Exploring the impact of R&D and climate change on agricultural productivity growth: the case of Western Australia*

Ruhul A. Salim and Nazrul Islam[†]

This article empirically examines the impact of R&D and climate change on the Western Australian Agricultural sector using standard time series econometrics. Based on historical data for the period of 1977–2005, the empirical results show that both R&D and climate change matter for long-run productivity growth. The long-run elasticity of total factor productivity (TFP) with respect to R&D expenditure is 0.497, while that of climate change is 0.506. There is a unidirectional causality running from R&D expenditure to TFP growth in both the short run and long run. Further, the variance decomposition and impulse response function confirm that a significant portion of output and productivity growth beyond the sample period is explained by R&D expenditure. These results justify the increase in R&D investment in the deteriorating climatic condition in the agricultural sector to improve the long-run prospects of productivity growth.

Key words: climate change, cointegration, generalized impulse response function, productivity growth, R&D expenditure.

1. Introduction

Sustained growth in agricultural production and productivity is essential for the economic prosperity of the Australian rural communities and the economy as a whole. Constrained by the availability of the key resource land associated with salinity and acidification and deteriorating climatic conditions, growth in agriculture relies mostly on technology and investment. Therefore, many researchers in Australia and elsewhere emphasize the importance of R&D expenditures in agriculture and show the high returns of public R&D to agricultural production (e.g., Coelli 1996; Alston *et al.* 1999; Ball and Norton 2002; Mullen 2007 and Mullen and Crean 2007). Because the standard economic theory provides little guidance as to the specified relationship between R&D and agricultural production, these empirical studies either

estimate the elasticity of agricultural output or productivity with respect to R&D expenditure or evaluate R&D as a source of efficiency using the 'frontier' type of estimator. This study, however, uses a different route to explain the long-run relationship between output (and productivity) and R&D expenditure using the time series econometrics.

Economic research on climate change and its impact on agriculture in Australia is scarce. Over the past centuries, human activities have significantly altered the world's atmosphere. For example, the increased concentration of greenhouse gas has led to global warming. As greenhouse gas emission continues to increase, global warming will go on and thereby giving rise to other changes in climate, particularly rainfall. These climate changes are likely to affect agricultural productivity in Australian agriculture. However, our knowledge about the impact of climate change is limited. Adaptation measures are also rarely discussed in the literature. Most existing studies on this topic are still qualitative and at the aggregate level, e.g., IPCC (2001), Foster (2004), and Kingwell (2006). Quantitative analysis, particularly efficiency and productivity measurement of uncertain agriculture under variable climatic conditions, is difficult because of unavailability of data and appropriate methodology (O'Donnell *et al*. 2006).

The aim of this paper is to contribute to the understanding of the importance of R&D and climate change in the Western Australian agricultural sector using aggregate time series data. We complement the findings of previous studies in several ways. First, we study the period starting in the late 1970s to 2005, characterized by many policy changes in relation to R&D and climate changes during the last three decades. Secondly, the availability of annual data on R&D and climate change permits an analysis of their equilibrium relationship to output as well as to productivity growth in the long run, as it has not been carried out traditionally in the literature. Thirdly, we attempted to explore the short-term or dynamic relationships between these variables and also shed light on the direction of their causal link. Finally, we employ the advanced *generalized forecast error variance decomposition* and *generalized impulse response techniques* of Koop *et al*. (1996) and Pesaran and Shin (1998) to determine the relationship between these variables beyond the sample period.

The rest of the paper proceeds as follows. Section 2 provides an overview of the Western Australia's agriculture followed by a critical review of the recent literature in Section 3. Data sources and the details of variable construction are given in Section 4. Section 5 presents the analytical framework followed by an analysis of empirical results in Section 6. Summary of findings and policy implications are provided in the final section.

2. An overview of the Western Australian agriculture

Agriculture in Western Australian differs from agriculture in the rest of Australian. It is one of the few sectors in Western Australia whose contribution

to the state economy far exceeds to its national counterparts. For example, Western Australia's national share in gross domestic product is 11 per cent, whereas her shares in the national gross value of agricultural production (GVAP) and the value of agricultural exports are 15 per cent each in 2006–2007. Between 2002–2003 and 2006–2007, the growth in this sector's export from Western Australia has been six per cent, while the same for the rest of Australian states has been declining at a rate of three per cent per annum (Islam 2009). The share of this sector's employment is approximately five per cent in Western Australia, whereas it is less than four per cent in the rest of Australian states. Although its share to the gross state product is only around 4 per cent, the agriculture sector plays a major role in the State's economic, social, and rural wealth. It also represents the State's biggest renewable primary production resource. The agriculture and food sector contributes more than $8 billion to the Western Australian economy each year and creates employment for more than 9 per cent of the State's workforce (DAFWA, 2007).

Western Australian agriculture is primarily based on extensive pastoral and cropping activities, which generate more than 85 per cent of the GVAP. The pastoral and cropping activities, generally called as 'broadacre'[1] agriculture, are however absolutely rain-fed. ABARE (Australian Bureau of Agriculture and Resource Economics) divides broadacre agriculture into three main climatic zones: High-rainfall, Wheat-sheep, and Pastoral zones. The main agricultural area of WA is comprised of the high-rainfall and wheat-sheep zones. These two zones together produce more than 95 per cent of State's GVAP, and the rest is produced in the pastoral zone (Islam 1999). About 73 per cent of the State's GVAP comes from the wheat-sheep zone. Given the climatic and topography conditions, this zone is utilized mainly for producing wheat and sheep. Meat, dairy, and horticultural commodities are the major outputs produced in the high-rainfall area. Owing to steeper topography and high humidity percentage, the production of grain crops is not very economical. Meat and horticultural commodities are also produced in the north of the pastoral zone. Overall, horticulture and dairy production contribute about 15 per cent to the State's GVAP, and they are not included in the analysis of this study.[2]

Agricultural commodities produced in Western Australian farms can be broadly classified as cereals, pulses, and oilseeds, livestock and poultry, milk, horticultural crops, and wool. Cereals include wheat, barley, oats, rice, sorghum, and triticale crops. Pulses include lupins, chickpeas, field peas, lentils, and faba beans. Oilseed crop is mainly canola. Sheep and lambs, beef cattle, pigs, and chickens are included under the livestock and poultry classification.

---

[1] Broadacre agriculture does not include horticulture and dairy. It includes crops and livestock farming for grains, meat, and wool production.
[2] The broadacre agriculture is only considered in this study because of the availability of input–output data.

Horticultural crops include wine grapes and other fruits, vegetables, flowers, and nursery plants. The intensity of production of these crops and commodities varies from region to region. Cereal grains mainly produced in the wheat-sheep zone dominate primary agricultural production in WA. It accounts for 47 per cent of GVAP in WA. Wheat alone accounts for about 34 per cent of the State's GVAP. Meat (livestock and poultry) and wool have respective shares of 21 and 10 per cent of GVAP in WA. Horticulture accounts for about 11 per cent in WA's total GVAP (Islam, 2009). Cereals, pulses, and oil-seeds and wool are dominant in terms of WA's share in the national agricultural production; these account for 33, 33, and 21 per cent of the State's GVAP. As the WA broadacre agriculture depends completely on rainfall, the main cropping season in WA begins in April and ends in October when the rainfall is most reliable.

