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Decile-based index drought insurance to help improve income stability for wheat producers in Australia

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ABSTRACT

Droughts are a major challenge to the financial sustainability of wheat growers in Australia. While adaptive farming practices can reduce exposure to drought risk, they may fall short when unfavourable climate conditions occur during critical stages of crop development. This study proposes a novel crop insurance solution: a decile-based index insurance policy with weighted payouts that align to rainfall deficits. We integrated 40 years of crop simulation data from the APSIM (Agricultural Production Systems Simulator; v7.10) to model theoretical wheat yields across 22 farms in the Australian wheat belt. The impact of drought on farm income was assessed, and the effectiveness of the proposed insurance structure was evaluated in terms of income stability and financial utility. Results indicate that, for optimally sown crops, the average financial gain from adopting the insurance contract was $182 per hectare, while the average drought-related loss was $71 per hectare. The insurance proved effective on 95 % of farms, significantly reducing income volatility. Notably, 82 % of farms experienced improved income certainty in the poorest 50 % of years, and average farm income increased by 21 % over the 40-year period when input costs were insured annually. Given the increasing frequency and intensity of droughts due to climate change, this targeted approach offers a compelling solution for enhancing resilience and income stability in wheat production. To our knowledge, this is the first study to design a drought insurance product explicitly around deciles on in crop rainfall with weighted payouts for wheat.

1. Introduction

Extreme weather events significantly impact the farms' productivity, leading to lower yields and income for farmers and other stakeholders in the local economy (Lesk et al., 2016). Climate variability affects almost 80 % of wheat-producing regions globally (Ray et al., 2015). For example, droughts increase the risk of food insecurity (Lipper et al., 2014). Dry spells during the growing season can be financially devastating for growers, especially at critical stages such as (i) after sowing when the seedling establishes itself Z0-Z3 (Zadoks et al., 1974), (ii) during booting and ear emergence, and (iii) during the stages just before grain fill, between Z7-Z8 (ProCrop, 2007). The impact of drought on agriculture has been the subject of extensive research (Odening and Shen, 2014; Mushtaq, 2018). Additionally, according to a survey by the National Farmers Federation, 81 % of Australian farmers reported that rainfall deficits and droughts were the most significant peril they faced (CelsiusPro, 2020).

The primary financial mechanisms farmers use to manage losses in the worst 10 % of years of drought in Australia include taking on more debt, drawing down on a loan facility, increasing earnings from off-farm, using insurance, drawing down farm deposits, injecting cash by selling non-streetwise assets (Topp, 2023; CelsiusPro, 2020). Of these, taking on more debt or drawing down a facility is the most popular mechanism, whilst insurance is the least popular (Kamal et al., 2023; CelsiusPro, 2020). Taking on more debt has long-term consequences for the farmer's balance sheet as not only does the debt need to be repaid, but an additional interest rate component needs to be considered, especially if interest rates go up and or if the debt cannot be repaid due to dry conditions continuing for several seasons. The ability to pay off debt becomes a burden if the farmer's balance sheet is not strong.

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Lending to the agricultural sector in 2022–23 increased by 5.3 % from $109.9 billion to $115.7 billion. Average finance payments as % of net income for all broadacre and dairy farms in 2022–23 in Australia stood at 8 %. In 2007–08, at the end of the drought, it stood at 55 % (Topp, 2023). Insurance could be an important tool growers use to help ease the burden of potential farm debt caused by drought. However, the use of insurance is not popular as there is a lack of understanding of how to insure losses associated with drought and dry spells using index insurance, and the premiums are perceived as being high compared to other forms of insurance (Hatt et al., 2012). Several reviews (ABARES 2012, NRAC 2012, IPART, 2016) have been conducted into options the Government can do to support this industry. However, progress on initiatives has been slow, which does little to help farmer engagement and, as a result, take-up on insurance remains small.

Generally, two types of insurance are used in the market: indemnity-based and non-indemnity insurance (Hartell et al., 2006). Indemnity-based insurance requires an assessor to evaluate the damage, often involving an excess payment to be made with claims often delayed and not received at a crucial time when it is needed the most (Wang et al., 2023, Freshwater et al., 1986). These are the main insurance contracts growers use; however they do not address lost yield. A non-indemnity insurance contract also known as an index insurance contract or a weather derivative (Gine, 2010), pays a fixed amount regardless of the damage (Barnett and Vedenov, 2004). The triggers of the contract are a proxy that represents the potential damage (Turvey, 2001). Payouts occur on confirmation of the data in the case of drought rainfall. Indemnity-based drought insurance is unavailable or too expensive in Australia (Hatt et al., 2012) hence the importance of developing appropriate non-indemnity-based contracts to address this gap.

Index Insurance can be a crucial tool for managing risks in agriculture (Conradt et al., 2015; Dalhaus and Finger, 2016). When combined with crop management strategies, insurance can enable farmers to take more risks and obtain higher crop yields. Optimally sowing a crop producers higher yields (Barratt et al., 2024) but also, opens the crop to yield loss events such as drought and frost. Adopting an index insurance policy based on low deciles of rain with weighted payouts could be a valuable risk management tool for farmers, especially in drought-prone areas. Farmers can protect themselves from accumulating debt caused by crop failures due to droughts using an index insurance solution structured to pay as conditions become drier throughout the season. This strategy has not yet been fully explored, and it could be a breakthrough for farmers.

It's important to note that current index-based insurance designs do not consider multiple triggers and weighted payouts. Instead, they are based on the entire season and typically rely on a single index, which exposes farmers to various forms of basis risk. Therefore, having a cover where multiple payouts are triggered the drier it gets with payouts weighted as the conditions become more extreme, could reduce the temporal basis risk associated with index insurance. Making it more effective and affordable in managing weather risks. By using optimal sowing strategies, multiple triggers and weighted payouts tied to in crop rain events, farmers can minimise the negative impacts of drought.

To investigate the performance of the strategy, we (i) determined the cost and impact of droughts on the farmer, (ii) developed a novel index insurance policy, with two triggers and weighted payouts, and (iii) examined the utility of the index-based drought insurance options that could provide financial protection to farmers from drought risks. We hypothesise that given climate volatility, farmers not using a non-indemnity index insurance solution may face higher risk and increased debt from multiple periods of dry spells.

The research makes a valuable contribution to the contemporary literature by proposing a shift in the perception of insurance from solely a reactive tool for managing drought risk to also serving as a proactive risk management tool. The study highlights the potential of an innovative decile-based insurance product, which is highly targeted and cost-effective. When these products are integrated with optimal crop management strategies, they have the potential to significantly mitigate income volatility during poor (e.g., drought) years and increase yield, thereby enhancing income in favourable years.

Given the escalating climate variability and the growing frequency of droughts (Budong et al., 2010), there is a pressing need for more precise and sustainable insurance policies. Our results show that these strategies have the potential to play a pivotal role in providing farmers with the means to achieve income stability during periods of drought.

2. Materials and methods

2.1. Study region

The research focused on individual farms in the Australian wheat belt (Supplementary Table 1). Wheat farms were selected from the three agroecological regions defined by the Grain Research and Development Corporation (GRDC) to ensure a diverse range of climatic conditions: north, south, and west (Greijdanus et al., 2014).

The northern grain region of Australia includes New South Wales (NSW) and Queensland (QLD) and is known for its mainly vertosol clay soils with a high-water holding capacity (WHC). The climate in this region is tropical, subtropical, and temperate, which allows farmers to grow both winter and summer crops. Many farmers in this region aim to produce high-protein wheat. Our study examined 10 farms in the northern region from sub-regions of QLD Central, NSW Central, NSW East, and QLD Southeast.

The southern grain region includes NSW, Victoria (VIC), and South Australia (SA) and is characterised by variable soils and a temperate climate. Yields in this region are highly dependent on spring rains, and many soil types have low WHC. As a result, growers mainly produce a winter crop. In the southern region, our study examined 8 farms from South Australia (SA), Vic Mallee, SA and Victoria (VIC) Bordertown-Wimmera districts, and VIC High rainfall regions.

Lastly, Western Australia (WA) is characterised by low soil fertility. Good winter and spring rains determine yields. In this region, the study examined 4 farms from the subregions of West Australia (WA) Central, WA Eastern, and the WA Sandplains.

2.2. Study design

Fig. 1 illustrates the schematic study design, which is centred around comparing the actions of farmers who have insurance with those who do not, particularly in relation to their sowing dates and the anticipated outcomes of these actions. The presence of index insurance provides wheat producers with the opportunity to strategically assess and manage risks, allowing them to develop and implement optimal crop management strategies. These strategies are specifically geared towards enhancing crop yield and subsequently increasing farmers' overall income.

