Chapter 1 - Introduction

1.1 Purpose of the research

Australia is the driest continent in the world excluding Antarctica. Farmers in Australia constantly battle with uncertainty about the weather and risk of serious financial consequences if unfavourable weather occurs. Weather risk has been a part of farming life since agriculture started in Australia and farmers have dealt with this unpredictability in a variety of ways. However, questions arise as to whether it is possible to create new tools for hedging weather risk, or whether existing hedging methods can be improved. In this regard, weather derivatives are a new risk management tool resulting from deregulation of energy markets in the United States but with potential applications in other industries. This market is still small in Australia and these tools have not been used by farmers on more than a few occasions. Despite the small present usage, there are important research questions about whether there is potential for widespread use of weather derivatives in Australian agriculture. This dissertation aims to discover whether weather derivatives can be useful to Australian farmers as a weather risk management tool.

1.2 Research objectives and hypotheses

The research questions that guided this research relate to the use of weather derivatives as a risk management tool by Australian farmers. The specific research questions are:

(i) What is the effective demand for weather derivatives in Australian agriculture?

(ii) What is the likely willingness to pay for weather derivatives by an average Australian wheat farmer?

(iii) Are weather derivatives a cost effective way for Australian farmers to hedge weather risk?

(iv) What obstacles prevent widespread uptake of weather derivatives for managing weather risk by Australian farmers?

While research has been undertaken on use of weather derivatives in energy markets in the United States and Europe, the volume of research on use of weather derivatives in

agricultural settings is much more limited. A few studies have focused on use of weather derivatives by farmers. These have primarily been in the United States with a few others in less developed countries such as Mexico. Therefore, this research contributes to the current body of literature by providing additional insight into use of weather derivatives by farmers. More specifically, it is the first study to analyse the use of these weather risk management tools in an Australian agricultural setting.

The intended outcome of the research is to provide the fledgling Australian weather derivative market and the Australian agricultural industry with an indication of the future of weather derivative use by agricultural producers of Australia. While the focus is on wheat producers in New South Wales and southern Queensland in the wheat-sheep belt; the research provides a basis for further analysis of weather derivatives in other Australian agricultural industries. There are four aims within this objective. First, examine the potential demand for these risk management products by wheat farmers. Second, determine the willingness to pay for weather derivative contracts by an "average" wheat farmer. Third, analyse the perceived problem of geographical basis risk. Fourth, analyse the efficiency with which specifically designed weather derivative contracts can reduce the risk exposure of wheat farmers due to the weather conditions. It is anticipated that this research will benefit agricultural producers and possibly, more importantly, it will provide information for Australian banks and other underwriters as they attempt to establish weather derivatives in their current risk transfer portfolios.

There are two hypotheses that underlie this research. The first null hypothesis is that farmers will be willing to pay for weather derivative contracts as hedging tools for weather risk management. The alternate hypothesis is that farmers will not demand weather derivative contracts for hedging weather risk. The second null hypothesis is that weather derivative contracts, specifically designed at a regional level, will provide an efficient means for farmers to reduce risk exposure associated with unfavourable weather. The alternate hypothesis is that such contracts will not provide an efficient means for farmers to reduce risk exposure from unfavourable weather conditions.

It is expected that other industries in Australia such as special events organisers, tourism, energy and construction will also be interested in these types of weather risk management products, however such potential demands are not considered in this dissertation.

1.3 Thesis outline

This dissertation presents a review of some of the risk management and weather derivatives literature, followed by three distinct pieces of research focusing on different areas of weather derivative use by Australian farmers. The first of these uses a theoretical optimal hedging model to determine the potential demand for weather derivatives by Australian wheat farmers. The theoretical willingness to pay by farmers is estimated from the model using historical price and yield data along with previously published elasticities and risk aversion levels. The second section focuses on one of the potential practical problems that could limit the uptake of weather derivatives by Australian wheat farmers. Using historical rainfall data for three regional locations it explores how the benefits of a weather derivative contract are affected by the geographical distance between the farmer and the location at which the rainfall data is recorded. The third section answers the question of how useful weather derivatives may be for reducing risk exposure of farmers from unpredictable and unfavourable weather events. A hypothetical weather derivative is constructed and used to analyse the risk-reducing ability of the instrument for two local government areas in New South Wales.

In detail, Chapter 2 is a review of published literature examining climatic and weather risk in Australian agricultural history with particular emphasis on yield risk, price risk and institutional methods of reducing risk. The review provides detailed background on weather derivatives including the history of the weather derivative market, its operation and potential end-users of weather derivative contracts. Weather derivatives are also compared and contrasted with more traditional crop insurance contracts. This is followed by discussion of issues regarding the practical implementation of weather derivatives in the agricultural industry in the context of geographical basis risk. The literature review then covers work undertaken on the contentious topic of the pricing of weather derivative contracts.

A more detailed discussion of the risk literature is presented in Chapter 3, as well as methods that can be used to account for risk in economic models. A theoretical optimal hedging model for a weather instrument is then presented, based on a model developed by Simmons and Rambaldi (1997). This optimal hedging model uses historical data on Australian wheat prices and yields with previously published estimates of the elasticity of supply and of the coefficient of absolute risk aversion for an "average" wheat farmer.

The potential demand for these instruments and the theoretical willingness to pay by an "average" farmer for this type of weather hedging instrument is determined from the optimal hedging model.

In Chapter 4 one of the perceived practical implementation problems for the inclusion of weather derivatives in risk management plans of agricultural producers in rural regions of Australia is explored. Geographical basis risk is defined followed by discussion of the perceived implications of geographical distance between different locations on the use of weather derivatives. The on-farm rainfall records for three farmers located in West Wyalong, NSW; Trangie, NSW; and Dalby, QLD are presented and a weather derivative contract constructed suitable for hedging insufficient growing season rainfall in the three regions. Then the on-farm rainfall datasets are used to calculate payouts from these contracts. The calculated payoffs using on-farm rainfall are first compared to the payouts that would occur if the weather derivative were written on a local Bureau of Meteorology weather station. Secondly they are compared to payouts calculated with the average rainfall from three local weather stations, and lastly they are compared to payouts calculated with rainfall data from Sydney Airport. The chapter concludes with discussion of the implications of distance and differences in rainfall between locations for the writing of agricultural weather derivative contracts.

The risk-reducing ability of weather derivatives for farmers is presented in Chapter 5. Some previous studies on efficiency of weather derivatives in agricultural settings are discussed then the model is introduced and data sources discussed. The analysis is based on historical yield data at Local Government Area (LGA) level and historical rainfall and temperature measurements from Bureau of Meteorology weather stations central to each area. Two local government areas are considered, the Bland LGA and the Narromine LGA, both located in New South Wales. The weather-yield relationship is determined using econometric techniques and the "best" weather-yield model for each LGA is used to construct weather derivative contracts and prices for these instruments. The efficiency analysis is undertaken for two local government areas using two different techniques for measuring the efficiency with which the weather derivative contract reduces the risk exposure of the farmer. Conclusions are then drawn from the efficiency analysis and suggestions made for further research.

Chapter 6 is the final chapter of this dissertation and is used to discuss the conclusions and implications from the research.

Chapter 2 – Literature Review

2.1 Introduction

Thousands of Australian children over the decades have learnt Dorothea Mackellar's well known words "I love a sunburnt country, a land of sweeping plains, of ragged mountain ranges, of droughts and flooding rains". These poetic words from 1908 still summarise the climatic and geographical extremes with which Australians, particularly rural Australians, contend on a daily basis. The Australian climate is known for its variability, particularly its high year-to-year rainfall variability. Such variability is influenced by the Southern Oscillation which is driven largely from the tropical Pacific Ocean and overlying atmosphere (BOM, n.d.). Australia's climate is dominated by the dry, sinking air of the subtropical high pressure belt which moves north and south with the seasons. This causes the rainfall pattern over Australia to be strongly seasonal and helps to define the main climatic regions in the country (BOM, n.d.). The influence of the high pressure belt means that Australia's rainfall is often low and variable. Eighty per cent of the continent has an average annual rainfall less than 600 mm and this is combined with high evaporation rates (BOM, n.d.). Most of Australia's primary production occurs in the temperate regions of the south and east and relies on winter rainfall.

Variability in Australian weather has always occurred and will continue to be unpredictable. As scientific discoveries push back the boundaries of weather knowledge, meteorologists become more efficient and accurate with their weather predictions. However, meteorologists can never predict future weather with one hundred per cent accuracy because of the inherent nature of the weather both spatially and temporally. These factors ensure there will always be unpredictable, extreme weather events (Paoli & Bass 1997:1). Weather events affect many parts of our modern world including agriculture, electricity production, construction, tourism and manufacturing, and therefore, unexpected changes in weather can greatly influence the performance of the Australian economy. Favourable weather conditions can increase profits for firms while unfavourable weather conditions can reduce both cash flow and profits, and ultimately affect the viability of firms. It is believed that "about one-seventh of the US economy is weather sensitive" (Challis 1999 quoted in Cao & Wei

2004:1066) and it is possible that such sensitivity is greater in Australia as much of the rural production from Queensland and New South Wales is linked to the Southern Oscillation.

2.2 Weather risk in Australian agricultural history

Australian agriculture is subject to weather and climatic risk and is one of the few sectors heavily reliant on local weather conditions for profits. Weather can affect demand for and supply of farming inputs and outputs. Changes in any demand or supply conditions faced by farmers have the potential to affect farm profitability.

Risk attributed to variability in weather is generally called weather risk and in agriculture has two distinct effects: volumetric yield risk and price risk. Weather risk refers only to the *unpredictable* component of weather fluctuations because if fluctuations in weather are predictable they create little risk as the farmer can plan his production cycle around these predicted events (Campbell & Diebold 2002:2). In this context yield risk is quite distinct from price risk (Yoo 2003:1) although in some situations the two risks may interact. Weather risk affects day-to-day operation of farming enterprises and influences many production decisions such as the timing of crop sowing, crop harvesting, fertiliser or insecticide applications, shearing, calving/lambing, drenching and many other farm operations. Timing of these activities takes weather unpredictability into account.

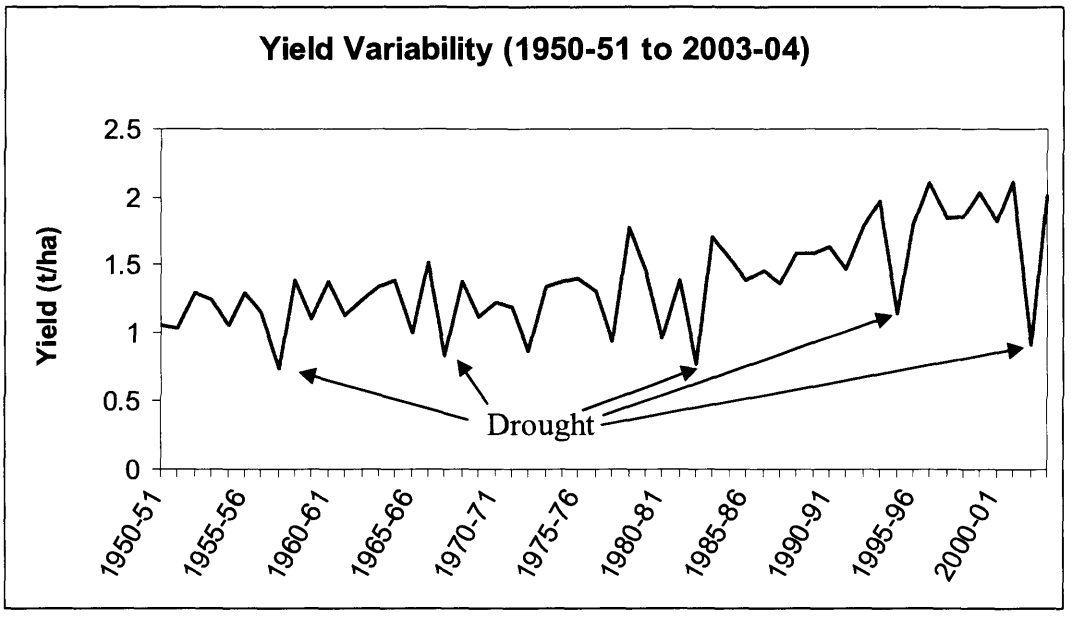
In general, for dryland agriculture, the likelihood of unfavourable and uncertain consequences can be calculated from historical data which usually has at least partial relevance to the future. Therefore, in an agricultural context, risk represents the probability of a "defined hazard" affecting the livelihood of producers (Angus 1991:39). The role of research in this context is to calculate the risk using probabilities with the best precision possible and presenting such risks as clearly and objectively as possible so that farmers' whose livelihood is affected can make informed decisions (Angus 1991:39). Agricultural commodities are biological in nature and, therefore, their production is depends on a variety of factors such as soil characteristics, soil fertility, climatic variation, weather, pests, diseases, varietal differences, planting conditions (including depth and planting rate), topography and aspect (Williams & Schroder 1999:78). This research focuses primarily on weather as a source of uncertainty and

changes in other factors are not addressed, although it is acknowledged that weather may interact with many other risk factors.

2.2.1 Yield risk

Climatic variability affects agricultural production primarily through its effect on yield. Variability in weather comes from changes in rainfall, temperature, frost, snow, humidity, sunlight and evaporation, although variability in rainfall is the dominant contributor to risk in crop production in most regions (Hutchinson 1991:55). Yield risk for Australian producers arises primarily from the variability of weather conditions which directly influences the variability of crop yields and the welfare of the farmer, with yields being highly correlated across regions (Simmons & Rambaldi 1997:157). Obviously, a farmer is more concerned about downside variability in yield, as upside movements in yield result in more grain and higher profits. Although yield and prices in many commodity markets are negatively correlated, Australia is a price taker for grain sold on the international market and so correlation of yields with profits is greater than it would be otherwise. This occurs because low yield in Australia does not induce high prices due to the relatively small proportion of Australian wheat in the international market. Thus low yields from Australian farmers often mean low profits.

Figure 2.1: Australian annual national wheat yield from 1950-51 to 2002-03.



Source: data obtained from ABARE 1995 and ABARE 2004.

Annual variability in Australian wheat yields using data from the Australian Bureau of Agricultural and Resource Economics (ABARE) is shown in Figure 2.1. The droughts in 1982, 1994 and 2002 each led to production of less than ten million tonnes, while the season following the 1982 drought season produced 22 million tonnes of wheat (Australian Wheat Board 2005 online). While this variability is due to a complex array of factors, weather conditions play a major part in determining yield. With specific regard to winter wheat grown throughout southern and southwestern Australia, 70-80 per cent of variability in yield is determined by spring rainfall which also affects grain quality (Holmes Sackett & Associates n.d.:2). A criticism of rainfall analysis as a determining factor of yield variability is that plant production is related mainly to water used and only indirectly to its supply (Angus 1991:40). However, from Figure 2.1, years in which supply of water was limited correspond to reduced yields thus showing, even if only indirectly, that rainfall affects yield variability. Figure 2.1 shows the gradual increasing trend in annual yield from technical improvements and shows that even with increased technology wheat yields are still subject to the vagaries of the weather.

Major droughts and floods in Australia cause environmental damage to the country as well as undermining the financial stability and profitability of farmers and the communities that rely on them. More than 80 per cent of profit generation in Australian broadacre agricultural operations occur in two years out of ten with the primary influence being weather (Rowe 1998:10). Variability in yield is also partially determined by temperature. The timing of the autumn break and the amount of spring rainfall are critical (Holmes Sackett & Associates n.d.:2), however, this information is not available when farmers make many of their production decisions. The optimal growing season to produce high yielding crops is one without water stresses during the generative and grain formation phases and with relatively low temperatures during the grain formation phase that maximises the duration of plant growth (Petr 1991:114; Ritchie 1991:104). Also, long exposure to air temperatures over 25°C leads to low yields and poor milling quality (Petr 1991:176).

One farmer has stated (A Wheat Farm 1994) that "weather is the nature of the game, you just have to accept the weather because you are a farmer; you can do nothing about the weather". While this comment is true from the point of view that a farmer cannot

change the weather, it fails to acknowledge that weather risk can be minimised in a variety of ways. Farmers over the centuries have been finding ways to minimise weather risk, even if their remedy for climatic variability may be purely to establish, on the basis of trial and error, a conservative farming system which provides a minimum livelihood in even the least favourable seasons (Angus 1991:47).

2.2.2 Price risk

Agricultural commodities are generally undifferentiated between suppliers and therefore farmers are price-takers as each farmer's produce cannot be distinguished from the produce of others (Williams & Schroder 1999:25). Over 80 per cent of Australian agricultural production is sold in a commodity form (Williams & Schroder 1999:25) and thus many farmers are susceptible to price risk due to their inability to influence or maintain prices.

Price risk is generated from unfavourable movements in the price of a commodity occurring between the time when the initial position is established and the conclusion of the commodity transaction (Williams & Schroder 1999:8). In the case of a wheat farmer, as soon as the producer is committed to planting he or she has taken a position in the market that is subject to price risk until the time of final cash settlement (Williams & Schroder 1999:8). Price risk is determined by the level of price instability which is in turn the result of several forces. Price risk for agricultural commodities can be caused firstly by inelastic demand from consumers combined with shifting supply (Williams & Schroder 1999:105) due to weather, production mix changes or farmer preferences.

Secondly, price risk can be caused by inelastic supply of agricultural products combined with shifting demand (Williams & Schroder 1999:105). This situation occurs when consumers are able to purchase alternative goods with ease but farmers may be locked into production and thus the level of production is fairly inflexible. Agricultural commodities have long production lead times and adjustments can take a number of years (Tomek & Peterson 2001:957). Sometimes a farmer may be unable to change the production mix at all due to limited information about suitable alternatives. Therefore, production is often fixed, at least in the short to medium term, while demand can shift to substitute commodities easily. There is often a high degree of price volatility associated with most agricultural commodities (Dunne 1999:168).

Thirdly, time lags between production planning and the realisation of production causes price risk (Williams & Schroder 1999:105). Farmers may estimate the probability of different prices for their commodity and come to a particular expectation based on prices at that time though there is no guarantee that their prediction will be accurate. Farmers may also assume that current price trends will continue into the future which may or may not happen. Often a farmer's expectation of future prices will influence his production decisions, so that his production follows prices, yet in many cases prices follow production (Williams & Schroder 1999:105) with farmers punished for overproduction with low prices. In this situation the volatility of prices will be higher. Lastly, price instability can be increased by the actions of speculators in commodity markets. If speculators respond to current price trends by buying or selling in anticipation of further price increases or decreases price instability may increase causing greater price risk (Williams & Schroder 1999:105).

2.2.3 Institutions to reduce risk

Variability in income results because farmers make decisions on actions before they know the outcomes and because outcomes are partially outside their control (Mishra 1996:8). Firms that are sensitive to weather risk have used a variety of methods to manage weather risk and to minimise the effects of price and yield variability on incomes, although the extent to which yield risk can be minimised is limited. History is full of examples of attempts to control or manage commodity prices (Williams & Schroder 1999:xix) and there are also examples of attempts to protect against yield risk.

A large range of schemes have been used to reduce price risk in agricultural commodity markets although some of the schemes did not have price stabilisation at heart, but rather were attempts to increase prices. Most of the schemes implemented occur at industry level either through industry bodies or government legislation. The first three of the schemes discussed below were designed to stabilise prices and hence reduce price risk while the remaining four schemes focused on raising prices received by farmers (Williams & Schroder 1999:114). The seven categories or types of stabilisation schemes summarised from Williams and Schroder (1999:107-114) are: (i) the reserve price which sets a minimum price floor above the currently trading market price for the commodity, or buffer stock schemes in which the relevant authority purchases the commodity to maintain the price at the required level; (ii) buffer funds which aim to

translate volatile market prices to a more stable price that is received by farmers; (iii) quotas that control the quantities farmers can produce; (iv) pooling where all revenues go into a central fund and then a net average cost is returned to growers after marketing and administrative costs have been subtracted; (v) price discrimination between markets for the same commodity such as a home consumption price scheme; (vi) supply diversion which is generally an ad hoc method where supply is either withheld or dumped into markets depending on the price; and (vii) tariffs or trade restrictions such as import quotas or customs duties.

The strategies and institutions used to reduce or mitigate weather risk can be broken into two broad categories. The first category is that of weather risk management which is carried out *ex-ante* and the second category is coping with weather risk which takes place *ex-post* (Mishra 1996:24). Weather risk management aims to achieve financial protection from weather conditions that adversely affect earnings. The solutions are designed to absorb an exact portion of the weather risk exposure leaving a residual risk that is commensurate with risk tolerance (Trueb 2003:5). Risk management includes activities that adjust or rearrange the use of resources to protect against future adverse events. This includes practices such as diversification both on- and off-farm (Mishra 1996:24) as well as obtaining insurance or using forward, futures and options contracts based on prices. Coping with risk involves smoothing income and consumption through activities such as borrowing or saving, and through pooled commodity markets (Mishra 1996:24).

The idea of diversification as a primary method of weather risk management is to reduce the risk to the overall return by selecting a mixture of activities that have net returns with low or negative correlations (Hardaker, Huirne & Anderson 1998:239). This may include diversification of production into several agricultural commodities, or diversification into unrelated products through the real estate, financial markets, stock exchanges or off-farm employment. Diversification into other agricultural commodities on-farm may only slightly reduce overall risk as output of these commodities is often highly correlated with adverse weather conditions affecting all outputs. In addition, as the number of diversified commodities increases it becomes more difficult to devote sufficient time to transfer price risk for any of the commodities (Williams & Schroder 1999:17). Nonetheless, a survey of Californian agriculture showed almost half of

producers use diversification as an indirect risk management tool (Blank, Carter & McDonald 1997:104). A possible opportunity for weather risk management in agricultural commodity diversification is to diversify spatially over a sufficiently wide area to reduce positive correlations due to weather effects (Hardaker, Huirne & Anderson 1998:239). Davis et al. (1997 cited in Just & Pope 2003:1250) find that correlation of peach yields decreased 2.28 per cent for each mile of geographical separation. However, spatial diversification adds to the complexity of farming and may actually result in increased risk if the farmer is pushed beyond his competency and knowledge base (Abadi Ghadim & Pannell 2003:116). Diversification into investments off-farm may provide an effective risk management tool (Hardaker, Huirne & Anderson 1998:240) but even the performance of some equities are correlated with weather. In Australia, a substantial portion of farm household income is received from non-farm sources. The cropping industry had average off-farm income per farm of 23.6 per cent and 10.8 per cent in 2002-03 and 2003-04 respectively while the mixed livestock and cropping industry had average off-farm income per farm of 45.4 per cent and 34.2 per cent in 2002-03 and 2003-04 respectively (Martin et al. 2005:10-11). Allocation of labour resources to off-farm employment may reduce variability in farm incomes and may allow farmers to maintain a specialisation in the agricultural commodities where they have greater efficiency. This can provide higher average returns and some insurance against price and weather risks (Abadi Ghadim & Pannell 2003:116). On the other hand, it has been claimed by Williams and Schroder (1999:18) that diversification into off-farm income does not provide the incentive, motivation or time to effectively manage price risk.

Insurance institutions have been used by farmers for decades to protect themselves against unexpected adverse events such as physical injury or death, fire, hail and floods. As an institutional response to agricultural risk, comprehensive crop insurance aimed at stabilising farmers' incomes began to develop over a century ago although public sector involvement was a later development (Mishra 1996:1-2). The Bureau of Agricultural Economics (1986:5) in 1986 noted a number of institutional and technical impediments to the provision of crop insurance by private companies. The impediments included correlated risks, high administrative costs, limited remote area sensing, ad hoc disaster relief and lack of crop insurance experience. Many of these impediments have either been removed or reduced, although the use and effectiveness of these crop insurance

schemes has varied over the years. In general, crop insurance can be useful if fluctuations in income are primarily due to variation in yield (Mishra 1996:34). However, crop insurance is still plagued by problems and as a result crop insurance schemes often require generous subsidies from governments if they are to continue to exist. The experience of the US is that despite significant subsidies and expanded coverage by the US government, crop insurance participation grew slowly and the government was still required to pass ad hoc disaster assistance legislation to cover droughts (Glauber 2004:1179). A more recent development in the crop insurance literature is that of area-yield insurance where the premium and indemnity are determined for a group of farmers. This provides an alternative design for crop insurance programs (Mishra 1996:49).

The social welfare issues associated with weather risk can be substantial and the Australian government has also responded on numerous occasions to extreme climatic events with Exceptional Circumstances Packages. Such disaster assistance assists farmers with long-term viability prospects to cope with short-term adverse events beyond their control (AFFA 2004:3).

Other mechanisms used to reduce price risk or hedge risk are forward contracts to "lock-in" prices for the commodities when farmers are in the production stage and transfer price risk to the buyer. When commodity prices rise, such forward contracts limit the ability for the farmer to receive increased profits (Williams & Schroder 1999:126). Forward contracts sometimes make farmers vulnerable to variations in yield or quality that make it difficult for farmers to deliver the promised commodity to the contracted buyer (Williams & Schroder 1999:136). The use of futures contracts and options contracts are also available as risk management tools for farmers although many farmers never hedge in these markets (Tomek & Peterson 2001:967). Trade in options contracts on agricultural commodity futures contracts began in 1984 in the US (Tomek & Peterson 2001:960). Their limited use by farmers may be due to a perception that futures and options contracts are risky (Tomek & Peterson 2001:964), or the price risk tools offered are not meeting their needs (Blank, Carter & McDonald 1997:104). Just and Pope (2003:1251) suggest that hedging with commodity futures and options is not a perfect insulator from risk due to the effects of basis and production risk, distance from central markets and other transactions costs. Whatever the reason, agricultural options

and futures contracts often have a low trading volume, one study showed that only 6.2 per cent of farmers use this type of hedging for price variability (Blank, Carter & McDonald 1997:104). Futures and options when used by farmers should not be a tool for generating profit but rather for offsetting reduced prices. Most futures and options contracts are closed out before delivery so that losses in the physical market mean gains in the futures market and vice versa (Williams & Schroder 1999:148,212).

2.3 Background to weather derivatives

2.3.1 What are weather derivatives?

Weather derivatives are a group of relatively new financial instruments that provide a means of managing exposure to changes in weather through capital markets. They offset the adverse effects of weather and consequent impact on sales, expenses and profits (Aquila 2000 online; Vinning 2000:310) by providing a payout based upon weather indices. Weather derivatives transfer climatic risk associated with fluctuation in the weather and climatic system (Werner 2000 online) from firms wishing to minimise weather related risk to firms either more able or willing to accept the risk in return for a premium. There are many hedging tools designed to protect those engaged in physical transactions in commodities against adverse price movements (Atkin 1989). Weather derivatives, on the other hand, provide protection to the buyer of the contract against weather-related changes in quantities (Campbell & Diebold 2002:1) by hedging weather-related volumetric risks. While weather derivatives directly hedge only volume, as quantity and price can be closely related to each other (Yoo 2003:1) they may also have an indirect effect on price risk.

2.3.2 History of weather derivatives

The weather derivative market originated primarily with deregulation of the United States energy market which resulted in demand for weather risk management tools to hedge against losses for energy distributors from weather. These firms saw potential efficiency gains from new ways of managing risk. Theoretical weather derivatives were designed in late 1996, with the first weather derivative trade occurring as an Over-The-Counter (OTC) degree-day swap transacted by Enron and Koch in September 1997 (Platts 2001 online). The market grew as more firms experimented with the new

instrument and in September 1998 the first international weather transaction took place, a degree-day swap traded between Enron and Scottish Hydro-Electric to protect Scottish Hydro-Electric against a warm winter in the UK (Platts 2001 online). In September 1999 the Chicago Mercantile Exchange (CME) introduced degree-day swaps for ten US cities which increased the size of the market and reduced the credit risk involved with trading weather contracts (Yoo 2003:1). By 2000 "some 1600 deals worth approximately $3.5 billion had been undertaken in the USA" (Nelken 2000:2). The CME was followed by several other exchanges that also added weather derivatives to their list of traded instruments, although with mixed results. In December 1999 I-WeX, a London based consortium including the London International Financial Futures and Options Exchange (LIFFE), added contracts based on temperature in London, Paris and Berlin (Cooper 2004:6; Platts 2001 online). The I-Wex temperature instruments were delisted in September 2003 as very low volumes traded. The Helsinki Stock Exchange added temperature-based derivatives in August 2002 but after a disappointing failure to trade the derivatives were delisted in March 2004 (Cooper 2004). The Tokyo International Financial Futures Exchange (Tiffe) intends to launch weather derivatives based on average monthly temperatures in four Japanese cities in spring 2005. The Tiffe launch follows expansion of the CME to include monthly and seasonal weather futures and options based on average daily temperatures in Tokyo and Osaka as well as a range of European based contracts (Cooper 2004:6). The CME has also expanded the range of traded weather derivatives globally with a current offering of eighteen U.S. cities, nine European cities and the two Asia-Pacific cities located in Japan (CME 2005a online). The New York Mercantile Exchange (Nymex) is also considering the addition of weather derivatives to their existing range of oil, gas and electricity contracts (Cooper 2004:6). However, despite the poor trade by LIFFE and Helsinki, trade in CME U.S. temperature-based contracts has grown, now trading around 4,000 contracts monthly, while the European based contracts trade around 265 per month (Cooper 2004:6). A survey conducted by Price Waterhouse found that the US market has grown to a $4.2 billion notional market value in 2001 (Evomarkets 2003b online).

Australia traded its first known official weather derivative in 2000, purchased by Southern Hydro Partnership in Melbourne (AFMA 2002:3). Trade in weather derivatives is still low in Australia with most trade undertaken by energy or hydroelectric firms. In 2002 the Australian Financial Markets Association (AFMA

2002:3) estimated that over 25 deals had been carried out by Australian counterparties and that the average nominal value of risk transferred in these trades was A$1 million. The market in Australia remains illiquid as there are no secondary markets in which risk can be offset or contracts closed, so options are held to maturity and cash settlement occurs the day following maturity of the option. The Australian market received a minor setback with the collapse of Enron Energy but other market makers have since emerged. A survey undertaken by Systma and Thompson of R.J. Rudden Associates Inc. (2002:7) found the collapse of Enron and other smaller energy merchants in the U.S. market appeared to actually "increase instrument liquidity and expand availability of products".

The number of companies directly involved with weather derivatives in Australia is growing although many of these firms would consider their commitments as experimental. Firms currently involved in underwriting weather derivatives in Australia include the National Australia Bank and the Deutsche Bank with many other interested players.

2.3.3 How do weather derivatives operate?

The majority of weather contracts traded to date have been based upon temperature, reflecting the dominance of energy firms in the market. However, there has also been a smaller volume of trade in contracts based on precipitation, snowfall, humidity, frost, streamflow or sunshine (Campbell & Diebold 2002:1).

Most contracts have many aspects in common: they are written on a calculated weather index relating to a measurable weather trait with measurements from a recognised independent weather recording station, an agreed strike index level and an agreed tick rate. The strike index level is the point at which the weather derivative will begin to payout and the tick rate is the agreed payout per index increment.

Temperature derivatives may be based on a temperature index or on actual temperature. Most commonly, the contract is based upon an index of degree days while the alternative is to base the derivatives on absolute maximum or minimum temperatures (critical day contracts). These are discussed further below. Precipitation, frost and snowfall derivatives are based on actual quantity of each respective element received.

These contracts can be structured to make a payout if there is too little or too much precipitation during a pre-determined period, or similar to the critical day structure, they can payout if there is too little or too much precipitation on a predetermined date. Frost contracts are generally structured to payout if there are more than a certain number of frosts in a pre-determined period.

