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Spatial variability in regional scale drought index insurance viability across Australia's wheat growing regions

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ABSTRACT

Wheat is key global food crop that is heavily influenced by climatic variability. There has been extensive research on improving forecasts and management practices to minimise climate related yield losses, but less on how to handle yield losses caused by climate variability. We investigated whether index insurance could be used to manage climate related losses, specifically from winter rainfall drought for wheat crops in Australia. We utilised 31 years of yield data from 15 of Australia's key wheat producing regions. The winter rainfall index was developed and tested using generalised additive regression models, allowing for non-linear effects. Models with the winter rainfall index explained significant variation in wheat yields in each of the regions assessed. Wheat yield models had cross-validated R^2 values > 0.5 for two-thirds of the 15 regions modelled and best explained wheat yields in the Mallee, Western Australia (cross-validated R^2 of 0.70). Calculated fair premiums ranged from $8.62 to $77.1 AUD/ha, while maximum liability was $59.25 to $212.12 AUD/ha. Throughout the eastern most wheat growing regions the winter rainfall index was consistently inefficient (i.e. not beneficial). In contrast, the winter rainfall index was financially efficient (i.e. beneficial) in the western wheat regions of eastern Australia and parts of Western Australia, with benefits of up to $97 AUD/ha and loss reductions of $9 AUD/ha. The spatial variability in insurance efficiency was explained by rainfall variance. As rainfall variance increased the efficiency of the winter rainfall index insurance for wheat decreased. Our findings have two important policy implications; (1) in areas where climate change is anticipated to increase rainfall variability risk-transfer options, such as index insurance, may become less viable and as such policies that support the development of index insurance without acknowledging or adjusting for variability in its benefit could lead to inefficient outcomes for both government and agricultural producers; and (2) where index rainfall insurance is not efficient then greater emphasise may need to be placed on developing alternate types of index insurance (e.g. using satellites) and/or on risk-management and climate adaptation strategies that minimise losses.

1. Introduction

Wheat covers more of the earth's surface than any other crop and with over 700 million tonnes produced annually it is one of the world's most important food crops (Hallam et al., 2013). Along with other crops, food demand for wheat is projected to increase

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sharply in the coming decades (Tilman et al., 2011). Meeting current and future demand for wheat is largely dependent on climatic variability (Ray et al., 2015). Climate variability significantly influences 79% of wheat harvesting regions worldwide and is responsible for annual yield fluctuations of ∼9 million tonnes globally (Ray et al., 2015). However, while there has been extensive research on improving forecasts and management adaptation practices to minimise climate related yield losses (Challinor et al., 2014), there has been less research on the best way to handle the financial consequences of yield losses caused by climate variability (Thornton et al., 2014).

Climate-variability driven crop losses undermine the financial sustainability of agricultural production (Odening and Shen, 2014; Mushtaq, 2018) and so it is important to identify efficient ways that losses from climate variability can be managed. Otherwise key global food crops may not be produced in the quantity required, thereby undermining global food security (Thornton et al., 2014; Willenbockel, 2012). Insurance has been used to manage yield losses, including climate induced losses for decades, but faces several challenges (e.g. Goodwin, 2001). In many parts of the world, certain types of insurance, such as full coverage of all losses (Multi-peril crop insurance or Named-peril crop insurance) is too expensive and unviable without subsidies and thus in some places food insecurity remains a risk that is not insured (Cavatorta and Pieroni, 2013; Jensen and Barrett, 2016). In areas without subsidies the prohibitive costs of MPCI insurance mean that farmers do not purchase insurance and remain exposed to significant climate risks (Odening and Shen, 2014).

To address the low uptake of insurance and thus farmer's high exposure to climate risks, index insurance products have been developed as a potentially more cost-effective means of insuring against particular aspects of climate risk (Barnett and Mahul, 2007). Index insurance has several benefits over indemnity insurance because it does not require expensive on-ground assessments and limits moral hazard resulting from information asymmetries or false reporting of losses. Index insurance offers a cheap and effective way for farmers to transfer climate risks. Despite its potential benefits, uptake of climate index insurance is often inhibited by significant basis risk (i.e. payouts may occur when losses do not, or vice versa), limited perils, lack of technical capacity, expertise, and data limitations (Odening and Shen, 2014).

Data limitations are a significant limiting factor, not only in designing contracts, but in assessing the benefit of index insurance for farmers. Many studies have used statistical approaches to quantify the benefit of index insurance at particular locations (e.g. Vedenov and Barnett, 2004), however, in many cases there is a lack of time-series farm level yield data to assess the viability of index insurance. Time-series data over multiple decades is required to assess the viability of index insurance, especially in parts of the world that experience highly variable precipitation and trends towards greater aridity (e.g. Africa, southern Europe, East and South Asia, and eastern Australia, Dai, 2011). Here we outline an approach for testing the viability of index insurance using regional scale time-series data from Australia's wheat growing regions. It is important to note that because we use regional scale data that our findings are affected by aggregation biases that mean farm-level risks are likely underestimated (Finger, 2012). Our findings are still nonetheless informative for regional scale level index insurance programs (e.g. that may be considered by industries or farmer co-operatives.

Numerous studies have investigated the feasibility and financial efficiency (i.e. economic benefit or utility) of climate index insurance, typically low rainfall or drought indices for agricultural producers (Adeyinka et al., 2016; Breustedt et al., 2008; Conradt et al., 2015; Dalhaus et al., 2018; Dalhaus and Finger, 2016; Turvey and Mclaurin, 2012). To date the focus of most research has been on the best way to quantify and develop indices to minimise basis risk (i.e. the risk that the index does not adequately correlate with losses) and on identifying the locations where a particular index is beneficial. Recently research has also focused on how basis risk and spatiotemporal adverse selection influence demand for index insurance (Jensen et al., 2018). Vedenov and Barnett (2004) showed the efficiency of index varied between regions for corn, cotton and soybean crops. Conradt et al. (2015) also show different benefits for rainfall index insurance for wheat across different counties in Northern Kazakhstan.

As mentioned above, these studies use farm-level yield data, which is rarely available over multiple decades, which would allow for an assessment of a range of climatic conditions. Further, while studies have identified that the benefit of index insurance varies between farms none have tested what the possible reasons for this variation. To address this knowledge gap here we test the relationship between climate and the spatial variability in the efficiency of index insurance. We use a long-term (31 years) regional scale wheat yield dataset from Australia's wheat growing regions covering over 1.5 million km^2, an area approximately equivalent to all of Germany, France and Spain combined. We are unaware of any other studies on index insurance that have been carried out over similarly extensive scale.

Using this extensive regional scale dataset we are able to investigate possible drivers that could explain spatial variability in the benefit of index insurance. Understanding the relationship between climate and the spatial variability in the benefit of index insurance has important implications. Climate change is expected to alter key aspects of climate, especially variability and intensity in rainfall and drought (Pendergrass et al., 2017; Thornton et al., 2014). Changes in rainfall variability projected under climate change, while uncertain, could be particularly pertinent for the security of food systems, with Thornton et al. (2014) arguing that it may be linked with increased food insecurity. If we can understand links between insurance efficiency and climate we may therefore have better understanding of how the viability of index insurance may change as climate variability decreases or increases.

We expect the benefits of index insurance to be spatially variable because other studies show index insurance benefits can vary substantially between different regions for the same crop (e.g. Vedenov and Barnett, 2004; Conradt et al., 2015). We also investigate how rainfall variability relates to spatial variation in the efficiency of rainfall index insurance. As insurance aims to minimise downside losses and increase income certainty, both of which are undermined by increased variance, we expect greater rainfall variance to correlate with lower index insurance efficiency. We discuss the policy implications of our findings for risk management and the management of agricultural losses under climate variability.

