



Index insurance benefits agricultural producers exposed to excessive rainfall risk

Jarrold Kath^{a,*}, Shahbaz Mushtaq^a, Ross Henry^b, Adewuyi Adeyinka^a, Roger Stone^a

^a Centre for Applied Climate Sciences, University of Southern Queensland, Toowoomba, Queensland, 4350, Australia

^b Queensland Farmers Federation, North Quay, Brisbane, Queensland, Australia

ARTICLE INFO

Keywords:

Weather index
Flooding
Extreme precipitation
Climate
Crop loss
Crop variability

ABSTRACT

Managing the risks of climate variability on crop production is central to ensuring financially viable farming systems and sustainable food production. Insurance provides a mechanism to manage and transfer climate risks. However, traditional multi-peril crop insurance (MCPI) is often too expensive and so other methods, such as index insurance, are being explored as a cheaper way to insure farmers against climate induced crop losses. Here we investigate the potential financial benefits of index insurance (protecting against excessive rainfall) for agricultural producers, namely sugar cane farmers in Tully, northern Australia. We used 80 years of historical climate and yield data to develop an excessive rainfall index. The index was developed and tested using generalized additive regression models (allowing for non-linear effects) and quantile regression, which allows relationships with lower quantiles (i.e. low yield events) to be assessed. From the regression models we derived relationships between the excessive rainfall index and sugar cane yield losses that were converted to insurance fair premiums (i.e. premiums that cover expected losses). Finally, we used efficiency analysis, based on Conditional Tail Expectation (CTE), Certainty Equivalence of Revenue (CER) and Mean Root Square Loss (MRSL), to quantify financial benefits to farmers if they purchased excessive rainfall index insurance. The regression model predicted sugar cane yields well (cross-validated R^2 of 0.65). The efficiency analysis indicated there could be financial benefit to sugar cane farmers if they were to use excessive rainfall index insurance. Index insurance (based on the assumption of a fair premium) could make farmers better off by \$269.85 AUD/ha on average in years with excessive rainfall (i.e. years with rainfall over the 95th percentile). Index insurance could offer a viable method for managing the financial risks posed by excessive rainfall for sugar cane producers in northern Australia. We are not aware of any other study demonstrating the potential benefits of excessive rainfall index insurance in the literature, but our results suggest this type of insurance may be viable for sugar cane producers, and other crops, in parts of the world where extreme rainfall poses a risk to the financial sustainability of production.

1. Introduction

Climate variability is a key cause of crop losses and accounts for a third of the variation in crop yields globally (Ray et al., 2015). Additional to threatening food security, crop yield losses from extreme climate variability undermine the financial sustainability of agricultural production (Odening and Shen, 2014). 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, full coverage of all losses (Multi-peril crop insurance or Named-peril crop insurance) is too expensive and unviable without subsidies (Jensen and Barrett, 2016). In areas without subsidies the prohibitive

costs of MPCPI mean that farmers rarely purchase this type of insurance and thus remain exposed to significant climate risks (Odening and Shen, 2014). Nonetheless, given that climate extreme events that decrease yields are expected to become more prevalent under climate change it is becoming more important for farmers to proactively manage climate risks (Shannon and Motha, 2015). To address the low uptake of insurance and thus farmers' high exposure to climate risks, index insurance products have been developed as a cost-effective and efficient means of insuring against particular aspects of climate risk (Barnett and Mahul, 2007).

Climate index insurance (also referred to as parametric, weather index or index-based insurance) pays the holder of the insurance

* Corresponding author. Centre for Applied Climate Sciences, Institute for Agriculture and the Environment, University of Southern Queensland, Toowoomba, West Street, Queensland, 4350, Australia.

E-mail address: kath.jarrod@gmail.com (J. Kath).

<https://doi.org/10.1016/j.wace.2018.10.003>

Received 6 March 2018; Received in revised form 22 October 2018; Accepted 24 October 2018

Available online 25 October 2018

2212-0947/ © 2018 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

contract when a certain value on an index (e.g. a percentile of rainfall) is realized (Barnett and Mahul, 2007). Climate index insurance typically has cheaper premiums than yield based insurance or revenue based insurance as it does not require expensive on-ground assessments and limits moral hazard resulting from information asymmetries or false reporting of losses (World Bank, 2007). The potentially cheaper premiums that climate index insurance offers mean that it may be a widely acceptable 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, limited perils, lack of technical capacity, expertise, and data (Odening and Shen, 2014). Given this, Odening and Shen (2014) argue that the development of effective climate index insurance products faces many challenges requiring attention and collaboration from scientists, policy makers and industry.

Fundamental to the potential success of climate index insurance is whether or not it is financially beneficial (or efficient) to farmers at a given premium. If a climate index insurance contract is not efficient, then there may be little motivation to purchase the product (Vedenov and Barnett, 2004). Alternatively, if climate index insurance is financially beneficial for a farmer, then it could be a valuable part of how they manage climate risks. Understanding whether a particular type of climate index could be beneficial to producers is an essential part in the development of viable insurance and essential for developing risk-transfer strategies that could help farmers persist under variable climatic conditions.

In addition to financial benefits to growers, climate index insurance (in combination with management changes) may also have the potential to enhance the resilience of growers to climate change (Linnerooth-Bayer and Hochrainer-Stigler, 2015; Surminski et al., 2016). The Intergovernmental Panel on Climate Change (IPCC) argues that, coupled with risk reducing measures, risk transfer options (i.e. insurance) will be needed for effective risk management under climate change (IPCC, 2012). Insurance, if well designed, thus has the potential to increase agricultural resilience to climate fluctuations and in doing so reduce societal burden and government subsidies through the spreading of risk (s) (Linnerooth-Bayer and Hochrainer-Stigler, 2015).

Sugar cane is a widely grown crop throughout the world and sensitive to climate variability (Everingham et al., 2012; Zhao and Li, 2015) and therefore a good candidate crop to explore the potential development of index insurance. Sugar cane production is impacted by multiple climate risks. At one extreme, drought and higher temperatures, which increase evaporation rates can reduce sugar cane yields (e.g. Brazil, de Carvalho et al., 2015). At the other extreme, excessive rainfall leading to water logging reduces growth and survival, and ultimately sugar cane crop yield (e.g. southern Florida, Gilbert et al., 2008; Glaz and Lingle, 2012; India, Gomathi et al., 2015). Extreme climatic events are likely to increase in intensity and frequency under climate change (Easterling et al., 2000) with likely negative effects on sugar cane production (Zhao and Li, 2015). Consequently, climate index insurance products could provide a valuable means of managing and transferring risk for sugar cane farmers in parts of the world exposed to recurrent extreme drought and/or rainfall.

Climate risk, in particular excessive rainfall (defined here broadly as rainfall amounts $\geq 70^{\text{th}}$ percentile that cause crop yield losses), is a major risk to sugarcane production in northern Queensland, Australia. Here we investigate the feasibility of an excessive rainfall index for insuring sugar cane production. We use a long-term (80 year) yield and climate dataset from Tully, northern Queensland, Australia. As a part of the study, we also surveyed farmers' perspectives about losses related to production risks to ensure our results are consistent with their on-the-ground experiences.

