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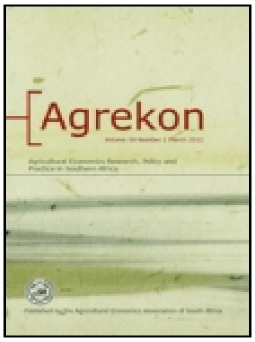

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# FARMERS' DEMAND FOR WEATHER-BASED CROP INSURANCE CONTRACTS: THE CASE OF MAIZE IN SOUTH AFRICA

H. Holly Wang*, Raphael N. Karuaihe**, Douglas L. Young***,
Yuehua Zhang****

## ABSTRACT

Weather index-based crop insurance offers farmers a way to mitigate production risk without the moral hazard, adverse selection and high administrative cost problems that plague conventional loss-based crop insurance. This is especially important for developing countries that lack government subsidised crop insurance programmes and high quality yield records. In this paper, we analyse weather-based crop insurance theoretically and provide an empirical application to South African maize producers. We examine several weather indices, investigate the farmers' demand with and without loaded premiums, and evaluate the benefits of weather index-based insurance to farmers with alternative risk preferences. Results show that the risk management efficiency of a contract has direct bearing on how well the index describes the production variability, especially a combination of two weather variables tend to describe production risk better than any single variable.

JEL Classification: C51, C61, G22, Q14

Keywords: crop insurance, risk management, South Africa, weather derivatives, multiple weather indices

## 1. INTRODUCTION

Weather constitutes the major production risk in agriculture. Floods and droughts can cause complete crop failures and place severe financial stress on growers (Leiva

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and Shankar, 2001). This is especially true in developing countries, where crop insurance is generally unavailable and where the government's ability to provide disaster relief is very limited (Maul, 2001; Barnett and Mahul, 2007; Miranda and Vedenov, 2001). In the United States, Europe, Japan and other developed countries, government-subsidised crop insurance programmes provide farmers with protection against weather-related risks (Glauber and Collins, 2002; Mahul and Wright, 2003; Yamauchi, 1986). However, these insurance programmes have been plagued with moral hazard and adverse selection problems and thus come at a high social cost (Martin *et al*., 2001; Coble *et al*., 1997; Skees and Reed, 1986).

Recent years have witnessed the emergence of index-based crop insurance programmes that allow farmers to protect themselves against their production and income risks. Two instruments, i.e. area-yield indices and weather indices, can reduce moral hazard and adverse selection problems.

Several countries have offered area-yield insurance (Miranda, 1991; Skees *et al*., 1997; Glauber and Collins, 2002), with indemnity payments based on average area yields in a pre-specified area. In the USA, for example, the Group Risk Plan uses county yields to determine payments. Providing such insurance requires a long and reliable time series of area-yield data, which is not readily available in many countries (Skees *et al*., 2001; Barnett and Mahul, 2007; Barnett, Barrett and Skees, 2008). This lack of yield data has led to weather index-based insurance, which relies on more readily available weather records.

Weather-based insurance has recently received considerable attention in the literature as a potential agricultural risk management tool (Barnett, Barrett and Skees 2008; Barnett and Mahul 2007; Sakurai and Reardon 1997; Skees and Ayurzana 2002; Martin *et al*., 2001; Turvey, 2001; Dischel, 2002). Most of these studies have focused on the pricing of weather derivatives.

Vedenov and Barnett (2004) addressed the efficiency of weather derivatives as risk management instruments for maize, soybean and cotton production in the USA. In a global effort to mitigate agricultural production risk in developing countries, the World Bank, in collaboration with other international development agencies, governments and/or local financial institutions, has embarked on pilot weather-based insurance programmes in a number of countries (Giné and Yang 2009; Cole *et al*. 2009; Hess and Hazell 2009; Meherette 2009; Hill and Robles 2011; Turvey and Kong, 2010; Fuchs and Wolff, 2011). However, most of these pilot projects (India, China, Mexico, Mongolia, Morocco and Nicaragua) are either rainfall-based or temperature-based. While rainfall alone, for example, may suffice in regions such as India (monsoon rains) as a single source of crop-yield variations, it may not adequately explain yield variations in other regions where "agricultural drought" is the main problem. Thus, there may be a need to exploit multivariate weather indices, which incorporate more than one weather event.

In this paper, we analytically examine farmers' demand for weather-index insurance within the expected utility framework, and then empirically apply the model in the South African context. The specific objectives of this paper are to:

(a) explore indices constructed using multiple weather variables and compare the predictive powers of these indices with their single-variable counterparts,
(b) investigate the optimal insurance coverage decisions from representative producers with alternative risk preferences and premium levels, and
(c) evaluate the efficiency of alternative index-based insurance using the producers' certainty equivalent income.

In the following sections, we will discuss the construction of weather indices and the development of weather-based insurance contracts. Then we compute the producer's net income for these contracts. Next, we present the expected utility model for producers' insurance decisions and conduct comparative static analysis using the mean-variance (M-V) framework. The empirical background presents the data used in the simulations. Finally, results and conclusions are given.

## 2. WEATHER INDICES

Existing weather derivatives are commonly indexed using one weather variable, such as rainfall (R), temperature (T), or growing degree-days (GDD). Indices can also be constructed as a joint distribution of multiple weather variables. Our objective is to choose a mixture of practical single-variable and multiple-variable indices that provide the best predictive power for crop yields. Thus, the following seven indices are selected using cumulative values of rainfall, temperature and growing degree-days over a crop-growing season. R, T and GDD are single variable indices of rainfall, temperature and growing degree-days, respectively. Q_RT is an index of quadratic combination of rainfall and temperature, and Q_RG is a quadratic combination of rainfall and growing degree-days. RQ_RT and RQ_RG are corresponding reduced quadratic forms when the cross term of the two variables is omitted.[2] Table 1 lists the functional forms of the selected indices.