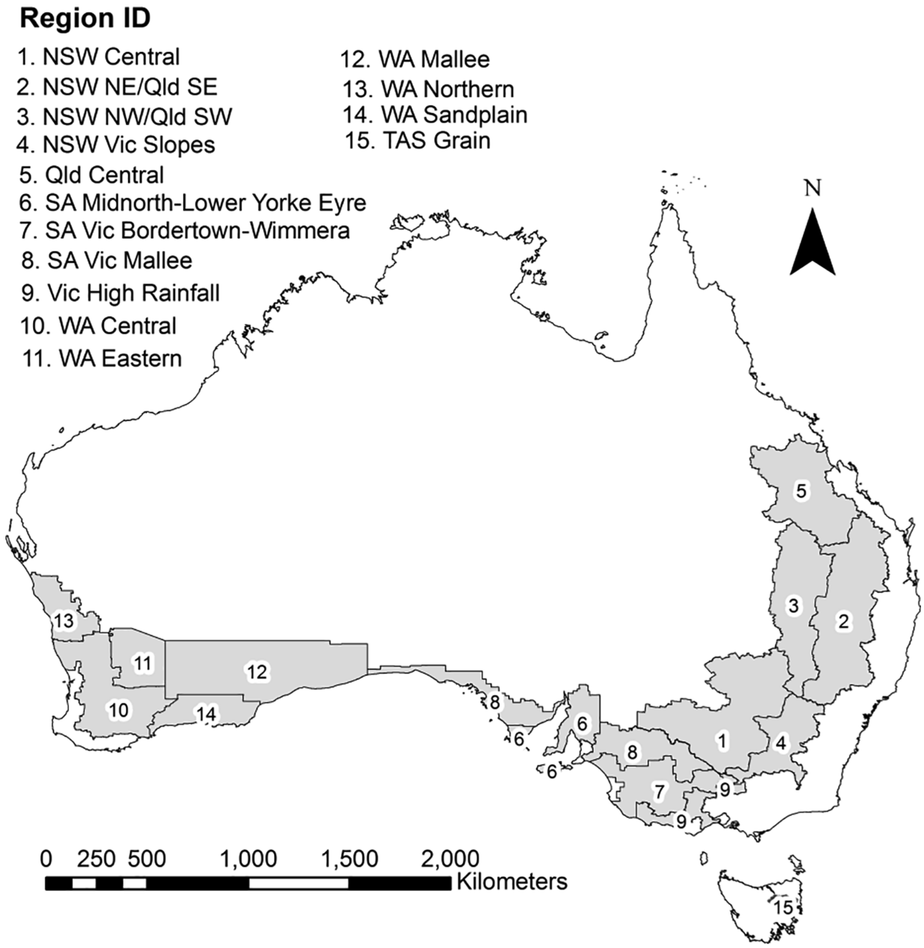


Fig. 1. Wheat growing regions that the winter rainfall index insurance efficiency was assessed across.

2. Study area and data description

2.1. Study area - Australia's wheat growing areas

The study covers Australia's wheat growing regions (Fig. 1). The area covers a range of climates (from Mediterranean to Temperate) with mean total rainfall over the winter growing season ranging from ~200 to 400 mm (Williams et al., 2015). Australia, and wheat growing areas in particular are frequently impacted by droughts. Droughts in 2006–2007 were associated with declines in wheat production of ~61% in some areas (Cockfield, 2009). Despite high variability in climate and yield, Australia, is one of the globe's key wheat breadbaskets (Ray et al., 2015).

2.2. Data description

We used annual wheat yield (tonnes/ha) data from 1982 to 2012 from Australia's wheat producing regions (15 in total; Fig. 1; ABARES, 2015). See Appendix A and B for descriptions of yield data. The rainfall index was developed as the total of rainfall during the winter growing season (April to September) for each region. Rainfall data was from 105 locations across the 15 regions for the time period 1982–2013 from the SILO climate database (Jeffrey et al., 2001). Zonal averages for each wheat region were produced for in-crop rainfall (April-September average). These stations were identified as significant for wheat production (after Williams et al., 2015). Price data, used to calculate gross revenues, was corrected for inflation. Data used in the study is summarised in Table 1.

3. Analytical approach

3.1. 4.1 Regressions relating yield to the winter rainfall index using generalized additive model (GAM)

Separate models were fit for each wheat growing region using a generalized additive model (GAM), which fits non-linear models

Table 1
Description of data and Rainfall indices used in the study.

Variable	Details and calculation methods	Mean (SD)	Reference
Wheat yield (tonne/ha)	Mean yield for each region and year from 1982 to 2012.	1.6 (0.9)	ABARES 2015
Winter rainfall index (mm)	Summed rainfall over the winter growing season covering April to September. The rainfall index (RI) for each year (i) is then the sum of daily rainfall (R_d) in winter season. ($WRI_i = \sum_{d=seasonstart}^{seasonend} R_d$).	251.3 (115.4)	Jeffrey, 2001
Price (AUD)	Consumer price index (CPI) adjusted price. Data from 1982 to 2012. The median price for this period was used in analysis.	298.2 (53.6)	ABARES 2015

SD = standard deviation

using a spline. GAMs allow arbitrary nonlinear transformations of the input variables to be fit by the data (Gelman and Hill, 2006). GAMs are a form of quadratically penalised generalised linear model (Wood 2004). The smooth (non-linear) components of the fit are fit using penalized regression splines to ensure overfitting does not occur. To prevent overfitting, penalized likelihood maximization is used, wherein the model (negative log) likelihood is modified by the addition of a penalty for each smooth function (Wood 2004; 2011). The Mgcv package (Wood 2011) was used to fit a GAM in R (R Development Core Team, 2016) In each region wheat yields were modelled as a function of total winter rainfall and year of harvest. Total winter rainfall served as the index and was defined as;

$$WR_i = \sum_{d=seasonstart}^{seasonend} R_d \tag{1}$$

Year of harvest was included to account for any temporal effects (e.g. changes in technology, management and production extent through time) (Verón et al 2015). Including year in the model implicitly detrended the yield data with yearly effects not constrained to be equal (Auffhammer et al., 2006; Verón et al., 2015). Winter rainfall was centred and detrended prior to model fitting (Gelman and Hill, 2006).

A regression model for each region was fit such that the response variable (wheat yield) at time *i* was fit with a smooth effect (f) for winter rainfall (WR) and year,

$$yield_i \sim N(\mu_i, \sigma); \tag{2}$$

$$yield_i = a + f(WR_i) + f(year_i) + \varepsilon_i$$

$$\varepsilon_i \sim N(0, \sigma^2)$$

The GAM model was validated using simple hold-out cross validation by randomly sub-setting the dataset (80/20) into an independent model building and validation component (Refaeilzadeh et al., 2009) and repeating the process 1000 times, from which we derived a mean cross-validated R^2.

3.2. Premium estimation based on predicted losses for climate index from regression models

Following Vedenov and Barnett (2004) we estimated wheat yield losses and premiums based on regression model predictions. To do this, predictions of yield losses in relation to the rainfall index were linked with the rainfall probability distribution. We calculated probabilities using the density function and gaussian smoothing kernel in R (Silverman 1986; R Development Core Team, 2016), generating 3000 values, for each of which losses were calculated (after Kath et al., 2018). The premium was calculated as a fair premium using these probabilities (adapted from Vedenov and Barnett, 2004; Chen, 2011).

$$P(x) = E[Loss] = \sum_{i=1}^{n} (IND_i \quad . \quad P(RI_i \quad)) \tag{3}$$

Here, *P(x)* denotes the insurance contract fair premium, *n* is the number of rainfall values for the part of the rainfall index probability distribution we are calculating losses from, *P(RI)* denotes the probability of each rainfall values level and *IND* represents the corresponding indemnity amount (adapted from Vedenov and Barnett, 2004; Chen, 2011). This was calculated for each of the percentile values (5th, 10th, 20th and 30th) that we investigated. Vedenov and Barnett, (2004) investigated the 5th, 10th and 20th percentiles and we add the 30th percentile to this to cover moderate drought impacts, which can still relate to low absolute rainfall levels for wheat cropping in parts of Australia. See Appendix C for the rainfall values corresponding to the 5-30th percentiles for each region.

3.3. Financial efficiency analysis of winter rainfall index insurance

Methods for efficiency analysis were adapted from Adeyinka et al. (2016) and Vedenov and Barnett (2004). Two financial efficiency analysis methods Mean Root Square Loss (MRSL) and Certainty Equivalence of Revenue (CER) were used to assess the efficiency of the winter rainfall index insurance contracts (see details for each method below). The impact of the insurance was analysed by finding the difference in revenue of the farmer without insurance and with insurance at different percentile coverage levels for each regression model. A positive revenue difference for CER implies that the contract will be efficient, whereas a negative difference implies efficiency for MRSL since the objective of the contract is to reduce losses.

Using efficiency analysis, we compare revenue with and without insurance. The revenue without contract is given by:

$$I_t = pY_t \tag{4}$$

and with contract is:

$$I_{t\alpha} = pY_t + \beta - \theta \tag{5}$$

where; I_t = revenue at time t without insurance, p = price of agricultural commodity, Y_t = yield at time t, $I_{t\alpha}$ = revenue at time t with alpha percentile levels of insurance (here the 5th, 10th, 20th and 30th percentiles of the rainfall index), β = insurance payout for that level of insurance in that year (predicted from the regression models) and θ = the yearly premium for that level of insurance and is constant for a given percentile level of cover throughout the years in question.

3.3.1. Certainty equivalence revenue (CER)

CER accounts for farmers' tendency to be risk averse and is a measure of willingness to pay (Adeyinka et a.,l 2016; Vedenov and Barnett, 2004). Most decision makers show some level of risk aversion (i.e. risk aversion $<$ 1) (Chavas, 2004). We assessed certainty equivalence revenue at risk aversion coefficients of 1, 2, 3 and 4, covering the range of most studies that assess risk aversion (Conine et al., 2017). The higher the value of the risk aversion coefficient, the more risk averse the individual and thus the more they are willing to pay for a certain income (e.g. by paying for insurance).