To date most climate index insurance products have focused on drought risks (but see Hazell et al., 2010), but with extreme rainfall events predicted to increase under climate change, excessive rainfall weather index insurance could become an increasingly important type

of insurance for agricultural producers. Increased extreme rainfall and, specifically, an increased intensity of extreme daily rainfall events is projected with high confidence for our study area under climate change (CSIRO, 2017). In the sugar cane producing areas of south-east Asia (e.g. Thailand, Indonesia, Philippines) there are projections for increased rainfall (Chotamonsak et al., 2011) that could lead to excessive rainfall-related yield losses suitable for insuring against using climate indices as outlined in this paper. We also expect the general framework and approach we outline to be applicable to investigating and insuring excessive rainfall impacts on other crop types (e.g. Rosenzweig et al., 2002; Hazell et al., 2010). The findings from this study are therefore of relevance to policy makers and sugar cane producers globally and especially in areas sensitive to periods of excessive rainfall. Specifically, we ask whether excess rainfall index insurance is efficient (i.e. beneficial) to sugar cane farmers. We discuss the implications of our findings for climate risk management.

2. Materials and methods

2.1. Study area

The study was undertaken in the Tully sugar cane producing area of northern Queensland, Australia (Fig. 1). The area is one of the most important sugar cane producing areas in Australia with annual sugar cane production of ca. 2.5 million tonnes per year (Tully Sugar Limited, 2017). The northern growing regions are predominantly a rain-fed production system and, therefore, exposed to rainfall variation risks. Tully, a major production area in northern Queensland, demonstrates the high variability in rainfall that farmers have to manage. The highest rainfall record in Tully was 7898 mm in 1950 and the lowest on record 2110.6 mm in 2002 (BoM, 2017).

2.2. Overview of analysis framework for assessing efficiency of climate index insurance for sugar cane

The framework for developing and assessing the efficiency of climate index insurance used in the current study is outlined in Fig. 2. The process comprises of 6 steps. First, is the construction of climate indices and their integration with sugar cane yield data. Second, the dataset was split randomly 70/30, so a model was built with a randomly selected 70% subset of the dataset ($n = 56$) and then tested on the remaining 30% of the dataset ($n = 24$). Third, regression models were constructed using the build subset. As part of step 3 we also verified our model results with on-ground farmer estimates of crop losses from excessive rainfall. Four, premiums and payouts were calculated based on the regression model from step 3. Five, efficiency analysis of the index

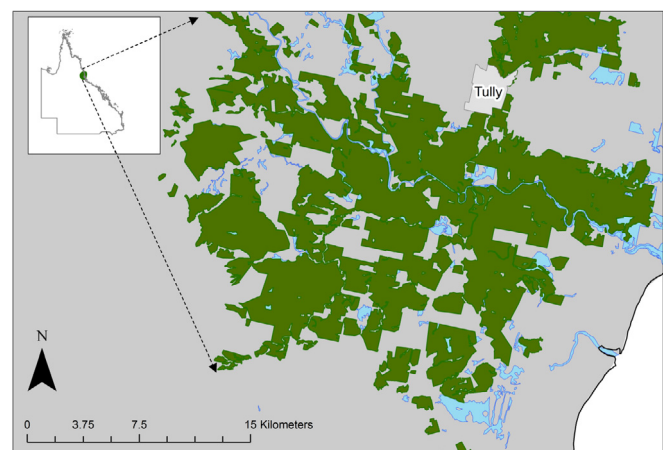


Fig. 1. The Tully sugar cane region. Green areas are sugar cane cropping areas, blue areas are water bodies. The labelled light grey area is the Tully Township.

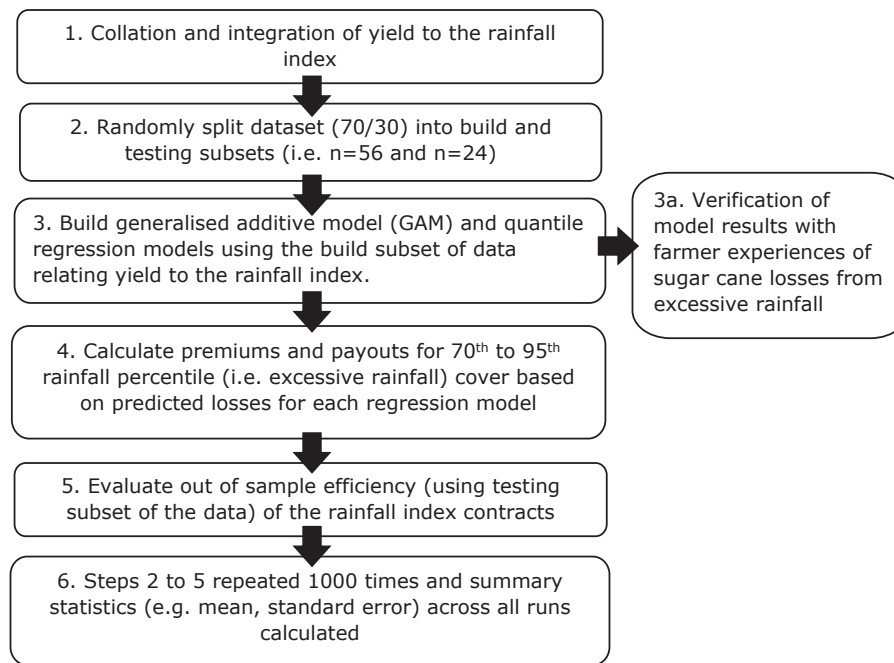


Fig. 2. Schematic of the analysis framework for assessing the efficiency of climate index insurance for sugar cane producer insurance.

based insurance was carried out on the out-of-sample testing subset of the data. We restricted efficiency analysis to the 70th, 80th, 90th and 95th percentiles because these are the rainfall index percentiles that correspond to excess rainfall that could lead to losses that a farmer could consider purchasing insurance to protect against. Finally, the process was repeated 1000 times so that the variability in the results (i.e. premiums, payouts and efficiency) could be assessed. The six steps are summarised below in Fig. 2.

2.3. Step 1: Collation and integration of yield and excessive rainfall index data

Sugar cane yields were total sugar cane yields (tonne/ha) for each year from 1930 to 2010 from the Tully sugar mill (Tully Sugar, 2011). Climate data were obtained from the Tully sugar mill station (BoM, 2017). The sum of rainfall over the growing season (after Everingham et al., 2016) was used to develop the insurance index. Price data were from 1972 to 2010 and were consumer price index (CPI) corrected. Details on variables and calculation methods are in Table 1.

2.4. Step 2 and 3: Regression model relating yield to climate indices

2.4.1. Generalized additive model (GAM)

Models were fit using a generalized additive model (GAM), which fits non-linear models using a spline. GAMs are an adaptation of

regression and generalized linear models that allow arbitrary nonlinear transformations of the input variables to be fit by the data (Gelman and Hill, 2006). The Mgcv package (Wood, 2011) was used to fit the GAM in R (R Core Team, 2016). Sugar cane yields were modelled as a function of rainfall and year of harvest. 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). The rainfall index was centred and detrended prior to model fitting (after Jewson and Brix, 2005; Gelman and Hill, 2006).

