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

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This report draws heavily on data collected in 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.

Foreword

Achieving gains in productivity is fundamental to the long-term success of Australia's agricultural industries and in particular, the grains industry.

ABARES has an extended tradition of estimating productivity growth for Australian broadacre agricultural industries. These estimates are of value to industry and government agencies concerned with achieving agricultural productivity growth including research and development organisations such as the Grains Research and Development Corporation (GRDC).

This study, funded by the GRDC, introduces two advances to ABARES traditional productivity estimation methods. First, it takes into account the effect of climate variability, which has long been observed to significantly influence traditional productivity measurements. Second, the study decomposes productivity growth into various 'pathways', allowing organisations, such as the GRDC, to separately consider the main sources of productivity growth.

Both advancements contribute to an improved understanding of trends in Australian broadacre agricultural productivity.



Phillip Glyde
Executive Director
May 2011

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Summary

ABARES produces time series total factor productivity (TFP) indexes for Australian broadacre agriculture based on farm survey data. TFP growth has historically been strong in the broadacre cropping sector—around 5 per cent a year between 1979–80 and 1997–98 (Nossal et al. 2009). However, TFP growth among cropping specialists has slowed considerably over the last decade to around –2 per cent a year between 1997–98 and 2006–07 (Nossal et al. 2009).

Interpreting these productivity trends and identifying potential policy responses has proved difficult due to two key measurement issues. First, agricultural productivity indexes are highly sensitive to climate variability. This is of particular concern given the well documented decline in average rainfall observed in much of Australia’s key agricultural areas over the past decade. Second, the policy implications of observed productivity trends can be difficult to identify. This is because there exist a range of mechanisms or pathways through which productivity changes may occur and not all are within reach of government policy.

This study introduces two advances to ABARES’ standard TFP index methodology for measuring productivity change, namely:

- climate data were matched to farm production data to produce climate-adjusted productivity
- a production frontier estimation technique was employed to facilitate decomposition of aggregate productivity change into key components, or productivity pathways.

Climate adjusted productivity

A climate-adjusted total factor productivity index was generated by mapping spatial climate data to individual farms in the ABARES farm surveys database using geographic information system techniques. Farm output responses to specific climate variables were estimated econometrically, leading to a climate effects index, demonstrating the total effect of climate variability on farm output and productivity.

Data on farm outputs and inputs were obtained from the ABARES farm survey database for broadacre cropping and mixed cropping–livestock farms over the period 1977–78 to 2007–08. Data on seasonal rainfall (winter season, summer season) and average minimum and maximum temperatures were obtained from the Australian Water Availability Project.

The climate effects index captured much of the annual variability in total factor productivity, particularly the effect of drought years. The climate variables demonstrated expected relationships: a strong positive relationship between rainfall and output and negative relationships between temperature extremes and output. In addition, climate sensitivity varied across regions and farm types, with the southern region demonstrating greater climate sensitivity relative to the northern and western regions and, cropping specialist farms showing more sensitivity relative to mixed farms.

A significant slowdown in productivity growth was observed over the past decade, even after controlling for deteriorating climate conditions. Climate adjusted productivity growth (among cropping specialists) averaged 1.06 per cent a year post 2000, in comparison to 2.15 per cent pre 2000. Average climate conditions (particularly in the form of rainfall) post 2000 were significantly below those observed pre 2000. Across all farms and regions, output was 11 per cent lower post 1999–2000 due to poorer climate conditions.

Productivity pathways

An econometric technique called stochastic frontier analysis was employed to estimate six production frontiers: for each of three GRDC regions (southern, western and northern) and for each of two farm types (all cropping farms, including mixed crop–livestock farms, and for specialist cropping farms only). A production frontier represents the maximum output that can be produced from a given level of inputs. In practice, the ‘best’ farms define the frontier and are described as technically efficient.

Estimating production frontiers over time allows (climate adjusted) productivity change to be decomposed into three main components:

- **Technical change (TC)** is the availability of new technologies and knowledge. It is represented by expansion of the production frontier—that is, the best farms getting better.
- **Technical efficiency change (TEC)** is an improvement in productivity through further adoption of existing technologies. Technical efficiency change is represented by farms moving closer to (or further from) the frontier.
- **Scale and mix efficiency changes (SME)** are changes in farm scale and input mix that influence productivity, typically in response to prevailing input and output prices.

An additional pathway to productivity identified in the report is the exit of poorly performing farms. Their exit can contribute to industry productivity growth by raising industry average productivity and freeing-up resources for use by other farms.

Results

Although the productivity decomposition varied across GRDC regions and farm types, several broad results were observed after controlling for the effects of climate.

- Technical change has been the primary driver of long-run productivity growth over the past three decades. Australia-wide, technical change increased, on average, by 1.5 per cent annually over the period 1977–78 to 2007–08 through development and adoption of new technology and management practices.
- However, the rate of technical change has slowed. For example, Australia-wide, technical change grew 1.95 per cent annually over the period 1977–78 to 1999–2000, but averaged only 0.4 per cent a year between 1999–2000 and 2007–08. The decline was most pronounced in the western and northern regions, but less severe in the southern region, especially among specialist cropping farms.

- Technical efficiency declined by around 0.3 per cent annually over the survey period. This implied that, Australia-wide, the gap between the best (most efficient) farms that define the frontier and the average farms (those with lower technical efficiency) has widened.
- Scale and mix efficiency initially declined, then increased, contrary to movements in the terms of trade (ratio of output to input prices). Australia-wide, scale and mix efficiency increased, on average, by 0.3 per cent a year between 1977–78 and 2007–08.
- In general, areas of poor technical efficiency were predominately located in marginal cropping areas. These areas are characterised by relatively low concentrations of specialist cropping farms, typically near the boundaries of GRDC regions. Such patterns could reflect, among other things, differences in land quality not accounted for in this study.

Conclusions

This study has demonstrated the importance of controlling for climate variability when estimating productivity. In this regard, the results were consistent with Sheng et al. (2010) in that even after controlling for climate conditions, productivity in the grains industry has slowed in recent years. Further, the method developed in this study for controlling climate variability has advantages over alternative approaches. In particular, it is sufficiently flexible to be calibrated to a wide range of farming areas, farm types and time periods.

Technical change was observed to be the key contributor to long-run productivity growth in the industry. However, across all regions, a gradual decline in the rate of technical change was observed over the sample period (1977–78 to 2007–08). Growth in technical change was offset by a small decline in technical efficiency over the period. Declining technical efficiency implies that the gap between the most efficient farms and the less efficient farms widened over the period.

A number of avenues for future research remain, including refining the climate variables and, in turn, generating an ongoing climate-adjusted TFP series. In addition, further consideration should be given to the determinants of technical efficiency, including human capital characteristics, land quality, and the role of risk and uncertainty.

The results from this study have direct implications for the size and mix of funding directed toward research and development, extension and climate adaptation activities across GRDC regions.

In particular the results suggest that technical change, the component of TFP expected to be directly affected by the size and composition of research and development investment is the key driver of productivity growth in the grains industry over the long run. Although TFP growth is also influenced by scale, mix and technical efficiencies, these effects have historically been of secondary importance.

1 Introduction

This project is one of a series forming the Harvesting Productivity initiative ABARES is undertaking for the Grains Research and Development Corporation (GRDC). The objectives of the initiative are to investigate trends in productivity growth in the Australian grains industry, and to consider how government policies, including research and development programs, may help maximise future productivity gains in the industry.

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 last decade. Among cropping specialists, productivity averaged around –2 per cent a year over the period 1997–98 to 2006–07 (Nossal et al. 2009). The slowdown has attracted substantial research attention in recent times. This has included measuring the extent of the slowdown, identifying potential contributing factors and investigating possible remedial measures (see for example Sheng et al. 2010).

This study introduces two advances to the aggregate productivity index methodology ABARES typically uses.

First, it accounts for the effects of climate variability on measured productivity by matching Bureau of Meteorology (BoM) 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 last decade. It is necessary to control for these changes in climate conditions to fully evaluate the extent of the productivity slowdown.

Second, it 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 changes into several key components or productivity pathways.

The two key productivity pathways considered in this study are:

- **technical change** (TC), representing development of new technologies or ‘the best farms getting better’
- **technical efficiency change** (TEC), 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 because different pathways can have unique sets of drivers and potential policy responses.

The report is structured as follows. Chapter 2 provides background information on productivity, production frontier theory, measurement issues, the various productivity pathways and their associated policy implications. Chapter 3 reviews previous research. Chapter 4 summarises the methodology and data sources used in this study. Chapter 5 presents the results of the study in detail. The final chapter discusses some of the policy implications and potential directions for future research.

2 Background

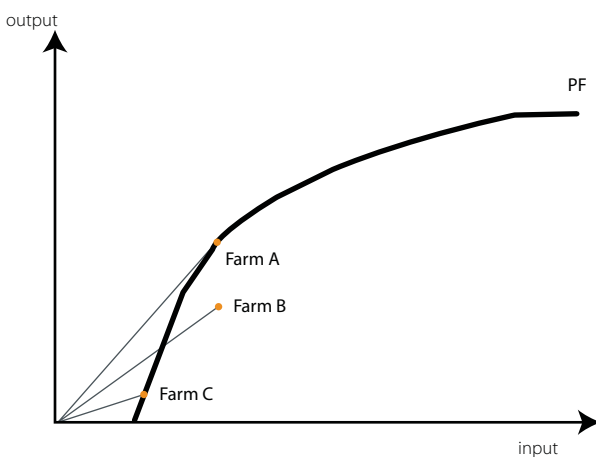
This chapter provides a formal outline of the various productivity pathways, including a summary of the underlying theoretical framework and a discussion of several practical issues relating to measurement and interpretation. Finally, some of the policy implications arising from the different aspects of productivity change are briefly considered.

Productivity

Productivity refers to measures of the relative ability of farms to convert inputs into outputs. A standard measure of productivity is total factor productivity (TFP), which is simply the ratio of total or aggregate output to total or aggregate input. In the case of agriculture, farms combine various inputs (namely land, labour, capital, materials and services and other natural resources) to produce various outputs such as crop and livestock products.

Productivity measurement is intended to monitor physical performance. It is primarily concerned with the quantities of outputs and inputs, independent of their prices, in contrast to profitability, which is a measure of financial performance, dependent on both quantities and prices. Productivity measures the relative physical performance of different farms and their relative change in performance over time.

1 Productivity and the production frontier



frontier represents the best available production technology for a particular industry at a particular point in time. Productivity (ratio of output to input) can be represented by the slopes of the lines connecting individual farms with the origin (figure 1).

Production theory

A more detailed analysis of productivity draws on the basic economic theory of production, including the concept of the production frontier and the various forms of efficiency. This section provides a brief overview of these concepts (see also Coelli et al. 2005.)

The production frontier

A production frontier (PF in figure 1) represents the maximum possible output that can be produced with a given level of inputs. For simplicity, the discussion is limited to a single-output single-input case. The production

Technical efficiency

Individual farms that lie on the production frontier are classified as technically efficient. For example, farms A and C are deemed to be technically efficient because they produce the maximum possible output given their input level. Farm B is technically inefficient because it lies below the frontier, and therefore produces less than the maximum possible output given its input level.

Scale efficiency

Scale efficiency relates to the effect of changes in farm size on productivity (the effect of returns to scale). Returns to scale refers to the relative increase in output achieved by a given proportional increase in all inputs. For example farm C is classified as scale inefficient and subject to increasing returns to scale, because increasing scale (while maintaining technical efficiency) would increase productivity. Conversely farms operating on the production frontier beyond farm A, exhibit decreasing returns to scale because further increases in scale decrease productivity.

Mix efficiency

In practice, farms combine inputs such as land, labour, capital, materials and services and other natural resources to produce multiple outputs (such as different crop and livestock products). The multiple input–output case introduces a third type of efficiency: mix efficiency. Mix efficiency refers to the effect of changes in the mix of either inputs or outputs on productivity (the effect of economies of scope).

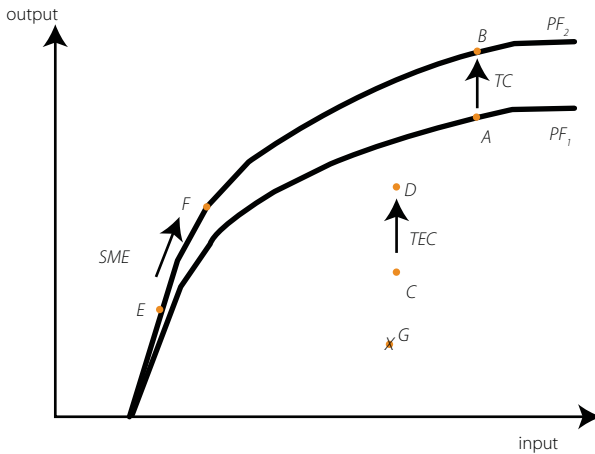
Allocative efficiency

Allocative efficiency refers to changes in the mix of inputs or outputs that improve profitability, for a given level of productivity. In production theory, a standard assumption is that given the technological constraints and prevailing input and output prices, farms choose input and output levels to maximise profits. For example, a farm that is both technically efficient and mix efficient may further increase profitability by altering the mix of outputs to reflect prevailing output prices.

Productivity pathways

Under the production frontier framework, growth in industry productivity may occur through a range of alternative mechanisms or pathways.

2 The production frontier and various productivity pathways



Note: TC = Technical change; TEC = Technical efficiency change; SME = Scale and Mix efficiency change; X = industry exit

Technical change

A key pathway to productivity in the long run is 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 2). 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; for example, farm movement from point A to point B in figure 1. In essence, technical change reflects technological progress: the availability of new technologies and management practices. In agriculture, formal agricultural research and

development (R&D) activities are expected to play an important role in developing new technologies and practices.