## 3. INSURANCE CONTRACTS

Assuming the grower only faces production risk and that weather-based insurance contracts are the only risk management instruments at his disposal, an indemnity function similar to the European options' payment structure can be constructed (Turvey, 2005; Martin *et al.*, 2001). The put option type of insurance is selected for weather factors when the concern is on insufficiency, and the call option type insurance is considered when the concern is on excessiveness of the weather factor.

Thus, the indemnity functions are defined as:

(1) $I(\tilde{\omega}) = \alpha Max(\omega_c - \tilde{\omega}, 0)$, for put options, and

(2) $I(\tilde{\omega}) = \alpha Max(\tilde{\omega} - \omega_c, 0)$, for call options,

where I( $\tilde{\omega}$ ) is the stochastic indemnity, $\alpha$ is the tick, $\tilde{\omega}$ is the stochastic weather index observed, and $\omega_c$ is the critical weather index value that would trigger a payment. The tick can be expressed as currency or output amount per unit of index, depending on the denomination of the indemnity schedule.

If production costs are assumed constant and ignored from the risky income, then the grower's income per unit of land is expressed in (3) when *n* shares of the insurance contract are chosen.

(3) $\tilde{\pi} = \tilde{y} + n[I(\tilde{\omega}) - (1+\lambda)P]$,

where $\tilde{y}$ is the stochastic yield, the output price is normalised to unity, and the tick of the insurance is normalised accordingly. This income is numerically equal to the production denomination, that is, tons per hectare. For an actuarially fair contract, the premium, *P*, will be the expected indemnity, that is, $P = EI(\tilde{\omega})$. A premium loading is considered to account for transaction costs, with $\lambda > 0$ as the loading factor.

When the risky output is linearly dependent on the weather index, we have

(4) $\tilde{y} = \mu + \beta(\tilde{\omega} - \overline{\omega}) + \tilde{\varepsilon}$ ,

where $E(\tilde{y}) = \mu$; $Var(\tilde{y}) = \sigma_y^2$, $E(\tilde{\omega}) = \overline{\omega}$; $Var(\tilde{\omega}) = \sigma_\omega^2$, $E(\tilde{\varepsilon}) = 0$, $Var(\tilde{\varepsilon}) = \sigma_\varepsilon^2$, and $Cov(\tilde{\omega}, \tilde{\varepsilon}) = 0$.

The beta coefficient, $\beta = \frac{Cov(\tilde{y}, \tilde{\omega})}{\sigma_\omega^2}$, is a commonly used measure of systematic risk. In the context of weather, it represents the undiversifiable risk of yield due to weather. $\varepsilon$ is the random error term in output that cannot be represented by the weather index, which is also the commonly referred to basis risk. Basis risk is an important concept in index-based insurance literature as discussed in Wang *et al*. (1998). Because $\beta$ is influenced by the grower's choice of the weather index, $\tilde{\omega}$, it is referred to as the index basis risk coefficient. For a put option type indemnity structure, $\beta$ is positive because of the positive co-variation between yield and the weather event, but negative for the call option contract.

## 4. EXPECTED UTILITY MODEL

Many decision models have been adopted in risk analysis, such as the safety first theory (Roy, 1952; Telser, 1955), and the prospect theory (Kahneman and Tversky, 1979). The expected utility model has been the dominating method used in decision under risks, especially in the modern agricultural insurance context (Coble *et al*., 1997; Coble *et al*., 2004; Wang *et al*., 1998; Wang *et al*., 2004; Vedenov and Barnett, 2004). Although this theory has been criticised (Loewenstein and Kahneman, 1991; Rabin, 1998), and the prospect theory has accumulated laboratory evidence, especially for inexperienced consumers (Barberis and Xiong, 2012), these consumers will learn over time, however, and their behaviour will match neoclassical models (Peter Knez *et al*., 1985; Don Coursey *et al*., 1987; Brookshire and Coursey, 1987; List, 2004). In this paper, we assume that farmers maximise their expected utility of income.

Given the profit function in (3), consider a representative grower who chooses the number of contracts to maximise his expected utility of final wealth at harvest, that is,

(5) $$\underset{n}{Max}\, E[U(w_0 + \tilde{\pi}]$$

where n is the number of contracts, $w_0$ is the grower's initial per hectare wealth at planting, and U(•) is the utility function representing the grower's risk preference. The value of the insurance product is measured by its Certainty Equivalent, *CE*, defined as:

(6) $$E[U(w_0 + \tilde{\pi}(n^*))] = E[U(w_0 + \tilde{y} + CE)]$$

where $n^*$ is the optimal number of contracts. Using the insurance at its optimal hedge level to mitigate the production risk is equivalent to giving the producer the *CE* income. Therefore, *CE* is a measure of the value, or efficiency, of the underlying insurance. The constant relative risk aversion (CRRA) utility function in (7), which has been widely used in crop insurance literature (Wang *et al.*, 2004; Coble, *et al*., 2004), is used in the empirical analysis.

(7) $$U(\tilde{w}) = (1-\theta)^{-1} W^{1-\theta}$$

where $\Theta$ is the CRRA coefficient.

Comparative static analysis is performed with respect to variables of interest, namely the basis risk coefficient, the relative risk aversion coefficient, and the premium-loading factor. For this purpose, we use the M-V model in (8) as an approximation to draw analytical results.

$$(8)\quad \underset{n}{Max}\, U^{w} = E(\tilde{w}) - \frac{\theta}{2E(\tilde{w})} Var(\tilde{w})$$

where $E(\tilde{w}) = \mu + w_0 - n\lambda P$ , and $Var(\tilde{w}) = \sigma_y^2 + n^2\sigma_{I(\omega)}^2 + 2nCov(\tilde{y}, I(\tilde{\omega}))$ . If from equation (4) we assume that $\tilde{\varepsilon}$ and $\tilde{\omega}$ are conditionally independent (given that they are uncorrelated by definition), then $\tilde{\varepsilon}$ and $I(\tilde{\omega})$ are uncorrelated. We can then write $Cov(\tilde{y}, I(\tilde{\omega}) = \beta Cov(\tilde{\omega}, I(\tilde{\omega})$ .

