# Frequency analysis of environment types associated with late-maturity alpha-amylase for Australian wheat under current and future climates

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## Abstract

Late-Maturity Alpha-Amylase (LMA), a grain quality defect triggered by cool temperatures during grain filling, can be attributed to the genetic make-up of some wheat varieties. Moderate to high levels of LMA can cause low Falling Numbers, costly downgrades in wheat quality, and exclusion of high yielding breeder lines from classification into milling grades. A predictive LMA model was applied to long term (1901-2019) temperature data at 24 locations across the Australian wheat belt. Quantitative analysis showed a strong association between distinct environment types and predicted levels of LMA during grain development. A comparative analysis is presented for frequencies of environment types associated with LMA levels derived from historical temperature data and projected 2030 climate scenarios. The results suggest no notable impacts of the projected warmer climate by 2030 for LMA risks. Benefits of the current research include guiding breeders on LMA risks and more informed decisions on LMA management, with positive follow-on effects for producers.

## Keywords

Predictive modelling, crop improvement, field scale, wheat breeding

## Introduction

Phenotypic expression of the grain defect late-maturity alpha-amylase (LMA) in some wheat genotypes has become a crucial issue for Australia's wheat breeding programs, and international wheat industries. Under the current Australian industry guidelines, unacceptable levels of LMA expression in advanced breeding lines can result in failure to meet falling number standards. Susceptible wheat lines can be excluded from classification into milling grades and breeding material discarded. The current pass/no pass LMA screening system limits the potential for wheat breeding to achieve genetic gains in new high yielding lines, and thus limits benefits for industry and producers.

While LMA is attributed to a genetic defect, it is also a complex issue controlled through genetic by environment interactions. Recent research has advanced knowledge of the genetics, timing and environments influencing LMA induction and triggering during grain filling (Derkx and Mares, 2020). LMA can be induced by cool-shock treatments, or periods of suboptimal mild temperatures in the absence of a cool treatment. Such details can further inform the predictive LMA framework recently developed to aid the wheat industry in quantifying actual field risks of LMA across the Australian wheat belt (Armstrong et al. 2019).

Through that research an LMA field incidence model was designed and calibrated using data obtained from growth environment and field trials (Mares, unpublished), and updated following publication of more recent experimental trials (Derkx and Mares, 2020). In addition, a new field research investment by the Grains Research Development Corporation (GRDC) is underway to obtain observed data for field validation of the LMA incidence model. This will enhance knowledge of the range of actual conditions that may trigger LMA in the field. Given variable risks of experiencing the low temperature conditions that may trigger LMA (Armstrong et al, 2019) across the Australian wheat belt, it is logical to consider whether projected shifts to a warmer climate in the near future may aid in reducing the relative risks of LMA.

The current study aims to examine the question by, (1) applying cluster analysis across 24 locations to generate a classification of environment types (ETs) based on temperature variations for a historical baseline period 1901-2019, and (2) apply these ETs to 2030 climate scenarios and compare the frequencies of ETs relative to the baseline historical period.

## Data and Methods

*Study Region*

Twenty-four locations (Figure 1) were selected across the Australian wheat-belt with good spatial coverage and continuous long-term daily weather data available for 1901-2019 from the Scientific Information for Land Owners database (Jeffrey et al. 2001).

