.

After model development, the selected model was driven by CERES-Wheat-based developmental predictors calculated from gridded ERA5-Land hourly temperature to reconstruct annual jointing and heading onset dates across China's winter wheat belt at 0.1° resolution for 1980–2024. For future projections during 2030–2100, the same predictor-construction procedure, equations, regional parameters, sowing dates, 15-day aggregation scheme, and geographic covariates were applied to bias-corrected GFDL-ESM4 hourly temperature under SSP2–4.5 and SSP5–8.5. This produced scenario-specific annual phenology maps for each grid cell and year. Booting onset DOY was operationally defined as 10 days before heading (Booting DOY = Heading DOY – 10), consistent with observed winter wheat phenology in China (Zhang et al., 2025), thereby providing a consistent large-scale representation of the booting window for subsequent LSF risk assessment. Spatial means and temporal trends in historical and future phenology were summarized using the Theil–Sen slope estimator (Lin et al., 2022), with trend significance evaluated using the Mann–Kendall test at $p < 0.05$ (Kendall and Gibbons, 1990; Neeti and Eastman, 2011).

2.6. Historical LSF event identification and yield reduction assessment

To quantify the historical LSF impacts on winter wheat yield, we integrated hourly temperature forcing, dynamically reconstructed phenology, and the experiment-anchored yield-reduction response model. Yield-reduction simulations were conducted for three cultivar resistance groups (cold-tolerant, moderately cold-tolerant, and cold-sensitive), each represented by an ensemble of five cultivars per group; group-level losses were calculated as the ensemble mean. To reflect regional planting structure, semi-winter cultivars were used for simulations in NS and HHS, whereas weak-spring cultivars were used for MYS. The historical assessment consisted of three steps: (1) identifying LSF events within stage-specific phenological windows, (2) characterizing within-event intensity–duration exposure and converting it to equivalent constant-temperature metrics, and (3) estimating event-level yield reduction and aggregating it to stage-level and annual cumulative yield reduction.

2.6.1. Dynamic LSF event identification within phenological windows

LSF events were identified from hourly 2 m air temperature series, $T(t)$, within the reconstructed jointing and booting sensitive windows. The jointing-sensitive window was defined from jointing onset to the day before booting onset, whereas the booting-sensitive window extended from booting onset to heading onset. To focus on physiologically relevant cold exposure, event detection was restricted to the nighttime period (18:00–08:00, Beijing Time). An LSF event was detected when $T(t)$ remained at or below an identification threshold, T_0 , for at least two consecutive hours ($L \geq 2$) during the nighttime window. We used $T_0 = 0^\circ\text{C}$ as a reference threshold because it represents the freezing point and is widely adopted in LSF risk identification (Frederiks et al., 2015; Zheng et al., 2015). The minimum duration requirement of $L \geq 2$ h was used to ensure sustained exposure and to maintain consistency with the controlled experiments, in which the shortest treatment duration was also 2 h. Threshold sensitivity was evaluated by repeating event identification using $T_1 = 1^\circ\text{C}$ and $T_2 = 2^\circ\text{C}$; these results are presented in the Supplementary Material, while the main text focuses on the reference definition ($T_0 = 0^\circ\text{C}$, $L \geq 2$ h). To characterize the regional climatology of LSF events, we additionally summarized total event counts, event minimum temperature (T_{min}), and event duration. Here, event duration refers to the total number of hours within an identified event for which $T(t) \leq T_0$.

2.6.2. Within-event severity profiling and equivalent constant-temperature exposure

For each identified LSF event, we characterized the embedded intensity–duration structure by profiling a sequence of within-event severity levels. Starting from the identification threshold T_0 , progressively lower thresholds T_k were generated as

$$T_k = T_0 - k \cdot \Delta \quad (9)$$

where $k = 0, 1, 2, \dots, K$, $\Delta = 1^\circ\text{C}$, and K was chosen such that $T_k \geq T_{\min}$ of the event. Each threshold T_k defines a “severity slice”, that is, one nested level of cold exposure within the same event.

For each severity level k , exposure duration D_k (h) was calculated as the cumulative time within the event during which the hourly temperature satisfied $T(t) \leq T_k$. We then quantified cumulative cold intensity using cold degree hours (CDH_k):

$$CDH_k = \int \max(0, T_k - T(t)) dt \quad (10)$$

which accumulates the temperature deficit (relative to T_k) over time and is zero whenever $T(t) > T_k$. With hourly temperature data, the integral was implemented as a discrete sum over event hours with a time step of 1 h.

Based on D_k and CDH_k , we derived an equivalent constant temperature $T_{eq,k}$ ($^\circ\text{C}$) that produces the same cumulative cold intensity over the same duration D_k :

$$T_{eq,k} = T_k - \frac{CDH_k}{D_k} \quad (11)$$

The pair $(T_{eq,k}, D_k)$ provided a standardized representation of event exposure that was consistent with the temperature–duration descriptors of the controlled experiments and could therefore be used directly as inputs to the yield-reduction response model.

2.6.3. Event-level yield reduction estimation and stage-level aggregation

For each identified LSF event and each within-event severity level k , the predicted yield-reduction fraction y_k was obtained from the yield-reduction response model as:

$$y_k = f(T_{eq,k}, D_k, S, \Phi) \quad (12)$$

where $T_{eq,k}$ and D_k describe the equivalent constant-temperature exposure (Section 2.6.2), S denotes the phenological stage (jointing or booting), and Φ represents cultivar-related covariates (growth habit and cultivar identity). Predictions were generated for the five representative cultivars within each resistance group, and the group-level loss at level k was defined as the ensemble mean across the five cultivars.

Because a single event yields multiple candidate exposures $(T_{eq,k}, D_k)$ across severity levels k , event-level potential yield reduction was defined as the maximum predicted loss within the event:

$$y_{event}^{pot} = \max\{y_k\} \quad (13)$$

This definition captures the most damaging intensity–duration condition embedded in the event’s thermal profile. By adopting this maximum value, we treated it as a conservative estimate of the event’s damage potential and avoided underestimation when temperature fluctuates within an event.

Within a given year and phenological stage, multiple LSF events may occur at a grid cell. Stage-level annual cumulative yield reduction was aggregated multiplicatively across events as:

$$Y_{stage}^{year} = 1 - \prod_j (1 - y_{event,j}^{pot}) \quad (14)$$

where Y_{stage}^{year} is the annual cumulative proportional yield reduction for a given phenological stage, and $y_{event,j}^{pot}$ is the proportional yield reduction

predicted for the j th LSF event. All proportional reductions were expressed as fractions ranging from 0 to 1.

Eq. (14) was adopted as a bounded working approximation in which the proportional reduction associated with each successive event acts on the attainable yield fraction remaining after preceding events. It therefore constrains the cumulative yield reduction to 0–100% without assuming that every event-level reduction acts on the original yield potential. This formulation is not intended to represent all physiological interactions among repeated frost events, such as recovery, compensatory growth, carry-over effects, or changes in crop susceptibility following earlier injury.

To evaluate sensitivity to this aggregation assumption, event-level reductions were also aggregated additively:

$$Y_{stage,add}^{year} = \sum_{j=1}^n y_{event,j}^{pot} \quad (15)$$

where n is the number of LSF events occurring within the corresponding grid cell, year, and phenological stage. The multiplicative and additive formulations were compared across the historical period, SSP2–4.5, and SSP5–8.5; the three cultivar-resistance groups; the combined, jointing, and booting phenological categories; and the three frost-identification thresholds ($T_0 = 0^\circ\text{C}$, $T_1 = 1^\circ\text{C}$, and $T_2 = 2^\circ\text{C}$). The absolute difference was calculated as the additive estimate minus the multiplicative estimate, and the relative difference was calculated as the absolute difference divided by the multiplicative estimate and expressed as a percentage.

Finally, annual cumulative yield reduction across the two sensitive windows (jointing + booting) was computed by combining stage-level losses using the same multiplicative formulation:

$$Y_{annual}^{year} = 1 - \left(1 - Y_{jointing}^{year}\right) \left(1 - Y_{booting}^{year}\right) \quad (16)$$

This metric represents the year-specific cumulative yield reduction attributable to LSF events occurring within the jointing and booting windows, rather than whole-season yield reduction.

2.7. Future LSF event identification and yield reduction simulation

Future LSF risk and associated yield reductions were projected under two CMIP6 scenarios (SSP2–4.5 and SSP5–8.5). To match the spatial resolution used in the phenology and risk assessment, GFDL-ESM4-derived hourly 2 m air temperature was first bilinearly interpolated to a $0.1^\circ \times 0.1^\circ$ grid. An additive bias correction was then calibrated over a historical reference period (1980–2009) and applied to future projections (2030–2100) (Feng et al., 2025). Specifically, for each grid cell x and hour-of-day index h (1–24), the additive bias term was estimated as

$$\Delta(x, h) = \overline{T_{obs}(x, h)} - \overline{T_{GCMs}(x, h)} \quad (17)$$

where the overbar denotes the climatological mean computed over all days within 1980–2009 at the same hour h . The bias-corrected hourly temperature was then calculated as

$$T_{corr}(x, t) = T_{GCMs}(x, t) + \Delta(x, h(t)) \quad (18)$$

where t is the hourly timestamp and $h(t)$ maps t to its hour-of-day.

Using $T_{corr}(x, t)$, future LSF events were identified and yield reductions were simulated using the same event definition, within-event severity profiling, and aggregation rules as in the historical analysis (Section 2.6), thereby ensuring methodological consistency between historical reconstruction and future projection. The performance of the bias correction was evaluated by comparing bias-corrected historical GFDL-ESM4 temperatures against ERA5-Land during 1980–2009 (Fig. S6). The corrected temperatures showed good agreement with ERA5-Land in both spatial patterns and regional summary statistics, with regional mean R^2 values exceeding 0.75 across NS, HHS, and MYS.

RMSE patterns indicated moderate hourly temperature errors, with slightly lower performance in parts of western MYS where terrain is more complex. Overall, the bias correction reproduced the key spatio-temporal characteristics of hourly temperature required for subsequent LSF event identification and yield-reduction simulation.

To assess the effect of explicitly representing future phenology, we conducted paired dynamic- and fixed-phenology simulations under each future climate scenario. In the dynamic configuration, annual jointing and booting dates were reconstructed for each grid cell and year using the bias-corrected future temperature forcing and were used to define the corresponding frost-sensitive windows. In the fixed configuration, the same future hourly forcing was retained, but stage dates were held at their grid-specific historical climatological means for 1980–2024. All other model settings were identical, and the comparison was repeated across cultivar resistance groups and frost-identification thresholds.

3. Results

3.1. Evaluation of prediction models and model-driven cultivar resistance grouping

Tree-based ensemble models outperformed SVR and linear models, with GBDT selected as the optimal yield-reduction model ($R^2 = 0.61$, RMSE = 14.99%; Fig. S7). SHAP analysis identified cultivar as the dominant predictor, followed by treatment duration and low-

temperature intensity, whereas developmental stage and growth habit had smaller contributions (Fig. 4b). Predicted yield reduction increased nonlinearly with decreasing treatment temperature and increasing exposure duration (Fig. S8). Residual-based classification further identified representative cold-tolerant, moderately cold-tolerant, and cold-sensitive cultivar groups for semi-winter and weak-spring wheat; for example, Xumai35 and Zhengmai7698 were classified as cold tolerant, whereas Taishan6426 and Xinmai26 were classified as cold sensitive (Table 1).

Among the candidate phenology models, RF was selected based on its predictive performance and stability under station-grouped cross-validation (Fig. S9). The selected model reproduced jointing and heading onset dates well, with R^2 values of 0.81 and 0.83 and RMSE values of 6.16 and 4.83 d, respectively (Fig. 4c–d; Fig. S9). Further evaluation showed that model-reconstructed phenology reproduced the dominant spatial pattern of earlier onset in MYS and progressively later onset toward NS, while preserving the subregional contrasts among NS, HHS, and MYS (Fig. S10a–b). Trend patterns derived from the reconstructed time series showed widespread phenological advancement, while retaining spatial differences in the magnitude of change among the three subregions (Fig. S10c–d). These results supported the use of the revised phenology model to define stage-specific windows for subsequent LSF identification.

