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Strategic use of index-based frost insurance to reduce financial risk and improve income stability for wheat producers in Australia

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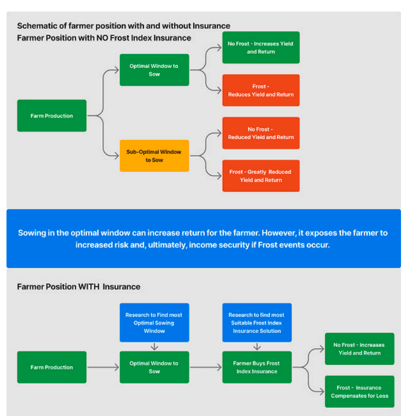
HIGHLIGHTS

- Frost damage impacts the financial sustainability of spring wheat production.
- We tested a new frost index insurance based on a heating degree days which enables farmers to optimally sow.
- Crop simulation indicate yield gains in all locations and show a frost index insurance contract can secure increased returns.
- Integrating frost index insurance with optimal cropping reduces financial impacts and enhances income stability.

GRAPHICAL ABSTRACT



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ABSTRACT

Context: Losses due to frost undermine the financial sustainability of growing spring wheat, which is often managed by the late sowing of crops. While late sowing may reduce frost risk, it can compromise yields due to increasing risks of heat and drought stress later in crop development.
Objective: To develop and test a novel targeted frost index insurance cover called the heating degree day temperature minimum call option, which allows farmers to plant earlier and increases their chances of attaining higher yields while also financially protecting them in case of a frost event.
Methods: The potential value of the insurance was investigated using crop simulation modelling. Based on the integration of the Agricultural Production Systems sIMulator (APSIM) modelling framework and index insurance structures for 22 frost-affected farms over 40 years in Australia's wheat growing regions, we (i) determined the

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Sowing
Management practices

optimal sowing date and potential yield benefits, (ii) estimated the yield impact of frost for crops sown on that date, and (iii) examined the utility of index-based frost insurance options that may financially protect farmers from frost risk if they sow on the optimal date, assuming they sow and insure their crops every year.
Results and conclusions: On all farms modelled, gains were made on those sowed on the optimal date. Where frost occurred regularly, the use of the targeted frost index helped secure increased returns and, therefore, benefits. The targeted integration of the frost index insurance with optimal sowing dates, especially for frost-prone regions, may be an important strategy for reducing financial impacts and enhancing income stability.
Significance: The use of the targeted frost index where frost occurred regularly could help secure increased returns and, therefore, benefits to farmers and the wider community. The targeted integration of the frost index insurance with optimal sowing dates, especially for frost-prone regions, may be an important strategy for reducing financial impacts and enhancing income stability in frost-affected food bowls globally. We are not aware of any similar study that has been conducted.

1. Introduction

Extreme cold weather has a major impact on productivity, which translates to reduced yields (Lesk et al., 2016). These reduced yields have financial consequences not only on the individual farmer's income but also on the up- or downstream income of stakeholders in the local economy. For wheat crops, frosts occurring after flag leaf emergence and around anthesis can be devastating for the grower. Extreme frost events in wheat production in Australia, as well as globally, represent a significant risk that needs to be managed to achieve more profitable outcomes for the growers and to ensure food security (Barlow et al., 2015).

The effects of frost in agriculture have been extensively researched both internationally (Budong et al., 2010; Kalma et al., 1992; Porter and Gawith, 1999; Woldendorp et al., 2008) and domestically in Australia (Barlow et al., 2015; Crimp et al., 2016; Zheng et al., 2015a). Zheng et al. (2015a) estimated the annual yield loss in Australia due to frost to be about 10 % of gross production, which results in $700 million in economic losses each year. Frost damage in wheat is usually spatially variable, as it is influenced by factors such as temperature, soil type and colour, soil moisture, cloud cover, wind speed, topography, crop species, crop nutrition, crop density, and sowing time (Anderson and Garlinge, 2000). Managing frost is a balancing act for the farmer. If the farmer sows early, they risk flowering in the high frost risk window, while late sowing risks yield loss due to terminal heat and drought stress (Chenu et al., 2013; Zheng et al., 2012; Ababaei and Chenu, 2019, 2020; Crimp et al., 2016; Flohr et al., 2017, 2018). Despite the warming in climate, farmers have increasingly been affected by frost (Zheng et al., 2015a; Collins and Chenu, 2022) and will be confronted by this problem for decades to come (Collins and Chenu, 2021). In the eastern Australian grain regions, the yield loss attributable to frost, including the loss due to delayed sowing strategies, was estimated to be as high as 38 % for mid-flowering cultivars (An-Vo et al., 2018; Zheng et al., 2015a).

The most commonly employed frost risk management strategy to maximise yield has been to sow crops late to delay the heading, flowering, and grain fill stages until after the main frost risk period (Frederiks et al., 2011, 2015; Fuller et al., 2009). Growers turn to this phenological solution to manage frost risk, which comes down to choosing the wheat variety and the timing to sow (Collins and Chenu, 2021; Flohr et al., 2018; Zheng et al., 2012). However, risk-averse growers tend not to sow at the optimal sowing date for yield potential to avoid frost damage. Crop insurance enables farmers to take calculated risks by adjusting sowing dates, potentially resulting in higher yields (Nguyen et al., 2024). It has been important for farmers to sow their crop at the optimal time for two reasons. First, sowing optimally provided them with the potential for greater tonnage and, hence, greater income, although it came with a risk. Second, knowing the potential for greater income, the purchase of insurance is less burdensome. In all the farms, sowing optimally provided a net gain to the farmers (APSIM), including the cost of insurance. Therefore, sowing at the optimal long-term sowing date for yield potential and a targeted index insurance structure may represent an innovative risk management solution for growers. This approach for managing frost risk may encourage growers to sow crops at the optimal time to increase yield while insuring their crops against potential losses due to frosts. To our knowledge, this approach has not been investigated previously.

Crop insurance can help reduce the financial impact of frost. Two types of insurance can be used: indemnity-based insurance and non-indemnity insurance. Indemnity-based insurance refers to an insurance policy that has an insurable interest. For example, the valued damage caused by hail, in which case the loss is evaluated by an assessor after the fact. Non-indemnity insurance refers to insurance that proscribes a contractual loss amount to be paid once an event occurs, where no assessment is required. Indemnity-based insurance products for frost are currently either not available in Australia or too expensive. For non-indemnity insurance, index insurance solutions show potential. However, as pointed out by Dalhaus et al. (2018), the current index insurance designs do not adequately account for the critical stages of crop growth. Furthermore, in their work on addressing the use of index insurance for a drought affecting winter wheat during anthesis in Europe, Dalhaus et al. (2018) found that incorporating adjustments for the phenological stages could reduce the temporal basis risk inherent in using index insurance and could generally improve the attractiveness of using index insurance to manage weather risk and thus the farmer's income. Temporal basis risk is one of three to consider when structuring index insurance. Temporal basis risk refers to the risk of timing when a structure should start and finish. An index insurance design incorporating changes in frost risk during different phenological stages may increase the farmer's income and represent a way for growers to maximise profitability. Hence, sowing in the optimal window and then managing frost risk via index-based insurance may be a viable option.

Frost impact can occur at all stages of crop development, but in wheat in Australia it is particularly damaging starting from flag leaf emergence Zadoks growth (Z39; Zadoks et al., 1974), around 25 days before flowering until ~10 days after anthesis (Zadoks growth stage Z69). In this research, we examined a novel index insurance structure that covers two types of frost risk, which we refer to as 'stem frost' and 'head frost'. First, 'stem frost' refers to frost that kills the flowering spikes, which can occur when plant temperatures drop below approximately -5 °C (Bell et al., 2015; Flohr et al., 2017; Frederiks et al., 2015; White and Edwards, 2007). Plant temperatures of -5 °C may occur when temperatures measured in the standard meteorological Stevenson screen are between -2 °C and -1 °C. However, there is no direct relationship between the temperature measured in the Stevenson screen and that of the actual plant (Frederiks et al., 2011, 2015; Fuller et al., 2009). Second, 'head frost' refers to an event that can occur when screen temperatures drop below 0 °C ~ 10 days after anthesis has commenced. This is a critical period for the grain set, and if the temperature drops, then this may result in reduced grain numbers.

The primary research question is whether crop insurance strategies, combined with optimal crop management to increase yield, could stabilise income when frosts occur and increase income during non-frost periods(Christopher et al., 2016)(Barnett and Mahul, 2007)(Fig. 1). The study took an alternative approach to index design, compared with Dalhaus et al. (2018) and Conradt et al. (2015). First, the proposed method follows similar lines with regard to phenology as Dalhaus et al. (2018) but differs in information about critical days, which are agronomically sourced directly at the farm and by an agronomist in this study. Second, the approach does not use growing degree days, as did Conradt et al. (2015), but rather threshold screen temperatures (i.e. targeted degrees) at two critical periods for frost sensitivity, namely (i) temperatures below 0 °C, −1 °C, and − 2 °C from flag leaf emergence, depending on the test sites climatology, until the end of flowering and then (ii) less than 0 °C for 10 days when flowering begins. The overall risk period corresponds to the Zadoks growth stages Z39 to Z70.

We hypothesised that a farmer's income would potentially increase if they sow during the optimal sowing window and then use index insurance to effectively compensate for frost damage should it occur (Bucheli et al., 2020; Thong et al., 2024) To test this, we took a sample of frost-prone farms representing the major grain growing regions of Australia and used crop simulation modelling for a standard cultivar (cv Hartog) to (i) determine the optimal sowing date at each studied location and the associated potential yield benefits compared with the current late sowing to reduce frost risk, (ii) estimate the long-term yield impact that frost has on crops sown optimally, and (iii) examine the utility of an index-based frost insurance option that may help to financially protect farmers from frost risk if they plant at the optimal sowing date for long-term yield (see Fig. 1). It must be noted that the aim of the study is illustrate the value of the insurance via a specific cultivar for a wide range of conditions (22 locations × 40 years = 880 environments).The approach could be expanded to look at particular farms and combine choices related to both cultivar (e.g. maturity type, frost sensitivity) and sowing date to minimise frost, heat and drought stress (Collins and Chenu, 2021; Flohr et al., 2017; Zheng et al., 2015a).

2. Materials and methods

2.1. Study region and climatic data

This research covered individual wheat farms across the Australian wheat belt. To achieve a good diversity of climatic conditions, the farms were selected in 22 locations (Table 1) within the three Grain Research and Development Corporation (GRDC)-defined agro-ecological regions: north, south, and west.

