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# An integrated framework for predicting the risk of experiencing temperature conditions that may trigger late-maturity alpha-amylase in wheat across Australia

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**Abstract.** Late-maturity alpha-amylase (LMA) is a key concern for Australia's wheat industry because affected grain may not meet receival standards or market specifications, resulting in significant economic losses for producers and industry. The risk of LMA incidence across Australia's wheatbelt is not well understood; therefore, a predictive model was developed to help to characterise likely LMA incidence. Preliminary development work is presented here based on diagnostic simulations for estimating the likelihood of experiencing environmental conditions similar to a potential triggering criterion currently used to phenotype wheat lines in a semi-controlled environment. Simulation inputs included crop phenology and long-term weather data (1901–2016) for >1750 stations across Australia's wheatbelt. Frequency estimates for the likelihood of target conditions on a yearly basis were derived from scenarios using either: (*i*) weather-driven sowing dates each year and three reference maturity types, mimicking traditional cropping practices; or (*ii*) monthly fixed sowing dates for each year. Putative-risk 'footprint' maps were then generated at regional shire scale to highlight regions with a low (<33%), moderate (33–66%) or high (>66%) likelihood of experiencing temperatures similar to a cool-shock regime occurring in the field. Results suggested low risks for wheat regions across Queensland and relatively low risks for most regions across New South Wales, except for earlier planting with quick-maturing varieties. However, for fixed sowing dates of 1 May and 1 June and varying maturity types, the combined footprints for moderate-risk and high-risk categories ranged from 34% to 99% of the broad wheat region for South Australia, from 12% to 97% for Victoria, and from 9% to 59% for Western Australia. A further research component aims to conduct a field validation to improve quantification of the range of LMA triggering conditions; this would improve the predictive LMA framework and could assist industry with future decision-making based on a quantifiable LMA field risk.

**Additional keywords:** crop modelling, decision support, environmental modelling, Oz-Wheat, risk management, wheat quality.

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## Introduction

Late-maturity alpha-amylase (LMA) is a grain-quality defect of major concern to Australia's wheat industry. Its occurrence is difficult to predict and incidence can result in a low falling number, similar to the effect of pre-harvest sprouting (Mares and Mrva 2014). A low falling number due to pre-harvest sprouting has long been associated with poor end-product quality and marketability (Bingham and Whitmore 1966; Edwards *et al.* 1989). Although this may not be the case for LMA (Newberry *et al.* 2018), the falling number test is unable to distinguish LMA from pre-harvest sprouting, and irrespective, a sample with low falling number does not meet receival standards or market specifications. Consequently, a low falling number measured at receival can result in price downgrades from milling quality to feed grade at a substantial financial loss to the producer.

Maintaining Australia's reputation for shipping high-quality milling grain is a critical industry issue, so the risks of LMA incidence must be managed. Current receival standards are guided by a strict classification system that requires LMA screening (Wheat Quality Australia 2015). In addition, lack of acceptance of established yet susceptible varieties, along with loss of advanced lines late in the breeding process, is a major impediment for industry. Kingwell and Carter (2014) have shown that estimated costs associated with LMA issues under current industry standards could translate to an annual loss of AU$18 million to producers, breeders and industry for Western Australia alone.

In order to mitigate LMA risk for the release of new milling-grade wheat varieties, Wheat Quality Australia (2015) requires breeders to utilise a screening protocol designed at the University of Adelaide as a means to support final classification assessments. Current LMA screening of breeding material based on a cool-temperature shock during later stages of grain development (Mrva and Mares 2001) ensures that standards for producing milling quality wheat are maintained. At present, neither the likely risk of LMA being expressed in the field nor the relative risk for different parts of the wheatbelt are well understood. Consequently, a predictive LMA model based on climatic conditions experienced in Australian wheat-growing regions could be of value to the wheat industry.

Previous research by Lunn *et al*. (1998) attempted to develop a predictive model for LMA based on meteorological conditions for the United Kingdom, with some guidance from earlier Australian research (Mares and Gale 1990; Mrva and Mares 1996*a*). That approach was not successful at the time because uncertainty in genotype × environment interactions for inducing LMA in a controlled environment confounded modelling with only weather data. For example, observations suggested that LMA could be induced following a transfer of plants between conditions that resulted in either a warm-temperature or cool-temperature shock (Lunn *et al*. 1998). LMA expression was also induced in a wheat variety (e.g. Pastiche) that had never expressed LMA under actual field conditions.

Results of more recent controlled-environment studies indicated that LMA expression was influenced by genotypic factors and could be readily triggered by exposure to a cool-temperature shock during the mid-grain-filling stage of development, occurring from about 25–35 days post-anthesis (Mrva and Mares 1996*a*, 1996*b*, 2001, 2002; Farrell and Kettlewell 2008; Mares and Mrva 2008, 2014; Barrero *et al*. 2013; Farrell *et al*. 2013). In phenological terms, this LMA sensitivity window extends from about 50% to 70% of the thermal time accumulated between flowering date and physical maturity.

Although previous experimental studies have identified some environmental conditions that can induce LMA expression, the range of conditions has yet to be verified in the field. This has resulted in questions for both wheat breeders and research scientists regarding the risk of LMA incidence and its management.

As such, the objective of this study was to develop an integrated predictive framework that can help to characterise the likely risk of LMA incidence across the wheatbelt. This study addresses two components for quantifying LMA risk. First is the development of a predictive model based on the capacity to diagnose the temperature regime(s) that might trigger LMA expression. Second is the connection of the LMA predictive model with wheat-production conditions across the Australian wheatbelt by linking it with existing spatial modelling capacity (Potgieter *et al*. 2006). Further work within this research project aims to verify potential LMA trigger conditions by comparing simulated results with measured data from field trials. A better understanding and validation of field conditions that may trigger LMA would enhance the LMA framework for simulating LMA incidence in the field. Such a predictive model would help industry to quantify actual LMA risk across the Australian wheatbelt and thus assist with decision-making in relation to managing LMA risk.

