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Productivity pathways: climate-adjusted production frontiers for the Australian broadacre cropping industry

Neal Hughes, Kenton Lawson, Alistair Davidson, Tom Jackson and Yu Sheng

Abstract

This study introduces two advances to the aggregate productivity index methodology typically employed by ABARES. First, it accounts for the effects of climate variability on measured productivity by matching spatial climate data to individual farms in the ABARES farm surveys database. Second, a farm-level production frontier estimation technique is employed to facilitate the decomposition of productivity change into several key components, including technical change and technical efficiency change.

The study makes use of farm-level data from the ABARES Australian agricultural and grazing industries survey database. An unbalanced panel dataset is constructed containing 13 430 observations (4255 farms) over the period 1977–78 to 2007–08. Spatial climate data, including winter and summer seasonal rainfall and average maximum and minimum temperatures, were obtained via the Australian Water Availability Project. These data were mapped to individual farms using Geographic Information System methods.

The study employed stochastic frontier analysis methods to estimate a production frontier with time varying technical efficiency effects of the form proposed by Battese and Coelli (1992). Production frontiers are estimated for each of the three major Grains Research and Development Corporation regions: southern, northern and western.

Selected climate variables are shown to display a high degree of explanatory power over farm output. The results confirm that deterioration in average climate conditions has contributed significantly to the decline in estimated productivity over the post-2000 period. Technical change is shown to be the primary driver of productivity growth in the industry in the long run, offset by a gradual decline in technical efficiency. After controlling for climate variability, a gradual decline in the rate of technical change is still observed.

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This report draws heavily on data collected in the ABARES surveys of broadacre industries. The success of these surveys depends on the voluntary cooperation of farmers, their accountants and marketing organisations in providing data. The dedication of ABARES survey staff in collecting these data is also gratefully acknowledged. Without this assistance, the analysis presented in this report would not have been possible. The Grains Research and Development Corporation and Meat & Livestock Australia both make a significant contribution to the funding for these surveys.

1 Introduction

Productivity growth in the Australian agriculture sector has historically been relatively strong, typically outstripping productivity growth in the rest of the economy. Within the agriculture sector, productivity growth has been particularly high among broadacre cropping farms, with estimated growth in total factor productivity (TFP) of greater than 5 per cent a year between 1979–80 and 1997–98 (Nossal et al. 2009).

However, it is now evident that agriculture productivity growth rates have slowed considerably over the past decade. Among cropping specialists, productivity change averaged around –2 per cent a year over the period 1997–98 to 2006–07 (Nossal et al. 2009). This slowdown has attracted substantial research attention in recent times; measuring the extent of the slowdown, identifying potential contributing factors and investigating possible remedial measures (for example, see Sheng et al. 2010).

This study introduces two advances to the aggregate productivity index methodology typically employed by ABARES. First, it accounts for the effects of climate variability on measured productivity levels, by matching Bureau of Meteorology climate observations to individual farms in the ABARES farm surveys database. Accounting for the effects of climate variability is important to better understand underlying productivity trends. Standard estimates of productivity are subject to substantial annual volatility owing to fluctuations in climate conditions. In addition, there has been a well-documented decline in average rainfall observed in much of Australia's key agricultural areas over the past decade. To fully evaluate the extent of the productivity slowdown, it is necessary to control for these changes in climate conditions.

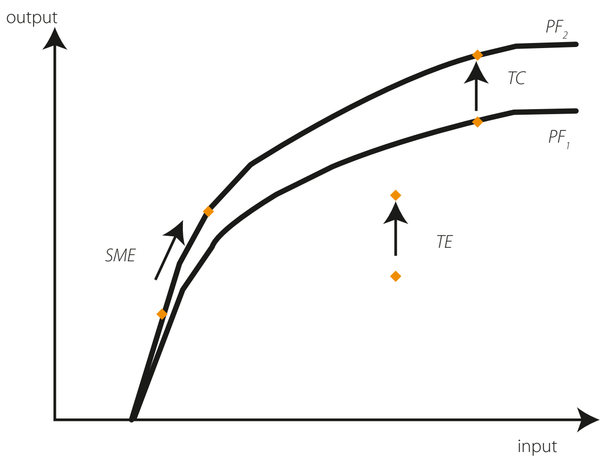
Second, this study employs production function estimation techniques, specifically stochastic frontier analysis. These techniques make full use of individual farm-level survey (and climate) data to provide a picture of the distribution of productivity levels across individual farms and, in turn, to decompose aggregate productivity change into several key components, or productivity 'pathways'.

Two key productivity pathways considered in this study are technical change, representing the development of new technologies or the 'best farms getting better', and technical efficiency change, representing the rate of adoption of available technologies, or the rate at which the 'average farms catch up to the best farms'. Decomposing productivity provides additional insights, as different pathways can have their own unique sets of drivers and potential policy responses.

2 Productivity pathways

This section provides a brief discussion of production frontiers and productivity decomposition. For a more detailed discussion, see O'Donnell (2009 and 2010). Key productivity components of interest include technical change (TC), technical efficiency change (TE) and scale and mix efficiency change (SME). Figure a illustrates each of these 'pathways' in the context of a single output, single input production technology.

a Key productivity change components



Technical change

Technical change is represented by an upward shift in the production frontier over time; a move from PF_1 to PF_2 (figure a). In essence, technical change reflects the availability of new technologies and knowledge. At an industry level, an improvement in productivity owing to an expansion of the frontier might be simplistically described as 'the best farms getting better'.

A key source of new knowledge on agricultural production is formal research and development (R&D) activities. This includes knowledge generated by domestic public R&D activities (such as those undertaken by Rural Research and Development Corporations/Companies) and R&D investments by private firms. In addition, new knowledge may be acquired through international research spillovers or informally through farmer experimentation and learning by doing.

Accurate information on the link between rural R&D and productivity and, more generally, on the social returns to rural R&D investment, is important from the perspective of determining the optimal level and composition of government investment in rural R&D. While there is general agreement that rural R&D contributes to productivity growth, quantifying the exact nature of the relationship between productivity growth and R&D remains difficult in practice.

Technical efficiency change

Technical efficiency change refers to improvements in productivity via the further adoption of existing technologies; that is, farm movement toward the production frontier (figure a). Improvements in industry productivity as a result of technical efficiency change could be described simply as 'the average farms catching up to the best farms'.

Technical efficiency change is driven by a process of diffusion of knowledge. The rate of adoption of technology is thought to be heavily influenced by human capital factors (such as the age, education level and experience of farm operators), as well as access to social networks. Another key determinant is the availability of information about new technologies. Traditionally, government extension services have played a key role in helping to gather, interpret and communicate information on the latest technologies, although private extension services are increasingly playing a role.

Scale and mix efficiency change

Additional pathways to productivity growth may include changes in scale efficiency and mix efficiency. Scale efficiency change will occur wherever firms change scale while operating under either increasing or decreasing returns to scale. For example, firms may increase in scale over time to exploit economies of scale, as demonstrated in figure a.

Mix efficiency change refers to changes in productivity due solely to changes in input or output mix (economies of scope). In this study, a combined measure of scale and mix efficiency is estimated. Changes in farm scale and mix are expected to depend on the profit-maximising behaviour of farm managers and, in turn, on prevailing input and output prices (O'Donnell 2010).

Exit of less efficient farms

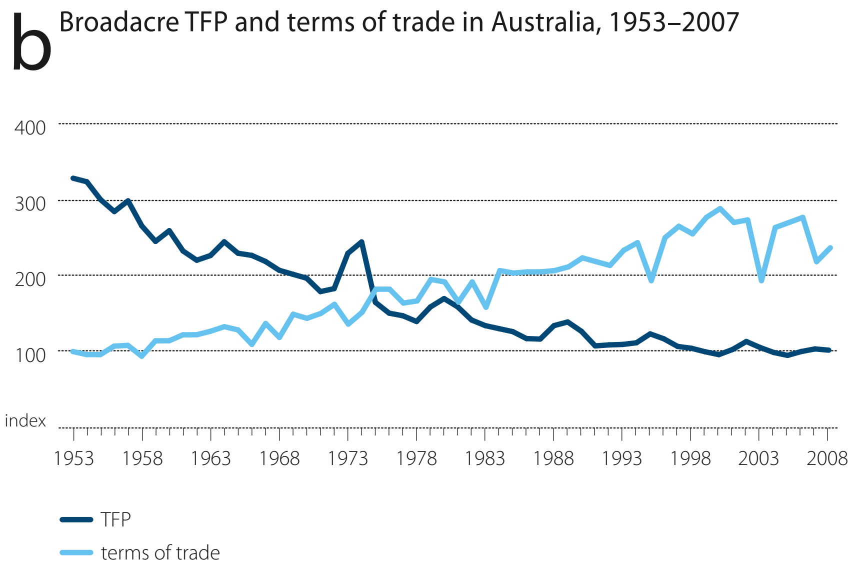
The exit of farms that are less technically efficient may contribute to industry productivity growth by removing less efficient farm operators from the industry or reallocating other inputs from the industry, including land. This process of adjustment will be driven largely by market forces. An important policy implication is the need to minimise any artificial constraints that limit the ability of markets to perform this allocative role.