The regression model for the response variable (sugar cane yield) *yield* at time *i* was fit with a smooth effect (*f*) for the rainfall index (RI) and year,

$$yield_i = a + f(RI_i) + f(year_i) + \epsilon_i \tag{1}$$

Where $yield_i \sim N(\mu_i, \sigma)$ and $\epsilon_i \sim N(0, \sigma^2)$

The model structure was kept simple so that it was transparent and suitable for the purposes of investigating and developing a climate index for insurance purposes. Complex models including numerous predictors and intricate model structures may be more suitable for long term yield forecasts (e.g. see Everingham et al., 2009; Everingham et al., 2016), but not necessarily for the development of climate index insurance, which needs to be simple and transparent so that it can be communicated to a range of stakeholders (Ntukamazina et al., 2017).

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

Variable	Details and calculation methods	Mean (SD)	Reference
Sugar cane yield (tonne/ha)	Data from 1930 to 2010	73.92 (17.19)	Tully Sugar (2011)
Rainfall index (mm)	Summed rainfall over the entire growing season covering 17 months from August 1st to December 31st the year after. This meant that yields in 1930 were a response to rainfall from 1st August 1929 to 31st December 1930. (after Everingham et al., 2016). The rainfall index (RI) for each year (<i>i</i>) is then the sum of daily rainfall (R_d) in each growing season. ($RI_i = \sum_{d=seasonstart}^{seasonend} R_d$). Data were from Station 032042 - Tully Sugar Mill QLD from 1930 to 2010	4892.66 (1152.86)	BoM (2017).
Price (AUD)	Consumer price index (CPI) adjusted price. Data from 1972 to 2010. The median price for this period was used in analysis.	61.82 (32.80)	Tully Sugar (2011)

SD = standard deviation.

The GAM model was validated using simple hold-out cross validation by randomly sub-setting the dataset (70/30) 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 .

2.4.2. Quantile regression

Quantile regression (QR) was used to assess the rainfall index relationship with the lower quantiles of the sugar cane yield distribution, not just the mean as is the case with traditional regression models (Cade et al., 2003). QR may have several advantages, and give different results, compared to traditional regression methods for developing index based insurance (Conradt et al., 2015). First, QR is less sensitive to outliers (Dalhaus and Finger, 2016). Second, QR can estimate relationships from the minimum to maximum response and provides a more holistic assessment of relationships between variables possibly missed by other regression methods (Cade et al., 2003). Third, as a particular quantile is focused on, not just the mean, it may explain low-yield events better (Dalhaus and Finger, 2016). Here we focus on quantiles 0.4, 0.3 and 0.2 because we are interested in low yield event responses to the excessive rainfall index (after Conradt et al., 2015; Dalhaus and Finger, 2016). For more information on QR as it relates to index insurance we refer the reader to Conradt et al. (2015). We used the rqPen (Sherwood and Maidman, 2017) and quantreg (Koenker, 2017) package in R (R Core development R Development Core Team, 2016) to fit quantile regression models.

2.5. Step 3a: Grower's survey

We used a structured questionnaire to survey 33 growers, from which we selected 11 canegrowers from the northern sugar cane growing region surrounding Tully. The aim of the survey was to generate deeper understanding of growers' insurance appetite and insurance requirements, current risk management strategies, risks perceptions and quantification. Participants were asked to estimate the losses they suffered from events relating to excessive rainfall during planting, the growing season and harvest. Responses to all seasons were analysed because excessive rainfall during any of the periods can negatively impact yields. We used the on ground survey data on estimated sugarcane loss to verify our regional long-term sugar cane yield model responses to excessive rainfall.

2.5.1. Verification of regression model results with farmer ground surveys

We compared regression model estimates of yield loss in response to excessive rainfall with farmer survey estimates from on-ground surveys using t-tests. Analyses were carried out in R (R Development Core Team, 2016). Comparisons were made between the farmer's estimates of the impact of excessive rainfall on yields compared to the models predictions of excessive rainfall impact on yields. Model estimates of yield loss were calculated as the percentage difference in predicted yields between when the rainfall index was at its lowest (i.e. 2485 mm) and highest (i.e. 8467 mm, when predicted yield losses would be their greatest).

2.6. Step 4: Premium estimation based on predicted losses for climate index from regression models

Following Vedenov and Barnett (2004) we estimated sugar cane 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 in R (R Development Core Team, 2016), generating 3000 values, for each of which losses were calculated. The premium was calculated as a fair premium (adapted from Vedenov and Barnett, 2004 & Chen, 2011)

$$P(x) = E[Loss] = \sum_{i=1}^n (IND_i \cdot P(RI_i)) \quad (2)$$

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 (70th, 80th, 90th and 95th) that we investigated.

2.7. Step 5: Efficiency analysis of climate index insurance for sugar cane

Methods for efficiency analysis were adapted from Adeyinka et al. (2015) and Vedenov and Barnett (2004). Three efficiency analysis methods, Conditional Tail Expectations (CTE), Mean Root Square Loss (MRSL) and Certainty Equivalence of Revenue (CER) were used to assess the efficiency (i.e. benefit) of the excess 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 CTE and 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 compared revenue with and without insurance. The revenue without contract is given by:

$$I_t = pY_t \quad (3)$$

and with contract is:

$$I_{t\alpha} = pY_t + \beta - \theta \quad (4)$$

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 70th, 80th, 90th and 95th percentiles of the excessive 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 throughout the years in question.

2.7.1. Conditional tail expectation (CTE)

CTE measures the hedging efficiency of insurance at different strike levels (Adeyinka et al., 2015). The CTE (also known as Conditional Value at Risk (CVaR)) analysis was measured at the 95th, 90th, 80th and 70th percentiles. This is the expected revenue in the worst 2, 3, 6 and 8 years in the 24-year out of sample period that we assessed. The purpose of this analysis is to assess whether insurance will increase the revenue of farmers in the worst (i.e. during excessive rainfall seasons) years. If the insurance contract is efficient, then the utility of the farmer, measured in terms of revenue, should increase in years when excessive rainfall is experienced. If the contracts are triggered in years that did not match with the years of excessive rainfall, the CTE decreases due to the deduction of the premium each year and so the insurance contract would be inefficient. Should the payout be equal to the premium every year when the contract was triggered, the farmer will be indifferent. For the 70th, 80th, 90th and 95th percentiles then the revenue with insurance is

$$CTE \alpha = \frac{1}{T} \sum_{i=1}^T I_{t\alpha} \quad (5)$$

Where; $CTE\alpha$ is the Certainty Equivalence Revenue with an alpha level of insurance. $I_{t\alpha}$ = revenue at time t with alpha percentile level of insurance.

2.7.2. Certainty equivalence revenue (CER)

CER accounts for farmers' tendency to be risk averse and is a

measure of willingness to pay (Vedenov and Barnett, 2004; Adeyinka et al., 2015). The logarithmic utility model of CER was adapted (Adeyinka et al., 2015). This model assumes that the farmer is risk averse, prefers more to less and that the percentage of wealth invested into production is constant irrespective of changes in wealth (Elton et al., 2003). Constant relative risk aversion was assumed (Henderson and Hobson, 2002; Adeyinka et al., 2015).

The Constant Relative Risk Aversion, based on the model of Elton et al. (2003) was:

$$CER \alpha = \frac{1}{T} \sum_{i=1}^T \text{Ln} I_{t\alpha} \tag{6}$$

Where; CER α is the Certainty equivalence revenue with an alpha level of insurance. $I_{t\alpha}$ = revenue at time t with alpha percentile level of insurance.