For our purposes, the predictive framework used long-term daily weather data from high-quality climate stations across the Australian wheatbelt. A biophysical crop model was applied to estimate time to flowering and timing of a cool-shock sensitivity window at grain development. The presence or absence of cool-shock conditions was evaluated within the window of LMA sensitivity. The methods used consider phenotypic and environmental criteria identified from prior research trials associated with Australian genotypes (Mrva and Mares 2001; Mares and Mrva 2008, 2014). The modelling approach currently focuses on temperature regimes alone; other genetic, biochemical and physiological factors are likely involved in LMA expression, but they are not addressed here.

The sensitivity window for a cool-shock-type expression is inherently linked to flowering time, which in turn is strongly controlled by wheat maturity type, seasonality of sowing date, and prevailing environmental conditions. For simulation modelling purposes, the presence of a cool shock within the sensitivity window was deemed to occur after two conditions were satisfied: first, a maximum daily temperature of 24°C needs to be exceeded; and second, within the remaining sensitivity window, a maximum daily temperature of <18°C must occur for at least any 3 days.

The frequency of years with the presence of a cool-shock regime was estimated for each shire across Australia's wheatbelt for two types of sowing scenarios: (*i*) weather-driven flexible sowing dates, which simulated the timing of sowing each year associated with traditional crop practices; and (*ii*) three fixed sowing dates, representative of early-, middle- and late-season planting dates within a preferred planting window for Australia's wheat-growing season.

Likelihood estimates were derived from the frequency analysis and transformed into putative-risk footprint maps to illustrate the likelihood of experiencing the cool-shock temperature conditions. An advantage of the predictive modelling framework is that it can be readily modified to diagnose a range of environmental conditions that may trigger LMA based on new information obtained through trials in semi-controlled environments or field experiments.

## Data and methods

### *Study area and long-term weather data*

The study region included the main wheat-producing shires of Australia, which extend across large regions of Queensland, New South Wales (NSW), Victoria, South Australia (SA) and Western Australia (WA) (Fig. 1). Digitised shire boundaries applicable for census purposes were obtained from the Australian Bureau of Statistics (http://www.abs.gov.au/).

Long-term weather data that included daily maximum and minimum air temperatures for 1901–2016 for Australia were

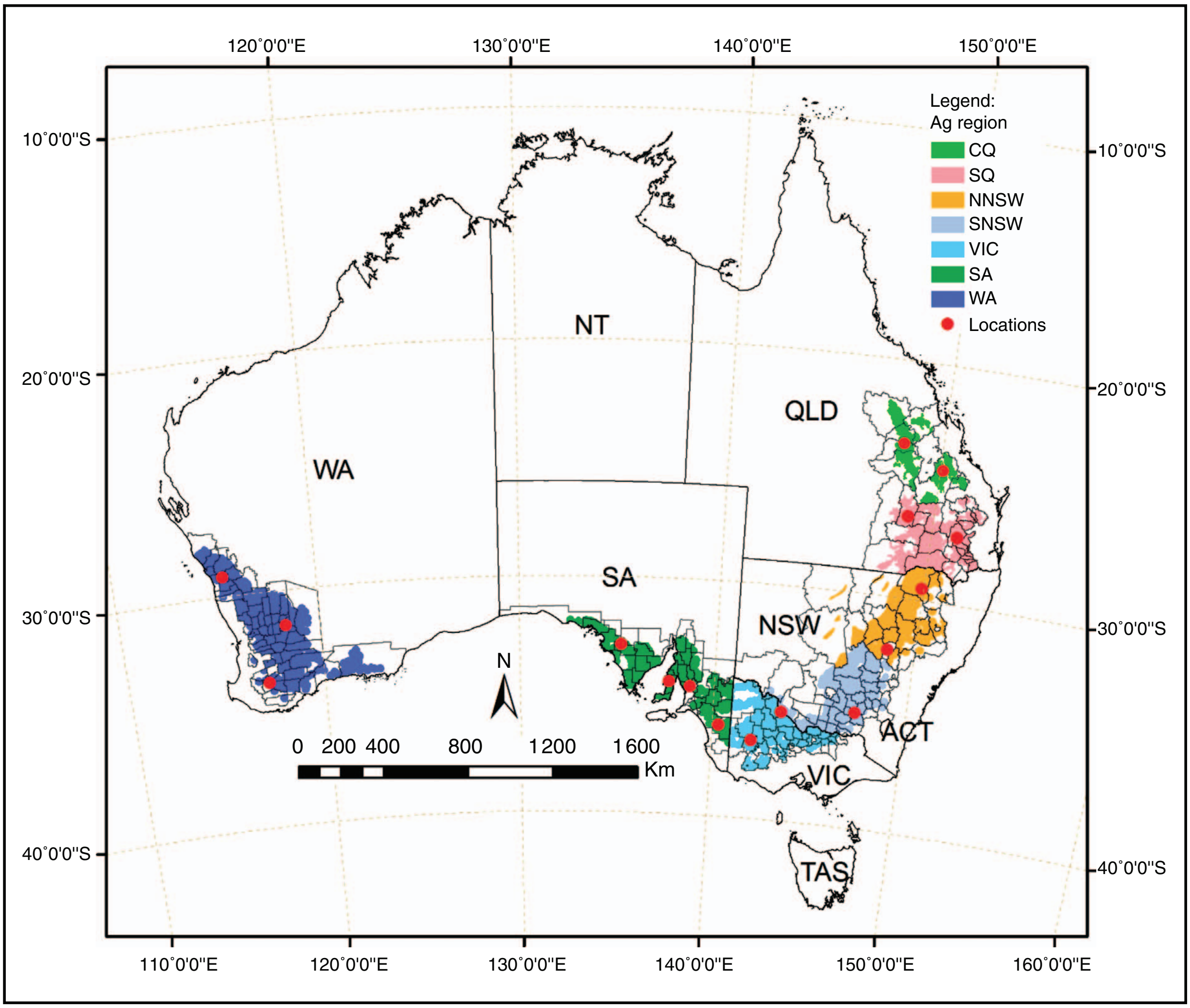


**Fig. 1.** Map of the Australian wheatbelt showing shire boundaries of wheat-producing shires (grey lines), broad winter-cropping area (all shading), distinct agro-climatic regions (different shading) and locations of reference sites for calibrating crop-phenology coefficients.

obtained from the SILO (Scientific Information for Land Owners, https://www.longpaddock.qld.gov.au/silo/) database for >1750 stations across the wheatbelt. SILO provides spatially and temporally consistent datasets that are applicable for research and information purposes. Where available, SILO daily weather data comprise observed records maintained by the Bureau of Meteorology (www.bom.gov.au/). Any missing data are then estimated by spatial interpolation (e.g. spline and kriging) with adjustments to account for the effects of elevation differences, as described by Jeffrey *et al*. (2001).