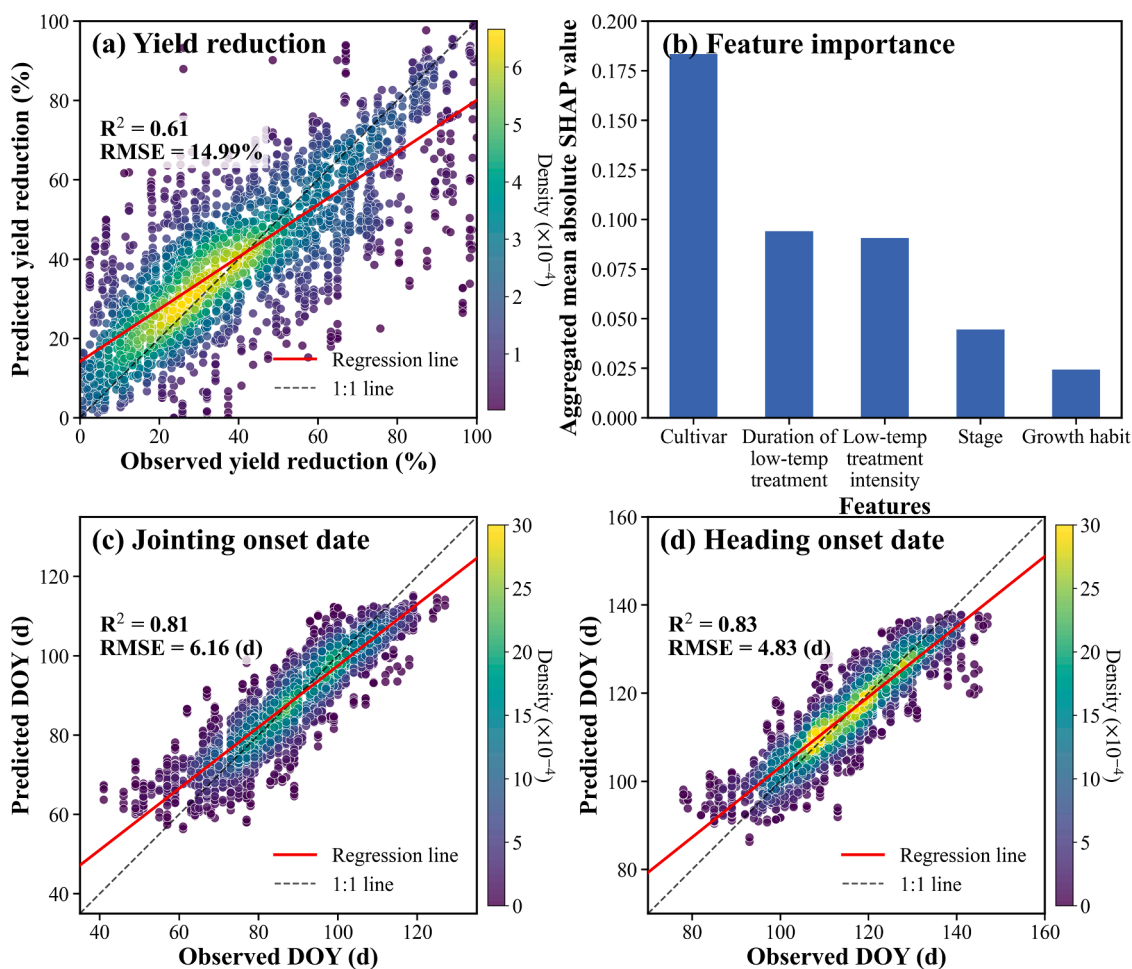


Fig. 4. Performance of the selected yield-reduction and phenology prediction models. (a) Observed versus predicted yield reduction (%) for the selected yield-reduction model (GBDT), with the 1:1 line shown for reference. (b) Global feature importance of the yield-reduction model based on mean absolute SHAP values. (c) Observed versus predicted jointing onset DOY for the selected phenology model (RF). (d) Observed versus predicted heading onset DOY for the selected phenology model (RF). In (a), (c), and (d), colors indicate point density; red lines denote fitted regression lines.

Table 1

Representative winter wheat cultivar ensembles (five cultivars per resistance group) identified by residual-based grouping.

Growth habit	Resistance group	Representative cultivars ($n = 5$)
Semi-winter	Cold-tolerant	Xumai35, Jintai182, Liangxing99, Lengzi863, Xumai30
	Moderately cold-tolerant	Shannong38, Bainong207, Aikang58, Yumai34, Jimai22
	Cold-sensitive	Taishan6426, Yannong19, Huaimai33, Xinong509, Zhoumai22
Weak spring	Cold-tolerant	Zhengmai7698, Shangyou1, Zhenmai12, Lengzi857, Fengdecun21
	Moderately cold-tolerant	Linmai7006, Xiaoyan22, Zhengmai366, Zhengmai9023, Lankao198
	Cold-sensitive	Yanzhan4110, Nuanzi58, Taishan4033, Xinmai26, Nuanzi979

3.2. Spatio-temporal variation in historical phenology and LSF events (1980–2024)

Winter wheat phenology over 1980–2024 exhibited a pronounced south–north gradient and widespread advancement (Fig. 5). Jointing onset occurred earliest in MYS (mean 71.1 DOY), followed by HHS (86.4 DOY) and NS (99.7 DOY), with a whole-region mean of 85.9 DOY and a south–north difference of approximately 28.5 days (Fig. 5a). Booting onset showed the same spatial ordering, occurring at 102.6, 112.4, and 123.6 DOY in MYS, HHS, and NS, respectively, with a whole-region mean of 112.3 DOY and a south–north difference of approximately 21.0 days (Fig. 5b). Trend maps indicated a spatially coherent shift toward earlier spring development (Fig. 5c–d). Across the entire winter wheat region, 98.5% of grid cells exhibited advancing jointing onset and 98.9% exhibited advancing booting onset, with statistically significant advancing trends accounting for 82.6% and 84.9% of grid cells, respectively.

Within the reconstructed frost-sensitive windows, historical LSF exposure was widespread but spatially heterogeneous (Fig. 6; Fig. S11), with 90.9% of winter wheat grid cells experiencing at least one event during 1980–2024. NS showed the largest event-free fraction (59.1%),

whereas only 5.4% and 4.6% of the grid cells remained event-free in HHS and MYS, respectively; recurrent exposure was strongest in MYS, where 30.2% experienced at least 16 events. Event characteristics also differed regionally: the 4–5 h duration class dominated overall (37.2%) and reached 51.4% in MYS, while events with $T_{\min} \leq -2^{\circ}\text{C}$ accounted for only 5.2% of the whole region. Stage-resolved results further showed that exposure was concentrated at jointing, with 90.8% of the grid cells experiencing at least one event, whereas 88.5% remained event-free during booting.

Historical LSF showed strong interannual variability (Fig. 7), with the largest regional annual peak occurring in MYS in 1998 at $1.49 \text{ events-pixel}^{-1}\text{-yr}^{-1}$. Jointing-stage events accounted for approximately 97.9% of the combined jointing–booting event frequency, whereas booting-stage events remained rare. Thus, the historical annual variability in LSF exposure was driven primarily by fluctuations in jointing-stage event occurrence.

3.3. Historical regional yield reduction risk under different cultivar resistance scenarios

Historical yield-reduction risk was spatially concentrated in MYS and decreased markedly with increasing cultivar cold tolerance (Fig. 8). Under cold-sensitive cultivars, areas with mean annual yield reduction $\geq 6\%$ accounted for 74.3% of MYS, 28.3% of HHS, and 14.6% of NS, indicating a clear south-to-north decline in high-loss area. In MYS, this high-loss fraction decreased to 20.3% under cold-tolerant cultivars, while the $<3\%$ loss area increased from 10.9% to 35.2%.

Historical yield reduction also showed strong interannual variability (Fig. 9). Under cold-sensitive cultivars, peak combined-stage losses reached 37.47% in MYS, compared with 22.83% in HHS and 14.54% in NS. Under cold-tolerant cultivars, the corresponding peaks declined to 16.50%, 9.72%, and 6.77%, representing reductions of approximately 53–57%. Across regions and resistance groups, jointing-stage losses accounted for approximately 97–100% of the combined-stage losses (Figs. S12–S13).

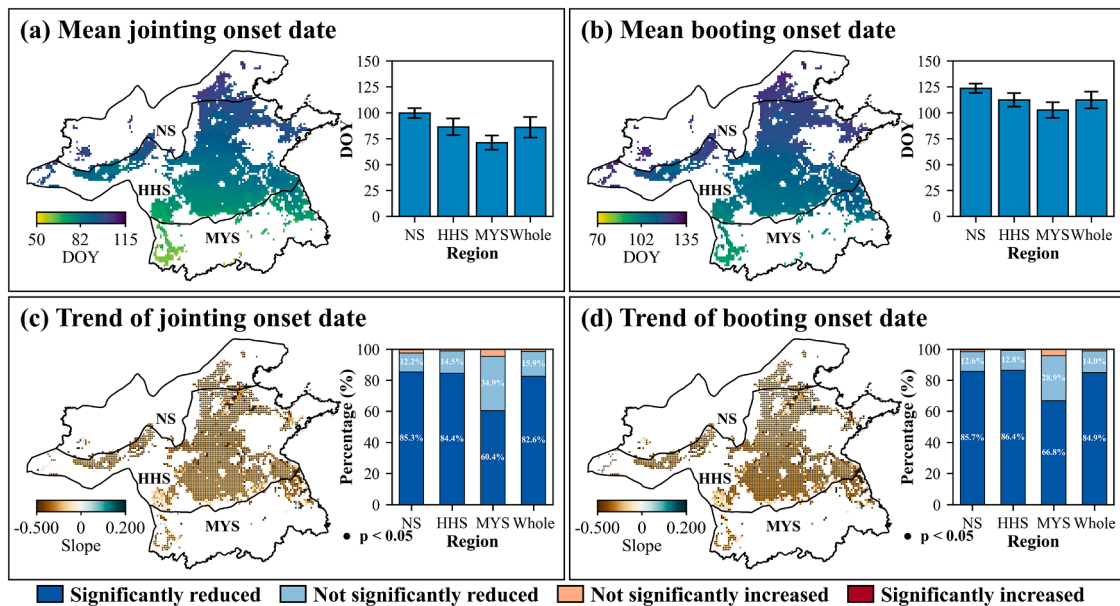


Fig. 5. Spatial patterns and temporal trends of reconstructed winter wheat phenology during 1980–2024. (a, b) multi-year mean onset DOY of the jointing and booting stages derived from the selected phenology model; insets show regional means ($\pm$ standard error) for the NS, HHS, MYS, and the whole region. (c, d) spatial distributions of Theil–Sen trends in jointing and booting onset dates; colors indicate trend magnitude (days yr^{-1}), filled dots denote statistically significant trends (Mann–Kendall test, $p < 0.05$), and inset stacked bar charts show the percentages of grid cells in different trend categories (Significantly reduced, Not significantly reduced, Not significantly increased, Significantly increased) for the NS, HHS, MYS, and the whole region.

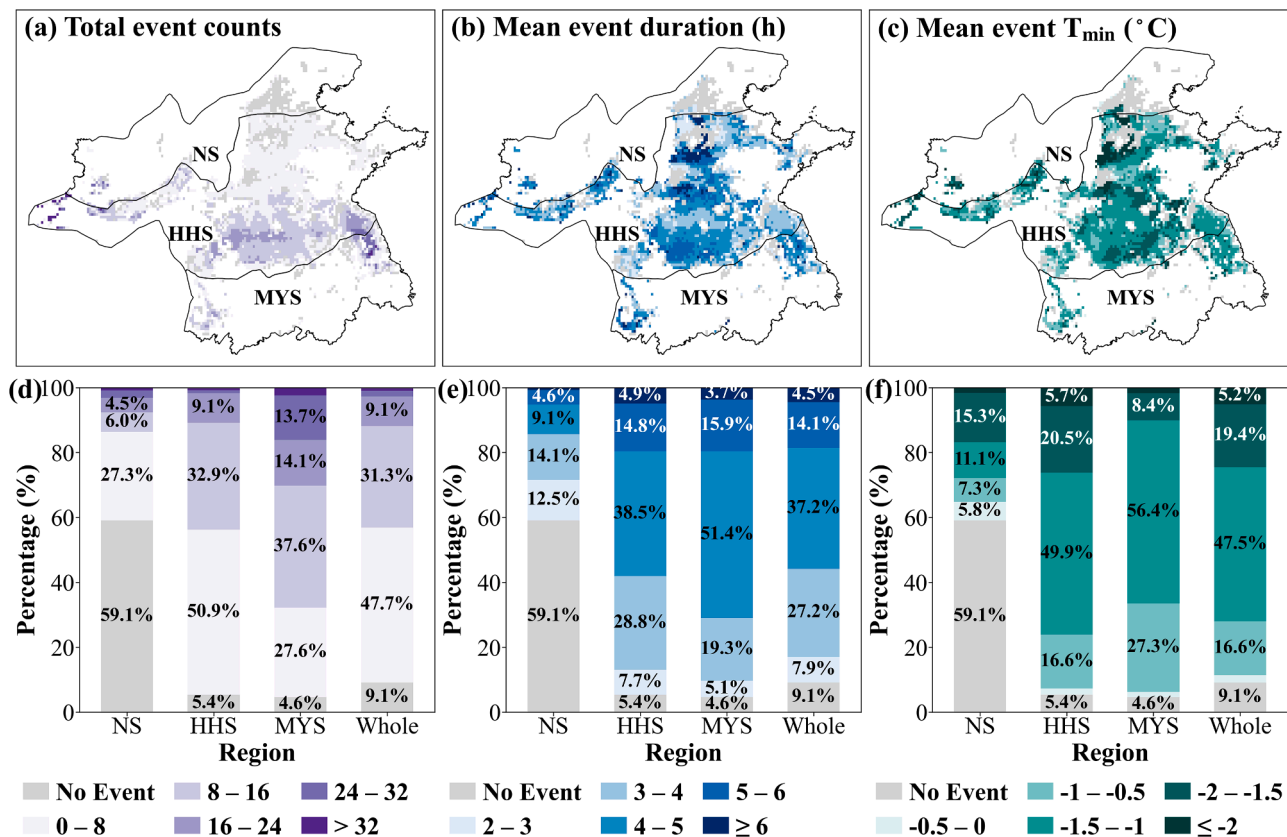


Fig. 6. Spatial characteristics of historical LSF exposure within the winter wheat sensitive windows (jointing + booting) during 1980–2024. (a) Cumulative number of identified LSF events per pixel. (b) Mean event duration per pixel (h), defined as the cumulative time under the identification threshold T_0 within an event. (c) Mean event minimum temperature ($T_{\min}$, °C) per pixel. (d–f) Stacked bar charts show the percentage distribution of pixel values for NS, HHS, MYS, and the whole region for (d) event counts, (e) event duration, and (f) event minimum temperature.

