The effects of weather on wheat yields in Victoria, Australia: an empirical study.

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This study looks at the impacts that weather variables have on wheat yields in the state of Victoria, Australia. Both basic measures (temperature and precipitation) and complex measures (evapotranspiration rate and the Standardised Precipitation Index) are used. Econometric analysis is used to estimate the effect these variables have on wheat yields for 1953-2011, whilst including non-linear, interaction terms and dummy variables for extreme weather events. The regression results show that variations from the average temperature and rainfall have a negative impact on yields. However, drought has a larger and more significant impact on wheat in Victoria than changes in precipitation.

1. Introduction

Evidence suggests that weather patterns are changing. It is widely accepted that this will have an impact on crop production. Australia, renowned for its climate, has undoubtedly begun to experience this change. Since the colonial era, Australia has been a producer of wheat for both trade and consumption (GrainGrowers Ltd, 2011). Output has grown significantly, with wheat now the most valuable crop under production in the country (Australian Bureau of Statistics (ABS), 2007). The future, however, is a cause for concern and is largely dependent on Climate Change. This study aims to identify the extent to which temperature and precipitation changes from 1953 to 2011 have impacted wheat yields in the state of Victoria.

This study begins by explaining the background and context of the wheat industry in Australia, and specifically Victoria. Wheat is most successful in the Southwest and Southeast of Australia (PricewaterhouseCooper (PwC), 2011b). Victoria ranks third for yields in the country (ABS, 2007), highlighting the importance of the state's production.

Weather variables are summarised. Precipitation has fluctuated over the study period with some cyclical patterns present but displaying an overall declining trend (Bureau of Meteorology (BoM), 2015). Preliminary data from Swan Hill (a farm in the Mallee region) shows some correlation between decreasing rainfall and yields (van Rees *et al*., 2011). Similarly, temperatures appear to be increasing. In the past 100 years, the temperature in Australia has increased by 0.7℃ (Department of Agriculture, Fisheries and Forestry (DAFF), 2006). This has coincided with growing concern over Climate Change globally, coinciding with the increased frequency and intensity of droughts (Wang *et al*., 1992).

A review of the current body of literature is then conducted; there is, however, limited research on Victoria specifically. The key study conducted by van Rees *et al*. (2011) focuses on the Mallee and Wimmera regions only. Hence, a wider body of literature is covered here analysing other states in Australia to gauge the extent to which – and how – weather variables are impacting wheat yields. Overall, yields are negatively affected by rising temperatures and falling rainfall, regardless of the state (Anwar *et al*., 2007; Ludwig and Asseng, 2006; van Rees *et al*., 2011).

Climate Change has been identified as a key threat to the future (Anwar *et al*., 2007; Department of Environment and Primary Industries (DEPI), 2014). Whilst this dissertation does not seek to predict future changes and impacts, it is worthwhile acknowledging the current stance of key writers in the field. The Victorian government is working to develop new strains of grain that can withstand rising temperatures and have reduced water demand (DEPI, 2014). Research by Anwar *et al*. (2007) prior to this found that yields are falling based on a variety of Climate Change Models. Ultimately, the literature demonstrates uncertainty in the future as a direct result of weather changes. This is subsequently supported by past data both within the current body of literature and the results of this study's empirical analysis.

Hence, the subsequent Section details the empirical Model for this study, the methodology, results and discussion. The Model used is based on Blanc's (2012) work. Although this focused on sub-Saharan Africa and a variety of crops, the study specifies two Models – one using basic weather indicators (precipitation and temperature); the other using complex measures (Standardised Precipitation Index (SPI) and Evapotranspiration Rate (ET)). The latter measures are previously unused in analysis of Australian crop production. Hence, using Blanc (2012) as a basis of this study, a new insight will be given into the effects of weather on crop yields in Victoria.

Data is collected from both ABS (2013) and BoM (2015) databases, with SPI and ET calculated from this. The results highlight non-linear relationships between weather variables and wheat yields, supporting the results of the current literature. Interestingly, a lack of rainfall has the largest impact on crops, but temperature changes present greater cause for concern given predictions of future changes. Fluctuations in rainfall have occurred throughout time, but a 3°C rise in temperature as suggested by some Models (Anwar *et al*., 2007) would have catastrophic impacts on wheat yields.

The conclusion of this dissertation is therefore that yields have been negatively impacted by weather pattern changes, making the future of the Victorian wheat industry increasingly uncertain.

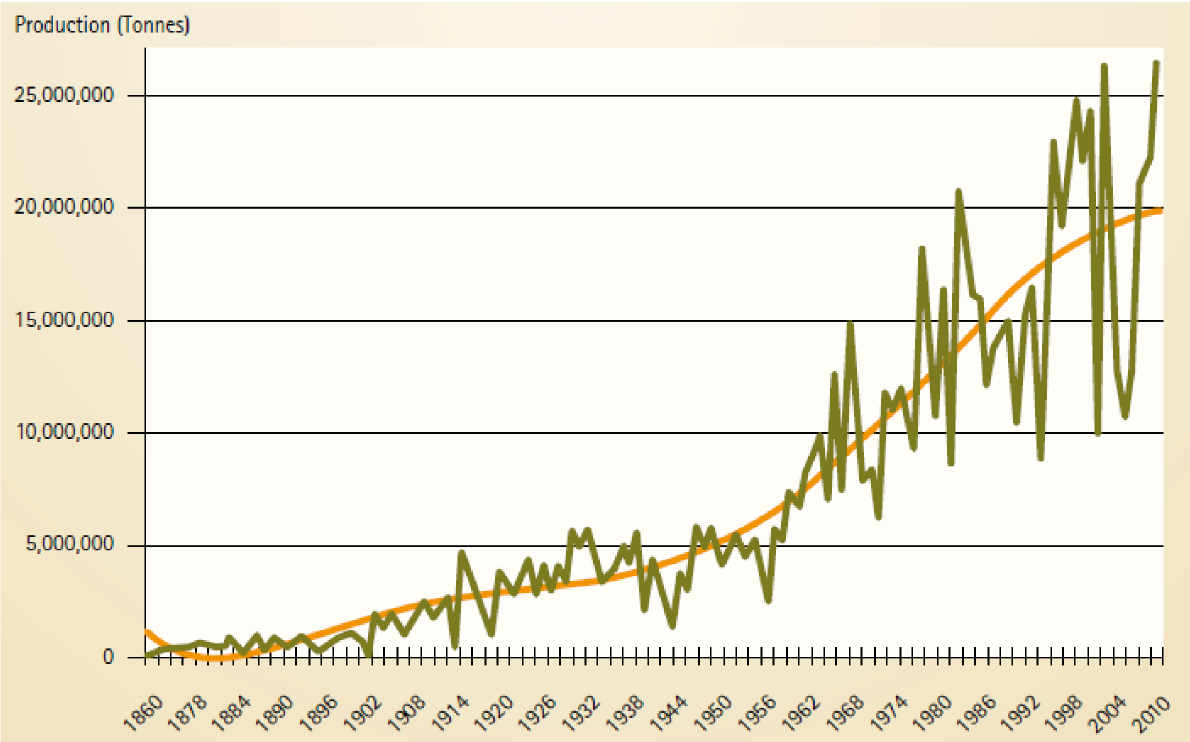
2. Background

2.1 The Wheat Industry

Wheat is one of the major grain crops produced globally. In the past 40 years, global consumption has doubled (PwC, 2011a). Accounting for only 3% of global output, Australia is not a major producer (ABS, 2007). However, the country equates to 15% of annual world trade (ABS, 2007) with key markets including Indonesia, Malaysia and Japan (GrainGrowers Ltd, 2011). The value of this trade is merely 4% of Australian GDP, but totals to 30% of Australia's exports (Luo *et al*., 2003). This makes wheat Australia's most valuable and largest crop under production (ABS, 2007).

Australia's history of wheat production dates back to the colonial era. From a meagre 5.4 tonnes harvested in 1790 (ABS, 2007), to 21,834 kilotons in 2009-2010 (PwC, 2011a), the wheat industry has grown substantially. Figure 1, taken from the GrainGrowers Ltd (2011) report on the wheat industry, shows that the boom in production occurred from the 1950s onwards, but has shown signs of slower growth in recent years as determined by the trend line.