### *Cool-shock trigger conditions associated with LMA induction*

The preliminary model developed here used temperature conditions similar to the cool-shock regime established from semi-controlled experiments for expression of LMA in Australian genotypes (Mrva and Mares 2001, 2002; Mares and Mrva 2008, 2014). These conditions were selected because this approach is currently applied to phenotype wheat lines for LMA screening under wheat classification guidelines (Wheat Quality Australia 2015). Further, knowledge is lacking on the differences in the effects of consecutive cool events or separate cool events on LMA expression.

Based on the experimental research, the following triggering criteria were applied to simulate conditions under which LMA triggering due to a cool shock might occur in the field:

- The cool shock temperature conditions are evaluated within the LMA sensitivity window, which extends from 50% to 70% of the thermal time from flowering to physical maturity.
- At least one observed daily maximum temperature exceeding 24°C occurs within the LMA sensitivity window.
- After the initial high-temperature condition is satisfied, cool-shock conditions are deemed to exist when a daily maximum temperature ≤18°C occurs for any 3 days or more in the remaining sensitivity window.

The initial high-temperature and cool-shock conditions do not need to be consecutive as long they occur within the sensitivity window. A binary yes/no result can then be recorded depending on whether the environmental conditions satisfied the criteria. The method also allows for the duration of exposure to be computed as an accumulated thermal time. The current framework is flexible and can be adapted to simulate incidence risk associated with other criteria as knowledge of triggering conditions develop (e.g. continuous cool-temperature regime, as noted by Mares and Mrva 2014).

### *Simulating the presence of cool-shock conditions at shire scale*

A crop-yield simulation model for Australian wheat ('Oz-Wheat') was selected for the long-term modelling. The model was chosen in part because of the spatial scale at which Oz-Wheat operates (shire-scale to regional) and in part for its suitability for Australian conditions. For simulation purposes, Oz-Wheat was modified to diagnose a targeted temperature regime for cool-shock-type conditions from input weather data within the sensitivity window at mid-grain-filling (as described previously).

Model simulations were conducted at each climate station from 1901 to 2016 for two scenarios, flexible and fixed sowing, and the annual results were aggregated to shire scale by using the Thiessen polygon weighting procedure applied in the Oz-Wheat shire-yield prediction model (Potgieter *et al*. 2006).

The flexible-sowing scenario utilised a broad planting window that set the earliest and latest sowing dates for each region and considered three representative wheat maturity types (slow, medium and quick). In this scenario, planting dates between late April and early July were determined dynamically based on the timing of accumulated rainfall >15 mm over a consecutive 5-day period. Planting windows varied from 45 to 60 days across the wheatbelt and extended from late April (Queensland) and early May (southern states) through mid–late June. The representative maturity type planted depended on when the rainfall conditions were satisfied. The slow-maturing variety was sown if conditions were met during the first 3 weeks of the planting window; a quick-maturing variety if conditions were met during the last 3 weeks; and a medium-maturing variety if conditions were met during the middle weeks. This scenario considered variable planting dates similar to a traditional wheat-management practice over years across the wheatbelt and involved different sowing dates for every year in the analysis. This introduces significant variability in flowering dates and, hence, the likelihood for cool-shock conditions to be present or absent in the sensitivity window each year.

For the fixed-sowing scenario, a series of diagnostic simulations was applied to monthly fixed sowing dates to allow seasonal variations in temperature conditions to be examined without confounding by time of sowing. In this case, a combination of sowing times and maturity types included slow-maturing, medium-maturing and quick-maturing varieties planted on 1 May, a medium-maturing variety planted on 1 June, and a quick-maturing variety planted on 1 July each year. Sowing a range of maturity types for the 1 May planting reflects recent adjustments to cropping practices such as trialled in South Australia for improving wheat yields (Hunt *et al*. 2016).

Flowering date is an important variable to help in estimating the timing of the sensitivity window during mid-grain-filling when LMA might be triggered. Flowering dates for the three maturity types (slow, medium, quick) were simulated in Oz-Wheat based on a thermal-time target in degree-days. Thermal-time values were obtained from calibration runs generated with the Agricultural Production Systems Simulator (Holzworth *et al.* 2014); for this purpose, APSIM version 7.7 was applied at 16 reference sites across the wheatbelt (see Fig. 1) for a period of 24 years from 1991 to 2014. For each location, the planting window was divided into equal periods of early, middle and late sowing dates. The representative slow-maturing (Sunbri), medium-maturing (Cunningham) and quick-maturing (Hartog) varieties, each with given coefficients for photo-thermal control of phenology (available in APSIM documentation, https://www.apsim.info/), were sown on a fixed date at the midpoints of the respective planting periods, which varied regionally within each state (Table 1). Flowering thermal-time targets required for use in Oz-Wheat were derived from the results of the calibration runs at each reference location.