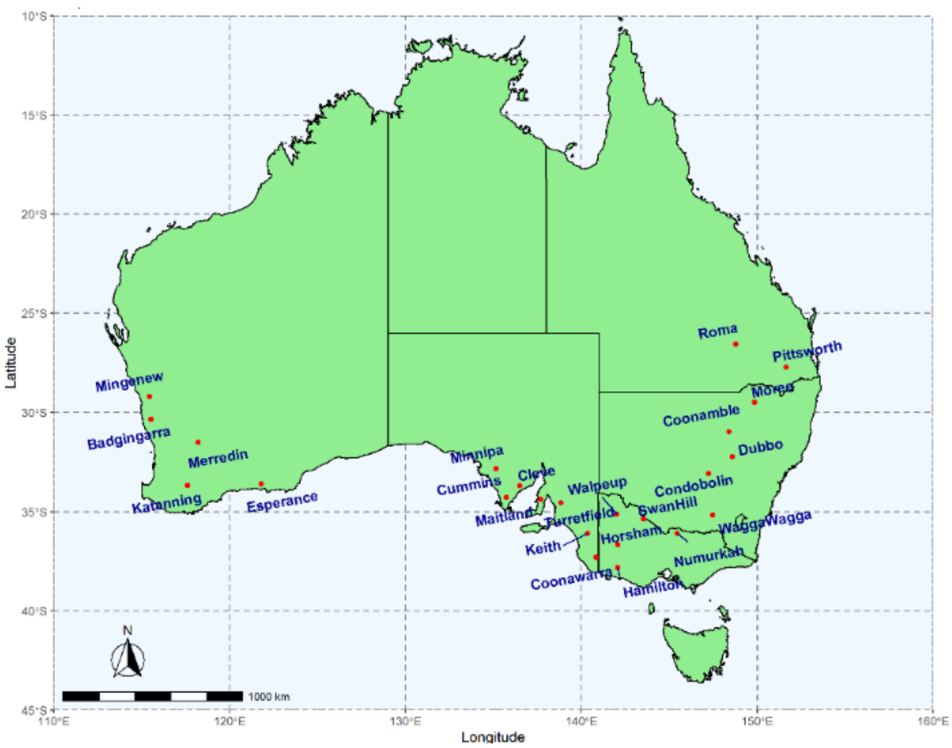


**Figure 1. Map of Australia with 24 locations selected for modelling simulations with SILO patched point station data (Jeffrey et al. 2001) for the years 1901-2019.**

*Historical and Future Climate*

SILO (Scientific Information for Land Owners) patched point station data (Jeffrey et al. 2001) with daily temperatures for baseline historical conditions from 1901-2019 was used as input for the model simulations. The daily weather data was also adjusted for future climate projected scenarios by 2030 for representative pathway concentrations RCP4.5 and RCP8.5; taken to reflect the full range of emission scenarios (e.g. Hassan et al. 2015). Adjusting the daily temperature data for 2030 climate conditions was done using similar methods as described by Hammer et al. (2020).

Projected monthly changes in daily maximum and average temperature by 2030 were derived for 24 locations (Figure 1) from analysis with 33 general circulation models (GCMs) for the reference period 1976-2005. Monthly changes in average temperature from August to November (i.e. associated with flowering and grain filling in winter wheat) were analysed to determine which GCM best represented the central tendency (median) of changes in average temperature for both emission scenarios among all 33 GCMs across the 24 locations. The predicted monthly changes in daily maximum temperature (used for LMA incidence modelling) from the selected model (ISPL-CM5A-MR) were used to adjust the historical weather at the 24 locations to reflect future daily climate.

*LMA Incidence Model Simulations*

A general framework for LMA modelling is described in Armstrong et al. (2019). In this case, the calibrated LMA field incidence model (unpublished, GRDC UQ00077) was applied to simulations for a reference wheat variety and a range of flowering dates; 15 Aug, 15 Sept, 15 Oct. The analysis focused on two key development periods, with Period 1 located from flowering to the start of the LMA sensitivity window, and Period 2 spans the LMA window considered to be the main period driving LMA incidence. Average daily maximum temperatures were extracted for these two periods and used for a cluster analysis of environment types (ETs). This allows for four general types of environment conditions to be examined, whereby both Period 1 and 2 can either be cooler or warmer, or Period 1 can be cooler and Period 2 warmer, or vice versa.

*Cluster Analysis of Environment Types (ETs)*
Cluster analysis was used to define four ETs using similar concepts to Chenu et al. (2011). In this case, a 'Partitioning around Medoids' (PAM) method was applied to over 8500 data points in favour of a CLARA (Clustering Large Applications) method, which is suited to subsampling across much larger datasets. Annual records derived from the 1901-2019 historical simulations were partitioned into four environment types. The partitioned cluster data was then reassigned into four ETs ranging from cooler (ET1) to warmer (ET4). Medoid values derived from the historical analysis were then applied to classify the annual results from simulations for the adjusted daily weather conditions (2030 climate) into four similar ETs.