2.3. Crop simulation

We utilised the Wheat module from the Agricultural Production Systems sIMulator (APSIM v7.10; Keating et al., 2003) to gather reliable data on wheat yields. APSIM-Wheat is a widely recognized tool for simulating the biophysical processes involved in agricultural production (e.g. Barratt et al., 2024, Chenu et al., 2017; Collins et al., 2021; Ababaei et al., 2020; Zheng et al., 2018; Hammer et al., 2019) and is known to perform well when it comes to simulating wheat production, with a root mean square error of less than 1 t/ha across a range of environmental conditions (Hao et al., 2021).

Reliable simulation of wheat phenology is essential for evaluating risk exposure and designing insurance structures based on in-crop rainfall. APSIM-Wheat has undergone extensive validation for phenological development across diverse Australian environments (e.g.,

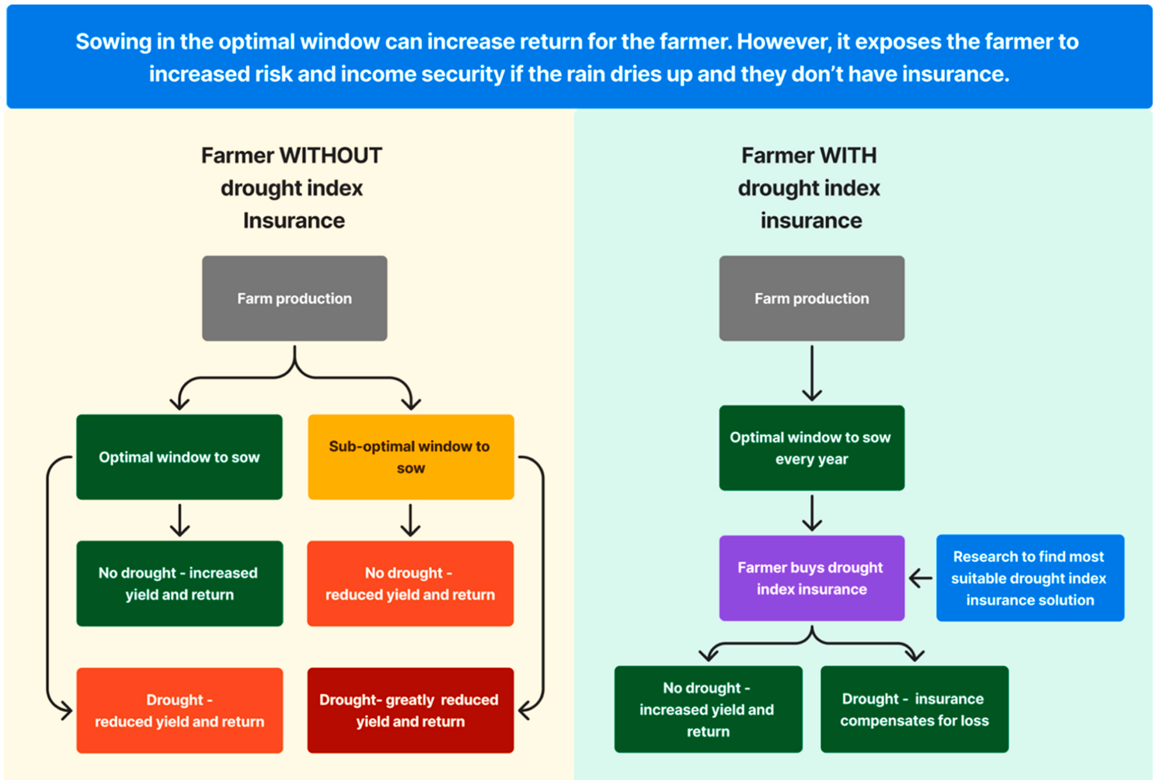

Fig. 1. Schematic showing potential actions by farmers regarding sowing dates and dry season index insurance and the likely outcomes of these actions.

Collins et al., 2021; Zheng and Chapman, 2016). As demonstrated by Zheng and Chapman (2016; personal communication), the model was calibrated and validated using nearly 3000 heading date observations from 202 sites, covering 52 cultivars and multiple sowing trials. The validation dataset encompassed a wide range of environments and seasons, including National Variety Trials, Crop Variety Tests in Western Australia, and various time-of-sowing experiments. The resulting parameter set—particularly thermal time to floral initiation, photoperiod sensitivity, and vernalisation sensitivity—has since been widely adopted, including in this study. This allows us to confidently simulate crop development stages (Zadoks scale) under varying seasonal and site conditions, which is critical for quantifying rainfall–yield relationships and assessing farmers' vulnerability to dry spells during sensitive growth stages.

APSIM requires daily weather data, which we obtained from the SILO database (Jeffrey et al., 2001) covering 1980–2019 (40 years) (Ritter et al., 2014). Using gridded data instead of weather station data reduced risk associated with rainfall and further improved the potential of WII in this research. Rainfall was based on a 5 km x 5 km grid to smooth out the rain events (Dalhaus and Finger, 2016).

Grain yield was simulated at the 22 studied locations with 10 different sowing dates (March 11, March 27, April 10, April 26, May 10, May 26, Jun 11, June 27, July 11, and July 27). The optimal sowing date was selected for each location based on achieving the highest long-term average (40 years) yield. As there are wide varieties of wheat that could be used for consistency purposes, we used the Hartog variety. After determining the best sowing date for each site, we calculated income and lost income caused by drought, using real prices adjusted for inflation. This income was then compared to the average income obtained over 40 years for each season.

2.4. Proposed insurance structure

We assume that growers will maximise yield by adopting optimal sowing times (Bell et al., 2015) and seeking additional income to purchase insurance to help protect their crops from a dry season. The cost of potential losses increases as the season progresses since more investment is made in the crop, making it crucial to recover these costs. The rate of wheat development varies considerably depending on the rainfall, genotype and location, which affects other pedoclimatic factors. As the crop matures, more inputs such as fertilised and herbicides are expensed to enhance yield and control weeds. At the same time, rain is needed to help the plant mature.

Wheat crops are particularly sensitive to water stress (i) after sowing when the seedling establishes itself (Z0-Z3; Zadoks et al., 1974), (ii) during booting and ear emergence (Z4–6), and (iii) just before grain fill (Z7-Z8). During Z4-Z8, significant costs are expensed on inputs such as fertiliser to increase yield, and this is when the farmer is more financially exposed if the rains dry up.

The proposed insurance structures are based on in-crop rainfall during the season and do not take into consideration other factors. The rational for this is that in crop rain is essential for yield. Payouts are calculated per mm of rainfall, increasing as rainfall decreases. The payout triggers are based on rainfall deciles (White et al., 1999). Over a risk period, rainfall is ranked in percentiles, with a decile 1 (D1) event including all the readings in the bottom 10 % of the data range and a decile 2 (D2) at the bottom 20 %. In the insurance structure, policies are triggered at a D2 event and then after a D1 event. Full payout is based on rainfall events at the 40-year low, less 30 %, which sometimes sees it close to a 100-year historical low. The lower the rainfall during the various stages of plant development, the higher the payout from the insurance structure.

The insurance structure design builds on the structures proposed by Dalhaus et al. (2018) and Conradt et al. (2015) and Kapphan et al., (2012) Firstly, the proposed design is similar to Dalhaus et al. (2018) as it utilises rainfall deficit as a measure of yield . However, it differs in that this insurance structure focuses on insufficient in-crop rainfall over the season. Secondly, instead of using growing degree days like Conradt et al. (2015), our approach is based on the relationship between rainfall and yield in a drought conditions (Dalhaus et al., 2020).

Both D2 and D1 events would mean a substantial loss of yield and, thus, a lack of income for the farmer to cover input costs. Therefore, two dry season triggers in one policy, each with different payouts per mm are used to supplement lost income (details in 2.4). These two options cover the impact of a decile 2 and decile 1 event on yield. An insurance structure that combines triggers based on plant developmental stages and input costs could help the farmer become more resilient to climate variability.

2.5. Cost of drought

Drought is the main risk Australian farmers identify with (CelsiusPro 2019). Understanding the cost of drought is crucial for evaluating whether purchased insurance structures effectively recover input costs as promised. It also helps to understand the amount of insurance that is needed to buy. To calculate this cost, the simulated average yearly income per season over 40 years, based on cumulative rain above the D2 event, was subtracted from simulated income based on cumulative rain less than a D2 event. The cumulative rain was calculated over the 140 days of the cropping cycle. These average numbers were then compared with the average insurance payouts of the proposed insurance structure to see if the claims helped the farmer recoup losses associated with drought.

2.6. Weather index insurance (WII) options

Index insurance is a non-indemnity type that does not require proof of loss. Before the risk period, the buyer and seller agree on the contract details, which pertain to a financial loss occurring once certain events related to the index occur. We assume that the grower will take the insurance every year.