The first order conditions to this maximisation are given by (see appendix A)

$$(9)\quad \lambda P n^2 - 2(\mu + w_0)n + \frac{\lambda P\theta\sigma_y^2 + 2\lambda P(\mu + w_0)^2 + 2(\mu + w_0)\theta Cov(\tilde{y}, I(\tilde{\omega}))}{2\lambda^2 P^2 - \theta\sigma_{I(w)}^2} = 0\,.$$

The solution to the above quadratic equation determines the grower's optimal hedging position in terms of the number of insurance contracts. For actuarially fair insurance contracts, the loading factor $\lambda$ is set at zero, and the solution to (9) becomes

$$(10)\quad n^* = -\frac{Cov(\tilde{y}, I(\tilde{\omega}))}{\sigma_{I(\omega)}^2} = -\frac{\beta Cov(\tilde{\omega}, I(\tilde{\omega}))}{\sigma_{I(\omega)}^2}\,.$$

In the M-V framework, the optimal hedge under actuarially fair (unbiased) price can be represented as the slope of the regression of the risky income on the contract indemnity schedule (Lapan and Moschini, 1994; Vukina *et al*., 1996).

This directly implies that

**Proposition 1.** Under actuarially fair premiums, the risk aversion levels do not affect the optimal insurance demand.

This proposition is also consistent with Lapan and Moschini, who asserted that the M-V solution implies that risk attitudes have no effect on the optimal hedge under unbiased prices.

Next, we consider the effect of changes in the index-specific basis risk coefficient, $\beta$ . From (10) we have

$$(11)\quad \frac{\partial n^*}{\partial \beta} = -\frac{Cov(\tilde{\omega}, I(\tilde{\omega}))}{\sigma_{I(\omega)}^2} \gtrless 0\,.$$

**Proposition 2.** Changes in optimal insurance demand in response to an increase in the basis risk coefficient (beta) depend on the relationship between the choice index and the underlying indemnity schedule. If the weather index and the indemnity function are positively (negatively) correlated, the optimal insurance demand decreases (increases) as the beta increases.

The intuition is that equation (11) can only be signed for a given weather index, but not uniformly for all indices. For example, if yields are affected by a common weather event, say rainfall (put option, $\text{cov}(\tilde{\omega}, I(\tilde{\omega}))>0$) for some growers, then (11) is positive. Otherwise, if the weather event is temperature (call option, $\text{cov}(\tilde{\omega}, I(\tilde{\omega}))<0$), then (11) is negative. However, in this case, we are considering one representative grain grower choosing from a number of weather indices at his/her disposal. This means that the underlying indemnity schedule is changing (and with it the whole notion of ceteris paribus is lost), every time the grower chooses another index.

This finding is consistent with the numerical results presented in tables 3 and 4. If we use $R^2$ as a proxy for $\beta$ (see appendix B), we see that there is no pattern developing with n* as $R^2$ increases across the indices. Therefore, we can only determine the relative efficiencies of the alternative weather indices by measuring the grower's certainty equivalent income across the indices, as shown in tables 3 and 4.

So far, the case of actuarially fair insurance contracts has been presented. When a premium loading is considered, the solution to (9) becomes (see appendix A)

$$(12)\quad n^* = \frac{\mu + w_0}{\lambda P} - \left( \frac{Var\left( \frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y} \right)}{\sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta}} \right)^{\frac{1}{2}}.$$

From the appendix, we see that, in order to ensure real roots for the quadratic expression, the denominator in the brackets above needs to be positive. Therefore,

$$(13)\quad \frac{\partial n^*}{\partial \theta} = \frac{\lambda^2 P^2 \left( Var\left( \frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y} \right) \right)^{\frac{1}{2}}}{\theta^2 \left( \sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta} \right)} > 0$$

It follows that

**Proposition 3.** In the presence of a premium loading, the marginal increment in the grower's relative risk aversion will lead to a corresponding increase in the optimal number of insurance contracts.

Proposition 3 says that the more risk averse the grower is, the higher the insurance coverage he/she would need to hedge his/her production risk. This is because when the premium is loaded, the grower reduces his/her coverage in order to restrict the extra premium payment. Now that the grower is more risk averse, he is willing to make a trade-off between the certain unfair premium payment and the risk-reducing effects by increasing his coverage.

Next, we consider the effects of changes in the price of insurance on demand for insurance. Using the same equation (12), we have

$$\frac{\partial n^*}{\partial \lambda} = -\frac{\mu + w_0}{\lambda^2 P} - \frac{1}{2}\left(\frac{Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta}}\right)^{-\frac{1}{2}}$$

$$(14) \qquad * \left(\frac{\left(\sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta}\right)\frac{\partial Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\partial \lambda} + \frac{4\lambda P^2}{\theta} Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\left(\sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta}\right)^2}\right)$$

where

$$(15) \qquad \frac{\partial Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\partial \lambda} = -2\frac{\mu + w_0}{\lambda^2 P}\sigma^2_{I(\omega)}\left(\frac{Cov(\tilde{y}, I(\tilde{\omega}))}{\sigma^2_{I(\omega)}} + \frac{\mu + w_0}{\lambda P}\right)$$

It is not possible to unambiguously sign equation (14) since it would depend on the farmer's initial wealth, and the level of premium loading, among other factors. However, *a priori*, we expect that the demand for insurance will be inversely related to the price of insurance. This will be achieved if the numerator of the last brackets in (14) is positive.