*Frequency Analysis of ETs*
Separate frequencies were determined at the 24 locations for ETs derived for the historical baseline period and adjusted daily temperatures for 2030 for both the RCP4.5 and RCP8.5 emission scenarios. Frequencies were computed based on number of years each environment type occurred within the 119 years of simulations, and the relative differences were compared across the climate scenarios.

## Results
Figure 2 shows the distributions of temperature changes by 2030 resulting in the choice of ISPL-CM5A-MR as the GCM for analysis of future climate. A comparative analysis (not shown) highlighted the strong inverse association between predicted LMA scores and the four ETs, as expected given the maximum daily temperatures in the LMA window (i.e. Period 2) are evaluated to assess the likelihood, and relative magnitude, of LMA incidence. Hence, ET1 and ET2 are associated with enhanced LMA incidence, while ET3 and ET4 are generally associated with reduced to no LMA incidence.

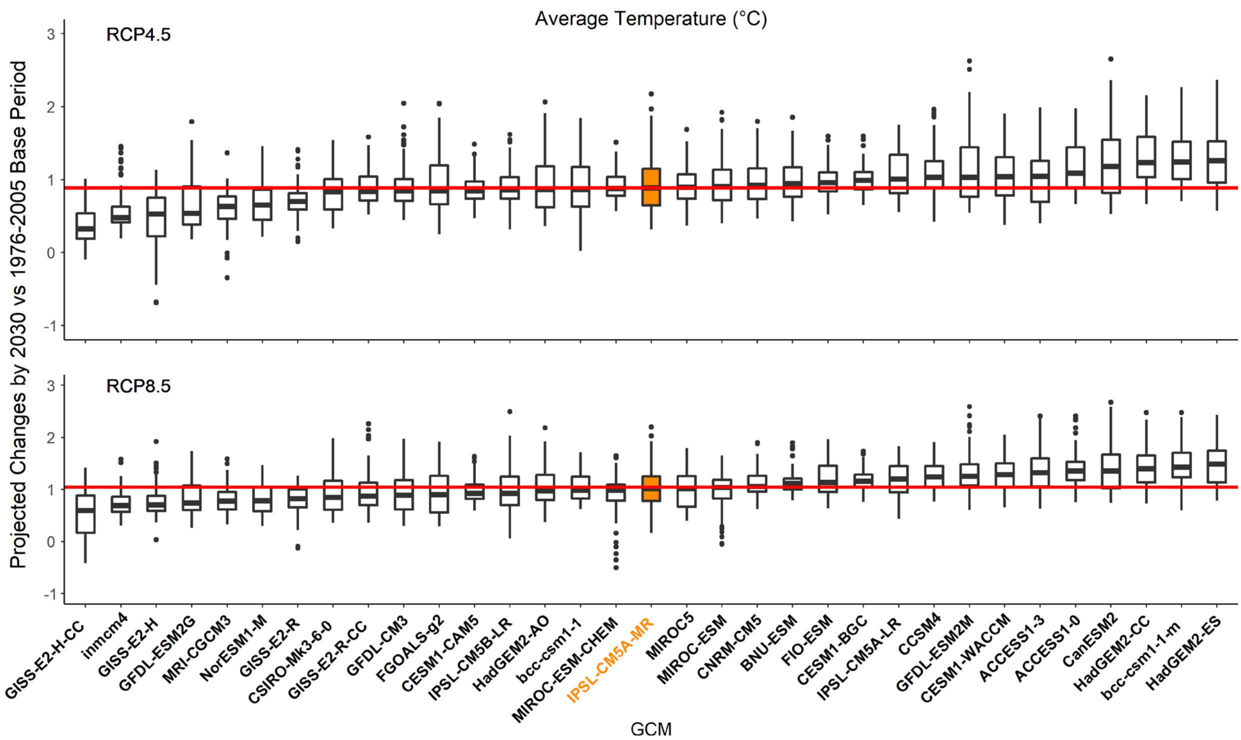


**Figure 2. Change in August through October mean temperature (◦C) by 2030 relative to 1976-2005 base period predicted by 33 GCMs, ordered by increasing shift in average temperature change. Red line is the median change across all models. Chosen GCM is highlighted.**

The relative frequencies of ETs across the 24 locations are shown by state in Figure 3. Frequency graphs for the baseline scenario show a large geographical spread of the relative risks of the four ETs, with expected higher risks of ET1 and ET2 in more southern locations. Interestingly, results for emission scenarios RCP4.5 and RCP8.5 indicated a relatively minor decrease in the frequency of ET1 and ET2 across the southern regions when compared to the baseline scenario; generally ~10 % or less. These results suggest the effects of global climate change may have less impact on the relative risks of LMA across the Australian wheat belt in the near future than might be anticipated.