To calculate insurance premiums, we have considered key findings from studies conducted by Kotlobovskii et al. (2018), Pietola et al. (2011), and Turvey (2001). Kotlobovskii et al. (2018) suggested that using two parameters in premium calculation could reduce the level of risk to the underwriter, leading to lower premiums while providing enough cover for the farmer's risk. Pietola et al. (2011) and Turvey (2012) addressed basis risk within the growing season and highlighted the importance of defining critical time periods of risk within the structure. Incorporating these findings into our design reduced premium value (Kotlobovskii et al., 2018) and basis risk by focusing on the most crucial events to yield and input cost. The risk period we have used here corresponds to 140 days of the season when in crop rain is most needed. Of the two insurance structures, cover 1 payout addresses input losses associated with a decile 2 event, while cover 2 addresses more advanced input losses associated with a decile 1 event. The policies work concurrently, so the drier it gets during the season, the more it pays.

The suggested amount of insurance to be bought aims to cover $300/ha of production costs, which is the average production cost in Australia in a low rainfall environment or $300,000 for a 1000-ha farm (SAGIT, 2022). The premium calculation involved two cumulative rainfall deficit options with a payout of $100,000 commencing at a strike equal to a D2 and a $200,000 payout for strikes commencing at a D1. Structured in a way to meet the rising costs of inputs as the plant matures, where the potential for a dry spell could cause financial issues. Maximum payout occurred at 30 % below the historical low over the 40-year period. In some cases, this low approximately corresponded to a historic low over 100 years. The strike, trigger, or attachment is the amount of rainfall (mm) required to initiate the insurance payout. The exit or cover length is the rainfall level (mm) at which the insurance pays out in full. The amount paid per mm is the sum insured divided by the difference between the strike and exit.

2.7. Insurance premium calculations

Premium calculations for our insurance policies are based on a methodology called 'return on risk' (World Bank, 2011). This method considers factors such as expected loss, probable maximum loss, payouts, volatility costs, and contract administration expenses. To calculate the probable maximum loss, we use a historical burn analysis, ie the times over history that the policy has paid out, this determines the maximum loss that could occur on each site given the parameters chosen. The maximum loss in all sites is set at $300,000. (World Bank, 2011). The burn analysis is a crucial part of the premium calculation process as it determines the historical loss the contract would have incurred over a predetermined period. For more information on the premium calculation methodology, refer to studies conducted by Henderson et al. (2002), World Bank (2011), Jewson and Brix (2005), and Spicka and Hnilica (2013).

In this research, 40 years of precipitation and seasonal phenological data were used to estimate the strikes i.e., decile 2 (D_2) and decile 1 (D_1); and the exit (E) for the risk period.

$$E = R * R_{min} \tag{1}$$

where R_{min} is the minimal in-crop rain over the 40 years. The payout (Pa) associated with a dry season having an in-crop rain (R) being below D_2 is given by,

$$\begin{aligned} Pa &= T_2 * (D_2 - R) \text{ if } D_1 < R \le D_2 \\ Pa &= T_2 * (D_2 - R) + T_1 * (D_1 - R) \text{ if } E < R \le D_1 \\ Pa &= T_2 * (D_2 - E) + T_1 * (D_1 - E) \text{ if } R \le E \end{aligned} \tag{2}$$

where T_2 and T_1 are tick values denoting the payouts per mm of in-crop rainfall below the strikes, respectively, associated with D2 and D1. It should be noted the maximum payout in a year the risk taker can obtain is equal to the yearly production cost.

The yearly payouts were averaged over 5-, 10-, 15-, 20-, 25-, 30-, 35- and 40-years periods i.e. 1980–1984, 1980–1989, 1980 – 1994 etc) and then these averages were averaged and added to the premium calculation. The yearly net premium to the risk taker is given by:

$$NP = \frac{\sum_{i=1}^{m} \mu_{(i*5)}}{m} + \sigma * 0.25 \tag{3}$$

where $\mu_{(n)}$ is the average payout over the last n years while σ is the standard deviation of payouts over the historical period and m is the number of 5-years periods in the historical period. The yearly gross client premium is then estimated at:

$$GP = 1.25 * NP \tag{4}$$

The Index-based drought insurance structures were designed to capture extreme dry season events that would cause the most damage (Breustedt et al., 2008). The insurance contract premiums depended on the predicted losses associated with droughts over 40 years. The less it rained, the more the contract paid out. The contract structure consisted of two options. The fair premium multiplied by 1.25 was used to reflect market prices.

2.8. Financial benefit of index-insurance options

Five assessment criteria were examined to measure the efficiency of the contract on farmer's income, with and without crop insurance (see Kath et al., 2019; Adeyinka et al., 2015; Vedenov and Barnett, 2004). The criteria correspond to (i) economic assessment by comparing crop income between virtual crops sown on the optimal date against the income of virtual crops with insurance, (ii) premium vs payouts assessment, (iii) assessment of the volatility of crop income using standard deviations, (iv) measurement of whether insurance will increase farmer's revenue in extreme drought via a Conditional Tail Expectation

(CTE) approach; and (v) assessment of the extent to which a dry season contract reduces downside risk (i.e., does insurance minimise the loss in poor years) via a Mean Root Square Loss (MRSL) approach.

2.8.1. An economic assessment of using insurance

An economic assessment of the insurance involved calculating the average gross income from 1000 ha of wheat sown at the optimal date. The assessment involved comparing the expected drought income (theoretical potential) to the average income (estimation of farmer's income) for the optimal sowing date, with or without insurance. The farmer would purchase the insurance annually for 40 years, and premiums were deducted from the drought income. If the income was higher with insurance, the contracts could be deemed efficient.

The estimates of farm income were based on APSIM's predicted "optimal" yield versus average yield multiplied by market prices for the wheat adjusted for inflation and insurance benefits (see Eq. 5). The yield is predicted from APSIM simulations and represents the yield that the farmer would harvest (i.e., yield that has potentially been affected by drought) on optimal sowing dates. Therefore, with insurance, farmer's wealth ($W_{\text{with insurance}}$) is equal to:

$$W_{\text{withinsurance}} = \widetilde{Y}_{\max} * \text{Price} + \text{Payout} - \text{Premium} \tag{5}$$

where $\widetilde{Y}_{\max}$ is the expected yield (sown at the optimum sowing date for long-term drought yield). Without insurance, farmer's wealth would be equal to:

$$W_{\text{withoutinsurance}} = \widetilde{Y}_{\max} * \text{Price} \tag{6}$$

The aim here is to demonstrate whether the wealth level with insurance is greater than the wealth level without insurance.

2.8.2. Premium versus payout assessment

The premium versus payout assessment aggregates the premiums paid and payouts received by the farmer each year over the 40 years. The payouts are claims because the insurance pays out over the represented 40 years. It also represents the burn or expected loss from the contract incurred by the insurer. If the payouts received by the farmer were equal to or greater than the premiums paid, then the contract was deemed to be efficient for the farmer. Farmers tend to look at this as a criterion when selecting insurance.

2.8.3. Measuring income volatility via standard deviation

The difference in the standard deviation (STDV) between wealth derived from drought income and normal income was examined by using Eq. 5. Similarly, the wealth derived from income through insurance, minus the premium, was calculated using the following Eq. 6.

If the use of insurance results in a decrease in the standard deviation of the farmer's wealth, then the insurance can be considered beneficial. This is because it reduces the volatility in the farmer's earnings.

2.8.4. Conditional tail expectation (CTE) assessment

To determine the effectiveness of insurance, we estimated the average income in the 50 % of the years with the lowest yield. We used Eq. 5, which considers both income and average income plus insurance payouts less premiums. Insurance is considered advantageous if the income with insurance minus premiums is higher than the income without insurance.

2.8.5. Mean root square loss (MRSL) assessment

To determine insurance efficiency based on the difference in the square root of average losses between using the optimum sowing date without insurance and then with insurance for the 50 % of years with the highest loss of income. The MRSL was calculated based on average losses, as farmers are typically concerned with below-average revenue. If the use of insurance results in a smaller MRSL value, it indicates that insurance is efficient.

3. Results and discussion

3.1. Optimal yield, drought and losses

We used APSIM-modelled data to estimate the potential gains and additional income a farmer could achieve by sowing optimally. This also helped us to calculate a drought's impact on yield and revenue. Optimal sowing resulted in a gain over the average expected yield for all farms (Table 1). Overall, if every farm sowed optimally over the 40 seasons an on average per year gain of $182 173 or 182.17 kg per 1000ha of crop sown would be made. On average, the gain across all the farms was 532 kg/ha. The lowest gain was 152 kg/ha in Ceduna, SA, and the highest was 922 kg/ha in Katanning, WA. In the case of Katanning, WA, the average production was 3.20t/ha, 4.12t/ha in a good year, and 1.67t/ha in a poor year, which needs to be managed.