Therefore,

$$(16) \qquad \frac{\partial n^*}{\partial \lambda} < 0 \text{ if and only if } \frac{\partial Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\partial \lambda} > \frac{-4\lambda P^2 Var\left(\frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y}\right)}{\theta \sigma^2_{I(\omega)} - 2\lambda^2 P^2}$$

It follows that

**Proposition 4.** Under conditions of sufficiently low initial wealth, higher transaction costs will make weather-based insurance less attractive as a risk-reducing instrument.

## 5. EMPIRICAL BACKGROUND AND DATA

We chose the maize industry in South Africa (SA) as an empirical case representing developing countries. SA is one of the largest economies in Africa and has a strong agricultural sector. It was among the first emerging markets to conclude some weather derivative transactions, albeit with specialty crops (Kansas City Bus. J., 2002). Its historic yield records are only up to provincial level, with limited or no data available at county or district level. Weather index-based crop insurance has advantages over production-based crop insurance.

SA has an essentially dual agricultural economy, comprising of a well-developed commercial sector and a predominantly subsistence sector in the rural areas. According to the National Department of Agriculture (NDA), only about 13% of SA's surface area can be used for crop production, of which 22 % can be classified as high-potential land. Agriculture contributes about 2.6 % to SA GDP, and 9 % of its formal employment.

The most important factor limiting agricultural production is the availability of water. Rainfall is distributed unevenly across the country. The two provinces chosen for this study, namely, North West and the Free State, are the main grain producing regions of the country in terms of planted acreage. The principal town of Vryburg in the North West Province is the centre of a large agricultural district, situated 1 200 metres above sea level and with an annual rainfall of 430 mm. Maize and sunflower seed are the main crops produced.

The Free State province is situated in the centre of the country. The province's central plains make the landscape quite flat and homogeneous. It is generally hot, making it suitable for growing maize and raising sheep. Field crops account for almost two-thirds of gross agricultural income in the province. Figure 1 shows a map of the maize growing areas of SA.

The required yield and weather data were obtained from two government agencies. The National Department of Agriculture provided the provincial yield data for maize for the period 1980–2003.[3] Two centrally located weather stations were selected, one in each province. The SA Weather Service, which maintains an extensive network of weather stations across the country, provided the daily data for rainfall and temperature for the two selected weather stations. The data were then accumulated into annual data for each growing season to match with the yield data. The growing (rainy/planting) season is from November/December to April/ May.

Besides the temperature and rainfall, growing degree-days are also calculated using the average temperature data. To construct the GDDs, a base temperature of 20 C, which is a daily mean temperature, was chosen for its best predictive power on maize yield.

The yield data were detrended to account for technological progress. A simple linear trend was used for this purpose. Then the functional relationship was explored between yield and one or a combination of weather variables. Table 1 presents the weather-yield functional forms used in this analysis. The estimated parameters for alternative functional forms are recorded in table 1 for the univariate linear rainfall index (R), temperature index (T), growing degree days (GDD) index, bivariate quadratic index of rainfall and temperature (Q_RT), rainfall and GDD (Q_RG), and the two corresponding reduced quadratic indices without the interaction terms, RQ_RT and RQ_RG.

The indices in all tables are listed in ascending order of $R^2$, although the rank of adjusted $R^2$ is slightly different. In general, the univariate indices do not have as good a fit as the bivariate indices. The best indices to predict production are the quadratic model with rainfall and temperature for the North West, and the quadratic model with rainfall and GDD for the Free State, respectively.

Next, the detrended yield, rainfall, temperature, and GDD data were tested for normality of their respective distributions, using the Shapiro-Wilk test. All the variables passed the normality test in both regions, as shown in table 2. We then simulated a sample of 2 000 random rainfall and temperature figures, and calculated the corresponding GDDs. We also simulated an independent random error sample of the same size. Based on the models and estimated parameters, a sample of corresponding yields was obtained.

## 6. RESULTS

Results from the expected utility maximisation model (5) are obtained numerically, using the GAUSS programme. Based on the utility function (7), the optimal number of insurance contracts is calculated for different values of the CRRA coefficient and premium-loading factors. The relative risk aversion levels are set at 0.5, 1, 2, 3, 4 and 5, covering a range from slightly risk averse to very risk averse decision makers. Loading factors of 0 (actuarially fair) and 0.1 are evaluated. The trigger weather index is set at the mean level of each weather index. Similarly, certainty equivalents of the grower's final wealth at harvest are obtained from model (6).

Results are presented in tables 3 to 5. Table 3 shows both the optimal number of contracts and the corresponding certainty equivalent measurements when no premium loading is considered. Table 4 shows similar results as in table 3, except that a premium loading of ten per cent is now considered. The weather indices in both tables are arranged in ascending order of their respective goodness of fit. Table 5 presents the ordinal ranking of the indices for actuarially fair, and for loaded contracts, respectively.

When no premium loading is considered, the M-V optimal number of contracts is expected to be constant irrespective of the level of risk preference per Proposition 1. For the expected utility model of equation (7), we observe that this number is almost constant, although slightly influenced by the risk aversion level, as seen in Table 3. This is probably because the mean variance model is only an approximation of the expected utility model. The representative grower studied with different risk preferences will buy about 1.4 shares of weather-indexed insurance per hectare of cropland.

Across alternative indices, the optimal coverage does not show a particular trend even though the $R^2$ is increasing, per Proposition 2. This is because a change in indices leads to an associated change in the underlying indemnity function. Therefore, it is not surprising that the optimal coverage level does not increase monotonically across the indices. However, if we hold the underlying indemnity function constant, grain growers with yields more positively correlated with the weather index, that is, those with lower basis risks should buy more of this type of insurance.