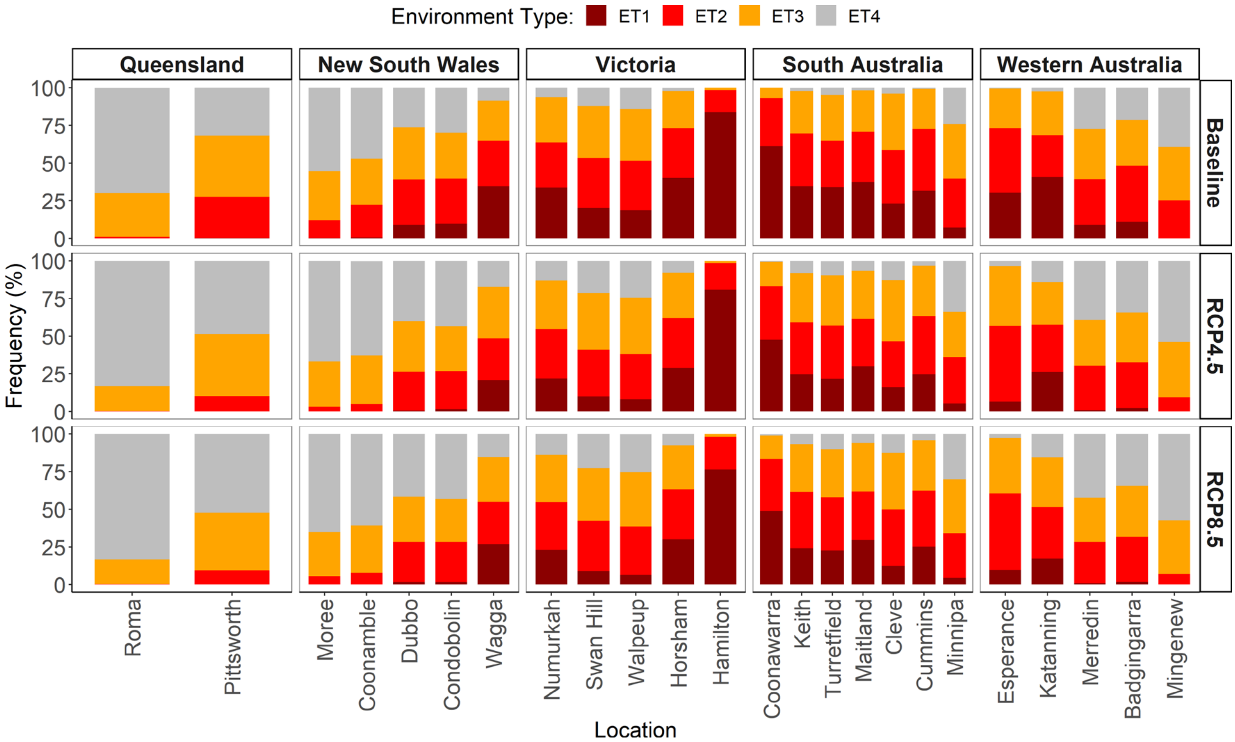


**Figure 3. Frequency (%) of four environment types across the 24 station locations for the baseline period (1901-2019) and projected changes by 2030 for greenhouse gas emission scenarios RCP4.5 and RCP8.5.**

## Conclusion

A calibrated LMA field incidence model was applied for simulations of multiple flowering dates at 24 locations across the Australian wheat belt. Analysis examined changes in the frequencies of the environment types, associated with likely incidence of LMA, for a baseline historical period and climate warming by 2030 for emission scenarios RCP4.5 and RCP8.5. Frequency results showed the variable geographic spread of risks of the cooler, more detrimental, ETs. However, the frequencies of cooler ETs between emission scenarios showed only minor variations despite reflecting a full range of global warming effects. The results suggest no notable impacts of projected warmer future climate for LMA risks in the near future.

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