The exit of less efficient farms and/or farm managers may result in improvements in either industry technical efficiency or industry scale efficiency (where exit occurs though a process of farm rationalisation). As such, isolating the effect of farm / farm operator exit from other factors influencing industry technical and scale efficiency remains difficult in practice.

Pathways to profitability

Terms of trade is defined as the ratio of output to input prices; changes in productivity and terms of trade jointly determine profitability. For most commodities, Australian primary producers are price-takers in domestic and international markets. Given that the terms of trade is largely beyond farmers' control, the main driver of long-term profitability growth is productivity growth. Long-term productivity improvements have historically enabled Australian farmers to offset the effect of a declining terms of trade on farm profitability (figure b).

Both technical change and technical efficiency improvements are unambiguously good for both productivity and profitability. However, scale and mix efficiency movements can potentially cause productivity and profitability to move in opposite directions. For example, O'Donnell (2010) notes that improvements in the terms of trade may encourage firms to expand scale (to increase profits) to the point where decreasing returns to scale are incurred, such that increasing profitability is associated with decreasing productivity. O'Donnell (2010) undertook an empirical assessment providing supporting evidence for such an effect in Australian agriculture.



Note: The terms of trade is the ratio of an index of prices received by farmers to an index of prices paid by farmers (ABARE 2009). TFP is the broadacre agriculture total factor productivity index (Nossal et al. 2010).

3 Measurement and interpretation

Decomposition of productivity change requires empirical estimation of production frontiers from panel data on firm output and input levels. Estimation of production frontiers is subject to a number of significant practical challenges, which have important implications for the interpretation of associated productivity estimates.

Quality differences in inputs and outputs

In practice, there are limits on how completely inputs and outputs can be measured. An important example in the context of agriculture is land quality. While land inputs are generally measured in quantity terms, there are important quality dimensions, including soil nutrient levels and water holding capacity. Non-controlled variation in the quality of input and/or output variables can lead to biased estimates of production frontiers and technical efficiency.

Natural resources and environmental conditions

Agricultural productivity is heavily influenced by the availability of key non-market natural resource inputs and prevailing environmental conditions, particularly moisture availability. Failure to control for moisture availability will clearly result in biased estimates of production frontiers and technical efficiency.

Risk and uncertainty

Agricultural production decisions, particularly in Australia, are made in the face of significant risk and uncertainty. Failure to account for risk and uncertainty could potentially result in biased estimates of production frontiers and technical efficiency levels. Issues of risk and uncertainty are not investigated in detail in this report, but are considered further in O'Donnell, Chambers and Quiggin (2010).

Measurement error and other statistical noise

All real world datasets are subject to some degree of measurement error and other sources of statistical noise. The presence of noise has important implications for the measurement of productivity. In particular, defining a production frontier by the best performing farms in a sample may be problematic, especially where there are outliers.

Interpretation of technical inefficiency

A common feature among all of these measurement issues is the potential to contribute to a general overestimation of technical inefficiency.[1] For example, farms may be classified as technically inefficient as a result of having relatively poor land quality rather than because

1 While these issues have a tendency to result in the general overestimation of technical inefficiency levels, they can also operate in the opposite direction for individual firms.

of any pure technical inefficiency. Where these potential sources of error are controlled for accurately, farm deviations from the frontier can safely be viewed as pure technical inefficiency, due solely to the managerial ability of farm operators.

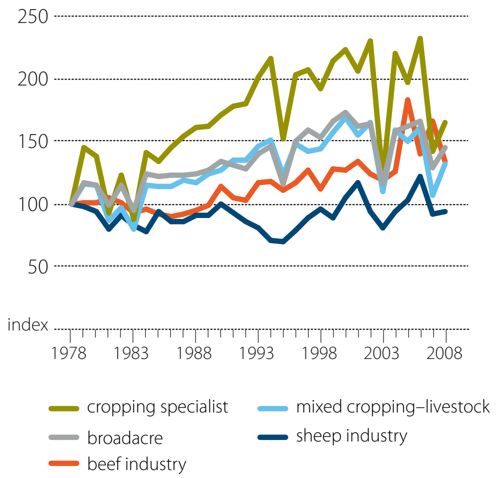
Ideally, the estimation techniques used adequately account for these measurement issues. In this study, several steps are taken to improve the reliability of estimates, including the use of econometric techniques to deal with noise (stochastic frontier analysis) and the incorporation of key natural resources / environmental inputs such as rainfall and temperature.

4 Previous research

Australian agricultural productivity trends: potential slowdown

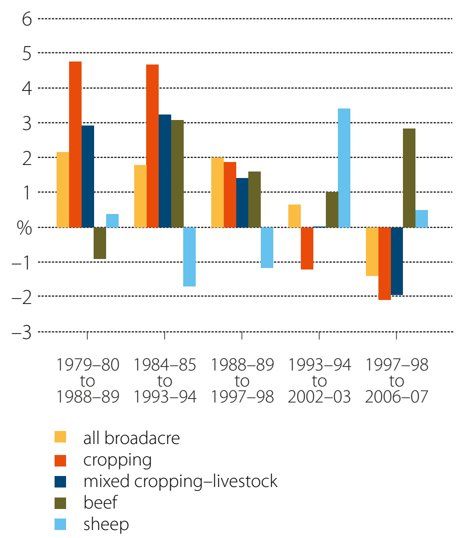
ABARES estimates time series TFP indexes for Australian broadacre agriculture industries using data from annual farm surveys and traditional indexing methodology (Nossal et al. 2009, Zhao et al. 2010). Positive annual average productivity growth of 1.5 per cent has been estimated for the broadacre agriculture sector over the period 1977–78 to 2006–07 (Nossal et al. 2009). There is significant volatility in productivity growth from year to year, much of this due to the effects of climate variability. In general, cropping specialists have outperformed livestock industries over the period, with 2.1 per cent average growth. However, there appears to have been a slowdown in productivity growth in the cropping sector, particularly from 2000 onward (figures c and d).

c Broadacre TFP indexes
1977–78 to 2007–08



Source: Nossal et al. 2010.

d Broadacre TFP growth short-term trends



Source: Nossal et al. 2010.

A number of potential causal factors for the slowdown have been identified, including the adverse climate conditions and reduced public R&D investment. Recent research has found that the slowdown can be considered a statistically significant structural change or 'turning point' (Sheng et al. 2010). Reduced moisture availability and R&D investment have both been shown to be correlated with the observed decline in productivity growth (Sheng et al. 2010).

Determinants of agricultural productivity: human capital, farm size and climate variability

ABARE (now ABARES) completed several studies investigating the determinants of broadacre agriculture productivity growth. These studies employed regression techniques to identify explanatory variables correlated with farm TFP indexes (Zhao et al. 2009, Kokic et al. 2006, Alexander and Kokic et al. 2005).

Explanatory variables have typically included human capital proxies (such as age and education) and measures of farm size and climate variables (such as moisture availability). A number of studies observed a significant positive relationship between farm size and TFP (for example, Kokic et al. 2006). A number of studies have also observed significant relationships between human capital variables (such as education levels) and farm TFP indexes (Zhao et al. 2009).

These previous studies made use of a moisture availability / water stress index developed by the Agricultural Production Systems Research Unit. All of these studies observed a significant positive correlation between the moisture availability index and productivity.

Estimation of production frontiers for agriculture

To date there has been limited application of farm-level production frontier estimation techniques to Australian agriculture. Previous studies include the work of Battese and Corra (1977), Battese and Coelli (1988), Fraser and Hone (2001) and Kompas and Che (2004).

Battese and Corra (1977) estimated stochastic production functions using a single year, 1973–74, of the ABARE Australian agricultural and grazing and industries survey (AAGIS). Battese and Coelli (1988) applied panel data stochastic frontier methods to three years of data (1978–79 to 1980–81) for a sample of dairy farms in New South Wales and Victoria. Individual farm technical efficiency levels ranged from 0.30 to 0.93 (Battese 1992).

Fraser and Hone (2001) estimated deterministic (data envelopment analysis) production frontiers for an eight-year balanced panel data sample of Victorian wool producers. They assumed constant returns to scale and estimated a mean technical efficiency level of 0.81. In addition, Fraser and Hone (2001) found TFP to be driven primarily by technical change, with technical efficiency change having minimal effect.