**Table 1. Locations of reference sites for APSIM calibration runs, their Bureau of Meteorology (BoM) station numbers, and sowing dates for reference varieties with slow, medium and quick maturity**

| State | Reference location | BoM station no. | Lat. | Long. | Sowing date for maturity type: Slow | Medium | Quick |
|---|---|---|---|---|---|---|---|
| Qld | Emerald | 35027 | –23.53 | 148.16 | 25 April | 15 May | 05 June |
| Qld | Banana | 39003 | –24.47 | 150.13 | 25 April | 15 May | 05 June |
| Qld | Dalby | 41023 | –27.18 | 151.26 | 11 May | 23 May | 05 June |
| Qld | Roma | 43091 | –26.55 | 148.78 | 11 May | 23 May | 05 June |
| NSW | Dubbo | 65012 | –32.24 | 148.61 | 11 May | 31 May | 20 June |
| NSW | Moree | 53027 | –29.50 | 149.90 | 11 May | 31 May | 20 June |
| NSW | Wagga | 73127 | –35.05 | 147.35 | 11 May | 23 May | 05 June |
| Vic. | Horsham | 79023 | –36.65 | 142.10 | 25 May | 07 June | 20 June |
| Vic. | Swan Hill | 77042 | –35.34 | 143.55 | 25 May | 07 June | 20 June |
| SA | Keith | 25507 | –36.10 | 140.36 | 11 May | 31 May | 20 June |
| SA | Maitland | 22008 | –34.37 | 137.67 | 11 May | 31 May | 20 June |
| SA | Minnipa | 18053 | –32.86 | 135.16 | 11 May | 31 May | 20 June |
| SA | Roseworthy | 23021 | –34.53 | 138.75 | 11 May | 31 May | 20 June |
| WA | Kojonup | 10582 | –33.84 | 117.15 | 11 May | 31 May | 20 June |
| WA | Merredin | 10092 | –31.48 | 118.28 | 11 May | 31 May | 20 June |
| WA | Mingenew | 8088 | –29.19 | 115.44 | 11 May | 31 May | 20 June |

### *Classification of putative risk and spatial extent*

The likelihood of experiencing temperature conditions similar to the cool-shock regime was estimated for each shire and then characterised more simply in terms of a putative risk. First, the frequency was computed of 'yes' cases for presence of cool-shock-type conditions during the sensitivity window for each shire. The frequency results were then mapped based on three broad putative risk categories: low, moderate or high.

Low risk was assigned where the frequency of cool-shock-type conditions appeared to be present for <33% of all simulated years. Moderate risk was assigned to a frequency range of 33–66% of all years, and high risk was assigned to a frequency >66%. In addition, the spatial extent of putative-risk footprints was quantified (percentage) based on the ratio of wheat-cropping area for each risk category (i.e. likelihood) relative to an estimate of the wheat-cropping area within each state. Analysis of Oz-Wheat output was done by using the R statistical computing language (R Foundation for Statistical Computing, Vienna), and generation of putative risk maps was done using ArcGIS version 10.5 software (Esri, Redlands, CA, USA).

### *Significance of flowering-date variability*

Flowering time as influenced by time of sowing, wheat maturity type, and prevailing weather is an important consideration for LMA risk modelling. Here, we considered the potential statistical significance of variations in flowering times across the wheatbelt. Analysis was done across shires within each state for the average flowering dates after planting on a fixed sowing date (1 May, 1 June and 1 July).

A Kruskal–Wallis test (Hollander and Wolfe 1973) was first applied to determine whether differences across rank sums of average flowering dates were significant. A Kolmogorov–Smirnov test (Wilks 1995) was then applied to distinguish significant differences among the distributions. Both tests were done using R.

### *Integrated model-simulation framework*

Figure 2 outlines the workflow for generating putative risk patterns at shire scale based on simulation results from Oz-Wheat and post-processing of the output data. External information related to crop phenology, management and cool-shock triggering was supplied to Oz-Wheat as look-up tables and hard-coded parameters. Additional input data included climate station identification and long-term daily rainfall and temperature weather data. Oz-Wheat was run at each station to determine whether cool-shock-type conditions within the sensitivity window occurred during each simulation year. Results were aggregated to shire scale across the wheatbelt based on areal weights computed for adjacent stations, using the Thiessen polygon method.

A frequency analysis was then applied to derive likelihood estimates for the percentage of years in which the target conditions appeared to be present within each shire, which was then classified into the three broad risk categories.

## Results

### *Putative risk of experiencing cool-shock conditions for flexible sowing dates*

Figure 3 shows a map of putative risk generated from analysis of results for the flexible sowing dates, a scenario similar to traditional weather-driven cropping practices. Although the map does not depict the actual risk, the results are indicative and show notable spatial patterns for the categories low (<33%), moderate (33–66%) and high (>66%) putative risk. Moderate and higher risks of experiencing cool-shock-type conditions

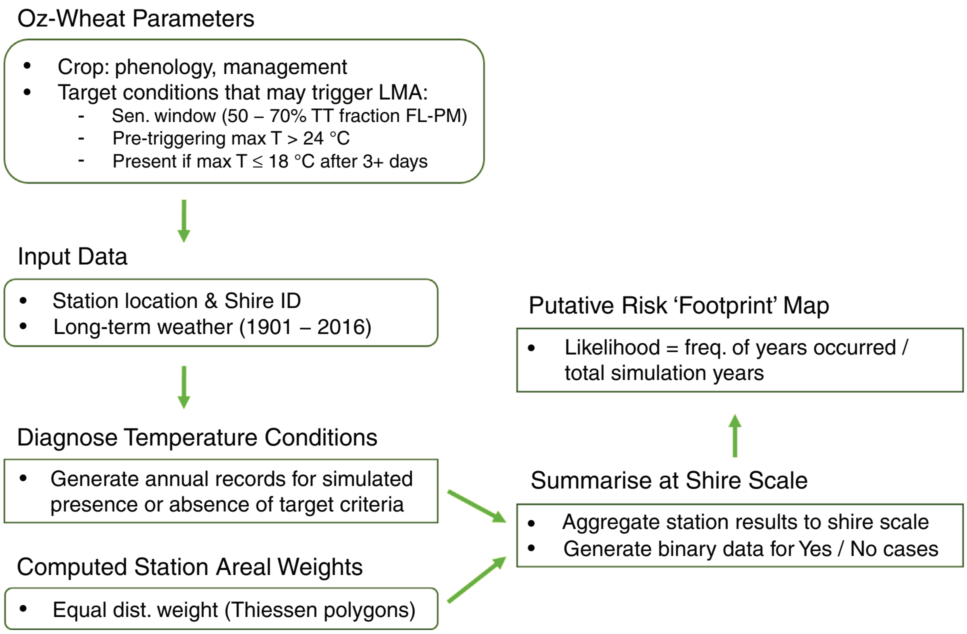


**Fig. 2.** Regional-scale analysis workflow applied for this study using Oz-Wheat modified for simulating one set of targeted temperature conditions similar to the cool-shock regime.