Technical efficiency change

A second pathway to productivity occurs through technical efficiency change. This is where farms improve productivity by adopting currently available technologies and thus move closer to the production frontier. For example, a farm's movement from point C to point D in figure 2. Improvements in industry productivity due to technical efficiency change can be described as the average farms catching up to the best farms. The rate of adoption of existing technologies is often considered to be influenced by farmers' human capital characteristics such as age, education, social networks and the nature of extension services that bring new knowledge to farmers' attention.

Exit of less efficient farms

A third pathway toward improvement in industry productivity is the exit of poorly performing farms, such as farm G (figure 2). Farms of relatively low productivity (technically inefficient) that leave the industry will raise the average productivity of the industry.

It is important to elaborate on the meaning of industry exit. In particular to draw a distinction between the exit of farms from a managerial perspective (the exit of legal entities or farm owners) and from a physical perspective (where inputs released are diverted to alternative uses).

Where farm owners/operators leave the industry and sell farms (and associated inputs such as land and capital) to a new operator, this should not necessarily be viewed as a pure industry exit. In particular, where a new operator improves farm productivity, such an event might

be viewed more as an improvement in technical efficiency. In contrast a pure exit from the industry would be where most farm inputs are diverted to an alternative use or industry. In the case of agriculture, a pure industry exit might involve a significant change in land use, for example, to industrial, residential or environmental use (including national parks).

Farm operator exits often occur through farm rationalisation, where farms are merged. Over time, this process leads to a reduced number of farms and a larger average farm size. This process of rationalisation may improve either industry technical efficiency (through the exit of technically inefficient operators) or industry scale efficiency. As such, isolating the effect of farm and/or farm operator exit from other factors influencing industry technical and scale efficiency remains difficult in practice.

Other pathways to productivity

Additional pathways to productivity growth may include changes in scale efficiency and mix efficiency. Scale efficiency change will occur wherever farms change scale while operating under either increasing or decreasing returns to scale. For example, farms may increase in scale over time to exploit economies of scale. Mix efficiency change refers to changes in productivity due solely to changes in input or output mix. An example of scale efficiency change is illustrated in figure 2 as movement along the production frontier, from point E to point F.

Some commonly noted historical trends in scale and input mix in Australian agriculture include:

- Australian farm sizes have tended to increase over time. The Productivity Commission (2005) noted a substantial decline in the total number of farms and an increase (approximately 23 per cent) in average farm size over the 20 years to 2002–03.
- The farm input mix has tended to increase in capital intensity relative to labour intensity, at least until the 1990s (Nossal et al. 2009).
- A recent trend toward increased use of materials and services inputs relative to land, labour and capital (Nossal et al. 2009).

Given the possibility of non-neutral technical change, large changes in scale and/or mix may not necessarily be associated with large changes in scale and mix efficiency. Non-neutral technical change refers to development of new technologies that over time alter the point of optimal scale or the optimal input or output mix. See O'Donnell (2009 and 2010) for detailed discussion of decomposition of these forms of efficiency.

Pathways to profitability

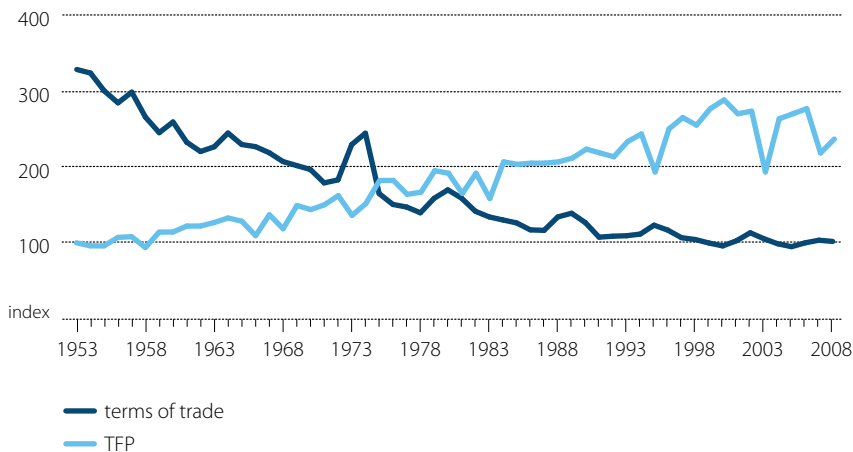
Although the focus has been on productivity, the primary objective of farms is, in theory, to maximise profit. Changes in productivity and farmers' terms of trade jointly determine profitability, where the farmers' terms of trade are defined as the ratio of output to input prices.

For most commodities Australian primary producers are generally price-takers in domestic and international markets: that is, the actions of an individual farmer cannot influence prices. Given that terms of trade are largely beyond farmers’ control, the main driver of long-term profitability growth is productivity growth. Although this trend has reversed somewhat in recent years, long-term productivity improvements have enabled Australian farmers to offset the effect on farm profitability of a persistent decline in terms of trade (figure 3).

In general, improvements in productivity will lead to improvements in profitability (under constant prices). Both technical change and technical efficiency improvements are unambiguously good for both productivity and profitability. However, for scale and mix efficiency, the relationship between productivity and profitability is more complex.

Mix and scale efficiency movements can potentially cause productivity and profitability to move in opposite directions. Price movements may induce producers to change their input/output mix or scale of operation to maximise profits. These production decisions may or may not increase productivity. For these reasons, not all observed falls in productivity should necessarily be viewed negatively.

3 Broadacre total factor productivity and terms of trade in Australia, 1953–2007



Note: 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
 Source: Nossal and Sheng 2010

For example, O’Donnell (2010) notes that improvements in the terms of trade may encourage farms to expand to the point where they incur decreasing returns to scale in which case increasing profitability is associated with decreasing productivity. O’Donnell (2010) undertook an empirical assessment providing supporting evidence for such an effect in Australian agriculture. In practice, however, these effects are likely to be of a short-run nature and in the long run the primary driver of profitability growth remains productivity growth achieved through technical progress and improvements in technical efficiency.

Policy implications

A primary motivation for decomposing productivity change is that each pathway may have a unique set of drivers and policy implications. In particular, policy initiatives intended to encourage technical change are expected to differ significantly from those directed at improving technical efficiency change.

Technical change

Technical change represents development or acquisition of new knowledge. A key source of new knowledge on agricultural production is formal R&D activities. This includes knowledge generated through domestic public R&D (such as that funded by rural research and development corporations and companies) as well as 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'.

New knowledge and technologies may generate increased productivity either through more efficient use of existing inputs (disembodied technological change), or through development of better quality inputs (embodied technological change). Disembodied technological change reflects changes in farm crop and livestock management practices arising from farmer experimentation or the findings of scientific research. Some examples of embodied technology include more advanced farm equipment (such as optical weed recognition), improved farm chemicals (such as selective herbicides), improved plant and animal genetics (such as drought tolerant crops) and new information technologies (such as the internet and global positioning system guidance).

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

Significant research effort has been committed to estimating the social returns to agricultural research (both in Australia and internationally) by establishing a statistical link between research effort and agricultural productivity (see, for example, Alston et al. 2000). Studies often rely on aggregate TFP estimates as their sole measure of productivity change. However, estimates of technical change should provide a more accurate indication of the extent to which changes in productivity have been due to changes in new knowledge and potentially, therefore, R&D investment. Other components of TFP (such as technical efficiency change and scale efficiency change) are expected to be relatively independent of R&D investment trends.

Technical efficiency change

Technical efficiency improvements reflect farmers making better use of currently available knowledge and technology. Technical efficiency change is driven by a process of diffusion of knowledge where, following development of new technology, there is gradual information

transmission and eventual adoption by farms. Some farms may adopt new technologies quickly (those located close to the frontier) while others may be slower to adopt (those located further from the frontier).

Human capital factors, such as age, education level, experience and access to social networks, are thought to heavily influence the rate of adoption of technology. Another key determinant is the availability of information on new technologies. This may be influenced by information technology and, in the case of agriculture, through public and/or private extension services.

Extension services can include components with both public and private-good characteristics: general collection and dissemination of information through broad mediums as well as those with a more narrow (private) focus, such as provision of information and advice tailored to specific farms. Traditionally, government extension services have played a key role in gathering, interpreting and communicating information on the latest technologies; recently the private sector has increasingly supplied extension services, especially farm-specific services.

In addition to providing extension services, governments may influence the rate of technology adoption by investing in information infrastructure, such as telecommunications, or by influencing farm operators' human capital characteristics by, for example, providing relevant education and training programs.

Exit of less efficient farms

Exit of less efficient farms contributes to industry productivity growth by freeing-up inputs for use by more efficient operators. This adjustment is largely driven by market forces which act to reallocate resources to their highest value use. An important policy implication is the need to minimise any artificial constraints that limit the market's ability to perform this allocative role. An example in the farm context is exceptional circumstances (drought support) programs. Persistent financial support to poorly performing farms may have a tendency to slow market driven adjustment to these farms (Elliston and Glyde 2008).

Measurement and interpretation

Decomposition of productivity change into the various pathways requires empirical estimation of production frontiers. Estimation of production frontiers is subject to a number of significant practical challenges that have important implications for interpreting associated productivity estimates.

Quality differences in inputs and outputs

Failure to account for quality differences in inputs and outputs can result in biased estimates of productivity. In agriculture, variation in land quality is of particular significance. While land inputs are generally measured in quantity terms, important quality aspects, such as soil quality, also need to be considered. In a production frontier framework, farms with poor land quality may be incorrectly classified as being technically inefficient because they may produce less output relative to farms with similar input (land) usage.

A common approach to estimating production frontiers is to aggregate all outputs into a single aggregate output and to aggregate inputs into a small number of categories, such as labour, capital, land, materials and services. Aggregation usually involves use of index number methods where prices are used as weights (for more detail on these methods see Zhao et al. 2010).

One approach to accounting for quality differences is to disaggregate output and input measures; for example, disaggregating an input into high and low quality classes and obtaining data on the usage of each. However, there are practical limits on the level of disaggregation, including the limited availability of data. In practice, some aggregation of outputs and/or inputs will be needed when estimating production frontiers. Researchers are required to make pragmatic decisions trading-off the practical advantages of aggregation against the potential loss of detail involved.

Natural resources and environmental conditions

Agricultural productivity is heavily influenced by the availability of key non-market natural resource inputs and prevailing environmental conditions. The availability of moisture is of foremost significance, particularly for dryland, broadacre farms, which are dependent on rainfall for crop and pasture production.

Failure to include moisture availability is likely to result in biased estimates of production frontiers and technical efficiency levels. For example, farms that have experienced relatively low moisture availability will be treated as being relatively technically inefficient. Further, in drought years, where climate conditions are poor across many farms, technical progress might be (incorrectly) estimated to decline.

One way to account for variation in natural resources and environmental conditions is to include climate variables, such as seasonal rainfall, as inputs to production alongside traditional market inputs, such as labour, land and capital. Other natural resource or environmental variables relevant to agricultural productivity can include land quality, temperature, wind conditions and frequency of extreme weather events (such as frosts and storms).

Another way to account for environmental characteristics is to estimate production frontiers separately for different regions. This approach effectively accounts for spatial differences in natural environmental conditions (such as soil quality) or any differences in regulatory and social environments. For example, there are significant differences between the agricultural environments of Western Australia and South Eastern Australia. In practice, data availability will constrain the amount of regional disaggregation that is possible.

Risk and uncertainty

Agricultural production decisions are made subject to significant risk and uncertainty, particularly in Australia where farms face extreme uncertainty over future climate conditions. However, standard productivity estimation techniques do not account for the effects of risk and uncertainty. Failure to account for risk and uncertainty has the potential to result in biased estimates of production frontiers and technical efficiency (O'Donnell et al. 2010).

To illustrate this, consider a farm that invests in some form of 'adaptive capacity', where farm inputs are committed toward protecting the farm against adverse future conditions. An example might be a farm that invests in drought tolerant crops, or some alternative water sources. In a wet year this farm may be observed to be technically inefficient, because it has invested in inputs that are used only in dry years, when such a farm may actually be technically efficient in expected (long-run average) terms.

Although issues of risk and uncertainty have significant implications for measuring productivity, they are not investigated in this report. The theoretical and practical tools with which to effectively account for risk in production environments are still in their infancy (for more detail on these approaches see O'Donnell et al. 2010).

Measurement error and other statistical noise

Statistical noise is unexplainable (random) variation in statistical variables. In statistical models, 'statistical noise' can arise from data measurement errors or through omitted explanatory variables.

All real world datasets are subject to some degree of measurement error. In the case of agricultural industries, data on farm inputs and outputs are mostly sourced from surveys of individual farmers. In practice, the data collection and collation are unlikely to be free from error. While including additional explanatory variables (for example rainfall or temperature) can reduce statistical noise, in practice, some will persist due to measurement error and the effects of random factors that are not possible to control.

The presence of statistical noise in data has two important implications for measuring productivity. First, defining a production frontier by the best performing farms in a sample may be problematic, especially if there are outlying observations. Second, comparing individual farm productivity levels may be problematic relative to aggregate productivity comparisons at an industry or region level which are likely to be more reliable in the presence of statistical noise.

This study employs stochastic frontier analysis to account for statistical noise in survey data in a systematic way; see 'Previous research' for more details on stochastic frontier analysis.

Interpreting technical inefficiency

A common feature among all measurement issues is a potential to contribute to spurious technical inefficiency; farm technical inefficiency that is actually the result of data measurement error, omitted input or output variables, inadequate accounting for quality differences, inadequate accounting of environmental characteristics or the effects of risk and uncertainty.