Among all the Australian States, productivity growth in WA broadacre agriculture has been consistently on the top (Islam 2004). Over the last 29 years, the average output growth of the WA broadacre agriculture was 3.74 per cent per annum (Figure 1). During the last two decades, the output trend has been fluctuating. Given the relatively stable movement of the input trend with an average annual growth of 1.72 per cent per annum, the trend in the movement of total factor productivity has also been fluctuating. As the WA broadacre agriculture depends fully on rainfall, the pattern of its movement appears to have mostly followed the pattern of total seasonal rainfall movement (Figure 2). This may imply that the productivity of WA agriculture also largely depends on the rainfall patterns that need to be tested.
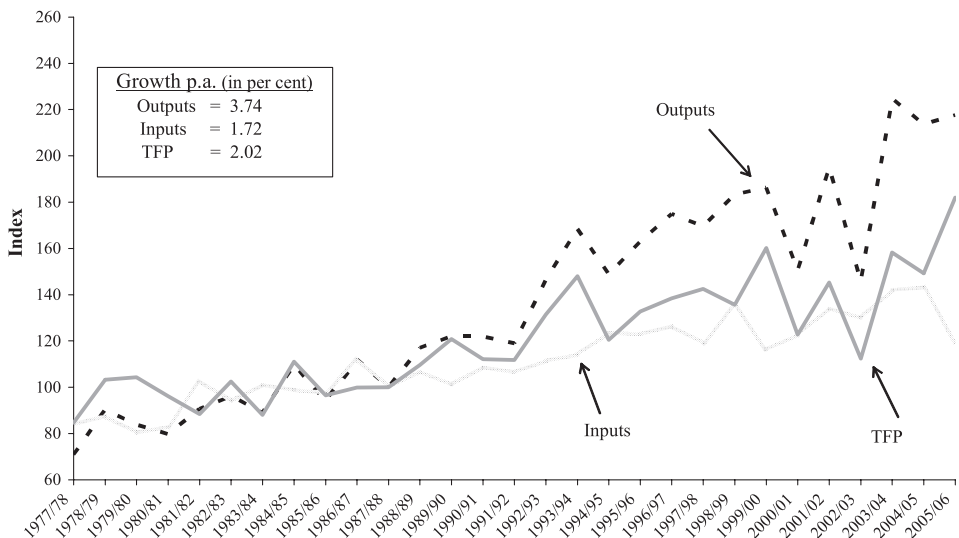
Figure 1 Output, input, and total factor productivity trends in broadacre agriculture 1977/78-2005-06 (1987/88 = 100).
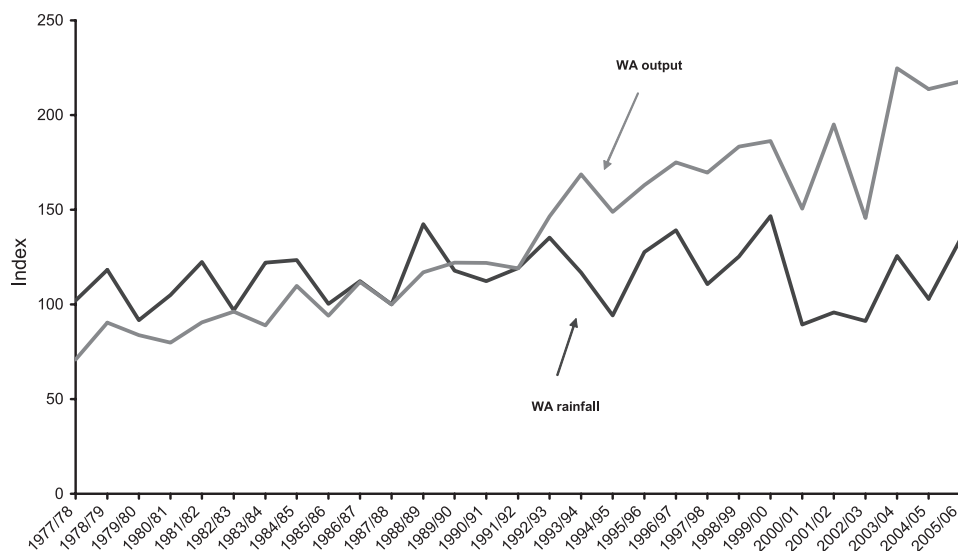
Figure 2 Trends in total agricultural output and rainfall in Western Australia, 1977–1978 to 2005–2006 (1987–1988 = 100). Note: The output series are indexed on average farm value of outputs using abare productivity database. The rainfall series is indexed on the total millimeter rainfall for the cropping season (April to October) in each year.

3. Review of literature

There has been a large body of empirical studies on the sources of productivity growth in agriculture in Australia and elsewhere. Higher productivity may result from many sources, but increase in the stock of knowledge is widely acknowledged as the main source of productivity growth (Hall and Scobie 2006). As it is not possible to quantify the amount of stock of knowledge, expenditure on R&D is commonly taken as the proxy for stock of knowledge, because it is R&D that increases knowledge (Griliches 1979). Besides R&D, climate is another factor that affects agricultural productivity to a considerable extent, because agriculture is arguably the most important sector in the economy that is highly dependent on climate (Antle and Mullen 2008). Climate has become more relevant issue for agricultural productivity in recent times because of global warming and greenhouse effects.

3.1 R&D expenditure and agricultural productivity

Up until the Mullen and Cox (1995) study, most previous analyses on the role of public investment in R&D in Australia were qualitative in nature (Harris and Lloyd 1991; Industry Commission, 1995). Using a unique data set described in Mullen *et al.* (1996), Mullen and Cox (1996) showed that the returns to research in broadacre agriculture in Australia may have been on the order of 15 to 40 per cent over the 1953 to 1988 period. They also concluded that the likely impact of research on agricultural productivity growth

can flow over many years, i.e., 15 to 40 years. The work of Mullen and Cox (1995) has been extended in another study conducted by Cox *et al*. (2002). Using the Afriat-Varian nonparametric technique, these authors computed the marginal impacts of research and extension expenditures on total factor productivity and estimated the internal rate of returns in the range of 12 per cent to 20 per cent in the Australian broadacre agriculture over the 1953–1994 period. Latter Mullen (2007) extended the previous data set developed by Mullen *et al*. (1996) to 2003 and demonstrated that the long-term trend in productivity for broadacre agriculture in Australia was around 2.5 per cent in that the domestic R&D activities might have contributed around 1.2 percent per annum.

Hall and Scobie (2006) estimate the contribution of R&D in the agricultural productivity in New Zealand during the period from 1926–1927 to 2000–2001. In this study, they adopt a capital theoretic approach in which they use estimates of the stocks of knowledge, both domestic and foreign, and find that foreign investment in R&D, through spillover effects, appears important in explaining productivity growth in New Zealand. They conclude that while knowledge generated through investment in R&D abroad is likely to have an important impact on productivity growth, it is also highly probable that a domestic research sector is required to identify relevant foreign knowledge that suits the New Zealand environment.

In a recent study on UK agriculture, Thirtle *et al*. (2008) computed total factor productivity (TFP) growth for the period of 1953–2005 and showed that public and private research and returns to scale explained 98% of TFP growth. Using cointegration and Granger causality, they demonstrated that Granger causality runs from the technology variables to TFP growth and not the reverse. Modeling the length and shape of the lag structures, they found that the rates of return to R&D using the data determined lags differ considerably from those obtained by imposing lag shapes. Finally, they concluded that the rates of return to public R&D are sensitive to the lag shape as well as to its length.