Here we use Constant relative risk aversion (CRRA) risk utility functions (after Chavas, 2004) to assess certainty equivalent revenue. When risk aversion (r) is equal to 1 than;

$$CER_\alpha (r = 1) = Ln(\mathrm{I}_{t\alpha}) \tag{6}$$

where; CERα is the Certainty equivalence revenue with an alpha level of insurance. $I_{t\alpha}$ = revenue at time t with alpha percentile level of insurance as outlined above.

When risk aversion (r) is > 1 then;

$$CER_\alpha \quad (r > 1) = (-\mathrm{I}_{t\alpha}^{1-r}) \tag{7}$$

3.3.2. Mean root square loss (MRSL)

The MRSL shows the extent to which a contract reduces downside risk below the mean (Vedenov and Barnett, 2004). Here we use MRSL based on the mean since we expect farmers to be concerned with below average revenue. For different contracts (5th, 10th, 20th and 30th percentile contracts), the MRSL may be computed to observe the extent to which the downside risk below the mean is minimized. Hence, if the MRSL reduces with insurance, then the contract is efficient at that percentile level.

$$\mathrm{MRSL}\alpha = \sqrt{\frac{1}{T}\sum_{t=1}^{T}[\max(p\bar{Y} - I_{t\alpha}, 0)]^2} \tag{7}$$

where; *MRSLα* is the Mean Root Square Loss with an alpha level of insurance, p = price of agricultural commodity, *Itα* = revenue at time t with alpha percentile level of insurance.

3.4. Assessment of the index premium and financial efficiency variability

Each regression model was constructed using a build subset (80% of dataset) and then used to predict observed yields not used to build the model in a test subset (20% of the dataset). The financial efficiency of the contract was also assessed on the out-of-sample subset of the dataset. Because performing only one split may give overly optimistic or pessimistic assessments of insurance contract efficiency we repeated the process 1000 times. Repeating the process 1000 times also allowed us to assess the variability in results. In the results then we present the mean estimated premiums and efficiency for each regression model (at the different percentile levels of cover tested). We tested for normality in the residuals using the Shapiro-Wilk test and provide these results in Appendix D.

3.5. Assessing the relationship between index insurance efficiency and rainfall variability

We related the efficiency (from both CER and MRSL analysis) of the winter rainfall index to the ratio of the square root of each regions mean rainfall over the log of its rainfall variance. Higher rainfall variance scores indicate regions with higher and more consistent rainfall, while low rainfall variance scores indicate regions with less and more variable rainfall. We used simple linear regression to relate the rainfall variance score to the efficiency measures across the regions and used bootstrapping (with 10,000 replications) to obtain R^2 and p-values. We tested for spatial auto-correlation, using Moran's test, and there was no evidence of this (Appendix E). Analysis was performed in R (R Development Core Team, 2016). The model structure is below.

Table 2
Regression results for the winter rainfall index model for each region.

Region	Winter rainfall index		Year		Adjusted R^2	*Cross-validated R^2
	F	p-value	F	p-value		
NSW Central	21.42	< 0.001	4.82	0.002	0.73	0.47
NSW NE/Qld SE	8.35	< 0.001	2.46	0.059	0.54	0.47
NSW NW/Qld SW	11.85	< 0.001	5.81	0.002	0.79	0.48
NSW Vic Slopes	17.96	< 0.001	5.10	0.001	0.77	0.52
Qld Central	4.45	0.021	4.33	0.002	0.61	0.53
SA Midnorth-Lower Yorke Eyre	15.64	< 0.001	7.26	< 0.001	0.74	0.55
SA Vic Bordertown-Wimmera	9.73	< 0.001	0.90	0.431	0.54	0.40
SA Vic Mallee	20.50	< 0.001	2.73	0.035	0.64	0.49
Tas_Grain	2.91	0.025	15.01	< 0.001	0.66	0.54
Vic High Rainfall	14.55	< 0.001	16.62	< 0.001	0.90	0.55
WA Central	12.20	< 0.001	12.75	< 0.001	0.63	0.53
WA Eastern	26.63	< 0.001	14.29	< 0.001	0.81	0.58
WA Mallee	13.90	0.001	7.48	< 0.001	0.71	0.70
WA Northern	15.85	< 0.001	19.41	< 0.001	0.75	0.55
WA Sandplain	9.48	0.005	40.26	< 0.001	0.58	0.60

*Cross validated R^2 is the mean R^2 from 1000 cross-validations. F, p-values and Adjusted R^2 are from model fit to entire (n = 31) dataset for each region.

$$efficiency_j \tilde{N}(\mu_j, \sigma); \tag{8}$$

$$efficiency_j = a + B_1(\log(rainfall\ \ variance\ \ score_j) + \varepsilon_j$$

$$\varepsilon_j \tilde{N}(0, \sigma^2)$$

4. Results

4.1. Model performance

The winter rainfall index was significant (at p = 0.05) in each of the regions assessed (Table 2). Models for wheat yields had cross-validated R^2's > 0.5 for two-thirds of the 15 regions modelled (Table 2). The model explained wheat yields best in the WA Mallee (with a cross-validated R^2 of 0.70). The model performed the poorest in wheat region in NSW (NSW Central, NSW NE/QLD SE and NSW NW/Qld SW) and SA (SA Vic Bordertown-Wimmera and SA Vic Mallee) (Table 2). Of these the poorest performing model (with a cross-validated R^2 of 0.40) was in the SA Vic Bordertown-Wimmera region.

Wheat yields were positively related to the winter rainfall index in each region, such that as the winter rainfall index increased so did predicted yield (Fig. 2). The relationship between the winter rainfall index and wheat yield was noticeably non-linear in most (11/15) of the wheat regions (Fig. 2). Strong non-linear associations were evident in SE QLD, NE NSW where results suggested that yields had little relationship with winter rainfall when it was above 300 mm, but declined sharply when winter rainfall was below 300 m (Fig. 2). The wheat regions VIC, SA Mallee, QLD Central, WA Mallee and WA Sandplain had linear relationships with the winter rainfall index (Fig. 2). Coefficient values extracted from the non-linear model are provided in Appendix F.

4.2. Premiums & payouts

Premiums (i.e. fair premiums or expected losses) varied considerably between regions and depending on the percentile cover (Table 3). The cheapest premiums ($8.62 AUD/ha) were estimated for the WA Mallee at the 5th percentile level of cover, while the most expensive premiums ($77.1 AUD/ha) were estimated for the NSW Vic Slopes at the 30th percentile cover level (Table 3). Maximum liability was also highest for the NSW Vic Slopes at $212.12 AUD/ha (Table 3). The lowest maximum liability was $59.25 AUD/ha for Qld Central.

4.3. Spatial variability in the financial efficiency rainfall index insurance

To compare the financial efficiency (i.e. benefit) of index insurance we used two financial efficiency assessment criteria – CER and MRSL. The efficiency of the winter rainfall index insurance varied spatially for both CER and MRSL (Figs. 3 and 4). Results for CER and MRSL were qualitatively similar with analyses providing consistent results about whether the winter rainfall index insurance was either efficient or inefficient for each region (Figs. 3 and 4). Based on CER the positive benefit of winter rainfall index generally insurance increased as risk aversion increased (Fig. 3). The index insurance was efficient, regardless of level of risk aversion only in south west QLD (SW Qld, NW NSW) (Fig. 3). In most regions the index insurance only became efficient at risk aversion levels of 2 and above (Fig. 3). In six regions the winter rainfall index insurance was inefficient regardless of the level of risk aversion (Fig. 3).