In practice, farm technical inefficiency might be interpreted as being a combination of spurious inefficiency (inefficiency owing to measurement issues) and genuine inefficiency (inefficiency resulting from 'managerial ability' or the human capital of farm managers). Although measurement error has a tendency to result in the overestimation of inefficiency, it can also operate in the opposite direction.

Ideally, estimation techniques should be selected to adequately account for these measurement issues. In this study, several steps were taken to ensure the reliability of estimates, including the use of econometric techniques to deal with noise (stochastic frontier analysis) and the incorporation of natural resources and environmental inputs such as rainfall and temperature. These steps are outlined in the following chapter.

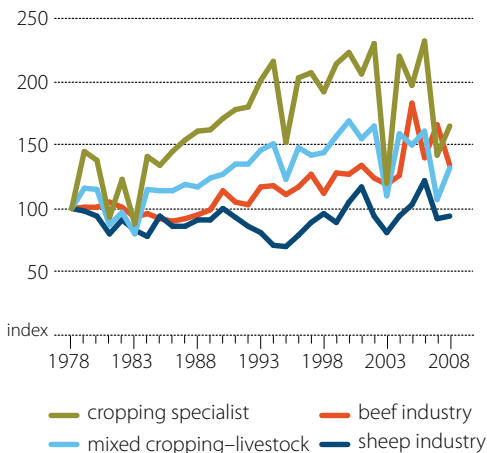
3 Previous research

Australian agricultural productivity trends

ABARES estimates time series TFP indexes for Australian broadacre agriculture industries using data from annual farm surveys. A summary of these indexes is contained in Nossal et al. (2009) and a description of the underlying concepts, data and methods used is in Zhao et al. (2010).

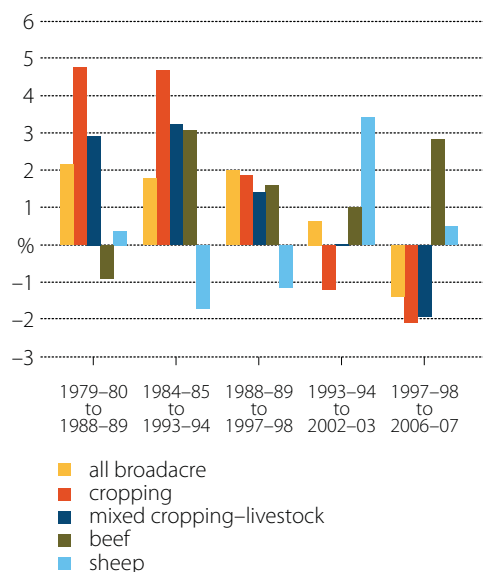
Average productivity growth of 1.5 per cent a year has been estimated for the broadacre agriculture sector over the period 1977–78 to 2006–07 (Nossal et al. 2009). However, the data show significant volatility in productivity growth from year to year, with much of this due to the effects of climate variability. In general, cropping specialists have outperformed livestock industries over the period. However, there appears to have been a slowdown in productivity growth in the cropping sector particularly from 2000 onwards (figures 4 and 5).

4 Broadacre total factor productivity indexes, 1977–78 to 2007–08



Source: Nossal and Sheng 2010

5 Broadacre total factor productivity growth short-term trends



Source: Nossal et al. 2010

The observed slowdown raises a number of important questions, namely:

- Is the slowdown statistically significant or is it the result of statistical noise and/or measurement issues?
- What are the potential causes of this slowdown?
- What are the policy implications of the slowdown and its associated causes?

A number of potential causes for the slowdown have been identified, including the decline in climate conditions and reductions in rural 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). Both moisture availability and R&D investment have been shown to be correlated with the observed decline in productivity (Sheng et al. 2010).

Determinants of agricultural productivity

ABARES has completed a number of studies investigating the determinants of broadacre agriculture productivity growth. These studies have 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).

Typical explanatory variables have included human capital characteristics (such as age and education), 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 and farm TFP indexes, such as a positive relationship between education and TFP (Zhao et al. 2009). Appendix A provides a more detailed review of these studies.

Previous studies have made use of a moisture availability/water stress index developed by the Agricultural Production Systems Research Unit (APSRU). All of these studies observed a significant positive correlation between this moisture availability index and productivity. Appendix D provides a comparison between the APSRU index with the alternative methodology developed in this report.

Estimation of production frontiers for agriculture

To date, application of farm-level production frontier estimation techniques to Australian agriculture has been limited. Appendix A contains a review of the limited number of previous studies which have estimated farm production frontiers including Battese and Corra 1977; Battese and Coelli 1988; Fraser and Hone 2001; Kompas and Che 2006.

4 Methodology

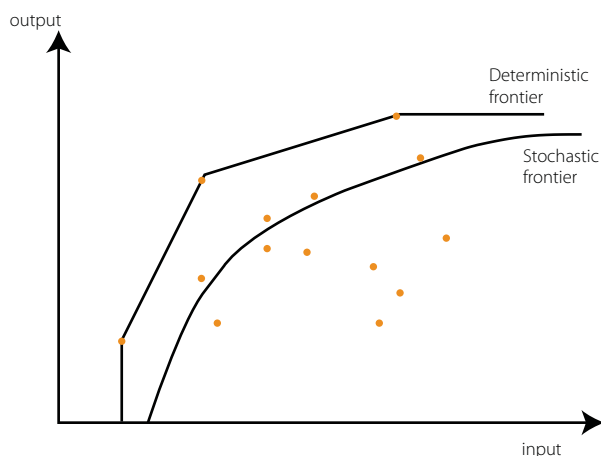
In this study, production frontiers for Australian broadacre agriculture were estimated using ABARES farm survey data. Estimation of farm production frontiers requires accurate data on farm outputs and inputs. In this study two classes of inputs are considered; 'market' inputs, such as land, labour, capital and materials and services and 'non-market' or climate-related inputs, such as rainfall and temperature.

This chapter provides a summary of the data sources used, including ABARES farm survey data and climate data. It also outlines the approach used to estimate production frontiers, known as stochastic frontier analysis.

Stochastic frontier analysis

Stochastic frontier analysis is an econometric method of estimating production frontiers which takes into account the presence of measurement error and other sources of statistical noise. As such, stochastic frontier analysis is suitable for estimating production frontiers with large, unit level datasets such as ABARES' farm survey dataset.

6 Stylised comparison of stochastic versus deterministic frontier estimation



Traditional deterministic approaches (data envelopment analysis), do not account for noise, potentially resulting in overestimation of technical inefficiency levels. Figure 6 represents a stylised comparison of the deterministic versus stochastic estimation of production frontiers. See Coelli et al. 2005 for more detail on stochastic frontier analysis techniques.

The key to the stochastic frontier analysis approach is specification of a 'composite error term' that explains farm deviations from the production frontier as a combination of technical inefficiency ' u ' and statistical noise

' v '. In the context of this study, stochastic frontier analysis involves estimation of an equation of the form:

$$(1) \quad Y_{i,t} = f(X_{i,t}^M, X_{i,t}^{NM}, t) + v_{i,t} - u_{i,t}$$

where:

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

f = production frontier function

X^M = 'market' inputs (land, labour, capital etc)

X^{NM} = 'non-market' inputs (rainfall, temperature, etc)

t = time (included to measure technical change)

$v_{i,t}$ = symmetrical random variable (noise)

$u_{i,t}$ = non-negative random variable (technical inefficiency)

The model specification used in this study follows that of Battese and Coelli (1992), which provides for time-varying technical inefficiency and assumes firm inefficiency effects are drawn from a truncated normal distribution. A 'Translog' functional form was chosen with separate quadratic time trend and climate responses. For more detail on the model specification, see appendix B.

Equation (1) was estimated using the FRONTIER software package produced by the Centre for Productivity Analysis (CEPA) at the University of Queensland (CEPA 2010). This software employs maximum likelihood estimation techniques to estimate production frontiers given output and input data.

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, 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, while the technical efficiency change component can be derived from the estimated technical efficiency parameters. Given estimates of technical change and technical efficiency change, scale and mix efficiency change can be derived as a residual. The methodology underlying this decomposition is outlined in detail in appendix B.

Stochastic frontier studies often estimate a technical efficiency model simultaneously with a production frontier model. Such an approach involves introducing a second equation to the model with additional variables to help explain firm technical inefficiency (u_i) levels. Suitable variables could, for example, include human capital characteristics such as age and education of farm operators. This approach has not been attempted in this study, but remains a potential subject of future research.

ABARES farm survey data

Farm-level data on output and market input use over the period 1977–78 to 2007–08 was drawn from the ABARES farm survey database. ABARES collects these data through the Australian Agricultural and Grazing Industries Survey, which samples around 1500 to 1600 broadacre farms each year.

The Australian Agricultural and Grazing Industries Survey data provide a representative sample of Australian broadacre agriculture, across five key agricultural industries, as defined by the Australian New Zealand Standard Industrial Classification, namely:

- **Cropping specialists:** farms engaged mainly in growing cereal grains, coarse grains, oilseeds, rice and/or pulses.
- **Mixed cropping–livestock:** farms engaged mainly in running sheep or beef cattle, or both, and growing cereal grains, coarse grains, oilseeds and/or pulses.
- **Beef:** farms engaged mainly in running beef cattle.
- **Sheep:** farms engaged mainly in running sheep.
- **Sheep–beef:** farms engaged mainly in running both sheep and beef cattle.

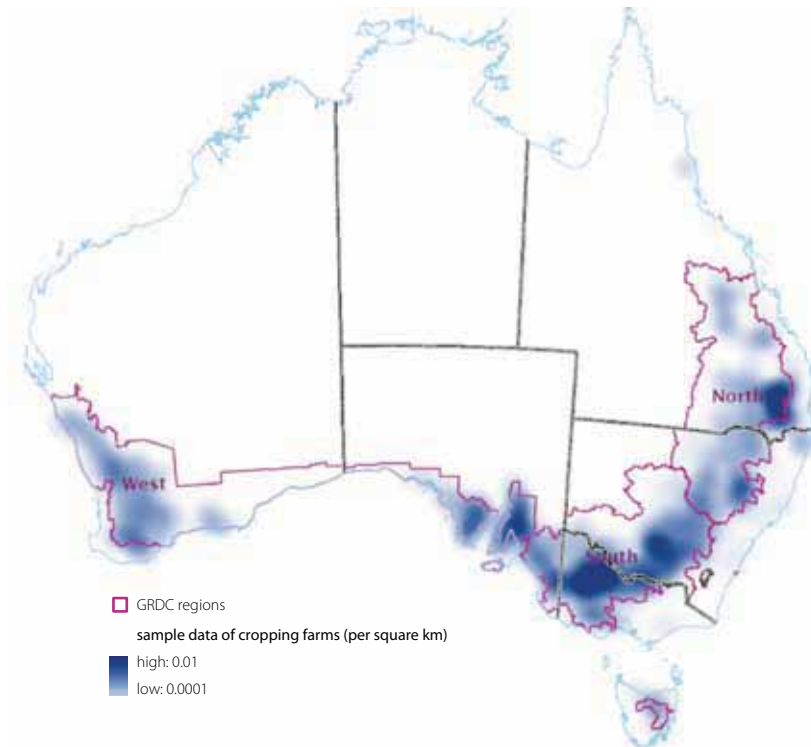
Although farms are classified into industries according to their degree of specialisation, most farms still undertake a range of activities in any given year. For example, farms classified as crop specialists may also undertake some livestock activities. Productivity analysis is limited to the farm-level, rather than the activity level, since input data are only available for the farm as a whole.

The survey has extensive regional coverage across Australia, including throughout each of the three major GRDC regions (southern, northern and western; see map 1). For the purposes of this study, the sample was limited to farms classified as either crop specialists or mixed cropping–livestock farms. Farms undertaking any irrigation were also excluded from the sample. The sample was further reduced by excluding farms with some extreme outliers (in the land and materials and services indexes) and those with inadequate location data (necessary for matching of climate variables). See table 1 for a breakdown of the final sample sizes, by industry class and GRDC region.

The Australian Agricultural and Grazing Industries Survey approach maintains a process of sample rotation, where a proportion of farms are dropped from the sample and replaced with new farms each year, resulting in an unbalanced panel dataset. The number of years that farms remain in the final sample varies significantly, with an average duration of 3.2 years.

This study makes use of farm-level output and input quantity indexes derived as part of ABARES regular 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; output and input index summary data are provided in appendix B. A more detailed discussion of ABARES indexing procedures is presented in Zhao et al. (2010).

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



1 ABARES farm data sample size, by industry class and GRDC 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.

Output index

Where broadacre farms produce multiple outputs, indexing techniques are used to aggregate individual outputs into a single output index for each farm (specifically a Fisher quantity index) using prices as weights. This involves a nested indexing procedure across the major categories of crops, livestock, wool and other farm income. For example, the crops category includes a variety of different crops (such as wheat, barley and oats) which are aggregated into a single crop output index. Similarly, the livestock category includes beef, sheep, lambs and other livestock. 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, namely:

- **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 data on the market value of various capital components, such as buildings, plant and machinery, livestock capital.
- **Materials and services quantity index:** covering a large range of inputs including materials, such as fertiliser, fuel, crop chemicals; and services, such as contract services, rates and taxes and administrative services.

Climate data

A well established limitation of existing measures of Australian agricultural productivity growth is a failure to account for the effects of climate variation, across time and across farms and regions. For this project, ABARES completed a brief review of the relationship between agricultural output and climate variability as well as the availability of data for key climate variables. This information was used to identify climate variables suitable to include as explanatory variables in the stochastic frontier analysis.