3.4. Projected shifts in future phenology and LSF events under two SSP scenarios (2030–2100)

Future winter wheat phenology retained a pronounced south–north gradient and advanced significantly across all regions during 2030–2100 (Fig. 10; Fig. S14). Under SSP2–4.5, mean jointing onset occurred at 67.2, 77.7, and 89.5 DOY in MYS, HHS, and NS, respectively, compared with 65.8, 75.3, and 86.4 DOY under SSP5–8.5. Phenological advancement was consistently stronger under SSP5–8.5, particularly in NS and HHS. At the whole-region scale, jointing advanced at -0.100 d·yr $^{-1}$ under SSP2–4.5 and -0.187 d·yr $^{-1}$ under SSP5–8.5. Under SSP5–8.5, NS showed the fastest jointing advancement (-0.242 d·yr $^{-1}$), whereas MYS showed the weakest trend (-0.143 d·yr $^{-1}$). By 2100, jointing onset in NS was approximately 6.3 d earlier under SSP5–8.5 than under SSP2–4.5.

Projected LSF exposure increased substantially under SSP5–8.5 during 2030–2100 (Fig. 11). At the whole-region scale, the proportion of winter wheat area experiencing ≥ 8 events increased from 89.0% under SSP2–4.5 to 96.4% under SSP5–8.5, while the proportion experiencing ≥ 16 events increased from 54.0% to 66.2%. HHS showed the highest recurrent exposure, with ≥ 16 -event area increasing from 56.7% to 69.5% between the two scenarios. The proportion of the whole-region area with event durations ≥ 5 h increased from 33.2% to 43.6%, and the area exposed to $T_{\min} \leq -1.5$ °C increased from 55.0% to 63.3%.

Stage-resolved spatial distributions of LSF event frequency, duration, and $T_{\min}$ are shown in Figs. S15–S17. At jointing, 99.9% of the winter wheat area experienced at least one event under both scenarios, while the proportion experiencing ≥ 16 events increased from 51.4% under SSP2–4.5 to 61.6% under SSP5–8.5. In contrast, 44.7% and 45.5% of the area remained event-free during booting, and only 2.6% and 5.1%,

respectively, experienced more than four booting-stage events.

3.5. Future regional yield reduction risk under SSPs and cultivar resistance scenarios

Projected spatial yield-reduction risk differed markedly among regions and cultivar resistance groups during 2030–2100 (Fig. 12). Under cold-sensitive cultivars, the proportion of area with mean annual yield reduction $\geq 6\%$ under SSP2–4.5 was 50.1% in HHS and 49.1% in MYS, compared with only 6.7% in NS. Under SSP5–8.5, this high-loss area increased to 56.0% in HHS and 11.1% in NS, but decreased to 37.3% in MYS, making HHS the most spatially extensive future high-risk region. Increasing cultivar cold tolerance substantially contracted these high-loss areas. Under cold-tolerant cultivars, the $\geq 6\%$ area declined to 1.5% in HHS, 0.6% in MYS, and 0% in NS under SSP2–4.5, and to 0.1%, 0%, and 0%, respectively, under SSP5–8.5.

Projected yield reduction showed pronounced interannual variability during 2030–2100 (Fig. 13; Figs. S18–S21). For cold-sensitive cultivars, the whole-region peak combined-stage loss was 37.42% under SSP2–4.5 and 28.42% under SSP5–8.5. Regionally, peak losses under SSP2–4.5 were 28.74% in NS, 39.80% in HHS, and 31.33% in MYS, compared with 39.19%, 29.93%, and 41.59% under SSP5–8.5, corresponding to increases of 10.44 and 10.26 percentage points in NS and MYS but a decrease of 9.87 percentage points in HHS. Cold-tolerant cultivars reduced regional peak losses by 49.8–58.8% under SSP2–4.5 and 50.7–55.6% under SSP5–8.5.

Regional comparisons showed a shift in the primary LSF yield-reduction hotspot from MYS historically to HHS under future climate conditions (Fig. 14). For cold-sensitive cultivars, mean combined-stage loss at T_0 was highest historically in MYS (10.02%), compared with

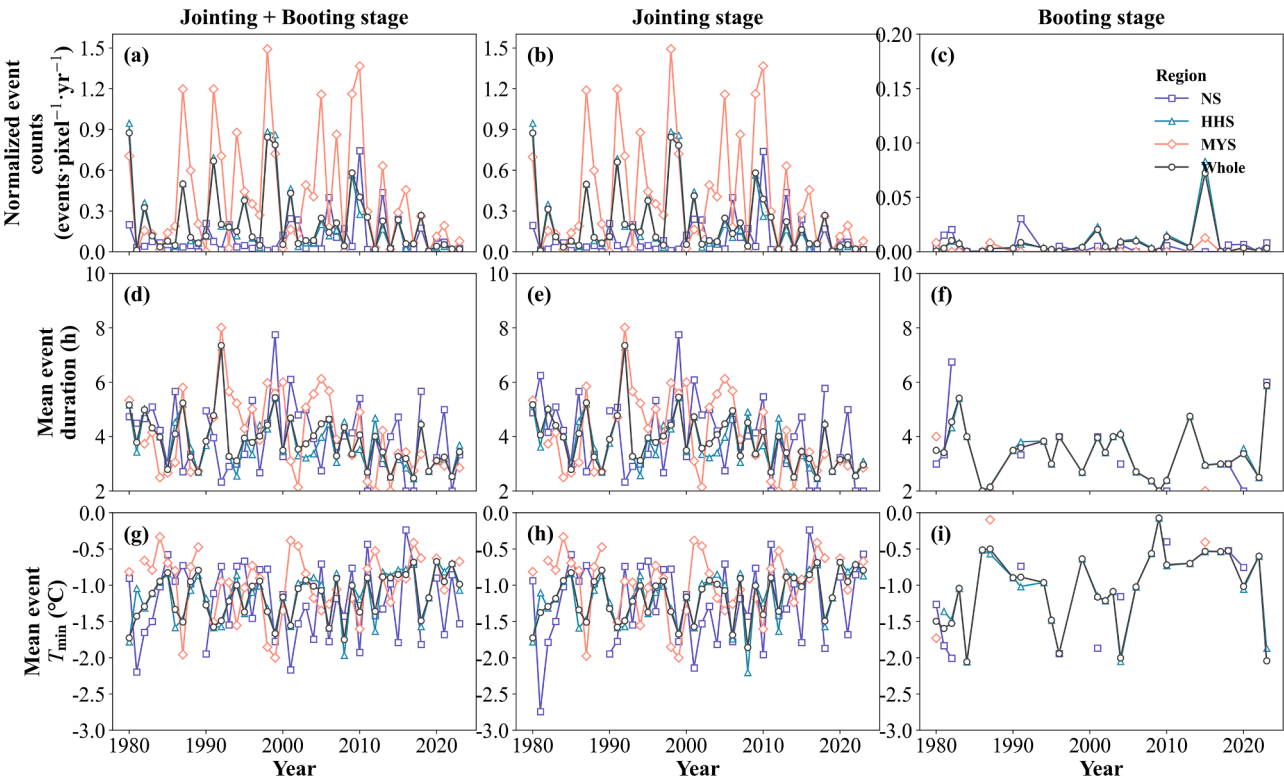


Fig. 7. Interannual variability of historical LSF characteristics during 1980–2024. Time series show normalized event counts (events·pixel^{−1}·yr^{−1}; annual regional total event counts divided by the number of winter-wheat pixels), mean event duration (h), and mean event minimum temperature (T_{min} , °C), stratified by phenological window (jointing + booting, jointing only, and booting only) and region (NS, HHS, MYS, and the whole region).

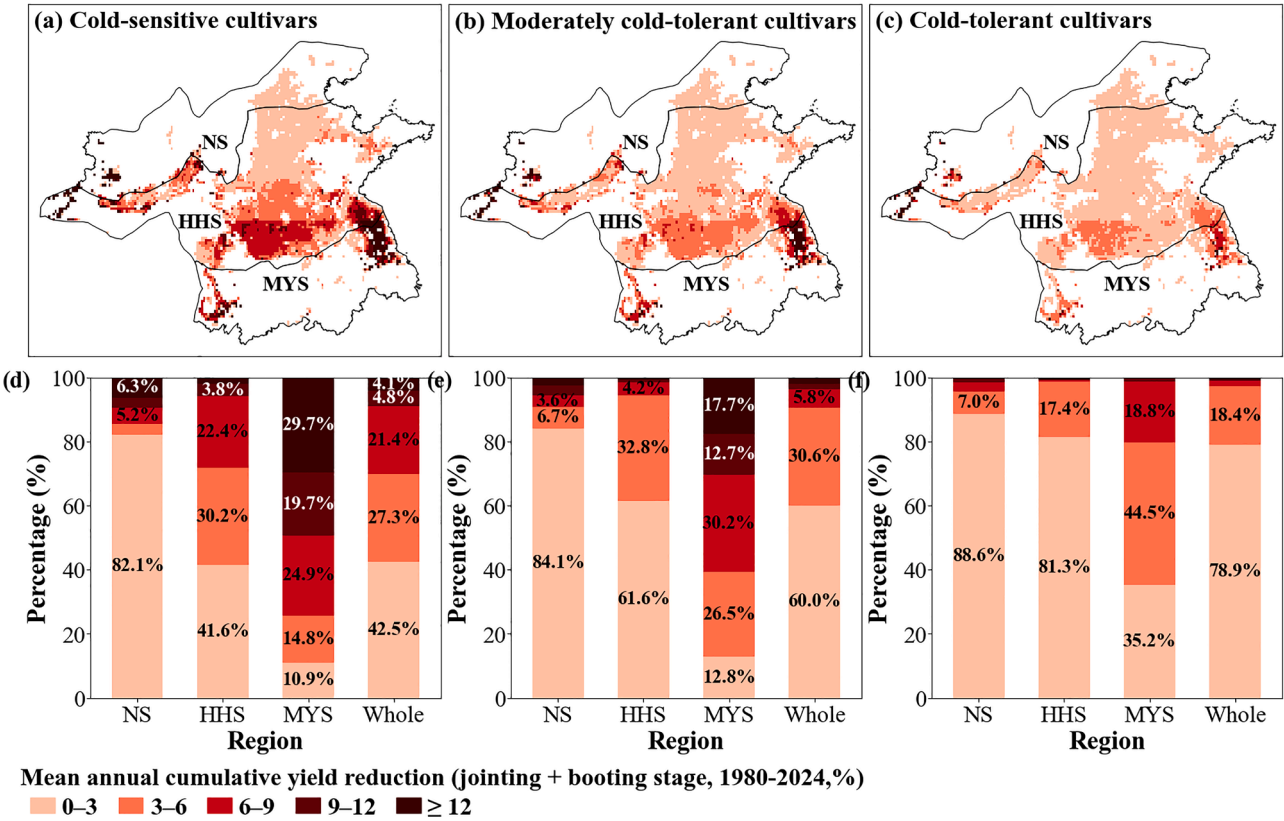


Fig. 8. Spatial distribution of historical mean annual cumulative yield reduction (%) attributable to LSF during 1980–2024, aggregated across the jointing + booting windows, under three cultivar resistance scenarios: (a) cold-sensitive, (b) moderately cold-tolerant, and (c) cold-tolerant. (d–f) Stacked bar charts show the percentage distribution of winter-wheat pixels in NS, HHS, MYS, and the whole region across yield-reduction classes (0–3%, 3–6%, 6–9%, 9–12%, and ≥12%).

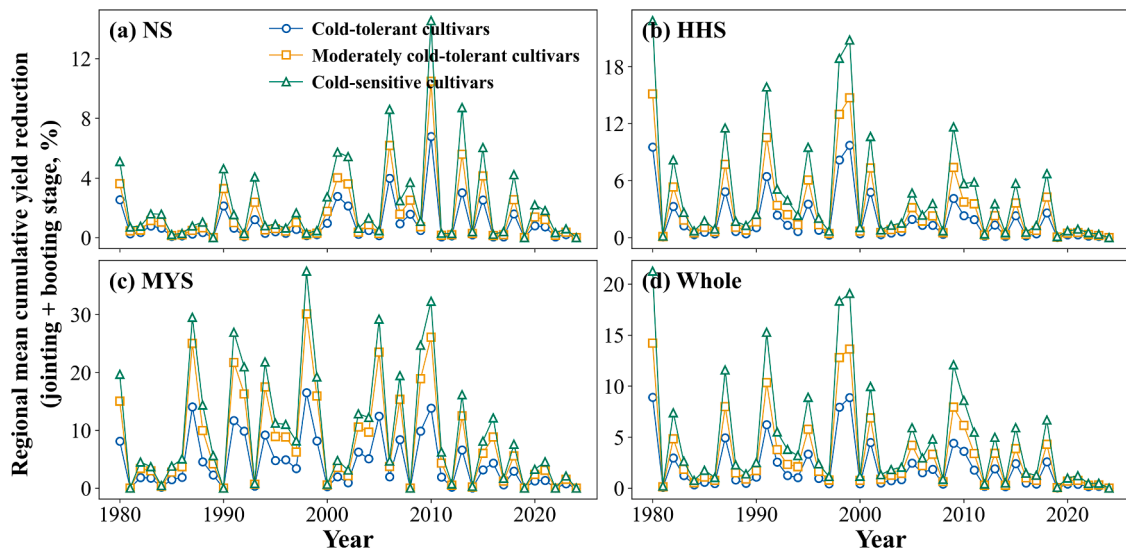


Fig. 9. Interannual variability of historical frost-induced yield reductions during 1980–2024. Time series show regional mean annual cumulative yield reduction (%) within the combined jointing + booting window for three cultivar resistance groups: cold-sensitive (green), moderately cold-tolerant (yellow), and cold-tolerant (blue). Panels show results for (a) NS, (b) HHS, (c) MYS, and (d) the whole region.