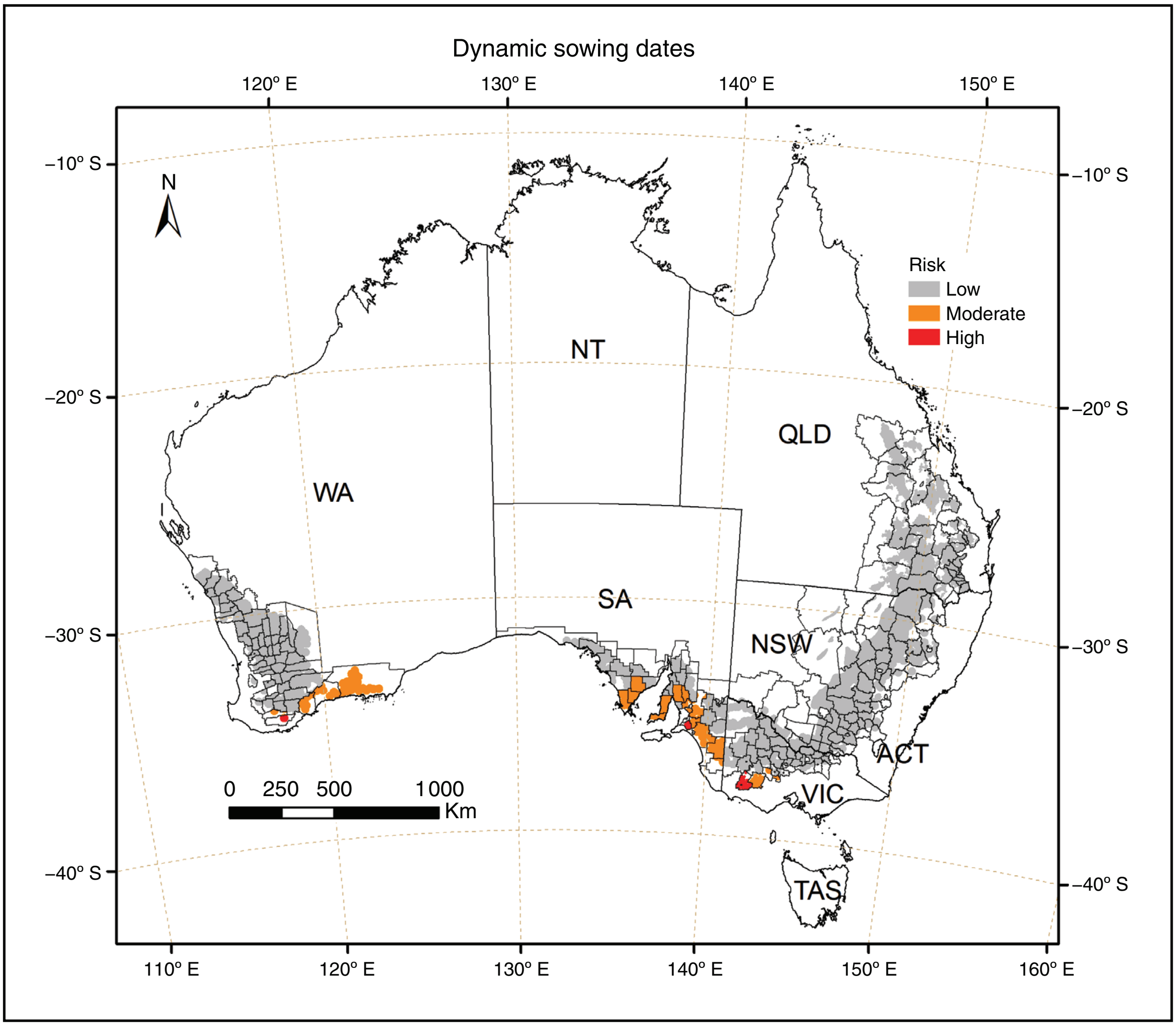


**Fig. 3.** Putative risks of experiencing temperatures of the cool-shock regime in the field for flexible sowing dates, based on weather data from 1901 to 2016.

were clustered along a narrow band of shires across the southern region of Australia. For Queensland and NSW, the risk was estimated to be quite low, with a computed mean across that wheatbelt of only 3% (Queensland <1% and NSW <5%).

Risks also appeared relatively low for 91% of the region in Victoria and for 85% in WA. A relatively small proportion of the wheatbelt was classed as high risk—less than a combined 6% of the wheat regions in WA, SA and Victoria. The moderate-risk class seemed to comprise a relatively small region of the wheatbelt in Victoria (5%) and slightly more in WA (15%), but the risk footprint was much more extensive in SA, impacting 40% of that region.

In general, the very broad spatial extent of the lower risk class might be expected because of the random variability introduced by different sowing dates each year, a range of maturity types, and inter-annual variations in prevailing weather. These results would be expected to vary for different sowing dates and maturity types, in particular for earlier sowing dates and early-maturing to medium-maturing varieties because cooler conditions are likely to be more frequent during the subsequent grain-filling period.

This possibility was examined based on results for scenarios of three fixed sowing dates, as detailed below.

## *Putative risk of experiencing cool-shock conditions for fixed sowing dates*

### *Variability of flowering day of year*

Environmental conditions are highly variable across the Australian wheatbelt. As such, the risk of flowering times (and subsequent grain-filling) coinciding with seasonally cooler temperatures is an important factor for LMA risk, and hence is an important consideration for predictive modelling. For illustrative purposes, the range of simulated flowering dates was analysed across the wheat-producing states.