The modelling of optimal sowing dates and yields also reinforced the strong correlation between rainfall and yield, which supports using a precipitation-based index solution that looked at rainfall deficits. An insurance solution is needed in a poor year of rain, where yields are down. Further, it should be noted that the additional gains in yield and, therefore, income made through optimal sowing could be used to help subsidise the premium costs for drought insurance.

3.1.1. Cost of drought and Weather Index Insurance (WII)

Across 22 farms, droughts caused growers to lose an average of $71,419 annually (Table 2) or $71.42 per ha of 1000ha sown over 40 seasons. This loss is typically added to the grower's debt and repaid when conditions improve. The highest cost was in Dubbo, NSW, at $108,280. On average, as the input cost for the 1000ha was $300,000, the policy only recovered 36 % of the costs, with the grower being better off by only 10 % over the 40 years. To improve this average, the parameters of the policy need to be altered. This is one positive attribute in using index insurance as the parameters can be changed to suit the needs of the grower. In contrast, in Ceduna, SA, the lowest average drought cost was $22,418, with only 7 % of costs recovered, but the farmers were better off by 47 %. The results showed the higher the average drought costs, the more input costs were recovered, yet the lower on average the benefit to the farmer was.

The average lower farmer benefit in Table 2, we theorise, has to do with the premium value, which results from the historical relationship between the rainfall and triggers and resulting payouts, similar to the findings of Kath et al. (2019). Testing insurance structure outcomes to make sure the insurance is fit for purposes is an important aspect that needs to be considered by buyers. Combining WII and insurtech solutions makes this possible. Figs. 2 and 3 below show the relationship between rainfall and triggers. This relationship is essential when structuring a parametric insurance contract. In the case of Dubbo the premium for the insurance was 9.54 % or $28.63/ha compared to 5.39 % or $16.6/ha in Ceduna (Table 3). The premium for Dubbo is higher as there are more payouts at a lower value, whilst the premium for Ceduna is lower, and the payouts are less but higher (see Figs. 2 and 3).

As a result, any potential cover should be tailored depending on the rainfall data for the farm, the higher the premium, the higher the payout. This supports the analysis by Bucheli et al., (2020), who tested the risk-reducing potential of WII if the index is tailored to the individual farm.

3.2. Index insurance premiums

The premiums calculated for each farm are summarized in Table 3. The premiums are based on 1000-ha farms and a payout worth equalling input costs of $300,000 (or $300 per hectare). The structure was designed around input costs, which are closely related to the phenology of the plant, with payouts escalating the dryer the conditions became. As the season progresses, so do the costs.

Narrabri had the highest estimated premium at 12.26 % of the sum

Table 1
Phenological of winter wheat crop showing that sowing optimally provides a gain to the farmer against non-optimal sowing.

Farm	APSIM ID	Grid		Sow Date (Optimal)	Maturity	Yield Expected (Average kg/ha)	Yield gained for sowing optimally (above Average kg/ha)
Roma	230	−26.57	148.79	10-May	27-Sep	1884	399
Dalby	55	−27.18	151.26	26-May	13-Oct	2835	241
Dubbo	70	−32.24	148.61	10-May	27-Sep	3651	766
Waikerie	265	−34.18	139.98	10-May	27-Sep	1757	338
Gunnedah	105	−30.98	150.25	10-May	27-Sep	4291	662
Gilgandra	90	−31.71	148.66	10-May	27-Sep	3445	768
Narrabri	190	−30.32	149.78	10-May	27-Sep	3619	717
Parkes	210	−33.14	148.16	26-May	13-Oct	4589	798
Urana	255	−35.33	146.03	26-May	13-Oct	2852	336
Wagga	260	−35.16	147.46	26-May	13-Oct	4120	585
Lake Bolac	130	−37.71	142.84	26-May	13-Oct	4056	369
S Walpeup	275	−35.12	142.00	10-May	27-Sep	2087	338
Pinnarro	215	−35.26	140.91	10-May	27-Sep	2070	366
Birchip	15	−35.98	142.92	26-May	13-Oct	2090	445
Ceduna	25	−31.9	133.42	10-May	27-Sep	653	152
Hopetoun	110	−35.73	142.37	26-May	13-Oct	2151	476
Balaklava	5	−34.14	138.42	10-May	27-Sep	2418	623
Roseworthy	235	−34.53	138.69	26-May	13-Oct	2973	819
Salmon Gums	245	−32.99	121.62	26-Apr	13-Sep	1391	302
Lake Grace	135	−33.1	118.46	10-May	27-Sep	1851	623
Katanning	120	−33.69	117.56	10-May	27-Sep	3204	922
Kellerberrin	125	−31.62	117.72	10-May	27-Sep	2062	680

Table 2
Summarizes the cost of a drought per farm and the ability of the insurance to cover the loss.

Farm	Average cost of drought over 40 yrs	Insurance payouts averaged over 40 yrs	Farmer is better off by%*	Ability of insurance to pay for Inputs costs in worst 40 yrs (%)
Roma	$62,424	$11,814	19 %	40 %
Dalby	$65,092	$15,732	24 %	82 %
Dubbo	$108,280	$11,109	10 %	40 %
Waikerie	$55,495	$13,804	25 %	85 %
Gunnedah	$103,210	$20,032	19 %	89 %
Gilgandra	$87,529	$18,866	22 %	84 %
Narrabri	$95,368	$22,040	23 %	93 %
Parkes	$103,627	$14,294	14 %	77 %
Urana	$105,575	$14,908	14 %	67 %
Wagga	$98,999	$13,076	13 %	64 %
Lake Bolac (SE)	$46,513	$13,749	30 %	64 %
S Walpeup	$72,522	$12,030	17 %	66 %
Pinnarro	$42,465	$15,419	36 %	82 %
Birchip	$98,773	$11,602	12 %	87 %
Ceduna	$22,428	$10,509	47 %	83 %
Hopetoun	$90,944	$11,629	13 %	61 %
Balaklava	$72,122	$6399	9 %	47 %
Roseworthy	$74,303	$9010	12 %	81 %
Salmon Gums	$23,120	$9055	39 %	57 %
Lake Grace	$51,487	$10,754	21 %	37 %
Katanning	$42,098	$9051	22 %	34 %
Kellerberrin	$48,841	$7386	15 %	22 %
Average	$71,419	$12,830	21 %	66 %

*Farmer is better off by %" is calculated by taking the average payout of insurance divided by the average cost of drought. The ability to recover inputs is calculated as a percentage claimed on $300,000 of inputs in the worst drought over the past 40 years.

insured or $36.78/ha, but as indicated, also the highest claim of 93 %, while Balaklava, WA, had the lowest premium at 1.62 % or $4.87/ha of the sum insured and one of the lowest claims. The average premium value was 6.28 % or $18.85/ha, with an average claim of 66 % in the worst drought in the 40-year risk period.

At Lake Bolac, NSW, for example, the historical 40-year low over a period of 140 days, from the optimal sowing date of 10 May until the end of anthesis, was 167.61 mm. The deciles were rounded down to the nearest 10. The entry point on cover 1 was at 280 mm, which represented a D2, and on cover 2, a D1, was at 250 mm. Once the attachment point occurred in cover one, a payment per mm of $614 was made until the maximum or exit or $100,000 was achieved. Likewise, in cover 2, a payment of $1507 would be made if the attachment point was achieved up until the maximum of $200,000 was paid. The payment per mm or tick size was determined by an assigned amount to each risk divided by the difference between entry and historic low less 30 %, which in this case is 117.3 mm. Interestingly, the 100-year historical low was 121 mm. The cover pays out in full at 117.3 mm. Therefore, if a similar event occurs, the farmer will recover all his inputs.

The average rainfall for Lake Bolac was 345 mm over the season, and in those years, that rain was well below the average payouts helped to compensate the grower. In 2006, 167.5 mm of in-crop rain fell. Farm income dropped from an average of $897,896 to $395,185. The insurance claim was $193,418. So, this year, the farmer's total income, less the cost of the insurance premium, was $588,603. Likewise, in 1982, 181 mm of rain fell. Farm income dropped from an average of $897,896 to $505,610. The insurance claim was $164,784. So, in that year, the grower's total income, less the insurance premium, was $649,970. Although both were below the income average, the farmer was significantly better off. Interestingly, a D2 event over the 40 years was recorded six times with ensuring payouts. The return period for the strategy was a payout of 1 every 6 years, which makes the cover more attractive to the grower.

3.3. *Efficiency of dry-season WII options to hedge lost income*

Overall, the research showed that using WII to hedge lost income caused by drought was efficient but more efficient on different farms. Bucheli et al. (2020) evaluated five special drought indexes: cumulative precipitation, standardised preparation, evapotranspiration soil moisture, and evaporative stress. They tested and found that the risk-reducing properties of the policies increased when the data used to create the index was specific to each farm. Here, we tested five measures of efficiency just on precipitation and found that a more tailored approach to the policy increased its risk-reducing qualities, but further, the policy was also more appropriate as it was based on conditions that had occurred at the farm in the past. We found that each policy responded differently in the tests and their risk-reducing qualities.

