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Integrating rainfall index-based insurance with optimal crop management strategies can reduce financial risks for Australian dryland cotton farmers

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ABSTRACT

Drought undermines the financial sustainability of farmers. While farmers have adopted various strategies to mitigate some drought impacts, they remain exposed to substantial drought risk. Insurance could be useful in managing climatic risks and for encouraging farmers to take sensible risks (e.g., changing their sowing date to increase yield), but it can be costly. Here, we tested whether the integration of a change in sowing date with rainfall index-based insurance could improve farmer profitability and income stability. We used the Agricultural Production Systems Simulator (APSIM)-Cotton model to simulate cotton lint yields for various sowing dates, taking into account different management strategies, across three dry-land cotton research farm sites – Dalby, Goondiwindi, and Theodore – from 1940 to 2022. We designed the index-based insurance payout when the average rainfall received during the growing season falls below a predefined level, such as the 5th, 10th, or 20th percentile of rainfall. Our study, which involved 3.9 million cotton lint simulations and 3,000 rainfall index-based insurance products, showed that combining a shift in sowing date with insurance can lead to an income improvement of up to 21.5% at some study sites. Additionally, in drought years, the income improvement for farmers who combined optimal sowing dates with rainfall index-based insurance was up to 48.0%. The framework developed in this study could aid in devising financial strategies to enhance farming resilience during climate extremes.

1. Introduction

Droughts pose a significant threat to agriculture by negatively impacting crop yields, driving up production expenses, and reducing profits. Climate change is predicted to alter climate patterns and increase the frequency and intensity of extreme weather events, including droughts [1]. With climate change, droughts are expected to exert a sustained impact on the agricultural sector that influences world food production [2]. Consequently, drought impacts on agriculture are becoming increasingly difficult and important to manage.

Farmers adopt various technologies and management practices to mitigate drought-related risks. For instance, when drought conditions are forecasted, farmers may reduce the crop area planted and, thus, inputs applied (e.g., fertilizers) to minimise the production costs [3], spread their risk by operating across multiple locations [4], or skip the cropping season. Shifting the sowing date is also an option to cope with drought [5]. As for many crops, including cotton, yields are highly correlated to initial environmental factors (e.g., rainfall, temperature, sunshine hours) and soil conditions (e.g., soil moisture content) during sowing dates. Thus, by adjusting the sowing time for better growing conditions, drought effects can be minimised.

Nonetheless, shifting sowing dates means changing cropping windows, which could expose farmers to risks later in the season, such as insufficient rainfall during important crop stages, increased risk of hail

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or heatwave events, or increased prevalence of insect attacks and diseases. Because of these risks, some farmers may be hesitant to shift sowing dates and instead choose a 'safer' sowing date not exposed to these risks, even if it results in lower overall yields on average. Agricultural insurance schemes offer an option to enable farmers to take 'acceptable risk' by switching to a better sowing date that could achieve higher yields that inherently they may be hesitant to undertake because of those other risks later in the season. Previous studies have suggested that agricultural insurance can influence farmers' behaviours, for instance, prompting shifts toward greener practices [6], fostering a greater willingness to adopt technology [7], and mitigating risk-averse tendencies that might otherwise lead to suboptimal input use due to uncertainty [8]. In such cases, risk-averse farmers may behave more akin to risk-neutral counterparts, optimising their input choices to maximise profits [8].

In the context of agricultural index-based insurance, mainly weather indices, satellite-based vegetation indices, and statistical models have been used to quantify crop yield losses so far [9-12]. Yet, there is a growing interest among governments and insurance companies in process-based model assessments, as observed in India [13,14]. Process-based crop models offer a timely advantage by providing insights into yield losses immediately after the harvest. This capability makes them invaluable for conducting thorough risk assessments and formulating adaptation strategies. The significance of this application is particularly pronounced in developing countries, where the remote locations of fields exacerbate the unavailability or high cost of collecting crop yield information. Moreover, the variable configuration of process-based models allows discriminating between influences on crop yields, attributing them to either weather or management factors. This ability is crucial for the design of insurance indices, ensuring only losses associated with weather should be covered by the insurance product [13,14].

Simulated crop yield from process-based (or bio-physical models) is an alternative data source for analyses that require long-term historical data where observed data are often unavailable. Process-based crop growth models are commonly used to simulate potential crop yield responses to different management practices and environmental conditions, uncovering relations that may not be fully explained empirically [15-17]. Some crop models offering cotton simulations include the Agricultural Production Systems Simulator (APSIM), Decision Support System for Agrotechnology Transfer (DSSAT) [18,19], Environmental Policy Integrated Climate (EPIC) [20], Simple and Universal Crop Growth Simulator (SUCROS) [21], and CropSyst [22]. Simulated results from these models serve as informative references to inform optimal solutions for adapting to climate variability and change while maximising farmers' profitability.

Recently, several relevant studies globally have focused on enhancing insurance products in different scenarios and changes through the application of bio-physical models. For instance, McNider et al. [23] used the coupled GriDSSAT – WaSSI model to simulate the water demand in watersheds stressed by irrigation. This work aims to define actuarial information for water insurance in scenarios where withdrawals may be reduced. In the U.S. Corn Belt region, Claassen et al. [24] integrated economic and biophysical models to assess the impact of federal crop revenue insurance programs on land use, cropping systems, and environmental quality. Tartarini et al. [25] proposed leveraging the WOFOST crop model and meta-modelling to reduce the basis risk in agricultural index-based insurance for winter cereals in Italy. Arumugam et al. [13] employed the DSSAT model to estimate rice yield and yield anomalies, supporting crop insurance implementation in India.

Despite the potential for insurance to be used to help farmers take 'productive' risks, there has been little research into this possibility. To our knowledge, there is no research on how to effectively combine climate adaptation measures with insurance to ensure that (i) adaptation remains economically viable and practical and (ii) insurance is affordable. In theory, implementing measures to adapt to climate change should lower the chances of losses caused by climate-related issues. As a result, insurance costs should decrease, making it more financially feasible. Moreover, insurance coverage can enable farmers to take more risks in improving their yields, as risks will be covered by insurance. However, this theory has yet to be tested. The lack of research on the integration of adaptation and insurance is a knowledge gap that is being addressed.