Kompas and Che (2004) estimated a stochastic production frontier and technical efficiency model for the Australian dairy industry for the period 1996 to 2000, making use of ABARE survey data. They estimated a dairy production frontier with constant returns to scale and observed a mean technical efficiency level of 0.87.

5 Methodology

This section provides a summary of the method used to estimate production frontiers, known as stochastic frontier analysis. The data sources used, including the ABARES farm survey data and climate data, are also outlined.

Stochastic frontier analysis

Stochastic frontier analysis is an econometric method of estimating production frontiers, which takes into account the presence of statistical noise. As such, stochastic frontier analysis is suitable for estimating production frontiers with large unit-level datasets such as the ABARES farm survey data. In contrast, the traditional deterministic approach (data envelopment analysis) does not account for noise, potentially resulting in biased estimates.

The key to the stochastic frontier analysis approach is the specification of a 'composite error term', which explains farm deviations from the production frontier as a combination of technical inefficiency (u) and statistical noise (v). This study involved estimating a production frontier with a 'translog' functional form and quadratic time trend and climate responses:

where:

$$Log(Y_{i,t}) = \beta_0 + \sum_{j=1}^{J} \beta_j Log(X^{M}_{j,i,t}) \;+ \sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{jk} Log(X^{M}_{j,i,t}).Log(X^{M}_{k,i,t}) \;+ \beta_t t + \beta_{tt} t^2 + \sum_{k=1}^{K} \alpha_k X^{NM}_{k,i,t} + \sum_{k=1}^{K} \pi_k {X^{NM}_{k,i,t}}^2 + v_{i,t} - u_{i,t}$$

$Y_{i,t}$ = aggregate output index of farm i in time period t

β_0 = constant term

$X^{M}_{j,i,t}$ = input indexes j (land, labour, capital and materials and services)

β_j = input parameters j

t = time trend

β_t, β_{tt} = time trend parameters

$X^{NM}_{j,i,t}$ = climate variables k (such as rainfall and temperature)

α_k, π_k = climate variable parameters

$v_{i,t}$ = symmetrical normally distributed random variable

u_i = non-negative truncated normal random variable.

The functional form of the technical inefficiency effects follows that of Battese and Coelli (1992), with time varying technical inefficiency drawn from a truncated normal distribution:

$$v_{i,t} \sim N(0, \sigma_v^2)$$
$$u_{i,t} = u_i e^{(-\eta(t-T))}$$
$$u_i \sim N^+(\mu, \sigma_u^2)$$
$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

$$\gamma = \frac{\sigma_u^2}{\sigma^2}$$

Where:

T = total number of time periods

η = inefficiency trend parameter

μ = technical inefficiency distribution parameter

(where $\mu = 0$ implies half normal model)

σ^2 = total error variation

γ = technical inefficiency contribution to total error variation.

The above model was estimated using the FRONTIER software version 4.1 (CEPA 2009), which employs an iterative maximum likelihood procedure.

Given the estimated model, ABARES standard farm-level TFP index can be decomposed into a variety of key components. First, a climate effects index (CE) can be constructed from the estimated climate parameters (α_k, π_k), demonstrating the relative effects of climate variability (across time and across farms) on farm output and productivity. From this a climate-adjusted TFP index can be derived ($TFPCA$).

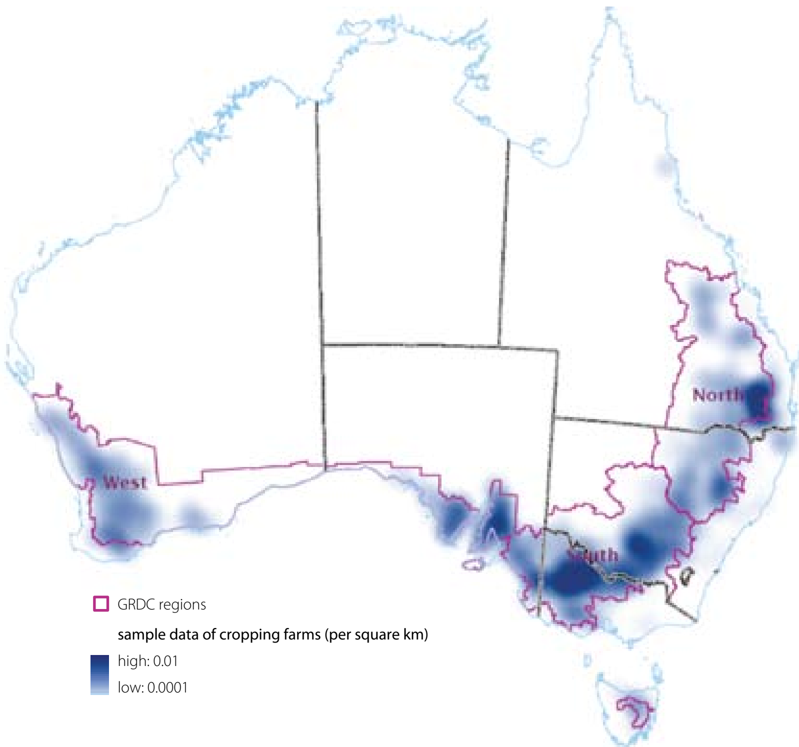
$TFPCA$ can then be further decomposed into technical change (TC), technical efficiency change (TE) and scale and mix efficiency change (SME). The technical change component can be derived from the estimated model time trend parameters (β_t, β_{tt}), while the technical efficiency change component can be derived from the estimated technical efficiency parameters (η, u_i). Given technical change and technical efficiency change, scale and mix efficiency change can be estimated as a residual. The methodology underlying this decomposition is outlined in detail in Appendix A.

ABARES farm survey data

Farm-level data on output and market input use over the period 1977–78 to 2007–08 were drawn from the ABARES farm survey database. ABARES collects farm-level data through the Australian agricultural and grazing industry survey (AAGIS), which samples around 1500 to 1600 broadacre farms each year.

The AAGIS provides a representative sample of Australian broadacre agriculture, specifically five key agricultural industries as defined by the Australian and New Zealand Standard Industrial Classification: cropping specialists; mixed cropping–livestock; beef; sheep; and sheep–beef. The survey has extensive regional coverage throughout each of the three major Grains Research and Development Corporation (GRDC) regions: southern, northern, and western (map 1).

map **1** Major GRDC cropping regions and ABARES farm survey data coverage (cropping specialists and mixed cropping–livestock farms)



For this study, the sample was limited to farms classified as either crop specialists or mixed cropping–livestock (to match GRDC requirements). Irrigation farms were also excluded from the sample. The sample was further reduced by exclusion of outliers and farms with inadequate location data (necessary for matching of climate variables). A breakdown of the final sample sizes by industry and GRDC region is found in table 1.

1 ABARES farm data sample size by industry class and region

	southern	western	northern	other	Australia
Total observations over 31-year period					
Crop specialists	3 138	1 134	1 410	181	5 863
Mixed cropping–livestock	3 624	1 524	1 743	676	7 567
Total	6 762	2 658	3 153	857	13 430
Average number of observations per year					
Crop specialists	101	37	46	6	189
Mixed cropping–livestock	117	49	56	22	244
Total	218	86	102	28	433

Note: Each observation corresponds to one farm in one year.

The AAGIS maintains a process of sample rotation where each year a certain proportion of farms are dropped from the sample and replaced with new farms, resulting in an unbalanced panel dataset. The number of years for which farms remain in the final sample varies significantly, with an average duration in the sample of 3.2 years.

This study makes use of farm-level output and input quantity indexes derived as part of the ABARES estimation of aggregate TFP indexes. The variables used in this study include an aggregate output quantity index and four input quantity indexes: land, labour, capital and materials, and services. A brief summary of the process involved in constructing these indexes is provided below; a more detailed discussion is presented in Zhao et al. (2010).

Output index

Most broadacre farms produce multiple outputs. Indexing techniques (involving the use of prices as weights) are used to aggregate individual outputs into a single output index for each farm (specifically a Fisher quantity index). This involves a nested indexing procedure. Broadacre outputs include the following major categories: crops, livestock, wool and other farm income. The crops category then includes a variety of different crops (for example, wheat, barley, oats), which are aggregated into a single crop output index. Each of the major output indexes are then combined into a single aggregate output index for the farm.

Input indexes

ABARES defines four major input indexes in its standard TFP estimation framework.

- *Land quantity index:* based on the average of the opening and closing area operated.
- *Labour quantity index:* combining data on hired labour, owner operator labour, family labour and shearing costs.
- *Capital quantity index:* combining the market value of various capital components such as buildings, plant and machinery and livestock capital.
- *Materials and services quantity index:* covering a large range of inputs, including materials such as fertiliser, fuel and crop chemicals, and services such as contract services, rates and taxes, and administrative services.