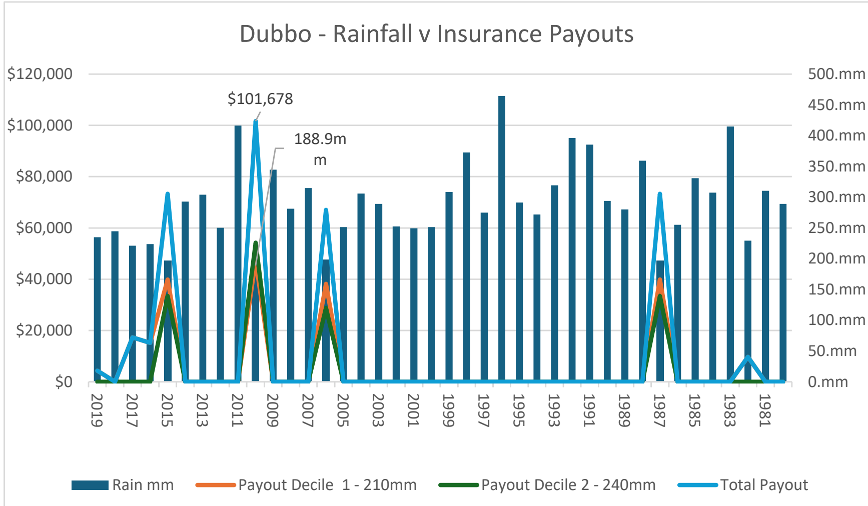

Fig. 2. Showing the relationship between Rainfall and Insurance Payouts at Dubbo, NSW.

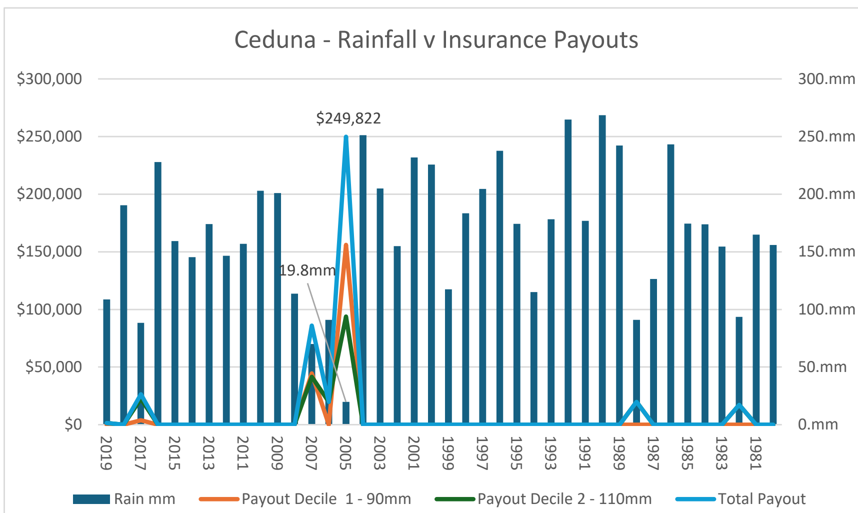

Fig. 3. Showing the relationship between Rainfall and Insurance Payouts at Ceduna, SA.

3.3.1. Economic assessment of using two dry season index insurance options

The results from the economic assessment of the insurance showed that using two dry-season index insurance policies provided additional long-term income at four sites out of the 22 studied (Fig. 4 and Table 4). Across the 22 sites and over 40 years, the results showed an average loss of $6097, with the highest loss of $17,522 in Dubbo, NSW, and the largest gain of $2148 in Salmon Gums, WA. This indicated that the use of the option was helpful in some regions but not others. Kath et al. (2019) also concluded similar results. On those farms where it was economical, the average annual gain in drought years was $1468. These gains and losses were marginal when considering each farm's income levels over 40 years. For example, the actual average loss over 40 years in Dubbo was $17,522 per annum, but when the cover was needed the most, i.e. in a drought, the lowest income was $90,988. The insurance claim was $262,981, which was sufficient to cover the inputs for the season's crop and ensure the grower is ready with a budget for the next season. And not have to draw down on his overdraft or take up a credit facility.

3.3.2. Premium vs payout assessment

The premium versus payout assessment for the 22 sites involved adding the premiums paid each year over 40 years (see Fig. 4). If the payouts received by the farmer were greater than the premiums paid over the period, then the contract was deemed efficient. Farmers look at this measure to gauge its worth.

At the Wagga Wagga farm in NSW, over 40 years, the enterprise paid $479,972 in insurance premiums and received $523,043 in payouts, indicating an efficient contract to the farmer, and perhaps a mispriced contract for the reinsurance provider. However, on the farm in Dubbo, NSW, the enterprise paid $1145,233 in premiums and only received $444,345 in payouts. This represented a loss of $17,522 per year, which could be argued as manageable given other input costs. This loss is the cost of shifting this risk from the farmer to the risk market, and it is regarded as the cost of the contract issuance or reinsurance profit. However, if we consider this cost in the context of shifting the risk, the contract is useful.

The sum of premiums paid were greater than the payouts over 40 years for 18 of the 22 sites, indicating that the insurance was inefficient for the farmer as he did not recover his costs. However, if the test showed a return, then it would suggest that the policy was potentially mispriced as the reinsurer would be making a loss. However, dividing the cumulative difference by 40 years to compute the annual losses, the difference was marginal and manageable in all instances at a farm level, so the insurance is efficient. Farmers often misguidedly assess the value of

Table 3
Insurance Structures and Premiums Relevant to a Dry Season. The table shows individual structures, attachments and exits of the policies.

Farm Location	40 yr Historic Low (mm)	Decile 2 - Cover 1				Decile 1 - Cover 2				Sum Insured	Premium %	Premium /ha
		Attachment (mm)	Exit (mm)	Tick	Maximum Payout	Attachment (mm)	Exit (mm)	Tick (mm)	Maximum Payout			
Roma	35	80	25	$1677	$100,000	40	25	$8861	$200,000	$300,000	8.66 %	$25.98
Dalby	35	80	25	$1860	$100,000	60	25	$5634	$200,000	$300,000	9.24 %	$27.71
Dubbo	60	100	42	$1724	$100,000	80	42	$5263	$200,000	$300,000	9.54 %	$28.63
Waikerie	30	90	21	$1449	$100,000	70	21	$4082	$200,000	$300,000	4.85 %	$14.54
Gunnedah	37	160	25	$746	$100,000	120	25	$2125	$200,000	$300,000	11.03 %	$33.08
Gilgandra	38	140	27	$886	$100,000	90	27	$3179	$200,000	$300,000	11.68 %	$35.05
Narrabri	15	120	10	$917	$100,000	70	10	$3385	$200,000	$300,000	12.26 %	$36.78
Parkes	66	170	46	$809	$100,000	120	46	$2718	$200,000	$300,000	7.76 %	$23.29
Urana	62	140	43	$1035	$100,000	90	43	$4292	$200,000	$300,000	5.09 %	$15.27
Wagga	114	190	79	$907	$100,000	170	79	$2217	$200,000	$300,000	4.00 %	$12.00
Lake Bolac	167	280	117	$614	$100,000	250	117	$1507	$200,000	$300,000	6.81 %	$20.42
S Walpeup	54	100	37	$1608	$100,000	80	37	$4739	$200,000	$300,000	4.57 %	$13.72
Pinnarro	49	140	34	$949	$100,000	110	34	$2654	$200,000	$300,000	6.49 %	$19.47
Birchip	42	120	29	$1109	$100,000	100	29	$2850	$200,000	$300,000	3.50 %	$10.49
Ceduna	19	110	13	$1040	$100,000	90	13	$2222	$200,000	$300,000	5.39 %	$16.16
Hopetoun	31	110	31	$1269	$100,000	90	31	$2222	$200,000	$300,000	4.14 %	$12.41
Balaklava	85	130	59	$1427	$100,000	120	59	$2222	$200,000	$300,000	1.62 %	$4.87
Roseworthy	85	170	59	$906	$100,000	160	59	$2222	$200,000	$300,000	4.17 %	$12.50
Salmon Gums	89	140	62	$1296	$100,000	120	62	$3500	$200,000	$300,000	1.76 %	$5.29
Lake Grace	99	160	69	$1109	$100,000	120	69	$2222	$200,000	$300,000	6.27 %	$18.80
Katanning	188	240	132	$928	$100,000	210	132	$2572	$200,000	$300,000	6.02 %	$18.07
Kellerberrin	113	150	79	$1423	$100,000	120	79	$2222	$200,000	$300,000	3.42 %	$10.26

Attachment" is the level in mm's that triggers the start of a payout.
"Exit" is the level in mm's the cover is paid out in full.
"Premium percentage "is the sum insured/ premium. It is the cost of the insurance.