Recently, Binenbaum *et al*. (2008) found evidence of a decline in the rate of return on public R&D investment in Australian agriculture using similar methodology to that of Mullen (2007). Nevertheless, the general conclusion that emerges from existing empirical studies that R&D yields relatively high returns seems indisputable.

3.2 Climate change and agricultural productivity

In addition to R&D, the impact of climate change on agricultural productivity has gained the serious attention of academics and government agencies in the recent years. Hence, there has been a diversity of studies for analyzing future climate change impacts in the literature. This paper reviews some previous studies related to agricultural productivity. In Australia, one of the earlier studies on this issue was by Ryan (1976) on New South Wales

Wheat-sheep farms. Ryan argued that 'weather' proxied by rainfall data had a significant effect on reducing average farm costs when it changed from 'bad' to 'good' between two periods and vice versa. Mullen and Cox (1994) used a time trend as a proxy for the weather condition while explaining the changes in TFP in Australian broadacre agriculture. They reported that after accounting for research outlays and education levels, time trend had significant negative impact on TFP. However, Mullen and Cox (1995) in a subsequent paper removed the time trend variable from their model on the grounds of collinearity with R&D expenditure. They used 'weather' as an index of pasture growth based on rainfall data and found that weather is significant in explaining TFP growth in the Australian broadacre agriculture during 1953–1988. Reyenga *et al.* (2001) find that climate change would alter the distribution of cropping in Australia, given the importance of climate and soil characteristics in determining average yields and the frequency of failed sowings. The authors note that the viability of some cropping regions across Australia would decrease if the number or frequency of poor seasons increases. Howden and Jones (2004) observe that carbon dioxide emission (CO_2), rainfall, and temperature change pose significant risk for Australia's wheat industry.

Mendelsohn *et al.* (2001) argue that climate sensitivity of agriculture depends on the stage of development that an economy belongs to. If the development of new technology encourages capital to be a substitute for climate, climate sensitivity of agriculture would be lower in developed countries than that of developing or less developed countries. To test this hypothesis, this study examines a climate response function for India, Brazil, and the USA and then compares these climate response functions. Based on this analysis, they concluded that increasing development reduces climate sensitivity of agriculture.

Torvanger *et al.* (2004) examine the impact of climate change on agricultural productivity in Norway. The study analyses the impacts of temperature and precipitation on yields of potatoes, barley, oats, and wheat over the period 1958–2001 and finds that in 18 per cent of cases there is a positive impact on yield from temperature and in 20 per cent of cases the effect of increased precipitation is negative on crop yields. However, these results are sensitive to the geographic area in Norway and the types of crops. For example, the effects of climate change grew stronger as one move from South to North, and in terms of crops, the strongest effect is found for potatoes. Similarly, negative effect of precipitation is more evident in the western part of Norway (i.e. Trøndelag and Nordland), and this negative effect is more pronounced for barley.

Kingwell (2006) analyses the negative effects of climate change and farmers' adaptation to this change in the context of the Australian agriculture. He argued that climate change in the rural regions of Australia is more likely to produce a diverse set of spatial impacts. Many traditional agricultural regions are likely to face a more challenging environment for crop, pasture, and animal production. These changes exert strong downward pressure on total

agricultural output. The author suggests several strategies including increase in investment in R&D and innovation for farmers' adaptation to climate change.

Kokic *et al.* (2005) predict the impact on Australia's agriculture of two climate change scenarios: (i) a moderate increase in both temperature and rainfall and (ii) a moderate increase in temperature and a decline in rainfall. The base period for the comparison is 1992–1993 to 2001–2002, and the scenarios are a subset of the CSIRO[3] (2001) climate projections toward 2030, and the prediction is made for wheat production. Under the first scenario, wheat yield is projected to increase by 2 to 9 per cent, and under the second scenario, it is projected to increase by 7 to 16 per cent. Interestingly in the second scenario that involves warming and a decline in rainfall, the southern and western regions are much worse off and the western region experiences a large variation in yield. However, in a very recent paper, Mullen (2008) notes that climate change affects the rate of agricultural productivity growth, but the rate of agricultural productivity growth exceeds the present rate of climate change.

4. Data sources and variable construction

4.1 Data sources

Annual data covering the period 1977–1978 to 2005–2006 are used in this study. Different data series are obtained from various sources. Agricultural inputs and output data were obtained from the ABARE's annual farm surveys of broadacre agriculture[4] industries, while R&D expenditure data were taken from the Department of Agriculture and Food, Western Australia (DAFWA). Rainfall data are collected from 242 weather stations in Western Australia.

4.2 Variable construction

In empirical studies, variable construction is a critical issue. This study requires some important variables such as TFP indices, R&D stocks, and climate change. In the literature, there has been huge debate on the measurement issues of these variables. The details of variable construction are given in the following.

4.2.1 TFP indices (TFP)
TFP indices are calculated using the standard Solow's growth accounting techniques, i.e., the output growth that is not accounted for input growth. In

---

[3] CSIRO stands for Australia's *Commonwealth Scientific and Industrial Research Organization.*

[4] Broadacre agriculture does not include horticulture and dairy. It includes crops and livestock farming for grains, meat, and wool production.

other words, productivity growth is measured as the growth in outputs less the growth in inputs. TFP figures for this study are obtained from ABARE's input–output data by applying Tornqvist index method following Islam (2004).

4.2.2 R&D expenditure (RD)

DAFWA is the main source of funding for the agricultural R&D activities in the State. Beside DAFWA, academic and private organizations also invest on R&D activities in this sector, but their share is very small, on an average approximately 12 per cent per annum. It is also difficult to get the data series on these investment expenditures. Hence, the R&D expenditure component of DAFWA's budget is used in this study. The main data series from 1953 to 1994 is sourced from Mullen *et al.* (1996), and then, the series was extended to 2006 by compiling R&D expenditure figures collected from DAFWA.

In most previous empirical studies, the R&D variable, constructed using the perpetual inventory method (PIM), has been used as a proxy for stocks of knowledge. Parham (2007) argued that R&D activity is not the only form of knowledge accumulation, as education, acquisition through technology licenses or capital equipment, and learning by doing also increase the stock of knowledge. An additional problem is in estimating benefits of R&D as it is complicated by the lag time between investing in R&D, adoption by farmers, and reaping a return on that investment. This lag time could be quite long because some inventions are slow to come forth, while others yield rewards more quickly (Alston *et al.* 1995). Chavas and Cox (1992) found the lag to be up to fifteen years between making an investment in research and having an effect on productivity. However, after taking effect, the benefits from an innovation may persist for thirty years or more.

In the PIM, it is assumed that the depreciation rate is constant, and hence, the variance in R&D expenditure is related to the change in real R&D expenditure. Therefore, estimates of R&D stock derived from the PIM are sensitive and imprecise, and the standard time series models become mis-specified if use these estimates (Parham 2007).[5] This study employs the growth of real gross value of R&D as a reliable proxy for the growth of R&D stock. Note that results obtained from standard time series techniques will then relate the growth rates of the variables in concern, because all data are in natural log form and their first differences are used in the vector error correction (VEC) model as specified in Section 5. To overcome the lag timing between investing in R&D and reaping return, this paper relate 5 years backward real R&D expenditure to the current output, for example, say 1977 output is affected by 1972 R&D investment and 1978 output is by 1973 investment and so on. Thirtle and Bottomley (1989) also used past R&D expenditure data in analyzing the impact of R&D and innovation on the UK Agriculture.