Figure 1: **Australian Wheat Production, 1860-2010**



Source(s): GrainGrowers Ltd (2011)

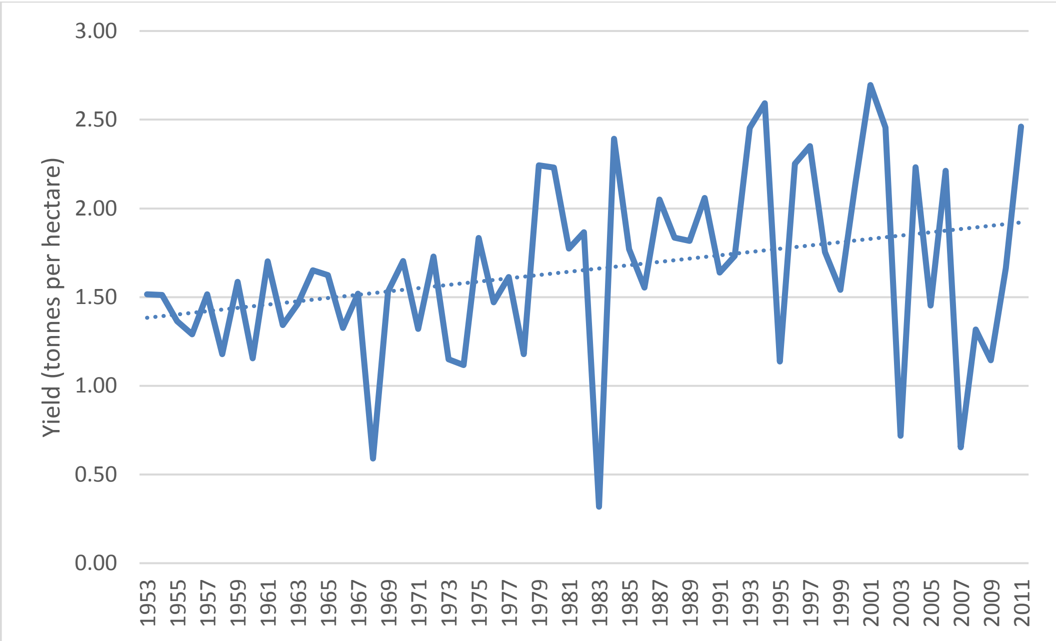
In early years, poor rainfall and inappropriate wheat varieties plagued production (ABS, 2007). Advancements in machinery and transportation allowed for larger areas to be cultivated and for wheat to be traded more freely (ABS, 2007). However, it was wheat breeding that enabled output to increase dramatically.

The value of this production is subject to fluctuations. War, depression and volatile market forces all affect prices. The European Union, Eastern Europe and the United States are key competitors (Linehan *et al.*, 2012). In 2003-2004, the harvest had a gross value of A$5.6 billion, with exports at over A$3.4 billion (ABS, 2007). Global imports of wheat are projected to grow even further, with estimates being 135% greater in 2050 than 2007 (Linehan *et al.*, 2012). This would equate to 2% annual growth of Australia's exports.

Wheat is grown across Australia but is most successful in the wheat belt of the Southeast and Southwest where rainfall is between 230mm and 500mm (PwC, 2011b). The East coast of Australia centres on domestic production. Approximately 5 million tonnes remains in Australia each year, half for production and half for animal feed (ABS, 2007).

Out of the eight states, Victoria ranks fourth for area under wheat production and total production, and ranks third for yield – ahead of New South Wales, Queensland and South Australia, with yields above the countrywide average (ABS, 2007). Appendix 1 contains graphs illustrating the change in area and production for the state for the time period concerned in this study (1953-2011). Figure 2 uses this information to demonstrate how yields have changed – this is the dependant variable used for the empirical analysis. Production fluctuates greatly in the state, but the general trend is for rising output and yields (as shown by the trend line in Figure 2). Wimmera and Mallee are two regions that are noticeably more productive than the countrywide average (GrainGrowers Ltd, 2011). These are situated in the Northwest of the state.

<u>Figure 2:</u> **Wheat Yields for the State of Victoria, 1953-2011**



Source(s): Author's calculations; Data Source: ABS (2013)

Victoria is, however, experiencing a decrease in Water Use Efficiency (WUE) that is leading to reductions in yields for harvest cycles with lower rainfall (GrainGrowers Ltd, 2011). The 1990s was the warmest decade on record, with further temperature increases predicted (Bindi and Howden, 2004). This will occur simultaneously with more variable rainfall making the future for Victorian wheat increasingly uncertain.

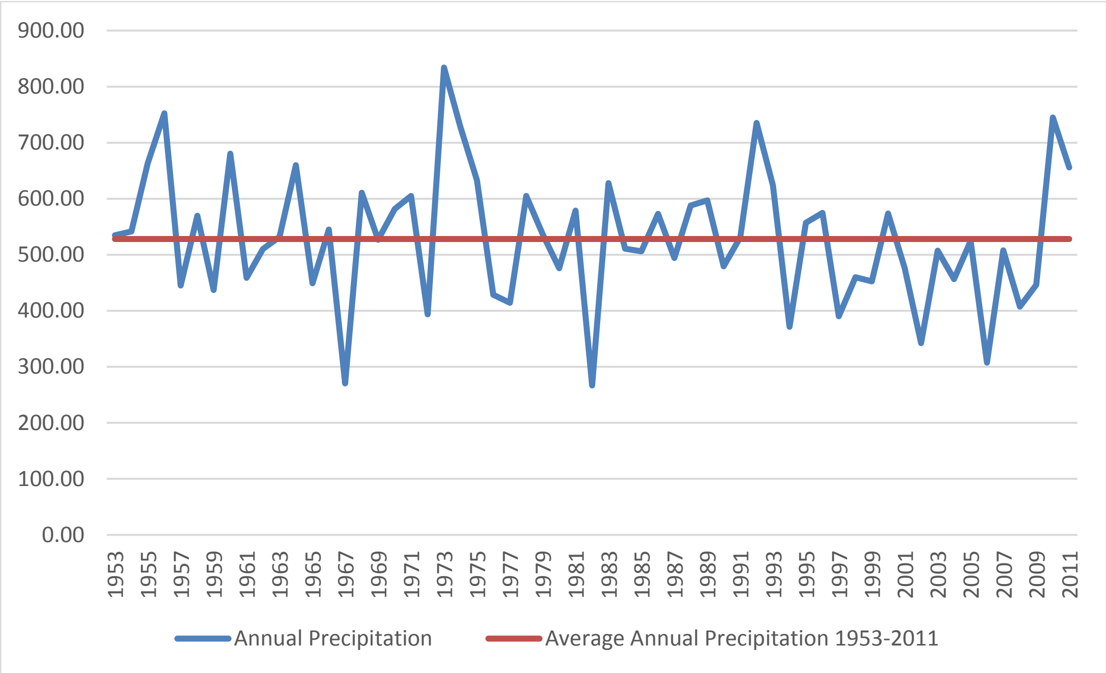
2.2 The Weather

Weather patterns have a profound impact on wheat yields, with Climate Change a major concern for Australia's future. Climate Change is therefore one of the key challenges for the wheat industry (ABS, 2007). Global warming affects wheat in three ways: the increase in CO_2 concentration; rising temperatures; and changes to rainfall and subsequent evaporative demands of the soil (Wang *et al*., 1992). In the last 100 years, temperatures across Australia have risen 0.7℃ on average and days of extreme heat have become more frequent (DAFF, 2006). Rainfall has simultaneously come to be more unpredictable and intense (Bindi and Howden, 2004).

This study will focus on rainfall and temperature to determine how these have affected wheat yields in Victoria from 1953 to 2011. Precipitation has fluctuated quite dramatically in the study period, with clear drought and flood years present. The harvests of 1982-1983, 1994-1995 and 2002-2003 coincided with substantial droughts (DAFF, 2005). The effect of this is reflected in the low productivity and value of the crop in those years.

Figure 3 illustrates annual precipitation in Victoria. Years of drought appear to be becoming more frequent since the 1990s. Interestingly, this coincides with the aforementioned record high temperatures. However, 2010 was one of the wettest years on record, ending a 13-year drought period that was categorised by higher minimum and maximum temperatures (van Rees *et al*., 2011).

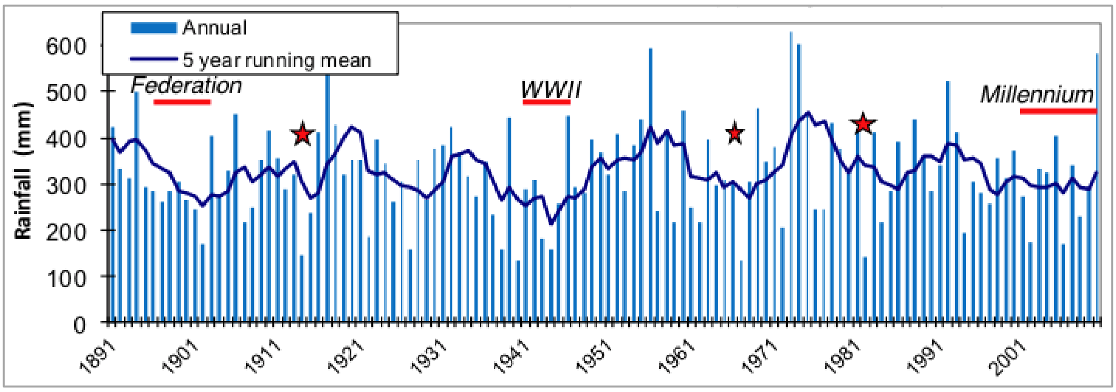
Figure 3: **Annual Precipitation for Victoria (mm), 1953-2011**



Source(s): Author's calculations; Data Source: (BoM, 2015)

Drought periods can therefore be short-term or long-term. Short-term droughts are single years in which rainfall is significantly lower than average, reducing crop yields (van Rees *et al*., 2011). Long-term droughts consist of any length of time where rainfall is below average, with temperatures often simultaneously higher than usual (van Rees *et al*., 2011). Figure 4, taken from van Rees *et al*. (2011), highlights three single year droughts (starred events) and three multi-year droughts (red line events) for Swan Hill. This is a farm in the Mallee region of Victoria and so is an interesting parallel to the empirical Section of this study. As can be observed, whilst not entirely predictable, there does appear to be a somewhat cyclical pattern to rainfall.

