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

* We are grateful to Drs Ross Kingwell, Felix Chan, Vilaphon Xayayong, two anonymous referees, and the copy editor of this journal for reading the earlier drafts and their useful comments which materially improved the quality and presentation of this paper. We would like to thank Shuddha Rafiq and AFM Kamrul Hassan, School of Economics & Finance, Curtin University for excellent research assistance. Usual disclaimer applies.
† Ruhul A. Salim (email: Ruhul.salim@cbs.curtin.edu.au), School of Economics & Finance, Curtin University, Perth, Australia. Nazrul Islam, Department of Agriculture & Food, WA and Graduate School of Business, Curtin University.
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 (GDP) 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’ 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.

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 oilseeds 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](https://example.com/figure1.png)  
**Figure 1** Output, input, and total factor productivity trends in broadacre agriculture 1977/78-2005-06 (1987/88 = 100).
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

![Figure 2](image_url)
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 (CO₂), 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

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\(^3\) 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 inno-
vation 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 expen-
diture. 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). 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 analyz-
ing 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 (CO₂), 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:

\[ Y_t = TFP_t L_t^\alpha K_t^\beta M_t^\gamma \]

where \( t \) is a time index, i.e. \( t = 1977, 1988, \ldots, 2005 \); \( Y \) is output; \( L \) and \( K \) are labor and capital inputs, respectively. TFP is the total factor productivity. \( \alpha, \beta, \) and \( \gamma \) 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:

\[ TFP_t = A_t RD_t^\delta RF_t^\gamma \]

where RD denotes the stock of R&D expenditure and RF is rainfall; \( \delta \) and \( \gamma \) 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:

\[ Y_t = A_t L_t \gamma K_t \beta M_t \beta RD_t \beta RF_t \]  

(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), 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:

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6 Unit root test results are not reported here to conserve space; however, results will be provided upon request.
\[ \Delta \text{TFP}_t = \alpha_1 + \sum_{i=1}^{l} \beta_{1i} \Delta \text{RD}_{t-i} + \sum_{i=1}^{m} \gamma_{1i} \Delta \text{TFP}_{t-i} + \sum_{i=1}^{n} \delta_{1i} \Delta \text{RF}_{t-i} + \sum_{i=1}^{r} \xi_{1i} \text{ECT}_{i,t-1} + u_{1t} \] (4)

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

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

where the variables RD, TFP, and RF 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 (\( \xi \)'s) by a \( t \)-test or joint \( F \)-test; (ii) the significance of the coefficients of each explanatory variable (\( \beta \)'s, \( \gamma \)'s and \( \delta \)'s) by a joint Wald \( F \) or \( \chi^2 \) 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 \( \chi^2 \) test, that is, taking each parenthesized terms separately: the (\( \gamma \)'s, \( \xi \)'s) and (\( \phi \)'s, \( \delta \)'s) in Equation (4); the (\( \beta \)'s, \( \xi \)'s) and (\( \gamma \)'s, \( \xi \)'s) in Equation (5); and the (\( \beta \)'s, \( \xi \)'s) and (\( \gamma \)'s, \( \xi \)'s) in Equation (6) (strong or long-run Granger causality).

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.

\[ \text{Source of clarification on weak or short-run Granger causality and strong or long-run Granger causality, please consult Soytas and Sari (2006).} \]
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

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<th>Null</th>
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<th>Statistic</th>
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<th>90% Critical value</th>
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</tbody>
</table>

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 1 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

<table>
<thead>
<tr>
<th>Equation</th>
<th>Short run</th>
<th>Long run</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wald $\chi^2$-statistics</td>
<td>Sources of causation $t$-Statistics</td>
</tr>
<tr>
<td></td>
<td>$\Delta Y$</td>
<td>$\Delta K$</td>
</tr>
<tr>
<td>$\Delta Y$</td>
<td>–</td>
<td>0.008</td>
</tr>
<tr>
<td>$\Delta K$</td>
<td>6.673**</td>
<td>–</td>
</tr>
<tr>
<td>$\Delta L$</td>
<td>1.619</td>
<td>2.355</td>
</tr>
<tr>
<td>$\Delta M$</td>
<td>7.999***</td>
<td>7.181***</td>
</tr>
<tr>
<td>$\Delta RD$</td>
<td>1.733</td>
<td>0.001</td>
</tr>
<tr>
<td>$\Delta RF$</td>
<td>1.071</td>
<td>0.047</td>
</tr>
</tbody>
</table>