Relationship between climate and plant growth

Plant growth is primarily determined by the availability of water, nutrients and energy. In Australia water availability is the primary limiting factor in this relationship (Cawood 1996; Raupach et al. 2008; Stephens 2002; Van Gool and Vernon 2005). Water 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 1996).

While ABARES farm survey data were available on an annual (financial year) time scale, climate data were needed at a sub-annual frequency (daily or monthly). This was because climatic variability within a year could significantly influence crop yields. The timing of rainfall within a cropping cycle is of particular relevance. Rainfall at key stages in crop development may

significantly increase yields while rainfall at other (out of season) stages may be less important. The importance of crop growing seasons varies across Australia. In southern areas, winter crops dominate, while further north both winter and summer crops are common.

A further requirement of the climate variables was that they be available at a suitable spatial scale, to facilitate derivation of farm-specific measures of climate according to geographic location (latitude and longitude) data.

Moisture

Several measures of moisture availability were investigated. One potential measure of moisture availability was farm-level evapotranspiration (the volume of water loss or use by plants). However, plant transpiration data were deemed unsuitable for this project because they:

- rely on satellite and remote sensing techniques and are not available before 1997
- were not available at a sufficiently fine spatial resolution
- are not entirely exogenous to the extent they are affected by farm management decisions (such as the timing of crop planting and fertiliser application).

Soil moisture or plant available water in the root zone was also considered as a measure of moisture availability. The CSIRO produces estimates of soil moisture as part of the Australian Water Availability Project (AWAP). However, these estimates rely on data on soil characteristics which have a number of limitations, including limited spatial resolution and varying coverage and methodologies used across regions. Additionally, soil moisture levels could be affected by farm management decisions (such as stubble retention and mechanical tillage).

In the absence of accurate soil moisture data, growing-season rainfall was considered an appropriate measure of plant moisture availability. Although rainfall data alone fail to fully incorporate differences in soil moisture and quality, these data were readily available at a suitable spatial and temporal resolution from the Bureau of Meteorology (BoM) and in interpolated form through AWAP. A number of sources support growing-season rainfall as an adequate proxy of moisture availability for Australian agriculture (Cawood 1996).

This study defined total rainfall over two crop growing seasons: winter (April to October) and summer (November to March), the latter being relevant in the northern region where summer cropping is common. A lagged summer rainfall variable (rainfall in the previous summer) was also considered, since summer rainfall may contribute soil moisture which benefits the following winter crops.

Temperature extremes

Farm-level temperature data are required to explain their effect on crop and pasture growth. Like rainfall, temperature data are available at high temporal and spatial resolution through AWAP. However, given the infrequent occurrence of extreme temperature events which impair plant growth, researchers needed to construct an appropriate measure of temperature variations rather than rely on an average or total measure.

Three measures of temperature variation were tested in this study, namely:

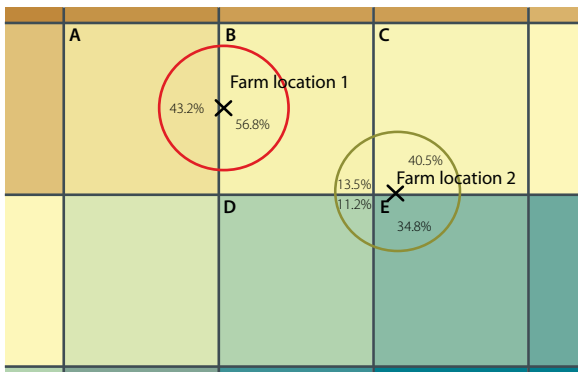
- **Threshold measures:** the days within growing seasons where maximum (minimum) temperatures exceeded (or fell below) various critical thresholds for crop growth.
- **Average monthly maximum and minimum temperatures:** considered a proxy for temperature extremes.
- **Growing degree days (GDD):** reflecting the average daily maximum and minimum temperatures relative to a base temperature.

In contrast to the GDD measures, both the threshold measures and the average monthly maximum and minimum temperatures correlated with farm output, as expected. Moreover, monthly minimum and maximum temperatures proved to have marginally superior explanatory power as proxies for exposure to temperature extremes.

Mapping climate data to individual farms

Climate data were obtained from AWAP—a joint project between the BoM, CSIRO, the Bureau of Rural Sciences (now ABARES) and the Australian National University. For details refer to www.bom.gov.au/jsp/awap, www.daffa.gov.au/brs/climate-impact/awap and www.csiro.au/awap/. 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.

7 Calculation of farm-level climate variables using spatial datasets



Farm-specific climate variables were generated using these rainfall and temperature ‘surfaces’ in conjunction with ABARES farm survey data of latitude, longitude and area operated. Area-weighted average climate variables were calculated using ArcGIS software, by representing each farm as a circle centred on a farm’s latitude and longitude with a radius chosen to match the farm area operated. For example, the average climate values for farm 1 in figure 7 were the area-weighted averages of 43.2 per cent of the values in grid cell A and 56.8 per cent of the values in grid cell B. Farm 2 uses weighted averages of the four grid cell: B, C, D and E.

Final climate variables

Summary statistics for the final climate variables constructed for this study are shown in table 2.

2 Climate variable summary data, by GRDC region and season, 1977–78 to 2007–08

Climate variable	Unit	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					343	(111)
Average maximum temperature	°C					31.8	(1.9)
Average minimum temperature	°C					17.8	(1.8)

Notes: GRDC = Grains Research and Development Corporation; SD = Standard deviation; °C = Celsius
 Source: Constructed from data from the Australian Water Availability Project

5 Results

Individual stochastic frontier models were estimated for each GRDC region (southern, western and northern) by two groups of grain growers (cropping specialists plus mixed cropping–livestock farms, and for crop specialist farms only)—a total of six frontier models (table 3).

3 Frontier models estimated

Industry	Southern	Western	Northern
Cropping specialists and mixed cropping–livestock	model 1	model 2	model 3
Cropping specialists only	model 4	model 5	model 6

Most parameter estimates proved statistically significant across all models (see tables 9 and 10 for parameter estimates).

This chapter presents and discusses the results from each stage of the analysis:

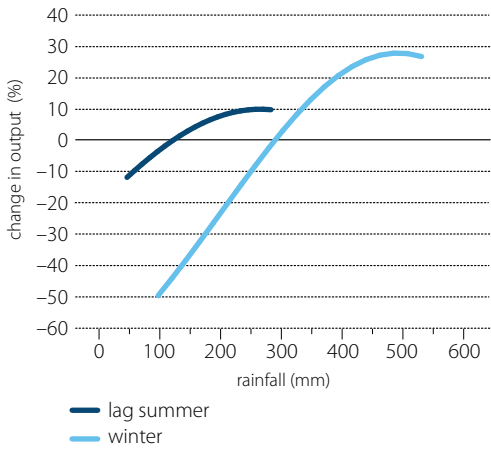
- climate variable response curves
- climate effects index
- climate adjusted productivity
- productivity decomposition
- technical efficiency levels.

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 figures 8, 9 and 10 (for the southern [model 1], western [model 2] and northern [model 3] regions respectively).

Figure 8 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, the effects of winter rainfall, summer rainfall and lagged summer rainfall were found to be of similar magnitude (figure 10).

8 Effect of winter and lagged summer rainfall on output in the southern region (model 1)

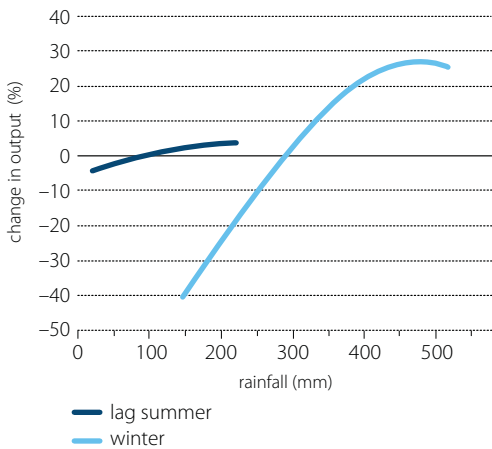


Note: Range is the 2.5 percentile to the 97.5 percentile of farm winter and lagged summer rainfall; the average winter rainfall was 291 mm and the average summer rainfall was 132 mm

In general, extremes of temperature typically have a negative effect on output, although the estimated responses varied across models (figures 11 and 12). Higher maximum temperatures and lower minimum temperatures were associated with lower output, all else held constant. Overall, however, the magnitude of temperature effects was small relative to the effect of rainfall.

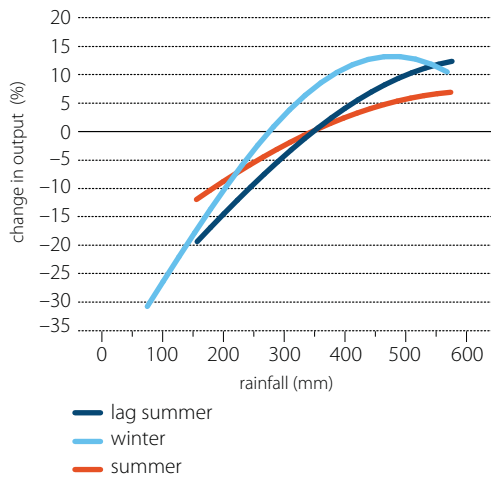
A number of interactions between specific climate variables were also found to significantly affect output. Results confirmed that temperature extremes increase the sensitivity of output-to-rainfall variation, while lagged summer rainfall was shown to act as a substitute for winter season rainfall (figure 13).

9 Effect of winter and lagged summer rainfall on output in the western region (model 2)



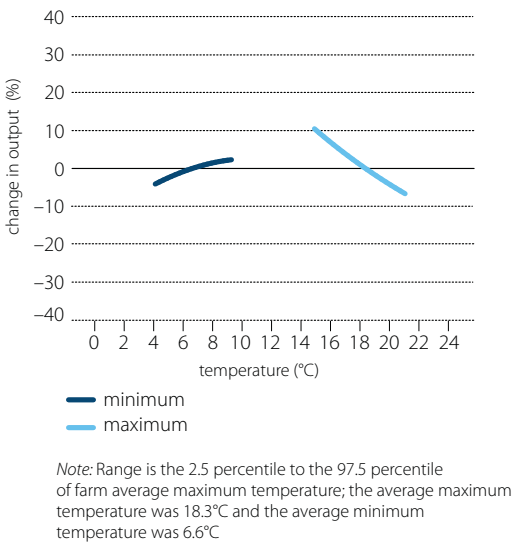
Note: Range is 2.5 percentile to 97.5 percentile of farm winter and summer rainfall; the mean winter rainfall is 290 mm and the mean summer rainfall is 90 mm

10 Effect of winter, summer and lagged summer rainfall on output in the northern region (model 3)

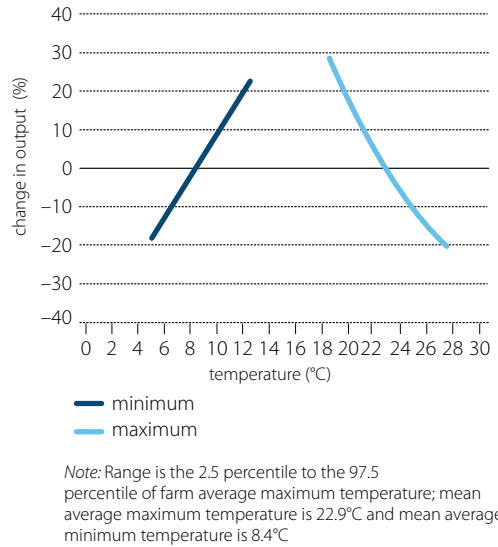


Note: Range is the 2.5 percentile to the 97.5 percentile of farm winter/summer rainfall; mean winter rainfall was 291 mm

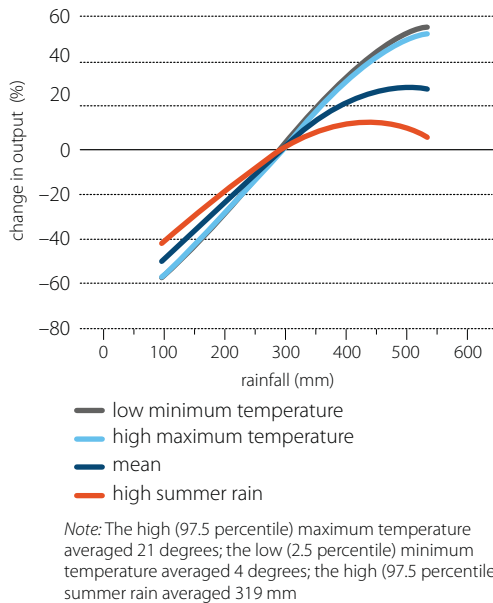
11 Effect of winter maximum and minimum temperatures on output in the southern region (model 1)



12 Effect of winter maximum and minimum temperatures on output for cropping specialists and mixed cropping–livestock farms in the northern region (model 3), 1977–78 to 2007–08



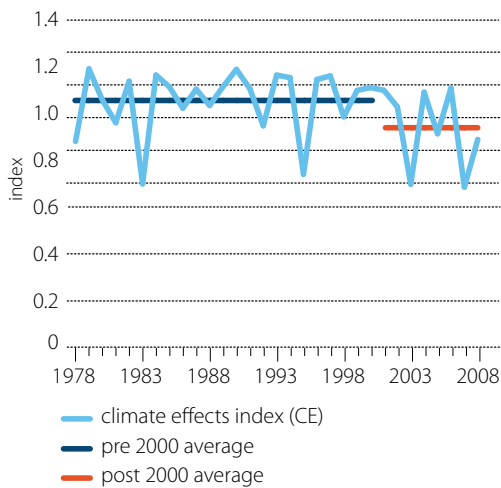
13 Effect of interaction terms on winter rain response in the southern region (model 1)



Climate effects index

The climate effects (CE) index represents the combined effects of rainfall and temperature variations on output holding all else constant including, for example, input/output mix and scale, technical efficiency change and technical change. Appendix D provides a comparison of the derived CE index with the water stress index (Stephens et al. 1989) used in previous ABARE studies by Zhao et al. (2009) and Kocic et al. (2006).