Figure 4: **Historical Rainfall, Swan Hill, Mallee Region, 1891-2010**

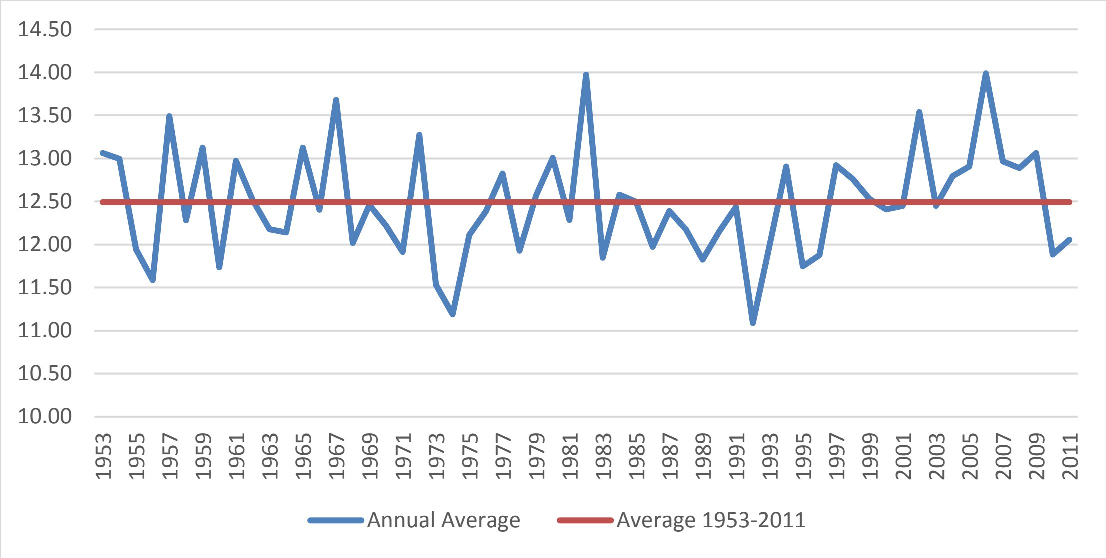


Source(s): van Rees *et al*. (2011)

Similar patterns can be observed for temperature, with a general upward trend. Figure 5 illustrates the average annual temperature for Victoria across the wheat growing regions. The 13-year drought period is reflected in above average temperatures, with another noticeable peak in 1982 (preceding the aforementioned low yields of the 1982-1983 crop). Interestingly, the temperature in 1992 was below average whilst the rainfall was above average and the crop yield was poor. This highlights the complexity of weather and its effects on yields, demonstrating that achieving optimal crop yields is highly uncertain. Any combination of high or low rainfall and temperature can have an impact.

Predictions for the future vary. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) believes that average temperatures in Victoria could increase somewhere between 1°C and 3°C by 2030, whilst rainfall increases up to 20% during summer months and decreases up to 10% in winter months (Wang *et al*., 1992). Yields are optimal when rainfall aligns with the start of the growing season and it is drier at the end of the season to increase the protein content of the grain (PwC, 2011b). The growing season runs from April through to October (autumn through to spring). Hence the predicted changes would forecast a fall in yields.

Figure 5: **Average Annual Temperature for Victoria (℃), 1953-2011**



Source(s): Author's calculations; Data Source: BoM (2015)

This Section has highlighted the significance of the wheat industry (globally, within Australia, and for Victoria as a state). Data shows that yields have increased on average in Victoria but have recently faced vast fluctuations. Weather is known to be a contributing factor. Basic weather data demonstrates further fluctuations that, preliminarily, appear to coincide with changes in yield.

Consequently, the aim of this study is to assess the effects of weather variables on wheat yields in Victoria. The Models specified have not yet been applied to research on the state. However, a number of other studies need to be understood to highlight the research so far. These have been conducted for both Australia and other wheat producing nations to determine how weather patterns have affected wheat yields. Some have then been combined with Climate Change predictions to estimate future yields. The subsequent Section will assess this body of literature.

3. Literature Review

The combined effects and interaction of all aspects of Climate Change determine the net impact on wheat yields (Ludwig and Asseng, 2006). Studies focusing specifically on the impact of weather on wheat production in Victoria are scarce. There is, however, a significant body of literature for other states in Australia. This Section will discuss the relevant findings looking first at results for temperature changes and then rainfall. Climate Change scenarios will then be covered to explain the existing approaches to the future. There are a number of limitations to the current research that will subsequently be briefly discussed.

3.1 Temperature

A number of studies have considered temperature and its impact on yields. Wheat yields are seriously affected by days with temperatures in excess of 30°C or below 2°C during September to November (van Rees *et al*., 2011). Since 1900, the average temperature in Australia rose between 0.7°C (DAFF, 2006) and 0.8°C (Anwar *et al*., 2007). CSIRO (2001 cited in DAFF, 2006) estimates a further rise of between 0.4°C and 2.0°C by 2030. However, there is a debate between whether the consequences of rising temperatures are positive or negative for wheat production.

Temperature increases affect wheat both directly and indirectly (Ludwig and Asseng, 2006). Heat stress is a direct cause of crop failure and reduced yields (van Herwaarden, 1998 cited in Ludwig and Asseng, 2006). The phonological phase – time for capture and use of light and water – is decreased, stunting growth (Anwar *et al*., 2007). Rising water demand is an indirect consequence (Lawlow and Mitchell, 2000; cited in Ludwig and Asseng, 2006). This can lead to increases in the evapotranspiration rate (Wang *et al*., 1992). This is the rate at which water evaporates from soil and transpires from plants (Blanc, 2012). As noted in the previous Section, decreased water use efficiency (WUE) is a growing concern in Victoria. Subsequently, evapotranspiration rates will be tested further in this study.

Location and soil type are consequently found to be two key aspects in the effects of temperature change. Different soils result in varied yield changes when tested under higher temperatures (Ludwig and Asseng, 2006). Sandy soil was found to be at maximum yields and so any further global warming will reduce yields. A similar study on clay soil tested under Mediterranean conditions (van Ittersum *et al*., 2003) found that temperature increases up to 3°C had a positive effect on yields. At higher temperatures yields decreased.

However, tests in Ludwig and Asseng's (2006) study have only been conducted for Western Australia. Results found that northern areas responded negatively to temperature increases whilst in southern areas yields rose (Ludwig and Asseng, 2006). In general however, temperature increases lead to a fall in yields as the growing season is reduced in length (Ludwig and Asseng, 2006). Similarly, Luo *et al*. (2005) found that high rainfall areas in South Australia were affected more by temperature changes.

Given the shift in growing season (ABS, 2007), and the classification as a higher rainfall state (Wang *et al*., 1992), this pattern may be present in Victoria. This study will analyse this further as derived in the subsequent Section.

Individual farm-level analysis in van Rees *et al*. (2011) did make some progress regarding temperature change in Victoria. The Mallee and Wimmera regions were the focal points. Trends since 2005 show that the Mallee region has experienced more days above 30℃ than the long-term average (van Rees *et al*., 2011). Simultaneously, yields decreased an average of 1.1 tonnes per hectare. Wimmera is also trending towards more days of extreme heat. In six of the eight years from 2002 to 2010, days of extreme heat were again above the long-term average and coincided with the end of the growing season (van Rees *et al*., 2011). This study aims to expand on this research by analysing a larger data set for Victoria as a whole and for a longer period of time.

3.2 Rainfall

There has been a significant body of literature focusing on rainfall, particularly in Australia. Lack of moisture is a major constraint across the country (Colls, 1993). Hence precipitation patterns are a focal point for the future of the grains industry in general, not just wheat.

Wheat areas are determined by soil type and rainfall (ABS, 2007). Rain should fall mostly in winter and spring at a minimal annual rate of 400-600mm. Yields decrease when crop available moisture (CAM) falls (GrainGrowers Ltd, 2011). Victoria has experienced significant CAM decline of 1.3mm per year since 1990 (GrainGrowers Ltd, 2011). Most is attributed to declining winter rainfall. The only way to maintain yields, according to industry experts, is to increase the WUE at the same rate as CAM declines through crop breeding (GrainGrowers Ltd, 2011). In Victoria, WUE has also declined.