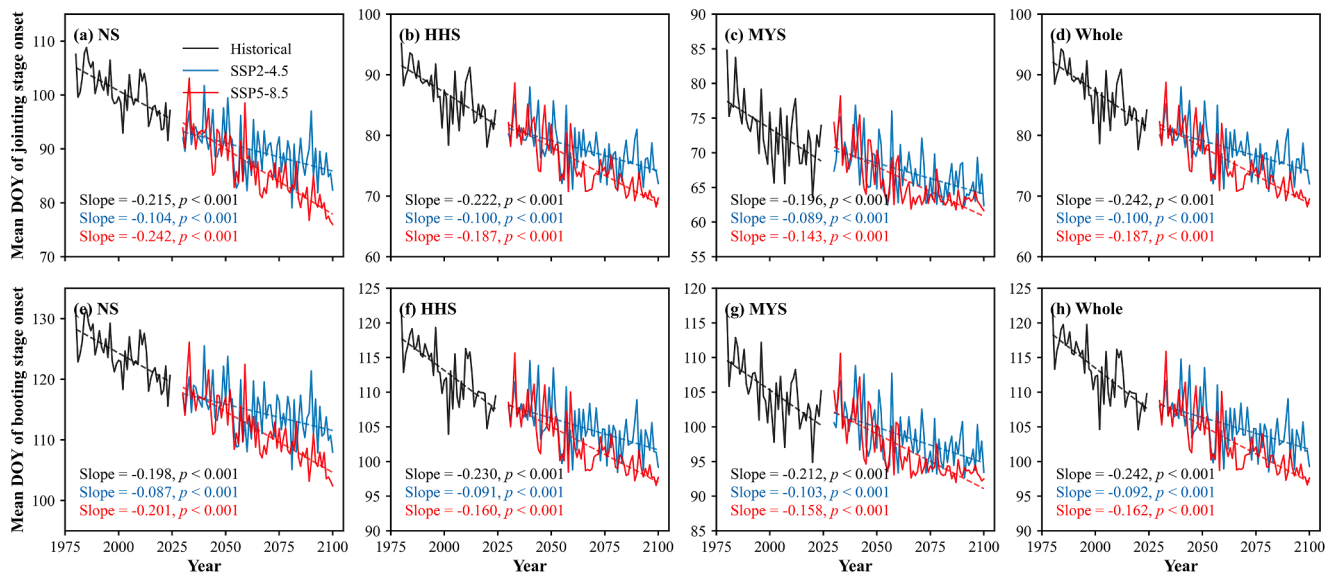


Fig. 10. Temporal evolution of regional mean winter wheat phenology under historical and future climate scenarios. Time series show the interannual variation in mean onset dates of the jointing stage (a–d) and booting stage (e–h) for NS, HHS, MYS, and the whole region during the historical period (1980–2024) and future projections (2030–2100).

4.55% in HHS, whereas HHS had the highest future losses, reaching 6.38% under SSP2-4.5 and 6.49% under SSP5-8.5. Increasing the frost-identification threshold substantially increased absolute losses; HHS loss under SSP5-8.5 increased from 6.49% at T_0 to 12.47% at T_1 and 18.83% at T_2 , while the cultivar-resistance ranking remained unchanged (Figs. S22–S23).

Comparison of the dynamic-phenology projections (Fig. 14 and Figs. S22–S23) with the fixed-phenology simulations (Fig. S24) showed that explicitly representing future phenology substantially increased projected LSF-induced yield reduction. For cumulative yield reduction across the combined jointing and booting windows, the study-area mean, averaged across the three cultivar resistance groups and three frost-identification thresholds, was 9.17% under dynamic phenology and 3.41% under fixed phenology for SSP2-4.5, a difference of 5.76 percentage points. Under SSP5-8.5, the corresponding values were

9.49% and 3.14%, respectively, a difference of 6.35 percentage points. Stage-specific comparisons showed that these differences arose predominantly during jointing, whereas differences during booting were comparatively small.

The additive aggregation produced higher cumulative yield-reduction estimates than the multiplicative aggregation across the evaluated combinations (Figs. S25–S27). Averaged across the 27 climate-condition, cultivar-group, and phenological-category combinations for each threshold, the absolute difference increased from 0.18 percentage points under T_0 to 0.62 and 1.45 percentage points under T_1 and T_2 , respectively. The corresponding relative differences were 6.75%, 10.88%, and 15.57%. Nevertheless, both formulations showed the same broad patterns: jointing-stage loss dominated the combined-stage estimates, booting-stage loss was comparatively small, and cumulative loss decreased with increasing cultivar cold tolerance. Thus, the qualitative

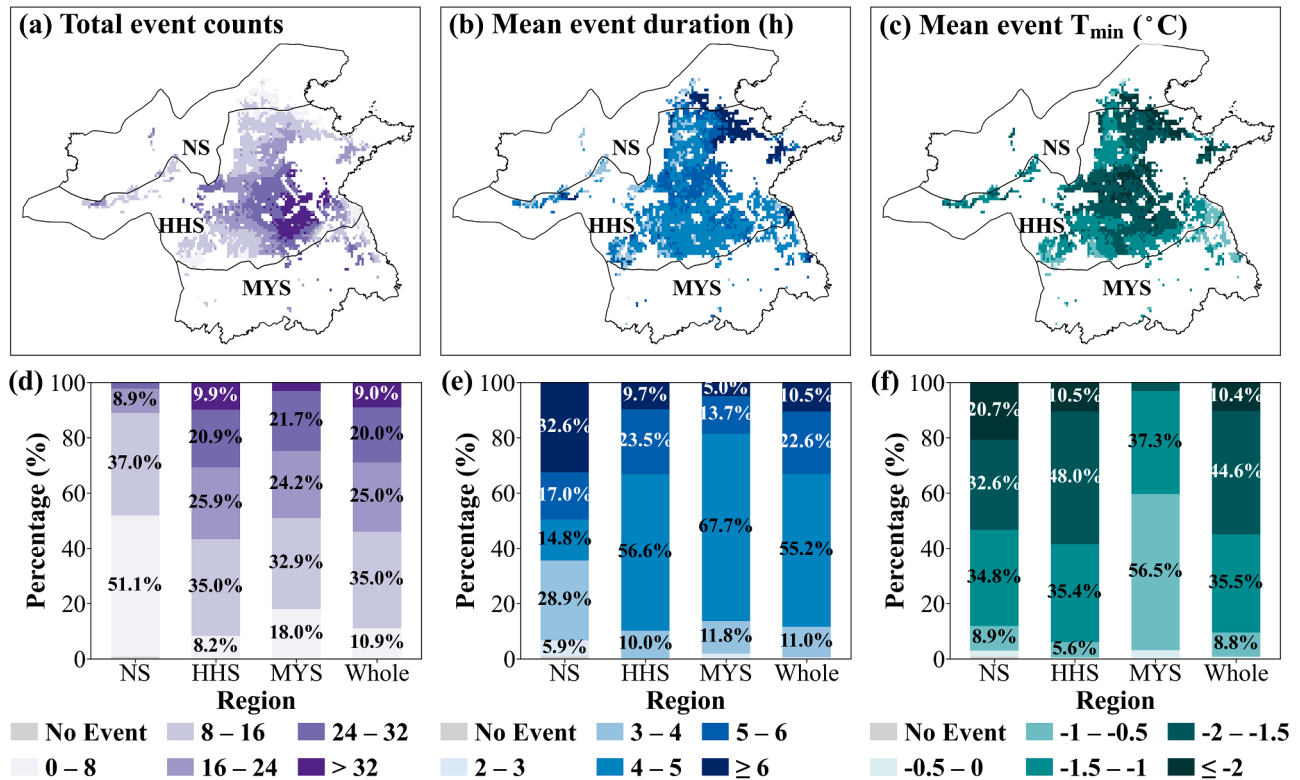
SSP2-4.5 (2030-2100)

Fig. 11. Spatial characteristics of projected LSF exposure within the winter wheat sensitive windows (jointing + booting) during 2030–2100 under SSP2-4.5 and SSP5-8.5. (a–c) Spatial distributions of cumulative event counts, mean event duration (h), and mean event minimum temperature (T_{min} , $^{\circ}C$) under SSP2-4.5. (d–f) Stacked bar charts show the corresponding percentage distribution for NS, HHS, MYS, and the whole region. (g–i) Spatial distributions of the same metrics under SSP5-8.5. (j–l) Stacked bar charts summarize the corresponding regional percentage distributions.

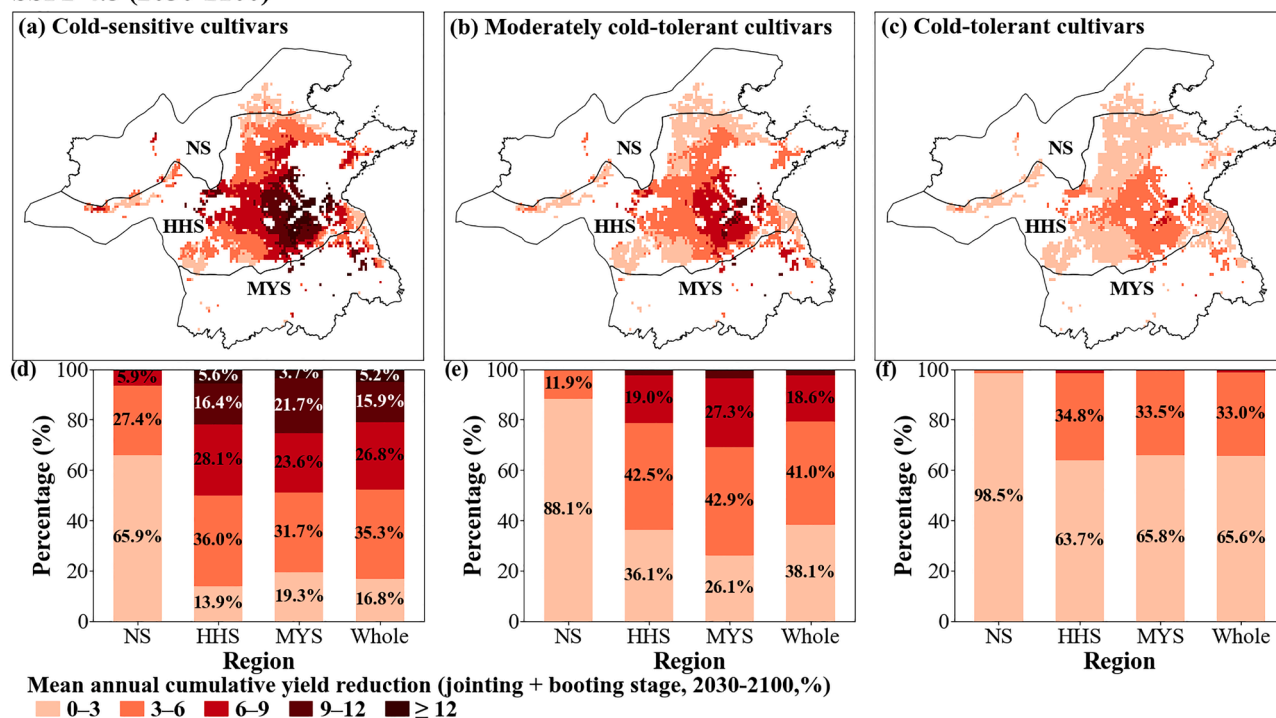
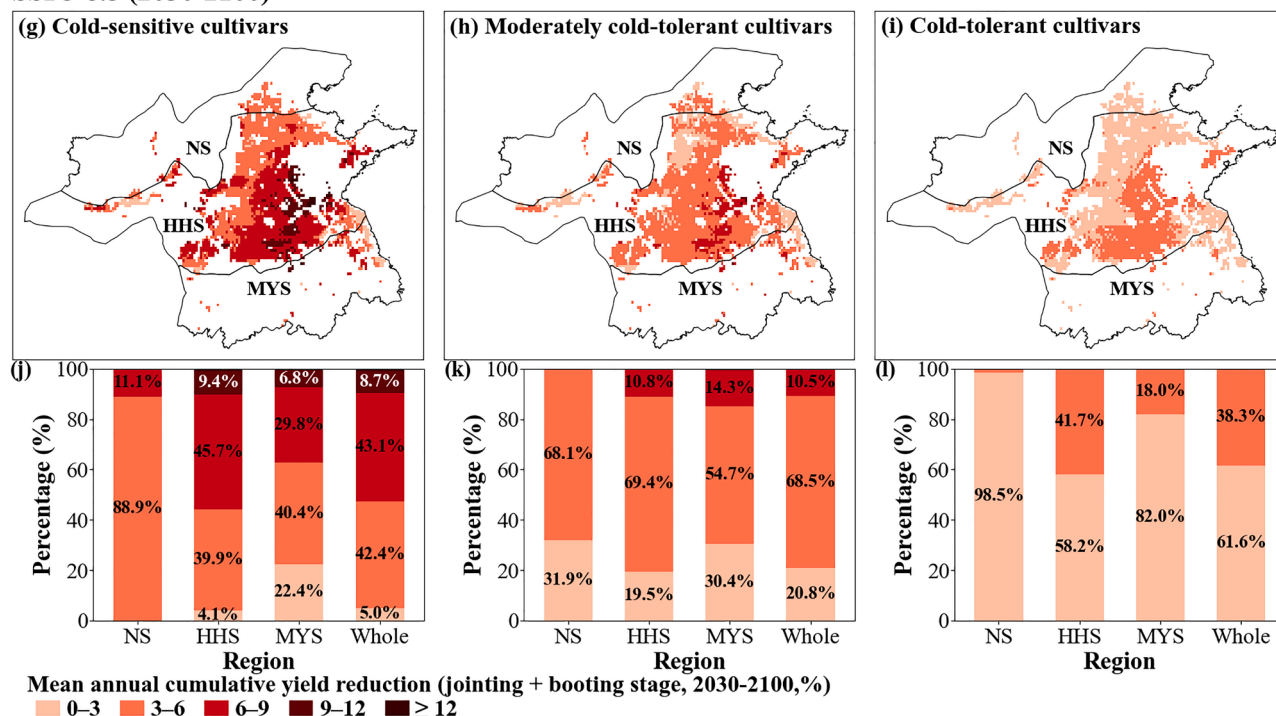
SSP2-4.5 (2030-2100)**SSP5-8.5 (2030-2100)**