Table 3 presents the CE values for an actuarially fair premium setting for the two provinces. The CEs change both across risk aversion levels and across the alternative indices. For example, consider the rainfall index (R) in the North West Province. The CE value increases from 1.7kg/ha when the risk aversion level is .5, to 16.8kg/ha when the risk aversion level is 5. Thus, at optimal levels of insurance, the more risk-averse grower will value the same insurance contract more highly.

When comparing across alternative indices, the CE increases as $R^2$ increases. Again, taking the North West Province in table 3 as an example, the CE increases from 1.7kg/ha for the rainfall index (R) to 7.5kg/ha for the rainfall-temperature quadratic index (Q_RT) when the CRRA coefficient is .5. Since the indices are arranged in ascending order of their $R^2$, the corresponding CE values rise in the same pattern. These results show the superiority of multivariate weather indices, in terms of their relative efficiencies, as potentially viable hedging instruments. Meanwhile, the GDD is better than temperature, and both are better than rainfall for both provinces.

However, we also observe a slight variation in the ordinal ranking of the CEs across the indices as the risk aversion level increases. As the CRRA coefficient increases, the ranking of the CE values changes only slightly. As a result, the results still follow the pattern of the $R^2$ ranking for the actuarially fair cases. Table 5 shows the discrepancies in the ordinal ranking across the different indices.

Although a higher $R^2$ indicates a higher correlation between the yield and the weather indices, it does not always guarantee a higher correlation between the yield and the indemnity payment, which is a truncated weather index. Furthermore, in contrast to the M-V model, the expected utility model takes into account the correlation and other relations based on higher moments between yield and the indemnity payment. As a result, higher CE value is not always achieved for a higher $R^2$.

If insurance companies offer such insurance, a transaction cost will be charged. Even for the market tradable weather derivatives, a slight premium load is also possible, as the investors in the derivative markets demand a risk premium. The numerical results in table 4 are similar to the ones in table 3, except that now we introduce a premium loading of 10% into the system.

For low values of the CRRA coefficient, the optimal insurance coverage is negative when no restrictions are imposed on the choice. This means that, as the price of insurance becomes more expensive, a low risk-averse grower becomes a net "short seller" of insurance contracts. The size of the short selling is larger for the poorer indices. This is because for the poorer indices that are less correlated to the yield risk, selling those contracts will not result in amplifying the risks from the production as much as those contracts that are more correlated to the yield. However, as the grower's risk aversion increases, the grower will not offer such insurance for sale for the given certainty equivalent income. He/she would still buy such insurance, although in lesser quantities compared with the no loading case. As a result, the optimal contract share increases as the risk aversion increases, as suggested by Proposition 3. There is a threshold for each weather index when the grower is indifferent between buying (selling) and avoiding the insurance, when the optimal choice is zero. Such thresholds can be observed for the Free State from Table 4, as CRRA is almost 1 for Q_RG, and about 2 for T.

When a grower offers the insurance for sale, the ranking in CE values across the alternative indices at the optimal contacts is reversed. Since the grower is a net seller to obtain the extra mean revenue, the risk is increased by offering the weather index insurance. The higher the basis risk between the grower's own yield and the weather index, the less total risk he/she accepts by offering such insurance, thereby increasing his/her utility. When the grower buys loaded insurance, his/her CE is lower than for the no load case for the higher cost and lower risk protection, which is consistent with Proposition 4. The ranking of the weather indices then becomes similar to the no load case. Table 5 also gives the rankings across the alternative indices when the premium is loaded. The only difference in ranking is for the near risk-neutral farmer who sells instead of buying insurance.

## 7. SUMMARY AND CONCLUSION

In contrast to previous work that suggests that a single-variable weather index suffices to develop an insurance contract, this study shows that insured growers can achieve a higher utility from multivariate weather indices. They may therefore be grossly under-insured if the underlying weather index is not properly constructed to better explain the variations in crop yield. Although this is quite obvious in theory, no such combination weather index is found in practice or in literature, and this paper aims to bring this to the attention of the insurance industry. We also report that the most important single weather index we found in the study area was GDD, and that the combination of rainfall and either temperature or GDD outperformed the single variable indices by a large margin in South African maize production.

Depending on the growers' risk preference, they may choose to buy or offer such insurance for sale if the price is not actuarially fair. The less risk-averse growers may join the insurance companies on the selling side of the market if allowed by the institution. In theory, this is just like trading options, although it is unlikely, considering transaction costs and institutional reasons.

The risk protection value of weather-indexed insurance follows the predictive power of the index on yield in general, though not exactly. There is a trade-off between choosing an index with a large number of weather variables that can improve on the efficiency of the contract, and choosing a single-variable index that is easily understood by the growers. In developing countries, local insurance companies and brokerage houses that want to enter the weather-based insurance market have to understand the pricing and valuation techniques for these contracts in order to quantify the level of risk they need to reinsure themselves against.

Therefore, further research could look into the construction of an appropriate weather index or indices which not only would improve the goodness of fit (or any other measure of correlation) on yield, but also is easily understood by the market participants.

## NOTES

1 Please note in the paper Yuehua Zhang is corresponding author.

2 Although log functions were also considered, they were dropped due to poorer performance in terms of goodness of fit when compared with quadratic functions.

3 Yield variability can be different for small and large farms. In this analysis, we use the state level yield data, which is an average of all types of farms to test the weather index. The weather-based insurance will pay an indemnity based on the weather index only, and all types of farms will bear basis risks.