To improve income stability in response to drought and climate variability and change, this study aims to test the effectiveness of combining adaptation and insurance. Our strategy involves integrating index-based insurance with changes to sowing dates for Australian cotton producers. While the present study focuses on index-based insurance, the proposed approach can also apply to other types of insurance, crops, and management practices globally.

Cotton is one of Australia's most important agricultural exports, contributing significantly to country's rural income. The cotton growing season lasts approximately six months, starting with sowing in September through October and ending with harvest in March through April [26]. Changes in weather patterns over the past two decades have negatively impacted the productivity of Australian cotton farms [27]. Globally, climate impacts on cotton production are also anticipated to worsen under climate change [2,28]. Consequently, identifying ways to incorporate risk management and insurance to mitigate the effects of climate variability and change on cotton production is a crucial problem with global relevance.

2. Materials and methods

2.1. Study area and focus crop

Cotton is among Australia's key agricultural exports, contributing substantially to rural earnings [29]. Cotton is cultivated in the subtropical regions of Australia, which are susceptible to the influence of the northern monsoon and temperate soft-season rainfall. Over the past decade, approximately 83% of cotton-producing farms in Australia have relied on irrigation, highlighting the dependency on water resources [30]. Consequently, cotton production is highly sensitive to water availability, as evidenced by the significant decrease in cotton production during the period of the Millennium Drought (2000-2010), which reduced irrigation supplies and, in turn, greatly reduced cotton production in 2009-2010 [29].

Fig. 1 depicts the study sites, including Dalby, Goondiwindi, and Theodore, within Australian agro-environmental zones, selected for cotton yield simulations and insurance analysis. Goondiwindi and Dalby sites have subtropical climate patterns, while Theodore belongs to the savanna zone. The average rainfall during cotton growing seasons corresponding to different sowing dates is shown in Fig. 2. The amount of rainfall received at each site over the growing season differs and varies within each site according to the sowing date. The rainfall distributions show that the interquartile ranges (IQR, i.e., 25^{th} percentile below (Q1) and above (Q3) the median) at each cotton site vary slightly. Among the cotton sites, Dalby generally experiences the highest median rainfall, followed by Theodore, then Goondiwindi. Particularly, Goondiwindi exhibits the lowest values of Q1 and minimum (Q1 – 1.5*IQR), followed by Theodore and Dalby.

2.2. Crop simulations with drought adaptation strategies

Process-based crop models, which are equipped with advanced plant physiological algorithms, can capture the effects of unprecedented events (e.g., extreme temperatures) in the growing seasons or management shifts, which have not been observed in the past, on yield. These models can provide insights into yield losses or anomalies influenced by various weather conditions and management practices. This information is crucial for risk assessments, adaptation planning, and the development of risk transfer strategies. Here, we tested an approach that

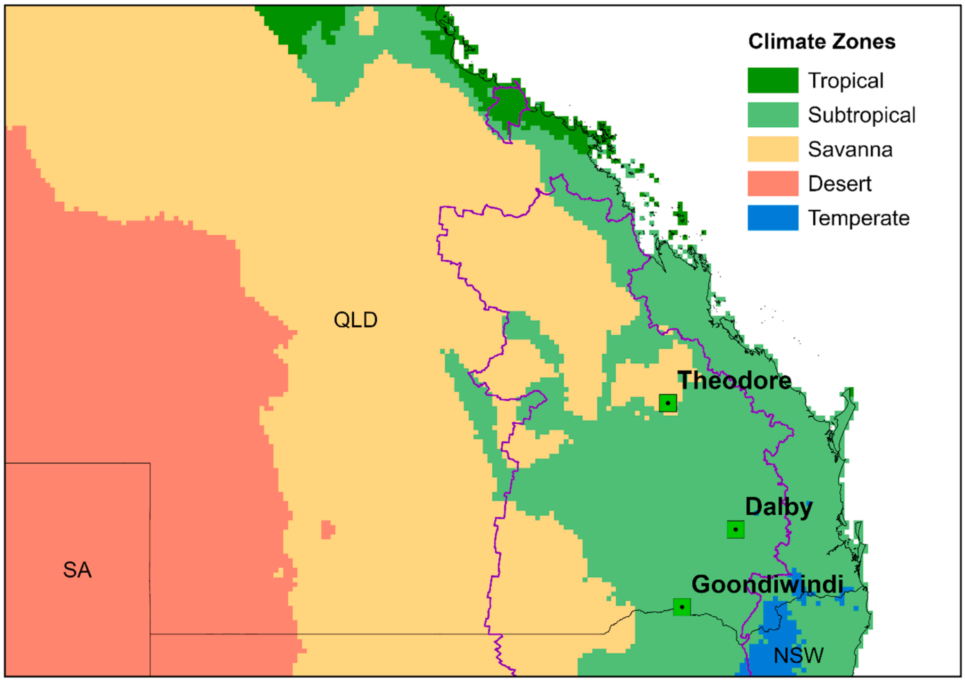

Fig. 1. Three study sites selected for cotton simulations including Dalby, Goondiwindi, and Theodore within Australian agro-environmental zones.