Fig. 12. Spatial distribution of projected mean annual cumulative yield reduction (%) attributable to LSF during 2030–2100, aggregated across the jointing + booting windows under SSP2–4.5 and SSP5–8.5. Maps show yield-reduction patterns under SSP2–4.5 for cold-sensitive (a), moderately cold-tolerant (b), and cold-tolerant cultivars (c), and under SSP5–8.5 for the same cultivar groups (g–i). Stacked bar charts (d–f, j–l) show the percentage distribution of winter wheat grid cells in NS, HHS, MYS, and the whole region across yield-reduction classes (0–3%, 3–6%, 6–9%, 9–12%, and ≥12%).

patterns were preserved, whereas the estimated magnitudes were sensitive to the aggregation method, particularly at higher frost-identification thresholds.

Comparison of the primary 30 m results (Fig. 14) with those obtained using the alternative 1 km product and the original 4 km-derived domain (Figs. S28–S30) showed that crop-domain selection affected

absolute regional yield-reduction estimates and some region–scenario responses. At the baseline frost-identification threshold, all three datasets identified MYS as the principal historical hotspot and HHS as the principal future hotspot. Across the three thresholds, jointing-stage frost remained the dominant contributor to cumulative yield reduction, and losses consistently decreased with increasing cultivar cold tolerance.

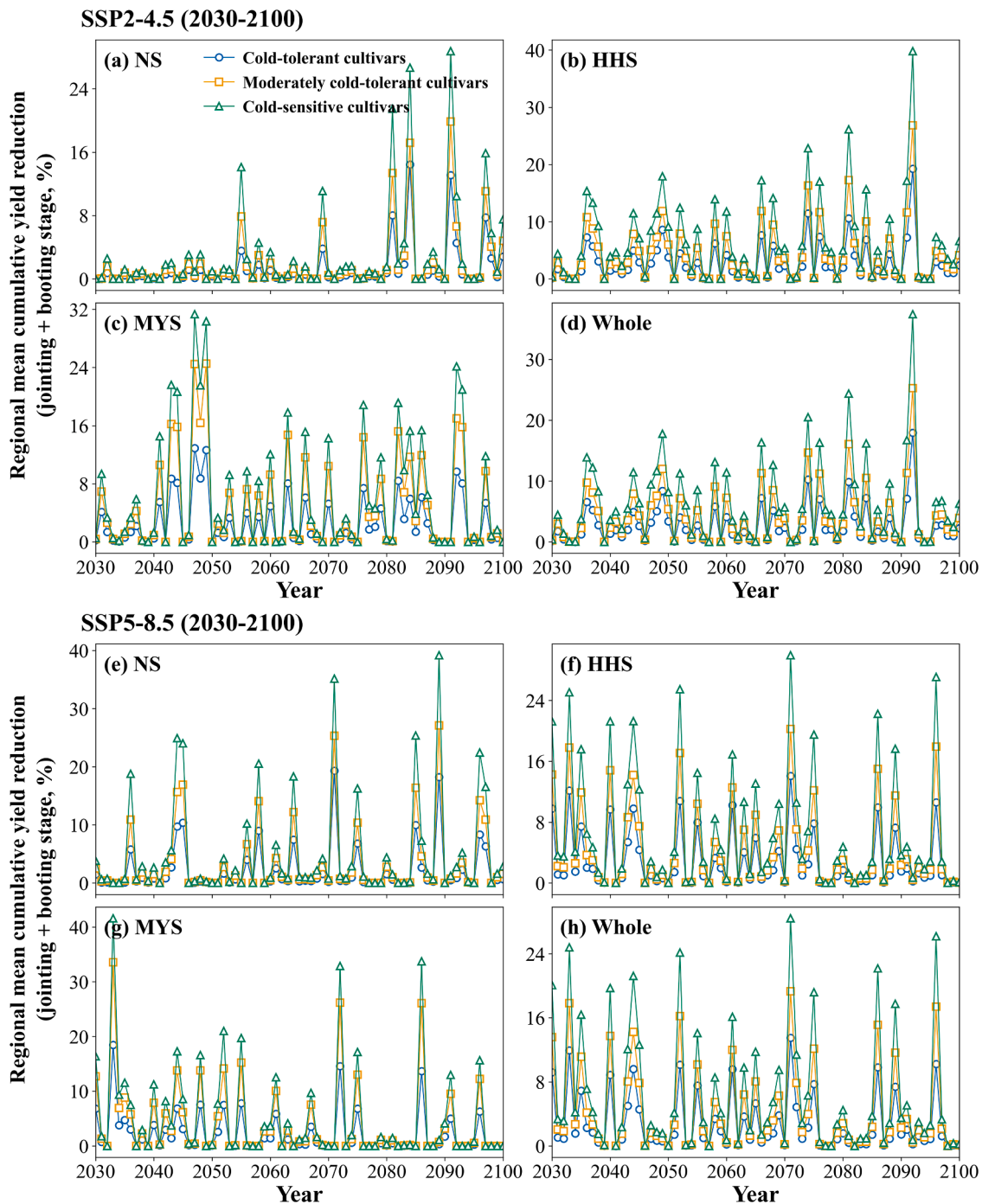


Fig. 13. Interannual variability of projected regional mean cumulative yield reduction during 2030–2100. Panels (a–d) show annual cumulative yield reduction (%) within the combined jointing + booting window under SSP2–4.5 for NS, HHS, MYS, and the whole region, respectively; panels (e–h) show the corresponding results under SSP5–8.5. Lines represent cold-sensitive (green), moderately cold-tolerant (yellow), and cold-tolerant (blue) cultivar groups.

However, the direction of the historical-to-SSP2–4.5 change in NS and the relative magnitudes of SSP2–4.5 and SSP5–8.5 losses in MYS differed among the datasets. Thus, the principal biological conclusions were robust, whereas absolute estimates and some regional responses remained sensitive to the crop domain.

4. Discussion

LSF risk in winter wheat is shaped not only by the occurrence of low-temperature events, but also by when those events intersect with biologically sensitive developmental stages and how strongly different

cultivars respond once exposure occurs. Our results indicate that historical LSF risk and yield reductions were concentrated mainly in HHS and MYS, while future warming advanced phenology and further reorganized risk across the winter wheat belt, with HHS becoming a key future hotspot and jointing-stage frost remaining dominant. Across both periods, cultivar resistance substantially reduced the magnitude of simulated losses. In the following sections, we discuss these findings from three perspectives: historical and future phenology shifts and spatiotemporal LSF exposure, the evolution of yield-reduction risk and the role of cultivar resistance, and the major uncertainties and adaptation implications of the present framework.

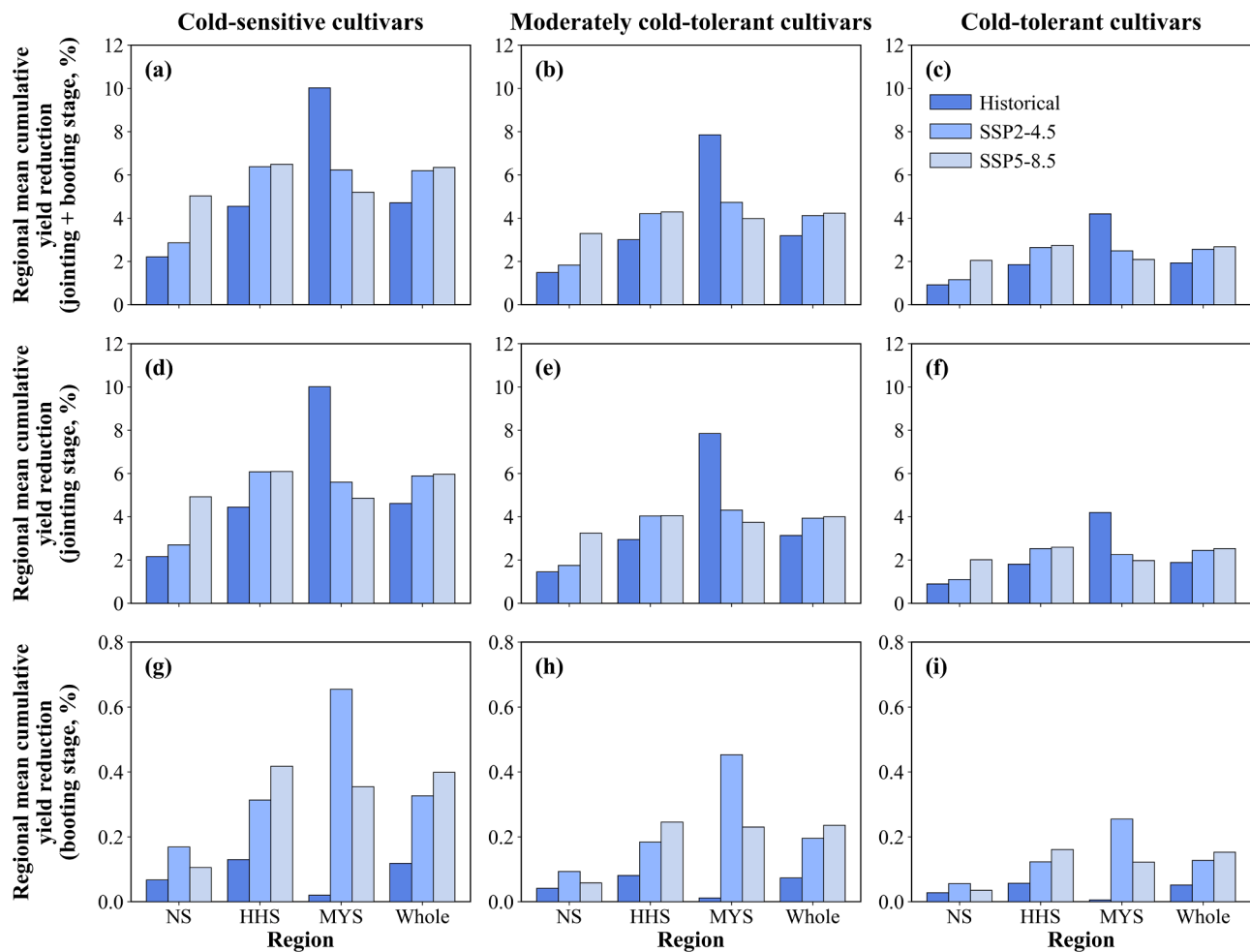


Fig. 14. Comparison of regional mean cumulative yield reduction under historical and future climate conditions at the baseline frost-definition threshold ($T_0 = 0^\circ\text{C}$). Bar charts compare historical, SSP2-4.5, and SSP5-8.5 conditions for cold-sensitive, moderately cold-tolerant, and cold-tolerant cultivars across NS, HHS, MYS, and the whole region. Panels (a–c) show losses aggregated across the combined jointing + booting window, panels (d–f) show jointing-stage losses, and panels (g–i) show booting-stage losses.

4.1. Historical and future phenology shifts and spatiotemporal LSF exposure

LSF remains an important agrometeorological hazard for winter wheat even under a warming climate because LSF risk depends not only on the magnitude of cold events but also on their timing relative to sensitive crop developmental stages. Our results show that warming reshapes LSF exposure through the interaction between climate-driven phenological advancement and the changing occurrence of cold events within sensitive developmental windows. Warmer late-winter and early-spring temperatures accelerate winter wheat development, shifting sensitive stages earlier in the season. However, earlier development does not necessarily reduce LSF risk, because spring temperature variability remains strong and cold-air outbreaks can still occur during these earlier windows (Shimono, 2011; Wang et al., 2018; Ren et al., 2019). This finding is consistent with Zohner et al. (2020), who demonstrated a similar warming-induced increase in LSF risk for natural vegetation across Asia, showing that this paradox is driven by a fundamental reorganization of the overlap between advancing plant phenology and episodic cold events, rather than a simple geographical shift of cold anomalies. Our finding that warming redistributes rather than uniformly reduces LSF risk is consistent with projections for South Korea, where phenological advancement and regional differences in cold-event climatology produced spatially heterogeneous changes in LSF risk (Kim et al., 2025).