MRSL winter rainfall index insurance was efficient, regardless of the percentile level of cover, for six of the regions and inefficient,

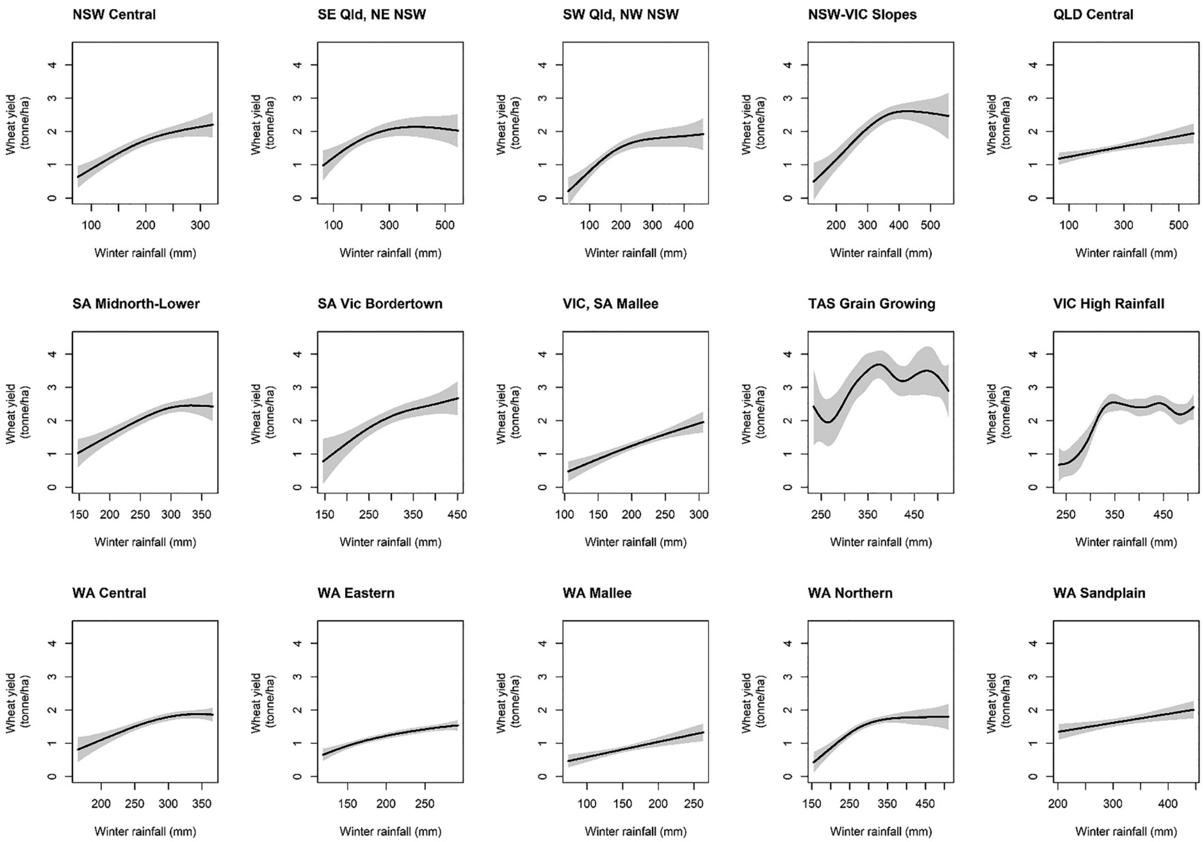


Fig. 2. Wheat yield relationship with winter rainfall for Australia's wheat growing regions.

Table 3
Fair premiums and max liability for each region for different percentiles of cover for the winter rainfall index.

Region	Percentile cover premium (2 se) $/ha				*Max liability (2 se) $/ha
	5th	10th	20th	30th	
NSW Central	22.12 (0.37)	31.75 (0.38)	45.41 (0.39)	56.22 (0.25)	145.66 (8.45)
NSW NE/Qld SE	19.29 (0.32)	30.36 (0.33)	37.63 (0.34)	39.75 (0.35)	130.49 (6.99)
NSW NW/Qld SW	22.54 (0.35)	39.22 (0.37)	52.56 (0.38)	56.03 (0.36)	195.85 (9.45)
NSW Vic Slopes	33.07 (0.54)	49.92 (0.52)	67.34 (0.51)	77.1 (0.41)	212.12 (11.36)
Qld Central	6.58 (0.31)	8.67 (0.3)	13.92 (0.29)	16.88 (0.25)	59.25 (4.78)
SA Midnorth-Lower Yorke Eyre	21.55 (0.31)	34.15 (0.31)	45.81 (0.31)	51.48 (0.3)	131.92 (6.75)
SA Vic Bordertown-Wimmera	37.56 (0.52)	44.03 (0.52)	51.5 (0.52)	59.12 (0.59)	135.38 (10.17)
SA Vic Mallee	18.36 (0.31)	24.73 (0.31)	36.34 (0.3)	42.57 (0.27)	122.71 (5.8)
Tas_Grain	19.97 (0.63)	32.09 (0.63)	37.86 (0.63)	38.45 (0.62)	108.66 (10.93)
Vic High Rainfall	34.33 (0.57)	54.3 (0.57)	58.81 (0.57)	58.99 (0.58)	153.69 (10.75)
WA Central	17.4 (0.24)	23.44 (0.24)	27.94 (0.24)	32.23 (0.21)	90.04 (4.55)
WA Eastern	16.47 (0.19)	23.32 (0.19)	30.81 (0.19)	34.88 (0.19)	92.82 (4.46)
WA Mallee	8.62 (0.18)	13.53 (0.18)	19.19 (0.18)	21.43 (0.17)	70.35 (3.85)
WA Northern	22.86 (0.23)	28.89 (0.23)	38.28 (0.22)	42.1 (0.2)	135.33 (5.56)
WA Sandplain	11.23 (0.37)	14.84 (0.37)	22.27 (0.36)	23.68 (0.37)	65.47 (3.95)

se = standard error; *the greatest predicted negative revenue anomaly (relative to the mean revenue) based on rainfall observations

regardless of the percentile level of cover in seven of the regions (Fig. 4). In the remaining two regions, WA central and WA eastern, insurance was efficient, based on MRSL, at 5-20th and 5-10th percentile levels of insurance respectively (Fig. 4).

Throughout eastern Australia, the eastern most wheat growing regions the winter rainfall index was consistently inefficient (Figs. 3 and 4). In these eastern most wheat regions both CER and MRSL analysis suggested that the financial inefficiency of wheat index insurance differed as the percentile cover of insurance increased (Figs. 3 and 4). For example, in the NSW Vic Slopes, using CER and a risk aversion of one, the negative efficiency of the 5th percentile index insurance cover of -$44 AUD/ha increased to -$18 AUD/ha with 30th percentile index insurance cover (Fig. 3). The NSW Vic Slopes was also where the winter rainfall index was the most

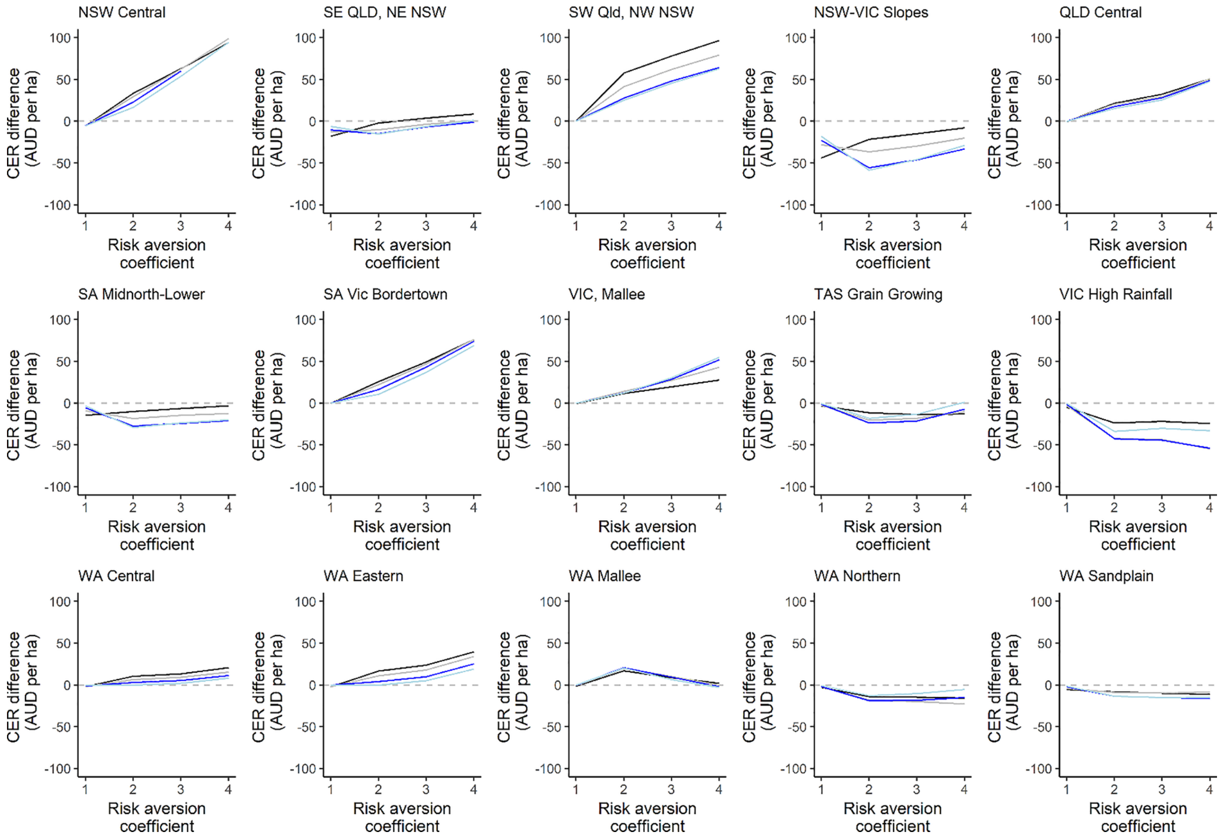


Fig. 3. Certainty equivalence revenue difference with winter rainfall index insurance (relative to no insurance) for percentile levels of insurance coverage; black = 5th, grey = 10th, blue = 20th and light blue = 30th. Positive values indicate insurance is financially beneficial. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

inefficient, with CER and MRSL efficiency analysis respectively predicting a value of -$59 AUD/ha (for 30th percentile cover and a risk aversion of two) and an increase of losses below the mean of $31 AUD/ha. In addition to the eastern wheat regions, the SA Midnorth-Lower Yorke Eyre, WA Northern and TAS Grain regions were all consistently inefficient for both types of efficiency analysis or percentile level of insurance cover (Figs. 3 and 4).