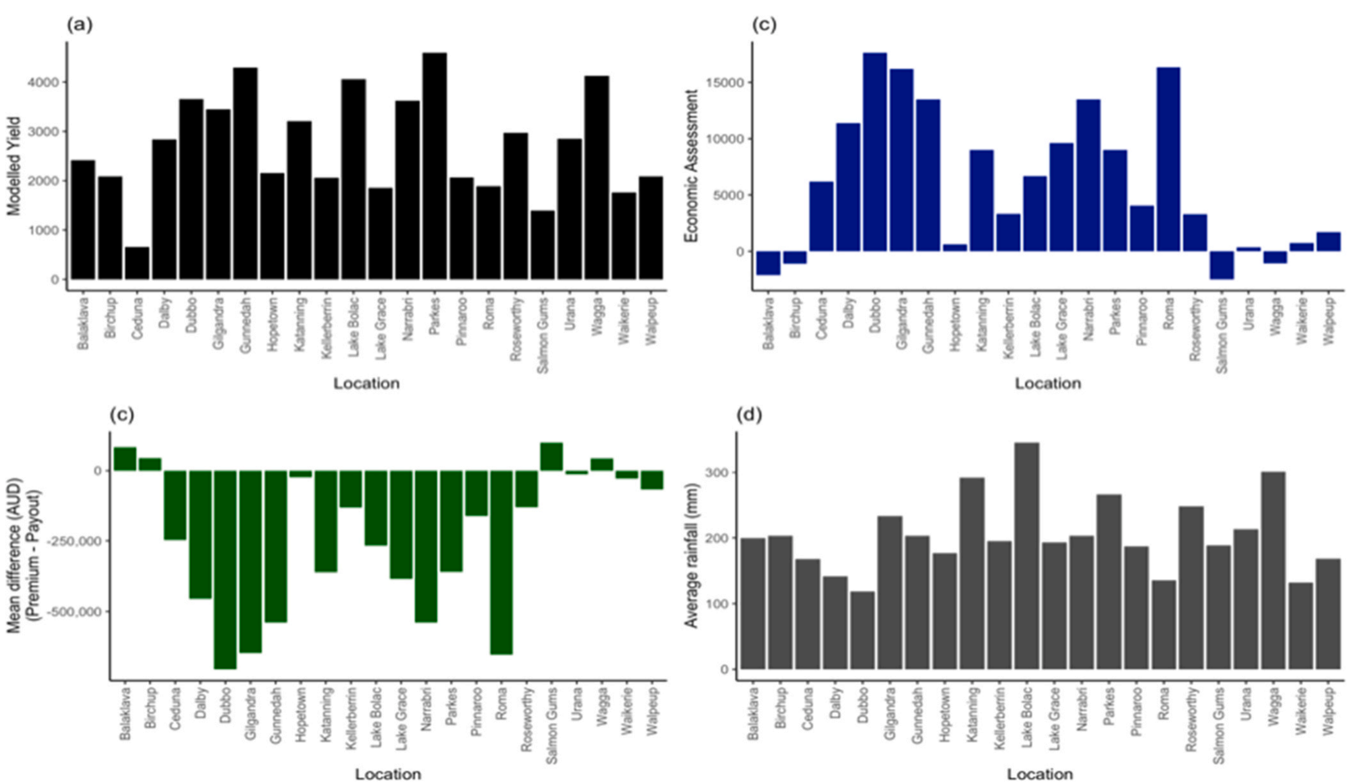

Fig. 4. Insurance premium results showing modelled Yield (Kg), Total Premium Paid less Payout ($), Economic Assessment ($), and Average Rainfall (mm) over 40 years at test sites.

insurance by determining if it pays for itself over time as a measure of its worth. The better assessment should be the return period of the insurance contract over time, as this is a determinant of the value of the premium. A premium value of 10 % may sound expensive, but if a claim has been made in the last 10 years, then it represents better value than one that cost 5 % and a claim has never been made.

Table 4
Shows the results of an economic assessment of the structure comparing a farmer's income with/without insurance. Note that a negative result is positive.

Farm	Economic assessment	Result
Roma	$16,321	no
Dalby	$11,369	no
Dubbo	$17,612	no
Waikerie	$741	no
Gunnedah	$13,492	no
Gilgandra	$16,183	no
Narrabri	$13,492	no
Parkes	$8991	no
Urana	$362	no
Wagga	-$1077	yes
Lake Bolac	$6674	no
Walpeup	$1694	no
Pinnaroo	$4049	no
Birchup	-$1115	yes
Ceduna	$6173	no
Hopetown	$607	no
Balaklava	-$2093	yes
Roseworthy	$3291	no
Salmon Gums	-$2483	yes
Lake Grace	$9625	no
Katanning	$9016	no
Kellerberrin	$3303	no

Even if the difference between the premium paid and payouts made results in a small loss, reducing the premiums can increase efficiency. This can be done by adjusting the option's threshold, strike, and cover length, but it may also decrease the payouts. Another approach to increase the efficiency of a contract is to lower reinsurance costs. This can be handled through greater numbers of policies across large regions. This lowers the volatility in the loss ratios due to the spatial nature of weather to which reinsurers need to make a profit and thus the less volatility.

Further, it could be argued that using increased technology in monitoring conditions could create further efficiencies in the cover. Growers may not take out a dry season contract every year as the forecast is more positive, and perhaps the farmer has a healthy subsoil moisture profile to help commence the season. Opting only to take it out when forecasts dictate suggests an additional management strategy. Anecdotally, this seems to be the case.

3.3.3. *Measuring income volatility via standard deviation*

One of the main reasons why farmers use insurance is to reduce the volatility of their earnings. A small standard deviation suggests that income is not volatile as the values are closer to the mean income. The larger standard deviation suggests that there is more variance in the results, and, in this case, the insurance is not doing its job in reducing the volatility in the earnings. Having a low value in the standard deviation helps maintain a constant cash flow, which is particularly important for farms heavily reliant on borrowing, as interest rates can be an additional cost factor. According to Topp (2023) this has been a problem in the past. Debt has been an issue in the past and will continue to be if growers do not find a means to finance drought. The differences in the STDV between drought income for crops sown optimally with and without insurance indicated that 21 sites out of the 22 showed that by using insurance, the volatility in earnings was reduced if a dry season contract was purchased annually for 40 years (see Fig. 5 and Supplementary Table 3).

The differences in STDV ranged from the lowest of −0.101389 at Pinaroo in WA to −0.016684 at Salmon Gums in WA. Reducing earnings volatility is one aspect credit providers look for in a farming operation when providing finance. This means that there is a steady cash flow where loan repayments can be made, providing comfort to financiers should loans be required to bridge gaps in income caused by droughts. Fund access is an important tool growers use in drought (Topp, 2023).

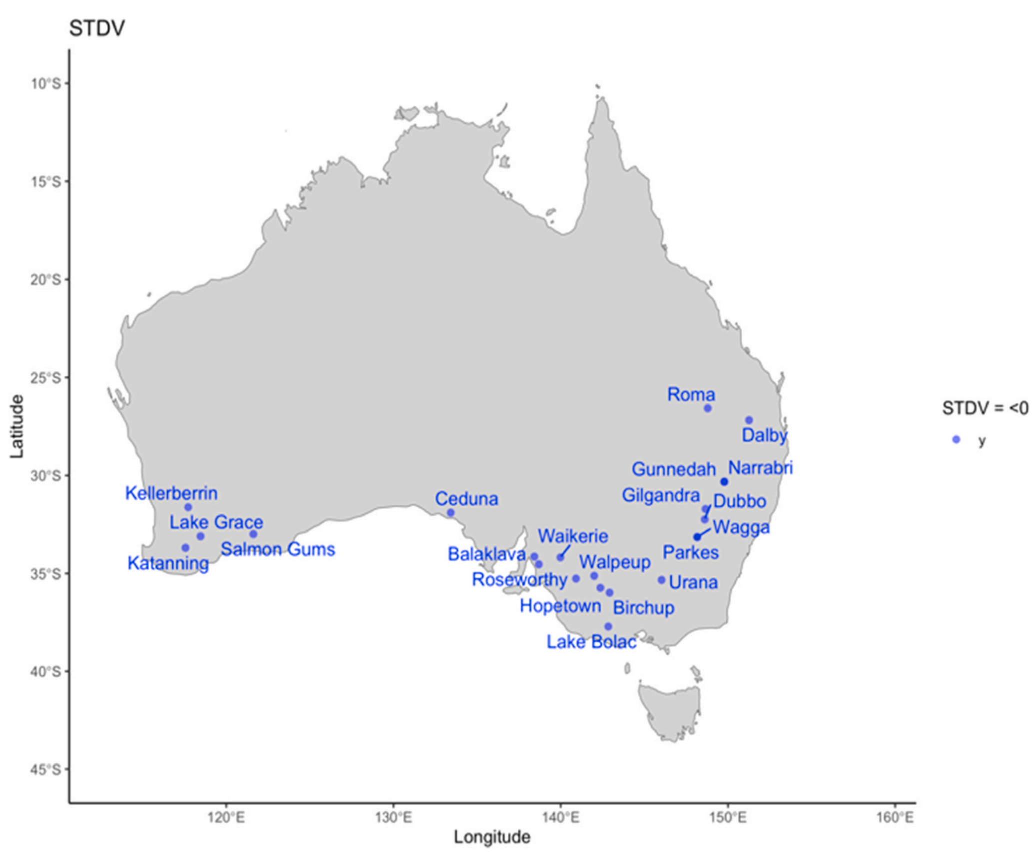

Fig. 5. Potential benefit of insurance based on Standard Deviation (STDV). The blue coloured names represent a positive effect. In all cases it shows a benefit.