The Australian northern grain region, encompassing New South Wales (NSW) and Queensland (QLD), is characterised as having mainly vertosol clay soils with high water storage capacity and tropical, subtropical, and temperate environments. Farmers can grow both winter and summer crops, and many aim to produce wheat that is classified as high protein. We examined farms in the northern region, specifically in the sub-regions of QLD Central, NSW Central, NSW East, and QLD

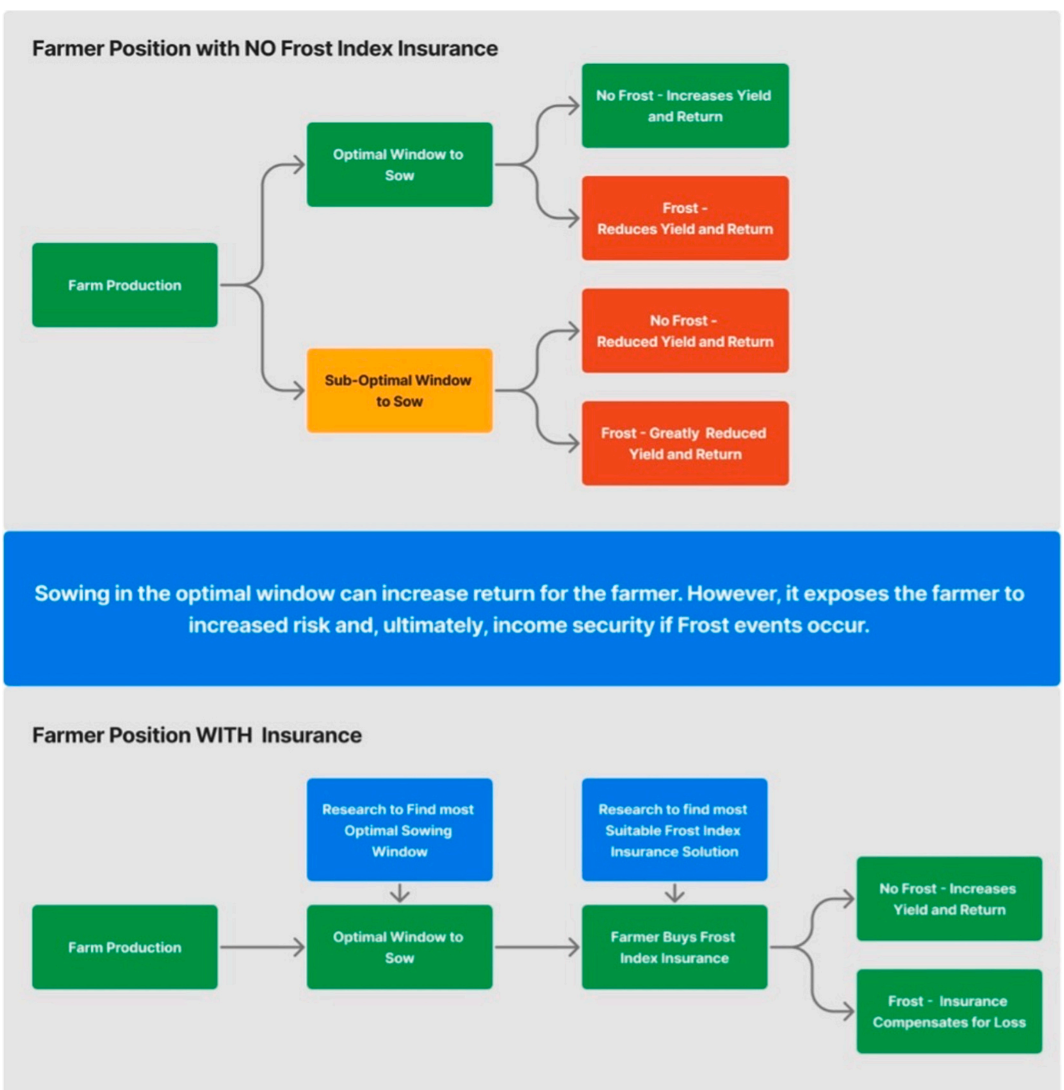

Fig. 1. Schematic showing potential actions by farmers regarding sowing dates and frost index insurance and the likely outcomes of these actions.

Table 1
Locations of farms assessed and their corresponding agro-ecological zones.

Farm	Latitude	Longitude	Zone
Roma	−26.57	148.79	QLD Central
Dalby	−27.18	151.26	NSW Northeast/QLD Southeast
Dubbo	−32.24	148.61	NSW Northeast/QLD Southeast
Waikerie	−34.18	139.98	NSW Northeast/QLD Southeast
Gunnedah	−30.98	150.25	NSW Northeast/QLD Southeast
Gilgandra	−31.71	148.66	NSW Northeast/QLD Southeast
Narrabri	−30.32	149.78	NSW Northeast/QLD Southeast
Parkes	−33.14	148.16	NSW Central
Urana	−35.33	146.03	NSW Central
Wagga	−35.16	147.46	NSW/Vic Slopes
Lake Bolac (SE)	−37.71	142.84	Vic High Rainfall
S Walpeup	−35.12	142	SA/Vic Bordertown-Wimmera
Pinnarro	−35.26	140.91	SA/Vic Bordertown-Wimmera
Birchip	−35.98	142.92	SA/Vic Bordertown-Wimmera
Ceduna	−31.9	133.42	SA Vic Mallee
Hopetoun	−35.73	142.37	SA Vic Mallee
Balaklava	−34.14	138.42	SA Mid North-Lower Yorke Eyre
Roseworthy	−34.53	138.69	SA Mid North-Lower Yorke Eyre
Salmon Gums	−32.99	121.62	WA Sandplain
Lake Grace	−33.1	118.46	WA Central
Katanning	−33.69	117.56	WA Central
Kellerberrin	−31.62	117.72	WA Eastern

Southeast, as well as the NSW and Victorian (Vic) Slopes (Table 1). The southern grain region is characterised by variable soils and a temperate climate. The yields are highly dependent on spring rains, and many of the soil types do not store water well, so the timing of the rain is critical. The studied farms in the southern region were in South Australia (SA), Vic Mallee, the SA and Vic Bordertown-Wimmera districts, and the Vic High Rainfall regions. Finally, the western region, which has low soil fertility, is classified as having a Mediterranean climate. The yields are determined by good winter and spring rains. The specific farms we studied in this region were in West Australia (WA) Central, WA Eastern, and the WA Sandplains.

The study region was further characterised using Bureau of Meteorology (BOM) frost day data. The BOM provides data on the number of days a year that the temperature drops below 0 °C. The BOM provides thematic maps covering regions that suffer from temperatures below 0 °C and hence have the potential for frosts (BOMs Provide Key Climate Groups, 2025). To make the study relevant, climate data from farms located within these regions were analysed to ensure that temperatures dropped below 0° and were then reconciled against frost losses within a dataset of simulated yield. Twenty-two sites were identified as suitable for the frost index insurance structure and to represent the cropping zones in the Australian wheat belt (Chenu et al., 2013; Zheng et al., 2015a).

2.2. Critical temperatures and phenological stages in the index insurance

The current study took an approach to index insurance design similar to that of Dalhaus et al. (2018) and Conradt et al. (2015), with the following modifications. First, the proposed method follows similar lines as Dalhaus et al. (2018) regarding crop phenology but differs in information about critical days, which are simulated with the wheat module of the Agricultural Production Systems sIMulator (APSIM) modelling framework (Zheng et al., 2015b; Holzworth et al., 2014; Keating et al., 2003) here. APSIM is accessible by farmers and advisors (https://www.apsim.info/). Second, the approach does not use growing degree days as did Conradt et al. (2015) but rather threshold temperatures (referred to here as 'targeted degree days') at two critical periods approximately corresponding to the reported periods of vulnerability to stem and head frost damage.

The wheat development rate varies greatly depending on the genotype and location, which affects temperature and other pedo-climatic factors. To model the effects of frost at critical developmental periods for this study, we postulated that in optimal growing conditions, anthesis of a mid-maturating variety typically occurs 150 days after sowing. Then, we counted back 25 days to approximate when the flag leaf emerged. From this date until 10 days after anthesis (i.e. a 35-day period), the crop was considered susceptible to stem frost and then head frost. In this study, stem frost is defined as frost that kills the spike, whereas head frost kills individual florets on the spike (Frederiks et al., 2011).

We used two insurance options (described in more detail in Section 2.4). One considered a 35-day critical period, including both stem and head frosts, with the risk period starting with the emergence of the flag leaf through booting, head emergence, and then anthesis and early grain filling (i.e. the Zadoks' growth stages between Z39 and Z70; Zadoks et al., 1974). Zheng et al. (2015a) suggested that threshold temperatures of between −2 °C and 0 °C, as measured by a Stevenson screen, during the 35-day risk period were often recorded when a stem or head frost would be likely. The second cover option focused solely on head frost. If temperatures dropped below 0 °C during the 10 days after anthesis, a head frost was likely. Both for stem and head frosts, a substantial loss of yield can occur at these critical stages of plant development. Therefore, we designed an insurance structure that incorporated phenological triggers relating to how the plant behaved at low temperatures. We believe this is the first step for the discussion on the use of index insurance for frost in agriculture.

2.3. Crop simulation and climate data

To obtain representative data, the APSIM-wheat module (v7.10) was used to simulate cv Hartog's phenology and yield in each of the 22 study locations using daily weather data from the SILO point-scale database (Jeffrey et al., 2001) for 40 years from 1980 to 2019. Representative soil types and management practices were chosen for each location following Chenu et al. (2013) and Collins and Chenu (2021). Although different wheat varieties have different characteristics, the study was illustrated for cv Hartog to assess the index-based frost insurance option in 40-year simulations across 22 locations.

APSIM is widely used to simulate biophysical processes in agriculturally based production systems (e.g. Ababaei and Chenu, 2019, Ababaei and Chenu, 2020; An-Vo et al., 2018; Chenu et al., 2017; Collins et al., 2021, Hammer et al., 2019; Zheng et al., 2018). Zheng et al., (personal communication) used a comprehensive validation dataset comprising 52 cultivars and 2958 observations from 202 sites, demonstrating that APSIM-Wheat can accurately simulate Hartog's phenology (specifically, 50 % heading dates and Zadoks scores near flowering) with an RMSE of approximately 4 days (Zheng et al., 2015b). Reviews of APSIM's performance show that it performs well for wheat, with a root mean square error < 1 t/ha across a range of environmental conditions (Hao et al., 2021).

We used a customised version of APSIM-Wheat (Zheng et al., 2015b; Chenu et al., 2019; Collins and Chenu, 2021), which estimated post-heading frost impacts on yield. To approximate the distribution of exposed heads from different tillers at susceptible post-heading stages, a yield multiplier was applied, starting at 1 (i.e. no yield loss) at the late-booting stage (Z45) and linearly decreasing to 0.1 (i.e. 90 % yield loss) by mid-heading (Z55), when most tillers would have reached the susceptible post-heading stage (Z49). Maximum susceptibility was maintained until the onset of dough development (Z80), with a constant yield multiplier of 0.1 for each day with a minimum temperature below 0 °C during Z49-Z80. Beyond Z80, the yield multiplier was gradually increased to 1, reaching full recovery by the end of dough development (Z89).

Crop simulations based on APSIM- Wheat were used to identify the best sowing dates and associated long-term yield for cv Hartog at each of the 22 studied locations. This assessment was conducted over a 40-year period using 10 different planting dates (March 11, March 27, April 10, April 26, May 10, May 26, June 11, June 27, July 11, and July 27) for each of the 22 studied locations. The date that produced the highest average predicted yield over 40 years was defined as the optimal sowing date (see Table 2).

We conducted two sets of APSIM simulations for all studied sowing dates. The first set predicted potential yield without frost impacts to determine the yield farmers could achieve if there were no frost events. The second set of APSIM simulations included frost impacts and provided predicted yields that farmers could achieve with frost events. The difference between the predicted 'non-frosted' yield and the predicted 'frosted' yield of crops is the potential yield lost due to frost, which was used to quantify the amount of income that would need to be covered by insurance.

2.4. Index insurance options

Index insurance is a non-indemnity type of insurance that requires no proof of loss. It is assumed and agreed between the buyer and the seller before the risk period that a financial loss will arise once certain events that pertain to the index occur. Risk periods, thresholds, and strikes are used to define when and how much a policy will pay. There are many international and domestic studies on the application and effectiveness of index insurance in agriculture (Adeyinka et al., 2015; Breustedt et al., 2008; Gine, 2010; Conradt et al., 2015; Dalhaus et al., 2018; Dalhaus and Finger, 2016; Kath et al., 2019; Turvey and Mclaurin, 2012; Barnett and Vedenov, 2004. Here, we assumed that the grower would buy the insurance every year.