Contrastingly to the results for temperature changes, clay soil is affected more by rainfall changes than sandy soils. This is because clay soil stores water closer to the surface and so evapotranspiration occurs quicker, hence less rainfall increases the risk of drought dramatically (Ludwig and Asseng, 2006). Regardless of type, soil water prior to anthesis (when the crop is fully functioning) must be sufficient to ensure maximum crop yields (Wang *et al*., 1992). Even after anthesis, sufficient CAM is critical to achieving full yield potential. Hence optimal rainfall is central to successful wheat production.

In semi-arid regions, an increase in rainfall may increase output (Ludwig and Asseng, 2006). However, a 25% fall in precipitation across the year could decrease yields by more than 25% (van Ittersum *et al*., 2003). Contrastingly, high rainfall zones suffer from nutrition loss and are at risk of floods when rainfall increases (Ludwig and Asseng, 2006). Both negatively impact yields.

Changes in rainfall can, however, have both positive and negative effects. According to both Luo *et al*. (2005) and Ludwig and Asseng's (2006) results, the effects of changing rainfall are not linear. Increases and decreases of significant levels will reduce yields. Hence, rainfall plotted against yield will be an inverted-U shape curve. Luo *et al*. (2005) note this is an area in need of further research. Consequently, this will be explored further in this study.

Interestingly, Ludwig and Asseng (2006) found that a 15% decrease in rainfall could be compensated for by a 2°C rise in temperature. However, this is only for northern and central areas of Western Australia covered in the study. Contrastingly, Luo *et al*. (2005) found that – for all locations in the study – median grain yield is positively correlated with rising rainfall when combined with increasing CO_2 concentration but negatively with rising temperatures. Rainfall, however, was the main determinant of changing yields with a coefficient of 0.88 compared to temperature (0.055) and CO_2 (0.0089) (Luo *et al*., 2005).

Again, there is limited research on Victoria. Ludwig and Asseng (2006) concluded that decreasing precipitation would be the main threat to Western Australian wheat crops. Winter rainfall has declined between 10% and 20% since 1970 (Ludwig and Asseng, 2006). Comparably, in South Australia (the driest Australian state) wetter sites were more sensitive to Climate Changes than rising CO_2 (Luo *et al*., 2003). Hence even smaller changes in rainfall may impact crop yields here more significantly.

The available research on the Mallee and Wimmera regions reflect most of these results. Conclusions of the research support that wheat yields are affected greatest by growing season rainfall (GSR, April to October) (van Rees *et al*., 2011). The correlation between falling GSR and yields is extremely strong. This will be assessed further in the subsequent Section for the whole of Victoria, as compared to just the Mallee and Wimmera regions.

For these areas though the data is compelling. The average GSR in southern parts of the Mallee region decreased from 239mm in 1990-2001 to 156mm in 2002-2009 (van Rees *et al*., 2011). If GSR falls below 150mm wheat will struggle to grow at all. The three-year running averages for GSR against yields showed strong negative correlations (van Rees *et al*., 2011). Similarly, the GSR in the Wimmera region has decreased since the 1990s with yields dictated by these changes. The harvests of 2002, 2004 and 2006 experienced GSR of 89mm, 65mm and 126mm less than average respectively (van Rees *et al*., 2011). These years all experienced below average yields.

A study on Birchip, a farm in the Mallee region, found that annual rainfall was extremely variable. The general trend was for lower rainfall in hotter decades (Anwar *et al*., 2007). This highlights the link between weather variables. Interdependence of variables will be explored further in the subsequent Section. For now, Anwar *et al*. (2007) concluded that the estimated decrease of 7% in rainfall in the next 30 years will have a significant impact when combined with other variables, but alone it will not cause widespread crop failure.

3.3 Climate Change

As has been established, Climate Change poses the greatest threat to the future of Australian wheat production. It is therefore valuable to summarise some of the literature on the future of the industry and of Climate Change scenarios.

Climate Change is a public good, meaning everyone is responsible for it and experiences the effects (Naughten, 1993). Therefore, it is widely considered that there are two ways to tackle Climate Change. The first is mitigation – offset global warming by, for example, reducing emissions (Naughten, 1993). This needs to be achieved on an international scale to be effective. The second is adaptation – reduce the damage experienced from Climate Change, which can be done on a regional scale (Naughten, 1993).

The Victorian government has subsequently made large investments into the future of the wheat industry through knowledge acquisition. The Grains Research and Development Corporation and the Victorian government have each invested A$3million in the construction of an Australian Grains Genebank at Horsham, north-western Victoria (DEPI, 2014). Here they acquire, test, develop and distribute genetic resources to create wheat strains that will adapt to Climate Change. However, so far it has been found that yields can be increased but the grain quality is falling (DEPI, 2014). This will have the largest impact on bread production, which requires higher quality grain.

Anwar *et al*. (2007) based their Model analysis on four climate variables (rainfall, maximum and minimum temperature, solar radiation) to calculate per degree warming on a monthly basis. This produced low to high global warming scenarios. Future wheat yields are highest under the low global warming Model as is to be expected, but coincides with increases in CO_2 concentration (Anwar *et al*., 2007). Yields fell by 29%, but with enhanced CO_2 this was 25% (Anwar *et al*., 2007). Similarly, McKeon *et al*. (1988; cited in Luo *et al*., 2003) found that Climate Change was more of an issue than rising CO_2 in a study of Queensland. Rising CO_2 levels are not exponentially beneficial though, and cannot offset the negative impacts of increasing temperatures and decreasing rainfall. All of the projected climate scenarios decrease yields (Anwar *et al*., 2007).

Based on the performance of the wheat industry over the past 100 years, Victorian farmers should be able to overcome issues Climate Change presents. However, adaptation will be key to this success and will ultimately reach an upper bound if the extent of Climate Change exceeds predictions (ABS, 2007). The Carbon Farming Initiative will ideally induce farmers into sustainable practices by offering compensation packages (PwC, 2011a). Much is still to be done to secure the future of the industry.

3.4 Opportunities in the Current Body of Literature

As has been explained in this Section, there has been limited research into the effects of weather variables on Victorian wheat specifically. Evidence from other studies suggests that falling rainfall and rising temperatures have had, and will continue to have, a negative impact on crop yields. Additional factors, such as adaptation and the role of CO_2 concentrations, alter the degree to which yields change but ultimately they are falling.

Hence, the subsequent Section will use Blanc's (2012) work as a basis for the empirical Model. Whilst this is a study of sub-Saharan Africa, the Model takes into account basic and advanced weather variables as will be explained. The literature reviewed in this Section will be taken into consideration throughout the analysis, including data sources and current findings for other states. This study seeks to build on this body of literature by analysing a larger dataset for Victoria than has been previously used. This includes a longer period of time, larger area (not just the Mallee and Wimmera regions) and with more weather variables included in the Models.

4. Empirical

4.1 Variable and data description

4.1.1 Yield and Area

Basic economic theory offers a production function in which output is dependent on land, labour and capital inputs. Wheat yields (measured in tonnes per hectare) will be the dependent variable in this Model, as marginal productivity of the land is key to maximising output efficiently. The area of land cultivated will be included as an independent variable to demonstrate how productivity decreases as marginal land is cultivated. Output and area under wheat production between 1953 and 2011 for the state of Victoria are obtained from the Australian Bureau of Statistics (2013) historical database. Yield is then calculated.

4.1.2 Precipitation

Yields are affected by a number of factors. The purpose of this study is to assess the effects of weather. The two main variables are therefore precipitation and temperature. Average precipitation during the growing season is calculated as this most affects yields (van Rees *et al*., 2011). Growing season rainfall (GSR) occurs between April and October.

Observations of average monthly rainfall were obtained for 30 weather stations using the Bureau of Meteorology's (BoM, 2015) weather database. Specific weather stations were chosen to cover all wheat producing areas across Victoria as rainfall varies greatly across the state. An average for the GSR was then calculated to represent the state as a whole.

4.1.3 Standardised Precipitation Index

A more complex rainfall measure – the Standardised Precipitation Index (SPI) – is also calculated to take account of extreme precipitation events. The SPI takes long-term, monthly precipitation data and calculates an index for 3-, 6-, 12-, 24- or 48-month timescales (World Meteorological Organisation (WMO), 2012). This study selects the 6-month timescale for April to September as this best reflects the GSR.

The SPI compares the precipitation for April-September against the same period for all chosen years. The data is fitted to a probability distribution, transformed to a normal distribution, and so presents the mean SPI as zero (Edwards and McKee, 1997 cited in WMO, 2012). Positive values demonstrate a greater than median rainfall and negative values illustrate a less than median rainfall. The critical values are presented in Table 1.