There are three types of degree day indexes calculated using the average daily temperature: Heating Degree Days (HDD's), Cooling Degree Days (CDD's) and Growing Degree Days (GDD's). In lay-person's terms, heating degree days occur on a calendar day on which people heat their homes, thus generally occurring during the winter months of the year. They are defined as the difference between 18°C and the average temperature on each calendar day (18°C – average daily temperature). On the other hand cooling degree days usually occur during the summer months, calendar days when people cool their homes and are defined as the difference between the average temperature on the day and 18°C (average daily temperature – 18°C). Growing degree days can be used by farmers to specify the number of calendar days where average temperature falls within some predetermined temperature range or above some baseline temperature favourable to crop growth or development (Garman, Blanco & Erickson 2000:2; Corbally & Dang 2002a:92).

The base temperature of 18°C used to calculate HDD's and CDD's was determined by the energy market as the neutral temperature. At this point consumers are expected to neither heat nor cool their homes. Although this temperature is widely accepted as the base temperature, a different base temperature would need to be determined in some climates so that energy use correlates better with HDD's and CDD's. The baseline temperature or temperature range in a GDD contract is explicitly defined since different crops have specific development thresholds and temperatures that must be reached in order for growth to occur (Corbally & Dang 2002a:92). In the US the baseline temperature for wheat is 4.44°C so if average daily temperature is below 4.44°C crop production is inhibited (Corbally & Dang 2002a:93). The total numbers of HDD's, CDD's and GDD's per calendar day are calculated as follows:

$$HDD = max\{18 - W, 0\}$$

$$CDD = max\{W - 18, 0\}$$

$$GDD = max\{W - baseline, 0\}$$

where W = daily average temperature calculated as the average of daily high and daily low temperatures and where *baseline* is the threshold temperature necessary for plants to grow (Nelken 2000:2; Corbally & Dang 2002a:92). For example, let the baseline temperature for wheat growing degree days be 5°C. If average temperature at the weather station on a particular day was 10°C then:

$$HDD = max\ \{18 - 10, 0\} = 8\ HDD's$$

$$CDD = max\ \{10 - 18, 0\} = 0\ CDD's$$

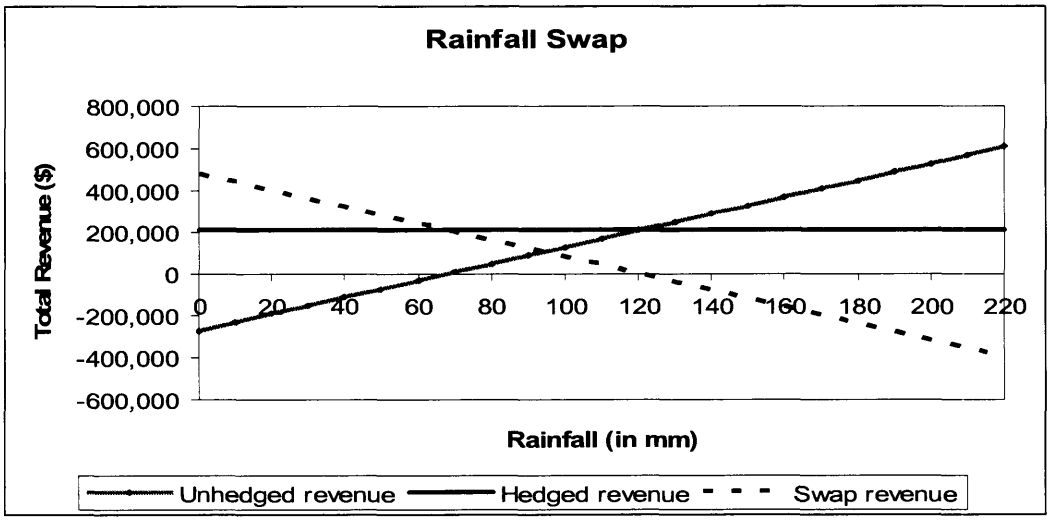
$$GDD = max\ \{10 - 5, 0\} = 5\ GDD's$$

giving eight HDD's, zero CDD's and five GDD's. If average temperature for the calendar day was 24°C, there would be zero HDD's, six CDD's and 19 GDD's.

The basic building blocks of weather derivative contracts include swaps, European options and futures, with the most common types of contracts traded being floors, caps, collars and swaps (AFMA 2002:6). Swaps and options were previously the only forms of weather derivatives through the OTC market, however commencement of the CME weather derivatives exchange introduced weather futures. In the weather derivative literature, swaps have a slightly different meaning to that of a swap in the financial literature. A swap is a financial contract used by two firms with opposite definitions of adverse weather to reduce the consequences of the weather on both parties (Vinning 2000:312). A swap requires a company to make a payment when a weather index rises above (falls below) a particular strike level, and entitles it to receive a payment when the index falls below (rises above) the same strike level. A company may thus be a payer or receiver, depending on the movement of the index (Corbally & Dang 2002b:112). A 'fair' swap will have an equal payout to both sides on average (Entergy-Koch 1998:9). Therefore, the two firms share the weather risk equally so no up-front premium is charged for this financial instrument (Zeng 2000:73). While this may seem like an efficient way for firms to manage risk, some authors suggest firms are in fact unwilling to enter into swap contracts for the following reasons (Corbally & Dang 2002b:113; Vinning 2000:312). First, an end-user is required to find a counterparty willing to enter into a swap at, or better than, a specific index level. Second, an end-user is likely to want to preserve the opportunity of upside potential in earnings if the weather is very favourable. Third, the correlation between weather and volume is rarely perfect and so may result in an inappropriate payout.

Assume that an end-user has decided to use a swap to hedge against insufficient rainfall during the growing phase of a wheat crop. If the end-user knows that the average historical rainfall during the growing season is 120mm, and he or she wanted to protect losses in revenue due to insufficient rain and wanted to minimise any premia payable, they could enter into a swap contract with the strike at 120mm. Therefore, as shown in Figure 2.2, the end-user has removed all volatility in revenue caused by weather variability in this phase of crop development. As long as other sources of revenue risk are absent, the end-user has set his or her revenue constant at $210,000. To achieve this result he or she receives payment when rainfall is less than 120mm and makes a payment when rainfall is greater than 120mm. This simple example ignores any loss the farmer may incur if an excess of rain occurs and the crop is ruined as a result.

Figure 2.2: Rainfall swap

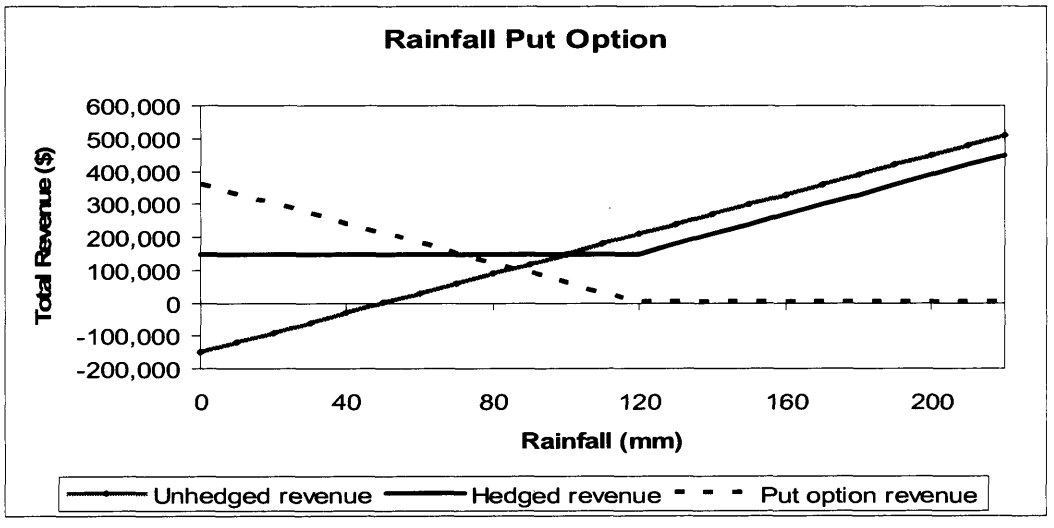


Adapted: Corbally and Dang 2002b:109

Weather options also have some differences to other financial options. In most situations, an option is a contingent asset or liability whose value at any given time is related to the price of the underlying instrument (Vinning 2000:312). However, unlike derivatives linked to the underlying price of an exchange-traded commodity, weather derivatives are linked to weather indices instead, such as temperature or rainfall. This distinction is important since weather cannot be traded (AFMA 2002:5). To obtain a value for these indices, a dollar amount called the tick size, is associated with each degree day or millimetre in the payoff calculation (Garman, Blanco & Erickson 2000:3). A weather put option is a financial contract that grants the purchaser the right to sell an

underlying index at a pre-specified strike and in exchange for this right the purchaser pays the seller a premium (Corbally & Dang 2002b:106-108). In this situation the seller agrees to pay the purchaser if the weather index is lower than the pre-determined strike (Zeng 2000:73; Cogen 1998 online) effectively establishing a floor for revenue without limiting the ability to take advantage of upside potential. Following the example used to illustrate the swap, end-users may be unwilling to release all possibility of increased revenue if the weather events are favourable. So instead, such end-users purchase a put option despite being required to pay a premium. This contract would have the same strike of 120mm and the same tick but leaves upside potential intact. Figure 2.3 shows that below the strike of 120mm the farmer's hedged revenue is constant at $150,000 and above strike the hedged revenue increases as the weather becomes more favourable. If rainfall during the period is below strike the farmer receives a payout and if rainfall during the period is above strike, the put option does not payout and the farmer forfeits the premium.

Figure 2.3: Rainfall put option

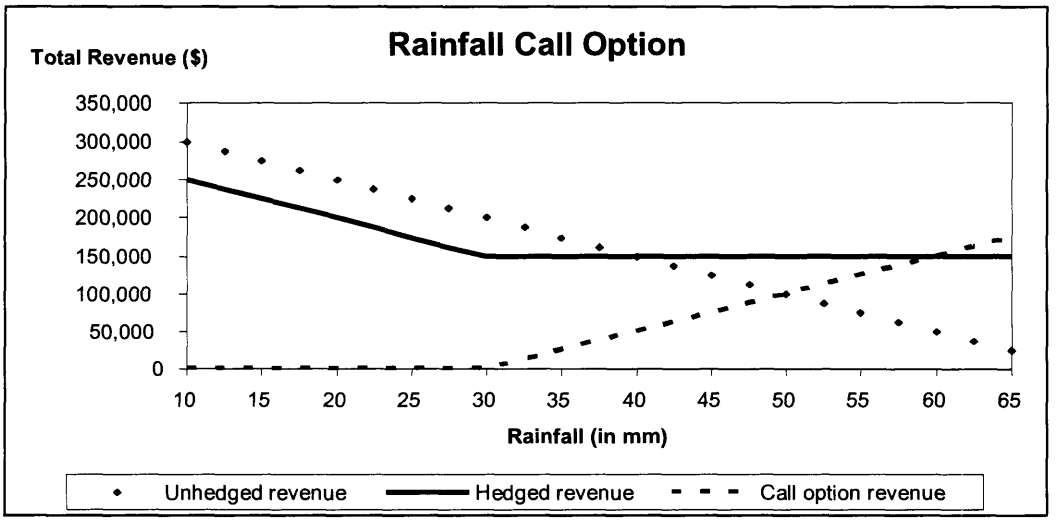


Adapted: Corbally and Dang 2002b:109

On the other hand, a weather call option is a contract that grants the purchaser the right to buy an index at a pre-specified strike in exchange for an up-front premium (Corbally & Dang 2002b:106-108). In other words, the seller or underwriter agrees to pay the buyer if the underlying weather index is greater than the pre-determined strike (Zeng 2000:73). This effectively caps the firm's costs and provides upside protection without limiting the firm's ability to take advantage of downside movement in the index. To

demonstrate the use of a call option assume the farmer discussed previously has a bumper crop heading towards harvest and wishes to hedge against the possibility of above average rain in the period before harvest. He or she purchases a call option with a strike of 30mm (Figure 2.4). This allows the farmer to benefit if there is little rain before harvest and so he harvests a good quality, high-yielding crop, forfeiting only the premium he paid for the call option. Conversely, if before harvest rain is greater than the strike of 30mm, the farmer is compensated by the option and so revenue is guaranteed at $150,000.

Figure 2.4: Rainfall call option

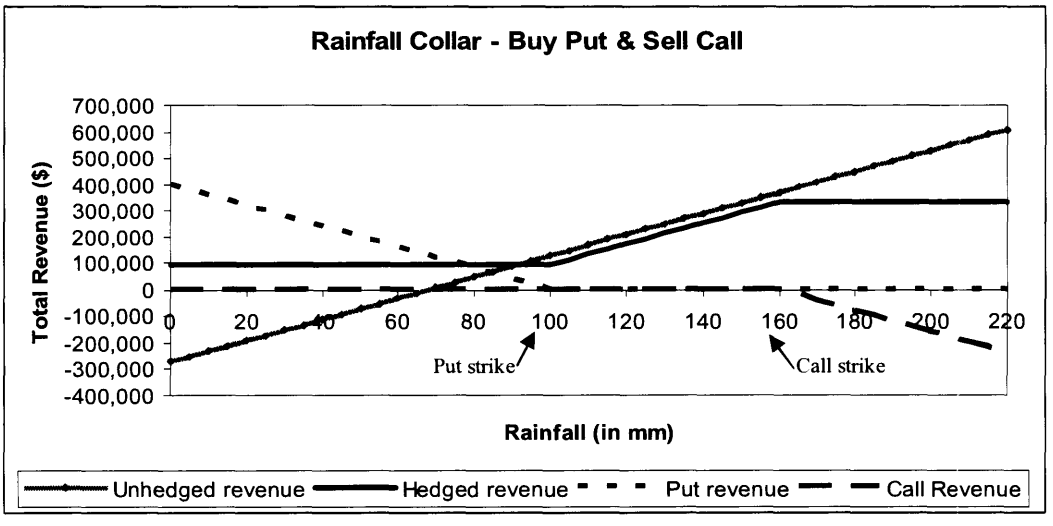


Adapted: Corbally and Dang 2002b:107

A collar is a combination of a call option and a put option and would generally be entered into as a means of reducing the up-front premium payable by the purchaser of a put option providing downside risk protection. To reduce the premium, the firm can consider various alternatives, such as setting the strike at a lower level so the firm retains more risk before the weather derivative put option pays out. Another option for the firm to reduce the premium due is to reduce the tick size payable thus reducing the maximum potential payout. This may lower the premium, but also means the contract will not provide as good a hedge for the weather risk. The third alternative is for the firm to sell a call option after it purchases the put option (Corbally & Dang 2002b:110). This type of collar can be constructed so the premiums cancel out, a zero-cost collar. Similarly, if the firm only wishes to partially offset the put premium, the call option call can be constructed with either a smaller tick size or with a strike set further away from

the long-term mean (an asymmetric collar). Figure 2.5 demonstrates the operation of such a collar. Assume the farmer previously discussed wants to hedge the risk of insufficient rain during the growing period, but is willing to forfeit some proportion of upside potential in order to reduce the premium paid. As before, the farmer purchases a put option to provide the hedge for insufficient rain, but now also sells a call option to reduce the premium required. If the farmer decides an asymmetric collar will best suit the situation, so remembering that mean rainfall during the growing period is 120mm, the put strike is set at 100mm. Thus there is acceptance of the risk of 20mm below average rain before receiving any payouts from the contract. However, the farmer is less willing to give up the benefits from above average rainfall during the period. Therefore, a decision is made to set the call option strike 40mm above the mean at 160mm. With the same tick levels for both options, when rainfall is below 100mm he receives payments and so revenue is constant at $95,000 and when rainfall is above 160mm payments are required and so revenue is constant at $335,000. Thus in practice, a collar achieves a similar position to a swap but with greater flexibility.

Figure 2.5: Rainfall collar



Adapted: Corbally and Dang 2002b:111

The payoffs from these options can be calculated with a simple formula that follows on from the method for calculating the number of HDDs and CDDs. The payoff for a call option irrelevant of the underlying variable (rain, temperature) is the amount of dollars per unit (the *tick*) multiplied by the maximum of either zero, or the total number of the

underlying weather variable, *weather*, minus the *strike* (Garman, Blanco & Erickson 2000:3).

$$Payoff\ Call:\ tick \times \max(0, weather - strike)$$
$$Payoff\ Put:\ tick \times \max(0, strike - weather)$$

Most weather derivative contracts are capped at some predetermined level to reduce the risk that extreme weather would cause to the position of the underwriter (Alaton, Djehiche & Stillberger 2002:17). The payoff formula with a cap then becomes (Garman, Blanco & Erickson 2000:3):

$$Payoff\ Call:\ Min\ [(tick \times \max(0, weather - strike)), mp]$$
$$Payoff\ Put:\ Min\ [(tick \times \max(0, strike - weather)), mp]$$

where *mp* is the maximum payout allowed in the contract.

The variety and diversity of possible weather derivative contracts is vast as the majority of weather derivatives are formed as individualised contracts and constructed to hedge specific risks of firms throughout a range of industries. Other weather derivative contracts may be based on Growing Degree Days (GDD's); absolute temperature otherwise known as critical day contracts; precipitation; snowfall; frost; wind and streamflow. The market has not embraced GDD's so much but this may be due to current market focus on utilities as well as similarity between GDD and CDD contracts. Considine (n.d.: 3) claims that due to this similarity standard weather contracts could be used to hedge commodity volume and in agricultural production systems. Critical day contracts have applications as a risk management tool for special events organisers (outdoor concerts), retail outlets and the hospitality industry, as these contracts allow the firm to hedge against extreme temperatures, an example of which is detailed in Section 2.3.4. These contracts can be designed to payout for an individual day or number of days that the temperature is above (below) some pre-determined level. Critical day contracts can also be designed based on rainfall, snowfall or frost.

The discussion to this point has concerned individually negotiated over-the-counter (OTC) contracts; however, there are some exchange traded contracts available on the Chicago Mercantile Exchange (CME). The CME offers futures and options contracts trading on their exchange based on the CME Degree Day Index which is the cumulative sum of daily HDDs or CDDs during a calendar month (Alaton, Djehiche & Stillberger

2002:4). The CME Degree Day Index is calculated in the same way as the degree day indexes used in OTC contracts although they are only currently specified for eighteen US cities, nine European cities and two Asia-Pacific cities (CME 2005a online). HDD/CDD Index futures operate the same way as futures in any other underlying commodity. The seller (purchaser) of a HDD/CDD Index future agrees to buy (sell) the value of the HDD/CDD Index at a specific future date (Alaton, Djehiche & Stillberger 2002:4). The notional value of one contract, or tick size, is $20 times the Degree Day Index. The futures contracts are quoted in terms of HDD/CDD Index points and cash settlement occurs after the final marking-to-the-market based upon the HDD/CDD Index with the final gain or loss applied to the customer's accounts (CME 2005a online). The popularity of traded weather futures has rapidly increased in the U.S. with the market taking off in the first half of 2002. It has continued to grow. Yet while overall market size has increased rapidly, the usefulness of these contracts to some sectors is minimal, especially the agricultural sector. As the futures contracts are solely temperature based, they are more useful for insurance companies, banks, hedging funds, utilities and as a method of speculating. This is because the contracts trade index points rather than the actual outcome of the weather. So, any firms can use these CME Weather Futures as a form of diversified investment, regardless of whether or not their business is affected by weather fluctuations.

2.3.4 End-users of weather derivatives

There is potential for firms in many sectors of the economy to use these new financial instruments in their risk management strategies. Potential users and current players in the weather derivative market are energy companies, agricultural firms, construction firms, manufacturing, gas and oil distributors, offshore operations, beverage industry, tourism, retailers, transportation, local government, and special events organisers (Evomarkets 2003a online). As weather derivatives can be structured individually they may suit a wide range of end-users, however, growth in this market requires firms to identify the impact of the weather on their revenues, costs and profits (Vinning 2000:317). Some examples of potential uses are now examined from known or possible contract specifications.

Agriculture faces many risks from weather and weather derivatives could provide a solution to the ensuing risks. Weather derivatives can stabilise an income stream made

inherently unpredictable by the weather (AFMA 2002:7). Two potential users of weather derivatives are discussed here, for wheat and dairy producers, although contracts could be negotiated for most agricultural commodities. Wheat producers require sufficient quantity of rain before sowing and during the growing phase to enable optimal wheat growth. Then during the maturing and harvesting phases rain is detrimental to quality as it lowers protein and increases moisture in the grain. This reduces grain value and increases the likelihood of rust formation or sprouting. If rainfall is the only variable affecting yield, a weather derivative can be structured to compensate the farmer for lost revenue from reduced yield due to unfavourable rainfall and may be designed to cover any part of the wheat growth or harvest stages. Consider a contract hedging yield loss from insufficient rainfall during the growth stage where each millimetre less rain than expected reduces yield. The farmer purchases a put option with a tick payout of $5,000 per millimetre for each millimetre under 110mm during the specified time period. If rainfall during the period was 60mm, the weather derivative would payout $5,000 x (110 – 60) = $5,000 x 50 = $250,000 which compensates for lower crop yield profit due to reduced yield. If rainfall during the period was 125mm, the weather derivative contract would not payout, and the farmer receives sufficient income from his crop to cover the cost of the premium. This farmer could alternatively negotiate a contract based on temperature or a combination of temperature and rainfall (AFMA 2002:7). Another example of weather derivative use in agriculture could be in a dairy situation. Dairy production is adversely affected by hot humid weather which reduces both quality and quantity of milk produced (Chen, Roberts & Thraen 2003:1). A call option purchased based on a temperature-humidity index could account for incremental changes in milk yield. The tick rate is determined and the farmer receives payouts if the index value increases above the strike which offsets any losses incurred from loss of milk quality or quantity. Other agricultural examples of weather derivative use include corn, soybeans and hay (Turvey 2001), cotton (Martin, Barnett & Coble 2001), and nectarines (Richards, Manfredo & Sanders 2003).

Energy companies face weather risk from unanticipated changes in temperature which affects their profitability. These risks can be attributed to differences in actual temperature from forecast temperature or to sudden extreme temperature shifts up or down. Temperature is usually described using a degree day index calculated using an

appropriate baseline for the particular site. To hedge against a reduction in energy sold due to a mild winter an electricity distributor could purchase a put option to payout when the heating degree day (HDD) index falls below strike. If strike is set at the regional average of 300 HDD's in the period 1st June – 31st July calculated from historical weather data and the tick is set at $7,500 per degree day and payout capped at one million dollars, then the firm has transferred the risk of below average energy sales to an external party. Some risk is still retained by the firm if the winter is extremely mild, the risk that the total number of HDD's will fall below 133 (a payout of one million dollars) which will cause loss in profits.

Other industries such as the beverage industry can also be affected by unfavourable weather events, even if they are anticipated. An example of the susceptibility of the food and beverage industry's profit to unfavourable weather is demonstrated by pubs, restaurants and café's relying on outdoor dining to attract customers. Poor weather discourages customers from visiting these establishments and so profits are reduced. Corney and Barrow, a group of bars in London experienced a drop in clientele if the temperature fell below some threshold during summer as people chose to go home instead of meeting friends after work to socialise. To compensate for this drop in revenue from cold summer afternoons the bars negotiated a critical day weather derivative that paid out a determined sum (£15,000) each day the temperature fell below the threshold (24°C) on a Thursday or Friday between June and September (Saunderson 2000 online). Another pub, the White Swan in London has negotiated a contract to receive a payout if the temperature on Friday and Saturday nights does not fall within an agreed temperature range (Artemis 2000 online).

Weather derivatives can also be used for one-off events such as agricultural shows or sporting events where people purchase tickets at the gate. These events are generally outdoor events and are often at the mercy of the weather. Concerts, tradeshows, field days or agricultural shows may purchase a call option to limit potential losses arising from adverse weather and associated reduced customer interest. The call option could be negotiated to payout if there is greater than 5 mm rain on the day of the event and the tick determined with respect to demand for entry into the event. In the case of rain, the event organiser could receive a payout compensating for reduced ticket sales.

Some current or past end users of weather derivatives throughout the world include: Peoples Energy, Atmos Energy, NICOR Inc., Madison Gas and Electric, SMUD, Vattenfall, Southern Hydro, Heating Oil Partners, Innergy, Innogy, Tokyo Gas, Star Gas, Osaka Gas, Griffith Consumers, Washington Gas and Electric, Energy East, Keyspan Energy, Nova Scotia Power, Centrica, Scottish Power, Tokyo Electric, AFSC (Trueb 2003:10), Massive, and Corney Barrow. Despite growth in the market as a whole and the end-user base, there remains a dominance of energy companies within the market. Weather derivatives may be more attractive to businesses that have previous experience with other types of financial options and futures (Considine n.d.:1) as they already possess much of the knowledge associated with these types of instruments.

While weather derivatives can be used purely for speculative purposes, in general end-user firms use weather derivatives to protect against adverse changes in various external factors and to smooth cash-flow. With regard to the opposite, or underwriting, position in contracts, it is insurance companies, commercial banks, investment banks, large energy companies and trading companies that are generally interested in underwriting weather hedges using custom OTC contracts based on weather statistics (Cogen 1998 online). These institutions all maintain large portfolios of diverse risk investments which offset risk obtained through the weather. However, Trueb (2003:8) claims there exists a supply and demand imbalance because hedgers tend to take the same side of the market. The Australian Financial Markets Association (AFMA) research opposes the Trueb claim by stating that although the weather derivative market was initially driven by energy companies, the increasing trend is for highly rated banks and insurers to provide weather derivatives to their diverse client base, utilising their strong balance sheets and risk management expertise (AFMA 2002:8). Many companies have also exited the market due to credit concerns, including: Aquila, PG and E, Reliant, Dynegy, El Paso, and Commercial Risk (Trueb 2003:7), although there is still a strong and growing base of firms willing to accept weather risk. These firms include ABN AMRO, ACE, Crédit Lyonnais, Deutsch Bank, Société Générale (Stoppa & Hess 2003:3), CDC Ixis, Swiss Re, XL Weather and Energy (Saunderson 2004:14-15), Entergy-Koch Trading, Goldman Sachs, GuaranteedWeather, Hess Energy and Trading Company, Partner Re, Rabobank, Renaissance Re (Trueb 2003:9), AXA Re, Cargill and the National Australia Bank.

2.3.5 Crop insurance vs. weather derivatives

Traditional forms of risk management for cropping enterprises have been discussed earlier in this chapter. Farmers have developed their own styles of risk management over the years. This discussion will focus on the differences between traditional crop insurance and weather derivatives.

Crop insurance is based upon the concept of risk pooling. When insurance companies pool risk they are using the natural variability in risk between different farmers and locations to lower their overall risk exposure. The idea is that each farmer faces risk, some of this risk is diversifiable and some is not. The law of large numbers says that if n identically distributed and independent incomes are pooled, the variance of average income approaches zero as n approaches infinity (Mishra 1996:39). Insurance companies use this principle to minimise their systemic (uncorrelated) risk through pooling, where a large number of individual farmers contribute premiums to a common fund that is then used to pay the claims of any one individual in the pool. The insurance company is willing to accept the farmers' risk as the total risk is averaged among a large number of producers so the insurer has diversified the non-systemic (uncorrelated) risk across the insurance pool (Goodwin & Smith 1995 cited in Harwood et al. 1999:49). Each individual farmer has effectively shared their risk in the pool, thus the individual farmer has the same expected income as before but the cost of each farmer's risk is reduced as the pool size increases (Mishra 1996:39). These pooling systems work because they make the assumption that only a small proportion of the insured farmers make a claim at any one time.

Problems with the pooling system can occur in areas with high systemic risk as adverse weather events usually affect yields over a large geographical area and a large number of farmers can make claims on the insurance fund simultaneously. In addition, yields from other crops and livestock may also be affected by the adverse weather event which increases the amount of financial damage to the region and subsequently the volume of insurance claims upon the insurer which can cause the fund to collapse. Policies are priced using an actuarial process to determine the expected payout based on historical weather data. However, to minimise the possibility of an insurance fund being over-committed financially, firms often charge premiums above the actuarially fair price. Farmers pay a premium substantially more than the expected loss without insurance.

For this reason Hardaker, Huirne and Anderson (1998:244) note that insurance will usually only be attractive to risk averters and then only for risks that are sufficiently serious to warrant paying the high premium. So generally a farmer will only justify the premium expenditure on insurance contracts for extreme events with a low probability of occurrence, as costs are often inhibitive for smaller risks. These extreme events are large risks that 'could threaten the continued existence of the farm business or that could seriously damage the welfare of the owners' (Hardaker, Huirne & Anderson 1998:244).

The long history of attempts to increase the proportion of US farmers participating in crop insurance programs reveals that demand for crop insurance is small without subsidised premiums (Glauber 2004:1191). In addition to overpricing of insurance contracts to mitigate against systemic risk, a farmer must also suitably satisfy other requirements to receive a payout from his insurance contract in the event of adverse weather. Firstly, under the individual approach the assessment of indemnity is made separately for each insured farmer (Mishra 1996:49). To qualify for a payout under this type of contract a farmer must be able to prove he has suffered a financial loss from adverse weather to be compensated (Alaton, Djehiche & Stillberger 2002:6). He or she must be able to prove that the low yield of the crop was caused specifically by adverse weather. In some situations this is difficult and in all situations must be time-consuming and possibly bureaucratic. Secondly, insurance contracts may require the farmer to pay a deductible or excess if the insured event occurs thus the individual claiming on their insurance must assume a portion of the value of the loss before the company will payout. The deduction offsets some of the insurer's systemic risk due to the high correlation of yields among individual farms, in addition to charging a high risk premium (Mahul 2001:593).

The widespread use of crop insurance as a risk management tool is also limited by market failure (Mishra 1996:41). This failure is due to asymmetries in information held by the insured and the insurer. Crop insurance contracts may be susceptible to manipulation and corruption by the insured. In agricultural insurance schemes the asymmetries are pronounced and a substantial volume of work has discussed these problems (Harwood et al. 1999:49; Newbery & Stiglitz 1981:165-66). The first problem is moral hazard which occurs when insured individuals do not take the appropriate level of care of their crop because they no longer have any incentive to do

so after buying insurance. Their actions may increase the underwriter's exposure to risk (Bureau of Agricultural Economics 1986:2). Glauber (2004:1185) reports some previous studies on moral hazard found differing results on the behaviour of farmers after purchasing crop insurance. One study of corn producers concluded that farmers acted with integrity, while another study found that farmer's input use tended to decline after purchasing crop insurance. The problem of moral hazard is difficult to overcome in a cost effective manner, and most attempts to control it by insurance companies have focused on increased monitoring of farmers behaviour (Bureau of Agricultural Economics 1986:2; Glauber 2004:1185). The second problem is adverse selection which occurs when a farmer has more information about the risk of loss than the insurer does, and so the insurer is unable to discriminate between clients with different risk levels (Bureau of Agricultural Economics 1986:2; Harwood et al. 1999:49). If it is not possible for the insurer to discriminate between farmers who represent different insurable risks, then producers who are able to determine that their expected indemnity is higher than the premium charged by the insurance company will be more likely to purchase insurance. Conversely, producers who determine that the premium is higher than their expected indemnity are less likely to purchase insurance (Glauber 2004:1180), leading to cross-subsidisation between high and low risk clients (Bureau of Agricultural Economics 1986:2). Thus, the insurer ends up in the potentially unprofitable situation where they are providing insurance to a group of high risk farmers who are more likely to claim against the pooled funds than the average farmer (Bureau of Agricultural Economics 1986:19). This is called the "lemon effect". Area-yield insurance has been developed to partially correct some of these problems as it avoids the moral hazard and adverse selection problems associated with conventional crop insurance. However, area-yield insurance still does not deter the government from feeling obliged to provide *ex post* political relief in the case of widespread crop losses, and hence, area-yield insurance does not limit the cost to the nation (Innes 2003:327). In many cases the actuarial success of a crop insurance scheme depends partially on the variability of the weather and partially on the ability of the insurer to minimise the problems of adverse selection and moral hazard (Glauber 2004:1183).