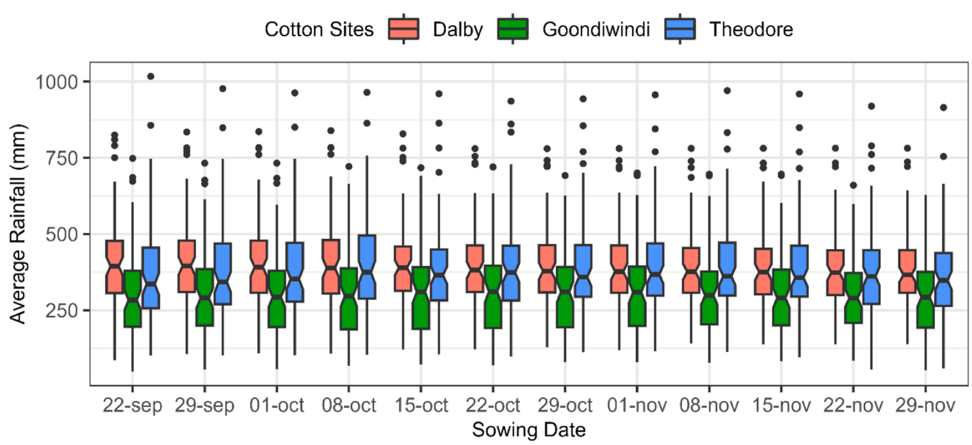

Fig. 2. Average rainfall during cotton growing seasons at different sowing dates across study sites over the period 1940-2022.

Table 1
Simulation configurations for cotton crops at the three study sites. The initial soil moisture is relative to 40-100% PAWC (mm). The baseline parameter values are underlined.

Site	Soil type	PAWC (mm)	Sowing dates	Sowing depths (mm)	Row spacing	Sowing densities (plants/m^2)	Initial soil moisture	Fertilizer
Dalby	Black Vertosol	301	22-sep 29-sep 01-oct 08-oct 15-oct 22-oct 29-oct 01-nov 08-nov 15-nov 22-nov 29-nov	25 <u>35</u> 45 55	Solid line Single skip row Double skip row	4 <u>6</u> 8 10	120, 150, 181, 211, 241, 271, 301	Soil available nitrogen at sowing (kg N/ha): 50, 60, 70, <u>80</u> Starter fertilizer: 30 kg MAP at sowing
Goondiwindi	Grey Vertosol	174					70, 87, 104, 122, 139, 157, 174	
Theodore	Black Vertosol	138					55, 69, 83, 97, 110, 124, 138	

leverages the benefits of combining adaptation options, simulated through a process-based model, with index-based insurance. This integrated approach aims to enhance the income stability of cotton producers in response to the challenges posed by drought and climate variability and change.

To assess drought adaptation strategies, this study used the APSIM-Cotton model (version 7.10) [31,32] to simulate cotton yield at three different sites within Queensland, Australia during the 1940-2022 period. Different combinations of agricultural practices and soil moisture levels (i.e., initial plant available water capacity at sowing), defined based on expert knowledge, were employed. Because the crop yield simulations represent a range of climatic conditions, farming techniques, and soil conditions, they offer insightful information into the most effective strategies for managing crops under varying climate conditions and agricultural practices. The simulated outputs served as the basis for integrating and optimising best management practices with insurance solutions. Summaries of the simulation configurations are presented in Table 1.

Crop failures were observed in some combinations of strategies and years, resulting in no simulated yields. These failures occurred when germination conditions specified within APSIM-Cotton were not met or when there were severe and prolonged adverse conditions during the cropping season, such as frost or heat waves. Furthermore, soil temperature played a crucial role in determining the planting dates for cotton crops in September. In real farming scenarios, farmers have the option to replant if seeds fail to germinate, but this process was not simulated. Combinations/years with no simulated yields were excluded from subsequent analyses.

The baseline biophysical parameters for simulations involved:

- Sowing depth: 35 mm
- Row spacing; solid line
- Planting density: 6 plants/m^2
- Available soil nitrogen at sowing: 80 kg N/ha

For each site, the simulations were carried out for seven levels of soil moisture at planting, which were expressed as a percentage of the plant's available water capacity (PAWC). PAWC is the maximum amount of water that can be stored in a soil profile and used by plants. The simulations were conducted for the variety S71BR and for all possible combinations for the period of 1940-2022. This resulted in 16128 times 82 years per site, leading to a total of 1,322,496 simulations per site.

2.3. Integrating drought adaptation and insurance options

We hypothesised that farmers could enhance their yield outcomes by implementing strategies made possible through insurance accessibility. Monthly rainfall averaged over the growing season (i.e., from sowing to harvesting) each year was selected as the index for the design of insurance options, denoted as *RI*. Index insurance production premiums P_{RI}were calculated for three different levels of insurance (5th, 10^{th,} and 20th percentile options). The percentile level, or predefined trigger levelK_{RI}, corresponds to when insurance pays out. For example, for the 10th percentile index-insurance option, when monthly averaged growing season rainfall falls below the historical 10th percentile, then the insurance begins to payout.

The premiums for each insurance were calculated by simulating 50,000 random values generated using the empirical density non-parametric distribution function. The edfun [33] package in R [34] was used to simulate the rainfall distribution. Rainfall in Australia shows a highly positively skewed and non-normal distribution, so a non-parametric distribution is best for simulating its distribution. From the simulated non-parametric rainfall distribution, premium costs were then calculated as the probability of falling below the 5th, 10th, and 20th percentiles, respectively, multiplied by the costs of payouts that occur once that percentile threshold is reached.

Here, the insurance indemnity *IND* is paid if the average rainfall *RI* received during the growing season falls below a predefined trigger level for rainfall K_{RI} as:

$$IND = \max(0, K_{RI} - RI) \times V \tag{1}$$

Here, *V*is the tick size converting physical units into monetary terms. To assess the effectiveness of integrating shifts in sowing time with different levels of insurance, we analysed the difference between the net incomes with and without insurance as:

$$NIC_{ins} = NIC - P_{RI} + IND \tag{2}$$

Here, we calculated the net income *NIC* using a fixed price *Pr* multiplying the simulated yield *Y*, i.e., $NIC = Pr \times Y$. Therefore, the percentage change in net incomes between those with and without insurance is derived as $\Delta NIC = 100 \times (NIC_{ins} - NIC)/NIC$. The premium was calculated as a fair premium (i.e. the volatility and processing costs were not included) (adapted from Vedenov and Barnett, 2004 & Chen, 2011).