Figure 4 summarises the average simulated flowering day of year among shires across each state for 116 years of

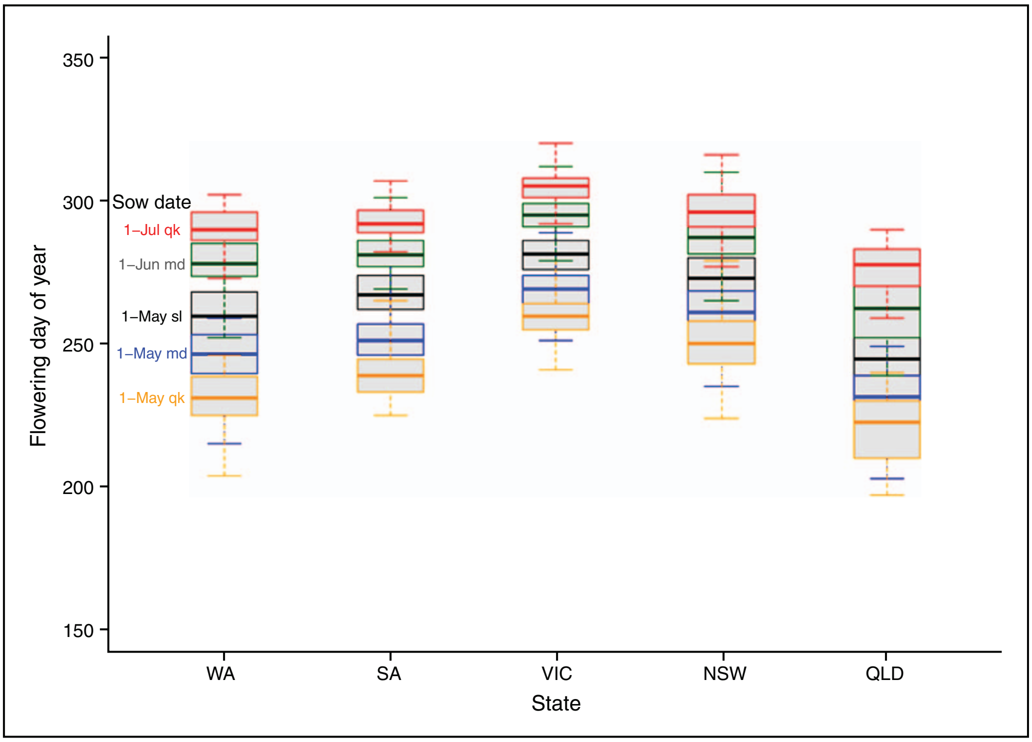


**Fig. 4.** Distributions of average simulated flowering dates for shires by state for 1 May, 1 June and 1 July sowing dates. Maturity types sown: sl, slow; md, medium; qk, quick. Boxplots show median flowering dates (bold lines inside boxes), 25th and 75th percentiles (upper and lower box limits), and data range (end whiskers).

simulations involving different fixed sowing dates and maturity types. Boxplots show the 25th and 75th percentiles (upper and lower box limits), median flowering day of year (bold line inside box) and data range (end whiskers). The results highlight the notable variability in distributions of average flowering dates for different sowing dates within each state, and across the wheatbelt. These variations reflect the large differences among regional climate conditions across Australia's range of latitudes.

Results of the Kruskal–Wallis rank sum test applied separately to each fixed sowing date showed differences among flowering dates to be highly significant ($P < 2.2e\text{-}16$) across the states. Further analysis with a Kolmogorov–Smirnov test show significant differences for all comparisons of distributions involving Queensland or Victoria ($P < 0.01$). Results were less significant for some (but not all) distributions of flowering dates for tests between SA and NSW, as well as between SA and WA ($P$ range >0.01–0.11).

### *Putative-risk footprints for fixed sowing dates*

Cool-shock-risk footprint maps were generated for various maturity types for 1 May, 1 June and 1 July fixed sowing dates based on analysis of the long-term weather data (1901–2016). Figure 5 shows the risk patterns for 1 May and 1 June fixed sowing dates and includes pie charts to show estimates of the wheat area (percentage) within each state assigned to the risk classes. Compared with the results for the flexible-sowing scenario, there was a large increase in both the magnitude and spatial extent of risk for many wheat-producing regions for the 1 May sowing date, except in Queensland. For example, the spatial extent of moderate-risk and high-risk classes increased notably from a slow-maturing to a medium-maturing variety. There was also a large increase in extent for the moderate-risk class from the medium-maturing to the quick-maturing variety, but the extent for the high-risk class increased only slightly.

Shires across Queensland tended to be characterised as very low risk, as indicated by a calculated mean risk of <5.5% for the quick-maturing variety planted on 1 May. Within NSW, 95–100% of the wheat region was also classed as low risk for the 1 May medium-maturing and slow-maturing scenarios; however, for the 1 May quick-maturing scenario, only 67% of the NSW wheat region was classed as low risk, with 31% classed as moderate risk and 2% as high risk.

The risks were much greater for wheat regions within SA, Victoria and WA for the 1 May sowing date and with a medium-maturing or quick-maturing wheat variety. For example, 58% and 49% of the wheat region in SA was classed as high risk for the quick-maturing and medium-maturing varieties, respectively. For the same scenarios in Victoria, 41% and 24% of the wheat region was also classed as high risk. Just 11% of the wheat region in southern WA was classed as high risk. However, risks for a slow-maturing variety sown on 1 May were notably reduced to <8%, 12% and 1% across Victoria, SA and WA, respectively.