Weather derivatives are distinctly different to crop insurance. They are suited to hedging weather risk associated with both extreme and non-extreme events that have a reasonably high probability of occurrence (Yoo 2003:1). For example, insufficient rain

during the growing period or excess rain before harvest. They are designed to meet the requirements of individual producers and can be constructed to suit any weather event such as compensation for loss of earnings due to periods of moisture deficiency (Alaton, Djehiche & Stillberger 2002:6).

Weather derivatives are generally designed to hedge particular risks for the holder of the contract irrelevant of whether the holder actually owns or grows the commodity for which the contract provides cover. In other words, the contract holder could purchase weather contracts purely for speculative or gambling reasons. It follows that the holder of a weather derivative does not have to prove a financial loss to the underwriter to receive any payout. The payouts are based only on the actual weather and regardless of how it affects the derivative holder. This means that weather derivatives do not have the problems of adverse selection and moral hazard because hedger's decisions after purchasing the contract do not influence the level of the payout (Mahul 2001:597) and no special knowledge is available to either party.

Another positive aspect of weather derivatives is the possibility of a sliding payout. As payouts are based on an index calculated from weather data, the weather derivative contract payout accumulates on the basis of severity rather than taking the form of a one-off large payout (Vinning 2000:315). Of course, they can also be designed as all-or-nothing type contracts with the contract paying maximum indemnity if the payout is triggered.

Weather derivatives are currently priced using a variety of techniques with little standardisation across market makers or markets. Different pricing methods are discussed later but note here that lack of consistency and transparency in pricing of weather derivatives causes some market apprehension. In the absence of transparency issues, a potential benefit from weather derivative contracts lies in the possibility of companies hedging each other's weather risk. In the derivatives market, two companies wanting opposite weather conditions may enter a contract to hedge each other's risk (Alaton, Djehiche & Stillberger 2002:6). Thus two companies desiring to take opposite positions may design a derivative product as a swap with zero premium. This would be impossible with an insurance contract since they always require an up-front premium.

In conclusion, weather derivatives can make a substantial impact on year-to-year profitability of farms by assisting farmers through adverse weather periods without incurring the usual problems of moral hazard and adverse selection that plague insurance policies.

2.3.6 Practical implementation issues

2.3.6.1 Geographical basis risk

There are some issues about practical implementation of weather derivatives in Australia. Geographical basis risk is particularly important and stems from problems when weather derivatives are written based on weather data from sites away from the hedger's crop. A farmer in this situation accepts risk associated with discrepancies between the rainfall he/she actually experiences and that at the weather station on which the contract is written. In some situations such basis risk may be substantial although it is expected to vary widely. Geographic basis risk may vary for one individual farm depending on the time of year the contract is structured to hedge. The problem of geographical basis risk is discussed in more detail in Chapter 5 where an analysis of rainfall differences between on-farm measurements and various weather stations is presented. It will be shown that although geographical basis risk warrants consideration and analysis for each individual situation, the problem doesn't seem to be important in terms of the payouts received from weather derivatives in the majority of years.

2.3.6.2 Market structure and thinness

The weather derivative market is still a thinly traded market despite growth over recent years. There is limited liquidity as most traded contracts are individually negotiated in the OTC market. A liquid market is one in which a high volume of contracts are traded, allowing market participants to buy and sell contracts easily (Williams & Schroder 1999:31). Market illiquidity means it can be difficult for firms accepting risk to pass on the risk through a secondary market. The lack of a secondary market means that when an underwriter accepts weather risk in return for a premium they have little opportunity to pass that risk to other institutions in Australia. Some underwriters do pass risk to the international weather risk management market through larger re-insurers.

The Chicago Mercantile Exchange (CME) began to trade weather derivative contracts for ten US cities in 1999. The weather futures contracts are traded on their electronic Globex system. CME aims to enlarge the size of the market and remove credit risk associated with trading weather contracts. Since 1999 the trade in weather futures and options on the CME has increased dramatically and achieved increased liquidity (Garcia 2001:9-10). The provision of some standardised contracts to the weather derivatives market through the CME has helped to stimulate development of the market as a whole (Hemsworth 2003:3). The ability to trade weather contracts on the CME has encouraged growth in liquidity of the market by allowing small transaction sizes leading to more investors and also by eliminating credit risk of participants through the clearing house (Garcia 2001:9-10). In addition, trade in weather derivatives on the CME can provide price discovery for other market participants as weather options and futures are quoted in real time and can be accessed by everyone, which increases transparency. Increased transparency and subsequent information exchange is an important benefit from the CME weather derivatives to energy distributors in the US who now often use both OTC and exchange-traded contracts (Hemsworth 2003:3).

The CME chose the cities for which contracts are available based upon population, variability in temperatures and activity seen in the OTC temperature market (CME 2005b online). The CME now trades HDD and CDD monthly and seasonal contracts in 18 US cities, nine European cities and two Asia-Pacific cities. Market makers in the OTC weather derivatives market can now use liquid, standardised and exchange-traded CME HDD/CDD swaps and options to pass on the risk they are accepting from non-standardised individualised contracts (CME 2005a online).

As the number of participants in the weather derivative market continues to increase, there will be additional pressure on market makers to become increasingly transparent in their pricing mechanisms. Many contracts have fallen through in the past because of discrepancies in pricing methods between market makers and end-users. Increasing transparency in pricing should in turn increase the number of active market participants by removing one of the main barriers to participation by smaller firms. Consequently, the liquidity of the weather derivative market should continue to increase. However, it is unlikely this market will ever be as liquid as some price hedging markets due to the nature of the weather and its inability to be fully standardised.

2.3.7 Pricing of weather derivatives

Weather derivatives are usually traded as non-standardised contracts in the Over-The-Counter (OTC) market and individual contracts are priced by underwriters without regard to transparency and without any industry standard pricing model such as the Black and Scholes model in the financial options market. Although pricing weather derivatives has been the focus of a substantial volume of research in recent years it remains an issue due to the lack of pricing standardisation and transparency in the industry. One author notes that rainfall derivatives have been shown to be beneficial to farmers but their use is inhibited by the lack of transparency in pricing mechanisms and the high premiums charged for these contracts (Trevor 2002:37). While a variety of factors have contributed to this situation the primary problem is that a direct application of standard option pricing theory, based on Black-Scholes formula, is inadequate for pricing weather derivatives (Brody, Syroka & Zervos 2002:189).

In 1973, Fischer Black and Myron Scholes presented the first "completely satisfactory" equilibrium option-pricing model (Cox & Rubinstein 1985:166) based on several assumptions: the stock pays no dividends during the option's life; the option can only be exercised at maturity; the stock price follows a random walk process; interest rates remain constant and known; and underlying prices are lognormally distributed (Rubash n.d.). Some of these assumptions can be relaxed and the model adjusted to still accurately price derivatives. However, this traditional method for pricing derivatives is inappropriate for weather instruments, as such products are an example of an incomplete market and the underlying instrument, weather, is not tradable (Alaton, Djehiche & Stillberger 2002:13; Brody, Syroka & Zervos 2002:189; Garcia 2001:21; Garman, Blanco & Erickson 2000:7; Nelken 2000:3; Platen & West 2004:2; Zeng 2000:72). Each of the assumptions of no-arbitrage, market completeness (Brody, Syroka & Zervos 2002:189) and the asset value following a random-walk process do not hold for weather derivatives. In theory the premia for weather derivatives should be determined by supply and demand (Zeng 2000:74), but continuous hedging only works when pricing options that are traded in larger quantities on the spot market, such as for stocks, commodities or some other assets (Nelken 2000:3). Weather is not tradable and weather derivative contracts are traded in the OTC market so a risk-free portfolio cannot be constructed (Garcia 2001:21).

The goal of a pricing scheme is to determine fair values (Zeng 2000:74). This is complicated by the fact weather derivatives accumulate value over the contract period, a feature similar to Asian-style options (Garcia 2001:21; Yoo 2003:2). Also, weather processes, particularly changes in temperature, do not follow a random walk process but rather tend to be mean-reverting violating the infinite variance requirement for a random walk. Historically temperature variables have tended to deviate from their long-term means only within relatively narrow bands (Garman, Blanco & Erickson 2000:7; Yoo 2003:4). Temperature is also serial correlated in that if temperature is high today it is likely to be so tomorrow or at most only slightly higher or lower. Weather is "approximately predictable" in the short run and "approximately random around historical averages" in the long-run (Garman, Blanco & Erickson 2000:7).

Research on pricing of weather derivatives is based on one of two main approaches, although some authors have divided approaches into three categories. Cao, Li and Wei (2003:12) loosely classify approaches into three categories: (i) historical burn analysis; (ii) insurance or actuarial valuation; and (iii) valuation based on dynamic models. The first method, "burn analysis", is commonly used by the insurance industry while the second method uses actuarial pricing techniques and is commonly used by the finance industry. While both methods have their strengths, they also have weaknesses so approaches measuring the "fair" value for these products will continue to be controversial (Garman, Blanco & Erickson 2000:6).

The lack of a standardised pricing methodology can lead to disagreement between different counterparties who may not be able to agree on the price at which to trade (Garman, Blanco & Erickson 2000:6). This is not helped by various market makers who view their pricing models as commercial secrets (Garcia 2001:22).

A third category of pricing methods uses Gaussian dynamic models of underlying weather processes and calculates the present value of expected future payoffs using a riskless rate (Davis 2001:1).

Burn analysis is a numerical approach based on historical weather data and is commonly used by the insurance industry for pricing insurance contracts. It asks the question "what would have been paid out for a certain option over the last 50 years?" (Nelken 2000:4). The technique, when applied to weather derivatives, uses historical

weather data from a particular site often converting this data into a weather index. A detailed analysis of the data is undertaken to determine the number of times the specified contract would have paid out during the sample period, the average of these payouts (Vinning 2000:316) and the associated expected or "fair" option value. This is the simplest valuation method but can result in pricing errors (Cao, Li & Wei 2003:13) which may occur in a number of ways. First, a key assumption in burn analysis is that the distribution of past payoffs accurately describes the distribution of future payoffs, although this may not be the case (Cao, Li & Wei 2003:13). Second, the integrity of the resulting expected values depend on good quality weather data to determine the weather process and the resulting payouts and anomalies such as leap years, change in location of a weather station or instrumentation, the urban heat island effect and El Nino events can drastically bias the expected values (Considine n.d.:4,6; Nelken 2000:4). Third, the expected value of the weather derivative changes significantly depending on the length of weather data series used. Cao, Li and Wei (2003:13) found the expected value of an HDD call option for Atlanta changed by 300 per cent if 20 years data was used compared to ten years data. The expected value differences were much smaller for New York, although the highest estimate was still 70 per cent higher than the lowest estimate (Cao, Li & Wei 2003:14). The length of the data series depends on the individual characteristics of each contract, however some authors state 10-20 years of weather data is optimal (Garman, Blanco & Erickson 2000:6), while others prefer between 20 and 30 years (Cao, Li & Wei 2003:14), and one author prefers a length of 50 years (Dischel 1998). Often 30 years of weather data is used as it effectively maximises estimation efficiency while being long enough to allow control over effects such as the heat island effect in city areas (Richards, Manfredo and Sanders 2003:2). Fourth, burn analysis does not take into account the market price of risk (Cao, Li & Wei 2003:14) and fifth, as payments are often capped, the expected payout of a zero cost swap does not necessarily equal zero (Nelken 2000:6-7).

Actuarial analysis is based on statistical analysis of the historical weather data and is commonly used by the insurance industry. Probabilities are attached to insured events and a fair premium calculated (Cao, Li & Wei 2003:14). This method may be combined with Monte Carlo simulations where a probability distribution function is fitted to the weather index data using random numbers generated from a numerical algorithm to construct weather scenarios (Garman, Blanco & Erickson 2000:8). This

allows simulation of large volumes of weather index values based on the parameters of the distribution, from which synthetic payout values are calculated. These then form the basis of the fair value of the derivative which is calculated as the average of the synthetic payouts after discounting for time (Garman, Blanco & Erickson 2000:8; Zeng 2000:75). However, actuarial analysis does not solve all pricing problems as the underlying weather indices are usually non-stationary and thus probabilities based on past data may not provide accurate estimates of the likelihood of future insured events. Weather indices are often characterised by long-term variations and trends with scales greater than the length of the historical record (Considine n.d.:4; Zeng 2000:72). An additional problem for both actuarial pricing and Black-Scholes pricing methodologies occurs with regard to precipitation. Rainfall is discontinuous, each calendar day can be described as either a wet day or a dry day, and there are numerous days when rainfall is zero. Another minor problem is that historical weather indices may exhibit a high degree of autocorrelation reducing the number of independent observations (Benth 2003:303; Cao & Wei 2004:1070; Zeng 2000:73). One author claimed the historical data for a Phoenix CDD call demonstrated significant autocorrelation for lags up to eight years (Zeng 2000:75). Yet despite a high level of uncertainty, weather processes do follow recurrent, predictable patterns (Cao, Li & Wei 2003:12) and combined with the problems described above, it makes it difficult for traditional actuarial techniques to provide reliable statistical inferences based on historical data (Zeng 2000:73). As with burn analysis, actuarial analysis does not take market risk into account. A more sophisticated model is required for this (Cao, Li & Wei 2003:14). In this context, the market price of risk is important since the fair value of a temperature derivative is affected by the fact temperature is non-tradeable, similar to stochastic interest rates and stochastic volatility which both command risk premiums in equilibrium (Cao, Li & Wei 2003:12).

The third method of pricing weather derivatives is dynamic stochastic models that usually involve modelling the underlying weather process (temperature or rainfall) and using the model to inform Monte Carlo simulations or analytical calculations. These dynamic models can be continuous or discrete and most allow for incorporation of seasonal patterns, mean reversion, jumps and changing volatility (Stern 2001:26). One of the main approaches to deal with incomplete markets is to introduce the "market price of risk". With little or no information about future temperature patterns, all the

risk and the uncertainty about these patterns are embedded in the market price of risk (Yoo 2003:2). Different authors have undertaken studies with different types of dynamic models and each propose their own solutions as a potential industry standard. Some authors propose simple methods which are based on the pricing methods outlined above while others propose more complicated models. Most dynamic models incorporate an Ornstein-Uhlenbeck process when modelling temperature and some use portfolios of weather derivatives to construct prices. Continuous temperature processes are usually mean-reverting with a Wiener process to model the randomness of temperature movements, then taking the expected value of the discounted future payoff using a risk free interest rate. This process is complicated and does not reflect persistent serial correlations often present in data on daily temperatures. Also it does not incorporate the market price of risk (Cao, Li & Wei 2003:14-15). Most authors agree that modelling based on a weather index is inferior to modelling weather processes directly (Cao, Li & Wei 2003:16; Garman, Blanco & Erickson 2000:5). These stochastic pricing models have been covered thoroughly by different authors. In the next few pages their main arguments will be paraphrased with changes where appropriate.

Garman, Blanco and Erickson (2000:8) suggest that burn analysis combined with mean-reverting Monte Carlo simulation offers maximum flexibility for pricing different instruments and claim this provides the necessary degree of accuracy and transparency to become an industry standard. Zeng (2000) employed the actuarial method and initially compared expected values using only historical data with expected values using Monte Carlo. He found the expected value is identical from these two methods as the simulation used the distribution based on historical data (Zeng 2000:75). However, he noted that the VAR with a ten per cent probability is significantly different when using Monte Carlo as compared to solely historical data, as the limited "historical dataset did not allow a reliable estimation of the values at the tail of the distribution" (Zeng 2000:75). He then added seasonal predictions of temperature into the pricing methodology to account for future expectations of the weather and refers to this as the biased sampling Monte Carlo approach (Zeng 2000:76-77). The June July August (JJA) predicted anomaly probabilities for the temperature (probability of JJA temperature being above, normal or below the mean JJA temperature) was used as a proxy for the probability that July CDD will be above, near or below the mean July CDD value (Zeng

2000:76). July CDD are assumed to be normally distributed and the distribution was then sampled so that the "numbers of samples corresponding to the highest, middle and lowest thirds" corresponded to the predicted probabilities of above, near or below average temperature (Zeng 2000:76). Thus the expected value of the synthetic payout values takes into account the predictions of future temperature rather than sampling evenly over the whole distribution. This method relies on the accuracy of weather forecasts.

Alaton, Djehiche and Stillberger (2002:7-9) use an Ornstein-Uhlenbeck stochastic process incorporating a mean-reverting property to describe temperature based on 40 years historical temperature data from Bromma Airport in Sweden. While the authors' state that the market price of risk must be incorporated to price weather derivatives since the underlying variable is not traded, they have assumed it to be constant to simplify their analysis (Alaton, Djehiche & Stillberger 2002:13). The authors first derive a pricing formula for a HDD call option with the underlying temperature process characterised by a Gaussian distribution (Alaton, Djehiche & Stillberger 2002:16). However, this pricing formula primarily only holds in winter and restrictions must be imposed to use this formula during summer months (Alaton, Djehiche & Stillberger 2002:17). In the second part of their work no distribution for the HDD index is assumed and instead Monte Carlo simulation is used to find an expected value, keeping the assumption of constant market price of risk due to difficulties associated with obtaining a better estimate (Alaton, Djehiche & Stillberger 2002:18-19). They then compare the two methods and find that prices are similar when using the formula or Monte Carlo simulation although prices depend on the value of market risk used (Alaton, Djehiche & Stillberger 2002:21). They conclude by suggesting the inclusion of stochastic volatility into temperature processes would be more realistic as would be inclusion of better estimates of market prices for risk (Alaton, Djehiche & Stillberger 2002:21).

Brody, Syroka and Zervos (2002:189) propose a dynamic model for temperature evolution "given by an Ornstein-Uhlenbeck process driven by a fractional Brownian motion". They use this model to price weather derivatives based on temperature using the expected discounted value approach (Brody, Syroka & Zervos 2002:193). This proposed model takes account of the low-frequency variability in weather data which

can lead to systematic underpricing when a standard Brownian motion is assumed (Brody, Syroka & Zervos 2002:193). The authors focus on two different weather derivatives and "prove their value functions can be identified with solutions of appropriate partial differential functions which can be solved by numerical procedures" (Brody, Syroka & Zervos 2002:190). They find that the price for a Central England Temperature CDD derivative is nearly 20 per cent greater when using fractional Brownian motion as compared to standard Brownian motion (Brody, Syroka & Zervos 2002:195). With regard to a cumulative temperature derivative over a fixed-length sliding window, the authors determine the best approach is to model daily 'spot' temperature using a fractional Ornstein-Uhlenbeck process with the cumulative temperature index as the sum of a fixed number of spot temperatures, which is consistent with the current actual practice in the market (Brody, Syroka & Zervos 2002:195), and priced using the expected discounted value approach. They also note that if there are some contracts with sufficient liquidity to justify themselves as 'underlying assets' in place of the weather variable, then other correlated contracts could be priced using the traditional Black-Scholes formula (Brody, Syroka & Zervos 2002:197).

Platen and West (2004) model weather processes using a discrete time model and derive fair prices of weather derivatives using a benchmark approach with historical and Gaussian residuals. Their fair pricing concept forms part of the benchmark approach and uses a "growth optimal portfolio which is a self-financing portfolio that maximises expected logarithmic utility from terminal wealth" (Platen & West 2004:2). This concept combines more general forms of the traditional Black-Scholes pricing method and the Law of Large Numbers that motivates the actuarial or present value pricing approach (Platen & West 2004:12). They show that a generalised actuarial price is obtained as the fair derivative price under the benchmark approach when the payoff is independent of the growth optimal portfolio, which they have assumed the payoffs to be (Platen & West 2004:4). They interpret the independence of weather derivatives from the growth optimal portfolio to mean the market price of risk is zero or an absence of weather risk premiums (Platen & West 2004:5). Despite this interpretation, they note that in reality the market is small and contracts are likely to attract a risk premium well above the fair price (Platen & West 2004:5). Once an assumption that the weather derivative payoff is independent of the growth optimal portfolio has been made, the fair

price of the option is given by the generalised actuarial pricing formula (Platen & West 2004:14). The fair value of a weather derivative is then the expected payout multiplied by a zero coupon bond price (Platen & West 2004:20). This method works for pricing weather derivatives as long as sufficient weather data is available and the assumption of a competitive liquid market in practice is maintained. Platen and West also describe a method of pricing weather derivatives called historical fair pricing which computes an estimated expected future payoff of a weather derivative using all historical data and is supported by the Law of Large Numbers. They found that at least 110 years of data is required for this method and shorter term data provide unreliable estimates of price (Platen & West 2004:21). Using a Gaussian distribution for the underlying weather index, the authors find an expression with a straightforward calculation that yields a fair derivative value for a European call option that is different from Black-Scholes as the underlying is normal rather than lognormal, but is similar to the prices obtained with the historical fair pricing approach (Platen & West 2004:23).

Yoo (2003) uses a stochastic Ornstein-Uhlenbeck process to model temperature with a Gaussian standard Wiener process to describe the temperature process (Yoo 2003:5). Accurate modelling of temperature is crucial to the pricing of weather derivatives. This model is chosen as "the daily temperature process shows significant seasonal behaviour that is not shown by other financial variables", and because daily temperature is mean-reverting (Yoo 2003:4). Goodness-of-fit tests were carried out to test the normality of the temperature processes residuals, and indicated that residuals are normally distributed (Yoo 2003:7). Yoo (2003:9-10) derives an analytical formula from this temperature model suitable for pricing CDD weather derivatives but, similar to Alaton, Djehiche and Stillberger (2002), the formula has problems in summer when temperatures are below 18°C, in which case Monte Carlo simulations are required instead. The Monte Carlo approach provides an unbiased estimate of the derivative's price (Yoo 2003:10). Seasonal temperature forecast probabilities are included in a similar way to that in Zeng (2000) and as with other authors the market price of risk is set constant due to the difficulty of obtaining a better estimate and it is noted that the model would be improved if the market price of risk were calibrated more rigorously (Yoo 2003:16). To test the accuracy of Monte Carlo, Yoo (2003:15-16) compares prices of the CDD derivative with no truncation in the temperature process with prices obtained from the pricing formula, and finds that accuracy of the Monte Carlo simulation is acceptable and

the changes in option prices due to the seasonal forecasts are small. Then the real case is tested where temperatures are truncated below 18 °C for CDD's and finds that "option prices obtained using Monte Carlo simulation are very sensitive to the seasonal forecast probabilities" (Yoo 2003:16).

Richards, Manfredo and Sanders (2003) use an equilibrium valuation model combined with Monte Carlo simulation to provide implicit estimates of the market price of risk (Richards, Manfredo & Sanders 2003:2). This provides numerical estimates of the market price of risk rather than setting it constant as other authors have done. Weather indices are non-linear, seasonal and mean-reverting, and so the equilibrium value of the weather derivative is found using numerical solution methods (Richards, Manfredo & Sanders 2003:6). The authors follow the method developed in Cao and Wei's (1999) working paper, since published (Cao & Wei 2004), and use Monte Carlo techniques to estimate the market price of risk for each weather model (Richards, Manfredo & Sanders 2003:7). This model considers an exchange economy with uncertainties driven by two state variables, the aggregate dividend and the temperature (Cao & Wei 2004:1069). Richards, Manfredo and Sanders (2003:7) estimate the market price of risk by "comparing weather derivative prices based on the time-series pricing formula to prices where yields depend on a weather index". The authors find that there is a large market price of risk ranging from 6.68 per cent to 7.22 per cent, and that these estimates are statistically significant (Richards, Manfredo & Sanders 2003:9). The authors also note that many of the simpler models that do not take into account the mean-reversion nature of temperatures and the need for inclusion of stochastic volatility consistently underprice weather derivatives, with mean-reversion, time-varying volatility and jump diffusion each leading to higher derivative prices (Richards, Manfredo & Sanders 2003:9-11). They claim the best model for a Californian growing-season CDD index is "a mean-reverting, geometric Brownian motion process with first-order autoregressive errors and a log-normally distributed jump term" (Richards, Manfredo & Sanders 2003:10).

Regardless of the method used to obtain a fair price for a weather derivative contract, it is highly likely that market makers in the industry typically add a substantial risk premium on top of the fair price. The fair price is the price at which both the weather derivative seller and buyer make zero profit in the long-run if the contract were

replicated many times. In other words, it is the minimum price at which a weather derivative may trade (Platen & West 2004:14). Thus, market makers typically charge a fee to cover administrative and overhead expenses as well as to make a profit (Platen & West 2004:14). In reality, some premium in addition to the expected cost must be charged by market makers to ensure that they remain profitable in the long term and hence have a motivation to provide these products in the future (Zeng 2000:74). This mark-up also provides a cushion for errors in the determination of the derivatives fair value (Cao, Li & Wei 2003:12). However, it appears that the additional premiums added to the fair price by market makers in this new industry are well above what can be justified by administrative costs. Platen and West (2004:25) note that in a liquid competitive market, zero risk premiums are expected to exist, but in an illiquid market such as the current emerging weather derivatives market, substantial liquidity premiums are likely to be charged. These large premiums are also providing the market makers with some higher level of assurance that they have covered the risk they are accepting, as even the longest weather records only provide a glimpse of past weather patterns, and do not necessarily allow for reasonable projections of future weather patterns and therefore accurate determination of the true expected value of the payouts. The large risk premiums mean that weather derivatives are often priced beyond their intrinsic value to farmers and therefore limit the uptake of these instruments in the agricultural industry (Trevor 2002:iv). A study undertaken into the potential use of weather derivatives in agriculture concluded that while there is potential for farmers to accurately hedge their climatic risk using weather derivatives, it is not cost effective for the farmer to do so due to high risk premiums charged in the OTC market and that they are unlikely to be cost effective for farmers other than large agricultural conglomerates (Trevor 2002:36-37).

Indicative, non-binding prices of weather derivatives are able to be obtained from the internet component of the weather risk management firm called GuaranteedWeather. This allows potential users to construct hypothetical weather derivatives by choosing the underlying variable, the weather station at which this variable is to be measured, the strike level and the tick level. The convention in the standardised market is that the strike is set half a standard deviation above or below the mean value (Garcia 2001:23). After setting these characteristics of the weather derivative, the contract is then priced, noting that these are only indicative prices and that final pricing is subject to execution

of appropriate documentation and agreement to standard terms and conditions for the transaction (GuaranteedWeather 2005 online). This site does not give any indication to the user of how prices are determined, but allows a user to obtain an estimate of how much an actual weather derivative contract may cost for a specific region. This could provide the user with some small amount of bargaining power with other market makers, as well as help the user to understand how different strike levels and tick levels affect the premium required by the seller.

Chapter 3 – Risk and an Optimal Hedging Rule

3.1 Introduction

In this chapter an overview of risk in the literature is discussed including different types of risk applicable to farmers, expected utility and risk aversion, and methods of accounting for risk. The discussion of risk is followed by presentation of an optimal hedging model used to determine the willingness to pay for climatic hedging products by an "average" Australian wheat farmer. The climatic hedging product used in this chapter is a "swap" which is discussed later. The swap is used as it has the beneficial property of a zero "actuarially fair price". Weather derivatives can be designed in the style of this basic "swap" and so this optimal hedging model analyses the willingness to pay for one type of basic weather derivative.

3.2 Risk in the literature

Risk is a familiar term that affects each day of our lives. Decisions must be made without full information and thus can involve some level of real or perceived risk. A distinction can be made between the terms risk and uncertainty. Risk can be defined as 'imperfect knowledge where the probabilities of the possible outcomes are known', and uncertainty can be defined as 'imperfect knowledge where the probabilities of the possible outcomes are not known' (Hardaker, Huirne & Anderson 1998:4). These boundaries between risk and uncertainty are often blurred and sometimes the probabilities are not easy to determine, and so a more common distinction between risk and uncertainty is that uncertainty is imperfect knowledge of an event and risk is the uncertain consequences associated with that event (Hardaker, Huirne & Anderson 1998:5; Williams & Schroder 1999:4). A variety of risks present themselves and influence farm decisions and can be broken down into two broad categories, business risk and financial risk. Business risk is a conglomeration of other risks that are all independent of the financing of the farm (Hardaker, Huirne & Anderson 1998:6), and include:

(i) Production risk which influences farm decisions by placing additional pressure for certain farm tasks to take place at certain times and can often result in reduced crop or livestock yields due to the unpredictable and erratic nature of weather.

(ii) Price or market risk which arises due to the changing nature of prices of both agricultural commodities and agricultural inputs and affects not only the prices received for the agricultural outputs produced, but also affects the types of land and area used to produce different agricultural products. Over the years there have been many schemes devised to either reduce or avoid price risk for farmers.

(iii) Institutional risk which generally results from changes in government legislation that result in some forced changes in either prices received for produce or changes to the quantities or products produced by individual farmers or by particular regions. These changes may relate to clearing of timber, allowable water use, enforced marketing bodies and other changes affecting farm production.

(iv) Human risk which is the risk associated with individual people operating the farm and may cause problems for the continued operation of the farm through incompetence, illness, death, family breakdown and accidents. This risk also incorporates the risk of negligence on the part of the operator or staff involved with the production of outputs (Hardaker, Huirne & Anderson 1998:6).

Different risks are more important for different producers depending on their experience, location, commodities produced, wealth and risk aversion. A survey conducted by Blank, Carter and McDonald (1997) of Californian farmers during 1992-1993 showed that farmers are affected by different risks. The survey respondents ranked sources of risk in order of importance with the overall results indicating that output prices and input costs are the most important sources of risk. Further analysis of the results showed that producers growing some types of crop ranked risks significantly different to other producers (Blank, Carter & McDonald 1997:104). Analysis of the relative impact of different types of risk upon farm revenue showed that for wheat producers yield risk is dominant over price risk, however for a variety of other crops this relationship was reversed (Blank, Carter & McDonald 1997:106).

The other category of risk, financial risk, stems from the method in which the farm enterprise is financed. As the amount of debt financing increases, the financial risk facing a farmer also increases and this type of risk multiplies with the business risks to

increase any impacts of business risk upon the farmer. A farmer is free from financial risk only if the farm has zero debt and is entirely self-financed (Hardaker, Huirne & Anderson 1998:6). The main component of financial risk is the risk of increasing interest rates which drives increases in compulsory loan repayments and can cause substantial reductions in farm profitability. Often debt capital is a large proportion of the farm's total capital and as interest rates rise it becomes increasingly difficult for farmers to allocate sufficient funds to interest and capital repayments. Other financial risks include the possibility of unanticipated calling-in of the loan by the lender and there can also be risk involved with the process of finding suitable debt finance when required, especially if the finance is required immediately (Hardaker, Huirne & Anderson 1998:6).

3.3 Expected utility and risk aversion

Expected utility models could be called the "standard" model for behaviour under risk in the agricultural economics literature (Buschena 2003:1242). The expected utility EU(x), is the expected value of the utility U(x) of a random variable x (Varian 1992:177). In other words, expected utility is the average utility associated with a certain outcome or payoff from a choice where the exact outcome is not known before the event occurs. An individual is considered to be risk averse if he is willing to accept a lower expected utility with certainty rather than allow the situation to play itself out and accept the end result which may be higher or lower than average or expected utility but which, on average, is higher than the certainty equivalent (Johansson 1991:138). Risk averse individuals have a concave utility function and the greater the concavity of this function, the greater the risk aversion of the individual (Varian 1992:177). The individual's risk aversion may be calculated using the Arrow-Pratt measure of absolute risk aversion (Pratt 1964:122):

$$r(x) = -\frac{U''(x)}{U'(x)}$$

where the second derivative of the utility function is divided by its first derivative (Varian 1992:177). The Arrow-Pratt measure of relative risk aversion which measures the elasticity of marginal utility, can be calculated using $\rho = -\frac{U''(x)x}{U'(x)}$ where the

second derivative of the utility function is multiplied by wealth and the result is then divided by the first derivative of the utility function (Robinson & Barry 1987:31; Varian 1992:189). An individual with a coefficient of relative risk aversion of 0.5 would hardly be risk averse at all, a value of 1.0 indicates a "normal" type of person who is somewhat risk averse, a value of 2.0 indicates a rather risk averse person, a value of 3.0 indicates the individual is very risk averse, and a value of 4.0 indicates that the individual is extremely risk averse almost to the point of paranoia (Hardaker, Huirne & Anderson 1998:102).