Climate data

For this project, ABARES completed a brief review of the relationship between agricultural output and climate variability and the availability of data for key climate variables. This information was used to identify suitable climate variables to include as explanatory variables in the stochastic frontier analysis.

In Australia, moisture availability is the primary limiting factor of crop and livestock growth (Cawood 1996, Stephens 2002, Raupach et al. 2008, Van Gool and Vernon 2005). Moisture availability is a function of rainfall as well as evaporation and soil quality characteristics. Although energy availability (solar radiation and temperature) is considered non-limiting in Australia, extreme temperature events (either high or low) can impair plant function and lower pasture or crop yields (Cawood 1995, 1996).

Moisture

The CSIRO produces estimates of soil moisture as part of the Australian Water Availability Project (AWAP). However, these estimates rely on soil quality data, which have a number of limitations, including limited spatial resolution and varying coverage and methodologies used across regions. Soil moisture measures are also potentially affected by farm management decisions. As such, soil moisture variables were considered unsuitable for this analysis.

In the absence of accurate soil moisture data, growing season rainfall is considered to be a reasonable measure of plant moisture availability (Cawood 1996). While rainfall fails to fully incorporate differences in soil moisture and quality, data are readily available at suitable spatial and temporal resolution from the Bureau of Metrology (and in interpolated form via the AWAP).

This study defines two seasonal rainfall variables: total rainfall over the winter crop growing season (from April to October); and total rainfall over the summer crop growing season (from November to March), which is relevant in the northern region where summer cropping is common. A lagged summer season rainfall variable (rainfall in the previous summer season) is also considered, since summer rainfall may contribute residual soil moisture of benefit to the subsequent winter growing season.

Temperature extremes

Like rainfall, temperature data are available at high temporal and spatial resolution via the AWAP. However, given that extreme temperature events impair plant growth, there is a need to construct an appropriate measure of temperature variations rather than an average or total measure.

A number of measures of temperature were tested in this study, including:

- *threshold measures*—the days within growing seasons where maximum (minimum) temperatures exceeded (fell below) critical thresholds
- *average monthly maximum and minimum temperatures*—considered a proxy for temperature extremes

- *growing degree days*—reflecting the average of daily maximum and minimum temperatures relative to a base temperature.

Both the threshold measures and the average monthly maximum and minimum temperatures demonstrated the anticipated correlation with farm output. However, monthly maximum and minimum temperatures proved to have marginally superior explanatory power as a proxy for exposure to temperature extremes.

Mapping climate data to individual farms

Climate data were obtained from the AWAP, which is a joint project between the Bureau of Meteorology, the CSIRO, ABARES and the Australian National University. This project has produced long time series of interpolated grids of key meteorological variables covering Australia at daily, weekly and monthly intervals at a 0.05 degree (about 5 km) resolution.

These rainfall and temperature 'surfaces' were used to generate farm-specific climate variables, given farm latitude, longitude and area operated information recorded in the ABARES survey data. Area weighted average climate variables were calculated using ArcGIS software by representing each farm as a circle centred on the farm's latitude and longitude, with radius chosen to match the farm area operated.

Final climate variables

Table 2 shows summary statistics for the final climate variables constructed for this study for each of the major GRDC regions.

2 Climate variable summary data, 1977–78 to 2007–08

climate variable	units	southern		western		northern	
		mean	SD	mean	SD	mean	SD
Winter season							
Total rainfall	mm	291	(113)	290	(96)	274	(127)
Average maximum temperature	°C	18.3	(1.8)	20.1	(1.7)	22.9	(2.3)
Average minimum temperature	°C	6.6	(1.4)	8.1	(1.1)	8.4	(1.9)
Summer season							
Total rainfall	mm	134	(73)	90	(55)	343	(111)
Average maximum temperature	°C	28.4	(2.3)	30.4	(2.6)	31.8	(1.9)
Average minimum temperature	°C	13.4	(2.0)	14.9	(1.8)	17.8	(1.8)

Note: Standard deviation (SD) in parentheses.
Source: Constructed from data from the Australian Water Availability Project.

6 Results

Coefficient estimates

Separate stochastic frontier models were estimated for each of the GRDC regions (southern, western and northern). For each region, frontier models were estimated for all sample farms (cropping specialists and mixed cropping–livestock) and then separately for crop specialist farms only (table 3). Across all models the majority of parameter estimates proved statistically significant. Parameter estimates are contained in Appendix B (tables 9 and 10).

3 Frontier models estimated

	southern	western	northern
Cropping specialists and mixed cropping–livestock	model 1	model 2	model 3
Cropping specialists only	model 4	model 5	model 6

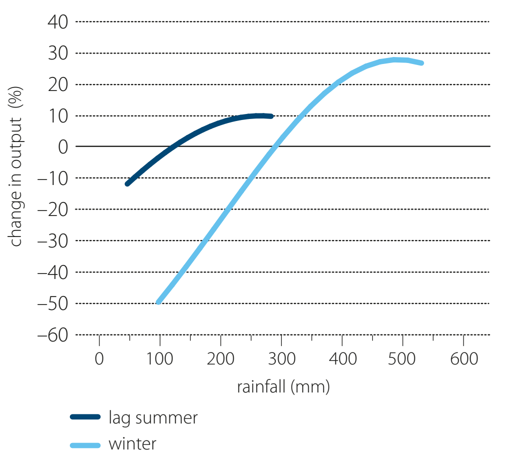
Climate variable response curves

Estimated coefficients for climate variables largely conformed to expected signs and magnitudes (tables 9 and 10). In each model, rainfall variables were included in quadratic form, allowing for a decreasing marginal gain from additional rainfall. Examples of the estimated effects of changes in rainfall (relative to the mean) on output are shown in figure e for the southern region (model 1) and figure f for the northern region (model 3).

Figure e illustrates how the marginal benefit of additional rainfall declines substantially in wet years, eventually reaching a point of decreasing returns under extremely wet conditions. In the southern region, the effect of rainfall in the winter growing season dominates that of other climate variables, although lagged summer rainfall has a statistically significant effect. In the northern region, winter rainfall, summer rainfall and lagged summer rainfall have effects of similar magnitude (figure f).

Estimated responses vary across models but generally confirm that extremes of temperature have a negative effect

e Effect of winter and summer lag rainfall on output (model 1 – southern region)

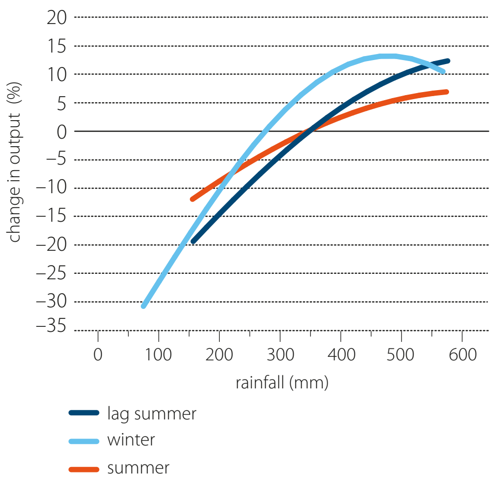


Note: Chart range is the 2.5 percentile to the 97.5 percentile of farm winter/summer rainfall. Mean winter rainfall is 291 mm; mean summer rainfall is 132 mm.

on output; all else held constant, higher maximum temperatures and lower minimum temperatures result in lower output (see figure g). Overall, however, marginal temperature effects are small in comparison to rainfall effects.

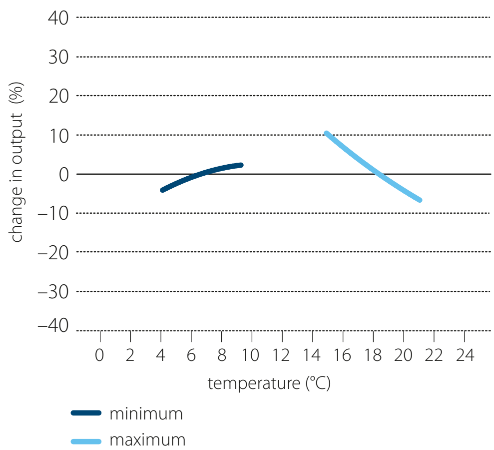
A number of climate variable interaction terms were also found to have a statistically significant effect on output. Temperature–rainfall interaction terms confirm that higher temperatures increase the sensitivity of output to rainfall variation, while lagged summer rainfall was shown to act as a substitute for winter season rainfall.

f Effect of winter, summer and summer lag rainfall on output (model 3 – northern region)



Note: Chart range is the 2.5 percentile to the 97.5 percentile of farm winter/summer rainfall. Mean winter rainfall is 274 mm; mean summer rainfall is 343mm.

g Effect of winter maximum/minimum temperature on output (model 1 – southern region)



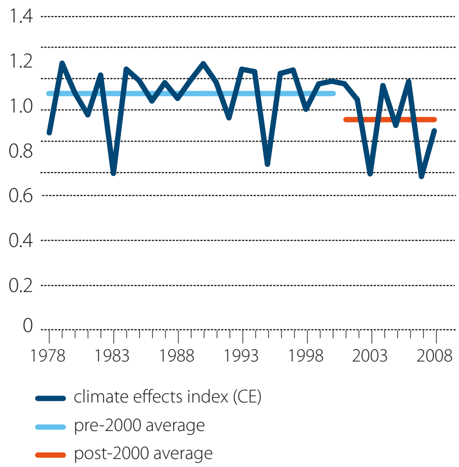
Note: Chart range is the 2.5 percentile to the 97.5 percentile of farm average maximum/minimum temperature. Mean average maximum temperature is 18.3 degrees; mean average minimum temperature is 6.6 degrees.