3.3.4. Assessing benefits during extreme drought events via conditional tail expectation

In terms of the average income in 50 % of the years with the greatest difference between incomes with and without drought, the results showed that only three farms out of the 22 were not better off (Fig. 6 and Supplementary Table 3)

Wagga Wagga achieved the best outcome, showing a difference of –$15,529, indicating that the insurance effectively maintains income in the poorest years. Dubbo was the lowest at + $6691, albeit the differences were small. According to Kath et al. (2018), using rainfall index insurance was effective in Tully, QLD. However, the study also suggests that the effectiveness of index insurance may be limited to specific regions and may not work consistently in a wider range of environments. Therefore, it is important to investigate the factors determining why index-based insurance is effective in some regions but not in others. We suspect that part of this discussion involves the temporal and spatial dispersion properties of rainfall and the way it is measured. This study used 5 km x 5 km gridded data sets to focus more on the farm's rain events. Plus, it helped reduce the "basis" risk of using one data source, a weather station. This provided a more even distribution of rainfall across all the farms, which helped account for the different parameters of each contract and the more robust results on the effectiveness of each cover.

3.3.5. Mean root square loss (MRSL) assessment

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 efficient. A negative change in variability implied that the contract was risk-reducing and, therefore, beneficial. Out of the 22 test farms, all but three had negative values, indicating that the insurance was efficient (Fig. 7 and Supplementary Table 3).

Where the MRSL is blue, it implies that the contract reduces risk. In the case of Wagga NSW, the result was −0.0177, and so the contract helped reduce the farmer's risk, whereas in Katanning WA, the result of 0.04086 suggests that no reduction in risk was observed.

Vendenov 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. The results of this study showed that 86.363 % of the contracts were efficient, based on MRSL analysis. Further, Kath et al. (2019) found that the MRSL test for efficiency for using weather-based index insurance for wheat contracts differed between the regions analysed. In contrast, this research showed higher efficiencies across most regions, which may have had to do with the insurance structure.

3.3.6. Summary of the financial efficiency across all farms

In summary, an efficiency test was assigned a "yes" if it was efficient or a "no" if it wasn't (Table 5). A score of 6 suggested that the cover was highly efficient, whilst a score of 1 suggested that it was still efficient but not as effective as the others.

The farm at Wagga Wagga received the highest score in efficiency, where 6 of the efficiency tests concluded a benefit to the farmer. Birchup, Balaklava, and Salmon Gum farms scored 5 in providing a benefit towards the farmer. A key question that arose from the research was why different farms received more benefits than others. More research needs to be done on this, but we theorise that with Wagga Wagga, Birchup, Balaklava and Salmon Gums, it had more to do with the volatility in the rainfall and how these played a part in the payouts. As an example, all four had little payouts in the last 10 years and volatile rainfall, which resulted in low premium values.

Further, it is worth highlighting a few important aspects concerning the efficiency of the structures. The importance of the design enabled the contract to be more efficient. First, utilising two phenologically aligned contracts meant that the cover focused more on how the plant behaved

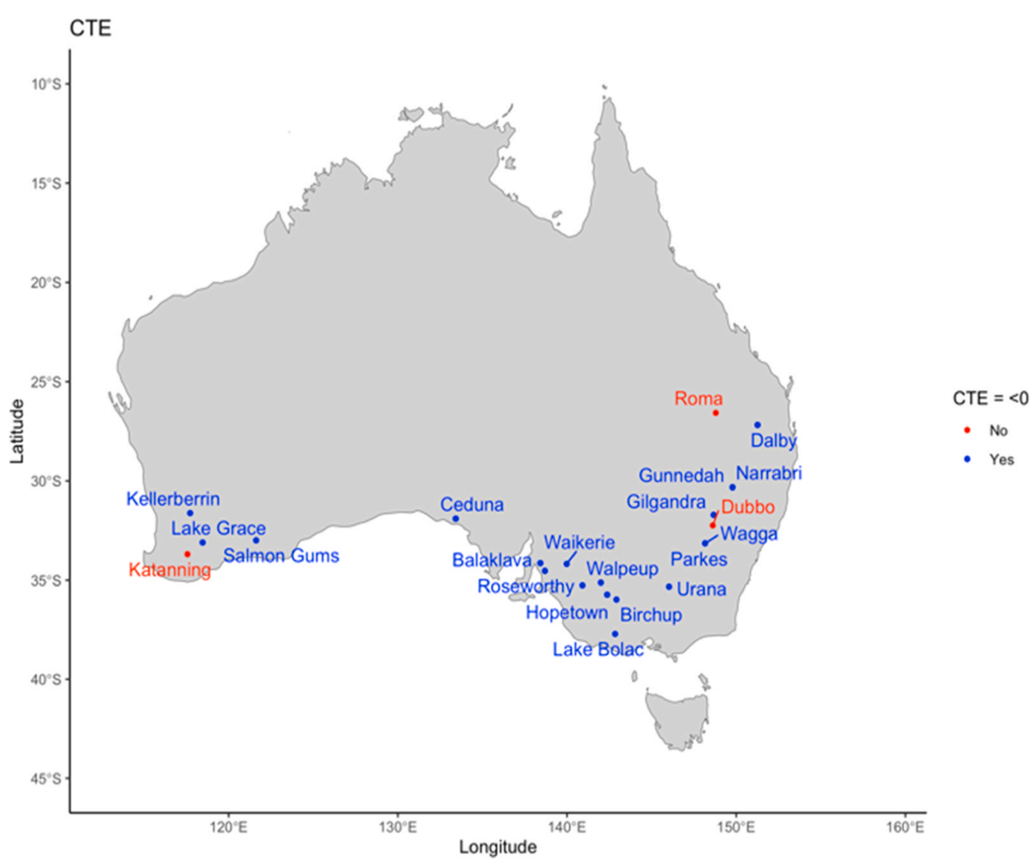

Fig. 6. Potential insurance benefits based on income in the poorest years (Certainty Tail Expectations). The blue coloured names represent a positive effect.