This mechanism also highlights an important limitation of traditional meteorological definitions of LSF. Operational frost monitoring systems commonly rely on fixed calendar windows or simple temperature thresholds, such as minimum temperatures below 0°C after a pre-defined date. While these definitions are operationally convenient, they implicitly assume that crop vulnerability occurs at similar times across regions and years, thereby neglecting spatial differences in crop phenology (Liu et al., 2016). In China, winter wheat phenology exhibits a pronounced south–north gradient, with the earliest sensitive stages occurring in the MYS and the latest in the NS. As a result, calendar-based frost definitions may misrepresent biologically meaningful exposure by failing to account for regional variation in crop development.

The phenology-aware framework used in this study helps explain the historical pattern of frost exposure. During the historical period, LSF events were widespread across the winter wheat belt, with 90.9% of winter wheat grid cells experiencing at least one event during 1980–2024. At the same time, exposure showed clear regional contrasts: the NS exhibited the largest event-free area fraction, whereas HHS and MYS experienced substantially more widespread recurrent exposure. Importantly, this pattern was driven less by rare extreme minimum temperatures than by repeated moderate cold events occurring within sensitive phenological windows. In agricultural terms, frost hazard is therefore better interpreted as cumulative biologically meaningful exposure rather than as a simple reflection of the coldest individual temperature event.

Historical LSF also exhibited pronounced interannual variability. In our simulations, several years were characterized by widespread frost exposure across the HHS, with particularly strong signals detected for early spring 1998 and March 2010. These years correspond to well-documented regional cold-surge events that caused substantial winter wheat damage across northern China. For example, the spring 2010 “late cold spell” in northern China produced prolonged low-temperature conditions during the jointing stage of winter wheat, leading to widespread crop damage across the Huang–Huai–Hai region. Remote-sensing analyses further confirmed significant vegetation growth setbacks during this period, with clear declines in NDVI and EVI signals across major wheat-producing areas (Wang et al., 2020). Earlier climatological studies also identified the late-1990s as a period with several severe early-spring cold-air outbreaks affecting the North China Plain, including the March 1998 event that resulted in large-scale winter wheat freeze injury (Zhong et al., 2007). The fact that these independently documented disaster years also emerge as high-exposure years in our reconstructed LSF dataset provides additional confidence that the phenology-based frost identification framework captures biologically meaningful frost hazards. More broadly, the strong year-to-year variability identified here is consistent with previous studies showing that late spring frost occurrence in northern China is largely driven by episodic cold-air intrusions rather than gradual changes in seasonal mean temperature (Xiao et al., 2018). In our results, this variability is expressed primarily through fluctuations in event frequency, whereas average event duration and minimum temperature vary less strongly among years. This pattern suggests that severe frost years are not necessarily those with the lowest $T_{\min}$ alone, but rather those in which frost-sensitive phenological stages coincide with repeated spring cold-air incursions.

Future projections indicate that this phenology–exposure relationship will persist but in a reorganized form. Under both SSP2–4.5 and SSP5–8.5 scenarios, winter wheat phenology continues to advance, with stronger shifts under higher warming levels. However, this advancement is spatially heterogeneous: MYS remains the earliest-developing region, whereas HHS and NS experience stronger phenological shifts. This spatial asymmetry changes the alignment between crop sensitivity and regional cold-event climatology. As a result, future LSF exposure reflects the interaction between climate-driven phenological advancement and changes in the frequency and persistence of cold events within sensitive developmental windows, whereas changes in event minimum temperature are comparatively small.

This framework also helps explain why HHS emerges as the most prominent future exposure region. It is characterized by a vast and relatively flat agricultural landscape, which allows cold-air outbreaks to spread efficiently over large areas (Zhong et al., 2007, 2008). Previous studies have also shown that spring LSF events in northern China are often associated with cold-air intrusions originating from Mongolia and propagating southeastward across the North China Plain (Yue et al., 2016). As phenological development advances under warming, these recurring cold surges can still intersect with sensitive crop stages, thereby sustaining or even amplifying frost exposure in HHS. The resulting pattern is therefore not a simple northward shift of historical LSF risk but rather a reorganization of frost exposure pathways driven by asynchronous phenological advancement and persistent regional climate variability.

Stage-specific patterns further clarify the mechanisms of LSF risk. Jointing-stage exposure remained dominant in both historical and future periods because this stage coincides with the most unstable phase of the spring transition and with crop de-acclimation. Booting-stage LSF events occur later in the season when background temperatures are generally higher, leading to lower average exposure probability. Nevertheless, occasional late cold surges can still produce substantial booting-stage damage in individual years.

4.2. Spatiotemporal evolution of yield-reduction risk and the role of cultivar resistance

While frost exposure determines when and where winter wheat encounters cold stress, the resulting yield reduction depends on how that exposure translates into biological damage. By combining reconstructed LSF events with yield-reduction functions derived from controlled freezing experiments, this study provides a physiologically grounded link between frost hazard and crop yield outcomes, addressing uncertainties often encountered in large-scale regional assessments worldwide (Whaley et al., 2004; Crimp et al., 2015, 2016).

Historically, frost-induced yield reductions were concentrated mainly in the HHS–MYS corridor, whereas NS generally exhibited lower losses. The highest mean losses occurred in MYS, where the combined-stage yield reduction reached 10.02% for cold-sensitive cultivars. This spatial concentration is broadly consistent with previous assessments identifying the Huang–Huai and southern winter wheat regions as important frost-risk areas (Xiao et al., 2018). This spatial pattern reflects the dominance of jointing-stage LSF events, which disrupt stem elongation and spike differentiation and therefore strongly influence final grain number.

Future projections indicate a redistribution rather than a uniform intensification of yield-reduction risk. Under both SSP2–4.5 and SSP5–8.5 scenarios, moderate-to-high loss areas expanded most clearly in HHS. This shift is consistent with previous studies suggesting that warming-induced phenological advancement may increase the overlap between sensitive crop stages and persistent spring temperature variability in the HHS (Li et al., 2005).

The dynamic-versus-fixed phenology experiment provides direct evidence for the importance of this phenology-mediated pathway. Averaged across cultivar resistance groups and frost-identification thresholds, dynamic phenology increased combined-stage yield reduction by 5.76 percentage points under SSP2–4.5 and 6.35 percentage points under SSP5–8.5, with most of the increase occurring during jointing. These results indicate that using fixed historical crop calendars can substantially underestimate future LSF risk.

Cultivar resistance emerged as a key factor controlling the magnitude of frost-induced yield reduction. In our simulations, replacing cold-sensitive cultivars with cold-tolerant cultivars reduced mean simulated losses by approximately half in the most vulnerable regions. Experimental and physiological studies have shown that cold-tolerant wheat cultivars often exhibit improved membrane stability, higher soluble sugar accumulation, and stronger antioxidant responses under freezing stress (Saeidi et al., 2012; Ji et al., 2017; Zhang et al., 2023; Lin et al., 2023). These traits help mitigate reproductive damage under comparable low-temperature exposure.

Stage-specific loss patterns further clarify the role of different LSF events. Because jointing-stage LSF events occur more frequently, they dominate the long-term average yield-reduction pattern. In contrast, booting-stage LSF events are less frequent but can still produce substantial yield reductions in individual years due to their direct effects on pollen fertility and floret survival.

4.3. Uncertainty and future implications

Several uncertainties should be considered when interpreting the projected magnitude of LSF risk and yield reduction. One uncertainty arises from the choice of LSF-identification threshold. Sensitivity experiments using alternative frost-identification thresholds ($T_0 = 0^\circ\text{C}$, $T_1 = 1^\circ\text{C}$, and $T_2 = 2^\circ\text{C}$) showed that absolute event counts and simulated losses changed substantially with the selected threshold. This is expected because agricultural frost damage is not triggered by a single universal air temperature, but arises from the interaction among physiological sensitivity, exposure duration, and prior thermal conditions (Kirchhof et al., 2025). Experimental and physiological studies suggest that near-freezing temperatures can already impose biologically

meaningful stress during de-acclimation, even when air temperature does not fall far below 0 °C (Frederiks et al., 2015). Higher thresholds therefore capture a broader spectrum of moderate cold events and produce larger cumulative losses. However, because this study focuses primarily on the spatiotemporal evolution of LSF risk, the key conclusions are less dependent on threshold choice than the absolute values are: the major regional gradients, stage-specific contrasts, and future redistribution of hotspots remained broadly consistent across thresholds.

Uncertainty also originates from the representation of future climate forcing. Future simulations were driven by a single bias-corrected GFDL-ESM4 hourly temperature dataset because the event-identification framework required continuous hourly forcing to resolve consecutive cold hours, exposure duration, and cold degree hours. The resulting projections should therefore be interpreted as conditional on GFDL-ESM4 rather than as the full range of outcomes represented by the CMIP6 ensemble. Differences among climate models in cold-surge frequency, diurnal temperature variability, and intra-seasonal temperature fluctuations may alter reconstructed phenology and the timing and severity of LSF events (Ji et al., 2024; Cadiou and Yiou, 2025). Future applications should incorporate multiple hourly CMIP6 products or rigorously validated temporal downscaling of multi-model daily temperature projections.

Because future LSF risk is strongly mediated by the timing of frost-sensitive developmental stages, uncertainty in phenological reconstruction represents an important consideration. Phenology-related uncertainty arises from using fixed regional mean sowing dates. Although these dates provide a physiologically relevant starting point for development accumulation, they do not capture within-region spatial variability, interannual management changes, or future sowing-date adaptation. The reconstructed phenological changes therefore primarily represent climate-driven development under fixed regional sowing-date assumptions, and uncertainty in stage timing propagates into the LSF-exposure and yield-reduction estimates.

An associated uncertainty concerns the extrapolation of the phenology model beyond the historical climate domain. In the warmest-10% holdout, RMSEs were 6.56 d for jointing and 5.19 d for heading, compared with 6.16 and 4.83 d under station-grouped cross-validation, while mean biases remained close to zero (Table S5). This modest decrease in accuracy supports model transferability toward the warmer end of the historical range but does not validate responses to conditions beyond it. Because late-century climates, particularly under SSP5–8.5, may exceed this range, the projected phenology and downstream yield reductions should be interpreted as conditional extrapolations rather than fully validated future responses.

Beyond uncertainty in when frost-sensitive stages occur, uncertainty also remains in translating frost exposure into yield reduction. The use of controlled freezing experiments is a strength of this study because it anchors the yield-reduction model in observed physiological responses. However, actual field losses are also influenced by canopy energy balance, soil moisture, snow cover, management, and microclimatic buffering. Screen-level 2 m air temperature does not necessarily equal canopy or tissue temperature, and this mismatch may either weaken or intensify frost injury depending on local conditions (Gusta and Wisniewski, 2013; Liu et al., 2020). Accordingly, this framework should be viewed as a mechanism-informed statistical approach rather than a fully process-based representation of wheat development and frost injury. Hybrid approaches that integrate interpretable machine learning with process-based crop models may improve robustness under future climate conditions and in out-of-sample applications (Ramesh and Kumaresan, 2025).

In addition, the LSF event-aggregation formulation introduces additional uncertainty. Although multiplicative aggregation provides a bounded estimate, cumulative yield-reduction magnitudes differed between the multiplicative and additive formulations, particularly at higher frost-identification thresholds, whereas the main stage- and

cultivar-related patterns remained consistent (Figs. S25–S27). Neither formulation explicitly represents recovery, compensatory growth, or interactions among repeated frost events; therefore, estimates for years with multiple LSF events should be interpreted cautiously.

Finally, uncertainty in crop-domain representation affects the spatial magnitude of regional yield-reduction estimates. Differences in spatial resolution, data type, and temporal coverage affected the retained grid cells and absolute regional yield-reduction estimates, particularly in fragmented MYS (Fig. 14; Figs. S28–S30). At the baseline threshold, however, all three datasets preserved the broad historical-to-future hotspot transition from MYS to HHS, while jointing-stage dominance and cultivar-tolerance effects remained consistent across datasets and thresholds. Notably, the 4 km-derived masks became temporally invariant after aggregation to 0.1°, providing a fixed-domain sensitivity test; their agreement with the primary 30 m analysis supports the robustness of the main conclusions to both dataset choice and historical domain treatment. The 30 m product was adopted for the main analysis because it directly maps winter wheat at fine spatial resolution. Because of its limited temporal coverage, historical changes may partly reflect changes in the mapped planting domain, whereas future projections represent yield-reduction risk within the fixed 2024 domain and do not account for future shifts in wheat cultivation.

These uncertainties also highlight the need for region-specific adaptation strategies. South Korean projections indicate that later-maturing cultivars may reduce spring-frost risk in the south, whereas greater frost tolerance is needed in central and northern regions (Kim et al., 2025). In early-sown Japanese spring wheat, ground rolling delayed spikelet initiation and jointing, illustrating a potential phenology-management option, although its applicability to winter wheat remains to be tested (Mizumoto et al., 2023).

Future work should extend this framework in three directions. One is to evaluate adaptive management scenarios, such as sowing-date adjustment, cultivar replacement, and changes in agronomic practice. A second is to incorporate multi-model climate ensembles and, where possible, canopy-scale temperature diagnostics. A third is to move toward multi-hazard assessment by considering frost together with drought and heat stress. Under continued warming, resilience in winter wheat systems will depend less on whether frost hazard disappears in an absolute sense than on whether sensitive crop stages can avoid persistent cold exposure during climatically unstable periods.