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# APPENDIX

## A. THE MEAN-VARIANCE MODEL

Taking the first order condition of (8) with respect to n,

$$\frac{\partial U^{w}}{\partial n}=-\lambda P-\frac{\theta\lambda P}{2(\mu+w_0-n\lambda P)^2}\left[\sigma_y^2+n^2\sigma_{I(\omega)}^2+2nCov(\tilde{y},I(\tilde{\omega}))\right]-\frac{\theta}{2(\mu+w_0-n\lambda P)}\left[2n\sigma_{I(\omega)}^2+2Cov(\tilde{y},I(\tilde{\omega}))\right]=0$$

Factoring out and rearranging the terms, we have

$$\lambda Pn^2-2(\mu+w_0)n+\frac{\lambda P\theta\sigma_y^2+2\lambda P(\mu+w_0)^2+2(\mu+w_0)\theta Cov(\tilde{y},I(\tilde{\omega}))}{2\lambda^2P^2-\theta\sigma_{I(w)}^2}=0\,.$$

For actuarially fair premiums, $\lambda=0$, and the equation becomes $n^*=-\frac{Cov(\tilde{y},I(\tilde{\omega}))}{\sigma_{I(\omega)}^2}=-\frac{\beta Cov(\tilde{\omega},I(\tilde{\omega}))}{\sigma_{I(\omega)}^2}$.

However when a premium loading is considered, the solution to the quadratic function is

$$n^*=\frac{\mu+w_0}{\lambda P}\pm\frac{1}{2}\left(\frac{4\frac{(\mu+w_0)^2}{\lambda^2P^2}\sigma_{I(\omega)}^2+4\sigma_y^2+8\frac{\mu+w_0}{\lambda P}Cov(\tilde{y},I(\tilde{\omega}))}{\sigma_{I(\omega)}^2-\frac{2\lambda^2P^2}{\theta}}\right)^{\frac{1}{2}}.$$

In order to ensure that we obtain real interior solutions, the square brackets must be positive. It is not difficult to see that the numerator of the square brackets is simply the variance of $2\frac{\mu+w_0}{\lambda P}I(\tilde{\omega})+2\tilde{y}$, which is positive.

Therefore the denominator is positive. Checking the second order condition, $2n^*\lambda P-2(\mu+w_0)<0$ or $n^*<\frac{\mu+w_0}{\lambda P}$.

Therefore we will have a unique solution of

$$n^* = \frac{\mu + w_0}{\lambda P} - \left( \frac{Var\left( \frac{\mu + w_0}{\lambda P} I(\tilde{\omega}) + \tilde{y} \right)}{\sigma^2_{I(\omega)} - \frac{2\lambda^2 P^2}{\theta}} \right)^{\frac{1}{2}}.$$

## B. THE BASIS RISK COEFFICIENT

It is difficult to compare $\beta$ across the different indices because it depends on the magnitude of the choice index.

A normalised and easy to use measure in regression is $R^2$. Although $R^2$ is defined as $1-\frac{\sum e_i^2}{\sum y_i^2}$, it is an estimator of □$=1-\frac{\sigma_\varepsilon^2}{E(\tilde{y}^2)} = 1-\frac{\sigma_\varepsilon^2}{\beta^2\sigma_\omega^2 + \sigma_\varepsilon^2 - \mu^2}$.

Therefore, $\beta = \sqrt{\frac{\sigma_\varepsilon^2}{\sigma_\omega^2(1-\Re)} + \frac{\mu^2 - \sigma_\varepsilon^2}{\sigma_\omega^2}}$.

Table 1: Parameter Estimates

| Weather Index | Model | R2 | AdjR2 |
|---|---|---|---|
| North West | | | |
| $R$ | $\hat{y}_{det} = -1.104 + 0.003R$ | .224 | .187 |
| $T$ | $\hat{y}_{det} = 6\ .3\ - 0.004T$ | .673 | .658 |
| $GDD$ | $\hat{y}_{det} = 3.392 - 0.007GDD_{20}$ | .775 | .764 |
| $RQ\_RT$ | $\hat{y}_{det} = 2\ .889 + 0.0114R - 1.8\ x0\ ^{-5}R^2 - 0.0354T + 4.1\ x0\ ^{-6}T^2$ | .786 | .739 |
| $RQ\_RG$ | $\hat{y}_{det} = 3.757 + 0.0083R - 8.68x10^{-6}R^2 - 0.0165GDD_{20} + 1.05x10^{-5}GDD_{20}^2$ | .852 | .819 |
| $Q\_RG$ | $\hat{y}_{det} = 5.277 + 0.0056R - 8.2x10^{-6}R^2 - 0.0202GDD_{20} + 1.25x10^{-5}GDD_{20}^2 + 4.29x10^{-6}R*GDD_{20}$ | .854 | .811 |
| $Q\_RT$ | $\hat{y}_{det} = 354.013 - 0.1019R - 4.3\ x0\ ^{-6}R^2 - 0.1686T + 1.9\ x0\ ^{-5}T^2 + 2.4\ x0\ ^{-5}R$ | .863 | .823 |
| Free State | | | |
| $R$ | $\hat{y}_{det} = -0.537 + 0.002R$ | .290 | .256 |
| $T$ | $\hat{y}_{det} = 1\ .2\ - 0.003T$ | .531 | .509 |
| $GDD$ | $\hat{y}_{det} = 1.944 - 0.005GDD_{20}$ | .616 | .598 |
| $RQ\_RT$ | $\hat{y}_{det} = -3\ .473 + 0.0069R - 5.6\ x0\ ^{-6}R^2 + 0.0435T - 6.2\ x0\ ^{-6}T^2$ | .652 | .574 |
| $RQ\_RG$ | $\hat{y}_{det} = -102.553 + 0.0228R - 6.21x10^{-6}R^2 + 0.0578T - 8.27x10^{-6}T^2 - 4.32x10^{-6}RT$ | .658 | .557 |
| $Q\_RG$ | $\hat{y}_{det} = -1.194 + 0.006R - 4.95x10^{-6}R^2 + 0.0053GDD_{20} - 1.64x10^{-5}GDD_{20}^2$ | .711 | .647 |
| $Q\_RT$ | $\hat{y}_{det} = -1.576 + 0.0066R - 5.0x10^{-6}R^2 + 0.0069GDD_{20} - 1.76x10^{-5}GDD_{20}^2 - 1.74x10^{-6}R*GDD_{20}$ | .712 | .627 |