2.7.3. Mean root square loss (MRSL)

The MRSL shows the extent to which a contract reduces downside risk below the mean (Vedenov and Barnett, 2004). In this project, we use the MRSL based on the mean since we expect farmers to be concerned with below average revenue. For different contracts (70th, 80th, 90th and 95th 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 strike level.

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

Where; MRSL α is the Mean Root Square Loss with an alpha level of insurance, p = price of agricultural commodity, $I_{t\alpha}$ = revenue at time t with alpha percentile level of insurance. \bar{Y} = the long-term average yield

2.8. Step 6: Assessment of the index premium and efficiency variability

Each regression model was built using a build subset (70% of dataset) and then used to predict observed yields not used to build the model in a test subset (30% of the dataset). The 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 we present the mean estimated premiums and efficiency for each regression model (at the different percentile levels of cover tested) with ± 2 standard errors ($\approx 95\%$ confidence interval).

3. Results

3.1. GAM regression modelling results

The excessive rainfall index had a relationship with sugar cane yields, with the lowest yields (and revenue) predicted when rainfall was its highest (Fig. 3a; Table 2). Model cross validation showed that the regression model explained 65% of the variation in yields (Table 2; Fig. 3b).

3.2. Quantile regression results

The rainfall index was significant at $p = 0.01$ for each tau level (0.2, 0.3 and 0.4) tested using quantile regression (Table 3). Coefficients for the relationship between the rainfall index and yield were negative and similar for each tau (linear coefficient -5.03 to -5.39) (Table 3). The significance of the rainfall index for each tau was also similar, although the t value was slightly higher, and p -value smaller, with a tau of 0.3

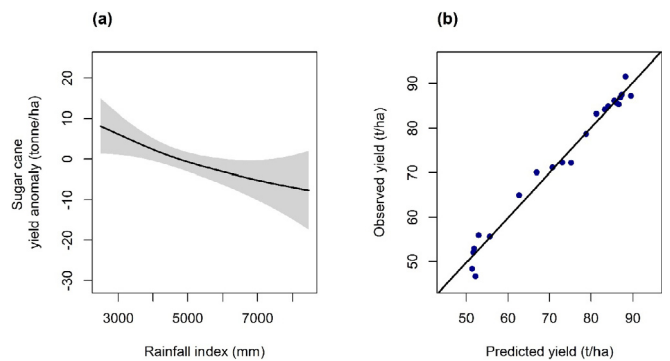


Fig. 3. (a) Predicted yield (anomaly relative to the mean) responses to the rainfall index from the GAM model. Grey shaded areas 95% confidence intervals, (b) mean predicted vs. observed sugar cane yield (tonne/ha) from the 1000 model cross validations from the generalized additive model.

Table 2

Sugar cane model with sugar cane yield (t/ha) ($n = 80$) as dependent variable results with approximate significance of smooth terms for predictors. Note model is non-linear so there is not one co-efficient for each predictor.

Predictor variable	^a F	^a p-value
Year	21.345	< 0.001
Rainfall index	7.227	< 0.01
*Adjusted R ²	0.71	
^Cross validated R ²	0.65	

[^]Cross validated R² is the mean R² from 1000 cross-validations.

^a F, p-values and Adjusted R² are from model fit to entire ($n = 80$) dataset.

Table 3

Sugar cane quantile regression model results ($n = 80$).

Tau	Predictor variable	Coefficient	SE	t	p-value
0.2	Year	13.30	2.24	5.93	0.011
	Rainfall index	-5.11	1.96	-2.61	< 0.001
0.3	Year	14.20	1.78	7.96	0.007
	Rainfall index	-5.03	1.82	-2.77	< 0.001
0.4	Year	13.25	1.70	7.80	< 0.01
	Rainfall index	-5.39	1.97	-2.73	0.008

SE = standard error.

and 0.4 (Table 3).

3.3. Comparison of farmer risk perception and regression model results

3.3.1. Grower survey results

Mean estimates from farmer surveys of yield loss from excessive rainfall during harvest, planting and the growing season ranged from 25 to 26.67 percent from farmer surveys (Table 4). Farmer estimates of losses from excess rain during planting were the most variable, ranging from 10 to 50% and with a standard deviation of 20.82 (Table 4). Farmer estimates on the effects of excess rain during harvest and the growing season all ranged from 20 to 30%, with standard deviations of 5.77 and 5 respectively (Table 4).

Table 4

Survey data for the northern sugarcane region from survey of farmers in northern sugar cane region.

Estimated loss (%)	Mean	Median	Min	Max	SD	n
Excess of rain during harvest	22.00	20.00	10.00	30.00	5.00	5
Excess of rain during season	25.00	25.00	20.00	30.00	5.00	3
Excess rain at planting	26.67	20.00	10.00	50.00	20.82	3

SD = Standard deviation.

Table 5
Two-sample t-tests comparing farmer survey and model estimates of yield loss from excessive rainfall. P-values > 0.05 indicate that there is no statistically significant difference between farmer and model estimates of yield loss.

Model vs. farmer estimate comparison	Mean farmer estimate (95% CI)	t	p-value
Excess rain during harvest	22.00 (11.61–32.39)	0.75	0.49
Excess rain during planting	26.67 (-25.05 to 78.39)	0.62	0.60
Excess rain during season	25 (12.58–37.42)	2.01	0.18

Mean yield loss, relative to ‘optimal’ rainfall conditions (i.e. when the rainfall index was its lowest) from the regression model was 19.19 percent. Farmers estimated crop losses from excessive rainfall during harvest, planting and during the growing season were all similar to model estimates (i.e. there was no significant difference (at $p = 0.05$) between farmer and regression model estimates of yield loss from excessive rainfall) (Table 5).

3.4. Estimated fair premiums

Premiums (i.e. fair premiums or expected losses) varied considerably depending on the regression method and the percentile cover (Table 6). The cheapest premiums (\$12.06 AUD/ha) were estimated from quantile regression at $\tau = 0.2$ at the 95th percentile level of cover, while the most expensive premiums (\$57.25 AUD/ha) were from the GAM at the 70th percentile cover level (Table 6). Maximum liability was estimated to be the highest for the GAM at \$363.22 AUD/ha and lowest at \$135.97 AUD/ha for quantile regression at $\tau = 0.2$ (Table 6). Premium rates ranged from about 7% to up to 16% (Table 6). For each model premiums and the premium rates were the lowest for 95th percentile cover and the highest for 70th percentile cover (Table 6).

3.5. Efficiency analysis of rainfall index

Examples of differences in revenue for each of the different methods for one of the 1000 out-of-sample tests that we carried out are shown in Fig. 4. Revenues below 0 indicate a year where a premium was paid, but no payout received. Revenues above 0 indicate a year when the rainfall index triggered a payout. Note that the out-of-sample years tested and shown here are randomly selected and so values between the different methods are not comparable in Fig. 4.

3.5.1. Conditional tail expectation (CTE)

The risk-reducing efficiency of excessive rainfall index contracts varied across rainfall percentiles and the model used to relate the rainfall index to yield. Contracts were efficient for all assessed percentiles when using CTE efficiency analysis (Fig. 5). The benefit of insurance increased with percentile of cover for each method, with 95th percentile cover consistently showing the largest benefit (Fig. 5). The

Table 6
Estimated fair premiums for the rainfall index for each of the different regression models.