Individuals may display different attitudes to risk as their wealth changes. Utility functions can display increasing, constant or decreasing absolute risk aversion with increased wealth. A utility function displays increasing absolute risk aversion (IARA) when the coefficient of absolute risk aversion increases as wealth increases (Jehle & Reny 1998:211). A common utility function that shows this trait is the quadratic utility function, $U(x) = a + bx + cx^2$ where $b > 0$ and $c < 0$ (Nicholson 2005:542; Robinson & Barry 1987:33). Increasing absolute risk aversion is generally seen as an undesirable trait (Varian 1992:189) as it is unlikely that an individual with great wealth will be more risk averse with a $10 investment than if their overall wealth was smaller. A utility function displays constant absolute risk aversion (CARA) when the coefficient of absolute risk aversion remains constant as wealth increases. An example of a utility function exhibiting CARA is the exponential utility function, $U(x) = -e^{-Ax} = -\exp(-Ax)$ where A is some positive constant (Nicholson 2005:543). Hardaker, Huirne and Anderson (1998:98) note that utility functions displaying CARA are not the most desirable, but due to their convenience, they have been used frequently in decision analysis. A utility function displays decreasing absolute risk aversion (DARA) when the coefficient of absolute risk aversion decreases as wealth increases thus an individual would be less concerned about the risk involved with a $10 gamble as the individual's overall wealth increases. Examples of utility functions that exhibit DARA are the logarithmic utility function, $U(x) = \ln(x)$ where $x > 0$, and also the power utility function $U(x) = x^c$ where $0 < c < 1$ (Hardaker, Huirne & Anderson 1998:99; Nicholson 2005:543). Decreasing absolute risk aversion is the most suitable scenario to impose for most individuals, implying that the individual is less averse to taking small risks when wealth is higher (Jehle & Reny 1998:212).

3.4 Accounting for risk

There are a variety of methods used to account for risk in the planning of agricultural production and the research that informs this production. Risk must be accounted for because the majority of people are risk averse; they dislike risk, and in agricultural situations where production is heavily reliant on factors out of the farmers' control, any downside risk can cause significant welfare problems for the rural population. Any significant deviations of weather from the 'norm' can lead to a situation with downside risk (Hardaker, Huirne & Anderson 1998:22). Severe situations of downside risk may result in intervention by government to provide for the rural population who are affected by the events that occur due to the unpredictability of the weather. Economists usually account for risk either using expected utility theory, econometric methods or risk programming techniques. This is not to say that these approaches constitute disjunctive alternatives. Many tests of hypotheses arising from expected utility theory have been undertaken using econometric approaches with great success, such as Bardsley and Harris (1987). Also, the early MOTAD (Mean of Total Absolute Deviation) approaches to agricultural decision making combined programming and expected utility theory. However, the artificial distinction between these three approaches is used here to facilitate discussion.

Hardaker, Huirne and Anderson (1998:138) note that it can often be difficult to apply a subjective expected utility model as this requires knowledge of a specific utility function for an individual but an efficient set of decision rules can be found by making some assumptions about the preferences of farmers. One of these efficiency rules is the mean-variance or E,V efficiency rule which states that scenario A is preferred to scenario B if scenario A has an equal to or greater than expected value than scenario B and the variance of A is less than the variance of B, and if the person prefers more to less and is not universally risk preferring (Hardaker, Huirne & Anderson 1998:142). This E,V rule provides an approximation of the expected utility maximisation. Stochastic efficiency methods may also be used, as they are based on direct expected utility maximisation (Hardaker, Huirne & Anderson 1998:145). First-degree stochastic dominance (FSD) requires that the person prefer more to less and it is based on the cumulative density functions (CDF's) of different scenarios. Scenario A dominates scenario B if the CDF of A lies entirely below and to the right of B (Hardaker, Huirne &

Anderson 1998:146). Second-degree stochastic dominance places an additional restriction on the utility function that the person is risk averse for all values of x, and in this situation A is preferred if the integral of A is less than the integral of B (Hardaker, Huirne & Anderson 1998:146). Third-degree stochastic dominance is occasionally used and this adds another restriction on the utility function that the coefficient of absolute risk aversion must be increasing (Hardaker, Huirne & Anderson 1998:148).

Risk can also be accounted for in a whole farm planning type of situation as the incorporation of all farm enterprises allows the farmer to determine which set of production practices will maximise expected profit at some level of risk suitable to the individual farmer's acceptance of risk. In most situations there are substantial profits to be made when there is high risk but the very nature of the high risk means that there are also substantial losses that may occur. People who are risk preferring may be happy to accept high levels of risk in the anticipation of receiving high profits. The whole-farm programming method takes account of risk by maximising the goals of the farmer subject to a set of certain constraints that must be met in production (Hardaker, Huirne & Anderson 1998:179). This is achieved through the use of linear programming, quadratic risk programming or MOTAD programming, each of which is described in more detail below.

Linear programming is the most common mathematical programming method used as it is the easiest. Linear programming can be used to incorporate a variety of different farm enterprises and farm resource constraints into one problem that can be solved using a software program. This type of model maximises expected profit after taking into account the resource and preference constraints imposed upon the solution (Hardaker, Huirne & Anderson 1998:181). A typical linear programming problem for a farm involves calculating expected activity net returns across different states of nature. One of the problems with linear programming is it does not account for any farmers other than those who are risk neutral, and therefore a quadratic risk programming model is sometimes used instead.

Quadratic risk programming requires that the distribution of total net revenue be normal or that the farmer's utility function be quadratic (Hardaker, Huirne & Anderson 1998:187). The assumption of a quadratic utility function is generally seen as undesirable as this implies that the farmer has increasing absolute risk aversion. An

assumption of normality for total net revenue can be suitable in some circumstances, particularly in a whole farm approach with multiple commodities being produced. However returns from individual agricultural activities are often skewed (Hardaker, Huirne & Anderson 1998:187). The benefit of the quadratic risk programming method of accounting for risk is it can be used to generate a set of farm system plans lying on the E,V efficient frontier (Hardaker, Huirne & Anderson 1998:187). When the speed and accuracy of computers was lacking in the past, many authors attempted to find linear programming approximations of quadratic risk programming models with the most widely used method being the MOTAD programming method (Hardaker, Huirne & Anderson 1998:189).

In MOTAD (Mean of Total Absolute Deviation) programming, a constraint is placed on the mean absolute deviation of net income instead of on its variance as in the quadratic risk programming method (Hardaker, Huirne & Anderson 1998:190). This method generates an E,M efficient frontier that approximates the E,V frontier, with M as mean absolute deviation. The advantage of using the MOTAD technique is that mean absolute deviation can be found using a linear expression and thus the technique is simple and only requires linear programming to find a solution. The solution is found by solving the model with M equal to some arbitrary high number, then the model is re-run with decreasing values of M until the value of M cannot be reduced any further (Hardaker, Huirne & Anderson 1998:191).

Despite the wide use of these programming models, the best way to account for risk in agricultural scenarios is to maximise expected utility directly. This can be done by using a non-linear software program to find a global optimum, but requires the utility function of the farmer to be known (Hardaker, Huirne & Anderson 1998:194). If a single utility function from a risk averse farmer is not possible because the problem involves a group of farmers, then utility-efficient programming should be used. This method generates a set of solutions using a range of coefficients for risk aversion (Pannell 1997:282). This set of solutions will be the stochastically efficient set for all producers whose coefficient of absolute risk aversion fits into the relevant range (Hardaker, Huirne & Anderson 1998:194-195).

3.5 Optimal hedging rule

A theoretical optimal hedging model based on the model developed by Simmons and Rambaldi (1997) is presented in this section. This optimal hedging model is based on expected utility and uses historical data on wheat prices, area sown, yields and quantity produced, along with previously published values of the Arrow-Pratt coefficient of absolute risk aversion and the elasticity of supply to determine theoretical optimal hedging levels for an "average" farmer.

It is assumed that wheat farmers' expected utility can be described using a weighted sum of expected profits and unanticipated variation in profits. Expected utility is specified as:

$$E(U) = E(\pi) - \frac{k}{2} E\left[(\pi - E(\pi))^2\right] \tag{3.1}$$

where $E(U)$ is the expected utility, $E(\pi)$ is the expected profit and k is the Arrow-Pratt coefficient of absolute risk aversion. This function is a member of the general class of E-V or mean-variance utility functions. "Unlike other mean-variance formulations, the version used here is Constant Absolute Risk Aversion (CARA) which is more desirable than the quadratic utility specification discussed by Anderson, Dillon and Hardaker (1977:89-90) which implies Increasing Absolute Risk Aversion (IARA)" (Rambaldi & Simmons 2000:347). CARA occurs in Equation 3.1 since the utility function implies that the risk premium, $\frac{k}{2} E\left[(\pi - E(\pi))^2\right]$, does not change with wealth. This CARA expected utility function should not be confused with the expected value variance utility function where variance refers to the variance of income and the functional form is IARA. In contrast, Equation 3.1 uses unanticipated variation in profits (income) and had the more desirable CARA functional form.

Production occurs within a one-year cycle so that producers maximise utility in period t conditional on information available in period t-1:

$$E_{t-1}(U_t) = E_{t-1}(\pi_t) - \frac{k}{2} E_{t-1}\left[(\pi_t - E_{t-1}(\pi_t))^2\right] \tag{3.2}$$

Prices are assumed to follow a simple first-order process with a multiplicative error term where u_{1t} is a normal random variable with zero mean and variance of σ_1^2:

$$p_t = p_{t-1}(1 + u_{1t}). \tag{3.3}$$

Realised production in period *t* is:

$$q_t = A_t Y_t \tag{3.4}$$

where A_t is area sown in *t-1* resulting in the area of wheat in period *t*, and Y_t is yield per hectare. The equation for yield, (3.5), incorporates a trend component, *T*, a multiplicative error term, u_{2t}, a normal random variable with zero mean and variance of σ_2^2 and two coefficients, *d* and *e*:

$$Y_t = (d + eT)(1 + u_{2t}) \ . \tag{3.5}$$

Australia is a relatively small global producer of grain with wheat accounting for around three per cent of annual world production (Australian Wheat Board 2005 online) so p_t and q_t are assumed to be independent so $E_{t-1}(u_{1t}, u_{2t}) = 0$. As Australia supplies only a small fraction of the world wheat market, farmers are effectively price takers both individually and collectively. Although in some cases farmers growing specialised varieties may be able to command price premiums, in the context of this study the assumption of independence between price and quantity is reasonable. Only relatively small increases in supply can be expected to result from adoption of these instruments and so downward impact of adopting weather derivatives or other climatic hedging products on prices faced by producers would be negligible.

Since A_t is known in period *t-1* it follows planned production is:

$$q_t^e = A_t(d + eT) \tag{3.6}$$

where, using more parsimonious notation, scripts on *q* denote expected value conditional on information available at *t-1*. Realised production is:

$$q_t = A_t(d + eT)(1 + u_{2t}). \tag{3.7}$$

The total cost function is assumed to be a quadratic function of production:

$$TC = a + bq_t^e + c\left(q_t^e\right)^2. \tag{3.8}$$

It then follows that profit in period t without hedging is:

$$\pi_t = p_{t-1}\left(1+u_{1t}\right)q_t^e\left(1+u_{2t}\right) - a - bq_t^e - c\left(q_t^e\right)^2. \tag{3.9}$$

Two simplifying assumptions have been made about costs to arrive at Equation (3.9). The first simplification is there are no cost savings from a failed crop which is equivalent to saying low yielding crops are as costly to harvest as high yielding, evenly spaced crops. The second simplification is the quadratic cost function which is argued can be viewed as a second order approximation to any higher-order differentiable cost function.

Realised profit in period t with hedging becomes:

$$\pi_t^h = p_{t-1}\left(1+u_{1t}\right)q_t^e\left(1+\left(1-h\right)u_{2t}\right) - hm - a - bq_t^e - c\left(q_t^e\right)^2. \tag{3.10}$$

where h is the proportion of u_{2t} that a farmer chooses to eliminate through hedging and m is the price of doing so. If markets for weather derivatives for farmers are to be viable, the instruments that are developed must be able to be supplied to the market, including transaction costs and risk premiums for underwriters, for less than the farmers' risk premium plus any actuarially fair premium. The hedge instrument proposed here is a 'swap' in the sense that the farmer receives a payment when rainfall is below a certain level and makes a payment when it is above that level. Since so far in Australia weather derivatives are only available as tailor-made OTC products, this structure is possible but it is more likely that products developed for farmers would actually be structured in a fashion similar to an option. One may imagine far more complex instruments making payments for rainfall that was excessive as well as deficient, and with the inclusion of temperature interactions, and with barrier features to protect underwriters. However, the instrument proposed here has the analytical advantage of having a zero 'actuarially fair price' and hence willingness to pay for it is equivalent to the farmers' risk premium for the risk that it eliminates. As such, this 'swap' is a simple product to base an exploratory study of potential demand upon.

Conditional expected profits then become:

$$E_{t-1}\left(\pi_t^h\right) = p_{t-1}q_t^e - hm - a - bq_t^e - c\left(q_t^e\right)^2 \tag{3.11}$$

Conditional expected utility is solved in a number of steps. Substitute Equation (3.10) and (3.11) into Equation (3.2), simplify, and, finally, take expectations conditional on information available at *t-1*:

$$\begin{aligned}
E_{t-1}(U_t) &= p_{t-1}q_t^e - hm - a - bq_t^e - c\left(q_t^e\right)^2 \\
&\quad - \frac{k}{2}E_{t-1}\left[\left(\begin{array}{l}\left(p_{t-1}(1+u_{1t})q_t^e(1+(1-h)u_{2t}) - hm - a - bq_t^e - c\left(q_t^e\right)^2\right) \\ -\left(p_{t-1}q_t^e - hm - a - bq_t^e - c\left(q_t^e\right)^2\right)\end{array}\right)^2\right] \\
&= p_{t-1}q_t^e - hm - a - bq_t^e - c\left(q_t^e\right)^2 - \frac{k}{2}E_{t-1}\left[\left(p_{t-1}(1+u_{1t})q_t^e(1+(1-h)u_{2t}) - p_{t-1}\left(q_t^e\right)^2\right)^2\right] \\
&= p_{t-1}q_t^e - hm - a - bq_t^e - c\left(q_t^e\right)^2 \\
&\quad - \frac{k}{2}p_{t-1}^2\left(q_t^e\right)^2\left(\sigma_{1t}^2 + \sigma_{2t}^2 + \sigma_{1t}^2\sigma_{2t}^2 - 2h\sigma_{2t}^2 - 2h\sigma_{1t}^2\sigma_{2t}^2 + h^2\sigma_{2t}^2 + h^2\sigma_{1t}^2\sigma_{2t}^2\right)
\end{aligned} \tag{3.12}$$

First-order conditions are obtained by differentiating expected utility with respect to planned production, q_t^e, and with respect to the amount of hedging, *h*, respectively:

$$\begin{aligned}
&\frac{\partial E_{t-1}(U_t)}{\partial q_t^e} = p_{t-1} - b - 2cq_t^e \\
&-kq_t^e p_{t-1}^2\left(\sigma_{1t}^2 + \sigma_{2t}^2 + \sigma_{1t}^2\sigma_{2t}^2 - 2h\sigma_{2t}^2 - 2h\sigma_{1t}^2\sigma_{2t}^2 + h^2\sigma_{2t}^2 + h^2\sigma_{1t}^2\sigma_{2t}^2\right) = 0
\end{aligned} \tag{3.13}$$

$$\frac{\partial E_{t-1}(U_t)}{\partial h} = -m - kp_{t-1}^2\left(q_t^e\right)^2\left(-2\sigma_{2t}^2 - 2\sigma_{1t}^2\sigma_{2t}^2 + 2h\sigma_{2t}^2 + 2h\sigma_{1t}^2\sigma_{2t}^2\right) = 0\,. \tag{3.14}$$

Solving these two first-order conditions separately for *q* and *h* has some computational advantages although could result in simultaneity bias so the model was solved both separately and simultaneously to understand the differences arising from the two solution techniques. Kahl (1983:603-605) discusses authors who have solved hedging ratios separately and simultaneously and the implications of each. Both solutions are presented below.

The model was operationalised using ABARE data and supply elasticities from previous studies to obtain parameters that could be used in a simulation. Because of severe non-linearities, the first order conditions can only be solved numerically, so to understand the basic structure of the model, *h* is set to zero and the production response to risk examined initially on its own (see Appendix 2):

$$\pi_t = p_{t-1}(1+u_{1t})q_t^e(1+u_{2t}) - a - bq_t^e - c(q_t^e)^2 \tag{3.15}$$

$$E_{t-1}(\pi_t) = p_{t-1}q_t^e - a - bq_t^e - c(q_t^e)^2 . \tag{3.16}$$

Substitute Equations (3.15) and (3.16) into Equation (3.2) to obtain conditional expected utility:

$$E_{t-1}(U_t) = p_{t-1}q_t^e - a - bq_t^e - c(q_t^e)^2 - \frac{k}{2}p_{t-1}^2(q_t^e)^2 E_{t-1}(u_{1t}^2 + u_{2t}^2 + u_{1t}^2u_{2t}^2) \tag{3.17}$$

then the first order condition with respect to the decision variable, planned production q_t^e, is found:

$$\frac{\partial E_{t-1}(U_t)}{\partial q_t^e} = p_{t-1} - b - q_t^e(2c + kp_{t-1}^2 E_{t-1}[u_{1t}^2 + u_{2t}^2 + u_{1t}^2u_{2t}^2]) = 0 \tag{3.18}$$

which solved for planned production and, taking expectations, becomes:

$$q_t^e = \frac{-b + p_{t-1}}{2c + kp_{t-1}^2(\sigma_{1t}^2 + \sigma_{2t}^2 + \sigma_{1t}^2\sigma_{2t}^2)} . \tag{3.19}$$

So an increase in wheat price increases the level of planned production, while an increase in the associated yield or price risks decreases the level of planned production. Planned production is decreased by larger values of k, the coefficient of risk-aversion, while if the farmer is risk-neutral, increases in risk as measured by the variance terms have no effect on the farmer's production decisions.

The next step is to solve the model parameters using data and previously published elasticities (see Appendix 2). In this case, mean values of wheat price, area, yield and quantity produced for the 5 year period 1997-98 to 2001-02 were calculated using data from ABARE (2004) adjusted using the Consumer Price Index to 1989-90 levels. These mean values are shown in Table 3.1 as P_{t-1}, A_t, Y_t and Q_t.

The values of σ_1^2 and σ_2^2 shown in Table 3.1, were calculated using data on prices from 1956-57 to 2001-02 and yield from 1950-51 to 2001-02, both obtained from ABARE (1995) and ABARE (2004). The value of σ_1^2 was obtained from Equation (3.3) in Excel by calculating the deviation of price in each year from the prices expected conditional

on information available in period *t-1* and then taking the variance of these deviations (Appendix 1). The variance of prices in the past has been influenced by WTO policies and it is assumed that such policy-driven volatility will continue.

Table 3.1: Mean values of model variables

Variable	Mean Value
P_{t-1}	$223/tonne
A_t	11,578 ('000 hectares)
Y_t	1.938 (t/ha)
Q_t	22,481 (kilo tonnes)
σ_1^2	0.033
σ_2^2	0.037

The coefficients *d* and *e* in Equation (3.5) were estimated using regression analysis with a single explanatory variable, trend *T*, to explain the dependent variable, yield. Thus the required regression is:

$$Y_t = \hat{d} + \hat{e}T\ (1 + u_{2t}) \tag{3.20}$$

which provided the estimates of *d* and *e* shown in Table 3.2 and is detailed in Appendix 2. The estimated values of *d* and *e* where then used in a spreadsheet with Equation (3.7) to obtain σ_2^2. Using national level yield volatility over time suppresses differences in yield volatility at the farm level so measures of farm yield volatility used here should be interpreted as lower bounds on yield volatility experienced by individual farmers.

Table 3.2: Model parameters

Coefficient	Value
b	148.67
c	0.0081
d	0.9706
e	0.0155
k	9.633E-8

The value for k (see Table 3.2) used in this dissertation was obtained from Simmons and Rambaldi (1997:164), who obtained the value after manipulation of the various estimates of risk aversion in Bond and Wonder (1980). The value used for the coefficient of absolute risk aversion is 9.633 x 10^{-8}, which corresponds to a coefficient of relative risk aversion of 0.265. If the coefficient of relative risk aversion is interpreted as an elasticity, this value seems reasonable compared to those obtained in other studies. Pannell (1997:285) states that a realistic range of the coefficient of absolute risk aversion for people in developed countries is between 1.0 x 10^{-7} and 1.0 x 10^{-4}, which means that the value used in this dissertation is slightly lower than this range indicating that farmers are expected to be more risk-neutral than the people in Pannell's range. A study by Abadi Ghadim and Pannell (2003) found that the observed range of risk preferences was wide. This same study (Abadi Ghadim & Pannell 2003:128) also found that the majority of farmers are risk averse supporting the results obtained by Bond and Wonder (1980:32).

The values of b and c are calculated as residuals after taking into account k, d and e, the elasticity of supply with respect to prices and mean values of the other variables (Appendix 2). The own-price elasticity of supply was obtained from Simmons and Rambaldi (1997:164) who averaged a range of previously published estimates to arrive at an elasticity of 0.60 based on a one year adjustment. This value was then incorporated into Equation (3.19) along with values of other parameters to calculate b and c. Equation (3.19) became:

$$q_t^e = \alpha + \beta p_{t-1} \tag{3.21}$$

where $$\alpha = \frac{-b}{2c + kp_{t-1}^2 E_{t-1}\left(u_{1t}^2 + u_{2t}^2 + u_{1t}^2 u_{2t}^2\right)} \tag{3.22}$$

and $$\beta = \frac{1}{2c + kp_{t-1}^2 E_{t-1}\left(u_{1t}^2 + u_{2t}^2 + u_{1t}^2 u_{2t}^2\right)} \tag{3.23}$$

The values of α and β were obtained from Equation (3.21) through algebraic manipulations and utilisation of the value for the own-price elasticity of supply as well as the mean wheat price and quantity (Appendix 2). These values were used in

Equation (3.23) with the coefficient of absolute risk aversion and values of the variables to calculate c. Coefficient b was obtained as a residual using Equation (3.22).

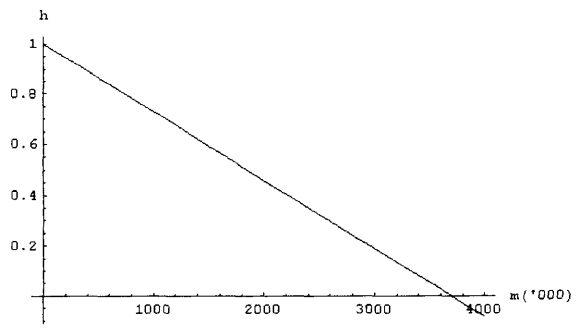
These coefficients and variable values were then used to solve for planned production, q_t^e, and the hedging ratio, h, using numerical techniques with the first-order conditions from Equations (3.13) and (3.14):

$$\frac{\partial E_{t-1}(U_t)}{\partial q_t^e} = 74.33 - 0.0165412 q_t^e + 0.000366187 h q_t^e - 0.000183094 h^2 q_t^e = 0 \qquad (3.24)$$

$$\frac{\partial E_{t-1}(U_t)}{\partial h} = -m + 0.000183094 \left(q_t^e\right)^2 - 0.000183094 h \left(q_t^e\right)^2 = 0 . \qquad (3.25)$$

These expressions were first solved separately for planned production, q_t^e and the amount of hedging, h respectively, with a range of values for m, the price of the hedge for the industry as a whole. The expressions are solved with m taking a range of values from zero to \$4million, which results in a range of hedging points that are graphed in Figure 3.1(a). The First Order Conditions were then solved simultaneously, using the same range for m with results reported in Figure 3.1(b). The figures show the optimal hedging ratios for a range of hedging prices and can be viewed as the agricultural industry's marginal value curves for the hedging instrument. As the two figures show, the results are essentially the same indicating simultaneity bias is not a significant factor in solving the model for these coefficient values.

(a) Solved separately



(b) Solved simultaneously

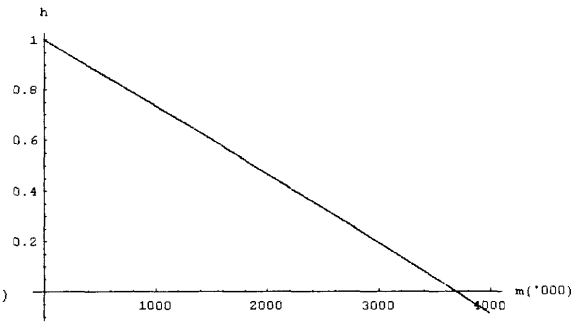
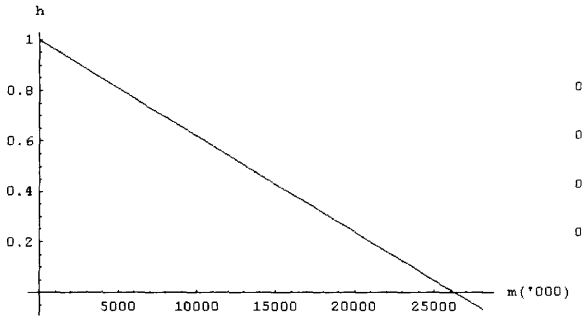


Figure 3.1: Optimal hedging ratios for a range of hedging prices

Figures 3.1(a) and 3.1(b) show that the optimal hedge ratio approaches zero as the industry price for the hedging approaches \$3.7million in 1989-90 prices, indicating demand for this type of hedging across the industry is likely to be low. This is a very

low risk premium being about 16.5 cents per tonne of wheat. However, as Abadi Ghadim and Pannell (2003:128) noted, in reality, farmers have a range of values for the coefficient of absolute risk aversion. Therefore, some farmers operating in more risky circumstances or with higher risk aversion may still demand significant amounts of this type of hedging product. There is a possibility that the estimates of risk aversion obtained by Bond and Wonder (1980:27) using the ELCE method described in Anderson, Dillon and Hardaker (1977) are too low. It has been found that in developing countries the level of risk aversion is much higher than the value utilised here. Rambaldi and Simmons (2000:252) estimated a higher value for the risk aversion coefficient for the Australian wheat industry using a time-series approach. To reflect the higher values used by these other studies, k was increased by a factor of ten to become 9.633×10^{-7} and the model re-run.

(a) Solved individually



(b) Solved simultaneously

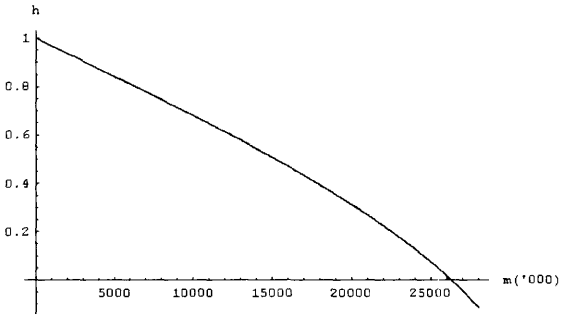


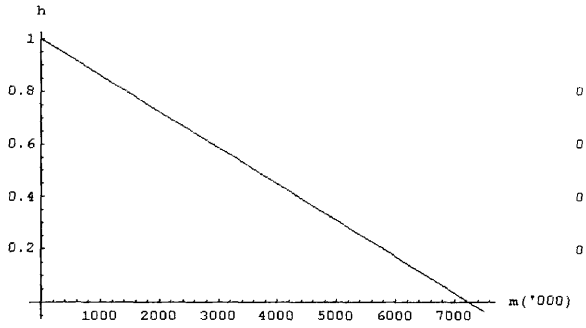
Figure 3.2: Optimal hedging ratios for a range of hedging prices with increased risk aversion

The sensitivity analysis on k (Figure 3.2) has shown, unsurprisingly, that farmers are much more willing to pay for weather hedging products as their level of risk aversion increases. Increasing k by a factor of ten resulted in farmers' willingness to pay increasing to just over $26 million, approximately half a per cent of revenue, rather than only $3.7 million previously. If one accepts the assumption that producer surplus is about 20 per cent of revenue then this figure corresponds to about 2.6 per cent of profits. Figure 3.2(b) also shows some curvature compared to Figure 3.2(a) which indicates that simultaneity bias becomes more of an issue as the coefficient of risk aversion increases.

Sensitivity analysis was also undertaken on σ_2^2 to investigate higher yield risk that may be associated with farm level yield volatility. The value of σ_2^2 used previously was calculated from national level yield data and it was noted that the value should be

interpreted as a lower bound on yield volatility experienced by individual farmers. The yield risk variable was doubled and the model re-run. Figure 3.3 shows the optimal hedging ratio with increased yield risk.

(a) Solved separately



(b) Solved simultaneously

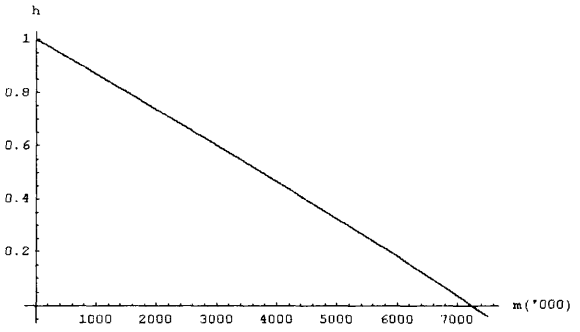


Figure 3.3: Optimal hedging ratios for a range of hedging prices with increased yield risk

The sensitivity analysis on σ_2^2 (Figure 3.3) has shown that farmers are more willing to pay for weather hedging products as yield risk aversion increases, but not to the same extent as an increase in risk aversion. Doubling σ_2^2 resulted in an almost equal doubling of farmers' willingness to pay to just over $7.2 million rather than $3.7 million previously. This figure is less than a quarter of a per cent of revenue but if one accepts the assumption that producer surplus is about 20 per cent of revenue then this figure corresponds to about 0.7 per cent of profits. The curvature of Figure 3.2(b) is slight compared to Figure 3.2(a) which indicates that simultaneity bias only becomes more of an issue with large increases in yield risk.

3.6 Conclusions and limitations of the model

Risk aversion amongst farmers ensures that they prefer stable rather than fluctuating yields, nonetheless this analysis indicates that their willingness to pay for such stability is relatively small. Using the lower value of the coefficient of absolute risk aversion k and the lower value for yield risk, the willingness to pay for weather risk products is 16.5 cents per tonne, which is almost negligible. For the higher value of the coefficient of absolute risk aversion, willingness to pay is about half a per cent of revenues or around 2.6 per cent of expected profits. With the higher value of yield risk, willingness to pay only increases to around 0.7 per cent of profits indicating that the level of risk

aversion of the farmer has greater effect on their willingness to pay than higher levels of yield risk. As farmers in different circumstances are likely to have different levels of risk aversion and different levels of yield risk, it is likely some farmers would be willing to pay less than the value determined by this theoretical model while other farmers would be willing to pay more.