To calculate the insurance premiums, key findings from the studies of Kotlobovskii et al. (2018), Pietola et al. (2011), and Turvey (2001) were incorporated into the design. Kotlobovskii et al. (2018) suggested that the use of two parameters in the premium calculation may reduce the level of risk to the underwriter and, hence, reduce the premium to be paid while providing enough cover for the risk that the farmer wishes to cover. Pietola et al. (2011) and Turvey (2001) addressed basis risk during the growing season and noted that it was crucial to define critical periods of risk within the structure. The adoption of these findings in the structure's design not only reduced premium value but also reduced basis risk by focusing on temperatures that were most crucial to the yield. The risk period used here corresponded to the 35 days when the crop was most susceptible to stem and head frost, as described above. Of the two components, Cover 1 addressed stem frost and had a threshold of either −2 °C, −1 °C, or 0 °C during the 35 days of frost risk, while Cover 2 addressed head frost and had a threshold of 0 °C during the 10 days after anthesis.

Table 2
Average yield gains from optimally sowing crops against the average yield gains on non-optimally sown crops.

Farm	Average Yield (kg/ha)**	APSIM Optimal Date	Optimally Sown Yield (kg/ha)	Optimal Gain (kg/ha)	Cash Gains (288/t)*
Roma	1586	26-Apr	1984	399	$86,080
Dalby	2594	10-May	2835	241	$69,474
Dubbo	2885	10-May	3651	766	$220,550
Waikerie	1419	10-May	1757	338	$97,437
Gunnedah	3552	26-May	4291	739	$212,934
Gilgandra	2677	10-May	3445	768	$221,126
Narrabri	2902	10-May	3619	717	$206,392
Parkes	3791	26-May	4589	798	$412,906
Urana	2516	26-May	2982	466	$237,617
Wagga	3535	11-Jun	4158	624	$179,626
Lake Bolac	3687	11-Jun	4777	1090	$314,007
Walpeup	1708	10-May	1748	40	$109,048
Pinnaroo	1704	10-May	2070	366	$105,348
Birchip	1645	10-May	2088	442	$233,824
Ceduna	500	10-May	653	152	$43,875
Hopetown	1675	26-May	2151	476	$136,960
Balaklava	1796	26-May	2447	652	$187,637
Roseworthy	2154	26-May	2973	819	$235,812
Salmon Gums	1057	26-Apr	1391	334	$96,178
Lake Grace	1229	26-Apr	1714	485	$139,703
Katanning	2256	10-May	3178	922	$265,403
Kellerberrin	1382	10-May	2062	680	$195,882
Averages	**2193**		**2753**	**533**	**$159,900** ***

* Represents the average price of 40 years adjusted for inflation.
** The average yield of all the sowing dates tested.
*** Gain made from optimal sowing is $300/ton x 533 kg gained.

The suggested frost index insurance aims to cover $300/ha of production costs, which is the average production cost in Australia, or $300,000 for a 1000-ha farm (Herbert, 2017). The calculation of the premium involved two heating degree day temperature minimum ($HDDT_{min}$) call option contracts. A heating degree day (HDD) is a cumulative measure in temperature degrees from a defined threshold over a nominated period. For example, a threshold defined as 0 °C and a payout of $50,000 per degree up to a maximum of $150,000 or 3 HDDs. In this example, if the temperature on day 1 of the critical period is −1 °C, −0.5 °C on day 2, and above 0 °C for the rest of the critical period, the number of HDDs is 1.5 °C, and the payout is 1.5 °C x $50,000 = $75,000 (see Supplementary Table 1). The risk period commences on a date deemed to be when the flag leaf emerges and ends 10 days after anthesis. In reality, it is usually determined by an agronomist, but it was estimated by APSIM-Wheat in this long-term nationwide simulation study.

Furthermore, discretion was used in choosing the cover lengths in each structure to make the cover affordable in regions where there is a high frequency of frosts. Typically, if there are multiple frosts, then payouts would be frequent and the premium expensive. For example, by extending the cover length (i.e. reducing the payout per HDD), the premium is more affordable, which means that the thresholds and triggers remain in line with events of frost that cause financial loss.

2.4.1. Insurance premium calculations

The premium calculations were based on the return on risk methodology, where we had an expected loss, a probable maximum loss, payouts, volatility costs, and contract administration expense (see Henderson and Hobson, 2002; Jewson and Brix, 2005; Spicka and Hnilica, 2013; World Bank, 2011 for the premium calculation methodology). Historical burn analysis (World Bank, 2011) was used to determine the probable maximum loss, which was fixed at $300,000 on each site. Burn or expected loss analysis is a critical component of the premium. It is the historical loss that a contract would have incurred over a predetermined time series.

In this research, 40 years of daily temperature and simulated phenology were used to estimate the HDDs for the risk period and the losses associated with a stem frost and a head frost. These losses were averaged over eight periods of 5, 10, 15, 20, 25, 30, 35, and 40 years from 1980 to 2020 (1980–1984, 1980–1989, 1980–1994, etc.). Then, these averages were averaged and added to the premium calculation.

The details of the premium calculation approach are provided below. We define the $HDDT_{min}$ for a day as

$$\mathrm{HDDT}_{\min}(t) = max\{0, \mathrm{T} - \mathrm{T}_{\min}(t)\} \quad (1)$$

where $T_{min}(t)$ is the minimum temperature of a day t, and T is a chosen temperature threshold (i.e. 0 °C, −1 °C, or − 2 °C, depending on the cover chosen for stem frost (Cover 1), and 0 °C for head frost (Cover 2). Given that the contract runs over a period, a cumulative approach is adopted and summed. Hence, $HDDT_{min}$ over a risk period is given by

$$\mathrm{HDDT}_{\min}([t_1, t_2]) = \sum_{t=t_1}^{t_2} max\{0, \mathrm{T} - \mathrm{T}_{\min}(t)\} - \varphi \quad (2)$$

where $[t_1, t_2]$ is the risk period, and φ is the strike level (i.e. the temperature value at which the index insurance option would start to pay out). A strike is used in a cumulative policy to determine when a policy starts to pay. In this research, no deductible was used (i.e. φ = zero).

The value of the financial loss due to frost damage for a particular year *i* (in AUD) is estimated by

$$\mu_i = \mathrm{HDDT}_{min,i}([t_1, t_2]) \times \chi \tag{3}$$

where χ (i.e., the tic value) is the value of the loss per HDD, expressed in AUD. The χ is discretionary and determined by the frequency of losses associated with the frost events occurring at each site over the risk period. The average value of the loss during a period from year *1* to year *n* ($n = 40$) is given by

$$\overline{\mu}_{(1\ \mathrm{to}\ \mathrm{n})} = \frac{\sum_{i=1}^{n} \mu_i}{n} \tag{4}$$

The standard deviation of loss in the same period is given by

$$\overline{\sigma}_{(1\ \mathrm{to}\ \mathrm{n})} = \sqrt{\frac{\sum_{i=1}^{n} \left(\mu_i - \overline{\mu}_{(1\ \mathrm{to}\ \mathrm{n})}\right)^2}{n}} \tag{5}$$

The insurance option premium (P) is then calculated by the average values of the losses in five yearly incremental periods over 40 years. Then, these averages were further averaged, represented by

$$P = \frac{1}{m}\sum_{j=1}^{m} \overline{\mu}_{(1\ \mathrm{to}\ 5)_j} + \frac{1}{m}\left(\sum_{j=1}^{m} \overline{\sigma}_{(1\ \mathrm{to}\ 5)_j} + \sum_{j=1}^{m} \overline{\mu}_{(1\ \mathrm{to}\ 5)_j}\right) \times 0.25 \tag{6}$$

where *m* is the total count of 5-year periods encompassed within the entire study duration. In the case of 40 years, *m* is 8. In line with common practice in the insurance industry, 0.25 is a constant that captures volatility in payouts, as well as the transaction and administration costs of insurance. Thus, our premium estimates approximate real-world prices.

2.5. Financial benefits of index insurance options

To examine the efficiency of the $\mathrm{HDDT}_{\mathrm{min}}$ policy relating to income, with and without crop insurance, five assessment criteria were examined (Adeyinka et al., 2015; Kath et al., 2019;Mushtaq et al., 2017; Vedenov and Barnett, 2004). The criteria corresponded to (i) an assessment of the volatility of crop income through standard deviations, (ii) the measurement of whether insurance will increase farmer revenue in years with extreme frost conditions via a conditional tail expectation (CTE) approach, and (iii) an assessment of the extent to which a frost contract reduces downside risk (i.e. whether insurance minimises loss in poor years) via a mean root square loss (MRSL) approach. This study considers crop insurance as an innovative risk management tool instead of a reactive one and takes a novel perspective on the problem of climate risk management in cropping systems. Access to insurance enables farmers to take additional risks and aim for higher yields by adopting best management practices. In case of frost, farmers can plant during risky periods to maximise yield, and the frost risks will be taken care of by the insurance products. This way, farmers can target higher yields and income while covering risks through insurance.

It is worth noting that most academic studies assess fair premiums when analysing crop insurance solutions (Dalhaus et al., 2020; Kath et al., 2019). However, this study takes into account commercial premiums to ensure its relevance for growers. If we were to use fair premiums, then most study locations would show a relatively positive impact of the integrated approach.

2.5.1. Measuring income volatility via standard deviation

The difference in the standard deviation (STDV) between the wealth derived from frosted income was examined using

$$\mathrm{W}_{\text{without insurance}} = \widetilde{Y}_{\max} \times \mathrm{Price} \tag{7}$$

The wealth derived from frosted income with insurance less the premium is

$$\mathrm{W}_{\text{with insurance}} = \widetilde{Y}_{\max} \times \mathrm{Price} + \mathrm{Payout} - \mathrm{Premium} \tag{8}$$

If using the insurance allowed for a reduction in the STDV of the wealth, then the insurance was considered beneficial, as it reduced volatility in earnings for the farmer.

2.5.2. Assessing benefits during extreme frost conditions via conditional tail expectation (CTE)

We used the Conditional Tail Expectation (CTE; Vedenov and Barnett, 2004)) method to calculate the potential loss in case of an extreme event. This method helps estimate the expected loss beyond a certain probability level. We compared the average incomes during the 50 % of the years with the lowest frosted yields. We examined the difference between the income with insurance payouts minus the premium cost, and the income without insurance. If the income was higher with insurance less the premium than the income without insurance, then the insurance was considered beneficial.

2.5.3. Assessing downside risk reduction benefit via mean root square loss

The differences in the square roots of the average losses were calculated for the 50 % of years with the highest losses in terms of frosted income using the optimum sowing dates without insurance and then with insurance. In this study, Mean Root Square Loss (MRSL; Vedenov and Barnett, 2004) was based on average losses since the farmer would be concerned with below-average revenue. If using insurance had a smaller MRSL value, then it meant that the insurance was efficient.

3. Results

3.1. Optimal sowing dates

Farmers tend not to sow in the optimal sowing window for yield to avoid the risk of damaging frost events at critical growth stages, which can have a devastating impact on yield and, subsequently, income (Frederiks et al., 2015). Optimal sowing has significant yield benefits, but the frost risk for most growers is considered too high. APSIM has estimated the yields for crops of cv Hartog sown on different dates: 11 March, 27 March, 10 April, 26 April, 10 May, 26 May, 11 Jun, 27 June, 11 July, and 27 July. The optimal sowing dates used in this study were those that produced the highest average predicated yields over 40 years when ignoring frost events (see Fig. 2, Table 2 and Supplementary Table 2). The gains on optimally sown crops (i.e. average yield difference between the optimal sowing date and all other nine sowing dates) averaged over all the sites and years equalled 533 kg/ha, which showed an average income gain of $159,900 over 40 years or an average gain of $160/ha. The largest gain of 922 kg/ha over all the sites was recorded for Katanning, WA (Table 2).