Model	GAM		Quantile regression ($\tau = 0.4$)		Quantile regression ($\tau = 0.3$)		Quantile regression ($\tau = 0.2$)	
	Premium (AUD/ha) ($\pm 2SE$)	Premium rate	Premium (AUD/ha) ($\pm 2SE$)	Premium rate	Premium(AUD/ha) ($\pm 2SE$)	Premium rate	Premium(AUD/ha) ($\pm 2SE$)	Premium rate
70th	57.25 (± 1.15)	15.76%	45.51 (± 2.57)	15.19%	39.72 (± 1.98)	13.40%	15.91 (± 0.93)	11.70%
80th	49.60 (± 1.02)	13.66%	42.22 (± 2.32)	14.09%	37.87 (± 1.82)	12.77%	15.79 (± 0.92)	11.61%
90th	33.07 (± 0.75)	9.10%	30.42 (± 1.57)	10.15%	29.04 (± 1.27)	9.79%	14.24 (± 0.79)	10.47%
95th	24.04 (± 0.55)	6.62%	22.48 (± 1.12)	7.50%	22.29 (± 0.95)	7.52%	12.06 (± 0.63)	8.87%
Max liability ($\pm 2SE$)	363.22 (± 13.43)		299.65 (± 18.18)		296.48 (± 17.76)		135.97 (± 16.67)	

SE = standard error; Max liability was set at the loss predicted at the highest value of the excessive rainfall index.

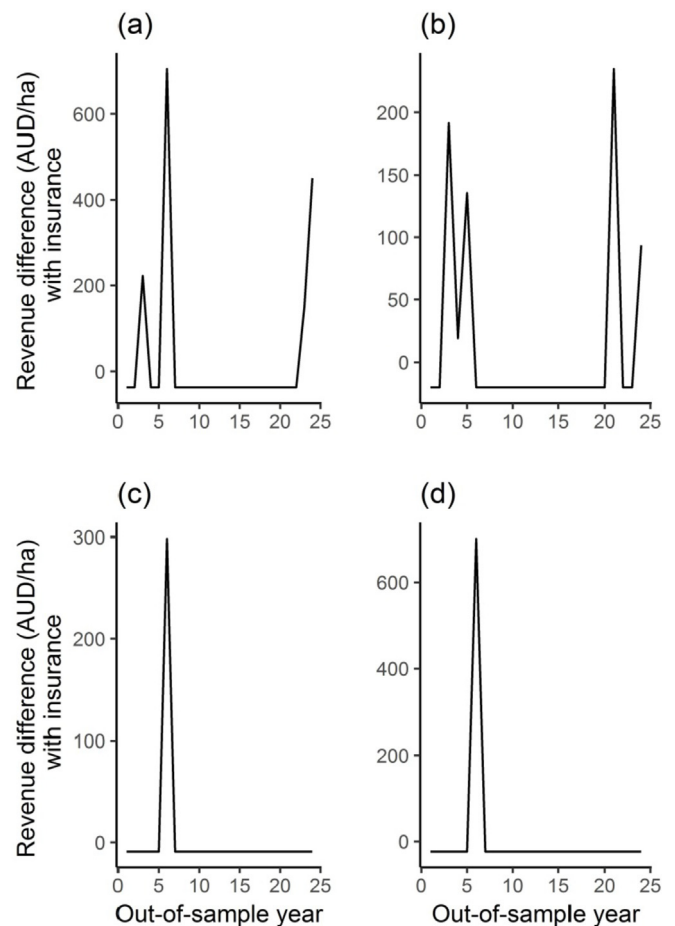


Fig. 4. Examples of difference in revenue (with insurance relative to no insurance) for each of the different methods. (a) GAM, (b) Quantile regression at $\tau = 0.4$, (c) Quantile regression at $\tau = 0.3$ and (d) Quantile regression at $\tau = 0.2$ for one of the 1000 out-of-sample tests that we carried out.

GAM and quantile regression with a tau of 0.4 and 0.3 showed similar magnitudes of benefit with positive mean differences of \$269.85, \$245.74 and \$243.96 AUD/ha respectively for 95th percentile cover (Fig. 5a, b and c).

3.5.2. Certainty equivalence revenue (CER)

Using the CER method all contracts were neutral or slightly inefficient at reducing risk, suggesting no positive cost-benefit resulting from indemnifying exposure to excessive rainfall risks (Fig. 6). Quantile regression at $\tau = 0.2$ showed neutral benefit (i.e. confidence interval for difference in revenue included zero) for the 90th and 95th percentiles (Fig. 6d). CER analysis suggested that 70th and 80th percentile were the most inefficient, corresponding to negative mean differences of up

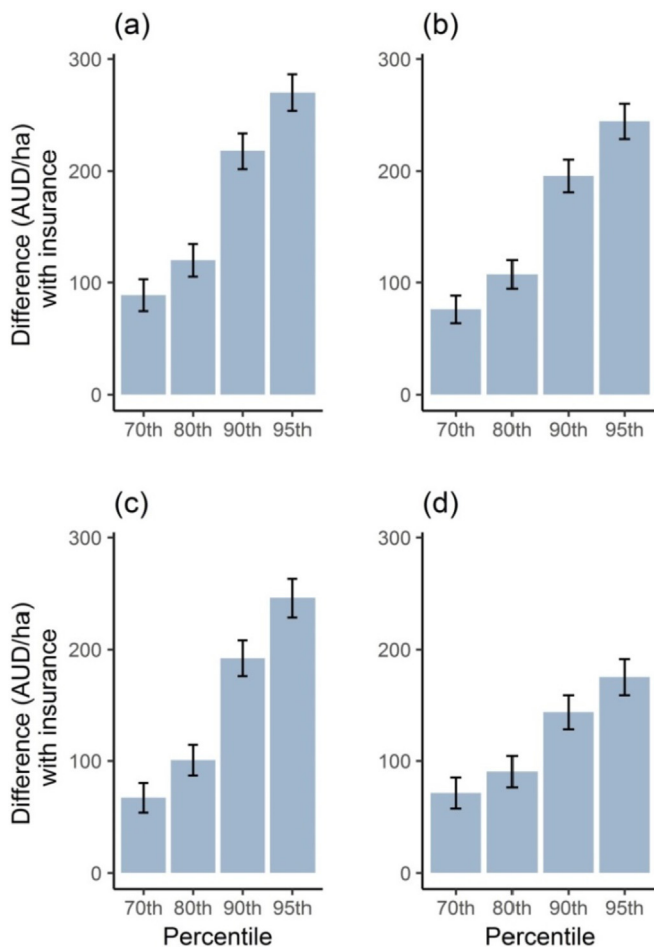


Fig. 5. Mean CTE efficiency results from the 1000 out-of-sample tests of the rainfall index for (a) GAM, (b) Quantile regression (tau = 0.4), (c) Quantile regression (tau = 0.3) and (d) Quantile regression (tau = 0.2). Errors bars are 95% confidence intervals.

to \$19.27 AUD/ha for the GAM at the 80th percentile of cover (Fig. 6a).