The issue is whether underwriters can supply rainfall-based hedging products to farmers for an overall cost exclusive of any actuarially fair premium, but inclusive of administration, marketing and underwriting risk costs of between 16.5 cents per tonne and around \$0.32 per tonne (if the higher value of σ_2^2 is used) or around \$1.16 per tonne (if the higher value of k is accepted) in 1989-90 dollars. If this is possible, then such hedging products would be of interest to 'average farmers'. If costs are higher, then it is still likely that some farmers who are specialised in production and unable to diversify production or unable for other reasons to reduce risk exposure would be willing to pay more for protection.

Application of this theoretical optimal hedging rule has shown that average farmers are unlikely to demand weather derivatives. However, assuming a farmer is in the category of possible users of the weather derivative, and decides to investigate use of a weather derivative contract, the questions then raised are, how efficient is this weather derivative contract in reducing the farmer's risk exposure? And what proportion of yield would be optimal for farmers to hedge?

Another important question is what weather data is best when constructing a weather derivative so that the premium to the farmer is minimised but the contract payouts still accurately hedge the weather risks? Chapter 4 focuses on this latter question and seeks to determine the accuracy of payouts to farmers with historical rainfall measurements from various Bureau of Meteorology locations.

Chapter 4 – Geographical Basis Risk

4.1 Introduction

In Chapter 3 a theoretical optimal hedging model was presented and used to determine the willingness to pay for climatic hedging products by Australian wheat farmers. The results from the theoretical optimal hedging model showed that an 'average' wheat farmer was unlikely to demand any type of climatic hedging products to reduce the economic consequences of yield variability. However, it was conceded that specialist wheat farmers or farmers unable to diversify production might be interested in these products. The results were dependent on assumptions about the coefficient of absolute risk aversion and there were some practical problems concerning the widespread adoption of weather derivatives by farmers. While those theoretical results indicated little interest by most farmers in weather derivatives there is evidence that at least some farmers are interested in these new risk management tools and some have even obtained a contract (NAB 2005). These latter farmers may be more risk averse farmers as described in Chapter 3 so more likely to be interested. Irrespective of who these farmers are and which category they fit into there are still important questions about whether weather derivatives in an agricultural setting can be used effectively to manage weather risk. This chapter focuses on the practical problem of geographical basis risk. That is, differences between rainfall measured on-farm and the weather station rainfall data that the contract is written upon.

Section 4.2 continues the discussion of geographical basis risk. A "standard" rainfall derivative for a "typical" wheat farmer is then developed based on currently available National Australia Bank (NAB) weather options to hedge risk associated with insufficient rainfall during the growing phase of the crop. The derivative is structured as a precipitation put option for the three month growing period adjusted to suit the region in which the farm is located. Section 4.3 presents an analysis of three farm level rainfall datasets followed by a comparison of these on-farm rainfall datasets to historical rainfall from three official Bureau of Meteorology (BOM) meteorological stations surrounding each farm. The farm level datasets are then compared to aggregated BOM rainfall data from the three respective surrounding stations and lastly, compared to

Sydney Airport rainfall data. These datasets are first compared and analysed for differences in rainfall on a spatial scale. This is followed by analysis of differences in the amount and scale of payouts when using historical BOM rainfall data due to the geographical dispersion of weather stations from the subject properties. Section 4.4 discusses implications from the study and suggests solutions for practical implementation of this research, as well as suggesting further analysis of this topic with a wider range of subject farmers.

4.2 Weather derivatives and geographical basis risk

As described in Chapter 2, weather variability is a source of uncertainty and risk for farmers because agricultural production depends on the weather. Weather often determines success or failure of crops and, in more extreme circumstances, can also influence the financial viability of the farm itself. In Australian wheat production weather risk causes yield variability and this variability tends to be highly correlated across regions (Simmons & Rambaldi 1997:157) which can sometimes result in price risk as well. Farmers over time have used a variety of risk management methods to reduce their vulnerability to weather risk, often through diversification of their farming activities to include additional commodities or financial instruments and sometimes through insurance. The approach of diversifying production is limited as a means of reducing risk, as agricultural commodities on individual farms tend to be highly correlated with adverse weather conditions often affecting all output.

As discussed further in Chapter 5, to efficiently offset the adverse effects of weather, payoffs from a weather derivative must be correlated with losses resulting from the weather event. Potential purchasers of weather derivatives as risk management tools are concerned not only with the price but also with how well the contract performs in reducing risk exposure (Vedenov & Barnett 2004:389). The correlation of payoffs to actual losses depends partially on the weather data that is used to determine the payoffs. One hurdle to be overcome for the widespread adoption of weather derivatives for agricultural purposes is the geographical basis risk, because underlying weather variables are measured at specific meteorological stations and so may be different from rain at the farm (Vedenov & Barnett 2004:390). Due to the high variability of weather in Australia, even small distances between a meteorological station and a farm can lead to major differences between actual crop losses and weather derivative payoffs and this

difference is likely to increase the further the distance. From a farmer's point of view, an ideal weather derivative contract would be written using on-farm rainfall data removing most geographical basis risk (Vedenov & Barnett 2004:390). Conversely, from an underwriter's view point, it would be difficult to find an opposing hedge to reduce the risk for a contract written on a single farm. It would increase the cost of the contract to the farmer possibly causing him or her to forgo the contract. It may be beneficial to both farmer and underwriter to negotiate a contract using amalgamated weather data from several close meteorological stations which might reduce the premium slightly or, to further reduce the premium, the farmer could agree to purchase a weather derivative based on Sydney meteorological weather data. This latter choice would give the underwriter more ability to on-sell the risk to a re-insurer thus reducing the premium to the farmer. However, would this contract provide benefits to the farmer? The question is whether the correlation between actual realised losses and payouts using meteorological rainfall data measured at different sites is sufficiently high to warrant the time and cost of obtaining a weather derivative. In this chapter an attempt is made to answer this question by analysing various rainfall datasets and possible historical payouts that might have been made if these contracts actually existed. A standard weather derivative contract is proposed to hedge against insufficient rainfall during the months of August, September and October for NSW wheat farmers and the months of June, July and August for Queensland farmers. These are the critical growing months for these regions.

An additional problem with individual specific farm level rainfall data, and also some official BOM rainfall data collected from smaller sites is possible error or moral hazard in collecting the weather data and sending it to the BOM for inclusion in official records. For efficient operation of the contracts, both the farmer and the underwriter need to be confident that the data used to determine a payoff cannot be tampered with. The underwriter may prefer to write weather derivative contracts using rainfall measurements recorded at larger meteorological stations where the entire collection process is automated. While automated measurements may increase the confidence of farmers, the downside is these larger meteorological stations are more sparsely located and may be farther from the farm and involve potentially more geographical basis risk.

The National Australia Bank (NAB) is a current participant in the weather derivatives market in Australia and has designed rainfall put and call options specifically for wheat growers enabling them to hedge against insufficient rainfall in May, in August-October and, also against excess rainfall in November/December (NAB 2005). These time frames suit NSW wheat growing regions and the "standard" weather derivative developed here for analysis uses the NAB options as a guide in this regard.

High rainfall during May is needed to enable sowing of crops and subsequent seed germination (Herbert 2004:3) while rain during the winter/spring period is important for growth and flowering. In New South Wales important months of rainfall for crop growth are August to October while in Queensland growth occurs earlier during June to August. Rainfall in this period determines the quantity of grain produced and so total yield is affected by insufficient rain. Harvest occurs in November/December for NSW and in September for QLD, and in this harvesting period rainfall may be detrimental as it may lead to the development of leaf and spike diseases. This reduces grain quality considerably and thus affects grade and price received for grain (Petr 1991:176). The NAB provides farmers with a choice of weather data for the formation of the contract. Farmers can choose a single BOM station or a combination of multiple BOM stations either using a simple average of measurements from three stations, or using more sophisticated weighted averaging based on relative distances from each of three BOM stations (pers. comm. T. Allom, 12 Jan. 2005). Farmers can also participate in setting both strike levels and tick price, directly influencing the premium and nature of the cover.

The developed "standard" rainfall contract is used to determine differences in payouts associated with rainfall variability for different sites. Theoretical payouts are calculated using historical rainfall data for each of the three farms with the contract characteristics described below. However, in reality, contract characteristics would be different for each farmer to incorporate more precisely the individual characteristics of each region and possibly preferences of each farmer. The "standard" rainfall contract used in this chapter is a precipitation put option for the three month period August to October for the NSW farmers and June to August for the QLD farmer, hedging against insufficient rain. Strikes were based on analysis of mean rainfall during these periods over the past ten years for each farmer. The strike is set at 90mm for NSW and at 60mm for QLD,

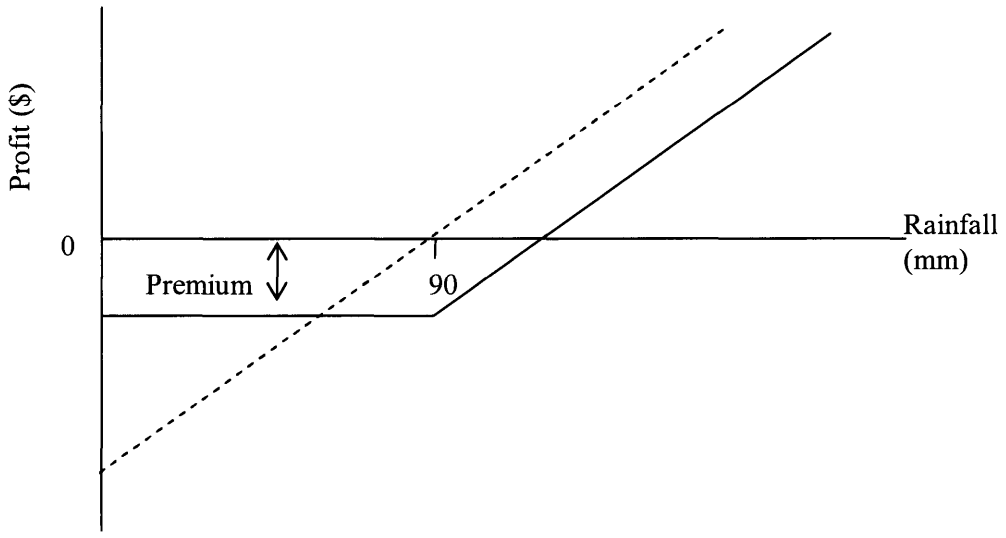
and tick at a payout of $5000 per millimetre below strike. The lower strike for QLD is because QLD is a summer dominant rainfall area and farmers usually sow into soil with higher moisture content than NSW and winter rain is needed to avoid moisture stress. This is rather than winter rains providing a large proportion of moisture requirement for the crop in NSW where rainfall patterns are more even throughout the year.

The payoffs from this put option are calculated as the number of dollars per millimetre (the tick) multiplied by the maximum of either zero or the difference between the strike and total rainfall during the period. The payoff to a NSW farmer from the purchase of a put option would be:

$$\begin{aligned} PayoffPut &= tick \times \max\left(0, strike - actualrain\right) \\ &= \$5000 \times \max\left(0, 90mm - actualrain\right). \end{aligned}$$

This put option is shown below graphically to demonstrate the premium, payoff and possible benefits to the farmer. The dotted line in Figure 4.1 shows with zero rainfall during the months August-October the NSW farmer's profit is negative as crop yield is insufficient to cover planting costs. Then, as rainfall during the growing period increases (approaching the long-term average) his unhedged profit increases and becomes positive after the strike, in this case after 90mm rain.

Figure 4.1: NSW farmer's payoff and profit associated with purchase of a rainfall put option.



The solid line in Figure 4.1 shows the NSW farmer's profit after purchasing a put option. By hedging with the rainfall put option the farmer puts a floor on downside risk from rain. Overall crop profit may still end up negative as the option covers only yield losses due to low rain and not price risk or other yield risks such as rabbits and the like. Leaving aside other risks, the NSW farmer's profit increases and the weather derivative does not payout as rainfall during the period increases beyond the strike of 90mm. The scenario for the QLD farmer is the same except the strike level is set lower at 60mm and the weather derivative only pays out to where 60mm of rainfall falls. This demonstrates the basic principle that farmers can forfeit some profit to minimise downside risk attributed to insufficient rain in the growing and flowering phases of the wheat crop.

4.3 Rainfall comparisons

4.3.1 Description of three rainfall analysis regions

This analysis is based on three individual farms selected through personal networks and chosen on the basis each had at least ten years of current rainfall measurements for their properties. The properties are located in three regions and were chosen to incorporate different rainfall patterns occurring in the wheat-sheep zone of Australia. Farmer A's property is located at West Wyalong in NSW, Farmer B's property is located at Trangie in NSW and Farmer C's property is located at Dalby in QLD. Rainfall data was also obtained from three weather stations surrounding each property from the Bureau of Meteorology (BOM 2005a, BOM 2005b). The following figures compare mean monthly rainfall for each farm to data from the three surrounding weather stations. Also a comparison of each farm's mean monthly rainfall to Sydney Airport data is considered. The data for mean monthly rainfall and associated annual rainfall distributions for each region show similarities between case study farms and the weather stations.

Farmer A receives average annual rainfall of 419mm and the region has an average yearly temperature maximum of 23.3°C and a minimum of 9.5°C (Bland Shire Council 2004 online). Figure 4.2 shows mean monthly rainfall over the ten year period 1995-2004 for Farmer A and three surrounding sites; West Wyalong Airport, Yalgogrin North (35km N) and Barmedman Post Office (28km SE), as well as for Sydney Airport. Over ten years, the correlation coefficients shown below in Table 4.1 and the comparison of

mean monthly rainfall in Figure 4.2 show that Farmer A's mean monthly rainfall is highly correlated with mean monthly rainfall at his three surrounding sites. However, there is a poor correlation between Farmer A's rainfall and rainfall at Sydney Airport.

Figure 4.2: Comparison of mean monthly rainfall for Farmer A, the West Wyalong region and Sydney Airport over a ten-year period, 1995-2004.

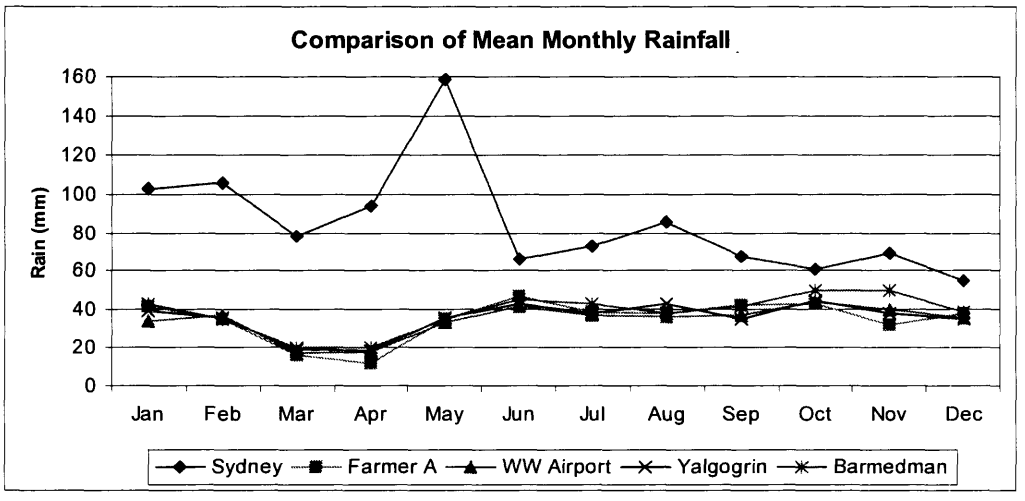


Table 4.1: Rainfall correlation coefficients for Farmer A and other sites

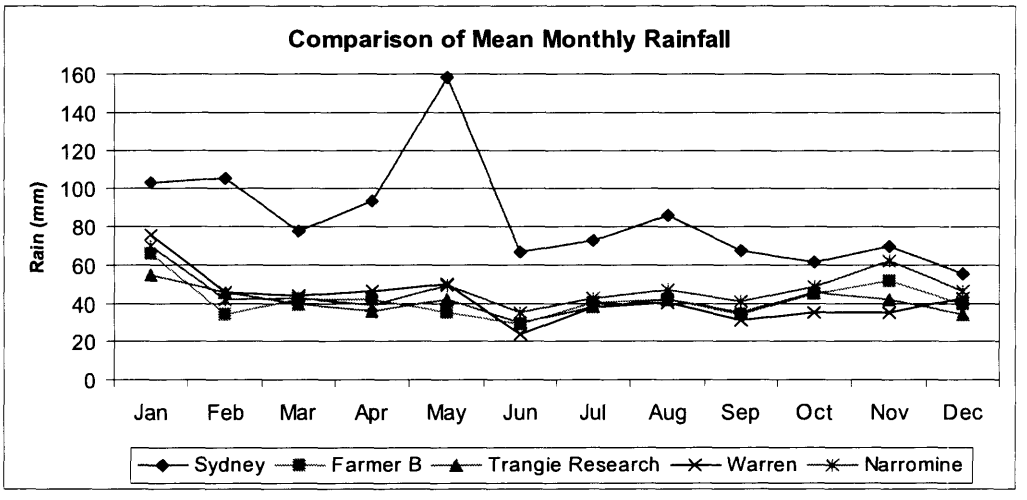
	Farmer A	West Wyalong Airport	Yalgogrin	Barmedman	Agg West Wyalong	Sydney
Farmer A	1.000	0.916	0.919	0.857	0.917	-0.180
West Wyalong Airport		1.000	0.949	0.948	0.988	-0.233
Yalgogrin			1.000	0.903	0.969	-0.126
Barmedman				1.000	0.975	-0.312
Agg West Wyalong					1.000	-0.240
Sydney						1.000

The average annual rainfall figures for each site using the 1995-2004 period confirm the lack of correlation shown in both Figure 4.2 and Table 4.1 between Farmer A and Sydney. Sydney Airport receives an average of 1017mm per annum, while Farmer A only receives an average of 419mm. Average annual rainfall is 410mm at West Wyalong Airport, 426mm at Yalgogrin North, and 460mm at Barmedman Post Office.

Mean monthly rainfall data in Figure 4.2 and the correlation coefficients in Table 4.1 indicate Farmer A could use rainfall data from any of the three surrounding weather stations or a combination of these stations and be reasonably sure any yield losses due to insufficient rain would be compensated by the appropriate weather derivative payout.

Farmer B receives average annual rainfall of 492mm and the region has an average summer temperature between 18-33°C and average winter temperature between 5-15°C (Narromine Shire Council 2005). Figure 4.3 shows mean monthly rainfall during the ten year period for Farmer B and the three surrounding sites: Trangie Research Station, Warren Post Office (38km N) and Narromine (25km SE), as well as mean monthly rainfall for Sydney Airport. Figure 4.3 shows patterns similar to those in Figure 4.2 for the West Wyalong region.

Figure 4.3: Comparison of mean monthly rainfall totals for Farmer B, the Trangie region and Sydney Airport over the ten-year period, 1995-2004.



Farmer B's rainfall is correlated with each of the three surrounding sites although the correlation coefficients in Table 4.2 below show the correlation is weaker than for Farmer A and his surrounding sites.

Table 4.2: Rainfall correlation coefficients for Farmer B and other sites

	Farmer B	Trangie Research	Warren	Narromine	Agg Trangie	Sydney
Farmer B	1.000	0.761	0.714	0.893	0.867	0.007
Trangie Research		1.000	0.762	0.780	0.907	0.392
Warren			1.000	0.661	0.920	0.532
Narromine				1.000	0.885	0.192
Agg Trangie					1.000	0.427
Sydney						1.000

Trangie region rainfall is poorly correlated to Sydney Airport rainfall, although analysis of monthly rainfall totals through each month of the period shows slightly more

correlation with Sydney Airport rain in the years 1996, 2000 and 2002. This partial correlation can be seen in Table 4.2 where the correlation coefficient between Warren and Sydney is 0.532 and between the aggregated Trangie region and Sydney is 0.427. Table 4.2 shows Farmer B and Sydney have almost no correlation in rainfall.

The ten-year average annual rainfall figures are 1017mm at Sydney Airport, 492mm at Farmer B's property, 484mm at Trangie Research Station, 507mm at Warren PO and 567mm at Narromine. Visual analysis of the monthly rainfall totals for each site during the 1995-2004 period suggests Farmer B may be better off considering Warren or the Trangie Research Station as data measurement sites for a rainfall option rather than Narromine despite the higher correlation coefficient reported in Table 4.2 for Farmer B and Narromine. Farmer B could also use average rainfall calculated from the three surrounding sites to be reasonably sure any yield losses due to low rain would be compensated by a weather derivative payout.

Farmer C has average annual rainfall of 568mm and the region has an average summer temperature between 30-35°C (Australian Agricultural College Corporation 2005 online). Figure 4.4 shows mean monthly rainfall for Farmer C and surrounding sites Bundaleer, Dalby Ag College and Mar-lee all in the Dalby region of QLD and mean monthly rainfall for Sydney Airport.

Figure 4.4: Comparison of mean monthly rainfall totals for Farmer C, the Dalby region and Sydney Airport over the ten-year period, 1995-2004.

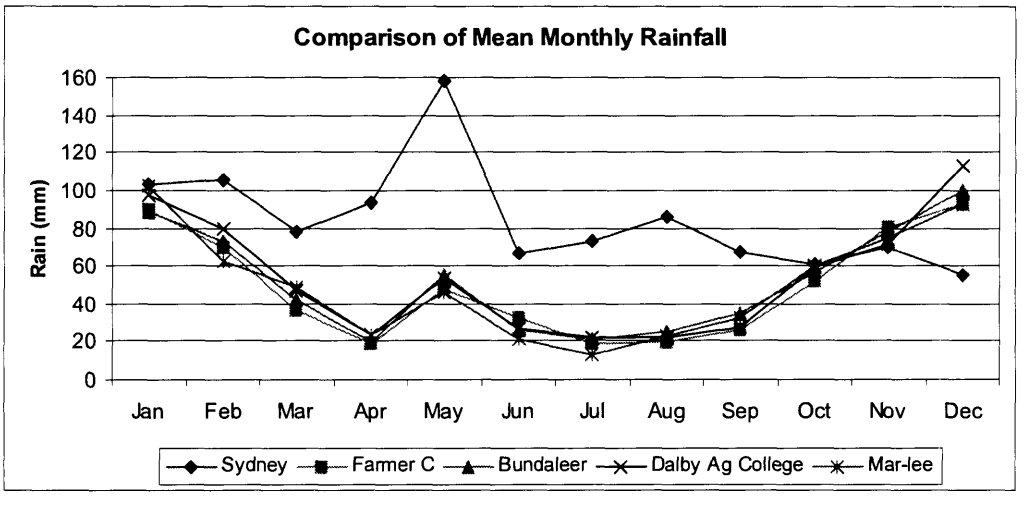


Figure 4.4 and the correlation coefficients in Table 4.3 below show that as with the previous two sites, rainfall of Farmer C correlates well with each of the three

surrounding sites in his region. The summer dominant rainfall pattern is readily noticeable in Figure 4.4 with mean rainfall equalling or greater than Sydney rainfall in the months of October, November, December and January.

Table 4.3: Rainfall correlation coefficients for Farmer C and other sites

	Farmer C	Bundaleer	Dalby Ag College	Mar-lee	Agg Dalby	Sydney
Farmer C	1.000	0.987	0.974	0.963	0.986	0.014
Bundaleer		1.000	0.986	0.969	0.994	0.034
Dalby Ag College			1.000	0.965	0.993	0.027
Mar-lee				1.000	0.984	0.008
Agg Dalby					1.000	0.011
Sydney						1.000

In Table 4.3 the correlation coefficients are very high for Farmer C and each of the three surrounding sites as well as the aggregated weather data, indicating near perfect correlation. These coefficients are higher for Farmer C and his surrounding sites than for the other two farmers as the distance between the sites is generally less for Farmer C. Both Figure 4.4 and Table 4.3 show almost zero correlation between Dalby region rainfall and Sydney Airport rainfall but this is expected given the different rainfall patterns of the two areas. The ten-year average annual rainfall figures for the Dalby region are higher than those for the two NSW regions due to the higher quantity of summer rainfall received although mean annual rainfall is still lower than in Sydney. Sydney Airport receives an average of 1017mm per annum, Farmer C an average 568mm per annum, and Bundaleer, the Dalby Ag College and Mar-lee receive 621mm, 637mm and 549mm average rainfall per annum respectively.

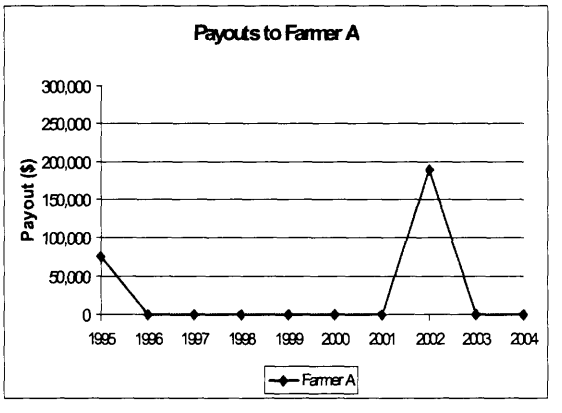
4.3.2 Comparison of payouts within each region

The base case used throughout this analysis is the rainfall and payouts to each farmer based on their own on-farm rainfall data. The rainfall totals have already been discussed and resulting payouts are now considered. Figure 4.5(a) shows the likely frequency and magnitude of payouts to Farmer A from a hypothetical put option when on-farm rainfall measurements are used to calculate the payout. Farmer A would have received payouts from the weather derivative in 1995 and 2002 while no payout would have occurred in the remaining eight years because cumulative rainfall was above the

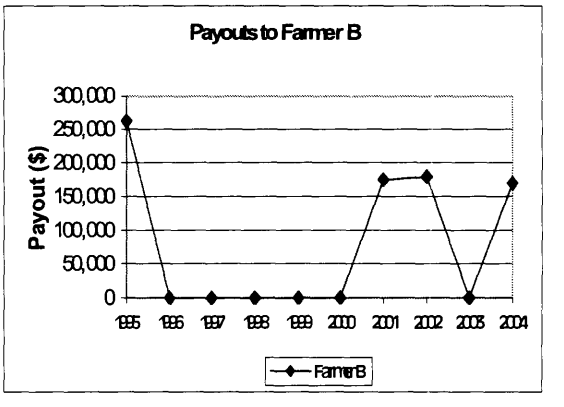
strike level of 90mm during the period August-October. On the other hand, in Figure 4.5(b) for the same contract period, August-October, Farmer B at Trangie would have received payouts in 1995, 2001, 2002 and 2004 while no payout would have occurred in the other six years with on-farm rainfall data.

Figure 4.5: Payouts to farmers using their own on-farm rainfall data for payout calculation.

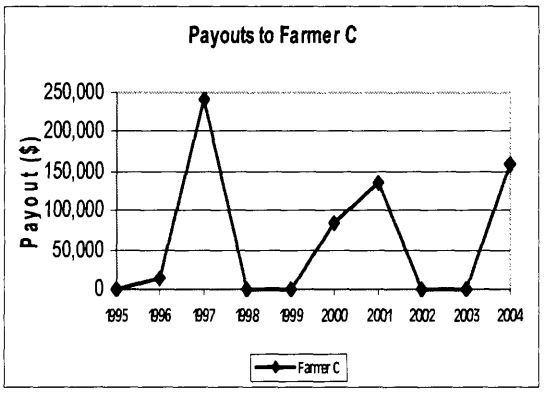
(a)



(b)



(c)

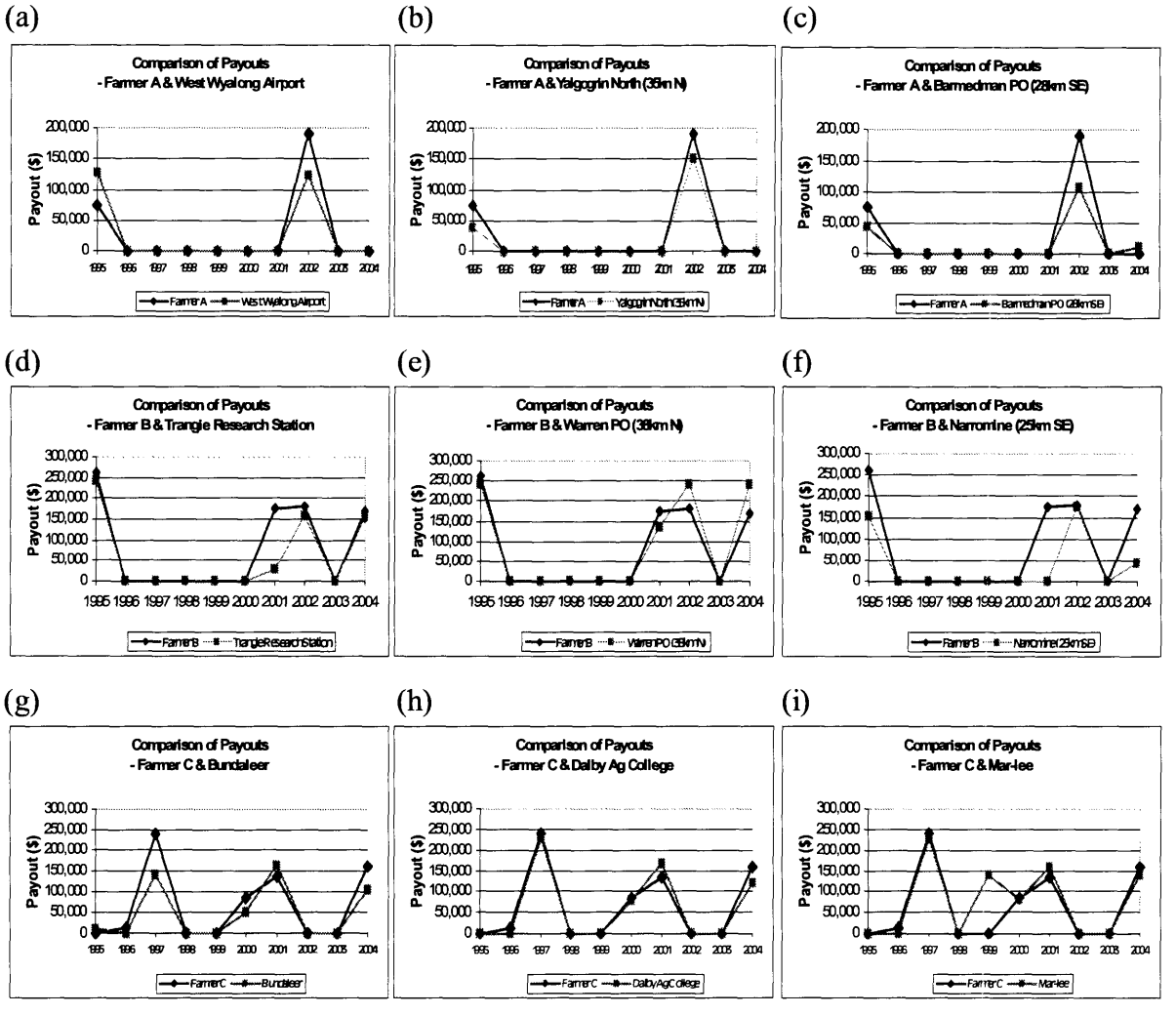


In Figure 4.5(c) the contract period was earlier, from June-August, to account for earlier flowering and harvest in Queensland. Based on measurements of on-farm rainfall during that period Farmer C would have received payouts in 1996, 1997, 2000, 2001 and 2004 with no payouts in the other five years.

Comparison of payouts using on-farm data with those from the surrounding sites allowed conclusions to be drawn about the extent of geographical basis risk experienced by each farmer. Differences in rainfall between each farmer's property and the three surrounding weather station sites resulted in different payouts received from the hypothetical put option.