In the absence of frost, gains can be made by sowing at the optimal sowing date, although planting at that date increased the risk of frost. Frost-induced losses in long-term average yields ranged from as high as 92 % in Roma to as low as 13 % at Lake Bolac, with the average loss across all sites at 39 % (see Fig. 2c). Furthermore, the frequency of frosts affecting optimally planted crops ranged from 2 % of the years at Lake Bolac to 61 % at Salmon Gums, with the average across all sites at 9 %. When planted at the optimal sowing date, frosted income at Lake Bolac improved by 2.6 % when frost insurance was used, while Salmon Gums's income decreased by 16.3 %. Therefore, adopting a correctly timed strategy or adopting a strategy using the phenology of the plant could yield a better outcome for the farmer.

Table 3 shows the APSIM-predicted frosted and non-frosted yields at Gilgandra, NSW. Based on the APSIM simulations, the suggested optimal date to sow cv Hartog in the absence of frost was 10 May (Fig. 3). If

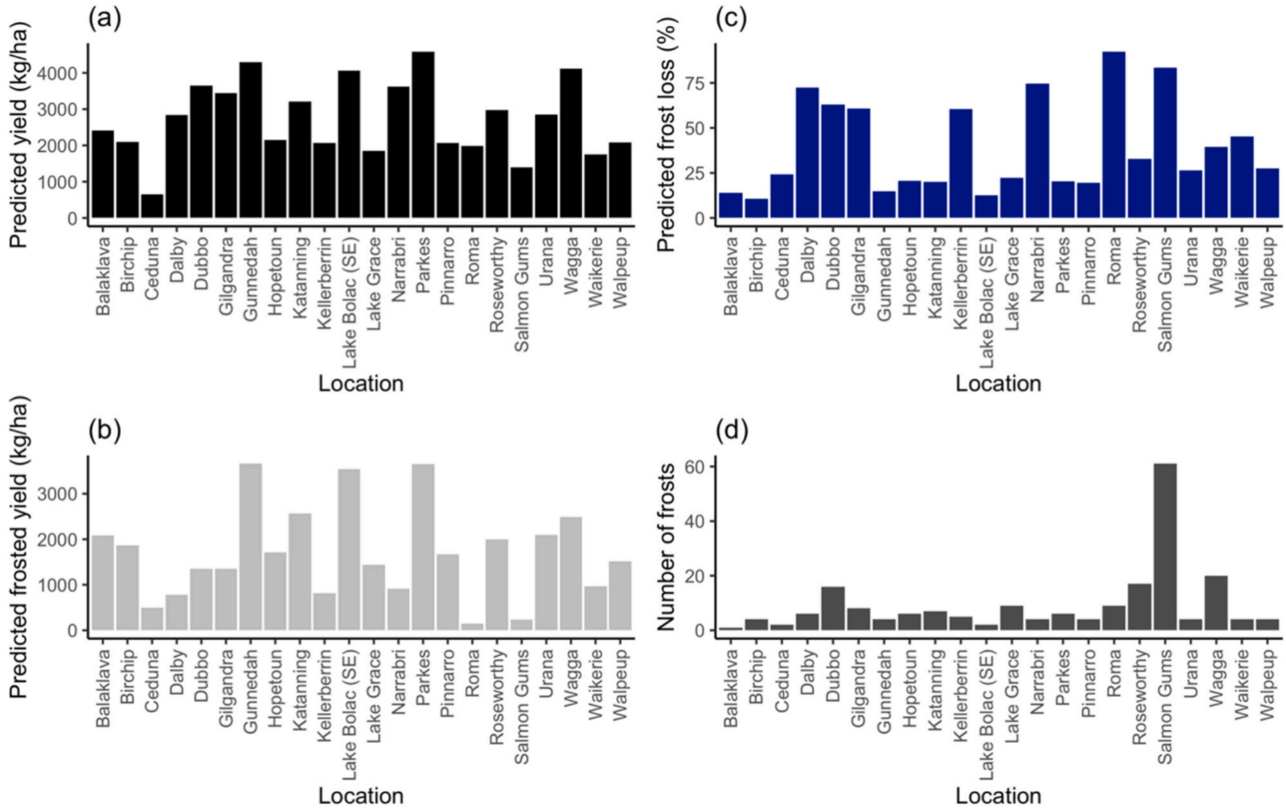

Fig. 2. APSIM-simulated dataset showing the frost summaries for the farms. Mean predicted 'non-frosted' (a) and 'frosted' (b) yields simulated by APSIM for the optimal sowing dates for selected farms at 22 locations across the Australian wheatbelt. Simulations were conducted using 40 years of historic climate data with sowing at the optimal sowing date specific to each location. The yield loss at each site is represented in (c), and the mean number of frosts when temperatures were less than 0 °C is shown in (d). The values represent the mean for 40 years of simulations at each site.

Table 3
Expected yield for the studied sowing dates showing non-frosted and impacts of frost and heat at the site at Gilgandra, NSW. Simulations were conducted over 40 years with APSIM-Wheat.

Date Sown	Average Predicted Non-Frosted Yield (kg/ha)	Average Predicted Frosted Yield (kg/ha)	Loss (%)
11-Mar	1592	44	97 %
27-Mar	2094	0	100 %
10-Apr	2654	0	100 %
26-Apr	3219	391	88 %
10-May	3445	1347	61 %
26-May	3259	2803	14 %
11-Jun	2953	2862	3 %
27-Jun	2749	2723	1 %
11-Jul	2556	2556	0 %
27-Jul	2247	2247	0 %

Hartog was sown on this date, an average yield without frost of 3445 kg/ha over 40 years could be expected. Compared with the other nine sowing dates simulated, this corresponded to an increased yield potential of 768 kg/ha, on average. With this optimum sowing date, yield loss due to frost was estimated to be 44 %. However, the average yield at Gilgandra of 3445 kg/ha for the optimal sowing date over 40 years dropped by 61 %, which corresponds to a frosted yield of 1347 kg/ha. Therefore, the use of frost insurance is important to insure against a financial loss associated with a frost if the crop is sown in the optimal window. The same analysis was repeated in the 21 other locations.

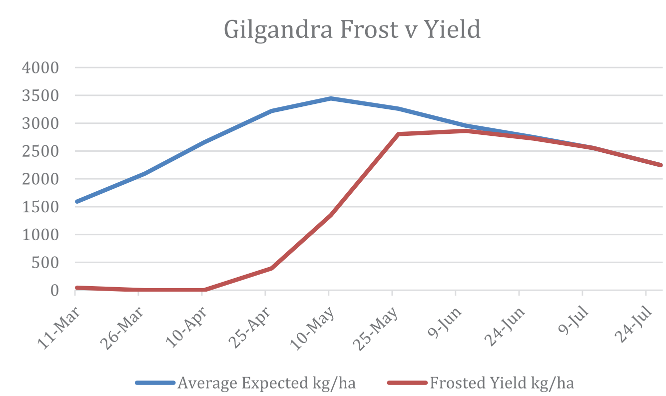

Fig. 3. Expected yields for different sowing dates with (orange line) and without (blue line) frost and heat impacts. Predicted yields for 10 sowing dates with (orange line) and without (blue line) frost impacts at Gilgandra. The data correspond to the average of 40 years of simulations with APSIM. The peak in the blue line showing approximately 3500 kg/ha on 10 May is the optimal sowing date. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. *Index insurance premiums*

Index-based frost insurance products were developed based on $HDDT_{min}$ contracts (see Supplementary Table 1). The premiums were based on predicted losses associated with frosts, and the structure comprised two insurance cover options. One option covered stem frost and had a threshold of either −2 °C, −1 °C, or 0 °C during the 35 days of risk period. The other covered head frost with a threshold of 0 °C during the 10 days after anthesis.

To illustrate this, for a maximum payout of $300,000, which is the equivalent of the standardised input costs of $300/ha for a 1000-ha farm, Cover 1 (stem frost) has in total $150,000 assigned to this risk and between $150,000, $75,000, $50,000, and $30,000 for each HDD (cover length), depending on the occurrences and intensity of the historic frosts (see Supplementary Table 3). For example, in Salmon Gums, WA, 61 occurrences of frost were recorded over the course of 40 years. To make the cover economical, the threshold for stem frost was −2 °C, incorporating a strike of 2 and a cover length of $50,000. Likewise in Birchip, Vic, there were four occurrences of frost. The threshold was 0 °C, there was 1 strike, and the cover length was $30,000. Similarly, Cover 2 (head frost) also has $150,000 assigned to this risk and between $50,000 and $150,000 for each HDD, once again depending on the frequency of the historic frost events. With an $HDDT_{min}$ index insurance policy, the farmer will receive a fixed amount for every HDD above 0 up to the maximum of $300,000 during the risk period (see Supplementary Table 1).

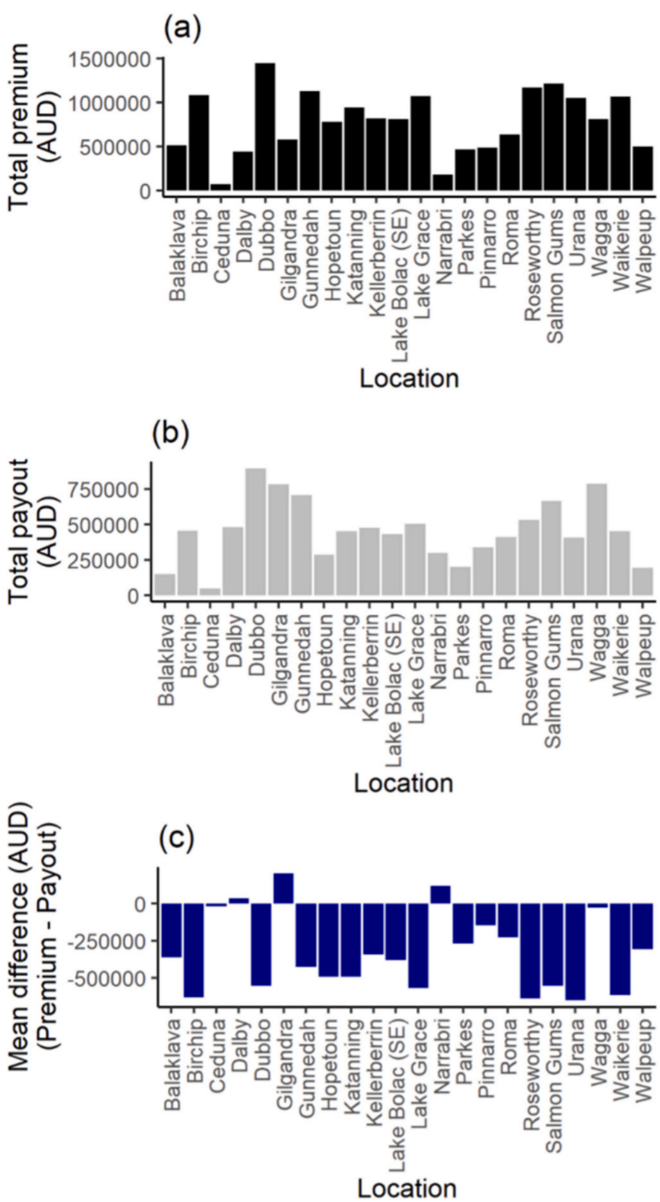

Fig. 4. Insurance premium results showing total premiums paid, total payouts, and mean differences over 40 years. Calculated premiums paid, payouts, and mean differences over 40 years for the 22 studied locations.