3.5.3. Mean root square loss (MRSL)

Based on MRSL analysis the contract was not efficient at reducing downside risk (losses below the mean) for any of the model types or percentile cover levels (Fig. 7). On average 70th and 80th percentile covers increased losses by the most for all methods. The quantile regression with tau = 0.2 showed no change in losses at the 90th and 95th percentile cover level (Fig. 7d). Quantile regression with a tau of 0.4 and 0.3, as well as the GAM, showed increased losses in the range of \$10 AUD/ha at the 90th and 95th percentile coverage level (Fig. 7b and d).

4. Discussion

4.1. An excessive rainfall index for sugar cane

Extreme climatic conditions can cause extensive crop losses and negatively impact farmer's revenue (Rosenzweig et al., 2002; Vedenov and Barnett, 2004; Ray et al., 2015). We investigated the efficiency of using a rainfall index insurance to help sugar cane producers in Tully, northern Queensland manage financial losses from excessive rainfall. Our results fit broadly with the results of other recent studies examining climatic effects on sugar cane yields in northern Queensland, Australia. Everingham et al. (2009, 2016) likewise explained just over two-thirds of the variation in sugar cane yields in their study for a more recent

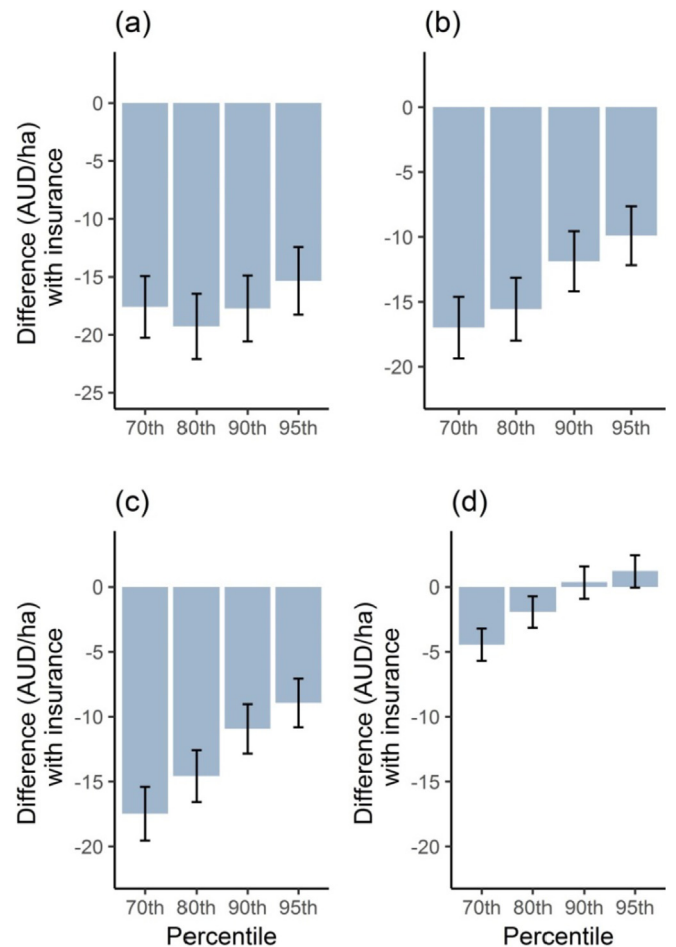


Fig. 6. Mean CER efficiency results from the 1000 out-of-sample tests of the rainfall index for (a) GAM, (b) Quantile regression (tau = 0.4), (c) Quantile regression (tau = 0.3) and (d) Quantile regression (tau = 0.2). Errors bars are 95% confidence intervals.

subset of Tully sugar cane data (1992–2013), which considered climate variables (e.g. SOI and rainfall). Although not explicitly assessed in their study Everingham et al. (2016) noted that high rainfall, which causes waterlogging and harvesting disruptions, would likely have negative effects on sugar cane yields. The relationship between rainfall and sugar cane yield we find in this study is consistent with this.

Our regression model results also fit with farmers expectations about yield losses associated with excessive rainfall. Furthermore, the GAM regression model yield loss predictions of approximately 20% are in agreement with estimates from other studies that have estimated losses from excessive rain/flooding on sugar cane yields of between 18 and 64% (Gilbert et al., 2008) and 15–45% (Gomathi et al., 2015). The good predictive performance of our regression model and its agreement with on-ground farmer surveys and other studies on sugar cane suggest our model is suitable for estimating revenue losses and calculating fair premiums to assess the efficiency of excessive rainfall index insurance for sugar cane producers.

4.2. Efficiency of excessive rainfall index insurance for sugar cane

The efficiency analysis of the excessive rainfall index insurance for sugar cane suggested benefits based on the CTE efficiency analysis. Ninety-fifth percentile cover estimated from the GAM insuring farmers against the most extreme rainfall, showed the most potential benefits for farmers at \$269.85 AUD/ha in the growing seasons with the highest rainfall. However, the contracts were found to be inefficient, or of

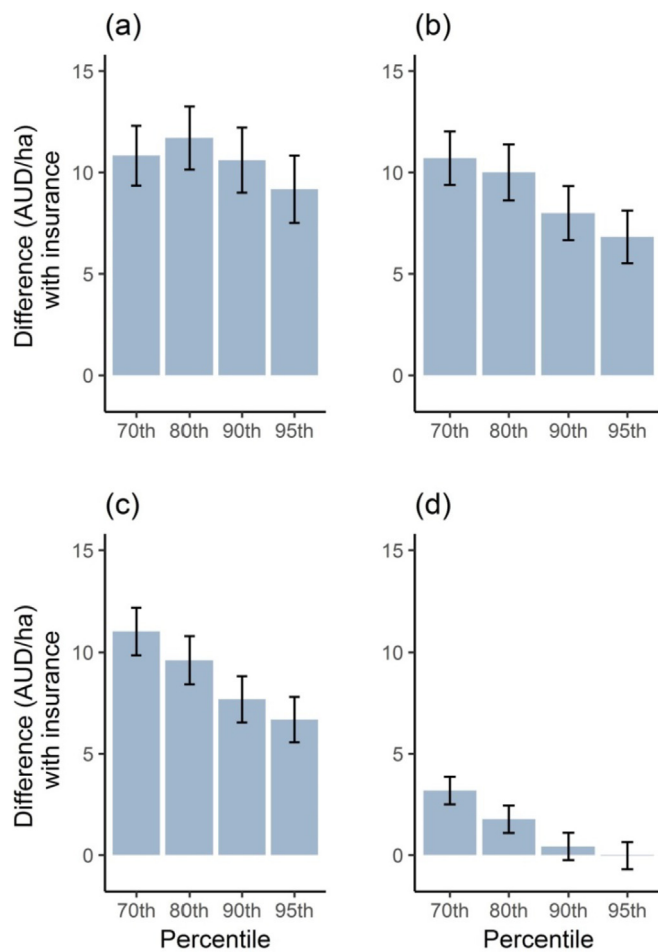


Fig. 7. Mean MRSL efficiency results from the 1000 out-of-sample tests of the rainfall index for (a) GAM, (b) Quantile regression (tau = 0.4), (c) Quantile regression (tau = 0.3) and (d) Quantile regression (tau = 0.2). Errors bars are 95% confidence intervals.

neutral benefit, when the CER and MRSL methods were used. This indicates that while excessive rainfall index insurance is beneficial in years of excessive rainfall, it could correspond to losses (although proportionally small, e.g. ca. \$10 AUD ha⁻¹ or 0.26% of the average gross revenue) when assessed over longer time frames using CER or MRSL efficiency analysis.