Climate effects index

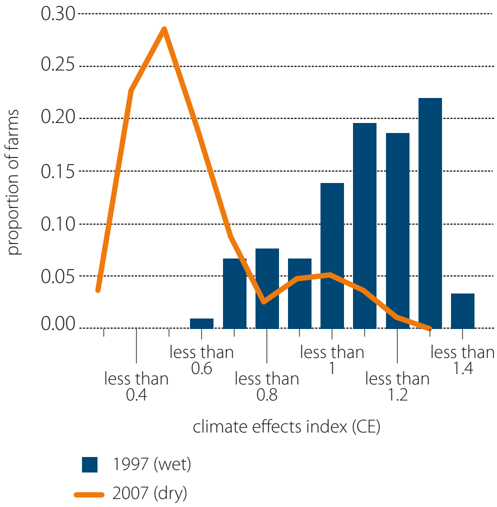
The climate effects index (CE) represents the combined effects on output of rainfall and temperature variations, holding all else constant. The annual mean climate index (across farms in all regions) is shown in figure h for the period 1977–78 to 2007–08.

The asymmetry of the annual variations largely reflects the quadratic relationship between output and rainfall (figures e and f). Average climate conditions (particularly in the form of rainfall) during the post-2000 period were significantly below those observed during the pre-2000 period, and this adversely affected output (as shown in figure h). Table 4 provides a summary of the average decline in output due to poorer climate conditions in the post-1999–2000 period.

h Mean climate effects index, all farms, all regions, 1977–78 to 2007–08



i Distribution of farm-level climate effects index, southern region (model 1), 1997 and 2007



4 Percentage change in mean climate effects index, 1999–2000 to 2007–08 relative to 1977–78 to 1999–2000.

	southern	western	northern	Australia
Cropping specialists and mixed cropping–livestock	–11.5%	–7.6%	–12.3%	–11.0%
Cropping specialists only	–14.2%	–9.2%	–11.0%	–13.0%

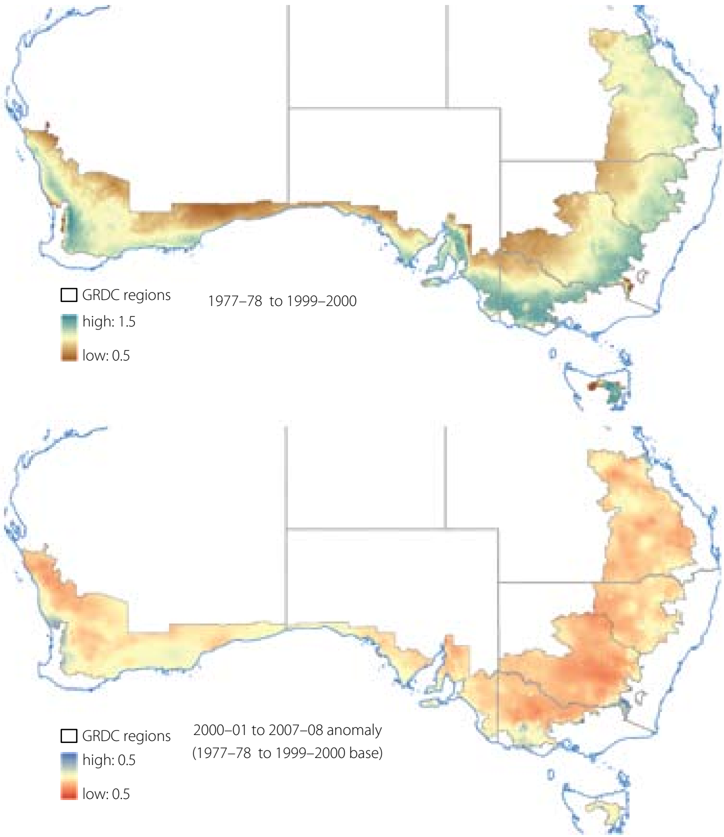
5 Standard deviation of mean climate effects index, 1977–78 to 2007–08

	southern	western	northern	Australia
Cropping specialists and mixed cropping–livestock	18.7%	11.3%	16.6%	15.1%
Cropping specialists only	24.8%	18.3%	15.9%	19.3%

The climate effects index displays greater variation in the southern region (table 5). This reflects both a higher degree of annual rainfall variability and a greater farm sensitivity to changes in winter rainfall. As is evident from Table 5 cropping specialist farms in the southern and western regions tend to display greater sensitivity to variations in climate variables relative to mixed cropping–livestock farms.

Substantial variation is observed in the climate effects index across farms within a region in each year. Figure i shows the variation in farm-level climate indexes for two representative years: 2006–07 (a 'dry' year) and 1996–97 (a 'wet' year). However, even within 'dry' years there may be individual farms experiencing 'wet' conditions. These results highlight the importance of a farm-level approach to controlling for climate variability.

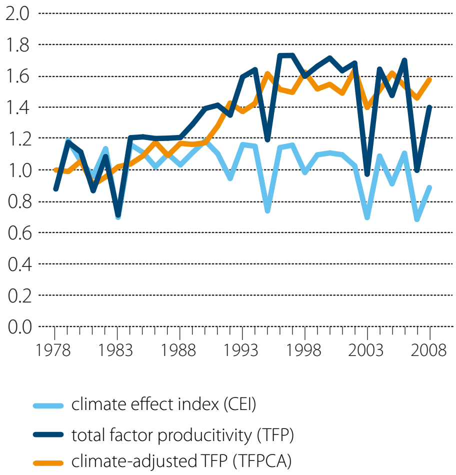
map **2** Map of climate effects index (models 1, 2 and 3), cropping specialists and mixed cropping–livestock, 1977–78 to 1999–2000 (top) and climate anomaly 2000–01 to 2007–08 (bottom)



Given the estimated climate parameters and the spatial rainfall and temperature data, maps of the climate effects index can also be generated. Map 2 depicts the average of the climate index over the period 1977–78 to 1999–2000 at each point (pixel) within each GRDC region. In this map, the climate effects index varies between 1.5 (green) and 0.5 (brown). Map 2 also displays a climate anomaly map, depicting the change in average climate conditions in the post-2000 period relative to the pre-2000 period—varying between –0.5 (red) and +0.5 (blue).

The observed patterns in climate conditions primarily reflect differences in average rainfall. As expected, agricultural activity is generally concentrated in the more favourable rainfall areas. The climate anomaly maps show that the deterioration in climate conditions has been most pronounced in central New South Wales and north-central Victoria (in the southern region) and in the northern portion of the western region. While most areas have experienced a decline in climate conditions, a minority of areas have experienced an improvement in average conditions post-2000.

j Climate-adjusted TFP, Australia
1977–78 to 2007–08



Productivity decomposition

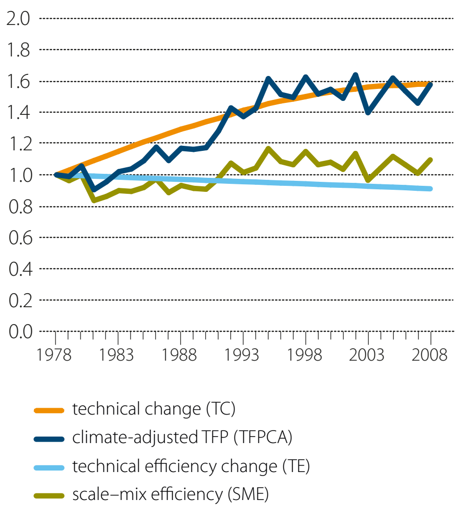
A summary of the productivity decomposition results by region and industry is contained in table 6. Figures j and k display the average estimated productivity trends across all farms in all regions (Australia—cropping specialist and mixed cropping–livestock farms). Figure j shows the climate-adjusted TFP index and the standard TFP index. As would be expected, the climate-adjusted series displays significantly less volatility. Figure k shows the decomposition of climate-adjusted TFP into technical change, technical efficiency change and scale and mix efficiency change components. Given the smooth functional forms assumed for technical change and technical efficiency change, any annual volatility remaining in climate-adjusted TFP is effectively assigned to scale and mix efficiency change.