Table 2: Normality Test

| Province | Variable | Shapiro-Wilk | p-Value |
|---|---|---|---|
| Northwest | Rainfall | .9648 | .5677 |
| | Temp | .9824 | .9425 |
| | GDD | .9704 | .6979 |
| | Yield | .9738 | .7784 |
| Free State | Rainfall | .9538 | .3505 |
| | Temp | .9515 | .3135 |
| | GDD | .9504 | .2984 |
| | Yield | .9444 | .2226 |

Table 3: Optimal Coverage and Certainty Equivalent Values for Actuarially Fair Insurance ($\lambda$[1] = 0)

| Weather Index | $\theta$[2] = .5 | | $\theta$ = 1 | | $\theta$ = 2 | | $\theta$ = 3 | | $\theta$ = 4 | | $\theta$ = 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $n^*$[3] | CE[4] | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE |
| North west | | | | | | | | | | | | |
| R | 1.37 | 1.7 | 1.36 | 3.3 | 1.36 | 6.6 | 1.36 | 10.0 | 1.36 | 13.4 | 1.35 | 16.8 |
| T | 1.45 | 5.7 | 1.44 | 11.4 | 1.44 | 22.8 | 1.43 | 34.3 | 1.42 | 45.9 | 1.42 | 57.5 |
| GDD | 1.42 | 6.2 | 1.42 | 12.4 | 1.41 | 24.9 | 1.41 | 37.5 | 1.40 | 50.3 | 1.39 | 63.1 |
| RQ_RT | 1.28 | 6.3 | 1.28 | 12.7 | 1.28 | 25.7 | 1.28 | 38.9 | 1.27 | 52.4 | 1.27 | 66.0 |
| RQ_RG | 1.43 | 6.6 | 1.43 | 13.3 | 1.42 | 26.6 | 1.42 | 39.9 | 1.41 | 53.3 | 1.41 | 66.7 |
| Q_RG | 1.39 | 6.6 | 1.39 | 13.1 | 1.39 | 26.4 | 1.38 | 39.7 | 1.38 | 53.0 | 1.37 | 66.5 |
| Q_RT | 1.29 | 7.5 | 1.29 | 15.1 | 1.28 | 30.1 | 1.27 | 45.1 | 1.27 | 60.2 | 1.26 | 75.3 |
| Free State | | | | | | | | | | | | |
| R | 1.43 | 1.7 | 1.43 | 3.5 | 1.43 | 7.0 | 1.43 | 10.5 | 1.43 | 14.1 | 1.42 | 17.8 |
| T | 1.52 | 3.6 | 1.52 | 7.3 | 1.52 | 14.6 | 1.51 | 22.0 | 1.51 | 29.5 | 1.51 | 37.1 |
| GDD | 1.43 | 3.9 | 1.43 | 7.7 | 1.42 | 15.6 | 1.42 | 23.5 | 1.42 | 31.5 | 1.41 | 39.7 |
| RQ_RT | 1.21 | 6.3 | 1.21 | 12.9 | 1.21 | 26.6 | 1.21 | 41.3 | 1.21 | 56.9 | 1.21 | 73.7 |
| Q_RT | 1.25 | 6.4 | 1.25 | 13.0 | 1.25 | 26.8 | 1.25 | 41.4 | 1.25 | 56.9 | 1.25 | 73.4 |
| RQ_RG | 1.20 | 6.6 | 1.20 | 13.4 | 1.20 | 27.9 | 1.20 | 43.5 | 1.20 | 60.4 | 1.20 | 78.7 |
| Q_RG | 1.2 | 6.5 | 1.2 | 13.3 | 1.2 | 27.6 | 1.21 | 43 | 1.21 | 59.7 | 1.21 | 77.7 |

[1]Loading factor

[2]CRRA coefficient

[3]Optimal number of insurance contracts

[4]The certainty equivalent income, denominated in production units of kg/ha.

Table 4: Optimal Coverage and Certainty Equivalent Values for Loaded Insurance ( $\lambda$ = .1)