---

[5] One of the referees also pointed out this problem of R&D stock constructed in the earlier version of the paper.

4.2.3 Climate change (rainfall (RF))

Quantifying global warming and change in climatic conditions is a difficult matter. The level of atmospheric carbon dioxide (CO_2), temperature, glacial runoff, precipitation, and the interaction of these elements affect agricultural production and productivity. Moreover, agriculture itself is a major contributor to increasing methane and nitrous oxide concentrations in the earth's atmosphere. Therefore, different researchers employ different proxies for the climate change variable. Ryan (1976) constructed the weather variable from unpublished rainfall data from the Commonwealth Bureau of Meteorology in Melbourne using annual rainfall deciles. A weighting scheme that places more weight on low rainfall years is used. Mullen and Cox (1994) used a crude proxy, namely a time trend, to represent variable climatic conditions. However, the authors removed that proxy in their subsequent study as the time trend is highly correlated with R&D outlays and constructed an index of pasture growth based on rainfall (Mullen and Cox 1995).

This study uses cumulative rainfall data in millimeters as a proxy for the climate variable. A similar variable is used in many national and international studies (e.g., Ryan 1976; Foster 2004; Foster and Rosenweig 2004a, 2004b and Hussain and Mudasser 2007). Monthly rainfall data from January 1977 to December 2006 was collected from 242 weather stations in Western Australia from the 'Patched Point Dataset and DAFWA weather stations' in DAFWA website. Because broadacre agricultural season extends from April to October, the cumulative rainfall data for these months in each year are used for the model estimation. Township and urban areas are excluded from this rainfall data construction.

5. Analytical framework

This paper employs a production function approach. The standard material-augmented Cobb-Douglas production function of the following form is adopted:

$$Y_t = \text{TFP}_t L_t^{\alpha} K_t^{\beta} M^{\chi} \qquad (1)$$

where t is a time index, i.e. $t = 1977, 1988, \ldots\ldots 2005$; Y is output; L and K are labor and capital inputs, respectively. TFP is the total factor productivity. α, β, and χ are labor, capital, and material share in output. This paper further assumes that TFP is driven by $R\&D$ activity and climate change (proxied by rainfall). Thus:

$$\text{TFP}_t = A_t \text{RD}_t^{\delta} RF_t^{\gamma} \qquad (2)$$

where RD denotes the stock of R&D expenditure and RF is rainfall; δ and γ are their respective weights. A is the part of technical progress not caused by the factors mentioned.

Substituting Equation (2) into Equation (1), the following equation is generated:

$$Y_t = A_t L_t^{\alpha} K_t^{\beta} M^{\chi} \text{RD}_t^{\delta} RF_t^{\gamma} \qquad (3)$$

We estimate Equation (3) as the baseline model and then estimate Equation (2) as the TFP equation to find the importance of R&D and RF in the production process of Western Australia.

To estimate Equations (2) and (3) where variables are in levels, the first step is to test the degree of integration of each of the series, i.e. to check whether the underlying data are stationary or I(0). As there are a number of tests developed in the time series econometrics to test the presence of unit roots, this paper uses two most popular methods: the augmented Dickey–Fuller test and the Philips–Perron test to all variables except the RF variable. The results of both of the tests indicate that all variables are nonstationary at levels while stationary in their growth terms, i.e. all variables were integrated of order one. Traditional unit root test may not be sufficient for RF variable when the data exhibit seasonal character. Therefore, HEGY test as suggested by Hylleberg *et al.* (1990) is used to check the unit root in the rainfall variable. Because we are using cumulative of the average monthly data from April to October, the rainfall variable appears to be stationary at levels, but the seasonal unit root tests did not reject the hypothesis of seasonal roots, so this variable should be considered with caution, as it might be I(0,1). Because the possibility of seasonal unit roots was rejected, there is no problem with introducing this variable in a cointegration regression, whether it is I(0) or I(1),[6] and thus, all series are expedient in a cointegration analysis. The data series involved in this article may have nonzero means and deterministic trends as well as stochastic trends. Similarly, the cointegrating equations may have intercepts and deterministic trends. Therefore, to carry out the cointegration tests, an assumption has to be made regarding the trend underlying the data. A constant term and a time trend are included in regression to take care of possible trends.

The test for cointegration reported in this study follows the Johansen (1988, 1991) and Johansen and Juselius (1990) maximum likelihood estimator procedures. Over the past few years, important advances have been made in cointegration techniques to estimate the long-run relationships. This paper explores the long-run dynamics among the variables within the framework of both the baseline and the TFP equations.

Next, we employ a VEC model owing Engel and Granger (1987) to both the baseline and TFP equations; however, a VEC model based on the TFP equation is of the following forms:

---

[6] Unit root test results are not reported here to conserve space; however, results will be provided upon request.

$$\Delta\text{TFP}_t = \alpha_1 + \sum_{i=1}^{l} \beta_{1i}\Delta\text{RD}_{t-i} + \sum_{i=1}^{m} \gamma_{1i}\Delta\text{TFP}_{t-i}$$
$$+ \sum_{i=1}^{n} \delta_{1i}\Delta\text{RF}_{t-i} + \sum_{i=1}^{r} \xi_{1i}\text{ECT}_{i,t-1} + u_{1t} \tag{4}$$

$$\Delta\text{RD}_t = \alpha_2 + \sum_{i=1}^{l} \beta_{2i}\Delta\text{vRD}_{t-i} + \sum_{i=1}^{m} \gamma_{2i}\Delta\text{TFP}_{t-i}$$
$$+ \sum_{i=1}^{n} \delta_{2i}\Delta\text{RF}_{t-i} + \sum_{i=1}^{r} \xi_{2i}\text{ECT}_{i,t-1} + u_{2t} \tag{5}$$

$$\Delta\text{RF}_t = \alpha_3 + \sum_{i=1}^{l} \beta_{3i}\Delta\text{RD}_{t-i} + \sum_{i=1}^{m} \gamma_{3i}\Delta\text{TFP}_{t-i}$$
$$+ \sum_{i=1}^{n} \delta_{3i}\Delta\text{RF}_{t-i} + \sum_{i=1}^{r} \xi_{3i}\text{ECT}_{i,t-1} + u_{3t} \tag{6}$$

where the variables RD_t, TFP_t, and RF_t are discussed earlier. ECTs are the error correction terms derived from long-run cointegrating relationship via Johansen maximum likelihood procedure, and $u_{i,t}$'s (for $i = 1,2,3$) are *iid* (independently and identically distributed) white noise error terms with zero mean. For the estimation purpose, Equation (4) is used to test causation from R&D and RF to TFP. Equation (5) is used to test causality from TFP and RF to R&D, while Equation (6) identifies causality from R&D and TFP to RF.