While the results of the productivity decomposition differ across regions and models, there are a number of common features.

Technical efficiency decline

Across all models technical efficiency is estimated to have declined gradually. Australia-wide, the rate of technical efficiency change is an annual average of around –0.3 per cent. This decline implies that the gap between the best (most efficient) farms (those defining the frontier) and the average farms (those with lower technical efficiency) has widened over the period. While farms overall are improving, the average farms have not been able to improve at the same rate as the best farms. This widening gap has acted as a drag on industry productivity growth.

k Productivity decomposition, Australia
1977–78 to 2007–08



Technical change the primary driver of productivity growth

Technical change is the key driver of long-run productivity growth in the industry. Australia-wide, the rate of technical change was an annual average 1.5 per cent, while TFP growth was an annual average 1.2 per cent for cropping specialist and mixed cropping–livestock farms. A primary driver of productivity growth for the industry over the period has been the expansion of the frontier; that is, the development and adoption of new knowledge/technology.

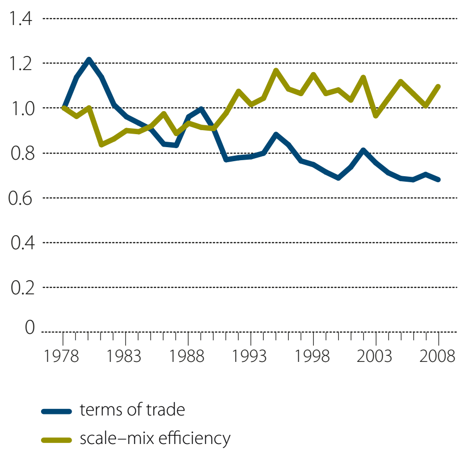
6 Estimated annual growth in productivity components

	pre-2000 1977–78 to 1999–2000	post-2000 1999–2000 to 2007–08	total 1977–78 to 2007–08
Cropping specialists and mixed cropping–livestock farms			
Australia			
Technical change (TC)	1.95%	0.40%	1.53%
Technical efficiency change (TE)	–0.30%	–0.34%	–0.31%
Scale–mix efficiency (SME)	0.35%	0.17%	0.31%
Climate-adjusted TFP (TFPCA)	2.00%	0.24%	1.53%
Southern			
Technical change (TC)	1.95%	0.45%	1.55%
Technical efficiency change (TE)	–0.34%	–0.35%	–0.34%
Scale–mix efficiency (SME)	0.35%	–0.26%	0.18%
Climate-adjusted TFP (TFPCA)	1.96%	–0.16%	1.39%
Western			
Technical change (TC)	2.25%	0.37%	1.74%
Technical efficiency change (TE)	–0.30%	–0.34%	–0.31%
Scale–mix efficiency (SME)	0.22%	1.30%	0.50%
Climate-adjusted TFP (TFPCA)	2.17%	1.32%	1.94%
Northern			
Technical change (TC)	1.70%	0.31%	1.32%
Technical efficiency change (TE)	–0.22%	–0.26%	–0.23%
Scale–mix efficiency (SME)	0.45%	0.37%	0.43%
Climate-adjusted TFP (TFPCA)	1.93%	0.42%	1.53%
Cropping specialists only			
Australia			
Technical change (TC)	2.31%	0.54%	1.84%
Technical efficiency change (TE)	–0.26%	–0.33%	–0.28%
Scale–mix efficiency (SME)	0.10%	0.85%	0.30%
Climate-adjusted TFP (TFPCA)	2.15%	1.06%	1.86%
Southern			
Technical change (TC)	2.27%	1.00%	1.93%
Technical efficiency change (TE)	–0.32%	–0.36%	–0.33%
Scale–mix efficiency (SME)	–0.03%	0.79%	0.19%
Climate-adjusted TFP (TFPCA)	1.90%	1.43%	1.78%
Western			
Technical change (TC)	2.81%	–0.42%	1.94%
Technical efficiency change (TE)	–0.08%	–0.09%	–0.08%
Scale–mix efficiency (SME)	–0.08%	1.56%	0.35%
Climate-adjusted TFP (TFPCA)	2.65%	1.04%	2.22%
Northern			
Technical change (TC)	1.97%	0.15%	1.48%
Technical efficiency change (TE)	–0.25%	–0.34%	–0.27%
Scale–mix efficiency (SME)	0.71%	0.38%	0.63%
Climate-adjusted TFP (TFPCA)	2.45%	0.19%	1.84%

Declining rate of technical change

Common across all models is a gradually declining rate of technical change. It should be noted that the decline in technical change is observed after controlling for the effects of deteriorating climate conditions. Australia-wide, technical change over the period 1977–78 to 1999–2000 was estimated at an annual average of 1.95 per cent, with an average of just 0.4 per cent a year over the period 1999–2000 to 2007–08 (cropping specialist and mixed cropping–livestock farms). Although the estimated rate of technical change declined, there is generally no indication of significant technical regress (negative technical change).

Scale and mix efficiency and the terms of trade, Australia
1977–78 to 2007–08



Scale and mix efficiency inversely related to terms of trade

The scale and mix efficiency component is observed to be inversely related to the farmers' terms of trade (figure I), declining initially and then increasing steadily thereafter, largely in line with terms of trade decline. This result is consistent with the theory and results of O'Donnell (2010), who emphasised the potential for farmers to make productivity-decreasing (but profitability-increasing) scale and mix decisions in response to improvements in the terms of trade.

Regional and industry-specific results

Annual average climate-adjusted TFP growth is highest in the western region, followed by the southern region and then the northern region. This is predominantly due to higher technical change and lower technical efficiency decline. Average climate-adjusted TFP growth during the period was higher among cropping specialists (1.84 per cent) in comparison with mixed cropping–livestock farms (1.53 per cent), again predominantly because of higher technical change.

For southern region cropping specialists, the decline in technical change was relatively modest, with annual average growth slowing to 1 per cent during the post-2000 period, in comparison with essentially zero growth for western and northern region cropping specialists (table 6). Much of this difference is due to the strong influence of climate variables in the southern cropping specialists model, such that most of the observed decline in productivity is explained by deteriorating climate conditions.

Technical efficiency levels

Technical efficiency scores represent farms' relative distance from the frontier (where a value of 1 indicates a 'best practice' farm lying on the frontier). A summary of mean technical efficiency scores is contained in table 7. The mean technical efficiency levels observed in this study are consistent with those observed in previous studies, with an average of around 0.8 across the different models. Higher mean technical efficiency was observed in the western region relative to the northern and southern regions, and, in general, mean technical efficiency was higher in the cropping specialist models.

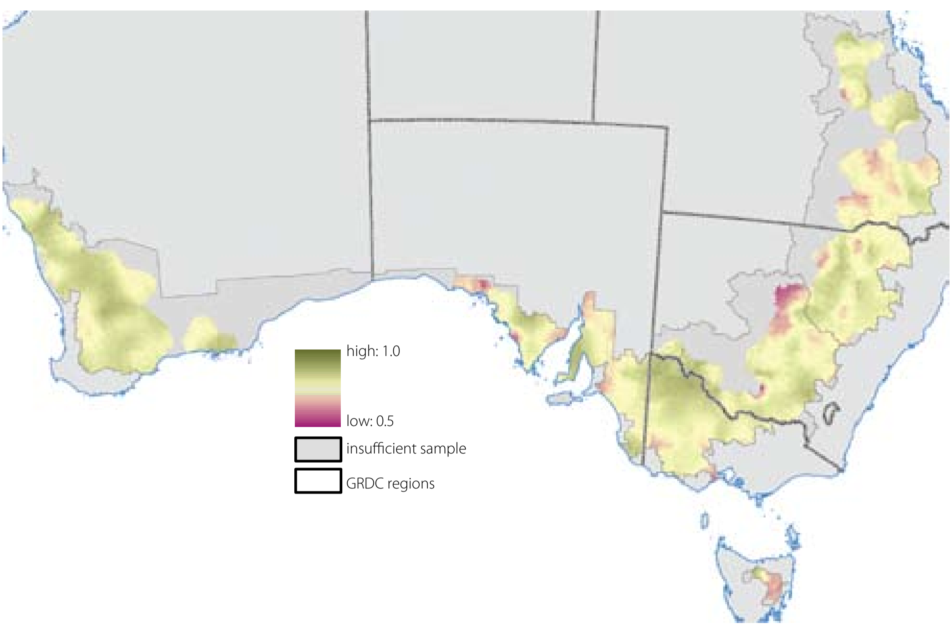
7 Mean technical efficiency levels

	Southern	Western	Northern
Cropping specialists and mixed cropping–livestock	0.79	0.80	0.78
Cropping specialists only	0.80	0.86	0.78

Map 3 is a map of farm technical efficiency levels for the southern, northern and western GRDC regions. For confidentiality reasons, farm technical efficiency scores are shown in interpolated form (each point represents the average technical efficiency score of all farms within a 50 km radius). Green denotes areas of higher efficiency (levels at or near 1), while red denotes areas of low efficiency (levels approaching 0.5).