Table 1: **SPI Values**

SPI values	
2.0 and more	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2.0 and less	Extremely dry

Source(s): WMO (2012)

Dummy variables for droughts and floods are used to take into account extreme weather events. Droughts were given a dummy value of 1 if the SPI was less than -1.0 and floods were given a dummy value of 1 if the SPI was greater than 1.0.

4.1.4 Temperature

Abnormally high or low temperatures can negatively impact crops. The temperature variable uses the average maximum and minimum temperature for each month from the selected 30 weather stations to give an average monthly temperature. This is then transformed into an annual average temperature for 1953 to 2011.

4.1.5 Evapotranspiration Rate

The additional complex measure used here is the evapotranspiration (ET) rate. This combines water loss from soils through evaporation and from crops via transpiration (Blanc, 2012). If water needs are not met, the crop yields can be affected. Due to data limitations, the reference ET rate (ETo) is calculated using the Hargraeves equation (Blanc, 2012):

Equation 1: **ETo equation**

$$ETo = 0.0023(T_{avg} + 17.8)(T_{max} - T_{min})^{0.5}R_a$$

Average temperature (T_{avg}), average maximum temperature (T_{max}) and average minimum temperature (T_{min}) are calculated from annual data as explained above. The R_a term is solar exposure (radiation), obtained from the BoM's database. It should be noted, R_a data is only available for each weather station from 1993 to 2011 and so an average for this period is calculated and used for all ETo rates generated for 1953 to 2011. Hence the ETo equation can be transformed into Equation 2 where $\overline{R_a}$ is the mean radiation for the chosen time period.

Equation 2: **Adjusted ETo equation**

$$ETo = 0.0023(T_{avg} + 17.8)(T_{max} - T_{min})^{0.5}\overline{R_a}$$

4.1.6 Omitted variables

Several variables are excluded from this study due to data limitations. Fertiliser type and usage, crop variety selection, crop management, diseases, pests and soil quality may all vary with weather patterns. There is insufficient data (or access) to use these variables. The focus is therefore solely on the impacts of weather on yields.

4.2 Production functions

Using the variables defined above, two Models are specified for this study (as derived in Blanc (2012)). These are shown in Table 2. Firstly, the temperature and precipitation (T-P) Model uses the basic weather variables as summarised in Equation 3. Equation 4 depicts the more complex variables in the ETo and SPI (ET-SPI) Model, which includes drought and flood dummies. Both of these Models use interaction terms to account for effects between variables (Blanc, 2012).

Table 2: **Model Specifications**

Model Specifications	
Equation 3: T-P Model	$Y_t = f(A_t, T_t, T_t^2, P_t, P_t^2, T \times P_t, T_t^2 \times P_t, T_t \times P_t^2)$ Where at time t, Y is the yield, A the area cultivated, T temperature and P precipitation.
Equation 4: ET-SPI Model	$Y_t = f(A_t, ETo_t, ETo_t^2, SPI_t, Drought_t, Flood_t, ETo \times SPI_t, ETo^2 \times SPI_t, ETo \times Drought_t, ETo \times Flood_t)$

Source(s): Blanc (2012)

4.3 Methodology:

Equations 3 and 4 are then transformed into regressions (equations 5 and 6). Blanc (2012) uses log-transformed values of yield and area to estimate elasticities, whilst the other variables are not log-transformed to produce semi-elasticities. This allows the assessment of, for example, a 1 ℃ temperature change or 10mm precipitation change on yields. This study calculates the change in each variable (first difference) – specified in StataCorp (2013) as a variable minus its value in the previous time period using: $changeInX = X - L.X$. This allows us to analyse the trends in effects of the variables as they change over time.

Table 3 contains the Ordinary Least Squares (OLS) regressions, showing the fully specified equations for each Model.

Descriptive statistics for key variables in both regressions are listed in Table 4. Table 4 gives a maximum yield between 1953 and 2011 that is over 8 times larger than the minimum. This highlights that yield can differ greatly through time. The standard deviation, meanwhile, shows that the yield varies by 0.51 tonnes per hectare (tonnes/Ha) from the average value (almost 31%). The aim of this study, therefore, is that the independent explanatory variables chosen may be able to explain some of this change.

Table 3: **Model Regression Equations**

Model Regression Equations	
Equation 5: T-P Model Regression Equation	$\Delta lnY = \beta_1 \Delta lnA + \beta_2 \Delta T + \beta_3 \Delta T^2$ $+\beta_4 \Delta P + \beta_5 P^2 + \beta_6 T.P +$ $\beta_7 T^2.P + \beta_8 T.P^2 + \beta_9$
Equation 6: ET-SPI Model Regression Equation	$\Delta lnY = \beta_1 \Delta lnA + \beta_2 \Delta ETo + \beta_3 \Delta ETo^2$ $+\beta_4 \Delta SPI + \beta_5 \Delta Drought + \beta_6 \Delta Flood$ $+\beta_7 \Delta ETo.SPI + \beta_8 \Delta ETo^2.SPI$ $+\beta_9 ETo.Drought + \beta_{10} ETo.Flood + \beta_{11}$

The descriptive statistics for SPI in Table 4 also show that droughts and floods occur given that the maximum and minimum are greater than 1.0 and -1.0 respectively as defined previously. Extreme weather events included in the regression may demonstrate some significance in their role. Contrastingly, temperature appears to have a very small spread of 11.09 °C to 13.99 °C giving a standard deviation of 0.63°C from the mean. However, given that Climate Change scenarios highlight the significance of a 2°C rise (Luo *et al.*, 2005) these temperature variations may have an impact on yields in the sample used in this study.

Table 4: **Descriptive Statistics for Key Variables**

Descriptive Statistics for Key Variables					
Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Yield (tonnes/Ha)	59	1.65	0.51	0.32	2.70
Area (Ha)	59	1,160,944	278,773	633,400	1,801,100
Precipitation (mm)	59	360.66	92.72	165.38	571.71
SPI (standard deviation from median)	59	0.0037	1.01	-2.51	2.05
Drought (dummy)	59	0.15	0.36	0	1
Flood (dummy)	59	0.19	0.39	0	1
Temperature (℃)	59	12.48	0.63	11.09	13.99
ETo (mm/day)	59	1.70	0.08	1.53	1.89

4.4 Results and discussion

4.4.1 T-P Model regression

Appendix 2 contains the regression results for a variety of Model specifications (1-4). The analysis will focus on the results presented in Table 5. This compares Model 3 against Model 4 to ensure the best analysis is provided. Model 3 has the best fit (R^2) whilst Model 4 has the greatest number of statistically significant variables.

Table 5: **T-P Model Regression Results**

T-P Model Regression Results				
Model 3 – dependant variable ΔlnY[1]				
	Coefficient	**Robust Std. Err.[2]**	t^3	$P > \|t\|^4$
ΔlnA	0.7762	0.3852	2.02	0.049
ΔT	-5.0313	19.0237	-0.26	0.793
ΔT²	0.1780	0.6936	0.26	0.798
ΔP	-0.0085	0.3759	-0.02	0.982
ΔP²	-0.0000	0.0002	-0.22	0.829
ΔT.P	-0.0020	0.0517	-0.04	0.969
ΔT²P	0.0001	0.0017	0.06	0.954
ΔTP²	0.0000	0.0000	0.36	0.718
Constant	-0.0002	0.0571	-0.00	0.997
Model 4 – dependant variable ΔlnY[5]				
	Coefficient	**Robust Std. Err.**	t^6	$P > \|t\|$
ΔlnA	0.8381	0.3934	2.13	0.038
ΔT²	0.0145	0.0054	2.72	0.009
ΔP²	0.0000	0.0000	1.86	0.069
ΔT.P	-0.0004	0.0002	-2.01	0.049
Constant	-0.0003	0.0554	-0.01	0.996

[1] R^2 value for Model 3 is 0.464

[2] Robust standard error

[3] T-statistic value – critical value 3.36 given 8 degrees of freedom in the Model at the 1% level.

[4] Probability of statistical significant value – critical value 0.05 for the 95% confidence level.

[5] R^2 value for Model 4 is 0.438

[6] T-statistic value – critical value 4.60 given 4 degrees of freedom in the Model at the 1% level.

The R^2 value shows that the independent variables explained 46.4% and 43.8% of the influences that affect annual wheat yields in Models 3 and 4 respectively. This suggests weather has an influence on yields and so each variable will now be analysed individually.