3. Results

3.1. Evaluation of drought adaptation strategies

This section represents the results of crop simulations that considered a range of climatic conditions, crop management practices, and soil moisture levels. While the main focuses are highlighted here, detailed analyses and results for cotton simulations can be found in Figure S1 in Supplementary information. Fig. 3 depicts the relationship between rainfall during growing seasons and simulated potential cotton lint yields at different sowing dates averaged over all combinations of crop management practices and soil moisture levels across the study sites over the period 1940-2022. The results indicate that the cotton yield generally has a positive relationship with rainfall amount during growing seasons. This finding is consistent with published research, such as Sultan et al. [35], who also found a positive correlation between annual rainfall and cotton yield in West Africa.

Fig. 4 shows the predicted potential cotton lint yield at different sowing dates averaged over all combinations of crop management practices and soil moisture levels over the period 1940-2022. The simulated lint yield at the Dalby site is generally higher than Goondiwindi and Theodore, irrespective of the sowing date. The yield variations within the site on different sowing dates are minor. However, sowing cotton late on 22nd October generally produces a better yield relative to other dates. A similar pattern can be observed when changing planting depth and planting density (see Figure S1 in Supplementary). By contrast, changing row spacing and soil moisture level have a substantial influence on cotton yield within the sites. More specifically, cotton yield is drastically reduced by planting with double skip row practice, followed by single skip row in comparison with solid line. Additionally, within sites, increasing initial soil moisture level increases cotton yield.

Our main objective was to showcase the potential benefits of integrating risk management and insurance, specifically indexed-based rainfall insurance and optimal sowing dates. Therefore, we restricted our analysis to only the integration of insurance with optimal sowing dates. Cotton producers can adjust their sowing date to select an optimal sowing window, which can impact both insurance premiums and the level of risk they are willing to take. Although other adaptation methods may lessen the risk, they do not have an impact on the risk window of the index insurance product.

3.2. Evaluation of index-based insurance options

3.2.1. The frequency of average payouts

This section presents the findings on the frequency of average

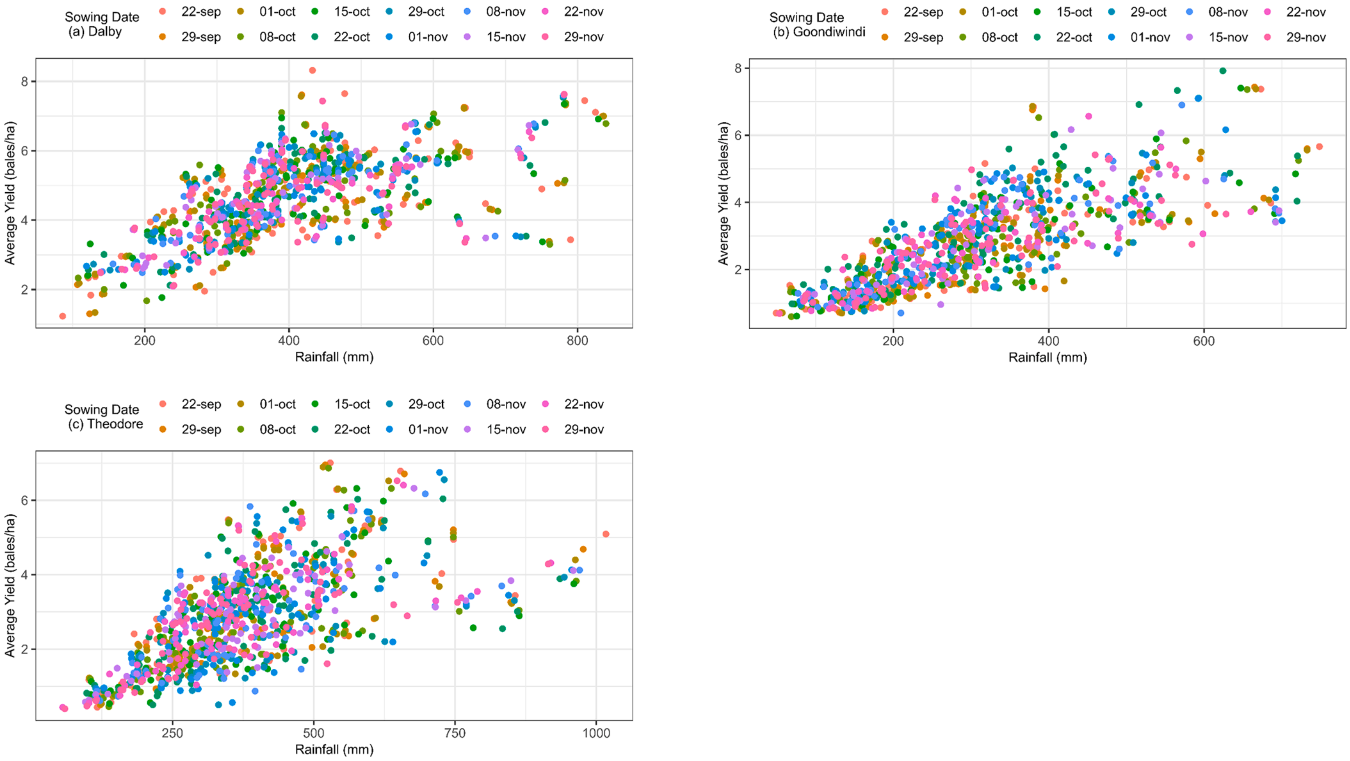

Fig. 3. Relationship between rainfall during growing seasons and simulated potential cotton lint yields at different sowing dates averaged over all combinations of crop management practices and soil moisture levels across the study sites over the period 1940-2022.