| Weather Index | $\theta$ = .5 | | $\theta$ = 1 | | $\theta$ = 2 | | $\theta$ = 3 | | $\theta$ = 4 | | $\theta$ = 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE | $n^*$ | CE |
| North west | | | | | | | | | | | | |
| R | -5.35 | 32.0 | -2.21 | 10.1 | -0.49 | .9 | 0.12 | .1 | 0.41 | 1.4 | 0.59 | 3.5 |
| T | -2.48 | 21.1 | -0.65 | 2.7 | 0.35 | 1.5 | 0.69 | 8.8 | 0.86 | 18.4 | 0.96 | 28.9 |
| GDD | -2.21 | 19.1 | -0.53 | 2.0 | 0.40 | 2.3 | 0.72 | 10.8 | 0.88 | 21.6 | 0.97 | 33.4 |
| RQ_RT | -1.58 | 13.2 | -0.29 | .9 | 0.45 | 3.6 | 0.70 | 13.4 | 0.83 | 25.2 | 0.91 | 37.9 |
| RQ_RG | -2.17 | 20.3 | -0.53 | 2.2 | 0.39 | 2.3 | 0.71 | 11.3 | 0.87 | 22.5 | 0.97 | 34.7 |
| Q_RG | -2.01 | 18.3 | -0.46 | 1.7 | 0.41 | 2.6 | 0.71 | 11.8 | 0.86 | 23.2 | 0.95 | 35.5 |
| Q_RT | -1.47 | 14.1 | -0.22 | .8 | 0.46 | 4.5 | 0.70 | 15.7 | 0.83 | 29.0 | 0.90 | 43.0 |
| Free State | | | | | | | | | | | | |
| R | -6.05 | 38.7 | -2.55 | 12.6 | -0.62 | 1.4 | 0.05 | 0.0 | 0.39 | 1.1 | 0.59 | 3.3 |
| T | -3.89 | 30.1 | -1.37 | 6.9 | 0.03 | .0 | 0.50 | 2.6 | 0.74 | 7.7 | 0.88 | 13.9 |
| GDD | -3.44 | 28.3 | -1.17 | 6.0 | 0.09 | .1 | 0.51 | 3.3 | 0.73 | 9.1 | 0.86 | 15.9 |
| RQ_RT | -1.03 | 6.3 | 0.06 | 0 | 0.57 | 6.8 | 0.77 | 19.1 | 0.88 | 33.6 | 0.94 | 49.7 |
| Q_RT | -1.21 | 8.1 | -0.12 | 0.0 | 0.55 | 6.0 | 0.78 | 18.0 | 0.89 | 32.1 | 0.96 | 47.8 |
| RQ_RG | -0.94 | 5.6 | 0.04 | 0.1 | 0.59 | 7.8 | 0.78 | 21.1 | 0.88 | 36.9 | 0.94 | 54.5 |
| Q_RG | -0.99 | 6 | 0.03 | 0 | 0.58 | 7.4 | 0.78 | 20.5 | 0.88 | 36 | 0.94 | 53.3 |

Table 5: Ranking Weather Indices

| Weather Index | R2 | AdjR2 | λ = 0 | | | λ = 0.1 | | |
|---|---|---|---|---|---|---|---|---|
| | | | CE ($\theta$ =.5) | CE ($\theta$ =2) | CE ($\theta$ =5) | CE ($\theta$ =.5) | CE ($\theta$ =2) | CE ($\theta$ =5) |
| Northwest | | | | | | | | |
| R | 7 | 7 | 6 | 7 | 7 | 1 | 6 | 7 |
| T | 6 | 6 | 5 | 6 | 6 | 2 | 5 | 6 |
| GDD | 5 | 4 | 4 | 5 | 5 | 4 | 4 | 5 |
| RQ_RT | 4 | 5 | 3 | 4 | 4 | 7 | 2 | 4 |
| RQ_RG | 3 | 2 | 2 | 2 | 2 | 3 | 4 | 2 |
| Q_RG | 2 | 3 | 2 | 3 | 3 | 5 | 3 | 3 |
| Q_RT | 1 | 1 | 1 | 1 | 1 | 6 | 1 | 1 |
| Free State | | | | | | | | |
| R | 7 | 7 | 7 | 7 | 7 | 1 | 5 | 7 |
| T | 6 | 6 | 6 | 6 | 6 | 2 | 7 | 6 |
| GDD | 5 | 3 | 5 | 5 | 5 | 3 | 6 | 5 |
| RQ_RT | 4 | 4 | 4 | 4 | 3 | 5 | 3 | 3 |
| Q_RT | 3 | 5 | 3 | 3 | 4 | 4 | 4 | 4 |
| RQ_RG | 2 | 1 | 1 | 1 | 1 | 7 | 1 | 1 |
| Q_RG | 1 | 2 | 2 | 2 | 2 | 6 | 2 | 2 |

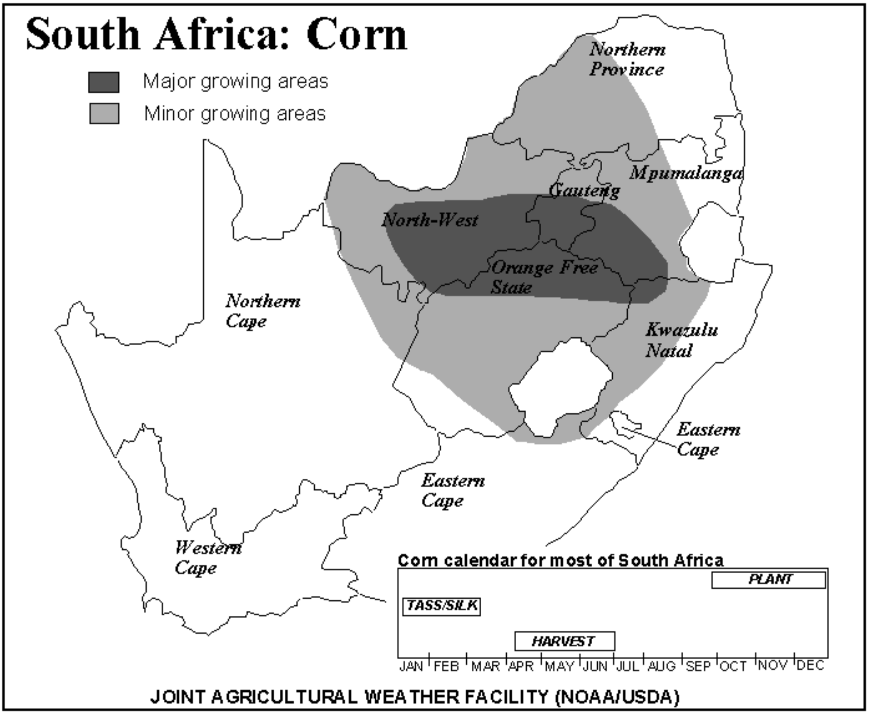


Figure 1: Map of South Africa's major maize growing areas