Area

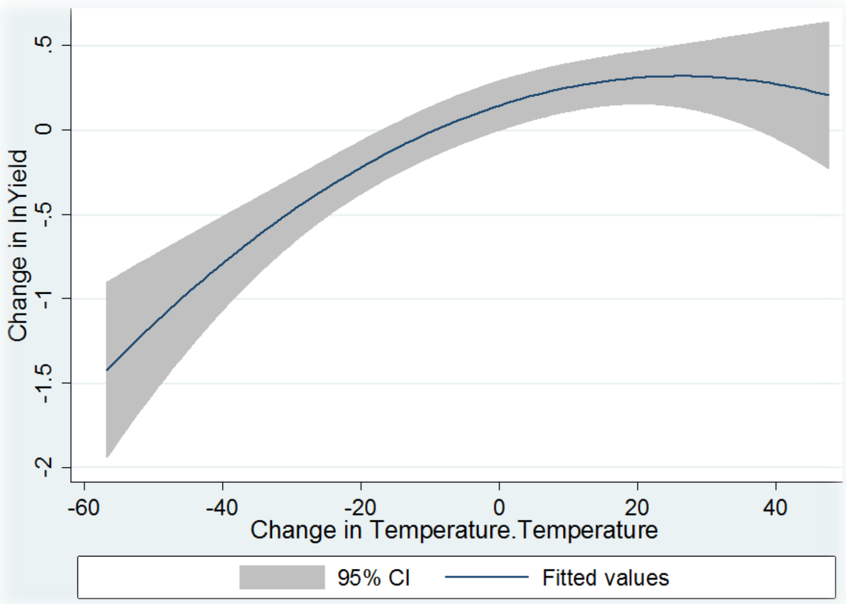
The p-value in both Models is less than the 0.05 critical value and so we can reject the null hypothesis at the 95% confidence level. Area is statistically significant and may be determining changes in yields. The coefficients indicate that a 1% increase in land cultivated causes a 0.8% increase in yields in both Models (when rounded to one decimal place), suggesting that marginal land productivity is growing. However, this assumes that there is access to new cultivatable land, which is not necessarily the case (GrainGrowers Ltd, 2011). Land availability is in decline across many parts of Australia, including Victoria.

Temperature

In Model 3, neither temperature term is statistically significant. However, the temperature change variable shows that a 1℃ increase in temperature would decrease yields by 50%. If this pattern were linear, this would mean that a 2℃ temperature increase (as predicted in many Climate Change Models) would eradicate wheat production from Victoria.

In Model 4, the squared temperature term is statistically significant and so indicates non-linear responses in yield to changes in temperature. This is to be expected as large increases (heatwaves) or decreases (cold periods) in temperature negatively impact the growth of crops. Figure 1 illustrates this non-linear relationship. Predicted values of the change in ln(Yield) for given temperature changes, along with the 95% confidence interval, are presented. A concave relationship exists, in line with the aforementioned expectations.

Figure 6: **Effects of ΔT^2 on $\Delta \ln Y$**



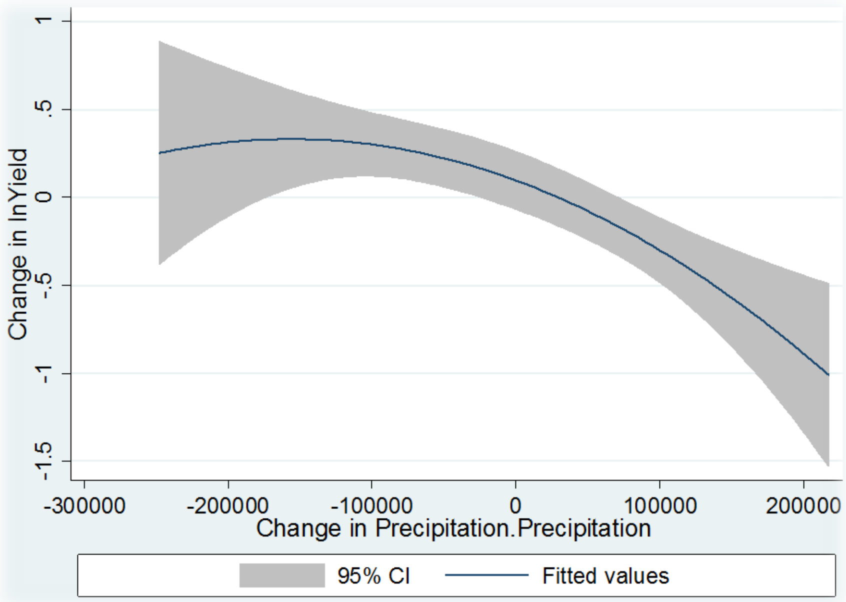
The evidence from both Models highlights the threat that the climate poses to wheat production. Temperature increases clearly have a negative effect on yields in this study.

Precipitation

Again, neither precipitation variable is statistically significant in Model 3, but the variables offer an explanatory insight into the effect on yields. A 100mm increase in precipitation would cause a fall of 0.8% in yields. This mirrors the literature as floods cause crop nutrition loss. However, it was expected that precipitation changes would give non-linear results as both significant increases and decreases have negative effects.

The non-linear response in yields is illustrated in Figure 2 from results in Model 4. However, P^2 is not statistically significant in either specification in Table 4, but was statistically significant in Model specification 2 (see Appendix 2). Therefore, it may be inferred that large amounts of precipitation (floods) and small amounts (droughts) have a negative impact on yields. As precipitation is calculated using the growing season rainfall only, Figure 2 does not include periods of rainfall outside of this. This means that a flood or drought outside of the growing season is not considered. Whilst rainfall in November through to March (Australian summertime) does not directly affect growth of wheat, extreme weather events can affect, for example, soil nutrition which may have an impact on crops in the following growing season (van Rees *et al.*, 2011).

Figure 7: **Effects of ΔP^2 on ΔlnY**



Temperature and Precipitation

Interaction terms were used to determine the relationship between variables. The temperature and precipitation interaction term in Model 4 is significant at the 5% level, suggesting that the effect of temperature is dependent on precipitation, and precipitation on temperature. Whilst these variables are not statistically significant in Model 3, they do show a stronger relationship. This reiterates the argument that both temperature and precipitation are important to the success of yields.

4.4.2 ET-SPI Model regression

Appendix 3 contains the regression results for a variety of Model specifications (1-11). This analysis will focus on the results presented in Table 6 (Model 7 and Model 9). As before, these have the best fit and greatest number of statistically significant variables respectively.

Table 6: **ET-SPI Model Regression Results**

ET-SPI Model Regression Results				
Model 7 – dependent variable ΔlnY[1]				
	Coefficient	**Robust Std. Err.[2]**	t[3]	$P > \|t\|$[4]
ΔlnA	1.094	0.371	2.95	0.005
ΔETo	3.732	39.704	0.09	0.926
ΔETo^2	-0.726	11.636	-0.04	0.950
ΔSPI	-0.402	11.461	0.09	0.972
ΔEToSPI	1.174	13.214	-3.55	0.930
ΔETo^{2}SPI	-0.579	3.843	0.39	0.881
Drought	-0.893	0.251	-0.06	0.001
Flood	0.075	0.193	-0.15	0.698
ΔEToDrought	0.276	0.124	2.22	0.031
ΔEToFlood	-0.030	0.144	-0.21	0.834
Constant	0.120	0.076	1.59	0.120
Model 9 – dependent variable ΔlnY5				
	Coefficient	**Robust Std. Err.**	t[6]	$P > \|t\|$
ΔlnA	1.108	0.384	2.88	0.006
ΔEToETo	0.456	0.279	1.63	0.109
ΔSPISPI	0.1237	0.036	3.46	0.001
ΔEToSPI	-0.090	0.044	-2.02	0.049
Drought	-0.725	0.213	-3.39	0.001

Table 6 continued from page 21				
Flood	-0.027	0.115	-0.23	0.816
Constant	0.111	0.067	1.65	0.104

[1] R^2 value for Model 7 is 0.560
[2] Robust standard error
[3] T-statistic value – critical value 3.17 given 10 degrees of freedom in the Model at the 1% level
[4] Probability of statistical significant value – critical value 0.05 for the 95% confidence level
[5] R^2 value for Model 9 is 0.5383
[6] T-statistic value – critical value 3.71 given 6 degrees of freedom in the Model at the 1% level

The R^2 values show that the independent variables explained 56% and 53.8% of the influences affecting annual wheat yields in Models 7 and 9, respectively. Each variable will now be analysed further.

Area

As for the T-P regression, area is statistically significant in both Models 7 and 9. However, these Models have coefficients indicating that a 1% increase in land cultivated causes a 1.1% increase in yields as opposed to 0.8% in the T-P Model. Again, land availability is questionable.

ETo

In none of the specified Models is ETo statistically significant, unless combined with an interaction term. This suggests that the evapotranspiration rate is not having an impact on yields. However, this contradicts both the literature and the T-P Model. There are two potential causes of this. The ETo equation was specified using solar radiation but a lack of data meant this term was transformed into an average (Equation 2). This could be affecting the ETo values that are generated and hence result in an insignificant coefficient being produced. Alternatively, the Hargraeves equation may be inappropriate for this study as compared to Blanc's (2012) work. Further research into alternative ETo equations would be necessary, but is beyond the scope of this study.