CTE analysis, while showing that the rainfall index insurance was beneficial in years of excessive rainfall for all regression models, showed differences in the magnitude of benefits between the different regression approaches and percentiles of cover. For example, 95th percentile cover estimated using quantile regression at tau = 0.2 showed the lowest benefits (\$175.23 AUD/ha) using CTE efficiency analysis compared to other methods, but unlike the other methods did not show negative revenues when using CER and MRSL efficiency analysis. Contracts developed using quantile regression at tau = 0.2 could therefore offer the best overall coverage for sugar cane farmers. Conradt et al. (2015) investigating wheat crops have also recently argued that quantile regression has several benefits over regression to the mean when developing climate index insurance contracts, and, like us, found better risk reduction for crops using quantile regression compared to regressions on the mean. Likewise, our results suggest that index based insurance developed quantile regression at a tau of 0.2 at a 90th and 95th percentile level of cover could offer a valuable risk transfer option for sugar cane producers by increasing their revenue to offset yield losses during seasons of excessive rainfall.

4.3. Implications for climate risk management

To date, climate index research has largely focused on insuring production losses against drought. Here we show that climate index insurance could also be successfully employed to cover production risks from excessive rainfall. We are aware of no studies that have demonstrated the positive efficiency of excessive rainfall index insurance for an agricultural crop (but see Hazell et al., 2010, for case studies on index insurance products used to cover excessive rainfall risk for agriculture in developing countries). Our results suggest that excessive rainfall index insurance could provide an important means for helping producers manage their climate risk in areas where excessive rainfall causes production losses. In the sugar cane producing areas of south-east Asia (e.g. Thailand, Indonesia, Philippines) there are projections for increased rainfall (Chotamonsak et al., 2011) that could lead to excessive rainfall related yield losses. More generally, as climate change intensifies the role of insurance, and index insurance as outlined in this paper, is also likely to become a more prominent risk management tool (Hoeppe, 2016) for a wide range of agricultural crops. We are aware of no analysis on index insurance to protect against sugar cane yield loss caused by excessive rainfall for south-east Asia, but our results suggest that excessive rainfall index insurance could provide a means to manage climate risks for production in these areas.

Demonstrating, as we have in this study, that index insurance could be developed to cover excess rainfall at the 90th and 95th percentile could have important policy implications, namely by offering a mechanism through which governments could reduce the costs of disaster recovery (Linnerooth-Bayer and Hochrainer-Stigler, 2015). For example, in Australia, excess rainfall (categorised as rainfall over the 95th percentile) is likely to trigger the National Disaster Relief and Recovery Arrangements (NDRRA), costing the government substantial money in disaster recovery. Natural disasters incur billions of dollars in tangible costs to individuals, businesses and governments. They have an enormous impact on people, the environment and our communities. In 2015, the total economic cost of natural disasters in Australia alone exceeded \$9 billion (Deloitte Access Economics, 2016). Given this, in Australia the National Rural Advisory Council (NRAC) considers index insurance to have potential for further development (National Rural Advisory Council Feasibility of agricultural insurance products in Australia for weather related production risks 2012). The results of our study also suggest some potential for index-based insurance to help governments reduce, or spread, the costs of excessive rainfall induced crop losses.

The climate index for excessive rainfall tested in the study only covered a portion of yield losses (ca. 20% relative to optimum rainfall index conditions). Other climate index based insurance products additional to those associated with excessive rainfall risks may therefore be needed to cover other climate related yield losses. For instance, a combination of drought and flood insurance could be designed for crops that are at risk of both weather extremes. In addition, tropical cyclone and storm events that cause sugar cane losses are an obvious extreme weather event that could be covered using climate index insurance. Tropical cyclone events, while a relatively rare occurrence at a given location, are likely to be associated with high yield losses and thus could be managed using index insurance. Finally, the use of farm level data, as opposed to the regional data used in this study, could also give important insights into whether there is any spatial variability in the efficiency of the excessive rainfall index.

Finally, the efficiency analysis results while positive are based on a fair premium. In practice, premiums would need to be higher to incorporate administrative costs and to cover systemic risks, which could make excessive rainfall insurance less beneficial. Nonetheless, the results based on fair premiums presented here do suggest some potential for excessive rainfall index insurance that is beneficial for farmers. Given actual premiums are likely to be higher other mechanisms (e.g. mutual funds) may need to be considered to make excessive rainfall

index insurance viable. For example, in some cases index insurance may be beneficial, but still not beneficial enough to cover ‘real-world’ costs (e.g. administrative fees) and as such mechanisms (e.g. access to credit, Boansia et al., 2017) to fund premium gaps to make the insurance index viable and beneficial to farmers may need to be considered. Investigating viable mechanisms to make climate index insurance feasible for farmers, governments and industry is an important applied area of future research for climate risk management in agriculture (Linnerooth-Bayer and Hochrainer-Stigler, 2015).

5. Conclusion

Managing the financial risks of extreme climate variability on crop production is central to ensuring the financial viability of farming systems and the sustainability of food production, especially under future climates where more extreme climatic conditions are anticipated. Here we have demonstrated the potential benefits of excessive rainfall index insurance for sugar cane growers in Tully, northern Queensland, Australia. Our analyses indicated that a farmer with excessive rainfall index insurance would be financially better off in years with excessive rainfall (under assumptions of fair premiums). Our results also suggest index insurance may be viable for sugar cane producers, and potentially other crop types, in parts of the world where extreme rainfall poses a risk to the financial sustainability of production.

Acknowledgements

We thank sugar cane growers for their involvement in the surveys. Many thanks to Julian Roberts, Claire Wilkinson, Russell Mehmet and Debbie Pilling from Willis Towers Watson for providing constructive feedback and reviews on earlier versions of the manuscript. The Queensland State Government, through the Drought and Climate Adaptation (DCAP) program, funded this project.