In Figures 4.6(a), (b) and (c) payouts based on Farmer A's on-farm data were compared to hypothetical payouts based on data from West Wyalong Airport, Yalgogrin North and Barmedman. Figure 4.6(a) and (b) show the same frequency of payouts but the magnitude differs. However, in Figure 4.6(c) the frequency of payouts increased when BOM data for Barmedman was used, as a small payout of $11,000 occurred in 2004. In general, sites surrounding Farmer A have lower payouts than if on-farm data were used in the calculation.

Figure 4.6: Comparison of payouts to farmers using on-farm data and surrounding BOM sites



Figures 4.6(d), (e) and (f) show the comparison of Farmer B's payouts to the payouts received from Trangie Research Station, Warren and Narromine respectively. In Figures 4.6(d) and (e) the differences are generally in magnitude rather than frequency of payouts, although in Figure 4.6(c) both magnitude and frequency differ. The

magnitude of payouts for Trangie Research Station is very similar to Farmer B except for 2001 where the payout is substantially lower. The payouts for Warren are all reasonably similar while payouts based on Narromine data are all smaller except for in 2002. This indicates that while Farmer B's monthly rainfall is fairly highly correlated with Narromine rainfall (Table 4.2), in the months August-October used to calculate payouts, the rainfall correlation of the two sites must be lower. Figures 4.6(g), (h) and (i) compare Farmer C's payouts based on on-farm data to payouts received based on data from Bundaleer, Dalby Ag College and Mar-lee respectively. In 4.6(g) the frequency of payouts is the same between Farmer C and Bundaleer, although in 1995 and 1996 each site has a small historical payout that the other does not have. In the remaining years, Bundaleer under-pays when compared to the payouts based on on-farm data in three out of four cases and over-pays in one case. The comparison of Farmer C's payouts to Dalby Ag College data payouts in 4.6(h) shows that these two sites record very similar historical payouts. A small payout is missed if Dalby Ag College data is used in 1996 although all other payouts are close to those based on on-farm data. Figure 4.6(i) shows the payouts to be very close to when on-farm data is used except in 1999 when a significant extra payout of $140,000 would have been received if Mar-lee data had been used. As with Bundaleer and Dalby Ag College, the Mar-lee data payout is zero in 1996 while a small payout would have been received if on-farm data had been used as a basis for the payouts.

An alternative way to analyse these payouts is to consider average per annum payout over the full ten-year period 1995-2004. Table 4.4 below shows the average per annum payouts calculated using datasets applicable to each farmer. The average payout figures shown in Table 4.4 relate to annual payout comparisons to provide information about geographical basis risk and how data from different weather stations affects farmers and underwriters. Based on these two pieces of information, Farmer A should use West Wyalong Airport data, Farmer B should use Warren data and Farmer C should use Dalby Ag College data, as these datasets provide payouts that are most similar to payouts the farmers would receive if on-farm data were used to calculate payouts.

Table 4.4: Comparison of average per annum payouts from hypothetical put option using different datasets over period 1995-2004

Average Payout	Farmer A	Farmer B	Farmer C
On-farm	$26,500	$78,750	$63,500
Surrounding Stations			
	West Wyalong Airport	Trangie Research Station	Bundaleer
	$25,100	$58,450	$47,250
	Yalgogrin North (35km N)	Warren PO (38km N)	Dalby Ag College
	$18,800	$86,000	$59,600
	Barmedman PO (28km SE)	Narromine (25km SE)	Mar-lee
	$16,300	$37,600	$75,000
Aggregated	$19,700	$57,983	$55,583
Sydney	$22,100	$22,100	$1,200

4.3.3 Comparison of payouts using aggregate regional data

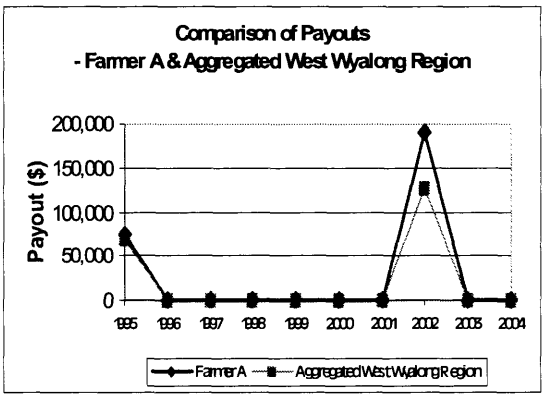
Another possibility for reducing geographical basis risk is to average data from the three surrounding sites and use this aggregate data to determine payouts. For simplicity, only the arithmetic mean of the three stations will be used here to make payout calculations although another approach would be to use statistical techniques to optimally weight rainfall data from the three sites.

Figure 4.7(a) below shows that average rainfall from surrounding sites fits Farmer A's property rainfall very well in nine out of ten years and in the year 2002 the payout is similar to that which would have resulted if only a single station were selected. Therefore, aggregate rainfall appears useful for Farmer A to be assured his payouts will be reasonably correlated with his crop losses. Farmer A's average on-farm payout is $26,500, so deciding on the basis of the average payout, Farmer A would be better off to chose a weather derivative based on West Wyalong Airport data, as the average

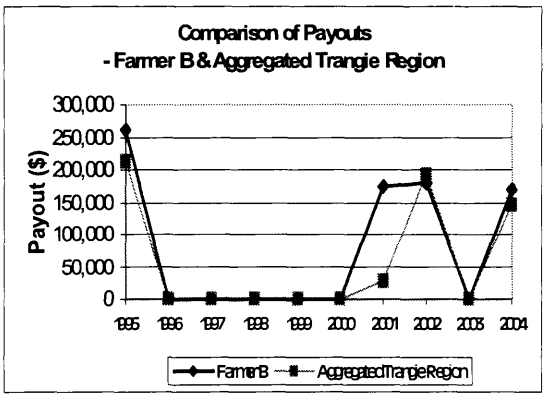
payout of $25,100 is closer than the ten-year average payout for the aggregated data of only $19,700.

Figure 4.7: Comparison of payouts to farmers using on-farm data and aggregated BOM data from surrounding sites.

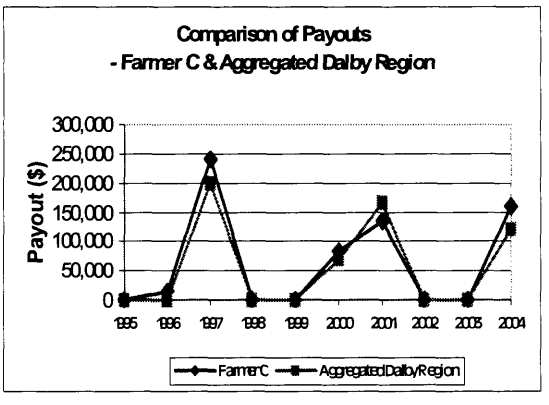
(a)



(b)



(c)



For Farmer B in Figure 4.7(b), aggregated data payouts correlate worse than when solely using Trangie Research Station data but correlates better than when Narromine data is used for payouts. The aggregated data still substantially underestimates the payout in 2001 that would be received if the farmer's on-farm data was used. Given these hypothetical historical payouts, Farmer B may prefer to use either Trangie Research Station or Warren individually, or may still consider using aggregated data if a longer comparison was available. The average payout for the aggregated data was $57,983 compared with an on-farm data average payout of $78,750 which would discourage Farmer B from aggregating data from the three surrounding sites. Another possibility could be to obtain an average from only two of the sites leaving Narromine out of the calculation. This may improve the fit of the aggregated data.

Figure 4.7(c) fits Farmer C's property rainfall fairly well in all of the ten years so the aggregated rainfall appears good for Farmer C and more likely to result in payouts correlated with crop losses. However, average payout for Dalby Ag College data is closer to Farmer C's on-farm data average payout of $63,500 than the ten-year average payout for the aggregated data of only $55,583. The reason for lower average payout for the aggregated data is the payouts using aggregated data slightly under-pay the farmer in four out of the five years when a payout would have been received using on-farm data.

4.3.4 Comparison of payouts using Sydney Airport data

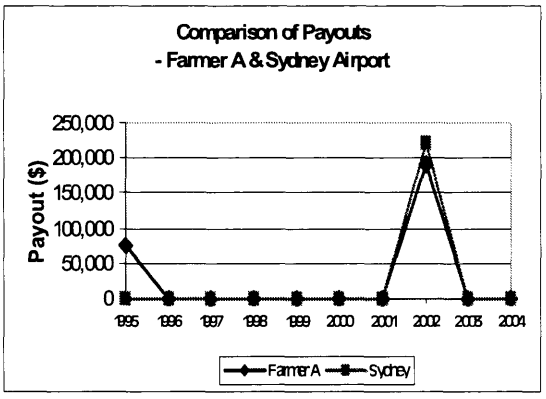
The third part of this analysis is to determine the differences in payouts when farmers' on-farm rainfall data is compared to Sydney Airport data. Each of the three regions, the West Wyalong region, the Trangie region and the Dalby region, is a considerable distance from Sydney and so differences in rainfall, and hence payouts, could be large compared to options based on on-farm data. This section compares payouts calculated with Sydney Airport data to payouts calculated with the three farmer's on-farm data to understand how severely distance affects weather derivative payouts to farmers.

Figures 4.8(a), (b) and (c) below show a payout is received only in 2002 when Sydney Airport data is used to calculate the payouts from the hypothetical put option. In each region, the farmers are worse off as they would have received more than one payout if on-farm data had been used.

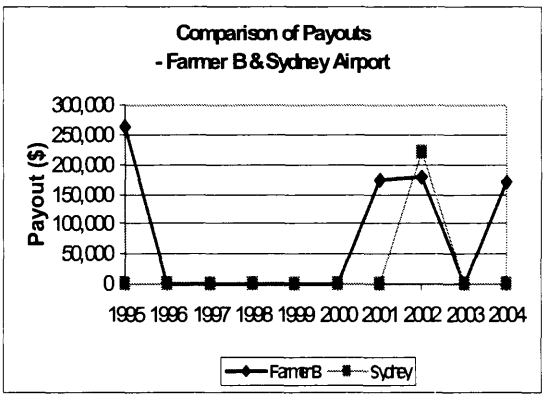
Figure 4.8(a) shows a difference in frequency of payouts to Farmer A when using Sydney Airport rainfall data. Farmer A misses a payout in 1995 but in 2002 the payout received is similar to the payout if on-farm data were used. The slight over-payment due to rainfall levels in 2002 does not make up for the loss of payment in 1995 although the average per annum payout for Sydney of $22,100 is not greatly different from Farmer A's average of $26,500. Figure 4.8(b) shows Farmer B missed three large payouts if he used a put option based on Sydney data. When using on-farm data, Farmer B would receive payouts in 1995, 2001, 2002 and 2004, while the Sydney Airport data pays out only in 2002. This poor correlation of payouts is confirmed by the average annual payout for Sydney Airport of only $22,100 compared to Farmer B's average payout of $78,750.

Figure 4.8: Comparison of payouts to farmers using on-farm data and Sydney Airport data.

(a)



(b)



(c)

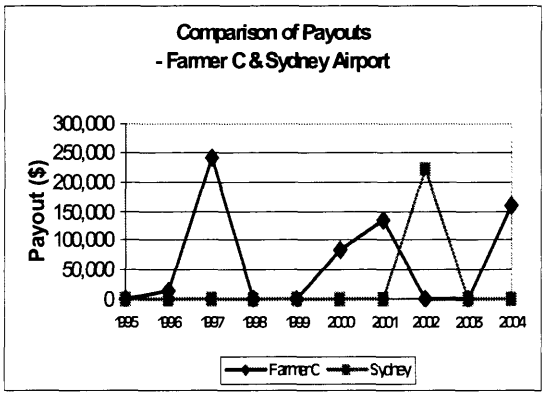


Figure 4.8(c) shows that there is no correlation between the payouts of Sydney Airport and the payouts based on Farmer C's on-farm data, as the only payout using Sydney data occurs in a year where no payout is required by Farmer C, but in the five years that payment is needed, none is made. This finding is not unexpected as the rainfall patterns are very different between Sydney and the Dalby region due to the geographical distance and topographical differences of the two areas.

Therefore, based on Figure 4.8 a rainfall put option written on Sydney Airport data to theoretically reduce the premium could be considered as a possibility for Farmer A if a longer period of on-farm data were available for comparison. This would allow further analysis of the correlation between payouts in the two areas. On the other hand, given the outlook from the 1995-2004 period the possibility of using Sydney Airport data for a put option seems unfeasible and unwise for both Farmer B and Farmer C. As Farmer C is located in Queensland, a more suitable capital city for comparison would be Brisbane as it is also located in a summer-dominant rainfall region.

4.4 Discussion

This study acknowledges the results from Chapter 3 that there is a potential but probably small demand by wheat farmers for climatic hedging tools. Also that any farmer operating in more riskier than average circumstances will be more risk averse and thus willing to pay for climatic hedging tools to protect against losses from unfavourable weather. The analysis in this chapter shows that farmers can hedge against lost profit due to rainfall variability during the wheat growing period by choosing to use weather derivative products written on rain. The rainfall data can be from either a single BOM station or an amalgamation of BOM stations that fit the particular on-farm rainfall data. The choice to base a weather derivative contract on an amalgamation of weather measurement sites is expected to lower the price of the contract by allowing the underwriter greater flexibility to find an offsetting risk, while simultaneously increasing the likelihood that payouts to the farmer will be similar to the payouts that would be received if on-farm rainfall data were used to calculate payouts. Some underwriters give farmers a choice of weather stations and assist the farmer to determine which weather stations or combination of stations fit the on-farm rainfall patterns most accurately (pers. comm. T. Allom, 12 Jan. 2005). The extent to which using an amalgamation of weather data to design the weather derivative lowers the premium required to purchase the contract is not evident due to the secretive nature of weather derivative characteristics in past deals. However, using regional weather data is expected to reduce the premium, even if only slightly. Nevertheless, even if it were to significantly reduce the premium, it is unlikely farmers from West Wyalong, Trangie or Dalby regions would deem the rainfall correlation high enough to warrant using Sydney Airport data. Surprisingly, high correlation of monthly rainfall between a farmer and one or more surrounding stations does not guarantee that payouts from those sites will be similar to the theoretical payouts received when using on-farm data.

It appears the geographical basis risk problem is smaller than many would imagine, at least in the three regions analysed in this study. Another study of geographic basis risk asked whether more distance between the production area and reference weather station reduced the effectiveness of weather derivative contracts, but found that there was not a clear linear relationship between distance and reduced effectiveness of weather derivatives (Chen & Roberts 2004:12-13). Chen and Roberts did not consider other

factors explaining these differences as they were more concerned with the existence of basis risk and whether it mitigates the usefulness of weather derivatives for dairy risk management, rather than why the basis risk occurs (Chen & Roberts 2004:1). A reduced emphasis on geographic basis risk is positive for widespread adoption of weather derivatives for use in agricultural settings and thus for the potential growth of markets for these weather products. The analysis also suggests that in some areas the weather stations used can be up to 20-40km away from the property and in most years rainfall would be sufficiently correlated between farm and measurement site to warrant effective use of a weather derivative contract despite the fact that rainfall can be extremely localised. This suggestion is drawn from the distances between stations used for the two NSW farmers, where distances from the central town ranged from 25-38km from surrounding towns where weather stations were located. This increases potential for weather derivatives to become more widespread as agricultural risk management tools, especially for broadacre cropping or fruit growers where insufficient rain has a direct impact on yield.

Although this points to a theoretical possibility of widespread adoption of weather derivatives by farmers it does not deal with the problems underwriters face writing such individualised contracts on small weather stations in remote regions of NSW and Queensland. The prospect of writing contracts on Sydney Airport data has been analysed here and although these three farmers would be unlikely to accept a contract based on Sydney data, it provides a useful suggestion for future analysis. In the U.S., standardised HDD/CDD contracts are available for 18 U.S. cities (CME 2005a online). A possible movement for Australia may be to develop several regional centres that serve as reference points for weather data for weather derivatives. For example, if there were three reference towns per state this may provide better rainfall correlation for farmers than attempting to hedge using Sydney Airport rainfall data and may also encourage underwriters to write more volume of contracts for each regional centre by allowing them to balance risks better. Writing contracts on multiple regional centres could allow them to on-sell a "bundle" of weather derivative contracts from "Regional Centre A" to re-insurance companies. Farmers would again be faced with more geographical basis risk, although it may provide a middle ground where underwriters and farmers are both willing to accept some of the risk due to unfavourable weather conditions.

While this chapter has indicated lower geographical basis risk in smaller regional areas and hypothetical payouts to farmers in most years where a payout is needed, the fact remains that very few real weather derivative contracts have been written in an agricultural setting in Australia. This may be due to a lack of knowledge on the part of farmers about this new risk management tool and also to the difficulties involved with negotiating suitable contract characteristics and price of the instruments. The contract strike level, contract period and tick rate each influence the price of the resulting weather derivative and provide a way for farmers to potentially reduce the contract premium. However, many farmers may find it difficult to estimate financially the relationship between unfavourable weather events and effects on final yield and profits. For example, what effect does each millimetre insufficient rain have on yield? Farmers may also be concerned with the cost effectiveness of weather derivatives as a risk management tool. In the current weather market most contracts trade with a premium much greater than the actuarially fair price and so may not be cost effective for use by farmers. The following chapter constructs actuarially fair options for different regions of NSW to determine the cost effectiveness of these contracts for reducing weather risk of the farmer. While in reality weather premiums are not actuarially fair the analysis provide a baseline for analysing the effectiveness of these types of products in an agricultural setting and thus provides an upper limit on their effectiveness.

Chapter 5 – Efficiency of Weather Derivatives

5.1 Introduction

Weather derivatives may have the potential to reduce profit variability from weather for farmers. However, an important consideration when using weather derivatives is their efficiency in reducing this profit variability. It was found in Chapter 4 that payoffs from a weather derivative are often not very different when using rainfall data from local BOM weather stations compared to the hypothetical payouts from using on-farm rainfall data. Given this result, if a farmer purchases a weather derivative written using rainfall data at some point in his region will the farmer's risk exposure actually be reduced? A key factor in demand and willingness to pay for weather derivatives in a practical application comes down to the question of how well weather derivatives perform. Do weather derivatives reduce variability in profits from unexpected and unfavourable weather events? With particular reference to Australian wheat producers, is the correlation between weather and yield sufficient to guarantee that contract payouts reduce downside risk from unfavourable weather?

A large body of work has been undertaken on the topic of pricing weather derivative contracts (Brody, Syroka & Zervous 2002; Davis 2001; Platen & West 2004; Richards, Manfredo & Sanders 2003; Turvey 2001; Zeng 2000) which was discussed in Chapter 2. Other research has looked at differences between weather derivatives and traditional crop insurance (Alaton, Djehiche & Stillberger 2002; Mahul 2001; Vinning 2000) also discussed in Chapter 2. Work has also been undertaken on demand for such instruments (Edwards & Simmons 2004) as discussed in the optimal hedging model of Chapter 3. This chapter focuses on determining the efficiency of weather derivative contracts designed for two regions of Australia. Some research has been undertaken on this topic in recent years with one study focusing on use of weather derivatives in dairy production and another on weather derivatives in corn, cotton and soybean production, both in the United States. Chen, Roberts and Thraen (2003) analysed the ability of weather derivatives to reduce weather-related profit risk for a representative dairy producer in Ohio. Using a utility maximisation framework they found weather derivatives used to manage profit risk increased producer utility substantially (Chen, Roberts & Thraen 2003:9). Vedenov and Barnett (2004) analysed efficiency of weather

derivatives in corn, cotton and soybean markets. They designed weather derivatives for six US crop-reporting districts that are major producers of these three commodities and concluded that, for these crop/district combinations, their weather derivatives could reduce risk exposure for farmers when contract specifications reflected regional differences. They also noted the complexity of the relationship between weather and yield and concluded the instruments must be designed specifically for each region resulting in less transparent contracts with higher administrative costs and highly specific markets.

In this chapter the framework developed in Vedenov and Barnett (2004) is used to determine the efficiency of weather derivatives in an Australian agricultural setting. The chapter focuses on two wheat-producing Local Government Areas (LGAs) in NSW to develop regional specific weather derivatives to protect wheat producers against unfavourable weather during the growing season. Section 5.2 discusses the data requirements and rainfall and yield data collected for the two LGAs, while Section 5.3 looks at difficulties in estimating robust weather-yield relationships and presents various econometric models of this relationship for each of the two regions. Section 5.4 focuses on determining a price for a particular style of weather derivative while Section 5.5 presents an efficiency analysis of these derivatives. Efficiency is analysed in- and out-of-sample using two methods, a Mean Root Square Loss technique and a value at risk analysis. Section 5.6 presents conclusions and discusses the potential of further work in this area.

5.2 Data sources

Local Government Areas (LGAs) have been chosen as the primary units for analysis because they are at a more disaggregated level than State data and therefore provide a focus on particular areas, although not at an individual farm level. While individual property analysis may seem more desirable, LGA data is more obtainable and is less vulnerable to moral hazard and therefore this semi-disaggregated data is used.

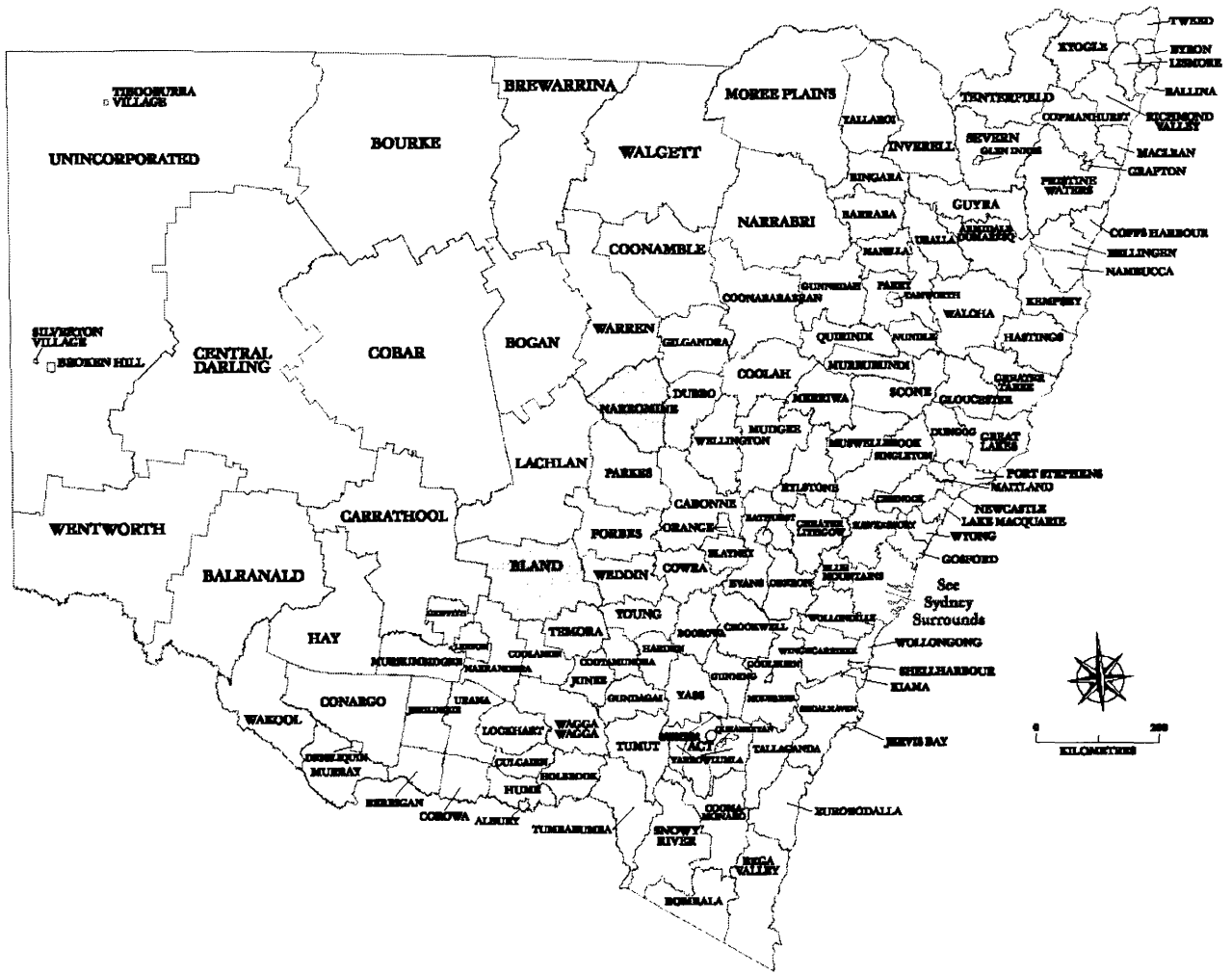
The boundaries of current NSW Local Government Areas are shown in Figure 5.1. As the name suggests, LGA's are designed for government purposes and over time LGA boundaries change slightly, so this wheat data may have some small errors as a result of changing boundaries.

The two LGAs chosen for this study are the Bland LGA located approximately 480 km west of Sydney and the Narromine LGA located approximately 440 km north-west of Sydney (see Figure 5.1). The sizes of the LGAs are approximately 8,560 square kilometres and 5,264 square kilometres respectively with approximate populations of 6,439 and 6,621 respectively (D'Arney 2003). Major agricultural commodities produced in these regions are crops, sheep, cattle and pigs in Bland LGA (Bland Shire Council 2004 online) and wheat, cotton, citrus, cattle, fat lambs, corn, barley, oats, sorghum, and lucerne in Narromine LGA (Narromine Shire Council 2005 online).

For each LGA, Bureau of Meteorology (BOM) weather stations were chosen as official sources of weather data for the hypothetical weather derivative contracts. Historical precipitation and daily average temperature data was needed for each LGA for the last 40 years. In reality, most weather stations have gaps in their data due to changes in measurement policies, relocation of weather stations, or temporary breakdown of measuring instruments. Also, many smaller weather stations are not manned all the time. So, even when a station measures a particular weather variable and instruments are operational there may be days with no recorded measurements due to illness of staff or other incidents preventing staff taking readings from the instruments.

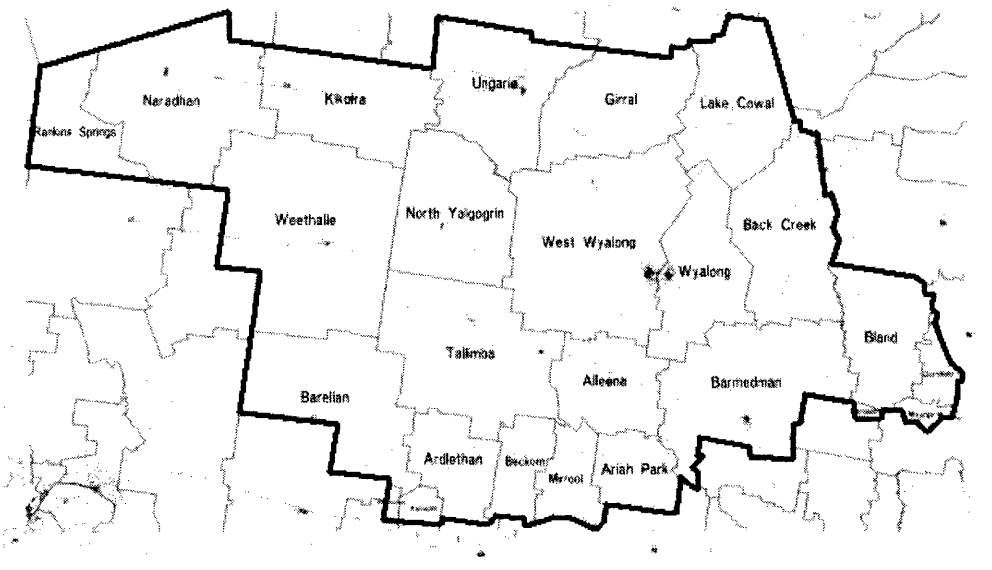
In each LGA no particular weather station had all the data required so one weather station was chosen with the most data and other data was sourced from different BOM stations within as close geographical proximity as possible. Gaps in temperature and rainfall data can be filled using simultaneous values from geographically close stations as an estimated value or, alternatively, historical mean values can be used (Aksoy 2000:419; Eischeid et al. 2000:1581).

Figure 5.1: Map – NSW Local Government Areas



Source: Adapted from Department of Transport and Regional Services 2005

Figure 5.2: Boundaries of Bland Local Government Area shown in bold.



Source: Geographical Names Board of New South Wales 2005

The boundaries of the Bland LGA are shown by the bold lines in Figure 5.2. The weather stations used for historical weather data for this region are West Wyalong Post Office for 1965-1994 rainfall; West Wyalong Airport for 1995-2004 rainfall; and Wyalong Post Office for 1965-2004 daily average temperature. No temperature measurements were recorded at Wyalong Post Office in October 1969 so gaps in data were filled using long-term October averages. Mean monthly rainfall and temperature for Bland LGA are shown in Figure 5.3; mean annual rainfall is 468.8 millimetres.

Figure 5.3: Bland LGA mean monthly rainfall and mean monthly temperature

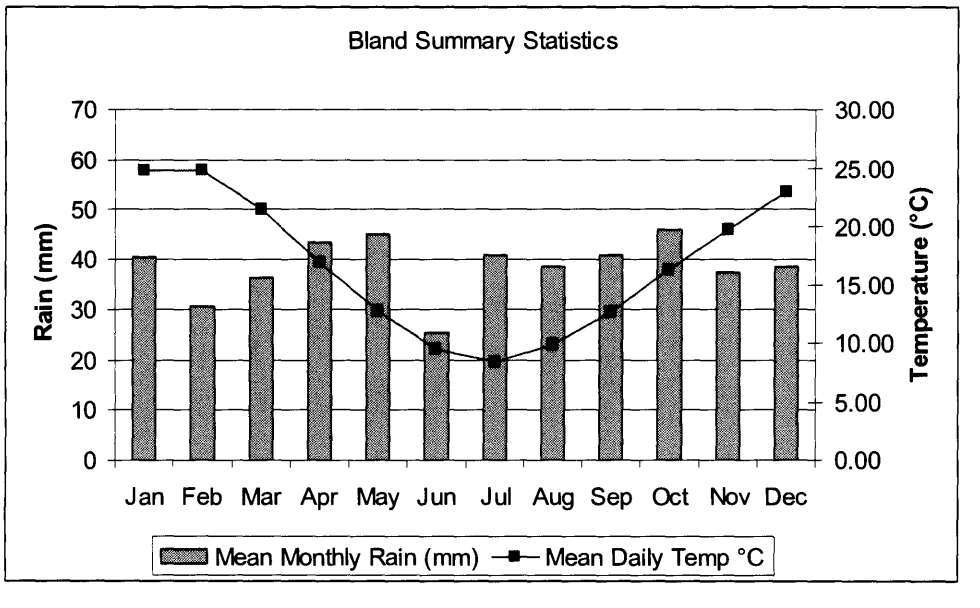
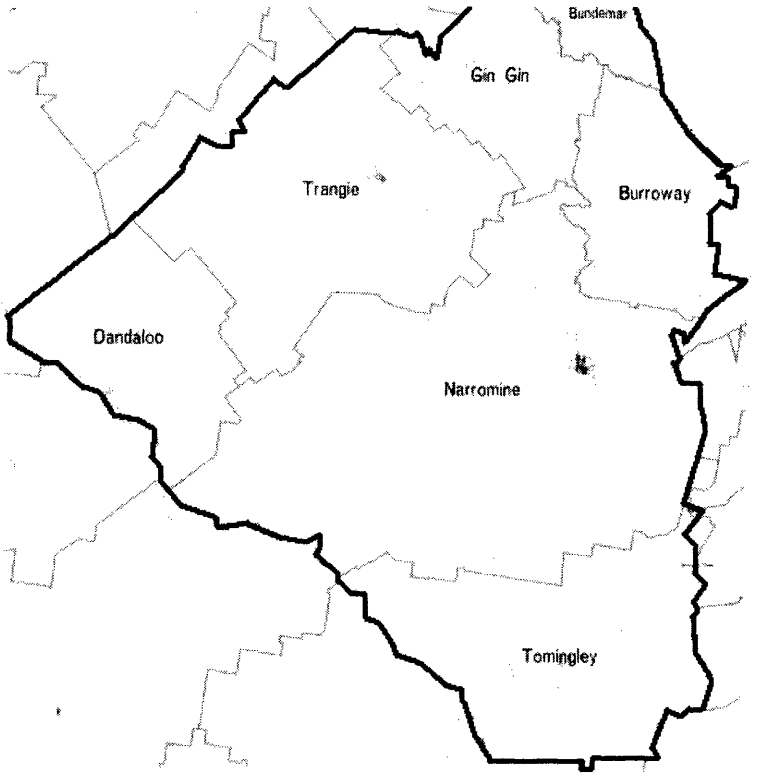


Figure 5.4: Boundaries of Narromine Local Government Area shown in bold.