14 Mean climate effects index for all cropping specialists and mixed cropping livestock farms, 1977–78 to 2007–08



The mean climate effects index (across all farms in all regions) is shown in figure 14 for the period 1977–78 to 2007–08.

The asymmetry of the annual variations largely reflects the quadratic relationship between output and rainfall. Average climate conditions post 2000 (particularly rainfall), were significantly below that observed pre 2000, adversely affecting output (figure 14).

Table 4 provides a summary of the relative decline in output due to poorer climate conditions post 1999–2000.

The CE index displays greatest variation in the southern region (table 5). This reflects higher annual rainfall variability and greater farm sensitivity to changes in winter rainfall. As is evident from table 5, cropping specialist farms in the southern and western regions tended

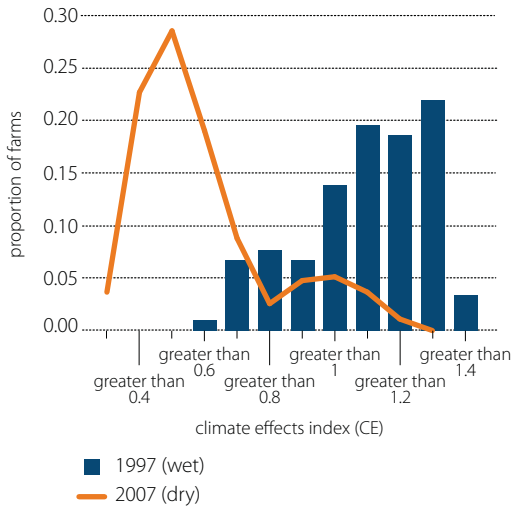
4 Percentage change in mean climate effects index, 1999–2000 to 2007–08 relative to 1977–78 to 1999–2000

Industry	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, 1999–2000 to 2007–08

Industry	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

15 Distribution of farm-level climate effects index, southern region (model 1), 1996–97 and 2006–07



to display greater sensitivity to variations in climate variables relative to mixed cropping livestock farms.

Substantial variation was observed in the CE index across farms within a region in any given year. Figure 15 shows the variation in farm-level CE indexes for two representative years 2006–07 (a ‘dry’ year) and 1996–97 (a ‘wet’ year). However, even within dry years, individual farms may experience wet conditions. These results highlight the importance of a farm-level estimate, rather than controlling for climate variability at a regional level.

Maps of the CE index were also generated from spatial rainfall and temperature data using estimated climate parameters. Map 2 depicts the average CE index (for cropping specialists and mixed cropping livestock

farms) over the period 1977–78 to 1999–2000 at each point (pixel) within each GRDC region. In this map, the CE index varies between 1.5 (green) and 0.5 (brown).

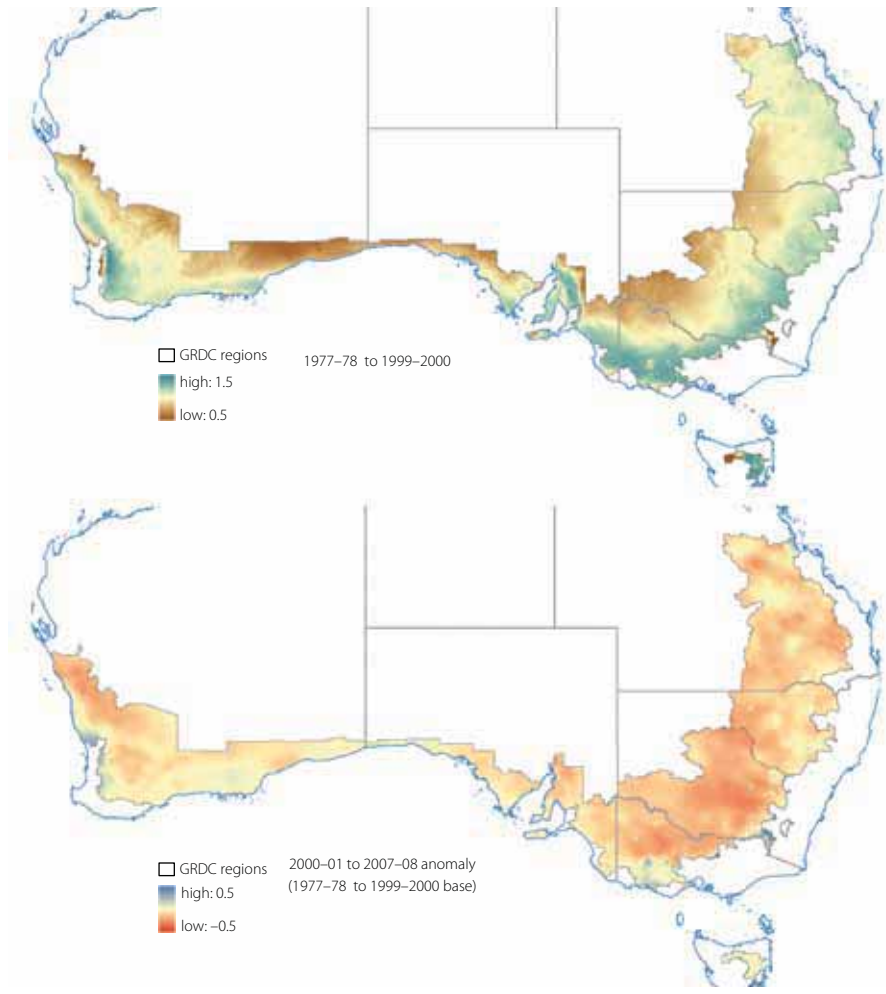
The observed patterns in climate conditions primarily reflect differences in average rainfall. As expected, agricultural activity is generally concentrated in the more favourable rainfall areas. These maps represent average climate outcomes over extended periods; in practice, spatial patterns in climate outcomes change from year to year. Such changes can be observed in the annual CE index maps presented in appendix D.

Map 2 also shows a climate anomaly map that depicts the change in average climate conditions in the post 2000 period relative to the pre 2000 period. It varies between –0.5 (red) and +0.5 (blue).

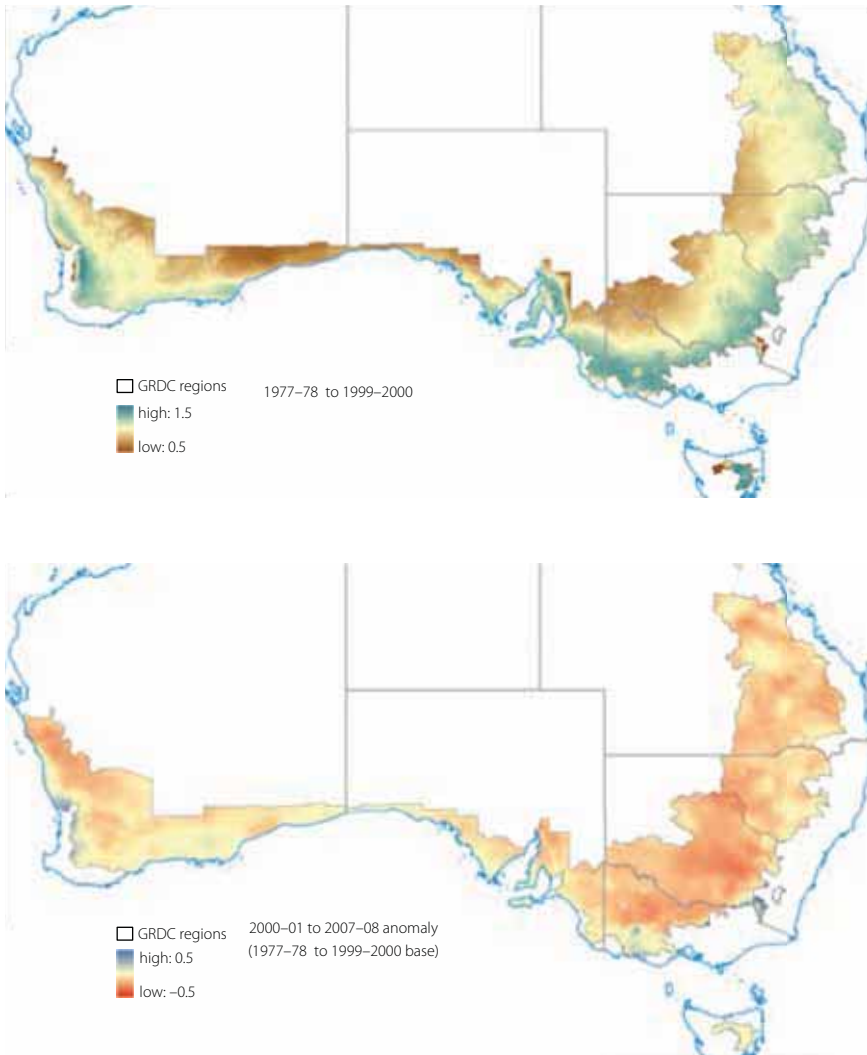
The climate anomaly maps show the deterioration in climate conditions has been most pronounced in parts of the southern region (central New South Wales and northern Victoria) and the western region (northern portion). While most areas have experienced a decline in climate conditions, a minority have experienced an improvement in average conditions post 2000. These relatively small areas were generally located adjacent to high rainfall zones.

Map 3 shows the same maps for cropping specialists only. In contrast to the broader cropping specialists and mixed cropping livestock farms model, the results for cropping specialists only display greater variation between high and low rainfall areas, given greater sensitivity of cropping specialist farms to changes in rainfall.

map 2 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)



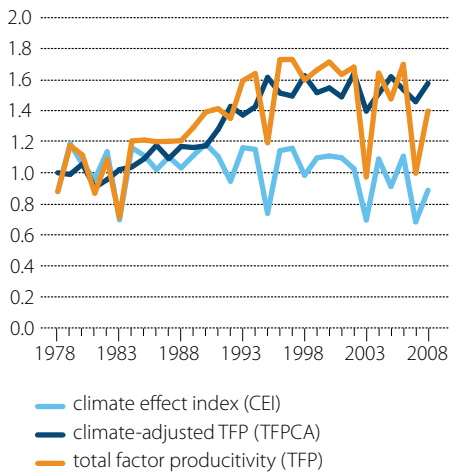
map 3 Climate effects index (models 1, 2 and 3), cropping specialists only, 1977– to 1999–2000 (top) and climate anomaly 2000–01 to 2007–08 (bottom)



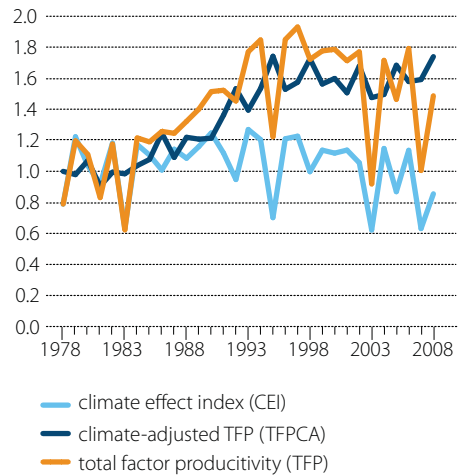
Climate adjusted productivity

Figures 16 and 17 show the average estimated climate adjusted productivity series for all cropping farms and for cropping specialists respectively; the climate adjusted series displays significantly less annual volatility than the raw productivity series discussed previously. A significant slowdown in total factor productivity growth is still observed over the last decade, after controlling for deteriorating climate conditions. A summary of the productivity decomposition results, by region and industry, is contained in table 6, and figure 18 compares climate adjusted productivity for each GRDC region (across all cropping farms).

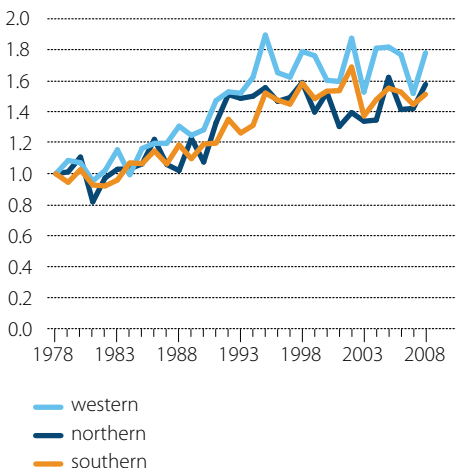
16 Average climate adjusted TFP for all cropping farms, 1977–78 to 2007–08



17 Average climate adjusted TFP for cropping specialist farms only, 1977–78 to 2007–08



18 Average climate adjusted TFP for all cropping farms by GRDC region, 1977–78 to 2007–08



Productivity decomposition

Figure 19 shows the decomposition of climate adjusted TFP into its three components: technical change, technical efficiency change, and scale–mix efficiency change (average for all cropping farms in all regions). Given the smooth functional forms assumed for technical change and technical efficiency change, any annual volatility remaining from the climate adjusted TFP series has been assigned to scale–mix efficiency change.

While the results of the productivity decomposition differ across regions and models, a number of features are common to all, in particular:

- technical change is the primary driver of productivity growth
- the rate of technical change has slowed
- technical efficiency is declining
- the scale–mix efficiency is inversely related to terms of trade.