Fig. 4 shows the calculated premium, total payouts, and mean differences for each studied location based on a 1000-ha farm. Panel (4a) shows that Dubbo had the highest estimated premium at 12.1 % of the sum insured or $42.2/ha, while Narrabri had the lowest premium at 1.5 % or $5.3/ha of the sum insured. It is interesting to note that Dubbo had 16 occurrences of frost whilst Narrabri had only 5, which intuitively makes sense as the risk of frost is higher for Dubbo. The average premiums were 6.6 % or $23.2/ha. From an insurance industry perspective, these premium estimates were in line with index insurance premiums sourced in Australia for similar covers.

Panel 4b shows the total payouts that each farm has claimed over 40 years; Dubbo naturally has the highest claims and highest premium. But Wagga, which has the second highest claim, has had more historical frost events ie 20 events than Dubbo, yet the premium value was 8.7 %, significantly lower than Dubbo. There were two main reasons for this. The thresholds for the cover in each case were the same, and strikes were identical in each case. The first reason for the difference had to do with the actual temperatures between the two sites. The Dubbo farm suffered from more low temperatures than Wagga. The lowest recorded temperature at Dubbo was −5.5 °C, whilst at Wagga, it was −2.5°. The second reason was that Dubbo suffered from more recent frosts than Wagga, and hence, these losses had a priority in the pricing algorithm.

Panel 4c shows the difference in the premiums paid over claims made over the 40 years. In most cases, this showed that the difference was negative towards the farmer and favoured the underwriter. Intuitively, this makes sense as the underwriter needs to factor in costs associated with the risk, profit margin and management of the cover. Where it was not the case it could be construed as a cover that was mispriced. Albeit the annual cost of having the cover towards the farmer as a result of the difference was marginal compared to the other expenses associated with the farming. Indicating that the cover was worthwhile.

3.3. Efficiency of frost index insurance options

3.3.1. Measuring income volatility

The income volatility was measured by calculating the Standard Deviation (STDV) with and without insurance. The differences in STDV between frosted income for crops sown optimally indicated that eight of the 22 sites were predicted to have reduced volatility in earnings if an $HDDT_{min}$ contract was purchased annually for 40 years (see Fig. 5; Supplementary Table 4). The blue-coloured locations show positive effects on reducing income volatility). Reducing the volatility of earnings is a key motivator for insurance, as it means that cash flow can be constant. This is more important for farms that are highly leveraged, as there is an interest component to be considered.

3.3.2. Assessing benefits during extreme frost conditions

We utilised the Conditional Tail Expectation (CTE) method to analyse the income with and without insurance. Looking at the average income in 50 % of the years with the largest disparity between incomes with and without frost, the findings revealed that only five out of the 22 farms were better off (see Fig. 6 and Supplementary Table 5). Income with insurance in another 10 farms was slightly worse by 5 % or indifferent, which suggested that small refinements in the structure resulting in reduced premiums could cause efficiency gains. As frosted income plus insurance less payouts were higher than frosted income, the use of insurance could improve the farmer's income.

The results suggested that the use of the $HDDT_{min}$ call structure could hedge the effects of frost. However, it needs to be further refined to benefit all regional frost-affected areas. The need for greater refinement falls in line with suggestions from Adeyinka et al. (2014), who conducted CTE tests for over 40 years for rainfall index insurance for wheat. Their results indicated that the insurance was positive in QLD and negative in WA, further highlighting the spatial elements of the usefulness of weather-based index insurance. Furthermore, research on using weather-based index insurance for sugar in Tully, QLD, showed that CTE

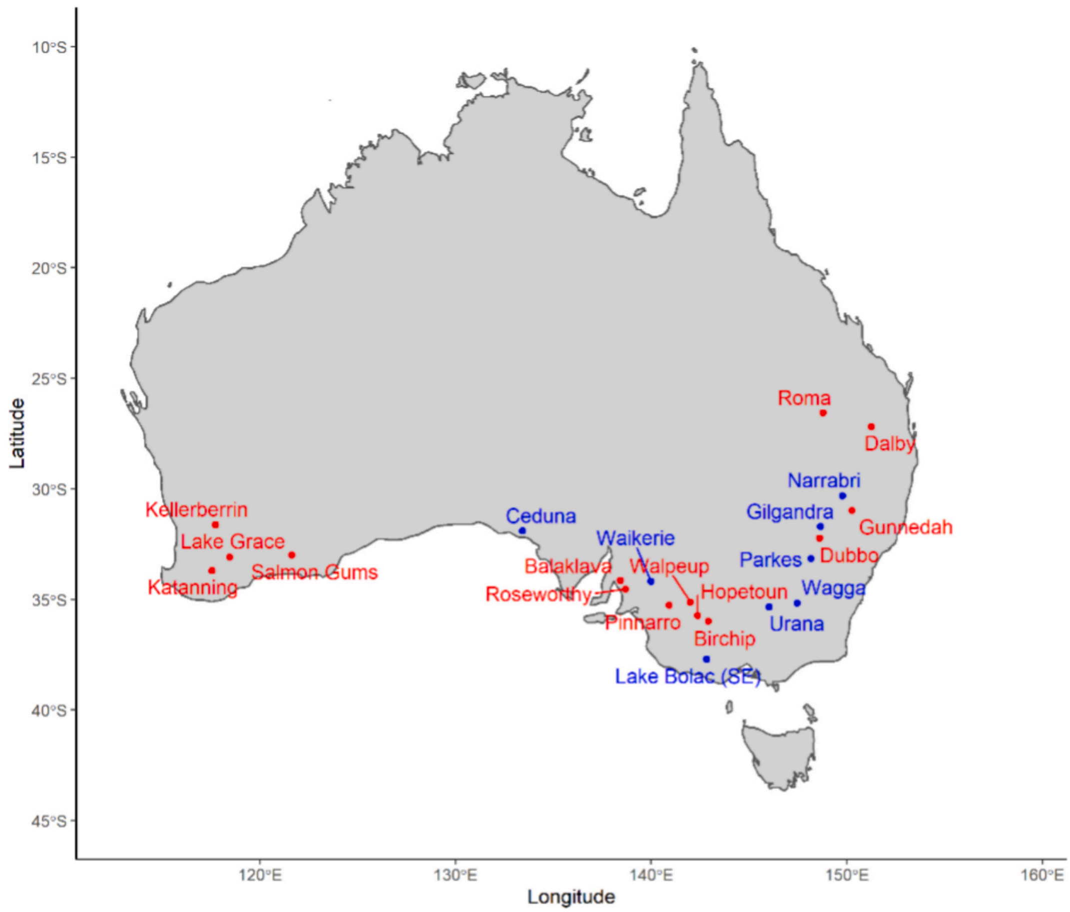

Fig. 5. Potential benefit of insurance based on the standard deviation (STDV). The blue-coloured names represent positive effects. Locations where the insurance had a potential benefit based on STDV. The blue-coloured names represent positive effects. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on a rainfall index was efficient (Kath et al., 2018). Interestingly, the conclusion from Kath et al. (2018) in Tully, QLD, may point to the spatial nature of the effectiveness of index insurance in that it can be effective for a small, clearly defined region but is inconsistent in a wide range of environments. The reasons why index-based frost insurance works in some regions but not in others should be explored in detail.

3.3.3. *Assessing downside risk reduction benefits*

Based on the MRSL analysis, related to the average losses in 50 % of the highest loss years over 40 years without insurance and with insurance, the results showed, once again, that the insurance was of limited efficiency across all the frosted regions. A negative change in variability implied that $HDDT_{min}$ was risk reducing and, therefore, beneficial. Out of the 22 test farms, six had negative values, indicating that the insurance was efficient (Fig. 7 and Supplementary Table 6).

Although it was not only about frost but included multiple weather risks, Vedenov and Barnett's (2004) study on the efficiency of weather-based index insurance for corn measured by MRSL showed that the use of contracts reduced risk exposure for the grower by 54.4 % on average. This was a greater reduction than the results of this study, which showed that only 27.3 % of the contracts were efficient, based on MRSL analysis. However, one important aspect when compared with this study was the drastically different performance between contracts. Vedenov and Barnett (2004), further suggested that optimal weather derivatives required complicated combinations of weather variables to achieve reasonable fits between weather and yield. Kath et al. (2019) also found that the MRSL test for efficiency for the use of weather-based index insurance for wheat contracts differed between the regions analysed.

4. Discussion

This study was conducted to develop insurance options and test them in a simple case study, i.e. for one wheat cultivar (cv Hartog) using a few sowing dates (15-d intervals) with effects of frost impacts modelled based on expert knowledge (Zheng et al., 2015b), and for a selection of environments (22 locations and 40 years of historical data). To have greater value to farmers, the developed approach could be applied to specific farms, and for best management practices related to both cultivars (i.e. maturity type and frost sensitivity, e.g. Celestina et al., 2023; Zheng et al., 2015a) and sowing dates (1-d intervals). Simulations could also be conducted to assist farmers adapting their management practice to each season, e.g. depending on available soil moisture at sowing (e.g. Zheng et al., 2018).

4.1. *Summary of financial efficiency*

A summary of the financial efficiency analyses is presented in Table 4. The financial efficiency analysis of using the $HDDT_{min}$ call option indicated that protection against frost damage could theoretically be adequately managed through $HDDT_{min}$ if there was a high frequency of frost events in which the resulting yield losses were high (>60 %). The total losses were not entirely recovered by the insurance, although the farmer was better off when the cover was found to be efficient by using CTE, the volatility of income, and MRSL. However, in those cases where frost events were few, the use of the $HDDT_{min}$ call to manage frost events could not be considered efficient.