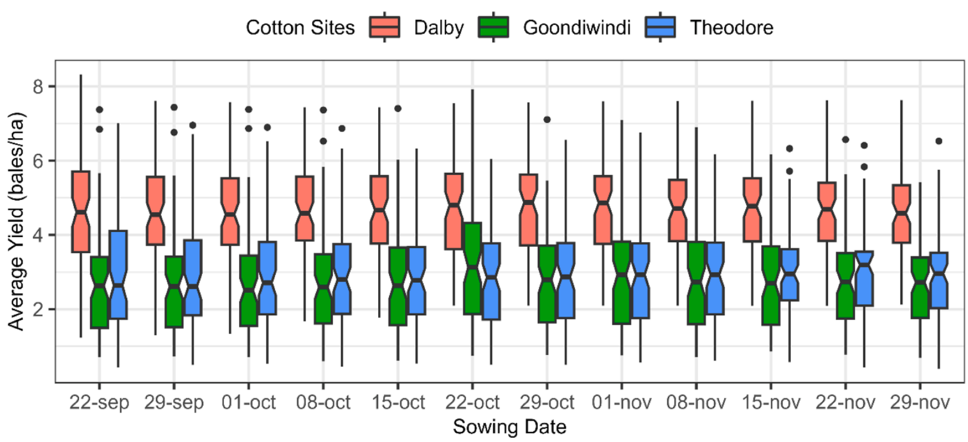

Fig. 4. Simulated potential cotton lint yield at different sowing dates averaged over all combinations of crop management practices and soil moisture levels across the study sites over the period 1940-2022.

payouts for each year across the three cotton sites. We used a tick size of AUD 20 per mm of rainfall to determine the payouts. This tick size helps to convert physical units into monetary terms, as explained in Eq. (1). In simpler terms, if the rainfall is below the set threshold, farmers will receive a payout of the tick value (AUD 20) multiplied by the amount of rainfall (mm) below the threshold (see the Dalby example below).

The fair premiums calculated at the 5th percentile level of drought insurance coverage for Dalby, Goondiwindi, and Theodore amounted to AUD 47.8, 28.7, and 30.4 per hectare, respectively (refer to Section 2.3 for calculation details). For example, the rainfall during the growing season (sowing on 29th September 1st or 8th October and harvesting on 27th January or 4th February) in Dalby in 2020 was 120mm, which is below the threshold (or trigger) level of 201mm by 81mm. The Dalby farmers will receive a payment of AUD 1620 (trigger rainfall * tick value) per hectare. The frequency of payouts at the 10th and 20th percentile levels of insurance coverage representing severe and moderate drought conditions are described in Figures S2 and S3 in the Supplementary materials.

Fig. 5 depicts the frequency of payouts across all simulations at the 5th percentile level of insurance coverage, averaged across different sowing dates for each year. The results of the analysis reveal that, over 83 years (1940-2022), Dalby and Goondiwindi exhibit the same frequency of payouts (18 events) compared to Theodore (14 events). It is worth noting that Dalby and Goondiwindi are geographically close to each other and have the same climate zone, as shown in Fig. 1. The maximum payout is AUD 2120 per hectare, which occurred in a drought event in 2014 in Dalby. Moreover, the payouts for Dalby are generally higher than those of the other locations. For example, an impressive 22.2% of Dalby's payouts exceed AUD 1000 per hectare, compared to 5.6% for Goondiwindi and 14.3% for Theodore. In terms of cumulative