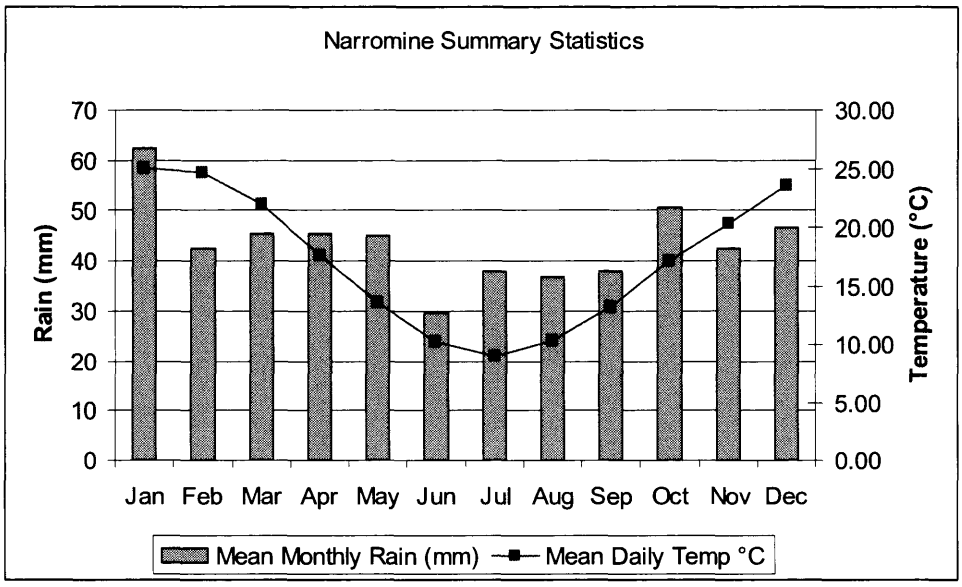


Source: Geographical Names Board of New South Wales 2005

The boundaries of Narromine LGA are shown by the bold lines in Figure 5.4. The weather stations used for historical weather data for this region were Narromine-Alagalah St for 1965-2004 rainfall; and Dubbo-Darling St for 1965-1999 temperature. Temperature data was sourced from Dubbo as there was no weather station within Narromine LGA with enough temperature observations. Temperatures for the Narromine LGA were assumed to be similar to recordings from Dubbo. Dubbo-Darling St stopped recording temperature in 1999 so temperature data stops at 1999 for the Narromine LGA in this study. The mean monthly rainfall and mean monthly temperature for Narromine LGA are shown below in Figure 5.5; mean annual rainfall is 523.9 millimetres.

The data is the best available data for these two regions, irrespective of a number of short-term periods when the data was clearly less than perfect.

Figure 5.5: Narromine LGA mean monthly rainfall and mean monthly temperature



The 1965-2000 wheat area, yield and production data for both Bland Local Government Area and Narromine Local Government Area were obtained from Fitzsimmons' (2004) publication on Winter Cereal Production Statistics. Data up to the current year (2001-2004) on wheat area, yield and production for Bland LGA was from the NSW Agriculture district agronomist at West Wyalong, Robert Thompson (Thompson 2005). His unpublished notes contain West Wyalong District wheat data incorporating Bland LGA and the portion of Weddin LGA west of the Weddin Range. Wheat production for West Wyalong District is approximately 60 per cent from Bland LGA and 40 per cent from the western portion of Weddin LGA (pers. comm. R. Thompson, 24 Feb. 2005). Therefore, the wheat area, yield and production figures used in this study were calculated as 60 per cent of West Wyalong District values. Equivalent data on Narromine's 2001-2004 wheat area, yield and production could not be obtained.

Table 5.1 shows the most recently available production and yield data plus expected revenue per hectare based on the most recent yield data for Bland and Narromine. The wheat price used throughout this study to convert yields into revenue is the 2003/04 price from the Australian Commodity Statistics annual publication by the Australian Bureau of Agricultural and Resource Economics (ABARE 2004).

Table 5.1: LGA wheat production data and weather stations (numbers in parentheses are the years the values were recorded)

Crop	State	LGA	Harvested Area in hectares	Yield (t/ha)	Price ($/t)	Expected Revenue ($/ha)	Weather Station
Wheat	NSW	Bland	150,000 (2004)	1.00 (2004)	$227.60 (2003/04)	$227.60	West Wyalong PO (1965-1994 rainfall) West Wyalong Airport (1995-2004 rainfall) Wyalong PO (1965-2004 temp)
Wheat	NSW	Narromine	107,700 (2000)	1.95 (2000)	$227.60 (2003/04)	$443.82	Narromine –Alagalah St (1965-2004 rainfall) Dubbo – Darling St (1965-1999 temp)

5.3 Weather-yield relationship

Wheat production is affected every day by the weather and a good yielding crop depends on favourable weather conditions. Temperature and rainfall are the main weather components affecting crop growth and yield variability and large deviations of these variables from optimal values create reduced yield (Hardaker, Huirne & Anderson 1998:8). For the two wheat farming districts used, winter/spring rainfall and temperature during the months August – October are important for growth and anthesis (flowering) and rainfall in this period partially determines yield (Alexander & Kokic 2005:7). Winter rain promotes plant growth and tillering while spring rainfall is essential for optimum grain development following anthesis (Seif & Pederson 1976:1113). Various studies of wheat yield and rainfall have found rainfall is important for crop yield and at least one study concluded winter rain (June-August) is important for yield (Cornish 1950 cited in Seif & Pederson 1976:1108). Another study identified seasonal rainfall as a major source of yield variability (Taylor, Storrier & Gilmore 1971 cited in Seif & Pederson 1976:1108). Seif and Pederson (1976:1109) conducted trials in the two LGA's utilised in this study and found mean anthesis dates ranged between 5 September and 30 October therefore the three month period August-October used for analysis comprises winter and spring rainfall in the period before and after anthesis. Wheat yield is also partially determined by grain formation and filling which is influenced by the length of time between anthesis and ripeness. The period of time between anthesis and ripeness is reduced by high temperatures and low yields may

result from this reduced period (Schelling et al. 2003:133-114). Gibson and Paulsen (1999:1842) found a shortening of the period between anthesis and ripeness of 1.3 days for each 1 °C increase in mean temperature above 20 °C. Temperature is important during crop growth since individual plants require warmth and sunlight to facilitate tiller production. Warrington, Dunstone and Green (1977:19) found high temperatures during the period from germination to double ridge increased yield through the production of a significantly higher number of mature ears at harvest. This requirement for warmth and sunlight can be measured in a number of ways, such as calculation of average temperature each day, or the maximum temperature each day, or by determining a baseline temperature at which plants begin to photosynthesize so growth occurs and then calculating Cooling Degree Days (CDD's) based on the baseline. Different plant species have different baseline temperatures and previous studies have used a number of different baselines. Turvey (2001:337) used a baseline of 10 °C to calculate degree-days for corn, soybeans and hay in Ontario while Vedenov and Barnett (2004) used 10 °C and 18 °C for corn, soybeans and cotton in the U.S. Fleege et al. (2004:3) used a baseline of 18 °C for nectarines, raisin grapes and almonds in California, while Schelling et al. (2003:113) calculated growing degree days for malting barley using a baseline of 3 °C. With regard to a wheat baseline, Cousens, Barnett and Barry (2003:1297) calculated growing degree days with a baseline of 0 °C in north-western Victoria, Shad et al. (2001:426) use 4.4 °C as their baseline in Pakistan and Corbally and Dang (2002a:93) use 4.44 °C as their baseline in the U.S. Given the variety of baselines used for agricultural commodities, in this study CDD's are calculated using a baseline temperature of 5°C.

Although there are well documented influences of weather variables on yield it is difficult to develop a model that accurately and fully describes the relationships between weather and yield, particularly at the regional level. Things are further complicated because factors other than rainfall and temperature influence crop growth and yield such as fertiliser applications and pests. This study estimates a weather-yield relationship for the two selected LGAs using econometric techniques. Weather-yield relationships were estimated using the methodology of Vedenov and Barnett (2004). The regression equation with both the highest R^2 and correct coefficient signs was selected. The R^2 statistic was used here rather than the adjusted R^2 used by Vedenov and Barnett (2004) as the adjusted R^2 cannot be interpreted as the proportion of variation in the dependent

variable explained by variation in the explanatory variables (Hill, Griffiths & Judge 1997:155). The models estimated are shown below in Table 5.2.

Table 5.2: Estimated weather-yield models

Model Type	Functional form
Monthly Observations	
Quadratic in absolute values	$Y_{\det} = \alpha_0 + \alpha_1 R + \alpha_2 T + \alpha_3 R^2 + \alpha_4 T^2 + \alpha_5 RT + \varepsilon$
Linear in absolute values	$Y_{\det} = \alpha_0 + \alpha_1 R + \alpha_2 T + \varepsilon$
Log-log in absolute values	$\log(Y_{\det}) = \alpha_0 + \alpha_1 \log(R) + \alpha_2 \log(T) + \varepsilon$
Cumulative Observations	
Quadratic in absolute values	$Y_{\det} = \alpha_0 + \alpha_1 R_{Cum} + \alpha_2 CDD_{Cum} + \alpha_3 R_{Cum}^2 + \alpha_4 CDD_{Cum}^2 + \alpha_5 R_{Cum} CDD_{Cum} + \varepsilon$
Linear in absolute values	$Y_{\det} = \alpha_0 + \alpha_1 R_{Cum} + \alpha_2 CDD_{Cum} + \varepsilon$
Log-log in absolute values	$\log(Y_{\det}) = \alpha_0 + \alpha_1 \log(R_{Cum}) + \alpha_2 \log(CDD) + \varepsilon$
Combined Observations	
Linear in absolute values (1)	$Y_{\det} = \alpha_0 + \alpha_1 R + \alpha_2 CDD_{Cum} + \varepsilon$
Linear in absolute values (2)	$Y_{\det} = \alpha_0 + \alpha_1 R_{Cum} + \alpha_2 T + \varepsilon$

R represents vectors of monthly rainfall observations for August, September and October, $[R_{Aug}]$, $[R_{Sept}]$ and $[R_{Oct}]$. T represents vectors of average monthly temperatures for August, September and October, $[T_{Aug}]$, $[T_{Sept}]$ and $[T_{Oct}]$. R_{cum} is total cumulative rainfall during the three month period, August-October. CDD_{Cum} is total cumulative Cooling Degree Days during the three month period, August-October with CDD's calculated using a baseline temperature of 5°C.

The models were estimated using historical LGA-level yield data collected from Fitzsimmons (2004) and Thompson (2005) for the period 1965-2004 and are reported in Table 5.3 below. To remove trends in yields over the 40-year period due to improvements in technology, a linear trend model was fitted:

$$Y_t^{tr} = \alpha_0 + \alpha_1 (t - 1965). \tag{5.1}$$

The detrended yields were then calculated as:

$$Y_t^{\text{det}} = Y_t \frac{Y_{2004}^{tr}}{Y_t^{tr}} \text{ for Bland and } Y_t^{\text{det}} = Y_t \frac{Y_{1999}^{tr}}{Y_t^{tr}} \text{ for Narromine.} \tag{5.2}$$

The best model for each LGA was then used as the weather index, with insignificant variables retained. The resulting models and their corresponding statistics are reported in Table 5.3.

Table 5.3: Best calculated weather-yield models (p-values in parentheses)

LGA	Index/Model	R^2
Bland	$\text{Ln(Ydet)} = -1.344 + 0.467\text{Ln}(\text{R}_{\text{Cum}}) - 0.035\text{Ln}(\text{CDD}_{\text{Cum}})$ (0.657) (0.000) (0.936)	0.3365
Narromine	$\text{Ydet} = 6.909 + 0.006\text{R}_{\text{Cum}} - 0.117\text{T}_{\text{Aug}} - 0.098\text{T}_{\text{Sept}} - 0.192\text{T}_{\text{Oct}}$ (0.000) (0.001) (0.305) (0.332) (0.063)	0.5433

The best model for each LGA, as shown in Table 5.3, was determined by choosing the model with the highest R^2 value and with appropriate signs on coefficients. The best weather-yield model for Bland based on this criterion is the log-log model in absolute values based on cumulative observations which had an R^2 value of 33.65 per cent. This model uses the natural log of cumulative rainfall observations and cumulative Cooling Degree Days (CDD's) over the three month period, August-October. It has the expected coefficient signs, positive for rainfall and negative for temperature. The Bland index model shows that the coefficient of the log of cumulative Aug-Oct rainfall is significant at a one per cent level while the other coefficients are not significant.

The best weather-yield model for Narromine is the linear model in absolute values with combined cumulative and monthly observations, specifically cumulative Aug-Oct rainfall observations and monthly temperature observations. This index model has an R^2 value of 54.33 per cent and expected coefficient signs. The rainfall coefficient has a positive sign and the temperature coefficients all have negative signs. In this model the intercept coefficient and the coefficient of cumulative Aug-Oct rainfall are both significant at a one per cent level, the coefficient of October temperature is significant at a ten per cent level and the remaining coefficients are not significant. A linear model may be criticised as an unrealistic relationship between weather and yield. Further

research should use a wider range of possible functional forms to achieve a higher weather-yield relationship, but in the context of this current work, the linear model in absolute values is considered a reasonable approximation of reality.

5.4 Pricing the weather derivative

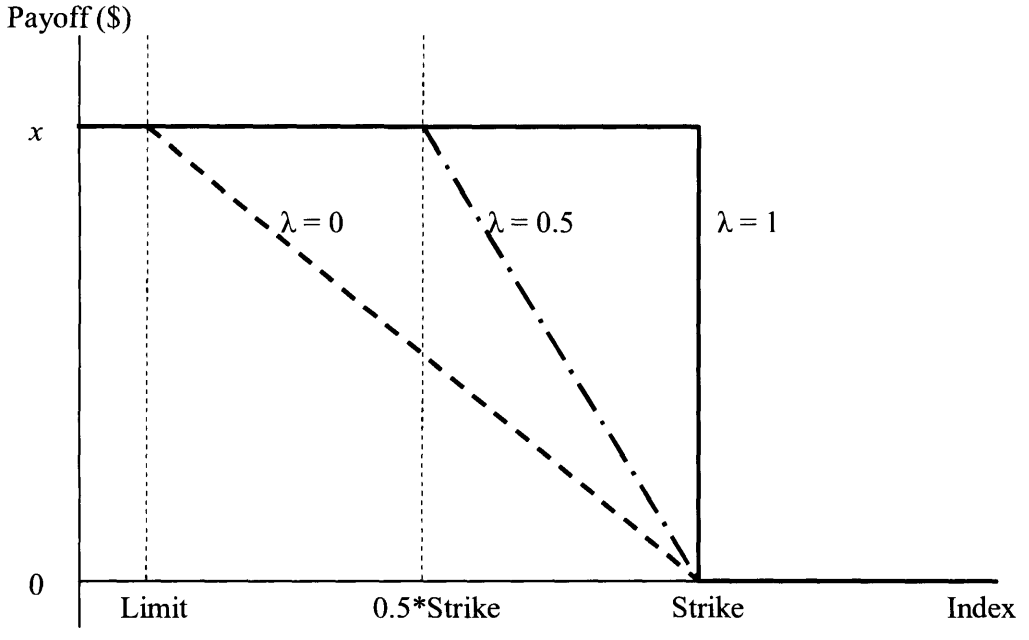
To determine the efficiency of a weather derivative contract, an appropriate contract must be specified and the premiums associated with this contract obtained. Vedenov and Barnett (2004) designed a simple weather derivative structure that allowed a proportional payoff to the contract holder up to some predetermined maximum payout. The structure of this weather derivative is shown in Equation 5.3. If the underlying index is greater than the strike the contract has no payout and the farmer should have a good crop yield as a result of favourable weather conditions. If the index value falls below the strike, the contract pays out proportionally until the maximum liability is reached. At any index value lower than the limit, λi^*, the weather derivative pays out the maximum liability, irrespective of how low the underlying index value is.

$$f(i|x,i^*,\lambda) = x \times \left\{ \begin{array}{ll} 0 & if \quad i > i^* \\ \dfrac{i^* - i}{i^* - \lambda i^*} & if \quad \lambda i^* < i \leq i^* \\ 1 & if \quad i \leq \lambda i^* \end{array} \right\} \tag{5.3}$$

where i is the underlying index, i^* is the underlying index strike level at which the contract begins to payout, and λ is the speed at which the payout approaches the maximum indemnity, x, where $0 \leq \lambda \leq 1$. For example, a wheat producer requires sufficient rainfall during the important growing months of August-October in order to receive a reasonable yielding crop. If the underlying index is solely in terms of rainfall in millimetres during this period the strike can be set at the point at which low rainfall begins to reduce crop yield, say at 100mm. If the maximum liability is \$1000 and λ is set at 0.45 the corresponding limit will be at 45mm. This is the point below which the contract pays a fixed maximum liability. If rainfall is above the strike at 125mm the farmer receives no payout. If rainfall is below the strike but above the limit at 70mm, the weather derivative will pay \$1000 x ((100-70)/(100-45)) = \$545.45. If rainfall is below the limit at 30mm, the contract will pay the farmer the maximum liability of \$1000.

The limit is determined by the value of λ used in the payoff calculations. As λ increases the limit approaches the strike and the speed at which the maximum liability is reached increases. This is shown in Figure 5.6 with different values of λ. When λ = 1 the contract has a binomial payout structure with an all-or-nothing payout. If the index falls below strike the full maximum liability is paid while if the index rises above strike then no liability is paid (see Figure 5.6). If λ = 0 the payout increases proportionally to the decrease in the underlying index. If λ = 0.5 the payout increases proportionally at twice the speed of when λ = 0 until it reaches the limit. So while payouts are proportional they increase at a faster rate than when λ = 0 (Figure 5.6).

Figure 5.6: Payoff structure of designed weather derivative



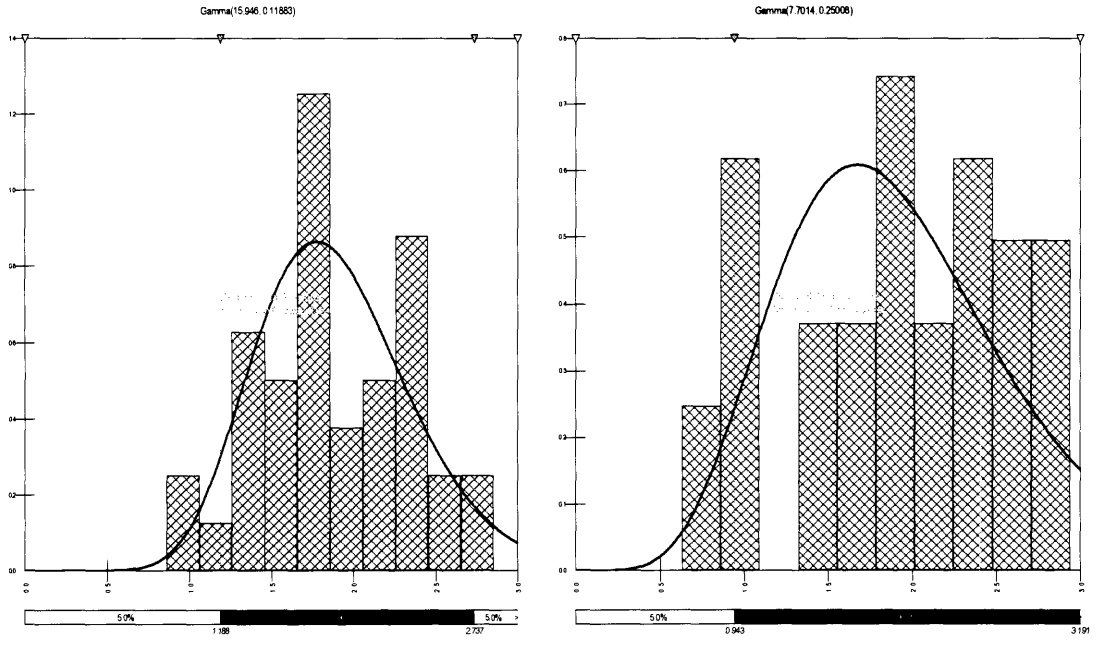
Source: Vedenov and Barnett 2004:393.

To calculate the price or actual value of this simple weather derivative contract the contract parameters and probability distribution of the underlying index must be known. The probability distribution for each LGA is measured from the best estimated indices in Table 5.3 using the Excel add-in program BestFit, which fits multiple distributions to input data. BestFit ranks the possible distributions on the basis of goodness of fit using three tests, the Chi-square test, the Anderson-Darling test and the Kolmogorov-Smirnov test. The three tests may rank distributions in different orders, so the user must then decide which distribution is the most favourable on the basis of inspection of the BestFit outputs. All three tests were considered when choosing the best distribution for the

indices. While the cumulative rainfall during the growing period of August-October is most important in this context, the "best" index model for both regions also happens to incorporate temperature (see Table 5.3). Therefore, the distribution of the index is different to a pure rainfall index which is commonly characterised by a gamma distribution (Aksoy 2000:420; Cho, Bowman & North 2004:1587; Janowiak & Xie 1999). This distribution has the favourable property of being bounded below by zero with no upper bound which suits cumulative rainfall. However, as the index models have a mixture of rainfall and temperature variables there is less intuitive connection to any particular distribution. Values of the index using the best index model for each LGA from Table 5.3 were based on historical meteorological data from 1965-2004 and used to obtain distributions from BestFit. After analysis of the various fits for each model a 2-parameter gamma distribution was chosen to describe the index distribution. The three test rankings from BestFit were reasonably similar, each test ranking the gamma distribution highly for both Bland and Narromine. The graphs obtained from BestFit are shown in Figure 5.7, while distribution parameters are in Table 5.4 below.

Figure 5.7: Plotted distributions of the underlying index from BestFit for (a) Bland LGA and (b) Narromine LGA.

(a) Bland (b) Narromine



The gamma distribution can represent many different shapes if the values of the two parameters are changed (Cho, Bowman & North 2004:1587). Its versatile shape means

it is often used to represent rainfall and in this case it also fits the precipitation-temperature index models well.

The probability density function of the gamma distribution (BestFit 1996) is shown below:

$$g(i) = \frac{\beta^{-\alpha} i^{\alpha-1} \exp\left(-\frac{i}{\beta}\right)}{\Gamma(\alpha)} \qquad i > 0, \quad \alpha > 0, \quad \beta > 0 \tag{5.4}$$

where α is a shape parameter, β is the scale parameter and i is the weather index model. The denominator of Equation (5.4) $\Gamma(\alpha)$, the incomplete gamma function (Aksoy 2000:420) evaluated at α, is given by:

$$\Gamma(\alpha) = \int_0^\infty i^{\alpha-1} e^{-i} di\,. \tag{5.5}$$

Table 5.4: Shape and scale parameters for gamma distributions from BestFit

	α	β
Bland LGA	15.9464	0.11883
Narromine LGA	7.7014	0.25008

The mean and variance of the gamma distribution are $\alpha\beta$ and $\alpha\beta^2$ respectively (Cho, Bowman & North 2004:1587).

Given this gamma probability density function *g(i)* for the underlying index the expected payoff and hence actuarially-fair price of the contract is (see Appendix 3):

$$\begin{aligned} \pi(x, i^*, \lambda) &= \int f(i|x, i^*, \lambda) g(i)\, di \\ &= x\int_0^{\lambda i^*} g(i)\, di + x\int_{\lambda i^*}^{i^*} \frac{i^* - i}{i^*(1-\lambda)} g(i)\, di \end{aligned} \tag{5.6}$$

The expected payoff and actuarially-fair price are equal to the maximum payout multiplied by the proportion of index values below the limit plus the maximum payout multiplied by the proportion of index values that fall between the limit and the strike. It is assumed in Equation (5.6) that the underlying index has a stationary distribution (Vedenov & Barnett 2004:394).

Equation (5.6) requires a strike i^* to be set as well as the remaining terms, the limit parameter λ and the maximum liability x. These two latter parameters are chosen by minimising the semi-variance or some other measure of downside loss with respect to x and λ (Vedenov & Barnett 2004:394) over the period 1965-1984. However, this method did not produce satisfactory non-zero values of x. Thus, x was set at 80 per cent of the mean LGA yield approximately covering the costs of growing the crop. A previous study found that a rule of thumb hedging strategy involving a hedge of 60 per cent of forecasted yields provided a hedge that performed as well or better than the hedge ratio estimates developed from either farm or county yield data (Miller & Kahl 1989:317). The value used in this chapter is 80 per cent as this essentially provides full cover to the farmer. It is unlikely a farmer would lose the entire crop and there is usually some cost savings associated with a ruined crop due to unfavourable weather events, as harvest costs are either negated or much reduced. Therefore, λ is chosen in Equation (5.7) below by minimising the semi-variance with respect to λ and with predetermined values for x and the strike. Semi-variance is minimised rather than the whole variance because farmers are assumed to be only concerned with downside variance (Vedenov & Barnett 2004:395).

The index series was divided into two subsets 1965-1984 for both regions and 1985-2004 for Bland and 1985-1999 for Narromine. The first subset was used to obtain the price/premium for the weather derivative contract and the second subset was used in the next section to analyse the efficiency of the contracts. As the index and therefore the price are in terms of yield (ie. wheat is the numeraire), the strike is set at long-run average yield. The contracts will payout to the farmer whenever the index drops below average yield. Thus, for Bland the strike was set at 1.61 tonnes per hectare and for Narromine at 1.43 tonnes per hectare. The parameter λ was found by substituting Equations (5.3) and (5.6) into Equation (5.7) and solving for λ using the *Mathematica* code in Appendix 3.

$$\min_{\lambda} \sum_{t=1}^{20} \left(\max\left\{ \bar{Y} - \left[Y_t^{\det} + f\left(i_t | x, i^*, \lambda\right) - \pi\left(x, i^*, \lambda\right) \right], 0 \right\} \right)^2 \tag{5.7}$$

where $Y_t^{\det}$ was the detrended historical yield and $\bar{Y}$ was the long-term average yield over the whole data period. Equation (5.7) has the maximum payout x and the limit parameter λ in terms of yield. To translate the maximum payout into money it was

multiplied by the 2003/04 wheat price of $227.60 per tonne (ABARE 2004), see Table 5.1. The resulting contract characteristics for both sites are presented in Table 5.5.

Table 5.5: Parameter values and premiums for designed weather derivative contract.

LGA	Strike	Limit		Maximum Liability ($/ha)	Premium ($/ha)	Premium Rate
		Absolute Value	Per Cent of Strike			
Bland	1.61t/ha	0.00t/ha	0.00%	$293.15	$12.93	4.41%
Narromine	1.43t/ha	0.44t/ha	30.76%	$260.37	$19.78	7.60%

From Table 5.5 premiums per hectare are low for both regions. In the Bland LGA, where the strike was set at 1.61 tonnes per hectare, the calculated premium was $12.93 per hectare and maximum liability was $293.15 per hectare. Thus as the index value decreases below the strike the contract begins to payout with full proportionality until the index reaches the lower limit of 0.00 tonnes per hectare when the contract reaches the maximum liability. The premium rate is very low for the Bland LGA so the farmer's premium on the contract is only 4.41 per cent of maximum liability. In the Narromine LGA the strike was set at 1.43 tonnes per hectare and maximum liability at $260.37 per hectare resulting in a calculated premium of $19.78 per hectare which is 7.6 per cent of the maximum liability. As the index value decreases below the strike the contract begins to payout with partial proportionally until the index reaches the lower limit of 0.44 tonnes per hectare after which the contract pays maximum liability. Here the payout reaches the limit quicker than for Bland as the value of λ is closer to one. As a weather pattern approaches the binomial the value of λ approaches one and the contract payout approaches an all-or-nothing payout structure. In the situation where λ is close to one, predicted yields only need to drop slightly below the mean yield for the farmer to receive the maximum liability. A binomial instrument of this type is a simpler instrument than the proportional payout instrument and could have significant advantages for marketing these instruments to farmers as the simpler structure makes them easier for farmers and agents to understand. However, this simpler instrument is only feasible for regions which show evidence of a "binomial" or "feast or famine" weather index.

To complete discussion of these hypothetical weather derivative contracts, recall the index test statistics in Table 5.3 showing these index models captured only 33.65 per cent and 54.33 per cent of the variation in detrended yields for Bland and Narromine respectively. Weather-yield relationships are difficult to determine and the weather-yield indices used here only partially capture this relationship. The best LGA indices have only a limited intuitive relationship between changes in weather and changes in the index value from the farmer's point of view and the best index model is significantly different for the two LGA's analysed in this study. This result is supported by Vedenov and Barnett (2004:395) who find that weather derivatives must be designed individually to account for differences in growing conditions, location and agricultural practices.

Further research should be undertaken to calculate weather-yield relationships for individual properties rather than the aggregated local government areas. An individual property relationship may capture the nuances of the weather-yield relationship better, which should increase the accuracy of the weather risk instruments as a hedging strategy. However, the majority of farmers would not have historical records of yields or weather for the required length of time. This would mean that historical precipitation and temperature data would probably have to be sourced from weather sites off-farm. Likewise, historical regional yields would probably have to be used in place of individual farm yield records, thus bringing the analysis back to the case used here. Even if the required length of data was available from a few individual properties, the risk analyst would still have to revert to a regional level to construct a weather-yield relationship for all properties without sufficient data. In addition, even if the full information on precipitation, temperature and yield exists, farmers may not accurately report the data. Thus in practice, the data limitations would necessitate the use of aggregated regional data. The LGA data was chosen as a practical and suitable regional aggregation for this study.

The premium rates calculated here can be compared to those reported by Vedenov and Barnett (2004:396) despite the difference in agricultural commodities analysed. The premium rates calculated for both sites are lower than the range of premium rates calculated by Vedenov and Barnett (2004:396), although those authors note that their premium rates turned out to be surprisingly high. The higher premium rates reported by Vedenov and Barnett (2004:396) could be explained by their higher values of λ and thus

the faster speed with which their payouts reach the maximum liability in comparison with the lower values of λ determined by this study. As a result, the distribution of payouts in this study would cover a greater range than the expected range from Vedenov and Barnett (2004) as here a greater movement in the index must occur to reach the maximum liability. This may explain the lower premiums obtained here.