Large areas of the wheat regions in Victoria, SA and WA were classed as moderate risk for the 1 May sowing date with all three maturity types. For quick-maturing, medium-maturing and slow-maturing varieties, respectively, this included 56%, 53% and

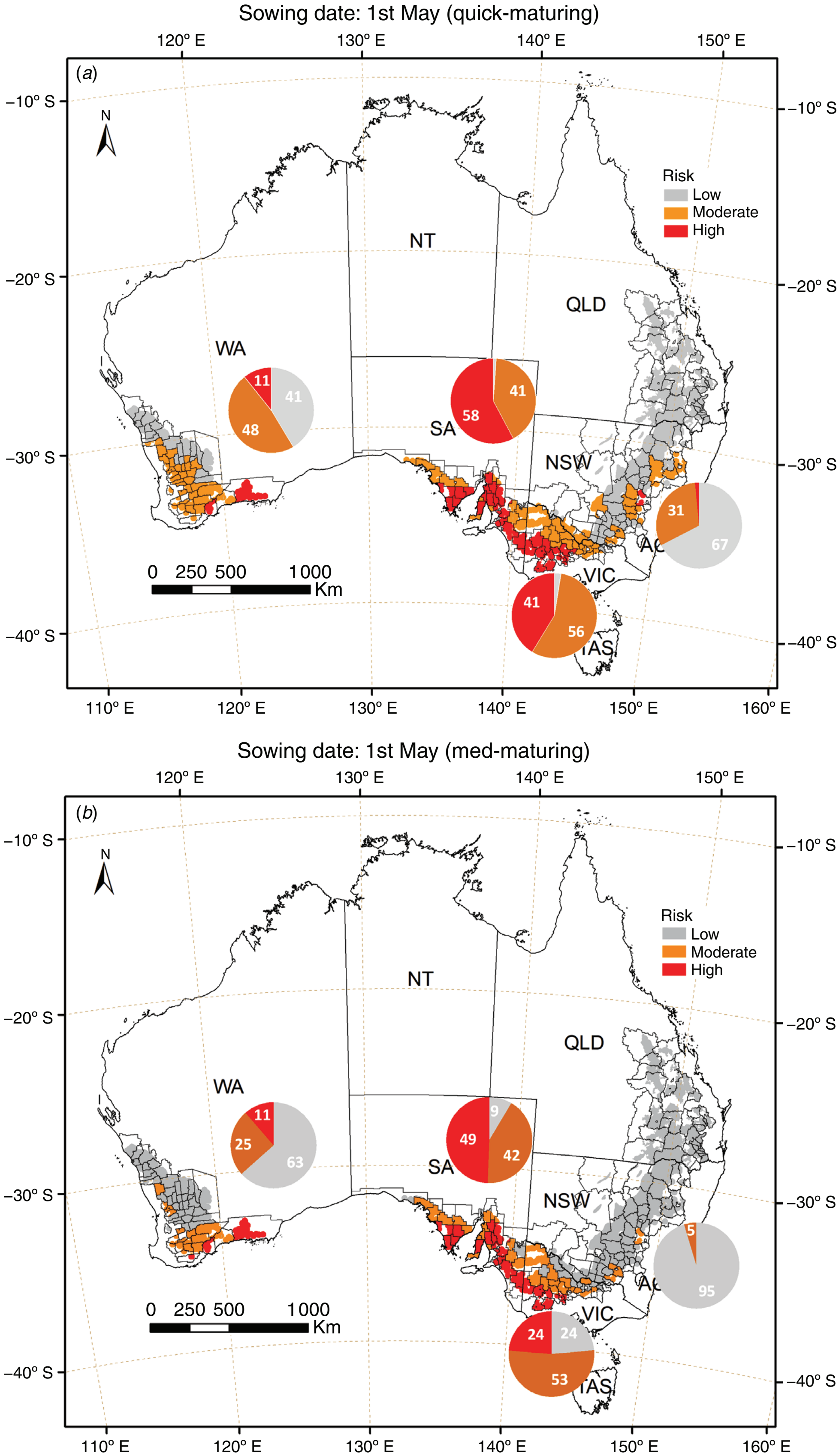


**Fig. 5.** Putative-risk footprint maps for experiencing temperatures of the cool-shock regime in the field for different scenarios of fixed sowing date and maturity type based on weather data from 1901 to 2016: (*a*) 1 May, quick-maturing; (*b*) 1 May, medium-maturing; (*c*) 1 May, slow-maturing; (*d*) 1 June, medium-maturing. Pie charts indicate percentage of land-use area associated with the broad risk classes. (*contd. on next page*.)