Technical change is the primary driver of productivity growth

Technical change has been the key driver of long-run growth productivity in cropping. Technical change has increased, on average, by around 1.5 per cent a year Australia-wide, exceeding average TFP growth for cropping specialist and mixed cropping–livestock farms (1.2 per cent a year). A primary driver of TFP growth for the industry over the period has, therefore, been expansion of the frontier through development and adoption of new management practices and technologies.

Rate of technical change has slowed

Nevertheless, even after controlling for climate effects, growth in technical change for all cropping farms (cropping specialists and mixed cropping–livestock farms) has gradually slowed across all models. While technical change over the period 1977–78 to 1999–2000 was estimated to have increased at an average annual rate of 1.95 per cent Australia-wide, the average dropped to just 0.4 per cent a year over the period 1999–2000 to 2007–08. Despite the estimated rate of technical change having declined, there is no indication of significant technical regress (negative technical change).

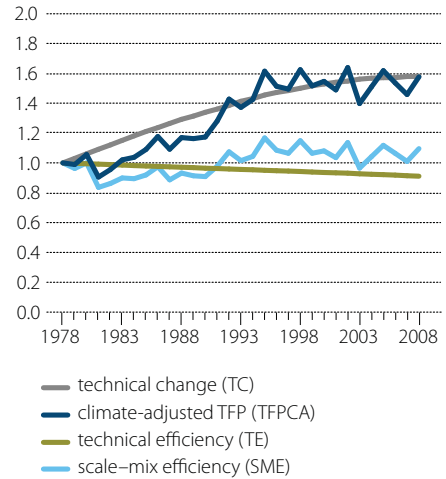
Technical efficiency is declining

Across all models, technical efficiency was estimated to have declined gradually over the past 30 years. Australia-wide, technical efficiency change declined, on average, by around 0.3 per cent a year. 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 are generally improving overall, 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.

Scale–mix efficiency is inversely related to terms of trade

The scale–mix efficiency component was observed to move in the opposite direction to farmers' terms of trade—declining initially then increasing steadily (figure 20). This observation

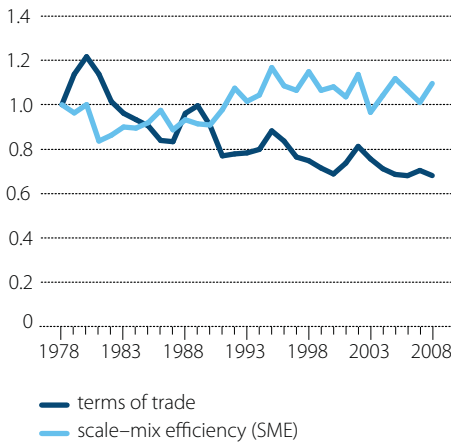
19 Productivity decomposition for all cropping farms, 1977–78 to 2007–08



6 Estimated average annual growth in productivity components

Productivity component	Pre 2000	Post 2000	Whole period
	1977–78 to 1999–2000 %	1999–2000 to 2007–08 %	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

20 Scale and mix efficiency and the terms of trade for all croppers, 1977–78 to 2007–08



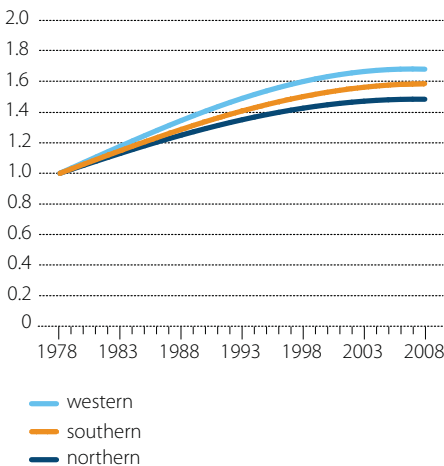
is consistent with O'Donnell (2010), who emphasised the potential for farmers to make productivity-decreasing (but profitability-increasing) scale–mix decisions in response to improvements in the terms of trade.

Results by region and industry

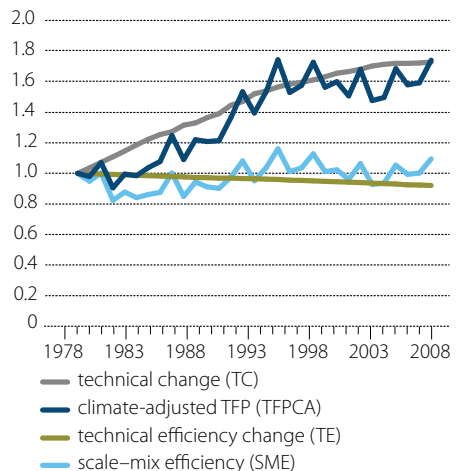
Average annual climate adjusted TFP growth was highest in the western region (1.7 per cent), followed by the southern region (1.5 per cent) and northern region (1.3 per cent). These outcomes are predominantly due to relatively higher technical change and lower technical efficiency declines. Technical change in each of the GRDC regions (for the all cropping farms model) is shown in figure 21.

The productivity decomposition for the cropping specialist only model is shown in figure 22. 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 due to higher technical change.

21 Technical change by GRDC region, 1977–78 to 2007–08

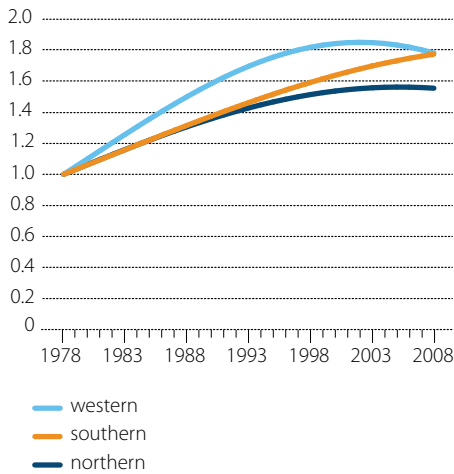


22 Productivity decomposition for cropping specialist farms, Australia, 1977–78 to 2007–08



Technical change, by GRDC region, for the cropping specialist only models is shown in figure 23. For southern region cropping specialists, the decline in technical change was relatively modest, with annual average growth slowing to 1.00 per cent during the post 2000 period in comparison.

23 Technical change for cropping specialists only by region, 1977–78 to 2007–08



Growth in technical change for cropping specialists in the western and northern regions post 2000 was approximately zero (table 6). Much of this difference is due to the strong influence of climate variables in the southern cropping specialists’ model, such that the majority of the observed decline in productivity is explained by deteriorating climate conditions.

Appendix E contains the full complement of regional productivity decomposition charts.

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.

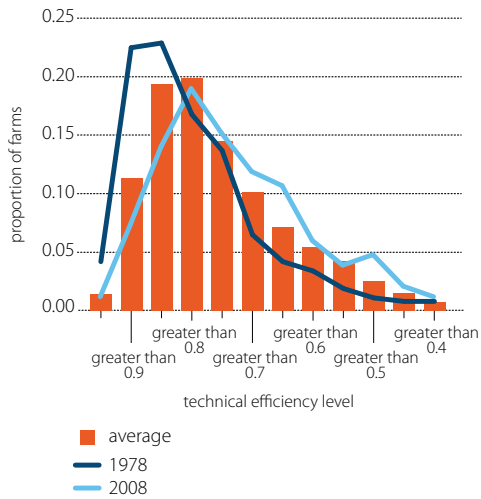
7 Summary of mean technical efficiency levels and average annual technical efficiency change

	Southern	Western	Northern
Cropping specialists and mixed cropping–livestock			
Mean technical efficiency level	0.79	0.80	0.78
Average annual technical efficiency change (%)	-0.34	-0.31	-0.23
Cropping specialists only			
Mean technical efficiency level	0.80	0.86	0.78
Average annual technical efficiency change (%)	-0.33	-0.08	-0.27

Figure 24 shows the distribution of farm-level technical efficiency scores for the southern region (derived from model 1) for 1977–78 and 2007–08 and the average achieved over the sample period. This distribution shifts to the right over time, given the estimated declining trend in farm technical efficiency levels.

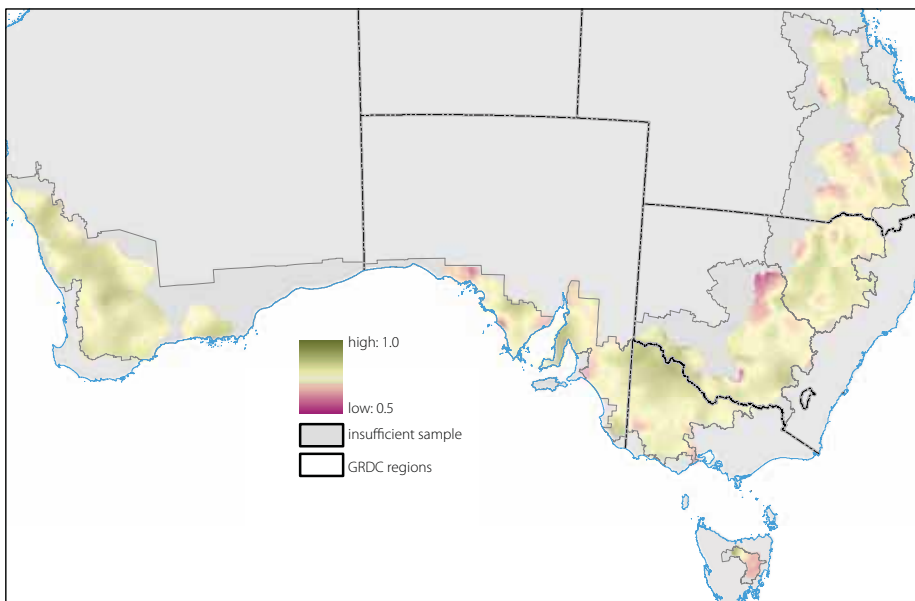
Maps 4 and 5 show farm technical efficiency levels for southern, northern and western GRDC regions (all cropping farms and cropping specialist farms, respectively). For confidentiality reasons, farm technical efficiency scores are interpolated (each point represents the average technical efficiency score of all farms within a 50 km radius). Green denotes areas of higher efficiency (levels at or near 1) and red denotes areas of low efficiency (levels approaching 0.5).

24 Distribution of farm technical efficiency levels for the southern region (model 1), 1977–78, 2007–08 and average over the whole period

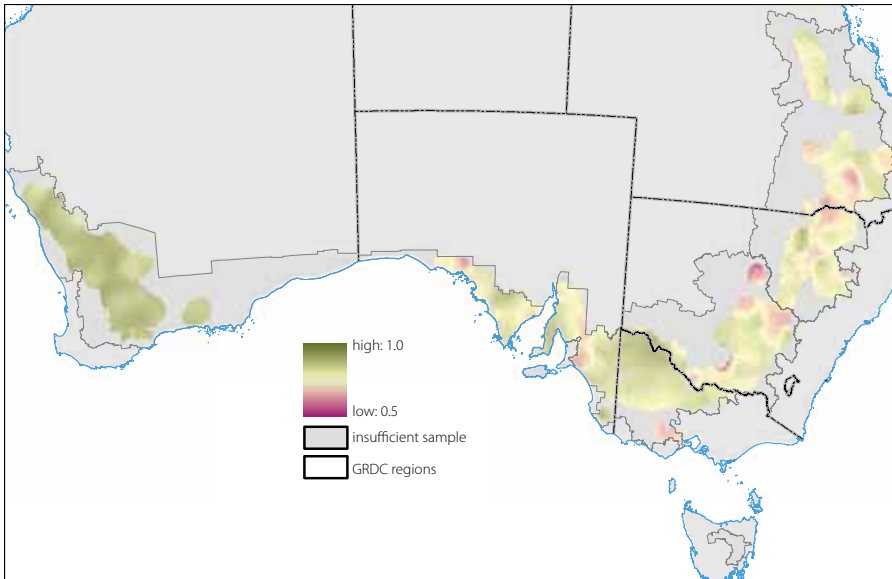


Spatial patterns in technical efficiency are likely to reflect, among other things, land quality and or climate factors not fully accounted for within the econometric model. In general, areas of poor technical efficiency tend to be located in relatively ‘marginal’ or opportunistic cropping areas, often 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), western (South Australian) sections of the southern GRDC region. Conversely, areas that involve a high concentration of cropping farms tend to display higher technical efficiency (for example, the Eastern Darling Downs in Queensland and the Yorke Peninsula in South Australia).

map **4** Average technical efficiency scores (models 1, 2 and 3), cropping specialists and mixed cropping–livestock, 1977–78 to 2007–08



map **5** Average technical efficiency scores (model 5, 6 and 7), cropping specialists only, 1977–78 to 2007–08



6 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 growth into its key components through application of production frontier estimation techniques. Both methodological developments have contributed to an improved understanding of productivity trends in the Australian grains industry.

Controlling for climate variability

A method for controlling for climate variability that involved combining farm survey data with spatial rainfall and climate data was developed. An advantage of this approach is that it does not require modelling of farm biological processes. In addition, the approach is flexible because it can be calibrated to a wide range of regions, time periods or industries.

The approach proved effective, with the chosen climate variables displaying a high degree of explanatory power. The estimated relationships between climate variables and farm output proved statistically significant and consistent with expectations. In addition, climate responses varied across regions and industries, with the southern region showing greater climate sensitivity relative to the northern and western regions. Further, 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 observed slowdown in productivity growth. Post 2000, declining climate conditions were estimated to have reduced output by around 17 to 18 per cent on average among cropping specialist farms in the southern and western regions.

Productivity decomposition

After controlling for climate variability, farm productivity was further decomposed into its key components: technical change, technical efficiency change, and scale–mix efficiency change. The productivity decomposition results confirmed that technical change—the adoption of new ‘best’ management practices and technologies by leading farms—has been the key driver of long-run productivity growth in Australia’s broadacre cropping industry.