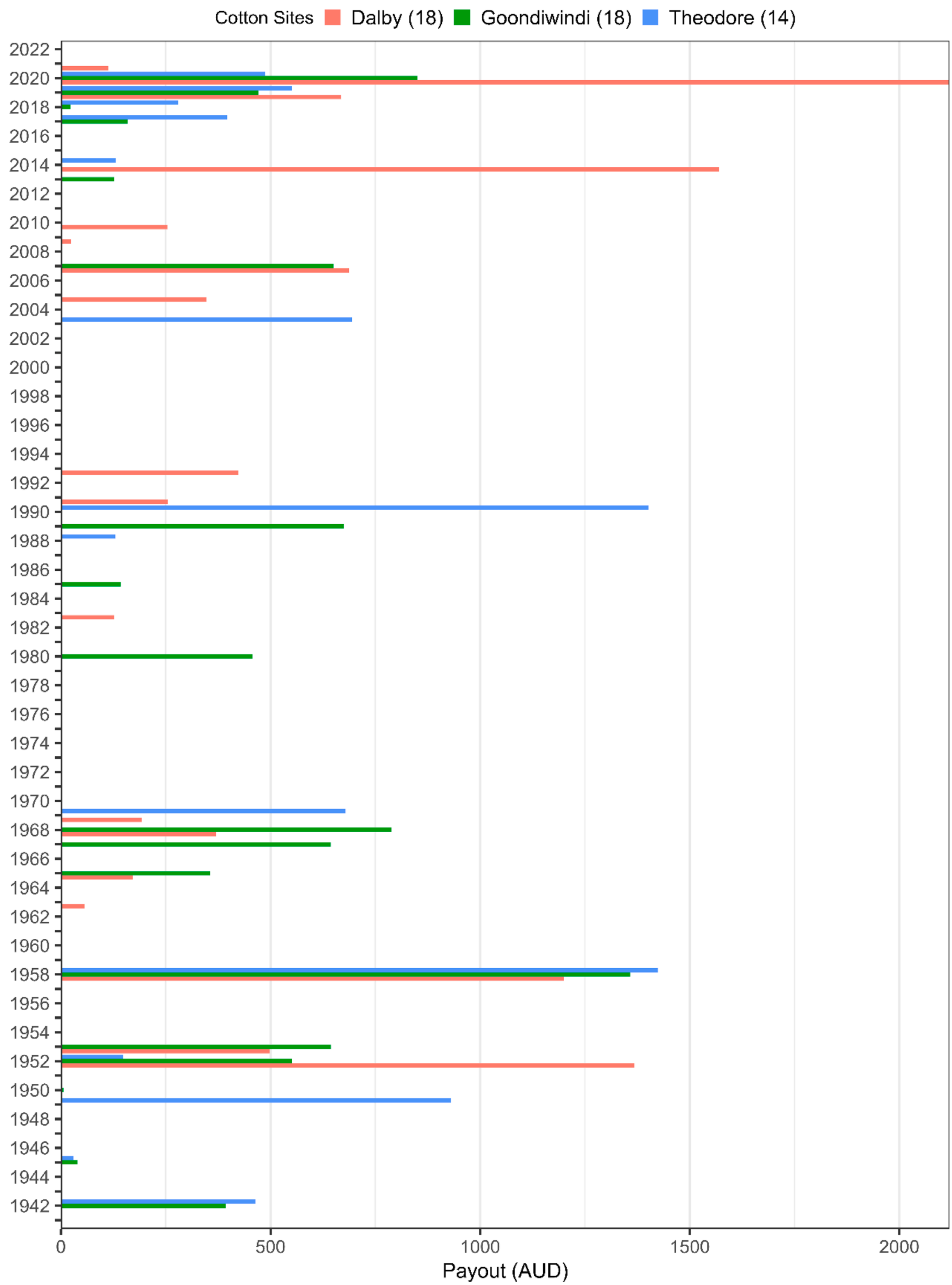

Fig. 5. The average payouts across all simulations at the 5th percentile level of insurance coverage for each year across cotton sites. The numbers in brackets show the frequency of payouts over 83 years (1940-2022).

payouts, Dalby, Goondiwindi, and Theodore amount to AUD 10445, 8334, and 7745 per hectare, respectively.

3.2.2. Comparison between incomes with and without insurance

3.2.2.1. All-year analysis. This section compares the income of cotton farmers with and without insurance coverage across three sites, considering the weather variations of all years. In addition, this section examines the impact of extreme drought conditions, when the farmer is most likely to suffer losses and rely on insurance, with a focus on farmers with insurance coverage at the 5th percentile level. Comparative analyses between farmers with and without rainfall index-based insurance, considering different sowing dates at 10th and 20th percentile levels of insurance coverage representing severe and moderate drought conditions, respectively, are reported in Figures S4 and S5 in the Supplementary materials.

In Fig. 6, a comparison is made between the income of cotton farmers who bought rainfall index-based insurance and those who did not. The comparison is based on different sowing dates and extreme drought conditions at the 5th percentile level of insurance coverage. Each element in the matrix shows the percentage change in income between insured farmers on the vertical axis and uninsured farmers on the horizontal axis for each sowing date. For example, in Fig. 6 (a), if farmers sow cotton on the 22nd of September and purchase rainfall index-based insurance, they could potentially earn around 1.4% more income compared to those who sow at the same time without insurance.

In general, by integrating sowing date and rainfall index-based insurance, income can increase by up to 10% in Dalby and Theodore, and as much as 21.5% in Goondiwindi. The analysis shows that insurance is beneficial between September 22nd and October 22nd in Dalby and from September 22nd to October 15th, as well as on November 29th, in Goondiwindi. However, in Theodore, insurance benefits are only evident on September 22nd, as well as on November 22nd and 29th using the same sowing dates.

Further analysis reveals that at Theodore, planting cotton on September 22nd and having insurance coverage will result in a higher income compared to planting on any other date without insurance. In other words, sowing cotton on any date with insurance results in higher income than sowing on 22nd September without insurance. This pattern is also observed at Dalby and Goondiwindi, for sowing cotton on 22nd October when insurance generates better income than sowing on any other dates without insurance, except for 22nd October at Goondiwindi. Notably, sowing cotton at Goondiwindi on 22nd October with insurance significantly increases income, up to 21.5%, in comparison with other sowing dates (before and after 22nd October) without insurance. At the Theodore site, sowing cotton with insurance coverage also often leads to better income compared to sowing later without insurance, although the differences are less remarkable. However, it is noted that sowing cotton between 22nd October and 1st November with insurance results in lower income than sowing on any other dates without insurance.

3.2.2.2. Drought-year analysis. In this section, we focussed only on years with rainfall level below the 20th percentile during the growing season to evaluate the extent to which a contract reduces downside risk (i.e., whether insurance minimises loss in poor years).

Fig. 7 illustrates comparative income differences between farmers with and without insurance, focusing on drought years only. The results are calculated for different sowing dates at the 5th percentile level of insurance coverage (extreme drought conditions). It is worth highlighting that over drought years, at Dalby, cotton farmers who purchase insurance experience considerably higher income compared to those without insurance, regardless of the sowing dates. Such benefits of