Spatial patterns in technical efficiency are likely to reflect, among other things, land quality and/or climate factors not fully accounted for within the econometric model. In general, areas of poor technical efficiency tend to be located in relatively 'marginal' or opportunistic cropping areas, and in areas with a relatively low concentration of cropping specialist farms, often located near the boundaries of the defined regions—such as the northern (New South Wales) and western (South Australian) sections of the southern GRDC region. Conversely, areas with a high concentration of cropping farms tend to display higher technical efficiency (for example, the Darling Downs region in Queensland and the Yorke Peninsula in South Australia).

map **3** Map of average technical efficiency scores (models 1, 2 and 3), cropping specialists and mixed cropping–livestock, 1977–78 to 2007–08



7 Conclusions

This study had two primary objectives: to develop a methodology for controlling the effects of climate variability on measured productivity; and to decompose productivity change into key components through the application of production frontier estimation techniques. Both of these methodological developments contribute to an improved understanding of trends in Australian broadacre agricultural productivity.

Controlling for climate variability

A method of controlling for climate variability was developed, involving the combination of farm survey data with spatial rainfall and temperature climate data. An advantage of this approach is that it does not require modelling of on-farm management practices. In addition, the approach is sufficiently flexible that it can be calibrated to specific regions, time periods or industries.

The approach proved effective, with the chosen climate variables displaying a high degree of explanatory power. Estimated relationships between climate variables and farm output proved statistically significant and consistent with prior expectations. Differing climate variable responses were observed across regions and industries, with the southern region showing greater climate sensitivity than the northern and western regions. Cropping specialist farms were observed to be more sensitive to climate variability than mixed cropping–livestock farms.

The results highlight the importance of controlling for climate variability when measuring productivity, particularly given the observed decline in climate outcomes in recent years. Across all regions, declining climate conditions were observed to explain a significant proportion of the slowdown in productivity growth. Post-2000, declining climate conditions were estimated to have reduced output by an average of around 17–18 per cent among cropping specialist farms in the southern and western regions.

Productivity decomposition

After controlling for climate variability, farm productivity was further decomposed into key components, including technical change, technical efficiency change, and scale and mix efficiency change. The productivity decomposition results confirmed that technical change has been the key determinant of long-run productivity growth in Australia's broadacre cropping industry.

Across all regions, a gradual decline in the rate of technical change was observed. For example, in the western region (among cropping specialists and mixed cropping–livestock farms), technical change was estimated to be 2.4 per cent a year over the period 1977–78 to 1999–2000, with growth of just 0.6 per cent a year over the period 1999–2000 to 2007–08. The decline in the rate of technical change post-2000 was observed to be most pronounced in the western and northern regions. In the southern region, the decline in the rate of technical change was relatively modest, especially among cropping specialist farms.

Growth in technical change was offset by a small decline in average technical efficiency levels over the period 1977–78 to 2007–08. Declining technical efficiency implies that the gap between the most efficient farms (those defining the frontier) and the less efficient farms has widened over the period. Australia-wide, technical efficiency change was estimated to average –0.4 per cent a year among cropping specialists and mixed cropping–livestock farms. Scale and mix efficiency change was observed to be inversely related to changes in the farmers' terms of trade index, consistent with O'Donnell (2010).

Future research

There remain a number of directions for future research, including application to livestock industries, further refinement of climate variables and the generation of ongoing climate-adjusted TFP series. Further refinements of the frontier estimation technique could include consideration of the determinants of technical efficiency, including human capital characteristics, as well as explicit treatment of land quality variation.

Appendix A: Productivity decomposition

Farm-level technical efficiency scores (TES) are defined, as in Battese and Coelli (1992):

$$TES_{i,t} = E\left(e^{-u_{i,t}} \middle| v_{i,t} - u_{i,t}\right)$$

Annual technical efficiency change (TEC), technical change (TCC) indexes are defined as in Coelli et al. (2005).

$$TEC_{i,t} = \frac{TES_{i,t}}{TES_{i,t-1}}$$

$$TCC_{i,t} = exp\left[\frac{1}{2}\left(\frac{\partial\ Log\ Y_{i,t-1}}{\partial t-1}\right) + \left(\frac{\partial\ Log\ Y_{i,t}}{\partial t}\right)\right]$$

Cumulative technical change (TC) and technical efficiency change (TE) indexes are defined as below, with $TC_{i,1} = TE_{i,1} = 1$

$$TC_{i,t} = TC_{t-1}.TCC_{i,t}$$

$$TE_{i,t} = TC_{t-1}.TEC_{i,t}$$

From the estimated frontier model, the climate parameters estimates ($\hat{a}_k\ \hat{\pi}_k$) are used to construct a farm-level climate effects index (CE). This index represents the total effect on farm output of deviations in climate variables (namely, seasonal rainfall and average maximum and minimum temperatures), holding all else constant.

The index is calculated as outlined below. The index is normalised to average climate conditions over the entire sample period (that is, 1 = Average climate conditions)

$$\hat{C}_{i,t} = \sum_{k=1}^{K} \hat{\alpha}_k X_{k,i,t}^{NM} + \sum_{k=1}^{K} \hat{\pi}_k {X_{k,i,t}^{NM}}^2$$

$$CE_{i,t} = exp\left(\hat{C}_{i,t}\right)$$

where:

$X^{NM}_{k,i,t}$ = climate variable k, observation for farm i in time period t

$\hat{a}_{k,}\, \hat{\pi}_k$ = climate variable parameters

$\hat{C}_{i,t}$ = Climate variable contribution to predicted value ($\widehat{log\,(Y_{i,t})}$)

$CE_{i,t}$ = climate effects index for farm i in period t

A farm-level total factor productivity (TFP) index is obtained separately via the standard ABARES indexing methodology (Zhao et al. 2010). A climate-adjusted farm-level TFP index is then defined as:

$$TFPCA_{i,t} = \frac{TFP_{i,t}}{CE_{i,t}}$$

A farm-level scale and mix efficiency (SME) index is then defined as a residual:

$$SME_{i,t} = \frac{TFPCA_{i,t}}{TE_{i,t}.TC_{i,t}}$$

For each index ($TFP, TE, TC, SME, TFPCA, CE$), regional and national averages are defined as the unweighted geometric mean of the farm-level indexes; for example:

$$TFP_t = \prod_{i=1}^{n} \left(TFP_{i,t}\right)^{1/n}$$

For the $TFPCA, TE, TC, SME$ indexes, mean annual growth between periods s and t is defined as:

$$\left(\frac{TFPCA_t}{TFPCA_s}\right)^{t-s} - 1$$

Appendix B: Estimation results

8 Explanatory variable description

variable	description
$Log_e()$	Natural logarithm
Land	Land quantity index
Labour	Labour quantity index
Capital	Capital quantity index
Mat_Ser	Materials and services quantity index
Time	Time trend (1978 = 1)
Winter_Rain	Total rainfall (mm) April to October
Summer_Rain	Total rainfall (mm) November to December
Winter_Tmax	Average monthly maximum temperature April to October
Winter_Tmin	Average monthly minimum temperature April to October
Summer_Rain_Lag	Total rainfall (mm) November to December of previous financial year