However, across all regions, a gradual decline in the rate of technical change—the rate at which the production frontier has been advancing—was observed. For example, in the western region (among cropping specialists and mixed cropping–livestock farms), technical

change declined from around 2.4 per cent a year between 1977–78 and 1999–2000 to just 0.6 per cent a year from 1999–2000 to 2007–08. The decline post 2000 appeared 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.

Moreover, growth in technical change was offset by a small decline in average technical efficiency levels over the study 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 been widening. Australia-wide, technical efficiency change was estimated to have averaged around –0.4 per cent a year among cropping specialists and mixed cropping–livestock farms.

Policy implications

The results from this study have direct implications for the size and mix of funding directed toward R&D, extension and climate adaptation activities across GRDC regions. They suggest that technical change, the component of TFP expected to be directly affected by the size and composition of R&D investment is the key driver of productivity growth in the grains industry over the long run. Although TFP growth is also influenced by climate conditions and changes in scale, mix and technical efficiencies, these effects have historically been of secondary importance and are largely outside the direct influence of most R&D activities (but not, in the latter case, extension activities, discussed next). Further, any shifts in R&D investment should also consider whether the balance of regional specific R&D serves to increase overall industry TFP growth by recognising that the productivity slowdown is more pronounced in the northern and western regions.

The results also point to the potential for increasing productivity in the grains industry through extension activities directed at inducing less efficient farms to adopt new technologies and best management practices. Significant technical inefficiency is estimated in this study: around 20 per cent across all farms and all years. However these results should be treated with caution given the potential for technical inefficiency to reflect excluded input characteristics, particularly land quality. Regardless of the extent of inefficiency, questions should be asked about the cost effectiveness of extension initiatives, as well as the nature and size of incentives that impinge on adoption decisions.

Further grains industry productivity gains are expected to stem from R&D directed at developing new agricultural technologies that mitigate the effects of adverse climate conditions, particularly low rainfall. This study highlights the significance of climate variability on cropping farm productivity levels. For example, while climate adaptation research and extension would be expected, at least in part, to benefit all GRDC regions, it would be particularly useful in the southern region which is more sensitive to rainfall variability and could benefit from regionally based technologies for conserving soil moisture and reducing plant transpiration rates.

Future research

This study highlighted several directions for further research, including applying stochastic frontier analysis to the livestock industries (beef, sheep and dairy), further refining selection of climate variables and generating a standard climate-adjusted TFP series as part of ABARES routine productivity reporting. Further refinements of the frontier estimation technique could include investigating the determinants of technical efficiency, including the role of human capital characteristics and land quality in influencing TFP.

Determinants of agricultural productivity: moisture and human capital

Past ABARE studies have confirmed the primacy of climate and the importance of various human capital characteristics of farmers in determining TFP.

Zhao et al. (2009) compared farm-level TFP indexes with a range of climate variables (including moisture availability), human capital characteristics (such as age and formal education), and management and farming practices (including farm size and crop diversity) over the period 1988–89 to 2003–05. The study demonstrated that moisture availability was highly positively correlated with TFP. In investigating the influence of climate, the study made use of a 'moisture availability index' developed by the APSRU, which ABARE had used previously (see Kokic et al. 2006). Several human capital characteristics were also found to be significant determinants of TFP, in particular, farmer education level.

The study by Kokic et al. (2006) also considered how a range of different explanatory variables might be correlated with farm-level TFP growth using a rural livelihoods framework (Ellis 2000). Kokic et al. (2006) considered natural capital (moisture availability), financial capital (such as, access to finance), human capital (including education), social capital (such as, Landcare membership), activities (including degree of crop specialisation), mediating processes (including direct drill and minimum till) and various risk factors (such as, moisture and commodity price variability). A key finding of this study was the dominant influence of moisture availability on TFP.

Determinants of agricultural productivity: farm size

Past ABARE studies have observed a positive correlation between farm size and farm TFP (see, for example, Alexander and Kokic 2005; Kokic et al. 2006; Zhao et al. 2009). Each study employed a 'dry sheep equivalents' conversion to measure farm size, whereby the area cropped and the numbers of beef and sheep were aggregated using predefined weights. Kokic et al. (2006) interpreted the dry sheep equivalent metric as a measure of land area adjusted for land quality.

More broadly, ABARE has found farm size (either measured by land area or dry sheep equivalents) to be positively correlated with farm financial performance (rate of return and cash income) in broadacre agriculture (see, for example, Hooper et al. 2002). In addition, ABARE has also found evidence of economies of size in Australian broadacre agriculture insofar as estimated farm unit costs (average costs) generally decrease with farm size (see, for example, Alexander and Kokic 2005).

Estimation of production frontiers for agriculture

There has, to date, been limited application of farm-level production frontier estimation techniques to Australian agriculture.

Coelli (1995) and Battese (1992) both reviewed studies applying frontier techniques to agriculture. Coelli (1995) found only two studies that had been undertaken for Australian agriculture: Battese and Corra (1977) and Battese and Coelli (1988). Battese and Corra (1977) estimated stochastic production analysis functions for a single year (1973–74) using data from the Australian Agriculture and Grazing Industry Survey. Battese and Coelli (1988) applied panel data stochastic frontier analysis methods to three years (1978–79 to 1980–81) using data from a sample of dairy farms in New South Wales and Victoria. The spread of individual farm technical efficiency levels was narrower for the New South Wales farms (0.55 to 0.93) than for the Victorian farms (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, with individual farm estimates ranging from 0.53 to 1.00. In addition, Fraser and Hone (2001) found that TFP was driven primarily by changes in technical change, with technical efficiency change having minimal effect.

Kompas and Che (2006) estimate a stochastic production frontier and technical efficiency model for the Australian dairy industry using ABARE Australian Dairy Industry Survey data for the period 1996 to 2000. They found that the estimated dairy production frontier displayed constant returns to scale. In addition, they estimated a mean technical efficiency level of 0.87, but ranging from 0.7 to 1.0.

Bravo-Ureta et al. (2006) undertook a large meta-analysis of 167 farm production frontier and technical efficiency studies across a range of developed and developing countries. They found that studies employing stochastic frontier analysis methods tended to generate lower mean technical efficiency estimates than non parametric deterministic methods (such as data envelopment analysis). The average mean technical efficiency level across the 117 studies applying stochastic frontier analysis methods was 0.77.

B Estimation methodology

Stochastic frontier analysis

This study involved estimation of a production frontier with translog functional form and quadratic time trend and climate responses as shown below:

$$\begin{aligned} \text{Log}(Y_{i,t}) = & \beta_0 + \sum_{j=1}^J \beta_j \text{Log}(X_{j,i,t}^M) + \sum_{j=1}^J \sum_{k=1}^K \beta_{jk} \text{Log}(X_{j,i,t}^M) \cdot \text{Log}(X_{k,i,t}^M) + \beta_t t + \beta_{tt} t^2 \\ & + \sum_{k=1}^K \alpha_k X_{k,i,t}^{NM} + \sum_{k=1}^K \pi_k X_{k,i,t}^{NM^2} + v_{i,t} - u_{i,t} \end{aligned}$$

Where:

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

β_0 = constant term

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

β_j = input parameters j (input elasticities)

t = time trend

β_t, β_{tt} = time trend parameters

$X_{k,i,t}^{NM}$ = climate variables k (including rainfall, 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 model specification follows Battese and Coelli (1992), with time varying technical inefficiency drawn from a truncated normal distribution:

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

Where:

T = total number of time periods

η = inefficiency trend parameter

μ = technical inefficiency distribution parameter (where $\mu = 0$ implies a 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 2010), which employs an iterative maximum likelihood estimation procedure.

Productivity decomposition

Given the above model, farm-level technical efficiency scores (*TES*) were defined, as in Battese and Coelli (1992):

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

Annual technical efficiency change (*TEC*), technical change (*TC*) indexes were defined following Coelli et al. (2005):

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

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

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

$$TC_{i,t} = TC_{t-1} \cdot TCC_{i,t}$$

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

A climate effects (CE) index was defined (see appendix E) and a farm-level total factor productivity index (TFP) was estimated separately using the standard ABARES indexing methodology (Zhao et al. 2010). A climate adjusted farm-level TFP index was then defined as:

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

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

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

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

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

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

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

appendix C 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 analysis parameter estimates for all cropping farms (cropping specialists and mixed cropping–livestock farms), by GRDC region, 1977–78 to 2007–08

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) x Log _e (Labour)	0.055*	(0.017)	0.027	(0.038)	0.018	(0.024)
Log _e (Land) x Log _e (Capital)	-0.042*	(0.012)	-0.016	(0.027)	-0.027	(0.016)
Log _e (Land) x Log _e (Mat_Ser)	0.044*	(0.013)	0.092*	(0.028)	-0.013	(0.018)
Log _e (Labour) x Log _e (Capital)	-0.017	(0.019)	-0.038	(0.036)	-1.86E-3	(0.029)
Log _e (Labour) x Log _e (Mat_Ser)	-0.025	(0.021)	-0.039	(0.037)	-0.097*	(0.035)
Log _e (Capital) x 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)
Other parameters						
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	6761	2658	3153			
Cross sections	2080	747	1064			
Time periods	31	31	31			

Notes: * indicates parameter significant at 5 per cent level; SE = standard error.

10 Stochastic frontier parameter estimates for cropping specialists only, by GRDC region, 1977–78 to 2007–08

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) × Loge(Labour)	0.078*	(0.028)	-0.022	(0.064)	-0.039	(0.040)
Log _e (Land) × Loge(Capital)	-0.019	(0.020)	-0.016	(0.049)	-0.019	(0.030)
Log _e (Land) × Loge(Mat_Ser)	0.040	(0.021)	0.072	(0.042)	1.37E-3	(0.030)
Log _e (Labour) × Loge(Capital)	-0.049	(0.029)	-0.061	(0.067)	6.61E-3	(0.049)
Log _e (Labour) × Loge(Mat_Ser)	7.29E-3	(0.033)	0.046	(0.061)	-0.063	(0.055)
Log _e (Capital) × Loge(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
Other parameters						
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	3137	1134	1410			
Cross sections	1111	380	559			
Time periods	31	31	31			

Notes: * indicates parameter significant at 5 per cent level; SE = standard error.

D Climate effects index

Calculating the climate effects index

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

The index was normalised to the average climate conditions observed during the period 1977–78 to 1999–2000 and calculated as:

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

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

where:

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

$\hat{\alpha}_k$ = climate variable parameters

$\hat{C}_{i,t}$ = climate variable contribution to predicted value ($\text{Log}(\widehat{Y}_{i,t})$)

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

Comparison of water stress index and climate effects index

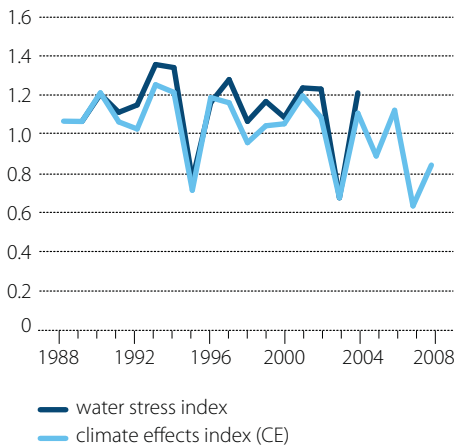
This section compares a water stress index used in previous ABARES studies with the climate effects index developed in this study.

A water stress (moisture availability) index developed by APSRU has been used in several previous ABARE studies (for example, Kocic et al. 2006 and Zhao et al. 2009). The APSRU index takes into account observations on rainfall, radiation, maximum and minimum temperatures, and location specific soil data (see Stephens et al. 1989). However, a key limitation of the water

stress index is that it was originally developed and calibrated to explain wheat yields in the western region.

A key advantage of the climate effects index methodology developed in this study is its flexibility. The climate effects index can be calibrated to any specific region, industry or time period and can also be adjusted and refined over time to include different climate variables. In contrast to the water stress index, the approach developed here can, for example, be easily calibrated to farms in the northern region, or extended to beef or sheep farms, if required. Another advantage of the climate effects index approach is that it does not rely on any models or assumptions about farm management practices.