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.
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>
<thead>
<tr>
<th>Years</th>
<th>Y</th>
<th>RD</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.53415</td>
<td>0.25626</td>
<td>0.16374</td>
</tr>
<tr>
<td>5</td>
<td>0.44228</td>
<td>0.73889</td>
<td>0.03396</td>
</tr>
<tr>
<td>10</td>
<td>0.30198</td>
<td>0.81971</td>
<td>0.01704</td>
</tr>
<tr>
<td>15</td>
<td>0.10982</td>
<td>0.84070</td>
<td>0.01448</td>
</tr>
<tr>
<td>20</td>
<td>0.03487</td>
<td>0.84925</td>
<td>0.01329</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Years</th>
<th>TFP</th>
<th>RD</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.82965</td>
<td>0.24362</td>
<td>0.44032</td>
</tr>
<tr>
<td>5</td>
<td>0.83019</td>
<td>0.58084</td>
<td>0.17325</td>
</tr>
<tr>
<td>10</td>
<td>0.71977</td>
<td>0.69415</td>
<td>0.09948</td>
</tr>
<tr>
<td>15</td>
<td>0.68833</td>
<td>0.75746</td>
<td>0.05769</td>
</tr>
<tr>
<td>20</td>
<td>0.65100</td>
<td>0.78438</td>
<td>0.04272</td>
</tr>
</tbody>
</table>

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 output 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% variability 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 variables 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 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


Appendices

Table 1  Correlation matrix for the variables in output equation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Y</th>
<th>L</th>
<th>K</th>
<th>M</th>
<th>RD</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>1.0000</td>
<td>(- - -)</td>
<td>(- - -)</td>
<td>(- - -)</td>
<td>(- - -)</td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>0.393 (0.039)</td>
<td>1.0000 ( - - -)</td>
<td></td>
<td>(- - -)</td>
<td>(- - -)</td>
<td>(- - -)</td>
</tr>
<tr>
<td>K</td>
<td>0.377 (0.048)</td>
<td>0.817 (0.000)</td>
<td>1.0000 ( - - -)</td>
<td></td>
<td>(- - -)</td>
<td>(- - -)</td>
</tr>
<tr>
<td>M</td>
<td>0.508 (0.006)</td>
<td>0.793 (0.000)</td>
<td>0.807 (0.000)</td>
<td>1.0000 ( - - -)</td>
<td></td>
<td>(- - -)</td>
</tr>
<tr>
<td>RD</td>
<td>0.319 (0.098)</td>
<td>-0.124 (0.531)</td>
<td>-0.367 (0.055)</td>
<td>-0.196 (0.318)</td>
<td>1.0000 ( - - -)</td>
<td></td>
</tr>
<tr>
<td>RF</td>
<td>0.430 (0.022)</td>
<td>-0.124 (0.529)</td>
<td>-0.052 (0.794)</td>
<td>-0.031 (0.877)</td>
<td>0.266 (0.172)</td>
<td>1.0000 ( - - -)</td>
</tr>
</tbody>
</table>

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

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>TFP</th>
<th>RD</th>
<th>RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>1.0000</td>
<td>(- - -)</td>
<td>(- - -)</td>
</tr>
<tr>
<td>RD</td>
<td>0.554 (0.002)</td>
<td>1.0000 ( - - -)</td>
<td></td>
</tr>
<tr>
<td>RF</td>
<td>0.486 (0.009)</td>
<td>0.266 (0.172)</td>
<td>1.0000 ( - - -)</td>
</tr>
</tbody>
</table>

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