9 Stochastic frontier parameter estimates, southern, western and northern regions (cropping specialists and mixed cropping–livestock farms)

explanatory variable	Southern (model 1)		Western (model 2)		Northern (model 3)	
	estimate	SE	estimate	SE	estimate	SE
Constant	–0.149	(0.145)	–1.301	(1.071)	0.180	(1.225)
Log$_e$(Land)	0.263*	(9.45E-3)	0.355*	(0.021)	0.177*	(0.012)
Log$_e$(Labour)	0.071*	(0.015)	0.087*	(0.024)	0.106*	(0.022)
Log$_e$(Capital)	0.184*	(0.010)	0.185*	(0.016)	0.196*	(0.014)
Log$_e$(Mat_Ser)	0.522*	(0.012)	0.453*	(0.019)	0.543*	(0.016)
Log$_e$(Land)^2	–0.058*	(5.87E-3)	–0.074*	(0.013)	–0.029*	(9.25E-3)
Log$_e$(Labour)^2	5.88E-3	(0.012)	0.037	(0.037)	0.122*	(0.029)
Log$_e$(Capital)^2	0.072*	(8.84E-3)	0.063*	(0.016)	0.128*	(0.013)
Log$_e$(Mat_Ser)^2	0.045*	(0.011)	0.024	(0.019)	0.102*	(0.016)
Log$_e$(Land)×Log$_e$(Labour)	0.055*	(0.017)	0.027	(0.038)	0.018	(0.024)
Log$_e$(Land)×Log$_e$(Capital)	–0.042*	(0.012)	–0.016	(0.027)	–0.027	(0.016)
Log$_e$(Land)×Log$_e$(Mat_Ser)	0.044*	(0.013)	0.092*	(0.028)	–0.013	(0.018)
Log$_e$(Labour)×Log$_e$(Capital)	–0.017	(0.019)	–0.038	(0.036)	–1.86E-3	(0.029)
Log$_e$(Labour)×Log$_e$(Mat_Ser)	–0.025	(0.021)	–0.039	(0.037)	–0.097*	(0.035)
Log$_e$(Capital)×Log$_e$(Mat_Ser)	–0.044*	(0.016)	–0.101*	(0.027)	–0.169*	(0.022)
Time	0.031*	(2.38E-3)	0.037*	(3.09E-3)	0.028*	(3.81E-3)
Time^2	–4.95E-4*	(7.07E-5)	–6.19E-4*	(9.22E-5)	–4.57E-4*	(1.09E-4)
Winter_Rain	3.43E-3*	(6.53E-4)	2.78E-3*	(1.28E-3)	1.85E-3	(1.35E-3)
Winter_Rain^2	–5.87E-6*	(3.41E-7)	–6.96E-6*	(4.91E-7)	–3.11E-6*	(5.33E-7)
Winter_Tmax	–0.126*	(0.020)	–0.022	(0.108)	–0.156	(0.106)
Winter_Tmax^2	5.00E-4	(7.36E-4)	–1.72E-3	(2.45E-3)	9.92E-4	(2.14E-3)
Winter_Tmin	0.130*	(0.032)	0.173*	(0.088)	0.145*	(0.043)
Winter_Tmin^2	–1.50E-3	(2.33E-3)	–7.39E-3	(5.31E-3)	–1.41E-3	(2.30E-3)
Winter_Tmax*Winter_Rain	2.79E-4*	(3.48E-5)	3.74E-4*	(6.86E-5)	2.10E-4*	(6.67E-5)
Winter_Tmin*Winter_Rain	–3.34E-4*	(4.17E-5)	–3.97E-4*	(8.16E-5)	–2.41E-4*	(6.55E-5)
Summer_Rain_Lag	3.17E-3*	(2.20E-4)	2.27E-3*	(4.48E-4)	3.20E-3*	(2.91E-4)
Summer_Rain_Lag^2	–3.40E-6*	(4.95E-7)	–1.41E-6	(1.10E-6)	–1.48E-6*	(3.36E-7)
Winter_Rain*Summer_Rain_Lag	–3.90E-6*	(6.05E-7)	–5.36E-6*	(1.05E-6)	–4.91E-6*	(4.79E-7)
Summer_Rain					1.12E-3*	(2.49E-4)
Summer_Rain^2					–9.09E-7*	(3.14E-7)
Composite error term coefficients						
σ^2	0.921*	(0.066)	0.152*	(0.040)	0.926*	(0.099)
γ	0.904*	(7.71E-3)	0.580*	(0.111)	0.887*	(0.013)
μ	–1.825*	(0.146)	0.110	(0.178)	–1.812*	(0.297)
η	–0.014*	(1.82E-3)	–0.014*	(5.35E-3)	–8.83E-3*	(2.66E-3)
Observations	6 761	2 658	3 153			
Cross-sections	2 080	747	1 064			
Time periods	31	31	31			

* Indicates parameter significant at 5 per cent level. SE is standard error.

10 Stochastic frontier parameter estimates, southern, western and northern regions (cropping specialists only)

explanatory variable	Southern		Western		Northern	
	estimate	SE	estimate	SE	estimate	SE
Constant	–0.322	(0.173)	–1.895	(1.985)	–3.216	(2.135)
Log$_e$(Land)	0.287*	(0.015)	0.340*	(0.039)	0.227*	(0.025)
Log$_e$(Labour)	0.095*	(0.023)	0.087	(0.049)	0.074*	(0.038)
Log$_e$(Capital)	0.160*	(0.016)	0.249*	(0.032)	0.158*	(0.027)
Log$_e$(Mat_Ser)	0.480*	(0.018)	0.411*	(0.034)	0.528*	(0.028)
Log$_e$(Land)^2	–0.091*	(0.011)	–0.053*	(0.025)	–0.036*	(0.017)
Log$_e$(Labour)^2	9.99E-4	(0.016)	0.078	(0.068)	0.103*	(0.041)
Log$_e$(Capital)^2	0.058*	(0.014)	0.060*	(0.029)	0.093*	(0.025)
Log$_e$(Mat_Ser)^2	0.030	(0.018)	0.028	(0.027)	0.072*	(0.024)
Log$_e$(Land)×Log$_e$(Labour)	0.078*	(0.028)	–0.022	(0.064)	–0.039	(0.040)
Log$_e$(Land)×Log$_e$(Capital)	–0.019	(0.020)	–0.016	(0.049)	–0.019	(0.030)
Log$_e$(Land)×Log$_e$(Mat_Ser)	0.040	(0.021)	0.072	(0.042)	1.37E-3	(0.030)
Log$_e$(Labour)×Log$_e$(Capital)	–0.049	(0.029)	–0.061	(0.067)	6.61E-3	(0.049)
Log$_e$(Labour)×Log$_e$(Mat_Ser)	7.29E-3	(0.033)	0.046	(0.061)	–0.063	(0.055)
Log$_e$(Capital)×Log$_e$(Mat_Ser)	–0.024	(0.026)	–0.162*	(0.046)	–0.122*	(0.037)
Time	0.032*	(3.75E-3)	0.053*	(5.95E-3)	0.034*	6.14E-3
Time^2	–4.15E-4*	(1.12E-4)	–1.06E-3*	(1.59E-4)	–6.02E-4*	1.74E-4
Winter_Rain	8.19E-3*	(1.30E-3)	7.09E-3*	(2.76E-3)	2.83E-3	2.24E-3
Winter_Rain^2	–8.06E-6*	(6.47E-7)	–1.85E-5*	(1.73E-6)	–3.64E-6*	9.01E-7
Winter_Tmax	–0.190*	(0.029)	–0.076	(0.196)	0.160	(0.185)
Winter_Tmax^2	2.60E-3*	(1.15E-3)	6.56E-4	(4.43E-3)	–5.46E-3	3.70E-3
Winter_Tmin	0.172*	(0.057)	0.189	(0.157)	0.048	(0.077)
Winter_Tmin^2	–1.88E-3	(4.09E-3)	–0.016	(0.010)	3.01E-3	4.15E-3
Winter_Tmax*Winter_Rain	1.64E-4*	(6.94E-5)	3.10E-4	(1.58E-4)	1.64E-4	1.09E-4
Winter_Tmin*Winter_Rain	–4.57E-4*	(7.30E-5)	6.81E-5	(2.32E-4)	–2.05E-4	1.09E-4
Summer_Rain_Lag	4.02E-3*	(4.05E-4)	4.43E-3*	(8.91E-4)	2.86E-3*	5.07E-4
Summer_Rain_Lag^2	–5.00E-6*	(9.31E-7)	–3.84E-6	(1.97E-6)	–1.10E-6	6.23E-7
Winter_Rain*Summer_Rain_Lag	–4.55E-6*	(1.18E-6)	–1.01E-5*	(2.25E-6)	–4.61E-6*	8.31E-7
Summer_Rain					1.66E-3*	4.41E-4
Summer_Rain^2					–1.30E-6*	5.45E-7
Composite error term coefficients						
σ^2	0.854*	(0.058)	0.192	(0.166)	0.984*	(0.159)
γ	0.877*	(0.011)	0.612	(0.334)	0.882*	(0.019)
μ	–1.731*	(0.130)	–0.408	(1.075)	–1.862*	(0.400)
η	–0.015*	(3.45E-3)	–5.48E-3	(0.011)	–0.011*	(4.19E-3)
Observations	3 137	1 134	1 410			
Cross-sections	1 111	380	559			
Time periods	31	31	31			

* Indicates parameter significant at 5 per cent level. SE is standard error.

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