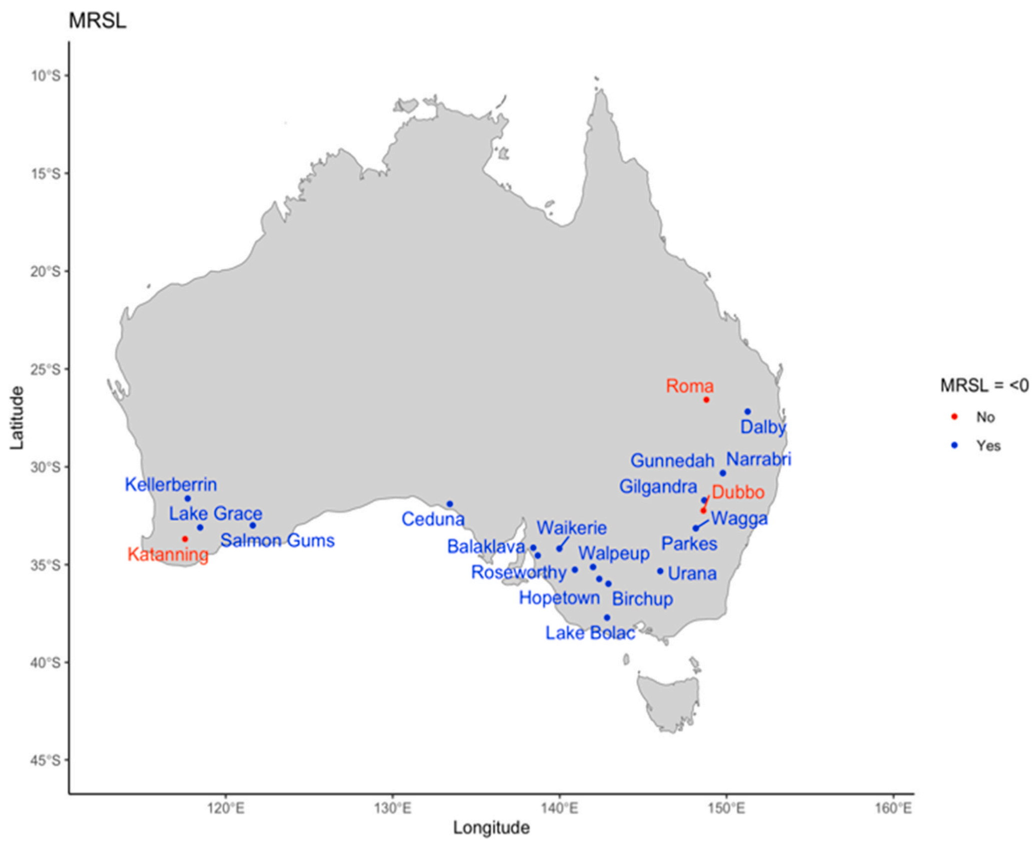

Fig. 7. Potential benefit of insurance based on Mean Root Square Loss (MRSL). The blue coloured names represent a positive effect.

Table 5
Summary of the financial efficiency analysis across all farms.

Farm	Gains Optimal Sow	Premiums v Payouts	Economic Assessment	Standard Deviation (STDV)	Conditional Tail Expectation (CTE)	Mean Root Square Loss (MRSL)	Rating***
Roma	y*	n**	n	y	n	n	2
Dalby	y	n	n	y	y	y	4
Dubbo	y	n	n	y	n	n	2
Waikerie	y	n	n	y	y	y	3
Gunnedah	y	n	n	y	y	y	3
Gilgandra	y	n	n	y	y	y	4
Narrabri	y	n	n	y	y	y	4
Parkes	y	n	n	y	y	y	3
Urana	y	n	n	y	y	y	4
Wagga Wagga	y	y	y	y	y	y	6
Lake Bolac	y	n	n	y	y	y	3
Walpeup	y	n	n	y	y	y	3
Pinnaroo	y	n	n	y	y	y	3
Birchup	y	y	y	y	y	y	5
Ceduna	y	n	n	y	y	y	3
Hopetown	y	n	n	y	y	y	3
Balaklava	y	y	y	y	y	y	5
Roseworthy	y	n	n	y	y	y	3
Salmon Gums	y	y	y	y	y	y	5
Lake Grace	y	n	n	y	y	y	3
Katanning	y	n	n	y	n	n	3
Kellerberrin	y	n	n	y	y	y	3

*y stands for Yes a "y" says the measure was positive.
**n stands for No a "n" says the measure was not positive.
*** the rating shows that number of "y" obtained over all the tests, 6 = a good cover.

to moisture. Secondly, as the cover was weighted, payouts could escalate and cover inputs sooner the drier the season became. (Vedenov and Barnett, 2004) suggested that optimal weather derivatives require complicated combinations of weather variables to achieve reasonable fits between weather and yield. This study aligns with this; however, the strategy is simple.

We found that using multiple attachment levels at D2 and D1 of the one index and then weighting the payouts so that the drier it gets, the more it pays, showed for greater gains in efficiency. Following on from Pietola et al. (2011), whose structure covered 38 % of the hedge, we found our approach in the worst year of drought covered, on average, 66 % of the $300,0000 worth of inputs recovered. Further, structuring the cover around optimal sow dates like Lebolis et al. (2014a) and Dalhaus and Finger (2016) helped reduce basis risk and increased the payouts when needed the most.

Targeting the structure enabled premium levels to better align with the contract's risk and return period. The results show that a targeted approach reduced the premium levels, which increased the contract's efficiency.

Overall, six assessments were carried out to test if the targeted WII could provide benefits (Table 5) to farmers. Gains were made on all farms, some rated higher than others. Wagga Wagga had the highest rating of 6 and Roma the lowest at 2. We suggest that the positive results came down to the design of the cover.

3.3.7. Limitations and further work

Despite the promise of index insurance in managing climate risks across agriculture, several limitations must be acknowledged. A key challenge is basis risk, the mismatch between payouts and actual losses. Farmers may experience significant damage yet receive no payout if environmental triggers (e.g. temperature or rainfall thresholds) are not met at the designated reference station. In some cases, basis risk may result from a lack of high-resolution, data, especially in remote farming. Limited access to historical yield and climate data also reduces the precision of risk modelling and pricing, and therefore, modelled yield data could be considered as more generalised and not farm-specific.

The research used modelled yield data from APSIM and not actual data. Although the model, developed by Keating et al. (2003) and updated by Holzworth et al. (2014), is a widely recognised tool for simulating biophysical processes, this may pose a challenge to the research. However, the variances in income due to drought appeared realistic, and the use of insurance proved beneficial. While APSIM is a robust and widely used tool, its simulations may not fully capture the actual rainfall and temperature variations and yield outcomes experienced in real-world conditions. As a result, there is a risk that the estimates of agricultural losses used in the design of the insurance structures may be skewed or not entirely representative of actual on-ground impacts. This limitation could influence the accuracy and effectiveness of the resulting parametric insurance models in reflecting real financial risk exposure. These approximations, though useful for initial modelling, highlight the importance of region-specific validation to ensure that the insurance products are well-calibrated to local risk profiles. Further in the validation of the insurance structure and premium values, there is a need to value the losses of drought over time. The 40 years of modelled data provide seasonal yield penalties caused by drought, which was essential to arrive at market realistic premiums. The modelled data provides for multi-decade examples of yield that in Australia cannot be sourced.

Various field tests have been used with farmers, and anecdotally, the yields seem relevant. The model has been verified to actual production (Barratt et al., 2024). Furthermore, throughout the research, we standardised the cost of inputs per hectare to provide a constant cost plus used a common variety for consistency. Understandably, this varies according to region and rainfall. This may alter the results slightly.

Finally, upon the conclusions of the research, we found some irregularities in the index structures related to rainfall patterns that are worth discussing. Firstly, the premiums are calculated before an event, while the payouts are calculated after an event. The precipitation index is meant to cover the entire growing period. The attachment levels for the insurance have been set based on specific rainfall events occurring over the entire season. This raises the question: what if a significant rain event occurred just before the contract expired, resulting in no payout and leaving the farmers at a loss? This is a basis risk issue that is beyond the scope of this paper. The aim is to test the novel index structure to see if the farmer would be better off implementing a "like" cover for drought annually. The policies are based on a cumulative approach over the growing season but since rain may fall at different times during the growing season, this can affect the outcomes. Therefore, a project for the future would be to research testing structures that cover risk at different crop growth stages with different payouts, such as covering emergence, establishment, and growth, to capture more targeted events.

It's important to note that index insurance is not designed to fully compensate losses but rather to stabilise income. Farmers and aquaculture operators still bear residual risk in extreme or compounding events. Furthermore, the financial efficiency of index insurance depends on regular use and relatively frequent triggering events. Infrequent yet severe events may result in underinsurance if coverage is not maintained consistently, while annual premiums may outweigh benefits in lower-risk settings.

4. Conclusion

The long-term impact of drought on a farmer's financial position can be significant, especially in a high-interest-rate environment. We have shown that purchasing index insurance policies annually can effectively mitigate the income loss caused by drought. Furthermore, it has been found that a structure that combines two triggers with weighted payouts in a single policy over the season can offer even greater benefits. It's important to note that yield loss occurs gradually throughout the season, as the lack of rain leads to reduced productivity for the farming enterprise. Therefore, integrating index insurance policies into the farm management contract can be highly advantageous for the farmer.

The optimally sown crop provides additional income, which enables compensation for the insurance premiums. In a drought, the insurance helps to increase his income. This is of value to the farmer and the local community and aids in reducing government handouts during droughts. Considering the increased climate variability and occurrence of droughts, more targeted insurance polices could play a critical role in helping farmers achieve income stability during droughts.

It's crucial to note that the field of index insurance is constantly evolving, and future research and testing will be instrumental in further improving its effectiveness. For example, using separate index insurance structures from emergence through grain fill could yield additional benefits to growers, but this needs to be tested, and work is planned for a future date.

CRediT authorship contribution statement

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

Consent to participate

All research participants provided informed consent to participate in this study.

Consent for publication

The authors confirm that all participants gave their informed consent for the publication of this study.

Ethics approval/declarations

This research was conducted according to the Netherlands Code of

Conduct for Research Integrity 2018 and its later amendments.

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Declaration of Competing interest

The authors declare no competing interests.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2025.109726.

Data availability

Data will be made available on request.

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