SPI, Drought and Flood

In the results for Model 9, the SPI^2 term shows, again, a non-linear response in yields, and is statistically significant demonstrating the importance of precipitation. As the SPI calculates the deviation from the mean, it highlights the importance of fluctuations in precipitation during the growing season. Drought is also statistically significant highlighting how a lack of crop available moisture causes a reduction in yields. The coefficient is larger than for floods, supporting that Victoria is more affected by a lack of rainfall than too much.

Model 7, however, contradicts itself. The SPI coefficient suggests that extremely wet periods have a negative impact on yields whilst drier spells would not. Contrastingly, the drought dummy (which shows extremely dry SPI events) is statistically significant and gives a reduction in yields. The flood dummy is not statistically significant, but also shows an increase in yields during extremely wet events. This contradiction suggests that droughts have a greater influence on yields than floods in terms of extreme weather events, but that when assessing fluctuations around the mean, increases above the mean cause larger effects. This is not the result that was to be expected. However, it may be explained due to the fact that there were quite simply more droughts in 1953-2011 than floods, and that, for years outside of these extreme events, Victoria experienced greater intensity of rainfall making minor floods more common and troublesome. This is supported by the literature and so demonstrates the complexity of rainfall and the resulting impact on yields.

Despite soil nutrition being excluded from this study, the significance of droughts suggests that this could be an area for further research to increase the strength of the Model.

ETo and SPI

The interaction of ETo and SPI has a large coefficient in Model 7 and is statistically significant in Model 9. This shows that temperature and rainfall depend on one another for their effects, which was to be expected given the results from the T-P Model.

4.4.3 Summary of Results

The regression results from the T-P and ET-SPI Models partly support the hypothesis for this study, arguing that large increases or decreases in temperature and precipitation have a negative effect on wheat yields in Victoria. Strong coefficients and statistical significance for squared terms in both Models highlight the non-linear relationship between weather and yields. However, some variables that were not statistically significant raise queries about the strength of the calculations for each variable, notably ETo.

4.5 Limitations and Further Research

One of the main limitations of this study is the exclusion of variables – influenced by weather patterns – that have an impact on wheat yields. Different fertilisers are selected based on rainfall and temperature, for example (GrainGrowers Ltd, 2011). However, inclusion of these variables would be extremely difficult on this scale due to the lack of data available.

Additionally, crop rotation is not considered which could greatly affect yields. Not all farms practice crop rotations and again data availability is limited (GrainGrowers Ltd, 2011). However, if major farms do not produce wheat for one growing season, this could affect the Model to a currently unknown extent.

Due to Model limitations, SPI has to be calculated using a 6-month average, which means one month of the growing season is lost in the calculation (WMO, 2012). This is not optimal when the focus of this study is weather alone. The alternative – to run monthly SPIs and track averages from this – would require obtaining daily data for each month which is again outside the scope of this study and would raise data limitation issues due to the length of the time period focused on (BoM, 2015).

Further research including variables that are determined by weather – soil quality, fertiliser choice, and crop management techniques to name but a few – could strengthen the Model and demonstrate the sheer scale of the wheat growing industry's reliance on weather patterns. Previous studies have built Models predicting future yields by incorporating Climate Change scenarios (DAFF, 2006; GrainGrowers Ltd, 2011; Linehan *et al*., 2012; Wang *et al*., 1992). These studies do not, however, incorporate more complex measures such as ETo and SPI. Hence building on this study by using Climate Change scenarios could be a direction for future research.

5. Conclusion

This study has sought to explain the impacts that weather has had on wheat yields in Victoria, Australia. The importance of the wheat industry was highlighted in the second Section. The success of the industry has a profound impact on the economy. Periods of drought in Victoria are increasingly prevalent, the impacts of which were to be a focal point in this study.

Section 3 highlights that substantial research has been conducted to assess how temperature changes affect Australia. Direct and indirect impacts are a cause for concern. This study focused on the indirect effect of increased water demand. The literature provided the fundamentals of understanding more complex temperature measures in the Australian context (Wang *et al*., 1992), including evapotranspiration. By adapting Blanc's (2012) work, and combining it with Australian research, this study managed to apply new measures that expanded on the current body of literature.

The same was achieved for rainfall. Across the country, Ludwig and Asseng (2006) found that precipitation had non-linear effects. The limited studies on Victoria concluded that rainfall is decreasing in the growing season, which has impacted wheat crops (GrainGrowers Ltd, 2011). Of most concern, this decrease regularly coincides with years of higher average temperatures (Anwar *et al*., 2007). Again, this study was able to expand on the literature by using a more complex measure (SPI) that has the ability to isolate extreme weather events from the averages.

Consequently, Section 3 allowed for the identification of opportunities in the current body of literature that were then incorporated into the empirical analysis. Section 4 explained the background to each variable considered. This was not without its limitations. Notably, the decisions to use a 6-month SPI and to develop an adjusted ETo equation created weaknesses in the study.

The Model specifications and subsequent regressions were based on Blanc's (2012) study on sub-Saharan Africa. This was adapted to fit the Australian context and Victorian dataset in this study. Consequently, a number of specifications were developed for each Model to consider the different options. The strength of these varied, but the Model of best fit and the Model with the most statistically significant variables were chosen for the analysis. All four specifications considered showed that yields increase as area increases. This does not consider land availability decline. Hence a solution to falling yields is not necessarily to cultivate more land exponentially.

Overall, the results for temperature corroborated the results of the current literature – increases in temperature cause declines in crop yield. However, the relationship was proven to be non-linear in the T-P Model – a fall in temperatures can reduce yields. The background data suggests that this is not a cause for concern in the long-term given the continued increase in temperature on average over the past 100 years. Additionally, the ETo was not statistically significant in the ET-SPI Model, highlighting a potential weakness in the adjusted equation used.

Similarly, precipitation had non-linear effects in the T-P Model. Combining this result with the SPI from the ET-SPI Model, it can be concluded that drought has a greater impact on yields than periods of increased rainfall. Interaction of the temperature-precipitation and ETo-SPI variables demonstrate the complexity of the effects. Again, this reflects the views widely held in the current body of literature whilst presenting a myriad of opportunities for future study.

Key limitations of this study can be addressed through further research. Alternative ET equations are available and could be tested to increase the statistical significance of the variable and SPI may be calculated on a monthly basis to account for the entire GSR. However, this would require extensive data sourcing beyond the scope of this study. Lack of data availability also prevented the use of variables such as soil nutrition and crop rotation. Including these in the Model, and using Climate Change predictions to estimate the future, is a direction that this study could take. The opportunity for expansion is both vast and relevant to the current body of literature.

Overall, this research achieved its objective. Weather changes in the study period have negatively impacted wheat yields in the state of Victoria. The results highlight the increased risk that the future holds because of Climate Change.

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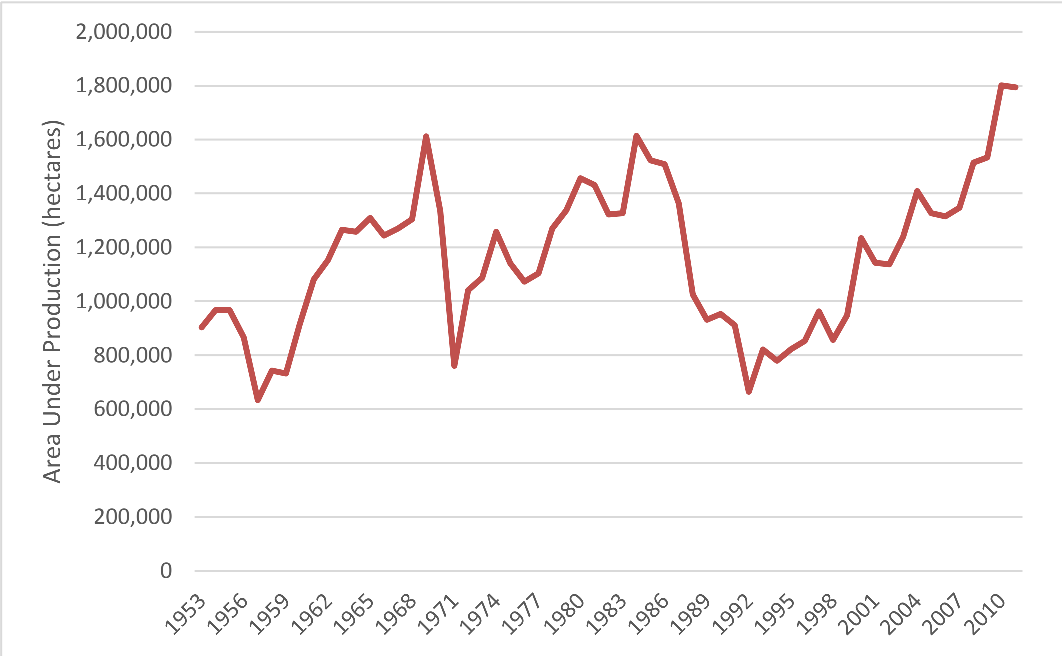
Appendices