5. Conclusion

This study developed a phenology-constrained, event-based framework to assess LSF exposure and associated yield reductions across China's winter wheat belt by integrating controlled low-temperature experiments, CERES-Wheat-inspired phenology reconstruction, machine-learning-based yield-reduction modelling, and historical and future hourly temperature forcing. The results demonstrate that climate warming does not simply diminish LSF risk but reorganizes it by altering the temporal overlap between frost-sensitive developmental stages and episodic spring cold events. Historically, yield-reduction risk was concentrated mainly in HHS and MYS, with the highest mean losses occurring in MYS. For cold-sensitive cultivars, mean yield reduction across the jointing and booting stages reached 10.02% in MYS, compared with 4.55% in HHS and 2.21% in NS. Under future climate conditions, the principal hotspot shifted toward HHS, where mean yield reduction reached 6.38% under SSP2–4.5 and 6.49% under SSP5–8.5 for cold-sensitive cultivars. This redistribution reflected both climate-driven phenological advancement and changes in cold-event exposure within the sensitive developmental windows. Jointing-stage frost consistently dominated historical and future cumulative losses, whereas booting-stage contributions were generally small. Explicit representation of phenological change was critical for future risk assessment. Compared with simulations in which phenology was fixed at its historical climatology, dynamic phenology increased combined-stage yield

reduction by 5.76 percentage points under SSP2–4.5 and 6.35 percentage points under SSP5–8.5, with most of this increase attributable to the jointing stage. Cultivar cold tolerance provided substantial additional buffering, with mean combined-stage yield reduction in HHS under SSP5–8.5 declining from 6.49% for cold-sensitive cultivars to 2.75% for cold-tolerant cultivars. These findings indicate that future LSF risk is governed not only by changes in cold-event climatology but also by climate-driven shifts in crop development. Phenology-aware monitoring, region-specific deployment of cold-tolerant cultivars, and adaptation strategies that account for developmental timing are therefore important for improving the resilience of winter wheat production under continued climate warming.

CRediT authorship contribution statement

Kunhao Jiang: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Min Su:** Validation, Supervision, Data curation. **Fangfang Liu:** Software, Resources. **Xiaoqi Kang:** Software, Resources. **Xinyi Fan:** Visualization. **Bin Chen:** Visualization. **Yingnan Wei:** Resources. **Linchao Li:** Writing – review & editing, Resources. **Qiang Yu:** Writing – review & editing, Supervision. **Gang Zhao:** Writing – review & editing, Visualization, Methodology. **Genghong Wu:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

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.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 32501784), the Shaanxi Province Basic Research Program (Youth, Grant No. 2025JC-YBQN-237), the Institute of Hefei Artificial Intelligence Breeding Accelerator Co. Ltd Funding (Grant No. GS2025ZX008), and the Chinese Universities Scientific Fund (Grant No. 1090225027).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.agrformet.2026.111487](https://doi.org/10.1016/j.agrformet.2026.111487).

Data availability

Data will be made available on request.

References

- Alsafadi, K., Alatrach, B., Sammen, S.S., Cao, W., 2024. Prediction of daily leaf wetness duration using multi-step machine learning. *Comput. Electron. Agric.* 224, 109131. <https://doi.org/10.1016/j.compag.2024.109131>.
- Anandhi, A., Perumal, S., Gowda, P.H., Knapp, M., Hutchinson, S., Harrington, J., Rice, C.W., 2013. Long-term spatial and temporal trends in frost indices in Kansas, USA. *Clim. Change* 120 (1–2), 169–181. <https://doi.org/10.1007/s10584-013-0794-4>.
- Bai, H.Z., Xiao, D.P., Wang, B., Liu, D.L., Tang, J.Z., 2022. Simulation of wheat response to future climate change based on CMIP6 multi-model ensemble projections in the North China Plain. *Front. Plant Sci.* 13, 829580. <https://doi.org/10.3389/fpls.2022.829580>.
- Barlow, K.M., Christy, B.P., O'Leary, G.J., Riffkin, P.A., Nuttall, J.G., 2015. Simulating the impact of extreme heat and frost events on wheat crop production: a review. *Field Crops Res.* 171, 109–119. <https://doi.org/10.1016/j.fcr.2014.11.010>.
- Cadiou, C., Yiou, P., 2025. Intensity and dynamics of extreme cold spells of the 21st century in France from CMIP6 data. *Earth Syst. Dyn.* 16 (5), 1759–1778. <https://doi.org/10.5194/esd-16-1759-2025>.
- Crimp, S., Bakar, K.S., Kokic, P., Jin, H., Nicholls, N., Howden, M., 2015. Bayesian space-time model to analyse frost risk for agriculture in Southeast Australia. *Int. J. Climatol.* 35 (8), 2092–2108. <https://doi.org/10.1002/joc.4109>.
- Crimp, S.J., Zheng, B., Khimashia, N., Gobbett, D.L., Chapman, S., Howden, M., Nicholls, N., 2016. Recent changes in southern Australian frost occurrence: implications for wheat production risk. *Crop Pasture Sci.* 67 (8), 801–811. <https://doi.org/10.1071/CP16056>.
- Eccel, E., Rea, R., Caffarra, A., Crisci, A., 2009. Risk of spring frost to apple production under future climate scenarios: the role of phenological acclimation. *Int. J. Biometeorol.* 53 (3), 273–286. <https://doi.org/10.1007/s00484-009-0205-8>.
- Ewert, F., Rötter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E., van Ittersum, M.K., Janssen, S., Rivington, M., Semenov, M.A., Wallach, D., Porter, J. R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P. P., Bartošová, L., Asseng, S., 2015. Crop modelling for integrated assessment of risk to food production from climate change. *Environ. Model. Softw.* 72, 287–303. <https://doi.org/10.1016/j.envsoft.2014.12.003>.
- Feng, Z.Q., Tan, M.L., Juneng, L., Tye, M.R., Xia, L.L., Zhang, F., 2025. Effects of solar radiation modification on precipitation extremes in Southeast Asia: insights from the GeoMIP G6 experiments. *Adv. Clim. Chang. Res.* 16 (3), 591–605. <https://doi.org/10.1016/j.jaccr.2025.04.009>.
- Ferrante, A., Cullis, B.R., Smith, A.B., Able, J.A., 2021. A multi-environment trial analysis of frost susceptibility in wheat and barley under Australian frost-prone field conditions. *Front. Plant Sci.* 12, 722637. <https://doi.org/10.3389/fpls.2021.722637>.
- Fredericks, T.M., Christopher, J.T., Harvey, G.L., Sutherland, M.W., Borrell, A.K., 2012. Current and emerging screening methods to identify post-head-emergence frost adaptation in wheat and barley. *J. Exp. Bot.* 63 (15), 5405–5416. <https://doi.org/10.1093/jxb/ers215>.
- Fredericks, T.M., Christopher, J.T., Sutherland, M.W., Borrell, A.K., 2015. Post-head-emergence frost in wheat and barley: defining the problem, assessing the damage, and identifying resistance. *J. Exp. Bot.* 66 (12), 3487–3498. <https://doi.org/10.1093/jxb/erv088>.
- Fu, Y.Y., Dong, J., Shen, R.Q., Peng, Q.Y., Li, X.Q., Zheng, Y., Pan, B.H., Dong, J.W., Qiu, B.W., Huang, J.X., Huang, X.J., Yuan, W.P., 2026. A 30-m annual distribution dataset of major crops in China from 2001–2024. *Sci. Data* 13, 1074. <https://doi.org/10.1038/s41597-026-07370-5>.
- Fuller, M.P., Fuller, A.M., Kaniouras, S., Christophers, J., Fredericks, T., 2007. The freezing characteristics of wheat at ear emergence. *Eur. J. Agron.* 26 (4), 435–441. <https://doi.org/10.1016/j.eja.2007.01.001>.
- Gu, L., Hanson, P.J., Post, W.M., Kaiser, D.P., Yang, B., Nemani, R., Pallardy, S.G., Meyers, T., 2008. The 2007 eastern US spring freezes: increased cold damage in a warming world? *BioScience* 58 (3), 253–262. <https://doi.org/10.1641/B580311>.
- Gusta, L.V., Wisniewski, M., 2013. Understanding plant cold hardiness: an opinion. *Physiol. Plant.* 147 (1), 4–14. <https://doi.org/10.1111/j.1399-3054.2012.01611.x>.
- Han, L., Zhao, J.Y., Gao, Y.J., Gu, Z.L., 2022. Prediction and evaluation of spatial distributions of ozone and urban heat island using a machine learning modified land use regression method. *Sustain. Cities Soc.* 78, 103643. <https://doi.org/10.1016/j.scs.2021.103643>.
- Hauduc, H., Neumann, M.B., Muschalla, D., Gamerith, V., Gillot, S., Vanrolleghem, P.A., 2015. Efficiency criteria for environmental model quality assessment: a review and its application to wastewater treatment. *Environ. Model. Softw.* 68, 196–204. <https://doi.org/10.1016/j.envsoft.2015.02.004>.
- He, L., Asseng, S., Zhao, G., Wu, D.R., Yang, X.Y., Zhuang, W., Jin, N., Yu, Q., 2015. Impacts of recent climate warming, cultivar changes, and crop management on winter wheat phenology across the Loess Plateau of China. *Agric. For. Meteorol.* 200, 135–143. <https://doi.org/10.1016/j.agrformet.2014.09.011>.
- Ji, H.T., Xiao, L.J., Xia, Y.M., Song, H., Liu, B., Tang, L., Cao, W.X., Zhu, Y., Liu, L.L., 2017. Effects of jointing and booting low temperature stresses on grain yield and yield components in wheat. *Agric. For. Meteorol.* 243, 33–42. <https://doi.org/10.1016/j.agrformet.2017.04.016>.
- Ji, W.B., Osman, R., Ma, J.F., Jiang, X.T., Wang, L.Q., Xiao, L.J., Tang, L., Cao, W.X., Zhu, Y., Liu, B., 2025. Improving process-based modelling to simulate the effects of low-temperature stress during pre-anthesis on the quality characteristics of wheat grains. *Plant Cell Environ.* 48 (2), 1574–1593. <https://doi.org/10.1111/pce.15217>.
- Ji, Y.D., Fu, J.Y., Liu, B.J., Huang, Z.Q., Tan, X.J., 2024. Uncertainty separation of drought projection in the 21st century using SMILES and CMIP6. *J. Hydrol.* 628, 130497. <https://doi.org/10.1016/j.jhydrol.2023.130497>.
- Jin, S., 1996. *Wheat Ecology of China*. China Agriculture Science Press, Beijing.
- Kendall, M.G., Gibbons, J.D., 1990. *Rank Correlation Methods*, 5th ed. Edward Arnold, London.
- Kim, Y.U., Asseng, S., Webber, H., 2025. Spring frost risk assessment on winter wheat in South Korea. *Agric. For. Meteorol.* 366, 110484. <https://doi.org/10.1016/j.agrformet.2025.110484>.
- Kirchhof, E., Campos-Arguedas, F., Arias, N.S., Kovaleski, A.P., 2025. Thresholds for spring freeze: measuring risk to improve predictions in a warming world. *New Phytol.* 248 (2), 563–575. <https://doi.org/10.1111/nph.70453>.
- Li, M.S., Wang, D.L., Zhong, X.L., Wang, C.Y., Su, C.H., Zhao, P., Yan, X.Y., Watanabe, Y., Yoshida, H., 2005. Research progress on frost damage in winter wheat. *J. Nat. Disasters* 14 (4), 72–78. <https://doi.org/10.13577/j.jnd.2005.0412>.
- Li, X., Cai, J., Liu, F., Dai, T., Cao, W., Jiang, D., 2015a. Spring freeze effect on wheat yield is modulated by winter temperature fluctuations: evidence from meta-analysis and simulating experiment. *J. Agron. Crop Sci.* 201 (4), 288–300. <https://doi.org/10.1111/jac.12115>.
- Li, X.N., Cai, J., Liu, F.L., Zhou, Q., Dai, T.B., Cao, W.X., Jiang, D., 2015b. Wheat plants exposed to winter warming are more susceptible to low temperature stress in the spring. *Plant Growth Regul.* 77 (1), 11–19. <https://doi.org/10.1007/s10725-015-0029-y>.