References

- Adeyinka, A.A., Krishnamurti, C., Maraseni, T., Cotter, J., 2015. The place of insurance in the future of Australian Drought Policy. Actuaries Summit 17–19 May 2015. Melbourne.
- Auffhammer, M., Ramanathan, V., Vincent, J.R., 2006. Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proc. Natl. Acad. Sci. Unit. States Am.* 103 (52), 19668–19672.
- Barnett, B.J., Mahul, O., 2007. Weather index insurance for agriculture and rural areas in lower-income countries. *Am. J. Agric. Econ.* 89 (5), 1241–1247.
- Boansi, D., Tambo, J.A., Müller, M., 2017. Analysis of farmers’ adaptation to weather extremes in West African Sudan Savanna. *Weather and Climate Extremes* 16, 1–13.
- Bureau of Meteorology (BoM), 2017. Climate Data Online. Australian Government Bureau of Meteorology (BoM), Melbourne, Vic., Australia Available at: <http://www.bom.gov.au/climate/data/>, Accessed date: 29 August 2016.
- Cade, B.S., Noon, B.R., 2003. A gentle introduction to quantile regression for ecologists. *Front. Ecol. Environ.* 1 (8), 412–420.
- Chen, Y., 2011. Weather Index Rice Insurance. A Pilot Study of Nine Villages in Zhejiang Province, China. Master’s Thesis. Management, Technology and Economics (MTEC). ETH Zurich.
- Chotamonsak, C., Salathé, E.P., Kreasuan, J., Chantara, S., Siriwitayakorn, K., 2011. Projected climate change over Southeast Asia simulated using a WRF regional climate model. *Atmos. Sci. Lett.* 12 (2), 213–219.
- Conradt, S., Finger, R., Bokusheva, R., 2015. Tailored to the extremes: quantile regression for index-based insurance contract design. *Agric. Econ.* 46 (4), 537–547.
- CSIRO, 2017. Climate change in Australia. Projections for Australia’s NRM regions. <https://www.climatechangeinaustralia.gov.au/en/climate-projections/future-climate/regional-climate-change-explorer/sub-clusters/?current=WTC&tooltip=true&popup=true>, Accessed date: 23 March 2017.
- Dalhaus, T., Finger, R., 2016. Can gridded precipitation data and phenological observations reduce basis risk of weather index-based insurance? *Weather, Climate, and Society* 8 (4), 409–419.
- de Carvalho, A.L., Menezes, R.S.C., Nóbrega, R.S., de Siqueira Pinto, A., Ometto, J.P.H.B., von Randow, C., Giarolla, A., 2015. Impact of climate changes on potential sugarcane yield in Pernambuco, northeastern region of Brazil. *Renew. Energy* 78, 26–34.
- Deloitte Access Economics, 2016. The economic cost of the social impact of natural disasters. Australian Business Roundtable for Disaster Resilience & Safer Communities.
- Easterling, D.R., Meehl, G.A., Parmesan, C., Changnon, S.A., Karl, T.R., Mearns, L.O., 2000. Climate extremes: observations, modeling, and impacts. *Science* 289 (5487), 2068–2074.
- Elton, E.J., Gruber, M.J., Brown, S.J., Goetzmann, W.N., 2003. *Modern Portfolio Theory and Investment Analysis*. John Wiley and Sons Inc., New York.
- Everingham, Y.L., Stoeckl, N.E., Cusack, J., Osborne, J.A., 2012. Quantifying the benefits of a long-lead ENSO prediction model to enhance harvest management—a case study for the Herbert sugarcane growing region, Australia. *Int. J. Climatol.* 32 (7), 1069–1076.
- Everingham, Y., Sexton, J., Skocaj, D., Inman-Bamber, G., 2016. Accurate prediction of sugarcane yield using a random forest algorithm. *Agron. Sustain. Dev.* 36 (2), 27.
- Everingham, Y.L., Smyth, C.W., Inman-Bamber, N.G., 2009. Ensemble data mining approaches to forecast regional sugarcane crop production. *Agric. For. Meteorol.* 149 (3), 689–696.
- Gelman, A., Hill, J., 2006. *Data Analysis Using Regression and Multilevel/hierarchical Models*. Cambridge university press.
- Gilbert, R.A., Rainbolt, C.R., Morris, D.R., McCray, J.M., 2008. Sugarcane growth and yield responses to a 3-month summer flood. *Agric. Water Manag.* 95 (3), 283–291.
- Glaz, B., Lingle, S.E., 2012. Flood duration and time of flood onset effects on recently planted sugarcane. *Agron. J.* 104 (3), 575–583.
- Gomathi, R., Rao, P.G., Chandran, K., Selvi, A., 2015. Adaptive responses of sugarcane to waterlogging stress: an over view. *Sugar Tech* 17 (4), 325–338.
- Goodwin, B.K., 2001. Problems with market insurance in agriculture. *American Journal of Agricultural Economics* 83 (3), 643–649.
- Hazell, P., Anderson, J., Balzer, N., Hastrup Clemmensen, A., Hess, U., Rispoli, F., 2010. Potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods. In: *International Fund for Agricultural Development and World Food Programme, Rome*.
- Henderson, V., Hobson, D.G., 2002. Real options with constant relative risk aversion. *Journal of Economic Dynamics and Control* 27 (2), 329–355.
- Hoeppel, P., 2016. Trends in weather related disasters—Consequences for insurers and society. *Weather and climate extremes* 11, 70–79.
- IPCC, 2012. Summary for policymakers. In: Field, C.B. (Ed.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, pp. 1–19.
- Jensen, N., Barrett, C., 2016. Agricultural index insurance for development. *Applied Economic Perspectives and Policy* 39 (2), 199–219.
- Jewson, S., Brix, A., 2005. *Weather Derivative Valuation: the Meteorological, Statistical, Financial and Mathematical Foundations*. Cambridge University Press.
- Koenker, R., 2017. *quantreg: quantile Regression*. R package version 5.34. <https://CRAN.R-project.org/package=quantreg>.
- Linnerooth-Bayer, J., Hochrainer-Stigler, S., 2015. Financial instruments for disaster risk management and climate change adaptation. *Climatic Change* 133 (1), 85–100.
- Ntukamazina, N., Onwonga, R.N., Sommer, R., Rubyogo, J.C., Mukankusi, C.M., Mburu, J., Kariuki, R., 2017. Index agricultural insurance products: challenges, opportunities and prospects for uptake in sub-Saharan Africa. *Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS)* 118 (2), 171–185.
- Odening, M., Shen, Z., 2014. Challenges of insuring weather risk in agriculture. *Agricultural Finance Review* 74 (2), 188–199.
- R Development Core Team, 2016. *R: a Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria ISBN 3-900051-07-0. <http://www.R-project.org>.
- Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. *Nature communications* 6.
- Refaeilzadeh, P., Tang, L., Liu, H., 2009. *Cross-validation*. In: *Encyclopedia of Database Systems*. Springer US, pp. 532–538.
- Rosenzweig, C., Tubiello, F.N., Goldberg, R., Mills, E., Bloomfield, J., 2002. Increased crop damage in the US from excess rainfall under climate change. *Global Environmental Change* 12 (3), 197–202.
- Shannon, H.D., Motha, R.P., 2015. Managing weather and climate risks to agriculture in North America, Central America and the Caribbean. *Weather and Climate Extremes* 10, 50–56.
- Sherwood, B., Maidman, A., 2017. *rqPen: penalized Quantile Regression*. R package version 2.0. <https://CRAN.R-project.org/package=rqPen>.
- Surminski, S., Bouwer, L.M., Linnerooth-Bayer, J., 2016. How insurance can support climate resilience. *Nature Climate Change* 6, 333–334.
- Tully Sugar, 2011. Yield dataset for the Tully sugar cane mill. Retrieved from: <http://www.tullysugar.com>.
- Tully Sugar Limited (2017). Retrieved from <http://www.tullysugar.com.au/index.php/products/operationalstatistics>.
- Vedenov, D.V., Barnett, B.J., 2004. Efficiency of weather derivatives as primary crop insurance instruments. *Journal of Agricultural and Resource Economics* 387–403.
- Verón, S.R., de Abelleira, D., Lobell, D.B., 2015. Impacts of rainfall and temperature on crop yields in the Pampas. *Climatic change* 130 (2), 235–245.
- Wood, S.N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)* 73, 3–36.
- Zhao, D., Li, Y.R., 2015. Climate change and sugarcane production: potential impact and mitigation strategies. *International Journal of Agronomy*, 547386.