25 Mean climate effects index versus mean water stress index for cropping specialists and mixed cropping–livestock farms in the southern region (model 1), 1987–88 to 2007–08

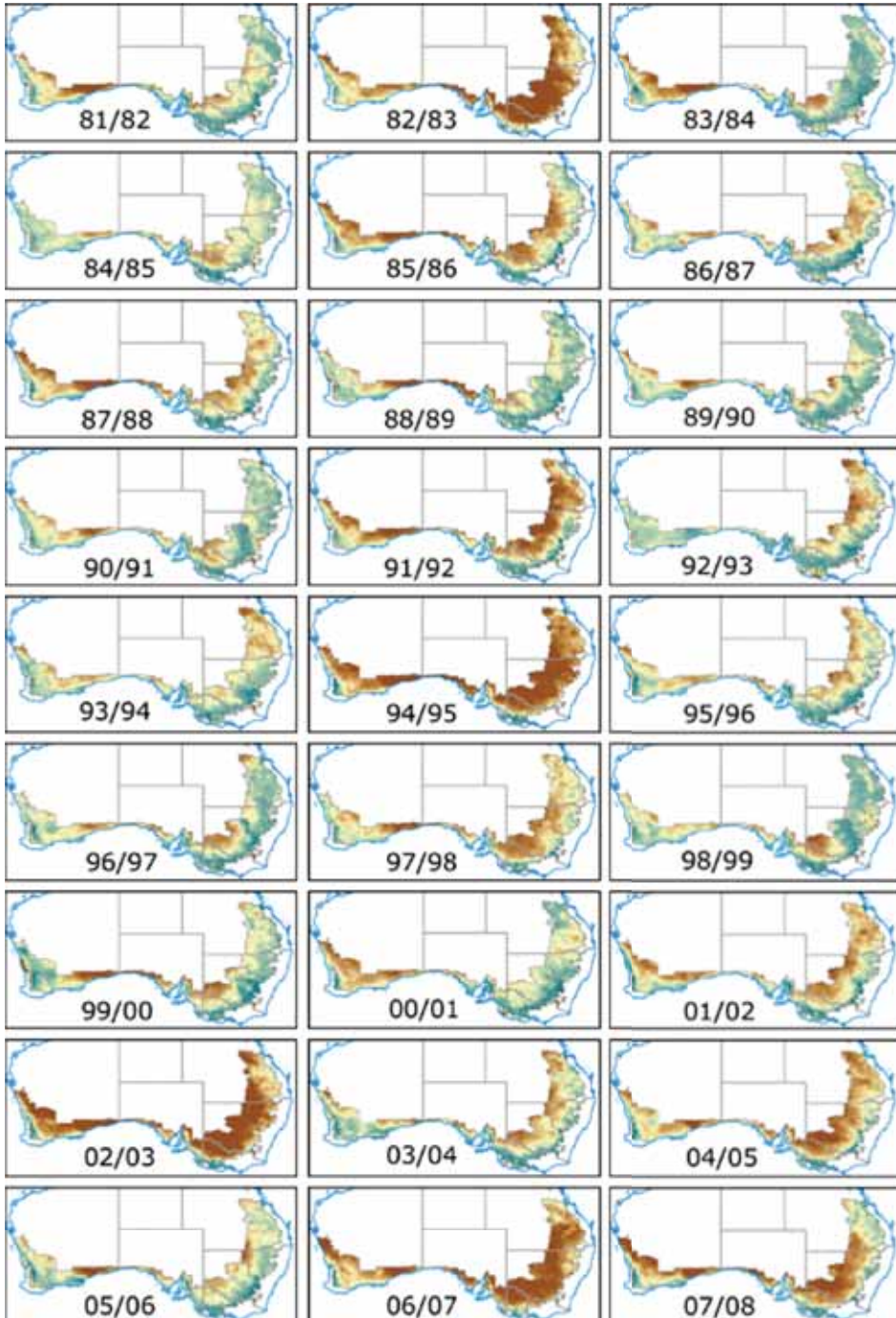


Note: The APSRU water stress index is available at farm level between 1988–89 and 2003–04 only

The climate effects index derived in this study displays a slightly more asymmetric response to rainfall variability than the water stress index (figure 25). In addition, the climate effects index is slightly less responsive to wet conditions and slightly more responsive to dry conditions relative to the water stress index.

Map 6 contains annual maps of the climate effects index, covering the period 1981–82 to 2007–08. The maps highlight substantial variation in the spatial pattern of climate conditions (especially rainfall) across different years.

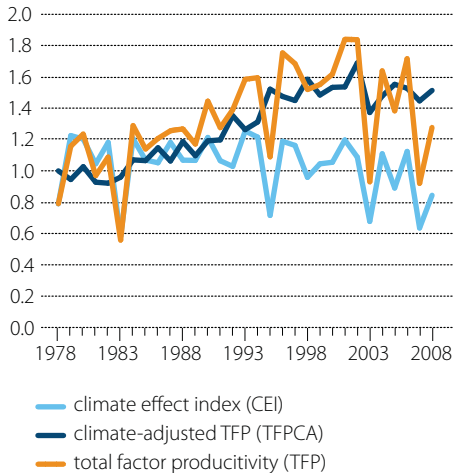
map 6 Annual climate effects index for cropping specialists and mixed cropping–livestock farms (models 1, 2 and 3), 1981–82 to 2007–08



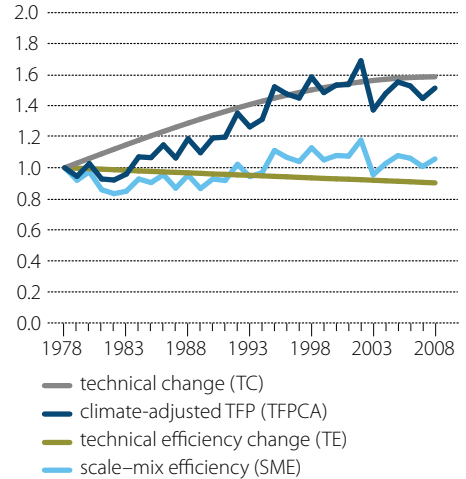
E Regional productivity charts

Southern region

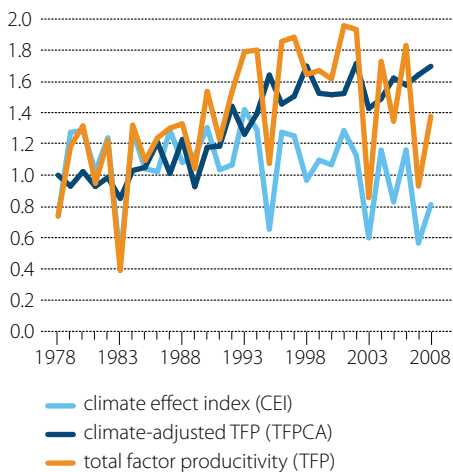
26 Climate adjusted TFP for cropping specialists and mixed cropping –livestock farms in the southern region (model 1), 1977–78 to 2007–08



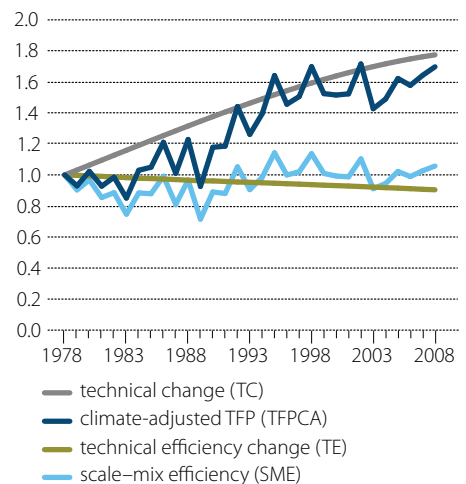
27 Productivity decomposition for cropping specialists and mixed cropping–livestock farms in the southern region, 1977–78 to 2007–08



28 Climate adjusted productivity for cropping specialists only in the southern region, 1977–78 to 2007–08

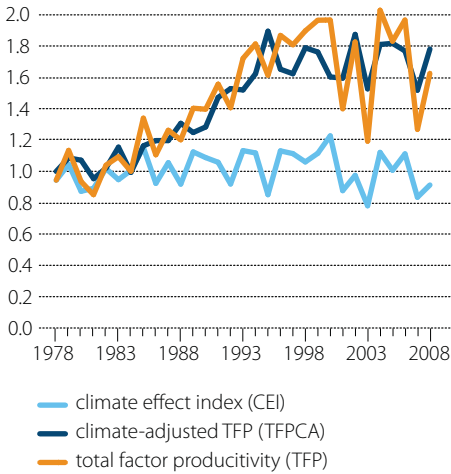


29 Productivity decomposition for cropping specialists only in the southern region, 1977–78 to 2007–08

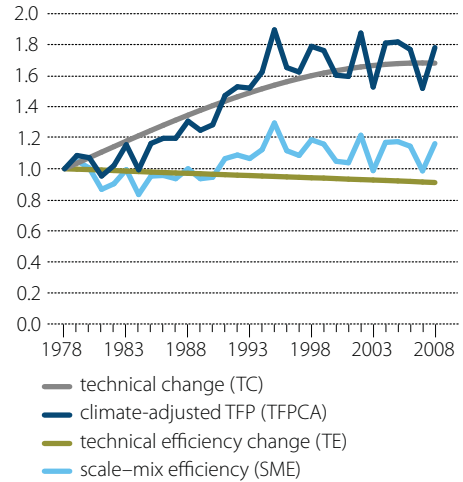


Western region

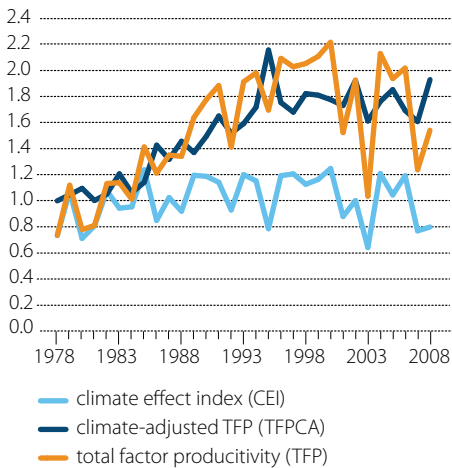
30 Climate adjusted TFP for cropping specialists and mixed cropping–livestock farms in the western region (model 2), 1977–78 to 2007–08



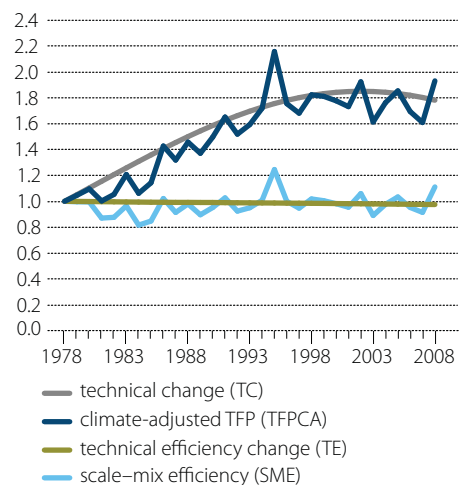
31 Productivity decomposition for cropping specialists and mixed cropping–livestock farms in the western region, 1977–78 to 2007–08



32 Climate adjusted productivity for cropping specialists only in the western region, 1977–78 to 2007–08

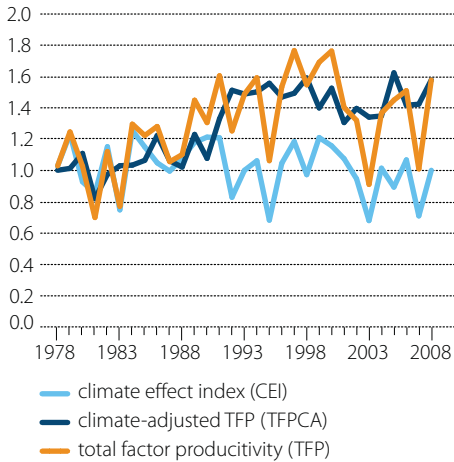


33 Productivity decomposition for cropping specialists only in the western region, 1977–78 to 2007–08

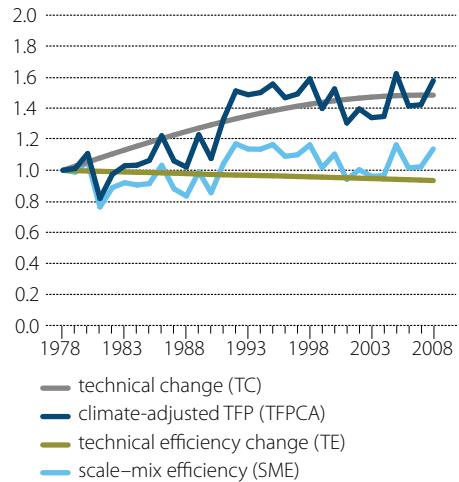


Northern region

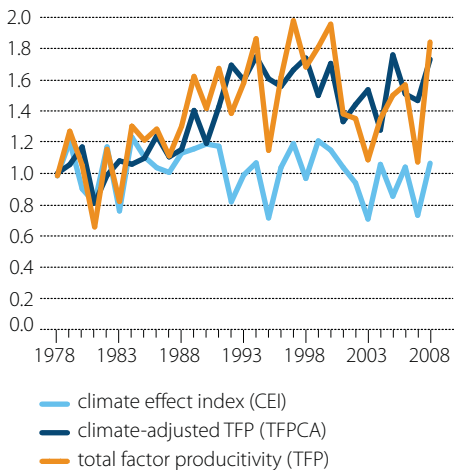
34 Climate adjusted TFP for cropping specialists and mixed cropping–livestock farms in the northern region (model 3), 1977–78 to 2007–08



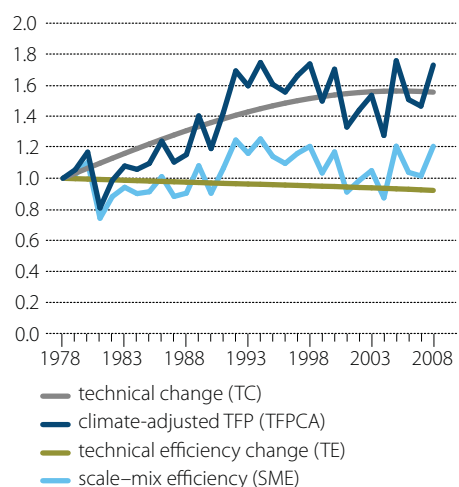
35 Productivity decomposition for cropping specialists and mixed cropping–livestock farms in the northern region, 1977–78 to 2007–08



36 Climate adjusted productivity for cropping specialists only in the northern region, 1977–78 to 2007–08



37 Productivity decomposition for cropping specialists only in the northern region, 1977–78 to 2007–08



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Australian Government Department of Climate Change and Energy Efficiency	Horticulture Australia Limited
Australian Government Department of Resources, Energy and Tourism	Industry & Investment NSW
Australian Government Department of Sustainability, Environment, Water, Population and Communities	Meat & Livestock Australia
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