The model opens up an additional channel of causality through ECTs, which is traditionally ignored by Granger (1969) and Sims (1972) testing procedures. Sources of causality can be identified through three different channels: (i) the lagged *ECT*'s (ξ's) by a *t*-test or joint *F*-test; (ii) the significance of the coefficients of each explanatory variable (β's, γ's and δ's) by a joint Wald F or χ^2 test (weak or short-run Ganger causality); (iii) a joint test of all the set of terms in (i) and (ii) by a Wald F or χ^2 test, that is, taking each parenthesized terms separately: the (γ's, ξ's) and (δ's, ξ's) in Equation (4); the (β's, ξ's) and (δ's, ξ's) in Equation (5); and the (β's, ξ's) and (γ's, ξ's) in Equation (6) (strong or long-run Granger causality).[7]

6. Analysis of empirical results

Before going to a more rigorous time series analyses, we work out partial correlation coefficients among output, TFP, R&D, and climate change variables

---

[7] For further clarification on weak or short-run Ganger causality and strong or long-run Granger causality, please consult Soytas and Sari (2006).

(Appendix Tables 1 and 2). The results show that both R&D and RF are strongly correlated with output and TFP growth. However, correlation coefficient cannot be used to draw meaningful conclusions about the long-run relationship between these variables. Therefore, the cointegration tests are performed. Tests for a cointegrating relationship between variables are conducted using the Johansen cointegration technique (Johansen and Juselius 1990). Johansen's cointegration test is sensitive to the choice of lag length. Arbitrary lag selection may produce misleading results. To carry out the cointegration test, the Schwartz Bayesian Criterion (SBC) is used to select the optimal lag length, i.e., the order of the VAR model. According to the SBC, appropriate lag length for the baseline model is 1. Table 1 reports the Johansen multivariate cointegration test for the baseline model. The test statistics and asymptotic 5% and 10% critical values are also shown in this Table. Both maximal *Eigenvalue* and *Trace statistics* (likelihood ratio test) reject the null hypotheses of $r = 0$ and $r \leq 1$, implying that there are at least two different cointegrating relationships between these variables. This result indicates stable long-run relationships exist between these variables, meaning that these relationships are not accidental. The equilibrium relationship means that the variables cannot move independently of each other. In effect, this finding suggests that R&D expenditure and climate change may contain important information regarding agricultural output in Western Australia. The existence of a cointegrating relationship between Y, R&D, and RF suggests that there must be Granger causality in at least one direction, but it does not indicate the direction of temporal causality between the variables. To identify the direction, a VEC modeling is used next. The VEC model not only

Table 1   Cointegration test for the baseline model

Null	Alternative	Statistic	95% Critical value	90% Critical value
Cointegration LR test based on maximal eigenvalue of the stochastic matrix				
$r = 0$	$r = 1$	68.7469**	40.5300	37.6500
$r \leq 1$	$r = 2$	39.3976**	34.4000	31.7300
$r \leq 2$	$r = 3$	22.9251	28.2700	25.8000
$r \leq 3$	$r = 4$	17.6384	22.0400	19.8600
$r \leq 4$	$r = 5$	10.6672	15.8700	13.8100
$r \leq 5$	$r = 6$	5.1000	9.1600	7.5300
Cointegration LR test based on trace of the stochastic matrix				
$r = 0$	$r \geq 1$	164.4752**	102.5600	97.8700
$r \leq 1$	$r \geq 2$	95.7283**	75.9800	71.8100
$r \leq 2$	$r \geq 3$	51.3307	53.4800	49.9500
$r \leq 3$	$r \geq 4$	33.4056	34.8700	31.9300
$r \leq 4$	$r \geq 5$	15.7672	20.1800	17.8800
$r \leq 5$	$r \geq 6$	5.1000	9.1600	7.5300

Note: Cointegration with restricted intercepts and no trend in the VAR. ***, **, and * denote parameters that are significant at or below 1%, 5%, and 10%, respectively 27 observations from 1978 to 2005. Order of VAR $= 2$. Variables included in the cointegrating vector are Y, L, K, M, RD, RF, and intercept. Eigenvalues in descending order are 0.92162, 0.76757, 0.57219, 0.47966, 0.32637, 0.17212, and 0.0000.
RD, R&D expenditure; RF, Rainfall.

provides an indication of the direction of causality, it also enables to distin-guish between short-run and long-run Granger causality. The results are reported in Table 2.

The results in Table 2 imply unidirectional causality running from RF and R&D to output in both the short run and long run. However, R&D is not sig-nificant in the short run, while RF is significant at 10% level of significance in the long run. These results indicate that R&D has less impact in the short run. This result is in line with the popular view that R&D has a lagged impact on output. Further, these results indicate that both R&D expenditure and output adjust to restore the long-run equilibrium relationship whenever there is a deviation from the equilibrium cointegrating relationship.

Next we perform the cointegration relationship with all the variables in TFP model (Eqn 2). Again, the SBC is used to select the appropriate lag length in the system. Up to six lags are tested, however, SBC suggests maxi-mum of 5 lags. Both maximal *Eigenvalue* and *Trace statistic* indicate that there is at least one cointegrating relationship between TFP, R&D and RF (Table 3). The estimation results of the TFP model by normalizing TFP to be unity is reported in Table 4. The long-run elasticities for both R&D and RF have the expected signs as those predicted by economic theory. However, the size of coefficient and significance level of R&D are similar to those of rainfall implying both R&D and rainfall strongly influences TFP in this region. The results from Table 4 show that a one per cent increase in R&D stock and RF would increase TFP by 0.497 and 0.506 per cent, respectively. These elasticity measures are in line with estimates reported in the literature, although our estimates are in the high range (for example, Thirtle and Bottomley 1989; Mullen and Cox 1995; Hall and Scobie 2006 and Mullen 2007). As the direct impact of R&D on output is partly accounted for by the TFP growth, this positive and large coefficient might capture spillovers effects (from private sector or other government sector's R&D) and possibly the extra return (through technical and allocative efficiency) arising from R&D. The spillover effects of R&D across states as well as the impact of public infrastructure on agricultural productivity growth in Australia are the subject of future investi-gation by the authors (Salim and Islam 2010).

Having identified the cointegrating relationship between TFP, R&D, and RF, we perform VEC modeling to capture the short-run dynamic adjustment of the variables. The result from the VEC model estimation for TFP equation is given in Table 5. Beginning with the results for the long run, the coefficient on the lagged error correction term is significant with the expected sign in the TFP Equation l at 1% level, which confirms the result of the bounds test for cointegration. The short-run coefficients of R&D (ΔRD) and RF have correct signs and are statistically significant at 1% level. The results show that R&D efforts significantly Granger-cause TFP in both short run and long run implying a unidirectional causality from R&D to TFP. Thus, an increase in R&D expenditure can have a positive impact on TFP in both short run and long run. There is also a unidirectional causality running from RF to TFP;

Table 2 Temporal causality results of the baseline model based on parsimonious vector error correction (VEC) models

| Equation | Short run | | | | | | Sources of causation t-Statistics | | Long run | | | | | |
| | Wald χ^2-statistics | | | | | | | | Joint Wald χ^2-statistics | | | | | |
	ΔY	ΔK	ΔL	ΔM	ΔRD	ΔRF	$ECT_{1,t-1}$	$ECT_{1,t-2}$	$ETC, \Delta Y$	$ETC, \Delta K$	$ETC, \Delta L$	$ETC, \Delta M$	$ETC, \Delta RD$	$ETC, \Delta RF$
ΔY	–	0.008	4.047**	6.041**	0.125	3.289**	−0.462	3.621***	–	4.971**	4.899**	5.053**	5.037**	4.970*
ΔK	6.673**	–	6.604***	0.552	9.306***	0.125	2.086*	3.426***	15.229***	–	15.046***	15.164***	15.193***	15.177***
ΔL	1.619	2.355	–	0.923	2.793*	0.826	2.357**	1.331	6.809***	6.856***	–	6.829***	6.809***	6.815***
ΔM	7.999***	7.181***	10.178***	–	8.190***	1.989	5.303**	3.981***	43.139***	43.290***	42.944***	–	43.242***	43.146***
ΔRD	1.733	0.001	0.072	0.028	–	0.161	−0.142	0.107	0.004	0.006	0.008	0.007	–	0.007
ΔRF	1.071	0.047	0.183	1.230	0.063	–	1.105	−0.307	1.159	1.604	1.619	1.649	1.915	–

Note: VEC model is based on an optimally determined (SBC) lag structure and a constant. ***, **, and * indicate significant at 1%, 5%, and 10% level, respectively. RF, Rainfall; RD, R&D expenditure; ECT, error correction term.