Notably, some of the tested policies were highly efficient at some

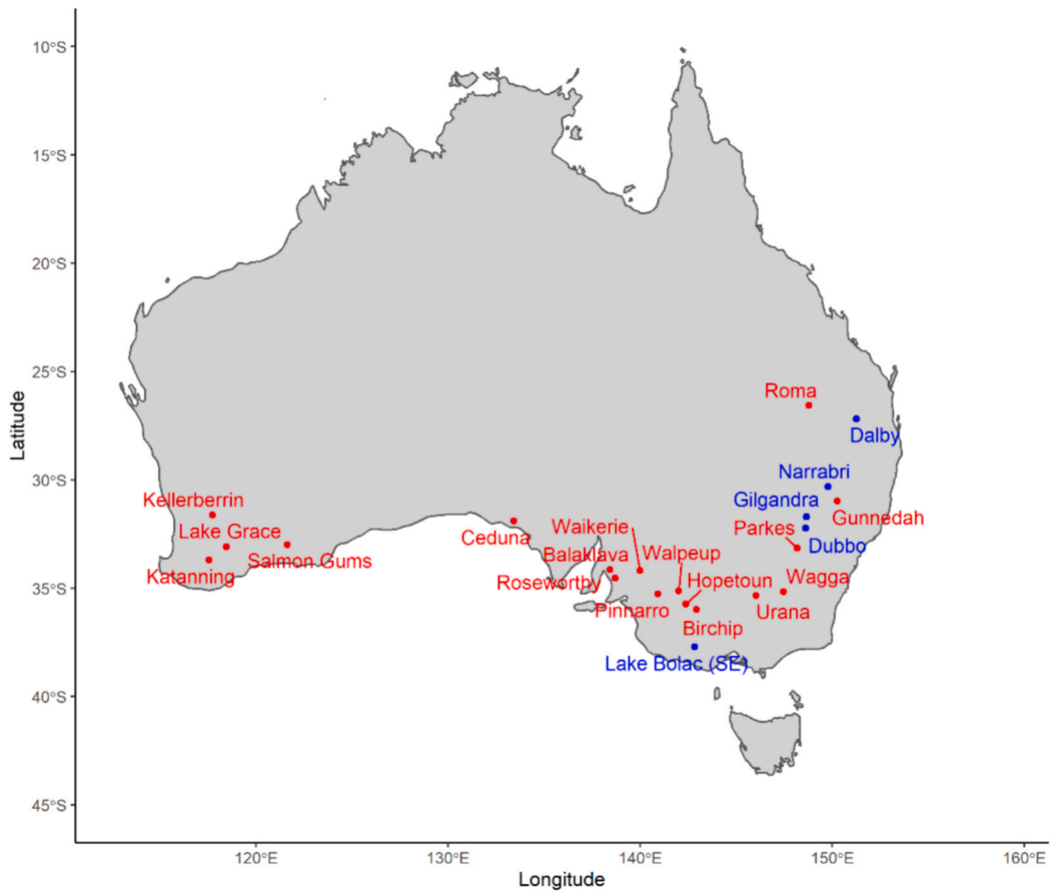

Fig. 6. Potential benefit of insurance based on income in the poorest years. The blue-coloured names represent positive effects. Locations where the insurance had a potential benefit based on income in the poorest years. The blue-coloured names represent positive effects. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

locations (e.g. Lake Bolac, Dalby, Wagga Gilgandra, and Narrabri) but not others (e.g. Pinnarro, Lake Grace, Birchip, Salmon Gums, Gunnedah, Katanning, Kellerberrin, and Hopetown) (see Table 4). Overall, optimally sowing assuming no frost did provide gains for all test sites, but hedging income against frost to further capitalise on these gains on some farms needs further consideration (see Supplementary Table). In terms of the financial efficiency of using $HDDT_{min}$, 40 % of the farms were better off. Furthermore, 36 % saw reduced volatility in earnings, 22 % had income in the poorest years, and 27 % were efficient. If the premiums were reduced, greater efficiencies would occur. The premium values were based on market-recognised methods (see Section 2.4.1). The calculation of the premiums as described was based on historical losses, with administration and volatility costs embedded in the premium. Historical losses cannot be changed, but administration and volatility costs could be reviewed. This will depend on reinsurance providers lowering administration costs, which could occur if more policies were taken up and greater efficiencies gained through the automation of the processing and settling of contracts.

4.2. Reducing basis risk to improving the use on index insurance

To enhance the consistency of insurance premiums and increase the adoption of insurance, it is important to address three significant basis risk issues related to index insurance. These issues should be carefully considered. Moreover, it is important to assess the effectiveness of various insurance coverage options. A comprehensive argument should be developed to justify why certain insurance covers are more effective than others in mitigating basis risk. Dalhaus and Finger (2016) suggested that the main issues with the uptake of index insurance could be summed as three points:

1) Design basis risk: the index does not include all the relevant information or parametrisation.
2) Spatial basis risk: the distance between the point measurement and the farm location differs (Leblois et al., 2014; Ritter et al., 2014).
3) Temporal basis risk: there are imperfect choices about timing (Deng et al., 2007; Díaz-Nieto et al., 2010).

Furthermore, Kelleher et al. (2001) considered that the measurement of the in-crop temperature and its recording is an additional basis risk issue. Although we believed that the $HDDT_{min}$ strategy, which was based on the phenology of the plant, was confirmed when initiating the cover with triggers generic to the plant, answering most of the basis risk questions, we still needed to understand why some policies were more efficient than others.

In Gilgandra, when the crop was planted on the optimal sowing date, there was a gain of 768 kg/ha. During the 35-day critical period, there were an average of eight frosts per season, leading to a potential income loss of up to 51 %. At this farm, the insurance strategy was highly efficient across the entire ensemble of efficiency measures compared to not taking frost insurance but planting on the optimal sowing date.

Similarly, at Birchip, which has an optimal sowing gain of 445 kg/ha, an average of four frost events per annum during the critical period, and a potential income loss of up to 11 %, the insurance strategy was highly inefficient. It's essential to note that the insurance structures were consistent across all sites. In the calculation of the premiums, we found that for those sites where the covers were more efficient, frost events that made up the loss calculations in the premium value occurred in

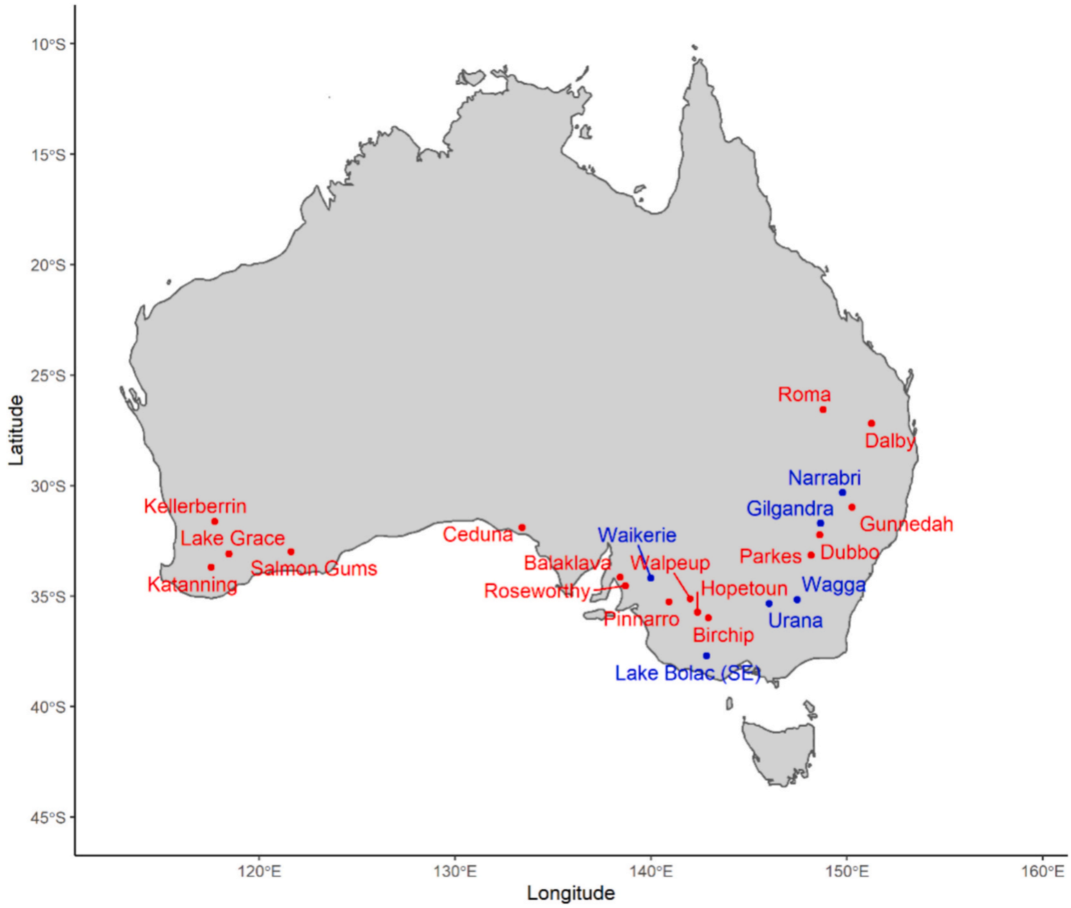

Fig. 7. Potential benefit of insurance based on the mean root square loss (MRSL). The blue-coloured names represent positive effects. Supplementary Table 6: Potential Benefit of Insurance Based on Mean Root Square Loss.
Locations where the insurance had a potential benefit based on MRSL. The blue-coloured names represent positive effects. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Summary of financial efficiency analysis across all the test sites on average for 40 years. In the table, y = yes ($HDDT_{min}$ is efficient), and n = no ($HDDT_{min}$ is inefficient). $HDDT_{min}$: heating degree day temperature minimum.

	Efficiency Summary					
Farm Location	Yield Gained From Optimally Sowing	Economic Assessment of the Insurance	Premium Versus Payout Assessment	Difference in Standard Deviation of Payouts	Conditional Tail Expectation	Mean Root Square Loss
Roma	y	y	n	n	n	n
Dalby	y	y	y	n	y	n
Dubbo	y	n	n	n	y	n
Waikerie	y	n	n	y	n	y
Gunnedah	y	n	n	n	n	n
Gilgandra	y	y	y	y	y	y
Narrabri	y	y	n	y	y	y
Parkes	y	y	n	y	n	n
Urana	y	n	n	y	n	y
Wagga	y	y	n	y	n	y
Lake Bolac	y	y	n	y	y	y
S Walpeup	y	y	n	n	n	n
Pinnarro	y	n	n	n	n	n
Birchip	y	n	n	n	n	n
Ceduna	y	y	n	y	n	n
Hopetoun	y	n	n	n	n	n
Balaklava	y	n	n	n	n	n
Roseworthy	y	n	n	n	n	n
Salmon Gums	y	n	n	n	n	n
Lake Grace	y	n	n	n	n	n
Katanning	y	n	n	n	n	n
Kellerberrin	y	n	n	n	n	n

earlier years and not in more recent times (i.e. the calculation of losses were more historical as opposed to more current). For example, Dubbo suffered from major frosts in 2018 and 2017, whilst the last major frost in Wagga was in 2012. This represents an important feature when pricing up index insurance structures, as the loss calculation is a critical component for the premium.

4.3. Improving spatial basis risk

Overall, the use of an $HDDT_{min}$ call as an insurance product to help mitigate frosts on crops sown optimally provided mixed results when used annually. We suggest this can be dramatically improved by a reduction in spatial basis risk. Reducing spatial-basis risk is currently being investigated by the BOM and the Commonwealth Scientific and Industrial Research Organisation (CSIRO). At present, the data used to price contracts are based on the national surface model of historical meteorological data on a 5 km × 5 km grid. It is anticipated that CSIRO's project on downscaling and increasing the granularity of the data will provide a more accurate picture of what happens in the paddocks. Using downscaled data to price options may provide insurance that is more closely aligned with the needs of the grower. Furthermore, the BOM has been researching the use of trusted private automated weather sites to increase data intake, which will refine the granularity of the data. Field trials are currently being conducted, and the hope is that obtaining data from additional sites around Australia will increase the granularity and accuracy of the data, which can then be applied to pricing more appropriate insurance. As part of an initiative with the GRDC, the CSIRO is working on a project to map heat and frost on a paddock basis. This will help refine the granularity of the risk areas. By using better-refined data to define the risk areas, we aim to reduce basis risk and increase the efficiency of the covers.

Similar to other cases of index-based products, the results are more highly efficient when the cover is more targeted, as suggested by Pietola et al. (2011). For example, using multiple indexes in the insurance, the gains at Roma are of a similar order to those previously reported by Pietola et al. (2011), where a basket of rainfall plus temperature index insurance managed to hedge about 38 % of a wheat grower's yield risk, with 62 % remaining as uninsured basis risk. Although the structures used by Pietola et al. (2011) were different and not focused on frost, the use of dual indexes seems to provide greater efficiency. Kotlobovskii et al. (2018) confirmed that index-based insurance in Russia is cost-effective. In their study on frost index insurance for tea, Huang et al. (2021) suggested that the compensation rate and basis ratio meet the basic requirements of insurance companies. Dalhaus and Finger (2016) suggested that the use of gridded data improves the potential of weather index-based insurance. Given the nature of frost, increasing the granularity of the data away from 5 km × 5 km to a smaller area may provide more efficient results and represent a further topic to investigate.