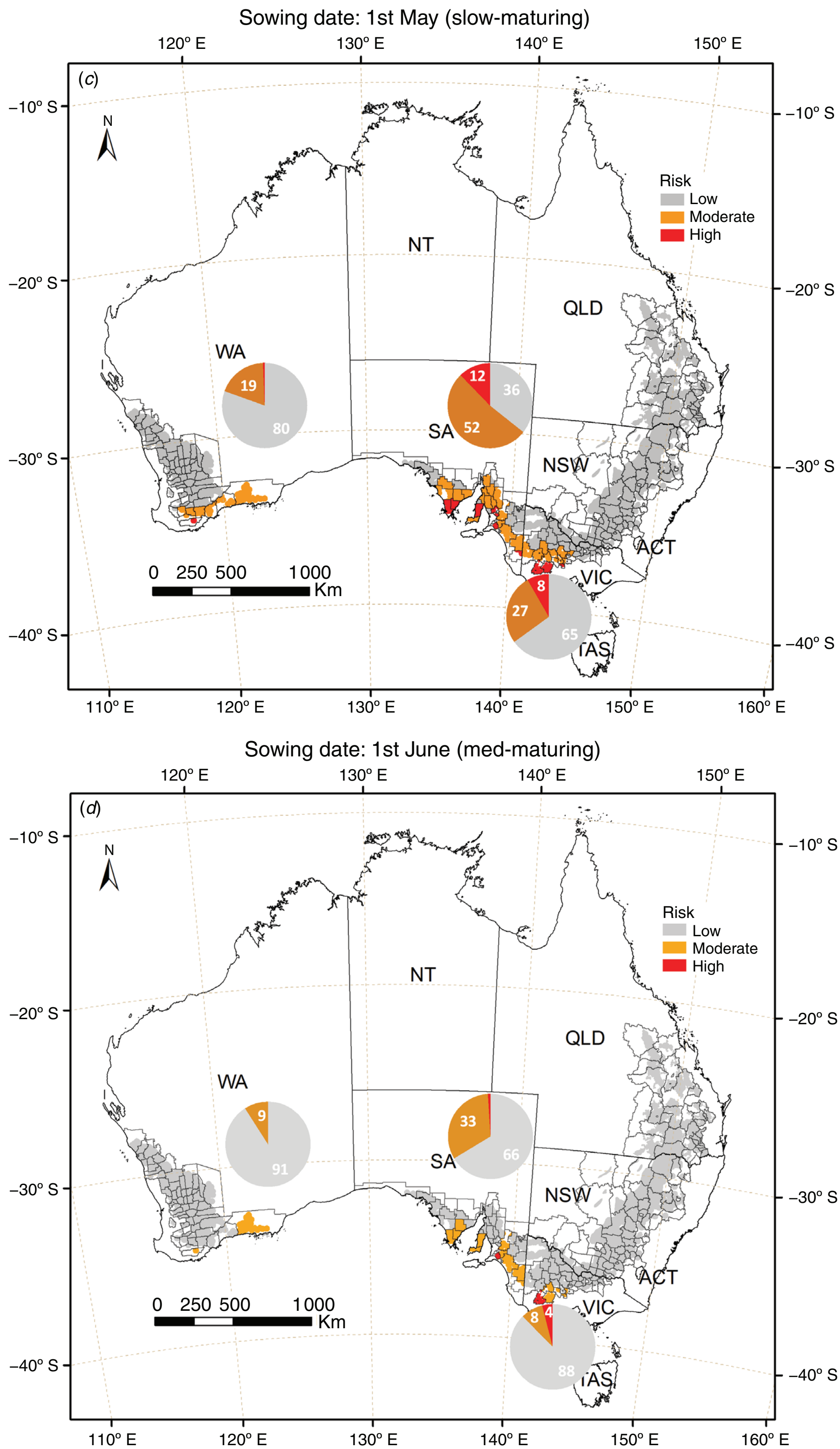


**Fig. 5.** (*Continued*).

27% of the wheat region in Victoria; 41%, 42% and 52% of the wheat region in SA; and 48%, 25% and 19% of the wheat region in WA. For a 1 June, medium-maturing scenario, 33% of the wheat region was classed as moderate risk across SA, and <10% across WA and Victoria. For all states, the risk was generally low for the 1 July, quick-maturing scenario (results not shown).

Further analysis was conducted for the fixed sowing dates and different maturity types to examine any changes in the putative-risk footprints due to variations in El Niño Southern Oscillation phases. Those results are not included as they provided no evidence for an effect of La Niña (cool) or El Niño (warm) conditions on the putative risks.

## Discussion

An LMA simulation framework was developed with guidance from previous research and applied to diagnose the presence of cool-shock conditions, similar to LMA screening, across the Australian wheatbelt. Other LMA-triggering conditions (e.g. cool period without a cool shock) and other genetic, biological and physiological factors are also likely involved in field expression (e.g. Mares and Mrva 2014). The putative-risk maps presented here are based on long-term climate information, and the likelihood estimates may vary for different climate periods, and in particular for more recent climate conditions.

Useful quantitative methods have been developed and demonstrated here for simulating LMA risk, which can be updated as knowledge on factors controlling LMA triggering advances. For this study, analysis was done for only one set of environmental conditions that may trigger LMA. Although such conditions can induce LMA under controlled screening, a further research component aims to verify conditions that may trigger expression in the field. A validated LMA-incidence model would allow for more precise quantification of actual LMA risk across the wheatbelt. Therefore, the putative risk maps shown here are not intended to be interpreted as actual LMA risk.

Despite these limitations, the results are a useful indicator of 'hotspot' regions where the relative risks of cool conditions are expected to be higher across the Australian wheatbelt. The results also show how risk patterns might change under different cropping strategies. For instance, the risk of cool-shock-type conditions in Queensland wheat regions was low regardless of cropping scenario. However, the wheat regions in southern NSW, Victoria, SA and WA were shown to carry more of the moderate and higher levels of risk for quick-maturing and medium-maturing varieties and earlier sowing dates.

Further, analysis of simulated flowering dates from this study showed that >50% of the average flowering dates (i.e. 25th–75th percentiles) occurred well before 7 September (day of year 250). Consequently, a much greater risk of cool-shock conditions would be expected owing to more frequent exposure to cooler daytime temperatures during late winter and early spring, in addition to cold fronts and frost events (Barlow *et al*. 2015). In order to reduce the risks further, planting of medium-maturing and quick-maturing varieties from mid to late June would likely be required.

However, there are many risk trade-offs to consider when designing optimal cropping strategies related to LMA management. Although later planting dates might reduce the risk of LMA, delaying flowering is known to reduce yield potential (Woodruff and Tonks 1983). Consideration of 'optimal flowering times' to maximise yield while reducing risks must take account of other damaging factors such as frost or heat stress at the time of grain development (Boer *et al*. 1993; Zheng *et al*. 2015; Flohr *et al*. 2017).

### *Implications for the Australian wheat industry*

Wheat Quality Australia classification guidelines currently address LMA risk through a strict policy to screen new milling quality varieties for the LMA defect. Here, we present an integrated framework for predicting risks of experiencing temperature conditions known to trigger LMA incidence in controlled-environment screening. This preliminary model requires enhancement and validation to be able to produce an actual LMA risk profile for field conditions; nonetheless, it demonstrates the value of applying such an integrated framework to quantify field risk in a spatial context as a means to inform industry.

An enhanced ability to characterise and integrate genotype × environment interactions that could influence LMA expression in the field would be invaluable for informing breeding systems and industry policy on LMA risk. With an improved and validated predictive model for LMA incidence in the field it would be possible to quantify LMA risk more precisely and would help industry to (*i*) examine and quantify the actual risk of LMA incidence at field scale, (*ii*) generate seasonal diagnostic data to identify 'hotspot' regions for likely LMA incidence, and (*iii*) improve breeding-systems management to support genetic gain for yield while managing LMA risk.

Further research is under way with the objective of verifying conditions that may result in LMA expression in the field.

## Conflicts of interest

The authors declare no conflicts of interest.

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