Table 3 Cointegration test for the total factor productivity (TFP) model

Null	Alternative	Statistic	95% Critical value	90% Critical value
Cointegration LR test based on maximal eigenvalue of the stochastic matrix				
$r = 0$	$r = 1$	42.7951**	22.0400	19.8600
$r \leq 1$	$r = 2$	14.4597	15.8700	13.8100
$r \leq 2$	$r = 3$	6.1525	9.1600	7.5300
Cointegration LR test based on trace of the stochastic matrix				
$r = 0$	$r \geq 1$	65.4072**	34.8700	31.9300
$r \leq 1$	$r \geq 2$	19.6121	20.1800	17.8800
$r \leq 2$	$r = 3$	6.1525	9.1600	7.5300

Note: Cointegration with restricted intercepts and no trend in the VAR. ** denotes that parameters are significant at level of 5%. Twenty-four observations from 1980 to 2005, respectively Order of VAR = 5. Variables included in the cointegrating vector are TFP, R&D expenditure, Rainfall, and intercept. Eigenvalues in descending order are 0.83189, 0.49632, 0.22613, and 0.00.

Table 4 Cointegrating vectors for the total factor productivity (TFP) model

Vectors	Cointegrated equation	Error correction term
1	$TFP_t = -209.661 + 0.497RD_t$*** (0.001) + $0.506RF_t$** (0.084)	-2.105 (0.059)

Note: Maximum likelihood estimates subject to exactly identifying restrictions. TFP is the normalized dependent variable. Cointegration with restricted intercepts and no trend in the VAR. 26 observations from 1980 to 2005. Order of VAR is 5, $r = 1$. Variables included are TFP, RD, RF, and intercept. *** and ** denote parameters that are significant at or below 1% and 5% respectively. Figures in the parentheses are P-values, respectively.
RD, R&D expenditure; RF, Climate change; RF, Rainfall.

Table 5 Temporal causality results of the total factor productivity (TFP) model based on parsimonious vector error correction (VEC) models

Equations	Short run			Long run			
	Wald χ^2-statistics			F-statistics	Wald χ^2-statistics		
	ΔTFP	ΔRD	ΔRF	ECT(s) only	ΔTFP, ECT	ΔRD, ECT	ΔRF, ECT
ΔTFP	–	7.918***	3.777***	-2.105*	–	7.529***	2.852*
ΔRD	3.027*	–	1.971	1.893	3.073*	–	4.119**
ΔRF	0.058	0.513	–	-0.280	0.039	0.080	–

Note: VEC model is based on an optimally determined (SBC) lag structure and a constant. ***, **, and * indicate significant at 1%, 5%, and 10% level, respectively.
RD, R&D expenditure; RF, Rainfall; ECT, error correction term.

however, the long-run chi-square value is significant at 10% level. Furthermore, TFP is the only variable that adjusts over time to restore the long-run equilibrium relationship between the variables.

6.1 Robustness checks

Granger causality test suggests which variables in the models have significant impacts on the future values of each of the variables in the system. However,

the result will not, by construction, be able to indicate how long these impacts will remain effective in the future. Variance decomposition and impulse response function provide this information. In other words, these two approaches give an indication of the dynamic properties of the system and allow us to gauge the relative importance of the variables beyond the sample period. Hence, this article conducts generalized variance decompositions and generalized impulse response function analysis proposed by Koop *et al.* (1996) and Pesaran and Shin (1998). The unique feature of these approaches is that the results from these analyses are invariant to the ordering of the variables entering the VAR system.

The variance decomposition measures the percentage of variation in output as well as in TFP induced by shocks emanating from R&D and RF. In other words, these error variance decompositions measure the relative contribution of each source of innovation for the forecast error variance. Estimates of variance decomposition are shown in Tables 6 and 7 for a 20 years time horizon.

The variance decompositions in Table 6 indicate that in the 1st year forecast horizon, 53 per cent of the forecast error variance of output is explained by innovations to its own process so that a high proportion of changes in it do appear to be exogenous. That forecast error variance remains approximately 44 per cent 5 years ahead, and the proportion of variance remains relatively high (a little over 30 per cent) even until 10 years, i.e. about 30 per cent of error variance is accounted for by its own innovation even after

Table 6   Generalized variance decompositions of output in the baseline model

Years	*Y*	RD	RF
1	0.53415	0.25626	0.16374
5	0.44228	0.73889	0.03396
10	0.30198	0.81971	0.01704
15	0.10982	0.84070	0.01448
20	0.03487	0.84925	0.01329

Note: All the figures are estimates rounded to five decimal places.
RD, R&D expenditure; RF, Rainfall.

Table 7   Generalized variance decompositions of total factor productivity (TFP)

Years	TFP	RD	RF
1	0.82965	0.24362	0.44032
5	0.83019	0.58084	0.17325
10	0.71977	0.69415	0.09948
15	0.68833	0.75746	0.05769
20	0.65100	0.78438	0.04272

Note: All the figures are estimates rounded to five decimal places.
RD, R&D expenditure; RF, Rainfall.

10 years forecast horizon. The remaining 70 per cent of the variability in out-put is explained by R&D and RF, and as the time elapses, their contribution to variability in agricultural output in this region increases significantly. The results presented in Table 7 show that R&D is the most influential variable in explaining the variation in TFP in the long run. After 5 years, 58% of the variation of the forecast error of TFP is explained by R&D, while that of 17% is explained by RF. However, after 20 years, R&D explains 78% vari-ability of TFP. Thus, the results confirm that R&D impacts TFP, while that of RF is negligible in the longer run.

To further illustrate the manner of response of the sample to a shock, the impulse response function analysis is conducted next. Through the dynamic structure of VAR, a shock to a variable directly affects itself and all of the endogenous variables. However, we present the results of shock on other vari-ables in the system. We start with the effect of the response of agricultural output and TFP to R&D over a 20-year period after the beginning of the shock to R&D. The estimated long-run effect of shocks to agricultural output and TFP therefore exhibits persistence and exceeds the initial shock. We can display these results in Figure 3.