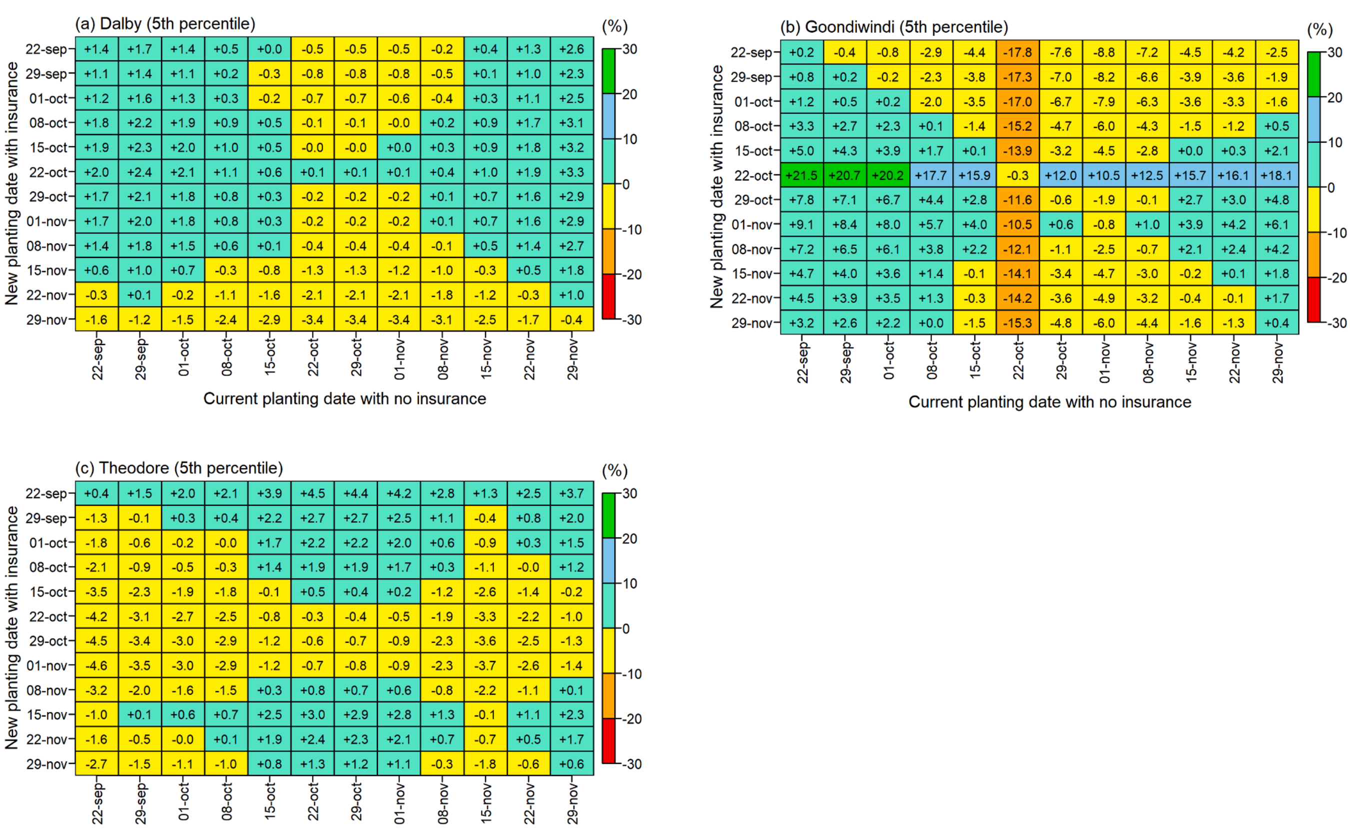

Fig. 6. Comparison of income percentage change between cotton farmers with and without rainfall index-based insurance given different sowing dates at the 5th percentile level (extreme drought) of insurance coverage for the three study sites (a) Dalby, (b) Goondiwindi, and (c) Theodore.

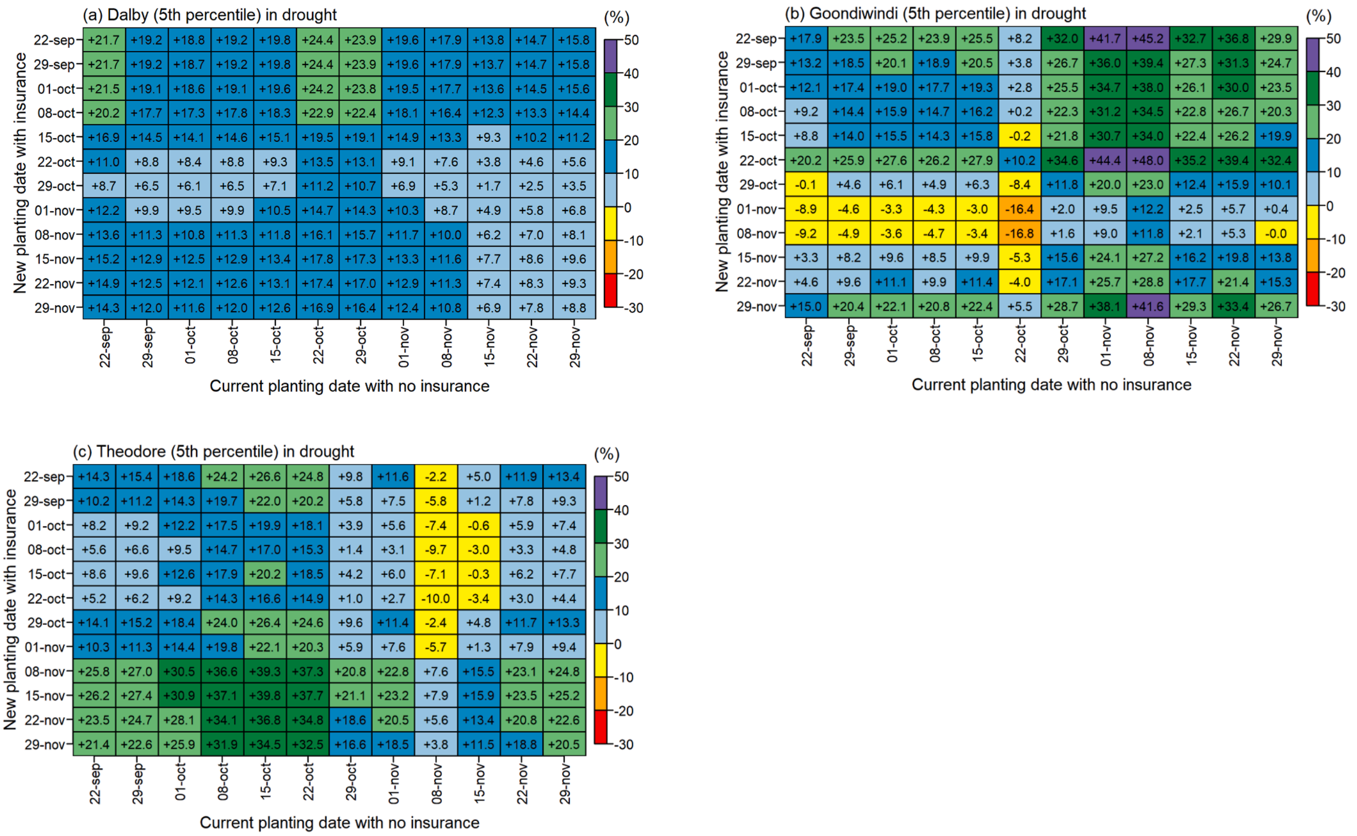

Fig. 7. Comparison of income percentage change under drought years between cotton farmers with and without rainfall index-based insurance given different sowing dates at the 5th percentile level (extreme drought) of insurance coverage, which is considered as under extreme drought condition for the three study sites (a) Dalby, (b) Goondiwindi, and (c) Theodore.

integrating rainfall index-based insurance are also evident at Goondiwindi and Theodore, except for a few scenarios. In particular, the income improvement by combining the optimal sowing dates with rainfall index-based insurance can reach up to 24.4%, 48.0%, and 39.8% compared to those without insurance at Dalby, Goondiwindi, and Theodore, respectively.