Throughout eastern Australia, for the western most regions (NSW Central, NSW NW/Qld SW, QLD Central and SA Vic Bordertown-Wimmera) financial efficiency analysis found that insurance was consistently beneficial (Figs. 3 and 4). Efficiency analysis also suggested that winter rainfall index insurance could be beneficial in the SA Vic Mallee and WA Mallee (Figs. 3 and 4). NSW Central was where insurance was the most efficient according to CER analysis at 20th percentile and risk aversion of four finding a benefit of $102 AUD/ha (Fig. 3). MRSL analysis on the other hand suggested that insurance was the most beneficial (in terms of reducing losses below the mean) for NSW NW/Qld SW at the 5th percentile level of cover, with reductions in losses below the mean of -$32 AUD/ha (Fig. 4).

4.4. Relationship between index insurance financial efficiency and rainfall variability

There was a negative relationship between the rainfall variance score, and CER (at the 10, 20 and 30th percentile levels of insurance cover) with bootstrapped R^2 values ranging from 0.21 to 0.80 across the range of risk aversion levels tested (Table 4). The relationship between rainfall variance and CER was strongest at the 10th percentile level of cover and weakest at the 5th percentile level of cover (Table 4). There was a positive relationship between rainfall variance and MRSL measures of insurance financial efficiency, with bootstrapped R^2 between 0.42 and 0.78 (Table 4). The strongest relationship between rainfall variance and MRSL was at the 30th percentile level of cover, while the weakest was at the 5th percentile level of cover (Table 4).

5. Discussion and conclusion

We investigated the financial efficiency of winter rainfall index (WRI) insurance across Australia's wheat growing regions. Models using the WRI performed well across most regions and relationships were consistent with others showing that precipitation variability is a key determinant of wheat yields in Australia (Ray et al 2015). Given the WRI's models ability to explain significant amounts of variation in wheat yields also suggested that in many areas it could be used as an index to transfer rainfall risks for producers wanting

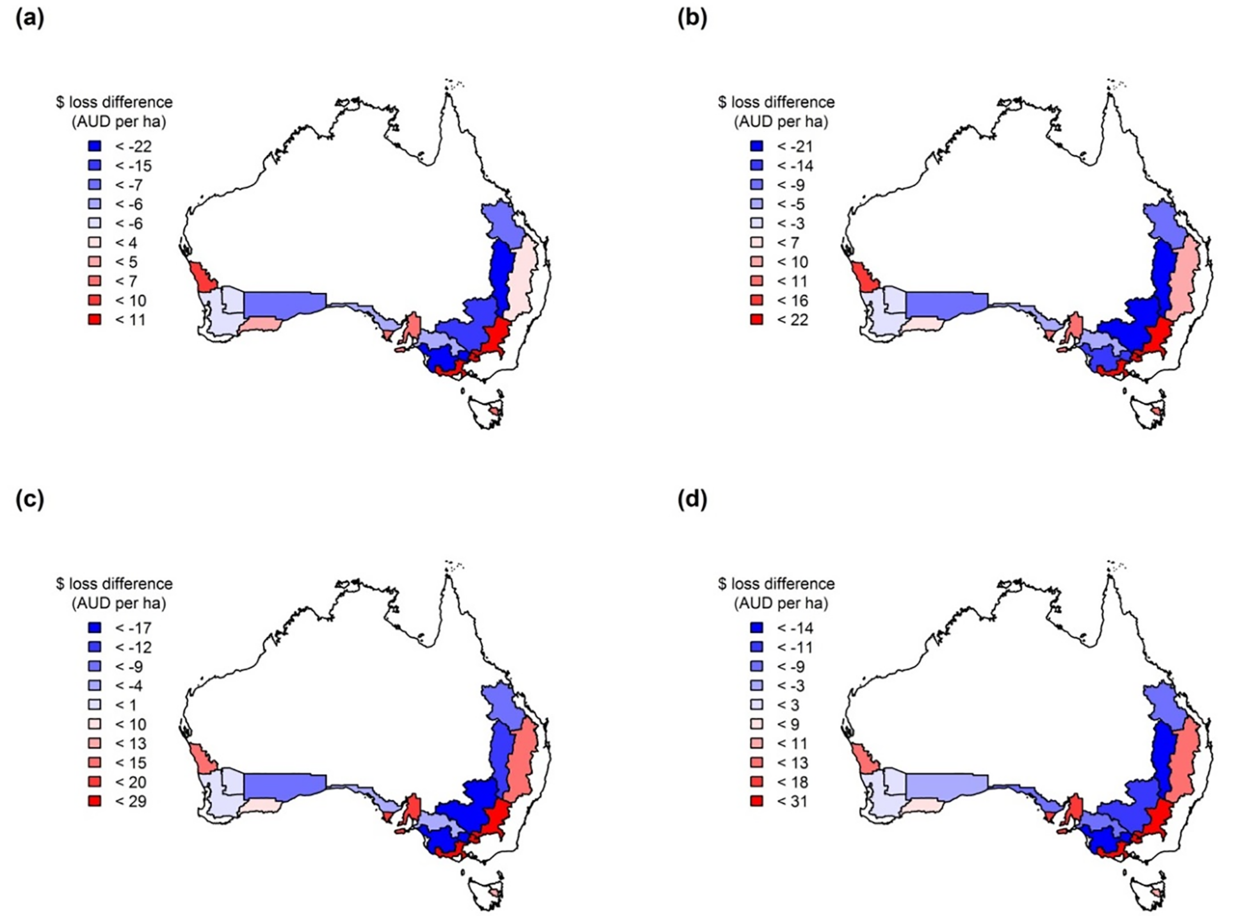


Fig. 4. Mapped efficiency (Mean root square loss) of winter rainfall index insurance for wheat at different percentile levels of insurance coverage (a) 5th, (b) 10th, (c) 20th and (d) 30th. Negative (blue) values indicate insurance is beneficial. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Relationship between insurance efficiency and the rainfall variance score for certainty equivalence revenue (CER) mean root square loss (MRSL). R^2 values are the bootstrapped median R^2 from 10,000 replications. r = risk aversion coefficient.

Percentile cover	Efficiency analysis	Beta of rainfall variance score (95% CI)	R^2(95% CI)
5th	CER (r = 1)	(-27.43 to 3.19)	(0 to 0.37)
	CER (r = 2)	(-16.48 to 4.9)	(0 to 0.26)
	CER (r = 3)	(-11.87 to 5.32)	(0 to 0.19)
	CER (r = 4)	(-41.72 to 3.6)	(0 to 0.38)
	MRSL	**(38.4 to 66.77)**	(0.55 to 0.68)
10th	CER (r = 1)	**(-98.73 to −95.82)**	(0.74 to 0.74)
	CER (r = 2)	**(-92.74 to −80.54)**	(0.71 to 0.71)
	CER (r = 3)	**(-85.56 to −69.34)**	(0.69 to 0.8)
	CER (r = 4)	**(-94.43 to −71.25)**	(0.71 to 0.71)
	MRSL	**(37.82 to 62.76)**	(0.54 to 0.78)
20th	CER (r = 1)	**(-110.73 to −86.27)**	(0.55 to 0.76)
	CER (r = 2)	**(-117.35 to −86.27)**	(0.57 to 0.72)
	CER (r = 3)	**(-101.86 to −68.56)**	(0.45 to 0.67)
	CER (r = 4)	**(-101.79 to −69.97)**	(0.44 to 0.72)
	MRSL	**(33.55 to 54.75)**	(0.47 to 0.74)
30th	CER (r = 1)	**(-195 to −87.41)**	(0.34 to 0.67)
	CER (r = 2)	**(-164.33 to −83.88)**	(0.31 to 0.72)
	CER (r = 3)	**(-141.57 to −62.67)**	(0.21 to 0.79)
	CER (r = 4)	**(-164.81 to −75.68)**	(0.29 to 0.75)
	MRSL	**(29.52 to 59.01)**	(0.42 to 0.64)

CI = confidence interval

to manage wheat yield losses from rainfall droughts (i.e. cumulative rainfall ≤ 30th percentile over the winter growing season). Other studies in other parts of the world have similarly concluded that rainfall index insurance could be a suitable means of transferring risks for wheat crops (Adeyinka et al., 2016; Conradt et al., 2015).