The left-hand side graph of Figure 3 shows the response in the output growth to a unit shock in R&D investment. A shock to R&D exerts zero effects on output initially; however, after first period, it then continuously exerts positive impact and reached to a maximum right after the period two, it decreases then although it stays remarkably high, and after that impact on output almost remains constant up to 20 years period and beyond. From these findings, it may be concluded that the effect of public R&D on output does not reveal immediately after the investment, but it starts after a year or so of investment, and for the full effect to be realized, one should wait for some years. This finding seems to suggest that public R&D has a lagged impact on agricultural output and justifies the argument that public R&D investment involves large decision and implementation lags (Alston *et al.* 2000; Esposti and Pierani 2001 and Mullen 2007). The effect of a shock to the R&D on TFP is sporadic (right-hand side graph) but remains positive and increasing till the end of the period.
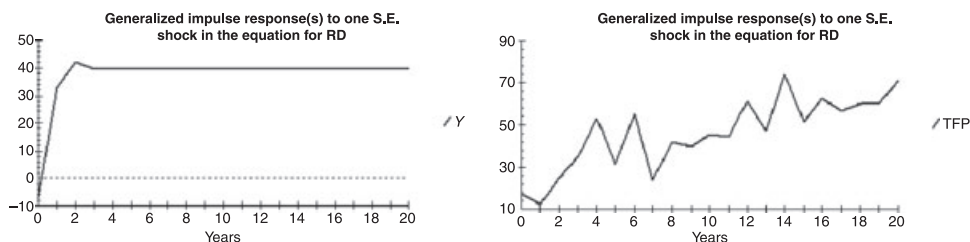
Figure 3 Generalized impulse response function in R&D Equation. Note: *Y* and total factor productivity stand for output and total factor productivity, respectively.
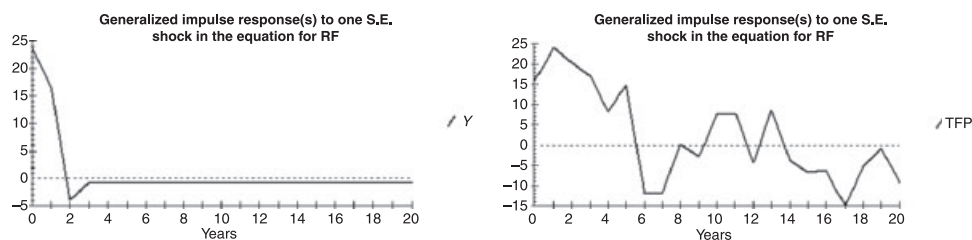
Figure 4 Generalized impulse response function in RF Equation. Note: *Y* and total factor productivity stand for output and total factor productivity respectively. RF, Rainfall.

Figure 4 shows that a one-unit S.D. shock on RF to output and TFP. The left-hand side graph shows that in response to a one standard deviation disturbance of RF on output is positive in the first year and negative in the following period. It turns out to be near positive or close to zero in third period and after that it dies out very quickly, implying that RF has greater influence on output in the short run and does not have any impact in the longer-term horizon. A one standard deviation disturbance originating from RF (right-hand side graph) produces over 20% of increase in TFP in the second period and then declines but remains positive until the sixth period and then dies out, implying that RF does not have a long-term impact on agricultural TFP. This result must be interpreted with caution because of the way that the TFP estimated is a 'black box' (residual) that capture the effects from everything other than factor inputs.

7. Conclusions and policy implications

This paper aims to examine the impact of R&D expenditure and rainfall on agricultural output and productivity growth in the long run using the standard time series techniques. The empirical results show that public R&D investment is important in the long run on agricultural output growth. The long-run elasticity with respect to R&D expenditure turns out to be 0.497 and that of climate change is 0.506. Based on cointegration and VEC modeling, the empirical result shows a unidirectional causality running from R&D to TFP growth in both the short run and long run. Although rainfall positively impacts on TFP, no significant causal relationship is found in cointegration and vector error correction modeling. Further, the variance decomposition and impulse response function confirm that a significant portion of output and productivity growth beyond the sample period is explained by R&D expenditure. These findings contrast with those of Hall and Scobie (2006) for New Zealand who found R&D expenditures had little impact on agricultural productivity growth from 1926–1927 to 2000–2001. However, the results in this paper are consistent with those of Mullen and Cox (1995) in the Australian context. They found that both R&D and weather variables are significant in explaining TFP growth between 1953 and 1988. Our results are also consistent with some more recent studies in Australia and elsewhere, for example

Reyenga *et al.* (2001), Torvanger *et al.* (2004), Howden and Jones (2004), Kokic *et al.* (2005), and Mullen (2008). All these studies demonstrate that climate change has a significant impact on agricultural output and productivity growth over time.

The implications of our findings are, therefore, straightforward. Proper utilization of rainwater and the increase in R&D expenditures in agricultural sector are needed in the deteriorating climatic condition to improve the long-run prospects of productivity growth. It may be noted that public investments in R&D and innovation could be important catalysts in facilitating farmers' adaptation to climate change.

References

Alston, J.M., Norton, G.W. and Pardey, P.G. (1995). *Science Under Uncertainty: Principles and Practice for Agricultural Research Evaluation and Priority Setting*. Oxford University Press, USA.

Alston, J.M., Pardey, P.G. and Smith, V.H. (eds.) (1999) *Paying for Agricultural Productivity*. The Johns Hopkins University Press, Baltimore and London.

Alston, J.M., Marra, M.C., Pardey, P.G. and Wyatt, T.J. (2000). Research returns redux: a meta-analysis of the returns to agricultural R&D, *Australian Journal of Agricultural Economics* 44(2), 185–215.

Antle, J. and Mullen, J. (2008). Climate change and agriculture: economic impacts, *Choices*, 23(1), 9–11.

Ball, V.C. and Norton, G.W. (eds) (2002) *Agricultural Productivity: Measurement and Sources of Growth*. Kluwer Academic Publication, Boston.

Binenbaum, E., Mullen, J.D. and Wang, C.T. (2008) Has the return on Australian public investment in agricultural research declined? Paper to be presented at the 2008 AARES conference in Canberra.

Chavas, J.P. and Cox, T.L. (1992). A Non-parametric analysis of the effects of research on agricultural productivity, *American Journal of Agricultural Economics* 74, 583–591.

Coelli, T. (1996). Measurement of total factor productivity growth and biases in technological change in Western Australian agriculture, *Journal of Applied Econometrics* 11, 77–91.

Cox, T., Mullen, J.D. and Hu, W. (2002). Nonparametric measures of the impact of public research expenditures on Australian broadacre agriculture, *Australian Journal of Agricultural and Resource Economics*, 41, 333–360.

DAFWA (2007). *Annual Report 2007*. Department of Agriculture and Food Western Australia, South Perth, WA.

Engel, R.F. and Granger, C.W.J. (1987). Cointegration and Error-Correction: Representation, Estimation and Testing, *Econometrica*, 55, 251–276.

Esposti, R. and Pierani, P. (2001) Building the knowledge stock: lags, depreciation and uncertainty in agricultural R&D, Universita Politecnica delle Marche, Departmento di Economia Working paper No. 145.

Foster, I. (2004). Rainfall Prospects for SouthWest WA for Winter 2004 – Analysis by the Bureau of Meteorology, Perth. Department of Agriculture, South Perth, WA April.

Foster, A. and Rosenweig, M.R. (2004a). Agricultural Productivity Growth, Rural Economic Diversity, and Economic Reforms: India, 1970–2000, *Economic Development and Cultural Change*, 52, 509–542.

Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods, *Econometrica*, 37, 424–438.

Griliches, Zvi. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of Economics*, 10(1), 92–116.