4. Discussion

Shifting sowing windows is an effective management practice for adapting cotton production to climate change. The timing of when cotton is planted is largely determined by climate factors that affect soil temperature [36]. The timing can also impact plant disease [37], weed encroachment [38], carbon export [39], as well as germination and plant growth [40]. By changing the date when cotton is sown, the risks it faces throughout its life cycle can be altered. In Australia's cotton industry, the shift towards earlier planting has been driven by changing climate conditions [36]. However, due to increased variability, adaptation responses regarding the planting date have become more dynamic, with the best time to plant changing yearly depending on seasonal conditions [36].

Since cotton is responsive to its surrounding environments, farmers adopt a variety of strategies to cope with unfavourable climate conditions and weather variability. According to a study by Afzal et al. [41] on managing planting time for cotton production, adjusting planting dates may play an effective role as an adaptation strategy to match the fruiting phase to favourable climatic conditions. Moreover, altering the planting time and other options like augmenting irrigation usage or transitioning to crops that can endure drought proves advantageous for farmers with limited access to irrigation and financial resources [42].

The impact of different sowing dates on cotton development and lint yield under various management practices was assessed based on crop model simulations. While crop models can serve as valuable tools to predict crop yield and estimate the extent of potential crop losses caused by specific climate events, their effectiveness in informing operational decisions for improved climate risk management is constrained by some limitations [43,44]. Such limitations include the simplification of complex processes and environmental interactions (e.g., biochemical processes at the leaf level, phosphorus response in crops, pests, diseases, and weeds dynamics, soil health), which cannot be fully accounted for in models but could noticeably impact crop yields [45]. Additionally, variations in farm management practices and technology adoption are not adequately integrated into the model, resulting in discrepancies between model predictions and actual outcomes. It is noteworthy to mention that management strategies that are optimised for present-day climates may not necessarily be optimal for future climates [46]. Will et al. [14] proposed the potential benefits of combining empirically parameterised agent-based models (ABMs) into process-based crop models to enhance the capture and reproduction of accurate crop yields. This combined approach would ultimately improve the design of index-based insurance and contribute to ongoing discussions on the reduction of basis risk [14,47].

This suggests that it is worthwhile exploring optimal strategies for risk reduction under different climate scenarios. Furthermore, an integrated approach that synergies the strengths of several approaches could be beneficial to overcome some of the individual limitations of the different approaches used in climate-related risk reduction. This study demonstrated that index-based insurance coupled with shifting sowing dates as a drought adaptation strategy could improve the farmers' income.

Insurance can also be used proactively in combination with optimal crop management strategies, instead of just being viewed as a reactive tool for risk management where payouts are made after an event. Based on our findings, farmers who change their sowing schedule and use insurance can experience benefits of up to 21.5% in certain study locations. These benefits are higher when our assessment is focused on drought conditions. This suggests that the strategic linking of management and insurance to help farmers take productive risks could be an important area of climate adaptation research that remains largely unexplored. Importantly, the approach we outline has wider implications and suggests that insurance could potentially be used to give farmers financial security and help facilitate the shifting of cropping activities and management actions to more profitable windows – an important adaptation option in a shifting climate.

Although index-based insurance has the potential to enhance the resilience and income of rural communities, the development of insurance markets is still limited. There have been multiple instances of insurance programs failing due to high costs or farmers not receiving compensation when they needed it most. These issues are often associated with basis risks. Improving index insurance has been challenging due to the lack of a conceptually sound standard for measuring and recognizing the quality of index insurance [48].

To combat the effects of climate change, integrating management practices with index insurance could provide a more affordable and cost-effective adaptation strategy. In general, index insurance can elevate crop yield and income, increasing farming resilience under a suitable agro-environment and ideal crop management strategies. However, it is not a one-size-fits-all remedy for all agro-environments and crop management practices. The efficacy of index insurance relies on a meticulously crafted index that addresses a significant portion of the risks farmers face. Future research may assess the effectiveness of combining insurance schemes with other practices, such as soil moisture level or crop diversification.

5. Conclusion

This study proposed an innovative framework that integrates index-based insurance and optimal crop management strategies to reduce financial risk related to droughts. The simulation findings for cotton crops across the three study sites within Australia indicated that farmers could improve their income stability by optimising the sowing date combined with insurance coverage. An essential insight from the study is that insurance can be a powerful tool for proactively mitigating risks in agriculture. Our research demonstrates that insurance can be utilised as a proactive tool alongside optimal crop management strategies, rather than just as a reactive measure for risk management payouts. In particular, our analysis highlights the effective integration of insurance with ideal planting windows. Our suggested integrated approach has other promising applications such as assisting farmers in selecting crops based on soil moisture levels.

In conclusion, the integrated approach developed in this study will facilitate the financial transformation of farming during extreme climate conditions by providing integrated crop management and insurance options that i) provide information about the crop management actions that will increase farmer profitability and ii) give farmers the confidence to invest in the profitable and resilience increasing management actions without suffering financial losses if severe drought conditions occur. This will help improve farmers' comprehension and knowledge of using insurance as a means of managing drought in their farm businesses.

CRediT authorship contribution statement

Thong Nguyen-Huy: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jarrod Kath:** Formal analysis, Methodology, Software, Visualization, Writing – review & editing, Conceptualization. **Louis Kouadio:** Data curation, Software, Writing – review & editing. **Rachel King:** Methodology, Writing – review & editing. **Shahbaz Mushtaq:** Conceptualization, Project administration, Resources, Supervision, Funding acquisition, Writing – review & editing. **Jonathan Barratt:** Funding acquisition, Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2024.100249.

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