As expected, and in agreement with other studies (Breustedt et al., 2008; Conradt et al., 2015; Vedenov and Barnett, 2004), we found high spatial variability in the financial efficiency of winter rainfall index insurance. Vedenov and Barnett (2004) found that the benefit of index insurance varied across locations for corn, cotton and soybeans. For example, for maize they found that based on CER, index insurance at the 5th percentile was three times (an extra ~ $10/ha) as beneficial in Marshall County, Iowa compared to Lee County, Iowa (Vedenov and Barnett, 2004). In Kazakhstan more recent studies have also observed spatial variability in the effectiveness of index insurance to reduce risk for wheat producers (Breustedt et al., 2008; Conradt et al., 2015). Commenting on the spatial variability in insurance efficiency, Vedenov and Barnett (2004) argued that as far as possible contracts need to be localised, as broad or blanket scale index insurance will likely be inefficient. Similarly we found for wheat crops in Australia that winter rainfall index (WRI) insurance is not only spatially variable.

While spatial variability in the financial efficiency of index insurance has been observed in various studies we are aware of no studies that have sought to investigate a possible driver of this variability. We hypothesised that spatial variability in the efficiency of index insurance would decline as rainfall variance increased. As expected, the benefit of WRI insurance contracts declined as rainfall variance increased, particularly so for CER measures of efficiency. Consequently our findings suggest that a significant portion (~30–65%) of the spatial variability in index insurance efficiency can be explained by rainfall variance.

5.1. Climate risk management policy implications

Our findings have important implications for policy makers and farmers within Australia. In Australia there has been limited research on index insurance (but see Quiggin, 1986) and so the understanding of index insurance is still relatively low across government policy makers at both state and federal levels. Australian farmers are also largely unaware of how index insurance could be used to manage climate related financial losses. This paper demonstrates that index insurance is a viable option at regional scales in several of Australia's wheat growing regions and thus provides critical information for policy makers and farmers who may be unaware of its possible use.

More broadly, and of relevance internationally, the relationship between precipitation variability and the financial efficiency (i.e. benefit) of insurance index noted in this study could have important implications for the current and future viability of this type of insurance. Under climate change rainfall variability is expected to increase over approximately two-thirds of the world's land mass (Pendergrass et al., 2017). In wheat growing areas of this study both daily and seasonal precipitation variability is projected to increase by up to 5% K^{-1}, while globally in other important wheat growing areas strongly affected by climate (e.g. eastern China, India, north America, eastern Europe and Russia) increases of precipitation variability of between 5 and 15% K^{-1} are projected (Pendergrass et al., 2017; Ray et al., 2015). Increased precipitation variability under climate change has been identified as a key risk for agricultural production and food security more generally (Thornton et al., 2014). Our findings suggest that agricultural financial sustainability or security, and specifically the ability to efficiently transfer climate risks, such as drought, may become increasingly unviable in areas where climate change increases precipitation variability. This has important policy implications, which we outline below.

Index insurance is often purported as an option for managing climate variability under climate change, especially in developing countries (Barnett and Mahul, 2007; Thornton et al., 2014). There is also much government and inter-government support globally for index insurance with numerous policies and schemes to support development of index insurance in a range of countries (Hazell et al., 2010; Devereux, 2016). Some have also argued that with climate change likely to lead to greater losses for agriculture in the future the question is not 'whether' governments should support agricultural insurance, but how (Clarke and Lung, 2015).

However, this study suggests that in areas of high precipitation variability index insurance might not be viable; instead policies focused on risk-management and climate adaptation (i.e. yield loss preventative approaches, such as crop diversification, change in varieties, increased irrigation effectiveness etc., Challinor et al., 2014) may be more successful than the development of winter rainfall index insurance.

Insurance companies could thus consider the development of alternative approaches, such as remotely sensed index insurance where rainfall index is not viable (e.g. Dalhaus and Finger, 2016; Bokusheva et al., 2016). The timing of crop growth phases is also an important consideration. Dalhaus et al. (2018) showed that using phenological information can decrease the basis risk of insurance contracts. In the current study regional phenolgoical information could be used to develop more targeted rainfall indice periods and in turn possibly improve the efficiency of index insurance in some areas. Conversely, in areas of lower precipitation variability index insurance could be a viable means of transferring risks by producers, potentially leaving them better off by stabilising income and reducing the magnitude of downside losses (i.e. losses below the mean).

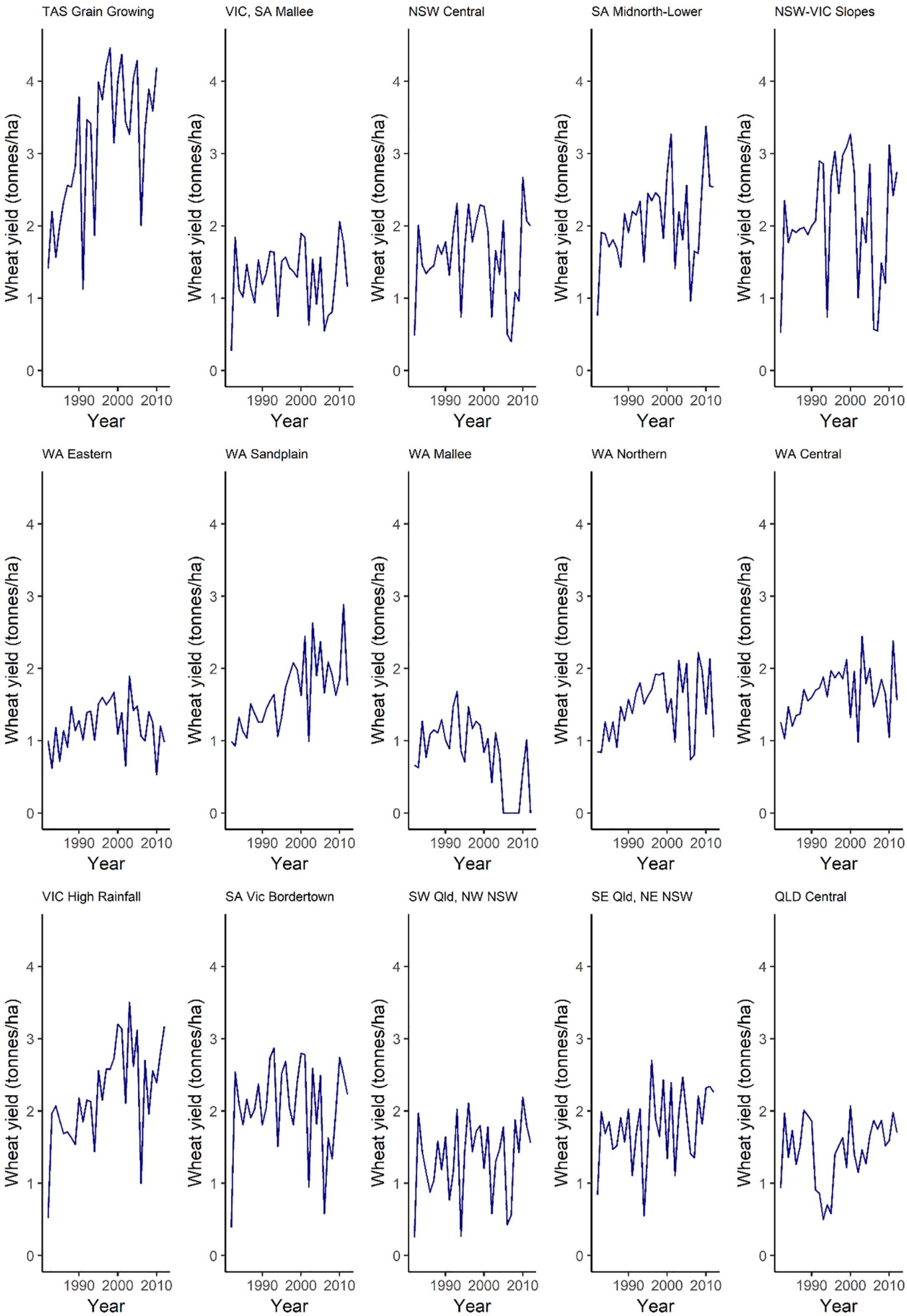
Finally, we would argue that nuanced approaches that acknowledge spatial variability in the benefits of index insurance are needed by policy makers. Recently, Jensen et al. (2018) have also highlighted the important policy implications of accounting for heterogeneity in the uptake and demand of index insurance and how failing to do so could lead to low quality products and low demand for insurance, especially in areas with high poverty rates. Broad blanket support of governments for the development of index insurance without acknowledging or adjusting for variability in its benefit could lead to inefficient outcomes for both government and agricultural producers.