Hall, J. and Scobie, G.M. (2006) The Role of R&D in Productivity Growth: The Case of Agriculture in New Zealand: 1927 to 2001, New Zealand Treasury Working Paper No. 06/01.

Harris, M. and Lloyd, A. (1991). The returns to agricultural research and the underinvestment hypothesis: a survey, *Australian Economic Review*, 24, 16–27.

Howden, M. and Jones, R. (2004) Risk assessment of climate change on Australia's wheat industry, in proceedings of the 4th International Crop Science Congress, Brisbane, Australia, 26 September – 1 October, 2004.

Hussain, S.S. and Mudasser, M. (2007). Prospects for wheat production under changing climate in mountain areas of Pakistan– An econometric analysis, *Agricultural Systems*, 94, 494–501.

Hylleberg, S., Engle, R.F., Granger, C.W.J. and Yoo, B.S. (1990). Seasonal integration and cointegration, *Journal of Econometrics*, 44, 215–238.

Industry Commission (1995) *Research & Development*, Report no. 44, AGPS, Canberra.

IPCC (2001). Climate Change: Impacts, *Adaptation and Vulnerability*. Cambridge University Press, IPCC, New York, USA.

Islam, N. (1999) *Western Australian Agriculture: Structure, Trends and Farming Systems*, Discussion Paper 99.18, Department of Economics, University of Western Australia, Nedlands.

Islam, N. (2004). An analysis of productivity growth in Western Australian Agriculture, *Academia Economic papers*, 32, 467–499.

Islam, N.. (2009) *The Nature and Performance of Agriculture in Western Australia: an Overview*, Bulletin No. 4782 DAFWA: http://www.agric.wa.gov.au/objtwr/imported_assets/content/amt/agec/bn_natureeconperf.pdf

Johansen, S. (1988). Statistical analysis of cointegrating vectors, *Journal of Economic Dynamics and Control*, 12(2–3), 231–254.

Johansen, S. (1991). Estimation hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models, *Econometrica*, 59(6) :1551–1580.

Johansen, S. and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration: with applications to the demand for money, *Oxford Bulletin of Economics and Statistics*, 52(2): 169–210.

Kingwell, R. (2006). Climate change in Australia: Agricultural impacts and adaptation, *Australian Agribusiness Review*, 14, 1–19.

Kokic, P., Heaney, A., Pechey, L., Crimp, S. and Fisher, B.S. (2005). Predicting the impacts on agriculture: A case study, *Australian Commodities*, 12(1), 161–170.

Koop, G., Pesaran, M.H. and Potters, S.M. (1996). Impulse response analysis in nonlinear multivariate models, *Journal of Econometrics*, 74, 119–147.

Mendelsohn, R., Dinar, A. and Sanghi, A. (2001). The effect of development on the climate sensitivity of agriculture, *Environment and Development Economics*, 6, 85–101.

Mullen, J.D. (2007). Productivity growth and the returns from public investment in R&D in Australian broadacre agriculture, *Australian Journal of Agricultural and Resource Economics* 51(4), 359–384.

Mullen, J.D. (2008) Rural Industries: Maintaining Productivity in a Changing Climate, Paper presented at the Australian Agricultural and Resource Economics Society, 5–8 February, Canberra.

Mullen, J.D. and Cox, T.L. (1994) R&D and productivity growth in Australian broadacre agriculture, an invited paper presented to the 38th Annual Conference of the Australian Agricultural Economics Society, Victoria University, Wellington, New Zealand.

Mullen, J.D. and Cox, T.L. (1995). The Returns from Research in Australian Broadacre Agriculture, *Australian Journal of Agricultural Economics*, 39(2), 105–128.

Mullen, J.D. and Cox, T.L. (1996). Measuring Productivity Growth in Australian Broadacre Agriculture, *Australian Journal of Agricultural Economics*, 40(3), 189–210.

Mullen, J.D. and Crean, J. (2007) *Productivity Growth In Australian Agriculture: Trends, Sources, Performance*; Research Report, Australian Farm Institute, Surry Hills, Australia.

Mullen, J.D., Lee, K. and Wrigley, S. (1996). Agricultural production research expenditure in Australia: 1953–1994, NSW Agriculture, *Agricultural Economics Bulletin* 14, 1–32.

O'Donnell, C., Chambers, R.G. and Quiggin, J. (2006) *Efficiency Analysis in the Presence of Uncertainty*, Risk and Uncertainty Program Working paper No. R06_2, University Of Queensland.

Parham, D. (2007) Empirical analysis of the effects of R&D on productivity: Implications for productivity measurement?, Paper presented at the *OECD Workshop on Productivity Measurement and Analysis, Bern, Switzerland, 16–18 October, 2006*.

Pesaran, M.H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models, *Economics Letters*, 58, 17–29.

Reyenga, P.J., Howden, M., Meinke, H. and McKeon, G.M. (2001). Global impacts on wheat production along an environmental gradient in South Australia, *Environment International*, 27, 195–200.

Ryan, I. (1976). Growth and size economies over space and time: Wheat-sheep farms in New South Wales, *Australian Journal of Agricultural Economics*, 20, 160–178.

Salim, R. and Islam, N. (2010). *Climate Change, R&D Investment, Spillover effects and Productivity Growth in Australian Agriculture (forthcoming mimeograph)*, Department of Agriculture & Food, Western Australia.

Sims, C.A. (1972). Money, income, and causality, *American Economic Review*, 62, 540–552.

Soytas, U. and Sari, R. (2006). Energy consumption and income in G-7 countries, *Journal of Policy Modeling*, 28, 739–750.

Thirtle, C. and Bottomley, P. (1989). The rate of return to public sector agricultural R&D in the UK, 1965–80, *Applied Economics*, 21(8), 1063–1086.

Thirtle, C., Piesse, J. and Schimmelpfennig, D. (2008). Modelling the Length and Shape of the R&D Lag: An Application to UK Agricultural Productivity, *Agricultural Economics*, 39, 73–85.

Torvanger, A.M., Twena, M. and Romstad, R. (2004). *Climate Change Impacts on Agricultural Productivity in Norway. Draft Report*. Center for International Climate and Environmental Research—Oslo (CICERO) Working Paper No. 2004:10, Blindern, Norway.

Appendices

Table 1 Correlation matrix for the variables in output equation

Variables	Y	L	K	M	RD	RF
Y	1.0000 (- - -)					
L	0.393 (0.039)	1.0000 (- - -)				
K	0.377 (0.048)	0.817 (0.000)	1.0000 (- - -)			
M	0.508 (0.006)	0.793 (0.000)	0.807 (0.000)	1.0000 (- - -)		
RD	0.319 (0.098)	−0.124 (0.531)	−0.367 (0.055)	−0.196 (0.318)	1.0000 (- - -)	
RF	0.430 (0.022)	−0.124 (0.529)	−0.052 (0.794)	−0.031 (0.877)	0.266 (0.172)	1.0000 (- - -)

Note: Significance levels in brackets. RD, R&D expenditure; RF, Rainfall.

Table 2 Correlation matrix for the variables in total factor productivity equation

Variables	TFP	RD	RF
TFP	1.0000 (- - -)		
RD	0.554 (0.002)	1.0000 (- - -)	
RF	0.486 (0.009)	0.266 (0.172)	1.0000 (- - -)

Note: Significance levels in brackets. TFP, Total factor productivity; RD, R&D expenditure; RF, Rainfall.