4.4. Improving pricing structure

The pricing of frosts was determined by the frequency and intensity of recent occurrences. However. in some cases where the frequency and intensity of frosts were similar, the pricing was skewed to frosts that occurred more recently. For instance, despite the similar intensity of frosts between Gilgandra and Birchip, the absence of frosts in Gilgandra for some time led to cheaper options. This could be observed in the 4.79 % premium for Gilgandra, substantially lower than Birchip's 9.04 %. This pricing methodology was systematically based on a loss calculation weighted towards the most recent years, resulting in cheaper premiums for areas with fewer recent frost events. Similar findings were noted in Narrabri, where the absence of frost events over the last five years allowed for a cheaper premium.

4.5. Designing an insurance contract based on plant phenology

There are limited studies on planting on the optimal date and then using index insurance to help maintain gains, as well as the use and effectiveness of index insurance that has a phenological component. Leblois and Quirion (2013), Kapphan et al. (2012), and Conradt et al. (2015) considered a phenological approach to insurance in the use of grower degree days to determine the start and end dates of covers and had mixed results. Pietola et al. (2011) were conclusive in their results that open-sourced phenological reports reduced the basis risk of index insurance based on weather. They found that weather events triggering indemnity payments should be structured with certain critical time regimes over their distribution during the growing season. As such, the structures used in this study correspond to the phenology of the plant sown on a critical day to optimise yield and having insurance during the critical reproduction stages, which is anticipated to help make the policies more attractive to growers.

5. Conclusion

We have tested a new frost insurance solution that enables farmers to take calculated risks and plant earlier, improving their chances of higher yields and providing financial protection in case of a frost event. The APSIM-Wheat simulations show that most optimally sown crops are subject to yield loss due to frost in the areas considered. Frost damage can occur pre-head emergence when temperatures drop below −2 °C, −1 °C, and 0 °C, possibly triggering a stem frost with a potentially dramatic or even catastrophic loss of yield and subsequent income. Temperatures below 0 °C around anthesis can reduce grain set, resulting in significant yield losses as well. The total losses caused by frost on the farms under study are estimated to be 39 % of the yield for optimally planted crops. On farms experiencing frequent frosts (i.e., more than five frost events during the estimated 35 days of sensitivity), the loss of yield and income is around 60 %.

On those farms where the frequency of frost events and hence losses are high, the use of frost index insurance, namely the use of $HDDT_{min}$, is efficient and even more efficient if no recent historical frost events or insurance losses have occurred because the premiums will be lower.

The use of index insurance is not efficient for farms with a low frequency of frost events, as the losses from such events have been relatively minor. The premiums across the 22 farms average 6.6 % of the sum insured. However, on the farms where frost losses are greater than 60 %, the premiums are slightly higher than 10 % in extreme cases. Based on the higher premiums at the high frost risk sites and where the use of $HDDT_{min}$ is efficient, the results indicate that, on average, the farmers will be better off by $121/ha when sowing during the optimal planting window and using targeted index frost insurance to cover frost risk.

Financial efficiency analysis indicates that protection for frost damage can be theoretically adequately managed through the $HDDT_{min}$ call if a high frequency of frost events results in significantly high losses of >60 %. Total losses are not recovered entirely by the insurance, although the farmer is better off if the cover is found to be efficient. In cases where frost events are not high but low to average, the use of an $HDDT_{min}$ call to manage frost events can be considered inefficient if used every year.

We envisage that, with an improvement in the climate prediction of frost occurrence, crop modelling, better access to data, and refinement in the tuning of structures, the targeted integration of frost index insurance with optimal cropping windows, especially for high frost-prone regions, can be an important strategy for reducing financial impacts and enhancing income stability.

Ethics statement

This research was conducted according to the Netherlands Code of

Conduct for Research Integrity 2018 and its later amendments.

Consent to participate

All the research participants gave their informed consent to participate in this study.

Code availability (software application or custom code)

The software used was primarily Microsoft Excel version 16.72.

CRediT authorship contribution statement

Jonathan Barratt: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jarrod Kath:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Shahbaz Mushtaq:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Brian Collins:** Writing – review & editing, Methodology, Conceptualization. **Karine Chenu:** Writing – review & editing, Investigation, Conceptualization. **Jack Christopher:** Writing – review & editing, Investigation, Conceptualization. **Duc-Anh An-Vo:** Writing – review & editing, Software, Methodology, Data curation.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2025.104306.

Data availability

The data are available upon a reasonable request to the authors.

References

Ababaei, B., Chenu, K., 2019. Recent trends in drought, heat and frost-induced yield losses across the Australian wheatbelt. Proceedings 36, 5. https://doi.org/10.3390/proceedings2019036005.

Ababaei, B., Chenu, K., 2020. Heat shocks increasingly impede grain filling but have little effect on grain setting across the Australian wheatbelt. Agric. For. Meteorol. 284, 107889. https://doi.org/10.1016/j.agrformet.2019.107889.

Adeyinka, A.A., Krishnamurti, C., Maraseni, T.N., Chantarat, S., 2014. The viability of weather-index insurance in managing drought risk in rural Australia. Int. J. Rural Manage. 12 (2), 125–142.

Adeyinka, A.A., Krishnamurti, C., Maraseni, T., Cotter, J., 2015. The place of insurance in the future of Australian drought policy. Actuar. Summit. https://doi.org/10.1177/0973005216660897, 17–19 may 2015. Melbourne.

Anderson, W.K., Garlinge, J.R. (Eds.), 2000. The Wheat Book: Principles and Practice (Bulletin 4443). Department of Primary Industries and Regional Development, Perth, Western Australia.

An-Vo, D.A., Mushtaq, S., Zheng, B., Christopher, J.T., Chapman, S.C., Chenu, K., 2018. Direct and indirect costs of frost in the Australian wheatbelt. Ecol. Econ. 150, 122–136. https://doi.org/10.1016/j.ecolecon.2018.04.008.

Barlow, K., Christy, B., O'Leary, G., Riffkin, P., Nuttall, J., 2015. Simulating the impact of extreme heat and frost events on wheat crop production: a review. Field Crop Res. 171, 109–119. https://doi.org/10.1016/j.fcr.2014.11.010.

Barnett, B.J., Mahul, O., 2007. Weather index insurance for agriculture and rural areas in lower-income countries. Am. J. Agric. Econ. 89 (5), 1241–1247. https://doi.org/10.1111/j.1467-8276.2007.01091.x.

Barnett, B., Vedenov, D., 2004. Efficiency of weather derivatives as primary crop insurance instruments. J. Agric. Econ. 29 (3), 387–403. https://doi.org/10.1111/j.1574-0862.2007.00204.x.

Bell, L.W., Lilley, J.M., Hunt, J.R., Kierkegaard, J.A., 2015. Optimising grain yield and grazing potential of crops across Australia's high-rainfall zone: A simulation analysis. *1.* Wheat. Crop Pasture Sci. 66, 332–348. https://doi.org/10.1071/cp14230.

BOMs Provide Key Climate Groups, 2025. http://www.bom.gov.au/iwk/climate_zones/map_1.shtml.

Breustedt, G., Bokusheva, R., Heidelbach, O., 2008. Evaluating the potential of index insurance schemes to reduce crop yield risk in an arid region. J. Agric. Econ. 59 (2), 312–328. https://doi.org/10.1111/j.1477-9552.2007.00152.x.

Bucheli, J., Dalhaus, T., Finger, R., 2020. The optimal drought index for designing weather index insurance. Eur. Rev. Agric. Econ. 48 (3), 573–597. https://doi.org/10.1093/erae/jbaa014.

Budong, Q., Zhang, X., Chen, K., Feng, Y., O'Brien, T., 2010. Observed long-term trends for agroclimatic conditions in Canada. J. Appl. Meteorol. Climatol. 49, 604–618. https://doi.org/10.1175/2009jamc2275.1.

Celestina, C., Hunt, J., Kuchel, H., Harris, F., Porker, K., Biddulph, B., Bloomfield, M., McCallum, M., Graham, R., Matthews, P., Aisthorpe, D., Al-Yaseri, G., Hyles, J., Trevaskis, B., Wang, E., et al., 2023. A cultivar phenology classification scheme for wheat and barley. Eur. J. Agron. 143, 126732. https://doi.org/10.1016/j.eja.2022.126732.

Chenu, K., Deihimfard, R., Chapman, S.C., 2013. Large-scale characterization of drought pattern: a continent-wide modelling approach applied to the Australian wheatbelt spatial and temporal trends. New Phytol. 198, 801–820. https://doi.org/10.1111/nph.12192.

Chenu, K., Porter, J.R., Martre, P., Basso, B., Chapman, S.C., Ewert, F., Bindi, M., Asseng, S., 2017. Contribution of Crop Models to Adaptation in Wheat. Trends Plant Sci 22 (6), 472–490. https://doi.org/10.1016/j.tplants.2017.02.003. Epub 2017 Apr 4. PMID: 28389147.

Chenu, K., Fletcher, A., Ababaei, B., Christopher, J., Kelly, A., Hickey, L., Van Oosterom, E., Hammer, G., 2019. Integrating crop modelling, physiology. Genetics and breeding to aid crop improvement for changing environments in the Australian wheatbelt. Proceedings 36, 4. https://doi.org/10.3390/proceedings2019036004.

Christopher, J., Zheng, B., Chapman, S., Borrell, A., Fredricks, T., Chenu, K., 2016. An analysis of frost impact plus guidelines to reduce frost risk and assess frost damage. Prog. Environ. Sci. 29, 171–172. https://doi.org/10.1016/j.proenv.2015.07.244.

Collins, B., Chenu, K., 2021. Improving productivity of Australian wheat by adapting sowing date and genotype phenology to future climate. Clim. Risk Manag. 32, 100300. https://doi.org/10.1016/j.crm.2021.100300.

Collins, B., Chenu, K., 2022. Change in abiotic stress and atmospheric CO_2 concentration significantly affected Australian wheat productivity over 1981-2018. In: Australian Agronomy Conference (18–22 September Toowoomba, Australia), p. 4.

Collins, B., Chapman, S., Hammer, G., Chenu, K., 2021. Limiting transpiration rate in high evaporative demand conditions to improve Australian wheat productivity. In Silico Plants 3. https://doi.org/10.1093/insilicoplants/diab006.

Conradt, S., Finger, R., Bokusheva, R., 2015. Tailored to the extremes: quantile regression for index-based insurance contract design. Agric. Econ. 46 (4), 537–547. https://doi.org/10.1111/agec.12180.

Crimp, S.J., Gobbett, D., Kokic, P., 2016. Recent seasonal and long-term changes in southern Australian frost occurrence. Clim. Chang. 139, 115–128. https://doi.org/10.1007/s10584-016-1763-5.

Dalhaus, Tobias, Finger, Robert, 2016. Can Gridded Precipitation Data and Phenological Observations Reduce Basis Risk of Weather Index–Based Insurance? Weather, Climate and Society 8. https://doi.org/10.1175/WCAS-D-16-0020.1.

Dalhaus, T., Finger, R., 2016. Can gridded precipitation data and phenological observations reduce basis risk of weather index-based insurance? Weather, Climate and Society 8 (4), 409–419. https://doi.org/10.1175/WCAS-D-16-0020.1.