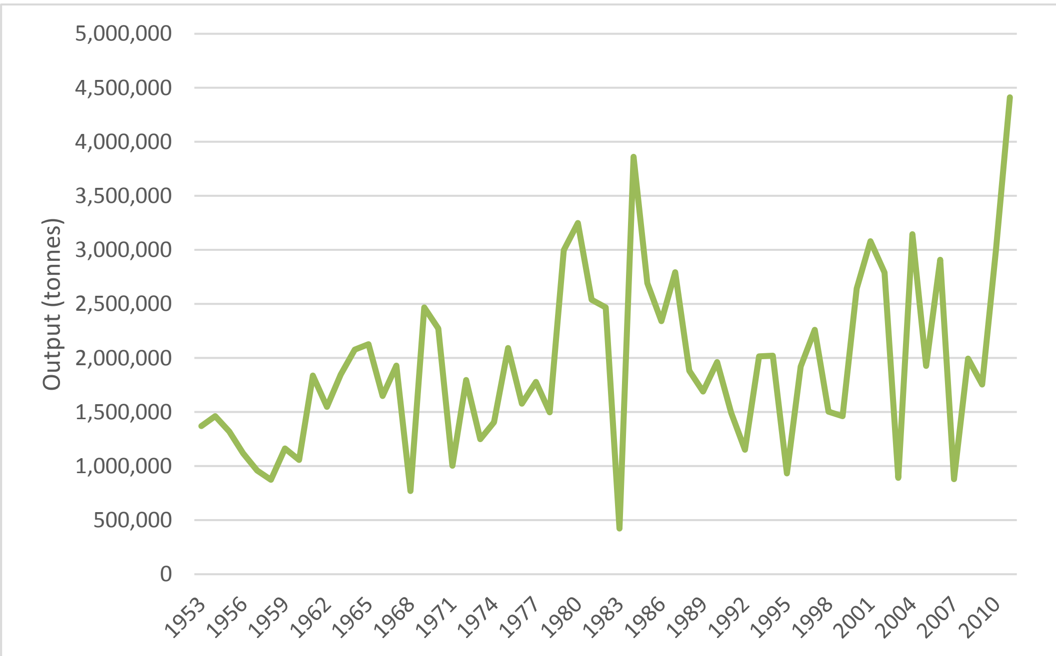
Appendix 1: Wheat Production Data for Victoria, 1953-2011

Figure 8: **Area under Wheat Production (hectares)**



Source(s): Author’s calculations; Data Source: ABS (2013)

Figure 9: **Output of Wheat Production (tonnes)**



Source(s): Author’s calculations; Data Source: ABS (2013)

Appendix 2: T-P Model regression results of all specified Models

Table 7: **T-P Model regression results of all specified Models**

	Model specification			
	(1)	**(2)**	**(3)**	**(4)**
ΔlnA	0.848 (0.391) [0.035]	0.782 (0.386) [0.048]	0.776 (0.385) [0.049]	0.838 (0.393) [0.038]
ΔT	0.590 (0.292) [0.048]	-6.061 (5.256) [0.254]	-5.031 (19.024) [0.793]	
ΔT^2		0.204 (0.184) [0.275]	0.178 (0.694) [0.798]	0.015 (0.005) [0.009]
ΔP	0.012 (0.009) [0.204]	-0.059 (0.029) [0.045]	-0.008 (0.376) [0.982]	
ΔP^2		0.000 (0.000) [0.001]	-0.000 (0.000) [0.829]	0.000 (0.000) [0.069]
ΔTP	-0.001 (0.001) [0.180]	0.003 (0.002) [0.097]	-0.002 (0.052) [0.969]	-0.000 (0.000) [0.049]
ΔT^2P			0.000 (0.002) [0.954]	
ΔTP^2			0.000 (0.000) [0.718]	
Constant	0.000 (0.056) [0.996]	-0.000 (0.055) [1.000]	-0.000 (0.057) [0.997]	-0.000 (0.055) [0.996]
Model R^2 value	0.419	0.460	0.464	0.438

Note(s): ( ) robust standard errors; [ ] probability values

Appendix 3: ET-SPI Model regression results of all specified Models

Table 8: **ET-SPI Model regression results of all specified Models**

	Model specification			
	(1)	**(2)**	**(3)**	**(4)**
ΔlnA	0.932 (0.389) [0.020]	0.935 (0.408) [0.026]	0.9927 (0.404) [0.026]	0.891 (0.371) [0.020]
ΔETo	0.823 (0.932) [0.381]	-0.814 (39.196) [0.984]	-6.559 (38.348) [0.865]	0.664 (1.072) [0.538]
ΔETo^2		0.479 (11.394) [0.967]	2.025 (11.139) [0.856]	
ΔSPI	0.853 (0.956) [0.377]	0.786 (1.933) [0.686]	-8.665 (13.328) [0.519]	1.073 (1.311) [0.417]
ΔSPI^2				
ΔEToSPI	-0.591 (0.568) [0.303]	-0.005 (0.056) [0.931]	10.259 (15.596) [0.514]	-0.703 (0.795) [0.380]
ΔETo^2SPI			-3.087 (4.583) [0.504]	
Drought				
Flood				
ΔDrought				0.026 (0.166) [0.877]
ΔFlood				-0.114 (0.173) [0.512]
ΔEToDrought				

Table continued on next page

ΔEToFlood				
Constant	-0.005 (0.056) [0.931]	-0.005 (0.056) [0.931]	-0.006 (0.057) [0.917]	-0.004 (0.057) [0.945]
Model R^2 value	0.426	0.426	0.431	0.430

Note(s): ( ) robust standard errors; [ ] probability values

<u>Appendix 3 continued on next page</u>

	Model specification			
	(5)	**(6)**	**(7)**	**(8)**
ΔlnA	1.127 (0.391) [0.006]	0.895 (0.377) [0.022]	1.094 (0.371) [0.005]	0.865 (0.404) [0.038]
ΔETo	0.993 (0.930) [0.291]	-3.221 (48.308) [0.947]	3.732 (39.704) [0.926]	-21.405 (60.272) [0.724]
ΔETo^2		1.049 (14.153) [0.941]	-0.726 (11.636) [0.950]	6.155 (17.558) [0.727]
ΔSPI	1.973 (0.916) [0.036]	-6.244 (13.999) [0.658]	-0.402 (11.461) [0.972]	18.171 (30.790) [0.558]
ΔSPI^2				
ΔEToSPI		7.625 (16.202) [0.640]	1.174 (13.214) [0.930]	-21.585 (36.254) [0.554]
ΔETo^{2}SPI		-2.368 (4.733) [0.619]	-0.579 (3.843) [0.881]	6.337 (10.684) [0.556]
Drought	-0.582 (0.216) [0.009]		-0.893 (0.251) [0.001]	
Flood	0.028 (0.120) [0.814]		0.075 (0.193) [0.698]	
ΔDrought		0.026 (0.197) [0.894]		-8.376 (5.836) [0.158]
ΔFlood		-0.080 (0.191) [0.675]		-6.654 (10.724) [0.538]
ΔEToDrought			0.276 (0.124) [0.031]	4.771 (3.389) [0.166]

Table continued on next page

ΔEToFlood			-0.030 (0.144) [0.834]	4.018 (6.503) [0.540]
Constant	0.077 (0.069) [0.266]	-0.005 (0.058) [0.933]	0.120 (0.076) [0.120]	-0.007 (0.059) [0.901]
Model R^2 value	0.510	0.433	0.560	0.454

Note(s): ( ) robust standard errors; [ ] probability values

Appendix 3 continued on next page

	Model specification		
	(9)	(10)	(11)
ΔlnA	1.108 (0.384) [0.006]	1.102 (0.359) [0.003]	1.129 (0.391) [0.006]
ΔETo			
ΔETo^2	0.456 (0.279) [0.109]	0.388 (0.287) [0.182]	0.285 (0.272) [0.300]
ΔSPI		1.175 (0.928) [0.211]	1.932 (0.921) [0.041]
ΔSPI^2	0.124 (0.036) [0.001]		
ΔEToSPI	-0.090 (0.044) [0.049]	-0.738 (0.564) [0.197]	-1.251 (0.552) [0.028]
ΔETo^2SPI			
Drought	-0.725 (0.214) [0.001]	-0.897 (0.235) [0.000]	-0.581 (0.215) [0.009]
Flood	-0.027 (0.115) [0.816]	0.071 (0.193) [0.716]	0.023 (0.120) [0.818]
ΔDrought			
ΔFlood			
ΔEToDrought		0.280 (0.109) [0.013]	

Table continued on next page

ΔEToFlood		-0.032 (0.136) [0.814]	
Constant	0.111 (0.067) [0.104]	0.122 (0.071) [0.091]	0.077 (0.069) [0.267]
Model R^2 value	0.538	0.559	0.510

Note(s): ( ) robust standard errors; [ ] probability values