Acknowledgements

The Queensland State Government, through the Drought and Climate Adaptation (DCAP) program, funded this project.

Appendix A

Plots of wheat yield through time for each of the regions assessed



Appendix B

Yield statistics for each region

Region	Mean	Sd	Min	Max
NSW_Central	1.59	0.60	0.40	2.67
NSW_NE_QLD_SE	1.79	0.50	0.55	2.70
NSW_NW_QLD_SW	1.35	0.54	0.25	2.19
NSW_vic_slopes	2.10	0.82	0.52	3.27
QLD_central	1.46	0.44	0.50	2.07
SA_midnorth	2.07	0.58	0.76	3.38
SA_vic_bdtown	2.07	0.63	0.39	2.87
SA_vic_mallee	1.29	0.43	0.27	2.06
TAS_Grain	3.21	0.99	1.13	4.77
Vic_high_rainfall	2.25	0.67	0.52	3.50
WA_central	1.66	0.36	0.98	2.44
WA_eastern	1.21	0.33	0.53	1.89
WA_mallee	0.82	0.49	0.00	1.68
WA_northern	1.48	0.44	0.74	2.22
WA_sandplain	1.65	0.50	0.93	2.88

Appendix C

Rainfall percentiles for each of the wheat regions assessed

Rainfall percentile	NSW Central	NSW NE QLD SE	NSW NW QLD SW	NSW vic slopes	QLD central	SA mid-north	SA vic bdtown	SA vic mallee	TAS Grain	Vic high rainfall	WA central	WA eastern	WA mallee	WA northern	WA sand-plain
5th	82.2	116.4	67.6	160.3	99.7	169.1	207.7	126.4	261.6	271.2	210.1	131.2	85.8	200.1	211.6
10th	112.4	150.3	104.7	217.4	111.7	202.6	225.6	136.3	308.4	303.2	229.7	141.1	105.7	218.9	215.5
20th	123.5	156.9	134.2	251.9	134.8	217.5	237.6	169.2	317.2	320.9	244.2	161.4	113.0	231.1	266.4
30th	163.1	178.2	141.3	285.6	165.4	232.0	279.2	188.2	360.5	342.3	258.2	177.8	121.2	268.0	273.4

Appendix D

Test for normality using the Shapiro wilks test

All but two regions (SA Vic Mallee and Tas Grain) showed no non-normality in their residuals. However, non-normality in the residuals is of minor significance for estimating the regression fit and Gelman and Hill (2006) argue this assumption is of little importance and generally do not recommend diagnostics of the normality of regression residuals.

Gelman A and Hill J. (2006) Data analysis using regression and multilevel/hierarchical models. Cambridge university press.

Region	p - value	Shapiro-Wilk normality test statistic	Residual degrees of freedom
NSW_Central	0.86	0.98	22.53
NSW_NE_QLD_SE	0.25	0.96	26.73
NSW_NW_QLD_SW	0.58	0.97	22.65
NSW_vic_slopes	0.53	0.97	21.97
QLD_central	0.41	0.97	21.95
SA_midnorth	0.24	0.96	23.04
SA_vic_bdtown	0.74	0.98	24.32
SA_vic_mallee	0.03	0.93	23.84
TAS_Grain	0.00	0.87	22.14
Vic_high_rainfall	0.70	0.98	17.10
WA_central	0.36	0.96	25.89
WA_eastern	0.37	0.96	25.17
WA_mallee	0.61	0.97	23.73
WA_northern	0.89	0.98	24.96
WA_sandplain	0.80	0.98	27.99

Appendix E

Moran's test for spatial autocorrelation for each of the efficiency measures across each region. The centroid of each region was used to perform the analysis.

Efficiency measure (percentile)	Moran's test for spatial-autocorrelation			
	observed	expected	standard deviation	p-value
CER_{5th} (risk aversion = 1)	−0.10	−0.07	0.08	0.62
CER_{10th} (risk aversion = 1)	−0.08	−0.07	0.09	0.54
CER_{20th} (risk aversion = 1)	−0.04	−0.07	0.09	0.36
CER_{30th} (risk aversion = 1)	0.00	−0.07	0.08	0.18
CER_{5th} (risk aversion = 2)	−0.15	−0.07	0.12	0.74
CER_{10th} (risk aversion = 2)	−0.18	−0.07	0.12	0.81
CER_{20th} (risk aversion = 2)	−0.19	−0.07	0.12	0.84
CER_{30th} (risk aversion = 2)	−0.20	−0.07	0.12	0.85
CER_{5th} (risk aversion = 3)	−0.07	−0.07	0.03	0.52
CER_{10th} (risk aversion = 3)	−0.07	−0.07	0.03	0.53
CER_{20th} (risk aversion = 3)	−0.08	−0.07	0.03	0.56
CER_{30th} (risk aversion = 3)	−0.07	−0.07	0.03	0.54
CER_{5th} (risk aversion = 4)	−0.07	−0.07	0.13	0.51
CER_{10th} (risk aversion = 4)	−0.08	−0.07	0.13	0.54
CER_{20th} (risk aversion = 4)	−0.12	−0.07	0.13	0.65
CER_{30th} (risk aversion = 4)	−0.14	−0.07	0.13	0.69
$MRSL_{5th}$	−0.08	−0.07	0.12	0.53
$MRSL_{10th}$	−0.06	−0.07	0.12	0.45
$MRSL_{20th}$	−0.06	−0.07	0.12	0.47
$MRSL_{30th}$	−0.07	−0.07	0.13	0.50
CER = certainty equivalence revenue				
MRSL = Mean root square loss				

Appendix F

Coefficients for regression models

Region	Parameter	coefficient
NSW_vic_slopes	s(rn)0.3	0.05519
NSW_vic_slopes	s(rn)0.4	−0.06854
NSW_vic_slopes	s(rn)0.5	0.02989
NSW_vic_slopes	s(rn)0.6	−0.07231
NSW_vic_slopes	s(rn)0.7	0.05819
NSW_vic_slopes	s(rn)0.8	0.65914
NSW_vic_slopes	s(rn)0.9	0.36017
QLD_central	(Intercept)	1.45742
QLD_central	s(yr)0.1	0.03298
QLD_central	s(yr)0.2	1.07845
QLD_central	s(yr)0.3	0.75630
QLD_central	s(yr)0.4	0.61431
QLD_central	s(yr)0.5	0.26775
QLD_central	s(yr)0.6	−0.17419
QLD_central	s(yr)0.7	−0.16808
QLD_central	s(yr)0.8	0.76511
QLD_central	s(yr)0.9	0.44459
QLD_central	s(rn)0.1	0.00000
QLD_central	s(rn)0.2	0.00000
QLD_central	s(rn)0.3	0.00000
QLD_central	s(rn)0.4	0.00000
QLD_central	s(rn)0.5	0.00000
QLD_central	s(rn)0.6	0.00000
QLD_central	s(rn)0.7	0.00000
QLD_central	s(rn)0.8	0.00000
QLD_central	s(rn)0.9	0.18687
SA_midnorth	(Intercept)	2.07194
SA_midnorth	s(yr)0.1	0.26974
SA_midnorth	s(yr)0.2	−1.57216
SA_midnorth	s(yr)0.3	−0.08669
SA_midnorth	s(yr)0.4	−0.49047