5.5 Efficiency analysis

The efficiency analysis undertaken in this context aims to determine the risk-reducing ability of a weather derivative for reducing a representative farmer's exposure to yield risk from unfavourable weather (Vedenov & Barnett 2004:396). Efficiency analysis is conducted on both in-sample (1965-1984) and out-of-sample (1985-2004 Bland, 1985-1999 Narromine) values of the index. Transactions costs have been excluded from the efficiency analysis and farmers are assumed to purchase the weather derivative contracts for actuarially fair prices. It was also assumed a representative wheat farmer from each region purchases the weather derivative (and no other yield risk management tools) to decrease their yield risk exposure from unfavourable weather events. For farmers with greater variation in yields than the LGA average, the risk-reducing ability of the weather derivative will vary from the efficiency analysis shown in this chapter under these assumptions. Whether the risk-reducing ability of the weather derivative would be greater or less as a result of the greater variation in yields depends on the weather-yield relationship for each individual farmer. Thus some farmers would find the weather derivative working more efficiently and others less efficiently than the results reported here.

The efficiency analysis incorporates two different measures of efficiency based on Vedenov and Barnett (2004:396-398). The first measure of efficiency is based on the Mean Root Square Loss measures in Equation (5.10) below and the second measure is based on the Value-at-Risk framework.

For each LGA and for each of the subsets, the revenues without the contract were:

$$R_t = pY_t^{\det} \qquad t = 1,.....,T \tag{5.8}$$

while revenues with the contract were (see Appendix 4):

$$R_t^{'} = pY_t^{\det} + f\left(i_t \middle| x, i^*, \lambda\right) - \pi\left(x, i^*, \lambda\right) \qquad t = 1, \ldots\ldots, T \tag{5.9}$$

where p is the 2003/04 wheat price from in Table 5.1. The first measure to be calculated, the mean root square loss (MRSL), is a function of the semi-variance from Equation (5.7). MRSL was calculated for revenues with and without the contract using:

$$\begin{aligned} MRSL_{without} &= \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left[\max\left(p\bar{Y} - R_t\ , 0\right)\right]^2} \\ MRSL_{with} &= \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left[\max\left(p\bar{Y} - R_t^{'}\ , 0\right)\right]^2} \end{aligned} \tag{5.10}$$

where $\bar{Y}$ is long-term average yield and R_t and $R_t^{'}$ are from Equations (5.8) and (5.9). The results are shown in Table 5.6 and the coding is in Appendix 4.

A negative sign on the percentage changes in the MRSL shown in Table 5.6 indicate that the weather derivative contract has reduced risk exposure.

There is negligible reduction in risk exposure for Bland both in- and out-of-sample. Results are similar for Narromine with negligible reduction in risk exposure in-sample and a negligible increase in risk exposure out-of-sample (Table 5.6). Using this efficiency measure there is no evidence of any reduction in risk exposure from purchasing the hypothetical weather derivative for Bland or Narromine.

Table 5.6: Efficiency of designed weather derivative using a Mean Root Square Loss (MRSL) technique. A negative percent change indicates a reduction in risk exposure.

	In-Sample (1965-1984)			Out-of-Sample (1985 – 2004)		
	Without contract ($/ha)	With Contract ($/ha)	Percent Change	Without contract ($/ha)	With Contract ($/ha)	Percent Change
Bland	$238.90	$238.50	-0.17%	$246.91	$246.78	-0.05%
Narromine	$319.70	$319.35	-0.11%	$227.53	$227.89	0.16%

The second efficiency measure calculates the value-at-risk (VaR) from the revenue distribution's cumulative density function at a given α% level using Equation (5.11):

$$\Pr[R < VaR_{\alpha}] = \alpha . \tag{5.11}$$

In this case α refers to the percentage area under the left tail of the cumulative density function.

The revenue subsets from each region, calculated both with and without the contract from Equations (5.8) and (5.9) respectively were entered into BestFit to allow it to fit a distribution. Revenues were not bounded at zero as the rainfall and index were previously. The distribution that fit the revenues best both with and without the contract, and in- and out-of-sample in both regions was the normal distribution. The cumulative density functions were used for each combination of contract, subset and location to analyse increases in efficiency from the weather contract with measurements based on the VaR technique. Table 5.7 shows the VaR measures calculated with normally distributed revenue. A positive change in dollars per hectare indicates an increase in efficiency or a decrease in risk exposure of the farmer.

Table 5.7 shows that contracts have very little effect for either region both in- and out-of-sample. The change in dollars per hectare with the contract is only $0.10 per hectare – a trivial amount. This result is consistent with the MRSL results for both the Bland LGA and the Narromine LGA.

In the first two rows of Table 5.7 the risk exposure is high shown by a low VaR coefficient. In this scenario, the weather derivative reduces risk exposure for Bland LGA both in-and out of sample, while it increases risk exposure out-of-sample for Narromine LGA. In the next two lines of Table 5.6 with a lower risk exposure shown by the higher VaR coefficient, the weather derivative now increases risk exposure for both Bland and Narromine LGAs.

The last two lines of Table 5.7 with the lowest level of risk exposure shown by the highest VaR coefficient show that the weather derivatives still increases risk exposure for both LGAs. For Narromine LGA, as initial risk exposure declines (shown by an increase in the VaR coefficient) the use of weather derivative contracts actually increases the risk exposure of the farmer.

Table 5.7: Efficiency of weather derivatives measured using Value-at-Risk (VaR) with revenues following a Normal distribution.

LGA	In-Sample (1965-1984)			Out-of-Sample (1985-2004)		
	Without contract ($/ha)	With contract ($/ha)	Change ($/ha)	Without contract ($/ha)	With contract ($/ha)	Change ($/ha)
			VaR 0.05			
Bland	$175.60	$175.70	$0.10	$202.40	$202.50	$0.10
Narromine	$53.00	$53.00	$0.00	$210.90	$210.70	- $0.20
			VaR 0.10			
Bland	$234.30	$234.30	$0.00	$260.80	$260.70	- $0.10
Narromine	$139.00	$139.00	$0.00	$259.80	$259.50	- $0.30
			VaR 0.20			
Bland	$305.40	$305.40	$0.00	$331.40	$331.30	- $0.10
Narromine	$243.00	$243.00	$0.00	$319.00	$318.50	- $0.50

5.6 Conclusions

This part of the study has aimed to determine efficiency of weather derivatives for wheat producers in two LGA's of NSW using methodology developed by Vedenov and Barnett (2004). The results indicate that the weather-yield relationship is difficult to capture in it's entirety, particularly at a regional level, as there are many factors which affect the yield of a crop. Thus econometric estimation of weather-yield indices provides fairly low explanatory value, which may partially explain the efficiency results. The explanatory power of the model for Narromine is within the range reported and the explanatory power of the model for Bland is only slightly below the range reported by Vedenov and Barnett (2004:392). To maximise the proportion of the weather-yield relationship captured by the index, weather contracts must be individually designed for each different location, and this requires location-specific historical data. While it is acknowledged that location-specific data would likely increase the explanatory power in the weather-yield relationships, data unavailability necessitates

estimation at the regional level for most producers. If location-specific data were available the efficiency of the designed weather derivative to reduce risk exposure may be enhanced, conversely moral hazard may be increased. This is an avenue for further research in the future.

The hypothetical weather derivative for Bland has a premium of $12.93 per hectare which is fairly small at 4.41 per cent of the maximum liability, $293.15 per hectare. This premium rate is below the range of premium rates found by other authors in similar work. The efficiency measures concur with each other, the mean root square loss technique indicating a very minimal increase in efficiency both in- and out-of-sample. The value-at-risk efficiency measure indicates a small reduction in risk exposure in- and out-of-sample at the higher levels of risk exposure (VaR 0.05) through the use of a weather derivative aimed to reduce profit variability due to unfavourable weather events. At the lower levels of risk exposure, when VaR is set at 10 per cent or 20 per cent, there is an increase in risk exposure out-of-sample. So for Bland, there is the possibility of small reductions in risk exposure or small increases in risk exposure, depending on the technique used to measure the changes in risk exposure to the farmer.

The hypothetical weather derivative for Narromine has a premium of $19.78 per hectare which is again fairly small, it is 7.60 per cent of the maximum liability, $260.37 per hectare. The efficiency measures showed even more disappointing results for Narromine. In-sample the mean root square loss technique indicated small increases in efficiency, while the value-at-risk technique showed zero effects on risk exposure. Out-of-sample the weather derivative decreased efficiency using both of the measuring techniques. Therefore, a farmer would be better encouraged to avoid using weather derivatives to hedge against variability in profits due to variability in weather.

Thus, despite capturing some proportion of the variation in yield variability with variation in weather variability, the designed weather derivatives for these two NSW regions appear to have little cost effectiveness for reducing risk exposure of farmers. Further study is required to apply this methodology to other LGA's in Australia to extend results presented here and determine whether in other locations the efficiency gains from using these contracts are greater. Currently transactions costs have been excluded from this study and even with this exclusion the weather derivative contracts appear inefficient. Thus, inclusion of transactions costs would make the efficiency of

these weather derivatives worse. Future work should include transactions costs in the efficiency analysis to account for the fact farmers are unable to purchase weather derivatives at their actuarially fair price and therefore any positive effect on the farmer's profitability will be lessened. Extension of the work to investigate location-specific weather-yield relationships and inclusion of other agricultural commodities would further strengthen the analysis, with potential for livestock or other agricultural industries to use weather derivatives for reducing profit variability due to adverse weather. Some analysis has been undertaken into the use of weather derivatives to hedge the risk involved with heat stress in dairy cattle in the U.S. (Chen, Roberts & Thraen 2003; Chen & Roberts 2004) and potentially there may be interest in these weather risk management products from livestock industries in Australia.

Chapter 6 – Conclusions

The potential for weather derivative contracts to provide Australian wheat farmers with a new weather risk management tool has been considered. Several objectives and hypotheses were proposed to guide the research. The objectives were to determine the potential demand for weather derivatives in Australian agriculture; to determine willingness to pay for weather derivatives by a representative wheat farmer; to determine efficiency of weather derivatives for managing weather risk; and to examine obstacles to widespread uptake of weather derivatives by Australian farmers.

The work was divided into four main sections comprising Chapters 2, 3, 4, and 5. In Chapter 2 an extensive review of the literature on history, use, design and pricing of weather derivatives was undertaken and there was an introduction to weather risk in Australian agriculture.

Chapter 3 provided a more detailed description of the risk literature followed by development of an optimal hedging model to determine potential demand for a particular type of weather derivative. The optimal hedging rule model indicated that an "average" farmer would probably find weather derivatives were not effective as weather risk management tools. Sensitivity analysis showed that more risk averse farmers or those with higher yield risk and unable to diversify production may be more interested in weather derivatives.

Chapter 4 explains the so-called problem of geographical basis risk resulting from possibly large geographic distances between weather stations and farms. Rainfall datasets from individual case-study farms were analysed and compared to rainfall datasets obtained from Bureau of Meteorology weather stations. Payoffs from hypothetical weather derivative contracts with different basis risks were compared and analysed for significant differences. It was found geographic basis risk is less of a problem than many believe and using combinations of weather stations provides a good rainfall fit for the case-study farms analysed, although high correlation of rainfall between weather stations does not guarantee high similarity in payouts to the farmer. However, the geographic distance between all three case-study farms and Sydney

Airport was too great for effective hedging. A possible way of satisfying underwriters' preferences for standardised weather stations could be to establish a collection of regional centres as sites for collection of weather data for all weather derivatives in that region. The number of such centres needed would require further research into the distribution of rainfall over geographical distances and consequences for payouts if only a few regional centres were established. It is possible only two or three regional centres per state would be needed allowing underwriters opportunities to have several contracts written upon the same location. This would require farmers to accept some level of geographic basis risk depending on their farm location in relation to the nearest regional centre. The way topography interacts with geographical basis risk may also need to be investigated.

An efficiency analysis was reported in Chapter 5 to determine the effectiveness with which weather derivatives could reduce the risk exposure of farmers in each local government area studied in Chapter 4. The analysis failed to show any significant increases in efficiency for farmers using weather derivatives to hedge against profit variability from weather as the contracts did little to reduce risk exposure of farmers. These results indicate weather derivatives would be unlikely to be taken up for weather risk management by farmers even if the derivative's price was zero unless better indices could be developed. Heaton and Lucas (1966 cited in Blank, Carter & McDonald 1997:108) state that unsuitable products are not utilised by farmers. Their definition of an "unsuitable" tool is one that is not expected to reduce risk exposure or is not expected to provide insurance against that exposure.

Two hypotheses underlying this research are now examined. The first hypothesis was that farmers would demand weather derivative contracts as hedging tools for weather risk management. This hypothesis has been rejected based on both the optimal hedging rule and the efficiency analysis. The second hypothesis was that weather derivative contracts specifically designed using regional level data could provide an efficient means for farmers to reduce the risk exposure associated with unpredictable and unfavourable weather conditions. The results reported in Chapter 4 on geographical basis risk support this hypothesis and indicate weather derivatives may be an efficient way for farmers to reduce weather risk exposure. It was concluded in this chapter the problems associated with geographical distance were smaller than generally perceived.

However, in the following chapter, analysis of efficiency of hypothetical weather derivative contracts designed to suit two regions in NSW indicated that these derivative products provided little reduction in risk exposure. Therefore, this hypothesis must also be rejected as there is little evidence to suggest that the contracts may indeed reduce the risk exposure of the farmer.

Appendices

Appendix 1: Calculation of σ_1^2

Year	Deflated price ($/t)	u_{1t}
1955-56	528	n/a
1956-57	559	0.0588
1957-58	514	-0.0800
1958-59	493	-0.0419
1959-60	504	0.0226
1960-61	510	0.0117
1961-62	533	0.0459
1962-63	519	-0.0271
1963-64	498	-0.0396
1964-65	474	-0.0485
1965-66	484	0.0217
1966-67	470	-0.0291
1967-68	481	0.0235
1968-69	402	-0.1644
1969-70	399	-0.0094
1970-71	387	-0.0293
1971-72	383	-0.0091
1972-73	361	-0.0591
1973-74	647	0.7936
1974-75	559	-0.1356
1975-76	467	-0.1655
1976-77	354	-0.2410
1977-78	358	0.0112
1978-79	421	0.1754
1979-80	461	0.0944
1980-81	427	-0.0731
1981-82	396	-0.0731
1982-83	394	-0.0047
1983-84	343	-0.1300
1984-85	344	0.0044
1985-86	307	-0.1093
1986-87	255	-0.1669
1987-88	257	0.0057
1988-89	311	0.2098
1989-90	265	-0.1458
1990-91	170	-0.3578
1991-92	252	0.4765
1992-93	224	-0.1088
1993-94	214	-0.0445
1994-95	283	0.3208
1995-96	299	0.0555
1996-97	241	-0.1949
1997-98	224	-0.0710
1998-99	209	-0.0663
1999-00	213	0.0196
2000-01	239	0.1222
2001-02	262	0.0956
2002-03	268	0.0240
	Variance u_{1t}	**0.0327**

Appendix 2: Mathematica code for optimal hedging model

Calculating *d*, *e*, *b* and *c*

Use the quit command to ensure that the *Mathematica* kernel is not already in use, then load the regression add-in section to *Mathematica*.

```
Quit
<<Statistics`LinearRegression`
```

The first step is run a regression to estimate value for *d* and *e* using Equation 3.20 and wheat yield data from ABARE 1950-2002. Enter the trend and yield data.

```
trend=Table[a,{a,52}];
yield={1.06,1.03,1.29,1.24,1.06,1.29,1.15,0.74,1.39,1.1,1.37,1.13,
  1.25,1.34,1.38,1,1.51,0.83,1.37,1.11,1.22,1.19,0.87,1.34,1.37,1.4,
  1.3,0.94,1.77,1.45,0.96,1.38,0.77,1.7,1.55,1.39,1.45,1.36,1.58,
  1.58,1.63,1.47,1.78,1.97,1.14,1.79,2.1,1.84,1.86,2.03,1.82,2.14};
data=Transpose[{trend,yield}]
```

Now run the regression. The {1, x} is the form of the *Mathematica* regression. The 1 is the intercept which represents *d*, and the x represents *e*.

```
regression=Regress[data,{1,x},x]
d=Part[regression,1,2,1,1,1]
e=Part[regression,1,2,1,2,1]
```

The regression line can be plotted with the raw data to see the trend in yield over time.

```
<<Graphics`MultipleListPlot`;
yieldregression=d + e trend;
MultipleListPlot[{data,yieldregression},AxesLabel→ {"trend",
  "yield"}]
```

Now *b* and *c* can be obtained using Equations 3.21, 3.22 and 3.23 using values of the variables and coefficients given in Tables 3.1 and 3.2. The value of the elasticity of supply is 0.60 as described in Chapter 3.

Equation 3.19 is divided into two parts and rewritten as Equation 3.21 with the first part labelled α and the second part labelled β. These are shown by Equations 3.22 and 3.23. α and β are calculated first, then used calculate *c* and obtain *b* as a residual.

From Equation 3.21, $q = \alpha + \beta p$. Elasticity of supply is expressed as $es = \frac{\partial S}{\partial P} \times \frac{P}{Q}$ with $es = q$ and $\beta = \frac{\partial S}{\partial P}$ and $\alpha =$ alpha.

```
Quit

price=223; quantity=22481; k=0.00000009633; u1=0.033; u2=0.037;
  es=0.60;
x=Solve[es□ beta*(price/quantity),beta]
beta=x[[1,1,2]]
```

Now rearrange Equation 3.21 to obtain α.

```
y=Solve[alpha□quantity-beta*price,alpha]
alpha=y[[1,1,2]]
```

Now that α and β have been calculated, b and c can now be obtained. Rearrange Equation 3.23 to obtain c.

```
c=(1-beta*k*price^2*(u1+u2+u1 u2))/(2 beta)
```

Substitute c into Equation 3.22 and rearrange to obtain b.

```
b=-alpha(2 c+k*price^2*(u1+u2+u1 u2))
```

Model without hedging

Use the quit command to ensure that the *Mathematica* kernel is not already in use, then load the two add-in sections to *Mathematica*.

```
Quit

<<Statistics`MultiDescriptiveStatistics`;
<<Graphics`MultipleListPlot`;
```

First, specify the expected utility function (Equation 3.2), the profit function (Equation 3.14) and the expected profit function (Equation 3.15)

```
exutility=exprofit-(k/2)(profit-exprofit)^2;
profit=p(1+u1)q(1+u2)-a-b q-c q^2;
exprofit=p q -a-b q-c q^2;
Expand[exutility]
```

Then obtain the conditional expected utility. The covariance terms are removed as price and quantity are assumed independent.

```
exutility=Expand[exutility]/.{u1 u2→0,u1 u2^2→0,u1^2 u2→0}
```

Solve First Order Condition for quantity, and take expectations.

```
Solve[D[exutility,q]□0,{q}]/.{u1^2→σ1^2, u2^2→σ2^2}
```

Solve for equilibrium quantity, substituting in values of variables and coefficients.

```
u1=σ1; u2=σ2;
Solve[D[exutility,q]□0,{q}]/.{b→148.67,c→0.0081,p→223,
  k→0.00000009633,σ1^2→0.033,σ2^2→0.032}
```

Plot quantity against price.

```
plotq=q/.Solve[D[exutility,q]□0,{q}]/.{b→148.67,c→0.0081,
  k→0.00000009633,σ1^2→0.033,σ2^2→0.032}

Plot[plotq,{p,0,600}]
```

This is a very straight line, which may indicate that k is too small. Reduce by a factor of ten to see the effect.

```
plotq=q/.Solve[D[exutility,q]□0,{q}]/.{b→148.67,c→0.0081,
  k→0.0000009633,σ1^2→0.033,σ2^2→0.032}

Plot[plotq,{p,0,600}]
```

Model with hedging of yield risk

Use the quit command to ensure that the Mathematica kernel is not already in use, then load the two add-in sections to Mathematica.

```
Quit

<<Statistics`MultiDescriptiveStatistics`;
<<Graphics`MultipleListPlot`;
```

First, specify the expected utility function (Equation 3.2), the profit function (Equation 3.9) and the expected profit function (Equation 3.10)

```
exutility=exprofit-(k/2)(profit-exprofit)^2;
profit=p(1+u1)q(1+(1-h)u2)-h m-a-b q-c q^2;
exprofit=p q -h m-a-b q-c q^2;
```

Then obtain the conditional expected utility, and take expectations conditional on information available at period *t-1*. The covariance terms are removed as price and quantity are assumed independent.

```
exutility=Expand[exutility]/.{u1 u2→0,u1→σ1,u2→σ2,u1 u2^2→0,
  u1^2 u2→0}
```

Obtain the two First Order Conditions:

```
d1=D[exutility,q]
e1=D[exutility,h]
```

Now, substitute coefficient values and variance values into first order conditions.

```
d2=D[exutility,q]/.{b→148.67,c→0.0081,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032}
e2=D[exutility,h]/.{b→148.67,c→0.0081,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032}
```

The next step is to solve the first order conditions separately. Solve twice the first derivative of expected utility with respect to quantity, with hedging set to zero in the first case and set to one in the second case. This gives the lower and upper bounds of quantity.

Solve First Order Conditions separately.

```
x1=Solve[d1□0,{q}]
x1/.{b→148.67,c→0.0081,p→223,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032,h→0}
x1/.{b→148.67,c→0.0081,p→223,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032,h→1}
```

Now solve the first derivative of expected utility with respect to hedging, setting quantity at the lower bound calculated in the previous step. As a check, this can be

solved a second time with the cost of hedging, *m*, set to zero. With $m = 0$, the proportion of hedging should equal one.

```
x2=Solve[e1□0,{h}]
σ1=Sqrt[0.033];σ2=Sqrt[0.032];
FOCh=x2/.{b→148.67,c→0.0081,p→223,k→0.00000009633, q→4500.37}
x2/.{b→148.67,c→0.0081,p→223,k→0.00000009633,q→4500.37,m→0}
```

Now solve for *m* by setting the expression FOCh = 0.

```
Solve[0□FOCh[[1,1,2]],{m}]
```

To obtain the optimal hedging ratio, plot FOCh with a range of values for *m*, the cost of hedging for the industry as a whole. The demand curve looks like:

```
Plot[FOCh[[1,1,2]],{m,0,3500},AxesLabel→{"m('000)","h"}]
```

Solve First Order Conditions simultaneously.

Use the quit command to ensure that the Mathematica kernel is not already in use, then load the two add-in sections to Mathematica.

```
Quit

<<Statistics`MultiDescriptiveStatistics`;
<<Graphics`MultipleListPlot`;
```

First, specify the expected utility function (Equation 3.2), the profit function (Equation 3.9) and the expected profit function (Equation 3.10)

```
exutility=exprofit-(k/2)(profit-exprofit)^2;
profit=p(1+u1)q(1+(1-h)u2)-h m-a-b q-c q^2;
exprofit=p q -h m-a-b q-c q^2;
```

Then obtain the conditional expected utility, and take expectations conditional on information available at period *t-1*. The covariance terms are removed as price and quantity are assumed independent.

```
exutility=Expand[exutility]/.{u1 u2→0,u1→σ1,u2→σ2,u1 u2^2→0,
  u1^2 u2→0}
```

Obtain the two First Order Conditions:

```
d1=D[exutility,q]
e1=D[exutility,h]
```

Now, substitute coefficient values and variance values into first order conditions.

```
d2=D[exutility,q]/.{b→148.67,c→0.0081,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032}
e2=D[exutility,h]/.{b→148.67,c→0.0081,k→0.00000009633,σ1^2→0.033,
  σ2^2→0.032}
```

The next step is to solve the first order conditions simultaneously. Set both first order conditions equal to zero and solve for quantity *q* and the proportion of hedging *h*. Price

is set at p = \$223 and the cost of the hedge to the industry is set at m = \$3207.14 which is the value for m that results from the previous section. Note m is in ('000)'s. The coefficient values and variance values are substituted into the Solve expression. Solve returns four solutions to this expression, the most appropriate solution is chosen.

```
p=223;m=3207.14;
x=Solve[{D[exutility,q]□0,D[exutility,h]□0},{q,h}]/.{b→148.67,
  c→0.0081,k→0.00000009633,σ1→Sqrt[0.033],σ2→Sqrt[0.032]}
```

As a check, this can be solved a second time with the cost of hedging, m, set to zero. With m = 0, the proportion of hedging should equal one.

```
p=223;m=0;
x=Solve[{D[exutility,q]□0,D[exutility,h]□0},{q,h}]/.{b→148.67,
  c→0.0081,k→0.00000009633,σ1→Sqrt[0.033],σ2→Sqrt[0.032]}
```

The next steps create the optimal hedging ratio. Mathematica is used to solve the two first order conditions simultaneously with m taking a range of values from zero to a value greater than the value obtained in the previous section when the equations were solved separately. Let the range of m be from 0 to 3500.

A list of corresponding h values is generated using the second solution from the above Solve command. To create the list, m is set as i (required by Mathematica) and the AppendTo command tells Mathematica to solve the simultaneous equations repeatedly for each value of m with a step value of one.

```
hlist={};
Do[(p=223;m=i;x=Solve[{D[exutility,q]□0,D[exutility,h]□0},{q,h}]/.{
  b→148.67,c→0.0081,k→0.00000009633,σ1→Sqrt[0.033],σ2→Sqrt[0.032]
  };AppendTo[hlist,h/.x[[2]]]),{i,1,3500,1}]
hlist;
ListPlot[hlist,PlotJoined→True,AxesLabel→{"m('000)","h"}]
```

Sensitivity analysis on the coefficient of risk aversion: the whole process is repeated with the new value for the coefficient of absolute risk aversion, remembering to put the new value for q into the first order condition when solved separately.

Appendix 3: Mathematica code for pricing the weather derivative

Bland

Use the quit command to ensure that the *Mathematica* kernel is not already in use, then enter Equation 5.3.

```
Quit
payout = x((strike-index)/(strike(1-λ)))
```

Now enter the probability distribution of the underlying index and plot the probability density function and the cumulative density function. The coefficients that shape the distribution are from Table 5.4.

```
<<"Statistics`ContinuousDistributions`";
gdist=GammaDistribution[15.9464,0.11883]
pdfunction=PDF[gdist,index]
Plot[pdfunction,{index,0,4}]

cdfunction=CDF[gdist,index]
Plot[cdfunction,{index,0,4}]
```

Enter Equation 5.6.

```
strike=1.61;
payoff=x Integrate[pdfunction,{index,0, λ strike}]+x
  Integrate[((strike-index)/(strike(1-λ)))pdfunction,{index,λ
  strike,strike},Assumptions→Re[λ]>0]
```

The detrended yields for 1965-1984 (20 years) calculated from Equation 5.2 and the index values calculated from the indices in Table 5.3 for the corresponding period are entered. This leaves the remaining 20 years (1985-2004) of detrended yields and index values to be used for the efficiency analysis.

```
Ytdet={0.856,3.255,0.969,2.406,2.203,2.304,1.317,1.757,2.135,2.087,
  1.892,2.424,1.022,2.571,2.426,1.366,2.226,0.560,2.792,2.226};
index={1.980,2.259,1.751,1.476,1.809,2.579,1.319,1.839,2.454,2.517,
  2.698,2.287,0.861,1.856,1.536,1.408,1.167,1.048,2.150,1.953};
```

Equation 5.7 is calculated in two parts for simplicity. First the maximisation is undertaken with Ybar calculated as the long-term average yield, using the whole 40 years of wheat yield data.

```
Ybar=1.61;
brackets=Max[{Ybar-Evaluate[Ytdet+payout-payoff],0}]
```

The second step to Equation 5.7 is the minimisation part of the equation to find a value of λ still using only 20 years of observations from 1965-1984. A constraint is set on the minimisation to restrict λ to a value between zero and one. The value of x is set at 80 per cent of expected yield.

```
x=0.8*Ybar
eq57=Minimize[{Sum[brackets^2,{t,1,20}],{0≤λ≤0.999999999}},{λ}]
```

The wheat price is entered from Table 5.1. The solution from Equation 5.7 is used to find the premium rate and the maximum liability of the weather derivative contract.

```
PricePerTonne=227.6;
PremiumRate=payoff*PricePerTonne/.{λ→eq57[[2,1,2]]}
maxliability=PricePerTonne(0+x)/.{}
```

Narromine

The same process is repeated remembering to insert the correct distribution parameters, strike, detrended yield values, index values and average yield for the Narromine LGA.

Appendix 4: Mathematica code for efficiency analysis

Calculating Revenues

Bland

To calculate the revenues with the weather derivative contract (Equation 5.9), go through all the code in Appendix 3 and then do this section of code for each LGA. Until this point, only the first 20 years of data have been used, however, revenues must be calculated for the whole 40 year period. Therefore, enter all the detrended yield values and index values as below. Then calculate the payout for each year from Equation 5.3.

```
WholeYtdet={0.85555,3.25525,0.96947,2.40621,2.20297,2.30400,
  1.31693,1.75651,2.13450,2.08723,1.89162,2.42436,1.02171,2.57084,2.
  42621,1.36611,2.22633,0.56038,2.79242,2.22611,2.16445,2.03203,2.02
  982,2.18948,1.98593,2.13768,1.83543,2.54579,2.75919,0.52517,2.3369
  0,2.59399,2.38456,3.13525,2.57199,2.98345,1.85567,0.92622,1.01010,
  1.00000};
index={1.980,2.259,1.751,1.476,1.809,2.579,1.319,1.839,2.454,2.517,
  2.698,2.287,0.861,1.856,1.536,1.408,1.167,1.048,2.150,1.953,2.298,
  2.170,1.849,1.952,1.647,2.120,1.535,2.264,2.856,1.372,1.439,1.858,
  1.844,2.321,2.416,2.238,1.769,1.442,1.767,1.692};
payout
```

Revenues with the weather derivative contract are then calculated from Equation 5.9, with λ set at the value obtained at the end of Appendix 3.

```
revenue=Evaluate[(PricePerTonne*WholeYtdet)+payout-
  payoff]/.{λ→1.547478354584953`*^-8}
```

Narromine

The same process is repeated remembering to insert the correct detrended yield values, index values and λ for the Narromine LGA.

Mean Root Square Loss

Bland

Use the quit command to ensure that the Mathematica kernel is not already in use then enter the revenues divided into in-sample and out-of-sample subsets, both with and without the weather derivative.

```
Quit

revenuewithout1={194.72,740.90,220.65,547.65,501.40,524.39,299.73,
  399.78,485.81,475.05,430.53,551.79,232.54,585.12,552.20,310.93,
  506.71,127.54,635.56,506.66};
revenuewithout2={492.63,462.49,461.99,498.33,452.00,486.54,417.74,
  579.42,627.99,119.53,531.88,590.39,542.73,713.58,585.38,679.03,
  422.35,210.81,229.90,227.60};
```

```
revenuewith1={194.37,740.32,220.48,547.70,501.18,523.56,299.91,
  399.54,485.08,474.27,429.61,551.19,233.08,584.87,552.21,311.03,
  507.01,127.94,635.07,506.33};
revenuewith2={492.02,461.99,461.74,498.00,451.91,486.07,417.75,
  578.84,626.94,119.66,531.96,590.14,542.48,712.96,584.68,678.47,
  422.17,210.89,229.72,227.48};
PricePerTonne=227.6;
Ybar=1.61;
```

The MRSL measures are calculated using the Equation 5.10.

```
MRSLwithout=Sqrt[(1/20)Sum[(Max[PricePerTonne*Ybar-
  revenuewithout1,0])^2,{t,1,20}]]
MRSLwithout=Sqrt[(1/20)Sum[(Max[PricePerTonne*Ybar-
  revenuewithout2,0])^2,{t,1,20}]]
MRSLwith=Sqrt[(1/20)Sum[(Max[PricePerTonne*Ybar-
  revenuewith1,0])^2,{t,1,20}]]
MRSLwith=Sqrt[(1/20)Sum[(Max[PricePerTonne*Ybar-
  revenuewith2,0])^2,{t,1,20}]]
```

Narromine

The same process is repeated remembering to insert the correct revenues and average yield for the Narromine LGA.

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