- Li, X.N., Pu, H.C., Liu, F.L., Zhou, Q., Cai, J., Dai, T.B., Cao, W.X., Jiang, D., 2015c. Winter wheat photosynthesis and grain yield responses to spring freeze. *Agron. J.* 107 (3), 1002–1010. <https://doi.org/10.2134/agronj14.0460>.
- Lin, F.F., Li, C., Xu, B., Chen, J., Chen, A.H., Hassan, M.A., Liu, B.B., Xu, H., Chen, X., Sun, J.Q., 2023. Late spring cold reduces grain number at various spike positions by regulating spike growth and assimilate distribution in winter wheat. *Crop J.* 11 (4), 1272–1278. <https://doi.org/10.1016/j.cj.2023.03.014>.
- Lin, M., Hou, L.Z., Qi, Z.M., Wan, L., 2022. Impacts of climate change and human activities on vegetation NDVI in China's Mu Us Sandy Land during 2000–2019. *Ecol. Indic.* 142, 109164. <https://doi.org/10.1016/j.ecolind.2022.109164>.
- Liu, L.L., Xia, Y.M., Liu, B., Chang, C.Y., Xiao, L.J., Shen, J., Zhu, Y., 2020. Individual and combined effects of jointing and booting low-temperature stress on wheat yield. *Eur. J. Agron.* 113, 125989. <https://doi.org/10.1016/j.eja.2019.125989>.
- Liu, Z., Yang, P., Wu, W., Li, Z., You, L., 2016. Spatiotemporal changes in Chinese crop patterns over the past three decades. *Acta Geograph. Sinica* 71 (5), 840–851. <https://doi.org/10.11821/dlxb201605012>.
- Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.I., 2020. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* 2 (1), 56–67. <https://doi.org/10.1038/s42256-019-0138-9>.
- Luo, Y., Zhang, Z., Cao, J., Zhang, L., Zhang, J., Han, J., Tao, F., 2022. Accurately mapping global wheat production system using deep learning algorithms. *Int. J. Appl. Earth Obs. Geoinf.* 110, 102823. <https://doi.org/10.1016/j.jag.2022.102823>.
- Marcellos, H., Single, W., 1984. Frost injury in wheat ears after ear emergence. *Aust. J. Plant Physiol.* 11 (1), 7–15. <https://doi.org/10.1071/PP9840007>.
- McMaster, G.S., White, J.W., Hunt, L.A., Jamieson, P.D., Dhillon, S.S., Ortiz-Monasterio, J.L., 2008. Simulating the influence of vernalization, photoperiod, and optimum temperature on wheat development rates. *Ann. Bot.* 102, 561–569. <https://doi.org/10.1093/aob/mcn115>.
- Mizumoto, A., Tanio, M., Nakazono, K., Watanabe, K., Uchino, A., Azuma, T., 2023. Early ground rolling is highly effective in delaying spikelet initiation in early-sown spring wheat. *Plant Prod. Sci.* 26 (4), 402–410. <https://doi.org/10.1080/1343943X.2023.2251183>.
- National Bureau of Statistics of China, 2023. *China Statistical Yearbook 2023*. China Statistics Press, Beijing.
- Neeti, N., Eastman, J.R., 2011. A contextual Mann–Kendall approach for the assessment of trend significance in image time series. *Trans. GIS* 15 (5), 599–611. <https://doi.org/10.1111/j.1467-9671.2011.01280.x>.
- Nuttall, J.G., Perry, E.M., Delahunty, A.J., O'Leary, G.J., Barlow, K.M., Wallace, A.J., 2019. Frost response in wheat and early detection using proximal sensors. *J. Agron. Crop Sci.* 205 (2), 220–234. <https://doi.org/10.1111/jac.12319>.
- O'Neill, B.C., Tebaldi, C., van Vuuren, D.P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.F., Lowe, J., 2016. The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* 9 (9), 3461–3482. <https://doi.org/10.5194/gmd-9-3461-2016>.
- Olsen, A.K.B., Persson, T., de Wit, A., Nkurunziza, L., Sindhoj, E., Eckersten, H., 2018. Estimating winter survival of winter wheat by simulations of plant frost tolerance. *J. Agron. Crop Sci.* 204 (1), 62–73. <https://doi.org/10.1111/jac.12238>.
- Ramesh, V., Kumaresan, P., 2025. Stacked ensemble model for accurate crop yield prediction using machine learning techniques. *Environ. Res. Commun.* 7 (3), 035006. <https://doi.org/10.1088/2515-7620/adb9c0>.
- Ren, S.L., Qin, Q.M., Ren, H.Z., 2019. Contrasting wheat phenological responses to climate change at global scale. *Sci. Total Environ.* 665, 620–631. <https://doi.org/10.1016/j.scitotenv.2019.01.394>.
- Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuarema, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Streffer, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob. Environ. Change* 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>.
- Richetti, J., Sadras, V.O., He, D., Leske, B., Hu, P.C., Beletse, Y., Cossani, C.M., Nguyen, H., Zheng, B.Y., Deery, D.M., Dreccer, M.F., Whish, J., Lilley, J., 2025. Challenges in modelling the impact of frost and heat stress on the yield of cool-season annual grain crops. *Front. Plant Sci.* 16, 1613432. <https://doi.org/10.3389/fpls.2025.1613432>.
- Saeidi, M., Eliasi, P., Abdoly, M., Sasani, S., 2012. Freezing tolerance of wheat cultivars at the early growing season after winter. *Afr. J. Biotechnol.* 11 (17), 4045–4052. <https://doi.org/10.5897/AJB11.3266>.
- Shimono, H., 2011. Earlier rice phenology as a result of climate change can increase the risk of cold damage during reproductive growth in northern Japan. *Agric. Ecosyst. Environ.* 144 (1), 201–207. <https://doi.org/10.1016/j.agee.2011.08.006>.
- Soualiou, S., Duan, F.Y., Li, X., Zhou, W.B., 2022. Crop production under cold stress: an understanding of plant responses, acclimation processes, and management strategies. *Plant Physiol. Biochem.* 190, 47–61. <https://doi.org/10.1016/j.plaphy.2022.08.024>.
- Stone, R., Nicholls, N., Hammer, G., 1996. Frost in northeast Australia: trends and influences of phases of the Southern Oscillation. *J. Clim.* 9 (8), 1896–1909. [https://doi.org/10.1175/1520-0442\(1996\)009<1896:FINATA>2.0.CO;2](https://doi.org/10.1175/1520-0442(1996)009<1896:FINATA>2.0.CO;2).
- Sutka, J., 1994. Genetic control of frost tolerance in wheat (*Triticum aestivum* L.). *Euphytica* 77 (3), 277–282. <https://doi.org/10.1007/BF02262642>.
- Tao, F., Zhang, L., Zhang, Z., et al., 2022. Climate warming outweighed agricultural managements in affecting wheat phenology across China during 1981–2018. *Agric. For. Meteorol.* 316, 108865. <https://doi.org/10.1016/j.agrformet.2022.108865>.
- Tao, F., Zhang, S., Zhang, Z., 2012. Spatiotemporal changes of wheat phenology in China under the effects of temperature, day length and cultivar thermal characteristics. *Eur. J. Agron.* 43, 201–212. <https://doi.org/10.1016/j.eja.2012.07.005>.
- Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Zalud, Z., Semenov, M.A., 2014. Adverse weather conditions for European wheat production will become more frequent with climate change. *Nat. Clim. Change* 4 (7), 637–643. <https://doi.org/10.1038/nclimate2242>.
- Wang, S., Chen, J., Rao, Y.H., Liu, L.C., Wang, W.Q., Dong, Q., 2020. Response of winter wheat to spring frost from a remote sensing perspective: damage estimation and influential factors. *ISPRS J. Photogramm. Remote Sens.* 168, 221–235. <https://doi.org/10.1016/j.isprsjprs.2020.08.014>.
- Wang, Z.B., Chen, J., Tong, W.J., Xu, C.C., Chen, F., 2018. Impacts of climate change and varietal replacement on winter wheat phenology in the North China Plain. *Int. J. Plant Prod.* 12 (4), 251–263. <https://doi.org/10.1007/s42106-018-0024-0>.
- Wen, Y., Chen, T., Li, X., Bai, T., Yao, K., Zhong, L., Chen, H., Liu, M., Huang, X., Liang, S., Miao, S., Huang, J., 2026. Mapping 20-years winter wheat dynamics in global primary planting areas using Gaussian mixture models with adaptive thresholds. *Earth Syst. Sci. Data Discuss.* <https://doi.org/10.5194/essd-2026-347>.
- Whaley, J.M., Kirby, E.J.M., Spink, J.H., Foulkes, M.J., Sparkes, D.L., 2004. Frost damage to winter wheat in the UK: the effect of plant population density. *Eur. J. Agron.* 21 (1), 105–115. [https://doi.org/10.1016/S1161-0301\(03\)00090-X](https://doi.org/10.1016/S1161-0301(03)00090-X).
- Xiao, K., Sun, Y., Wu, W., Zhou, X.W., Zhang, Z.C., Lai, Q.Y., Huang, C., Xiong, Z.H., Xin, Q.C., 2025. Quantifying the contribution of triple compound extreme events to global yield loss of major staple crops from 1982 to 2016. *J. Integr. Agric.* 24 (10), 4078–4099. <https://doi.org/10.1016/j.jia.2025.04.038>.
- Xiao, L.J., Liu, L.L., Asseng, S., Xia, Y.M., Tang, L., Liu, B., Cao, W.X., Zhu, Y., 2018. Estimating spring frost and its impact on yield across winter wheat in China. *Agric. For. Meteorol.* 260–261, 154–164. <https://doi.org/10.1016/j.agrformet.2018.06.006>.
- Xie, L.L., Li, Y., Zhang, Z.Y., Siddique, K.H.M., Song, X.Y., 2025. Exploring the combined effects of drought and drought–flood abrupt alternation on vegetation using an interpretable machine learning model and R-vine copula function. *Agric. For. Meteorol.* 370, 110568. <https://doi.org/10.1016/j.agrformet.2025.110568>.
- Xu, H., Wu, Z.C., Xu, B., Sun, D.Y., Hassan, M.A., Cai, H.M., Wu, Y., Yu, M., Chen, A.H., Li, J.C., 2022. Optimized phosphorus application alleviates adverse effects of short-term low-temperature stress in winter wheat by enhancing photosynthesis and improved accumulation and partitioning of dry matter. *Agronomy* 12 (7), 1700. <https://doi.org/10.3390/agronomy12071700>.
- Yan, S.Z., Wang, C.L., Ran, X.Z., Wang, Z.T., Xiao, J.H., Li, Y.L., 2002. The frequency of late frost injury and its preventing method in wheat planted areas in Huanghuai region. *Henan Meteorol.* 10 (4), 40–41. <https://doi.org/10.3969/j.issn.1673-7148.2002.04.023> (in Chinese).
- Yue, Y.J., Zhou, Y., Ye, X.Y., 2016. Assessing wheat frost risk with the support of GIS: an approach coupling a growing season meteorological index and a hybrid fuzzy neural network model. *Sustainability* 8 (12), 1308. <https://doi.org/10.3390/su8121308>.
- Zhang, Q.J., Wu, D.L., Gao, J., 2025. Variation of winter wheat phenology dataset in Huang Huai Hai Plain of China from 1981 to 2021. *Sci. Data* 12 (1), 1203. <https://doi.org/10.1038/s41597-025-05368-Z>.
- Zhang, Y., Cai, H.M., Liu, L.Z., Xu, H., Chen, X., Li, J.C., 2023. Screening of varieties resistant to late-spring coldness in wheat and effects of late-spring coldness on the ultrastructure of wheat cells. *Agronomy* 13 (12), 3011. <https://doi.org/10.3390/agronomy13123011>.
- Zhang, Z., Luo, Y.C., Han, J.C., Xu, J.L., Tao, F.L., 2024. Estimating global wheat yields at 4 km resolution during 1982–2020 by a spatiotemporal transferable method. *Remote Sens.* 16 (13), 2342. <https://doi.org/10.3390/rs16132342>.
- Zheng, B.Y., Chapman, S.C., Christopher, J.T., Frederiks, T.M., Chenu, K., 2015. Frost trends and their estimated impact on yield in the Australian wheatbelt. *J. Exp. Bot.* 66 (12), 3611–3623. <https://doi.org/10.1093/jxb/erv163>.
- Zheng, D.X., Yang, X.G., Minguez, M.I., Mu, C.Y., He, Q., Wu, X., 2018. Effect of freezing temperature and duration on winter survival and grain yield of winter wheat. *Agric. For. Meteorol.* 260–261, 1–8. <https://doi.org/10.1016/j.agrformet.2018.05.011>.
- Zhong, X., Mei, X., Li, Y., Yoshida, H., Zhao, P., Wang, X., Han, L., Hu, X., Huang, S., Huang, J., Sun, Z., 2008. Changes in frost resistance of wheat young ears with development during the jointing stage. *J. Agron. Crop Sci.* 194 (5), 343–349. <https://doi.org/10.1111/j.1439-037X.2008.00320.x>.
- Zhong, X.L., Wang, D.L., Li, Y.Z., Zhao, P., Yan, X.Y., Sun, Z.F., 2007. Risk assessment of frost damage after jointing stage of wheat in the Huang–Huai wheat region. *J. Appl. Meteorol. Sci.* 18 (1), 102–107. <https://doi.org/10.11898/1001-7313.20070118>.
- Zohner, C.M., Mo, L.D., Renner, S.S., Svenning, J.C., Vitasse, Y., Benito, B.M., Ordóñez, A., Baumgarten, F., Bastin, J.F., Sebald, V., Reich, P.B., Liang, J.J., Nabuurs, G.J., de-Miguel, S., Alberti, G., Antón-Fernández, C., Balazy, R., Brändli, U. B., Chen, H.Y.H., Chisholm, C., Cienciala, E., Dayanandan, S., Fayle, T.M., Frizzera, L., Gianelle, D., Jagodzinski, A.M., Jaroszewicz, B., Jucker, T., Kepfer-Rojas, S., Khan, M.L., Kim, H.S., Korjus, H., Johannsen, V.K., Laarmann, D., Lang, M., Zawila-Niedzwiecki, T., Niklaus, P.A., Paquette, A., Pretzsch, H., Saikia, P., Schall, P., Seben, V., Svoboda, M., Tikhonova, E., Viana, H., Zhang, C.Y., Zhao, X.H., Crowther, T.W., 2020. Late-spring frost risk between 1959 and 2017 decreased in North America but increased in Europe and Asia. *Proc. Natl. Acad. Sci. U.S.A.* 117 (22), 12192–12200. <https://doi.org/10.1073/pnas.1920816117>.