Dalhaus, T., Musshoff, O., Finger, R., 2018. Phenology information contributes to reduce temporal basis risk in agricultural weather index insurance. Sci. Rep. 8 (1). https://doi.org/10.1038/s41598-017-18656-5.

Dalhaus, T., Barnett, B.J., Finger, R., 2020. Behavioural weather insurance: applying cumulative prospect theory to agricultural insurance design under narrow framing. PLoS ONE 15 (5), e0232267. https://doi.org/10.1371/journal.pone.0232267.

Deng, X., Barnett, B.J., Vedenov, D.V., West, J.W., 2007. Hedging dairy production losses using weather-based index insurance. Agric. Econ. 36, 271–280. https://doi.org/10.1111/j.1574-0862.2007.00204.x.

Díaz-Nieto, J., Cook, S.E., Läderach, P., Fisher, M.J., Jones, P.G., 2010. Rainfall index insurance to help smallholder farmers manage drought risk. Clim. Dev. 2, 233–247. https://doi.org/10.3763/cdev.2010.0050.

Flohr, B.M., Hunt, J.R., Kirkegaard, J.A., Evans, J.R., 2017. Water and temperature stress define the optimal flowering period for wheat in South-Eastern Australia. Field Crop Res. 209, 108–119. https://doi.org/10.1016/j.fcr.2017.04.012.

Flohr, B.M., Hunt, J.R., Kirkegaard, J.A., Evans, J.R., Lilley, J.M., 2018. Genotype × management strategies to stabilise the flowering time of wheat in the south-eastern Australian wheatbelt. Crop Pasture Sci. 69, 547–560. https://doi.org/10.1071/cp18014.

Frederiks, T.M., Christopher, J.T., Fletcher, S.E.H., Borrell, A.K., 2011. Post head-emergence frost resistance of barley genotypes in the northern grain region of Australia. Crop Pasture Sci. 62, 1–10. https://doi.org/10.1071/cp11079.

Frederiks, T.M., Christopher, J.T., Fletcher, S., Borrell, A.K., 2015. Post head-emergence frost in wheat and barley: defining the problem, assessing the damage, and managing the risk. J X Bot. 66, 3487–3498. https://doi.org/10.1093/jxb/erv088.

Fuller, M., Christopher, J., Frederiks, T., 2009. Low-temperature damage to wheat in head – Matching perceptions with reality. In: Gusta, L., Winiewski, M., Tanino, K.

(Eds.), Plant Cold Hardiness: From the Laboratory to the Field. CABI Books, CABI International Press, Oxfordshire, UK. https://doi.org/10.1079/9781845935139.0012.

Gine, X., 2010. The Promise of Index Insurance. The World Bank, Washington, D.C.

Hammer, G., Messina, C., Wu, A., Cooper, M., 2019. Biological reality and parsimony in crop models—why we need both in crop improvement!, in silico. Plants 1 (1), diz010. https://doi.org/10.1093/insilicoplants/diz010.

Hao, S., Ryu, D., Western, A., Perry, E., Bogena, H., Franssen, H.J.H., 2021. Performance of a wheat yield prediction model and factors influencing the performance: a review and meta-analysis. Agric. Syst. 194, 103278. https://doi.org/10.1016/j.agsy.2021.103278.

Henderson, V., Hobson, D.G., 2002. Real options with constant relative risk aversion. J. Econ. Dyn. Control. 27 (2), 329–355. https://doi.org/10.1016/s0165-1889(01)00052-5.

Herbert, A., 2017. An international BENCHMARKING COMPARison of Australian Crop Production and Profitability. GRDC Publication. Project number AAM000001.

Holzworth, D.P., Huth, N.I., Devoil, P.G., Zurcher, E.J., Herrmann, N.I., Mclean, G., Chenu, K., Van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., Brown, H., Whish, J.P.M., Verrall, S., Fainges, J., Bell, L.W., Peake, A.S., Poulton, P.L., Hochman, Z., Keating, B. A., 2014. APSIM - evolution towards a new generation of agricultural systems simulation. Environ. Model Softw. 62, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009.

Huang, C., Chen, J., Sun, C., Wu, L., Tao, H., Lin, H., 2021. Classification design of the meteorological index insurance for cold-frost damage on tea in Fujian province. Chin. J. Eco-Agric. 29 (12), 2074–2083. https://doi.org/10.12357/cjea.20210304.

Jeffrey, S.J., Carter, J.O., Moodie, K.B., Beswick, A.R., 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environ. Model Softw. 16, 309–330. https://doi.org/10.1016/S1364-8152(01)00008-1.

Jewson, S., Brix, A., 2005. Weather Derivative Valuation: The Meteorological, Statistical, Financial and Mathematical Foundations. Cambridge University Press. https://doi.org/10.1017/cbo9780511493348.

Kalma, J.D., Laughlin, G.P., Caprio, J.M., Hamer, P.J.C., 1992. The Bio Climatology of Frost, vol. 2. Biotechnol Adv, Berlin. https://doi.org/10.1007/978-3-642-58132-8_1.

Kapphan, I., Calanca, P., Holzkaemper, A., 2012. Climate change, weather insurance design and hedging effectiveness. Geneva Pap Risk Insur Issues Pract. 37, 286–317. https://doi.org/10.1057/gpp.2012.8.

Kath, J., Mushtaq, S., Henry, R., Adeyinka, A., Stone, R., Marcussen, T., Kouadio, L., 2018. Index insurance benefits agricultural producers exposed to excessive rainfall risk. Weather Clim Extrem. 22, 1–9. https://doi.org/10.1016/j.wace.2018.10.003.

Kath, J., Mushtaq, S., Henry, R., Adeyinka, A., Stone, R., Marcussen, T., Kouadio, L., 2019. Spatial variability in regional scale drought index insurance viability across Australia's wheat growing regions. Clim. Rick Manag. 24, 13–29. https://doi.org/10.1016/j.crm.2019.04.002.

Keating, B., Carberry, P.S., Hammer, G., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J., Silburn, M., Wang, E., Brown, S., Bristow, K., Asseng, S., Smith, C., 2003. An overview of APSIM, a model designed for farming systems simulation. Eur. J. Agron. 18, 267–288. https://doi.org/10.1016/S1161-0301(02)00108-9.

Kelleher, F.M., Rollings, N.M., Poulton, D.M., Cornish, P.S., 2001. Temperature variation and frost risk in undulating cropland. Conf. Austr. Agron. Tas 10. https://doi.org/10.13140/2.1.2049.7924.

Kotlobovskii, I.B., Budanova, M.M., Lukash, E.N., 2018. Development potential of regional parametric insurance programs in Russia. Finan. Theory Pract. 22 (2), 106–123. https://doi.org/10.26794/2587-5671-2018-22-2-106-123.

Leblois, A., Quirion, P., 2013. Agricultural insurances based on meteorological indices: realizations, methods and research challenges. Met. Apps 20, 1–9. https://doi.org/10.1002/met.303.

Leblois, A., Quiron, P., Sultan, B., 2014. Price vs. weather shock hedging for cash crops: ex ante evaluation for cotton producers in Cameroon. Ecology 101, 67–80. https://doi.org/10.1016/j.ecolecon.2014.02.021.

Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature 529, 84–87. https://doi.org/10.1038/nature16467.

Mushtaq, S., An-Vo, D., Christopher, M., Zheng, B., Chenu, K., Chapman, S.C., Christopher, J.T., Stone, R.C., Frederiks, T.M., Monirul Alam, G.M., 2017. Economic assessment of wheat breeding options for potential improved levels of post head-emergence frost tolerance. Field Crop Res. 213, 75–88. https://doi.org/10.1016/j.fcr.2017.07.021.

Nguyen, T., Kath, J., Kouadio, L., King, R., Mushtaq, S., Barratt, J., 2024. Integrating rainfall index-based insurance with optimal crop management strategies can reduce financial risks for Australian dryland cotton farmers, Sustainable Futures, 2024–12. DOI. https://doi.org/10.1016/j.sftr.2024.100249.

Pietola, K., Myyrä, S., Jauhiainen, L., Peltonen-Sainio, P., 2011. Predicting the yield of spring wheat by weather indices in Finland: implications for designing weather index insurances. Agric. Food Sci. 20 (4), 269–286. https://doi.org/10.23986/afsci.6024.

Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat: A review. Eur. J. Agron. 10, 23–36. https://doi.org/10.1016/s1161-0301(98)00047-1.

Ritter, M., Musshoff, O., Odening, M., 2014. Minimizing geographical basis risk of weather derivatives using a multi-site rainfall model. Comput. Econ. 44, 67–86. https://doi.org/10.1007/s10614-013-9410-y.

Spicka, J., Hnilica, J., 2013. A methodical approach to design and valuation of weather derivatives in agriculture. Adv. Meteorol. 2013, 8. https://doi.org/10.1155/2013/146036.

Thong, Nguyen-Huy, Kath, Jarrod, Kouadio, Louis, King, Rachel, Mushtaq, Shahbaz, Barratt, Jonathan, 2024. Integrating rainfall index-based insurance with optimal crop management strategies can reduce financial risks for Australian dryland cotton farmers, sustainable. Futures 8, 100249. https://doi.org/10.1016/j.sftr.2024.100249.

Turvey, C.G., 2001. Weather derivatives for specific event risks in agriculture. Rev. Agric. Econ. 23, 333–351. https://doi.org/10.1111/1467-9353.00065.

Turvey, C.G., Mclaurin, M.K., 2012. Applicability of the Normalized Difference Vegetation Index (NDVI) in Index-Based Crop Insurance Design. AMS271-284. https://doi.org/10.1175/WCAS-D-11-00059.1.

Vedenov, D.V., Barnett, B.J., 2004. Efficiency of weather derivatives as primary crop insurance instruments. J. Agric. Econ. 36 (2), 387–403. https://doi.org/10.1111/j.1574-0862.2007.00204.x.

White, J., Edwards, J. (Eds.), 2007. *Procrop - Wheat Growth and Development*. NSW Department of Primary Industries.

Woldendorp, G., Hill, M., Doran, R., 2008. Frost in a future climate: modelling interactive effects of warmer temperatures and rising atmospheric [CO2] on the incidence and severity of frost damage in a temperate evergreen (Eucalyptus pauciflora). Glob. Chang. Biol. 14 (2), 294–308. https://doi.org/10.1111/j.1365-2486.2007.01499.x.

World Bank, 2011. Weather Index Insurance Course 2011. https://doi.org/10.1596/26889.

Zadoks, J.C., Chang, T.T., Konzak, F.C., 1974. A decimal code for the growth stages of cereals. Weed Res. 14, 415–421. https://doi.org/10.1111/j.1365-3180.1974.tb01084.x.

Zheng, B., Chenu, K., Dreccer, M.F., Chapman, S.C., 2012. Breeding for the future: what are the potential impacts of future frost and heat events on sowing and flowering time requirements for Australian bread wheat (*Triticum aestivium*) varieties? Glob. Chang. Biol. 18, 2899–2914. https://doi.org/10.1111/j.1365-2486.2012.02724.x.

Zheng, B., Chapman, S.C., Christopher, J.T., Frederiks, T.M., Chenu, K., 2015a. 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, B., Chenu, K., Doherty, A., Chapman, S., 2015b. The APSIM-wheat module (7.5 R3008). https://www.apsim.info/wp-content/uploads/2019/09/WheatDocumentation.pdf.

Zheng, B., Chapman, S.C., Chenu, K., 2018. The value of tactical adaptation to El Niño–Southern oscillation for East Australian wheat. J. Clim. 6, 77. https://doi.org/10.3390/cli6030077.