SA_midnorth	s(yr)0.5	0.16874
SA_midnorth	s(yr)0.6	−0.42059
SA_midnorth	s(yr)0.7	0.16231
SA_midnorth	s(yr)0.8	−1.60603
SA_midnorth	s(yr)0.9	0.74026
SA_midnorth	s(rn)0.1	−0.14363
SA_midnorth	s(rn)0.2	0.10129
SA_midnorth	s(rn)0.3	−0.03034
Region	Parameter	coefficient
SA_midnorth	s(rn)0.4	−0.07059
SA_midnorth	s(rn)0.5	−0.05347
SA_midnorth	s(rn)0.6	−0.06754
SA_midnorth	s(rn)0.7	0.00919
SA_midnorth	s(rn)0.8	0.45335
SA_midnorth	s(rn)0.9	0.24978
SA_vic_bdtown	(Intercept)	2.07032
SA_vic_bdtown	s(yr)0.1	0.16927
SA_vic_bdtown	s(yr)0.2	−1.02143
SA_vic_bdtown	s(yr)0.3	0.02448
SA_vic_bdtown	s(yr)0.4	−0.34850
SA_vic_bdtown	s(yr)0.5	0.07627
SA_vic_bdtown	s(yr)0.6	−0.25784
SA_vic_bdtown	s(yr)0.7	0.09798
SA_vic_bdtown	s(yr)0.8	−0.96581
SA_vic_bdtown	s(yr)0.9	0.49544
SA_vic_bdtown	s(rn)0.1	−0.09625
SA_vic_bdtown	s(rn)0.2	−0.00190
SA_vic_bdtown	s(rn)0.3	0.02751
SA_vic_bdtown	s(rn)0.4	0.05068
SA_vic_bdtown	s(rn)0.5	−0.03363
SA_vic_bdtown	s(rn)0.6	0.03089
SA_vic_bdtown	s(rn)0.7	0.01524
SA_vic_bdtown	s(rn)0.8	0.31735
SA_vic_bdtown	s(rn)0.9	0.50864
SA_vic_mallee	(Intercept)	1.28774
SA_vic_mallee	s(yr)0.1	−0.17364
SA_vic_mallee	s(yr)0.2	−1.74610
SA_vic_mallee	s(yr)0.3	−0.05829
SA_vic_mallee	s(yr)0.4	−0.58718
SA_vic_mallee	s(yr)0.5	0.17413
SA_vic_mallee	s(yr)0.6	−0.47245
SA_vic_mallee	s(yr)0.7	0.19294
SA_vic_mallee	s(yr)0.8	−1.84682
SA_vic_mallee	s(yr)0.9	0.25345
SA_vic_mallee	s(rn)0.1	0.00411
SA_vic_mallee	s(rn)0.2	0.01123
SA_vic_mallee	s(rn)0.3	−0.00581
SA_vic_mallee	s(rn)0.4	−0.01286
SA_vic_mallee	s(rn)0.5	−0.00079
Region	Parameter	coefficient
SA_vic_mallee	s(rn)0.6	0.00842
SA_vic_mallee	s(rn)0.7	0.00342
SA_vic_mallee	s(rn)0.8	0.07225
SA_vic_mallee	s(rn)0.9	0.35309
TAS_Grain	(Intercept)	3.20645
TAS_Grain	s(yr)0.1	−0.05550
TAS_Grain	s(yr)0.2	0.03199
TAS_Grain	s(yr)0.3	0.02642
TAS_Grain	s(yr)0.4	0.12242
TAS_Grain	s(yr)0.5	−0.03349
TAS_Grain	s(yr)0.6	0.10300
TAS_Grain	s(yr)0.7	−0.03008
TAS_Grain	s(yr)0.8	0.58570
TAS_Grain	s(yr)0.9	0.54246
TAS_Grain	s(rn)0.1	−0.69933
TAS_Grain	s(rn)0.2	−1.61970
TAS_Grain	s(rn)0.3	0.98029
TAS_Grain	s(rn)0.4	−1.04319
TAS_Grain	s(rn)0.5	0.61821
TAS_Grain	s(rn)0.6	−0.56678
TAS_Grain	s(rn)0.7	0.08043
TAS_Grain	s(rn)0.8	−2.00283
TAS_Grain	s(rn)0.9	−1.65123
Vic_high_rainfall	(Intercept)	2.24613

Vic_high_rainfall	s(yr)0.1	−1.03310
Vic_high_rainfall	s(yr)0.2	−3.07041
Vic_high_rainfall	s(yr)0.3	−0.15404
Vic_high_rainfall	s(yr)0.4	−1.92692
Vic_high_rainfall	s(yr)0.5	0.22090
Vic_high_rainfall	s(yr)0.6	−1.36505
Vic_high_rainfall	s(yr)0.7	0.35925
Vic_high_rainfall	s(yr)0.8	−3.97183
Vic_high_rainfall	s(yr)0.9	0.21005
Vic_high_rainfall	s(rn)0.1	−0.30515
Vic_high_rainfall	s(rn)0.2	−1.15771
Vic_high_rainfall	s(rn)0.3	−0.11321
Vic_high_rainfall	s(rn)0.4	−1.29577
Vic_high_rainfall	s(rn)0.5	−0.06183
Vic_high_rainfall	s(rn)0.6	−0.80890
Vic_high_rainfall	s(rn)0.7	0.36961
Region	Parameter	coefficient
Vic_high_rainfall	s(rn)0.8	−2.30934
Vic_high_rainfall	s(rn)0.9	0.45828
WA_central	(Intercept)	1.65516
WA_central	s(yr)0.1	0.02987
WA_central	s(yr)0.2	0.00514
WA_central	s(yr)0.3	0.00838
WA_central	s(yr)0.4	0.01903
WA_central	s(yr)0.5	−0.00842
WA_central	s(yr)0.6	0.02114
WA_central	s(yr)0.7	−0.00746
WA_central	s(yr)0.8	0.11540
WA_central	s(yr)0.9	0.24208
WA_central	s(rn)0.1	−0.07093
WA_central	s(rn)0.2	0.06444
WA_central	s(rn)0.3	−0.00505
WA_central	s(rn)0.4	0.05272
WA_central	s(rn)0.5	−0.00850
WA_central	s(rn)0.6	−0.05537
WA_central	s(rn)0.7	0.01011
WA_central	s(rn)0.8	0.31999
WA_central	s(rn)0.9	0.19652
WA_eastern	(Intercept)	1.20871
WA_eastern	s(yr)0.1	−0.05360
WA_eastern	s(yr)0.2	−0.00640
WA_eastern	s(yr)0.3	0.02080
WA_eastern	s(yr)0.4	0.03148
WA_eastern	s(yr)0.5	−0.01031
WA_eastern	s(yr)0.6	0.03626
WA_eastern	s(yr)0.7	−0.01199
WA_eastern	s(yr)0.8	0.23044
WA_eastern	s(yr)0.9	0.06125
WA_eastern	s(rn)0.1	−0.01641
Region	Parameter	coefficient
WA_eastern	s(rn)0.2	0.09651
WA_eastern	s(rn)0.3	0.00207
WA_eastern	s(rn)0.4	0.06054
WA_eastern	s(rn)0.5	−0.01169
WA_eastern	s(rn)0.6	0.05604
WA_eastern	s(rn)0.7	−0.00459
WA_eastern	s(rn)0.8	0.24998
WA_eastern	s(rn)0.9	0.29776
WA_mallee	(Intercept)	0.82290
WA_mallee	s(yr)0.1	0.51910
WA_mallee	s(yr)0.2	−1.09576
WA_mallee	s(yr)0.3	0.35566
WA_mallee	s(yr)0.4	−0.34749
WA_mallee	s(yr)0.5	0.09207
WA_mallee	s(yr)0.6	−0.21048
WA_mallee	s(yr)0.7	0.11938
WA_mallee	s(yr)0.8	−0.79257
WA_mallee	s(yr)0.9	0.70079
WA_mallee	s(rn)0.1	0.00000
WA_mallee	s(rn)0.2	0.00000
WA_mallee	s(rn)0.3	0.00000
WA_mallee	s(rn)0.4	0.00000
WA_mallee	s(rn)0.5	0.00000
WA_mallee	s(rn)0.6	0.00000

WA_mallee	s(rn)0.7	0.00000
WA_mallee	s(rn)0.8	0.00000
WA_mallee	s(rn)0.9	0.20271
WA_northern	(Intercept)	1.48323
WA_northern	s(yr)0.1	0.05374
WA_northern	s(yr)0.2	0.09753
WA_northern	s(yr)0.3	0.02014
WA_northern	s(yr)0.4	0.07966
Region	Parameter	coefficient
WA_northern	s(yr)0.5	−0.02459
WA_northern	s(yr)0.6	0.07576
WA_northern	s(yr)0.7	−0.02650
WA_northern	s(yr)0.8	0.32809
WA_northern	s(yr)0.9	0.31613
WA_northern	s(rn)0.1	0.10874
WA_northern	s(rn)0.2	0.00159
WA_northern	s(rn)0.3	0.01856
WA_northern	s(rn)0.4	−0.04332
WA_northern	s(rn)0.5	−0.00490
WA_northern	s(rn)0.6	0.04302
WA_northern	s(rn)0.7	0.00448
WA_northern	s(rn)0.8	0.43903
WA_northern	s(rn)0.9	0.34620
WA_sandplain	(Intercept)	1.65452
WA_sandplain	s(yr)0.1	0.00000
WA_sandplain	s(yr)0.2	0.00000
WA_sandplain	s(yr)0.3	0.00000
WA_sandplain	s(yr)0.4	0.00000
WA_sandplain	s(yr)0.5	0.00000
WA_sandplain	s(yr)0.6	0.00000
WA_sandplain	s(yr)0.7	0.00000
WA_sandplain	s(yr)0.8	0.00000
WA_sandplain	s(yr)0.9	0.37203
WA_sandplain	s(rn)0.1	−0.00031
WA_sandplain	s(rn)0.2	0.00062
WA_sandplain	s(rn)0.3	−0.00021
WA_sandplain	s(rn)0.4	−0.00053
WA_sandplain	s(rn)0.5	−0.00021
WA_sandplain	s(rn)0.6	−0.00046
WA_sandplain	s(rn)0.7	0.00021
WA_sandplain	s(rn)0.8	0.00258
WA_sandplain	s(rn)0.9	0.17901

Appendix G. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2019.04.002.

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