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Weather shocks, adaptation and agricultural TFP: A cross-region comparison of Australian Broadacre farms

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A B S T R A C T

This paper investigates the dynamic impact of weather shocks on agricultural total factor productivity (TFP) of Australian broadacre industry, by applying a Panel Error Correction model (PECM) to the data of 32 agricultural regions over the period 1978–2013. In response to weather shocks, farmers take adaptive actions by adjusting their output and input structures to alleviate weather-induced loss in productivity. Moreover, farmers in regions with the least favorable climate condition are found to adapt to weather shocks more rapidly than those in regions with more favorable climate condition. Our finding highlights the importance of public policies to encourage farmers to improve adaptive capacities in the events of weather shock.

1. Introduction

Climate change is recognized as an important threat to the sustainability of agricultural production throughout the whole world. In addition to global warming, increasingly severe weather conditions have unleashed the negative impacts on agricultural productivity more frequently in recent decades (Mendelsohn et al. 1994; Deschenes and Greenstone 2007; Schlenker and Roberts, 2009; Fisher et al., 2012; Cárdenas et al., 2016; Liang et al., 2017; Ortiz-Bobea et al., 2018). In the meantime,farmers typically take adaptive actions, such as adopting new technologies and modifying output and/or input structure, to minimize the negative climatic effects (Howden and Hayman, 2005; Garnaut, 2011; Yang and Shumway, 2016). For example, some farmers have opted for using weatherproof seeds for cropping and new livestock breeds or species (Porter et al., 2014), while others choose altering the crop rotation pattern (Walthall et al., 2012; Porter et al., 2014) and building shelter and nursery houses for livestock (Darwin et al., 1995).[1] Since implementing these adaptive options may require considerable efforts and time (Quiggin and Horowitz, 2003), climatic effects in the short term may differ from those in the long term, generating complex dynamic productivity responses to weather shocks and climate change that vary over time and differ across regions. The net productivity effects of weather shocks will depend on the adaptive capacities of farmers, which in turn could enlarge cross-region disparity in agricultural productivity performance.

For decades, the concerns over climate change and variation have inspired a substantial body of research to explore the impact of climate change on agricultural productivity (Rosenzweig and Iglesias, 1994; Mendelsohn and Dinar, 1999; Olesen and Bindi, 2002; Quiggin and Horowitz, 2003; Calzadilla et al., 2013; Liang et al., 2017; Chambers and Pieralli, 2020; Chambers et al., 2020). Generally, these studies agree that climate change and variabilities affect agricultural productivity both directly and indirectly. On the one hand, climate change and short term variabilities affect precipitation, temperature, atmospheric concentration of carbon dioxide (CO2) and tropospheric ozone (IPCC, 1996, 2007; Stern, 2007; Garnaut, 2011) which transform the agro-ecological system (Walthall et al., 2012), and thus directly affect the agricultural productivity. On the other hand, both the adverse seasonal conditions such as droughts, flooding and other climate variation can reshape farmers' expectation and trigger their adaptive responses, which induce

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[1] Darwin et al. (1995) estimated that farmers adjusting outputs and inputs on existing farmland could offset 79 to 88% of the 19 to 30% of world reduction in wheat and some other grains.

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changes in the output-input relationship.

However, majority of these studies focused on determining the net impact of climate change and variation on agricultural productivity, and could not provide useful evidence of farmers' adaptation behaviors. Even in the cases when farmers' adaptation had to be considered, the channels through which farmers adapt to weather shocks were hypothetically assumed based on some ad hoc model settings without supports from empirical evidence. Consequently, how farmers respond to the changing climate condition and whether these responses efficiently alleviate the impact of climate change and variation on agricultural productivity are still unknown to the public.

This paper aims to investigate farmers' adaptive behaviors, by analyzing the dynamics of region-level agricultural productivity in response to weather shocks. To achieve the goal, we develop a theoretical framework to demonstrate the potential channels through which farmers adapt to weather shocks, and then design an empirical strategy to examine the validity of these potential adaptation channels. The model is tested by using the region-level data for the Australian broadacre agriculture. We do so for two reasons. On the one hand, the industry mainly consists of the non-irrigated crop and livestock enterprises. Rainfall is the main source of soil moisture for non-irrigated crops and pasture grasses and temperature is a crucial indicator of the length of growing seasons. On the other hand, a consensus of weather projections indicated that warmer and drier weather, with more extreme events, had significantly changed the pattern of rainfall and temperature in Australia since the mid-1990s (Rosenzweig and Iglesias, 2006).[2]

Our empirical analysis starts with constructing a set of production accounts for the non-irrigated agriculture in 32 regions in Australia over the period 1978–2013. Using this dataset, we apply a Panel Error Correction model (PECM) (; Pesaran et al., 1999; Im et al., 2003; Blackburne and Frank, 2007) to estimate the convergence speed from the short-term to the long-term equilibria in response to weather shocks. The convergence speed is then linked to farmers' adaptive behaviors to uncover potential response channels, such as changing the output mix and input structure. We then investigate how these adaptation behaviors may differ across regions with different ways of production and under different types of weather shocks. In doing so, we split the sample regions into the high rainfall, wheat-sheep and pasture zones. Each of these zones captures the particular way of agricultural production in Australia, defined by their climatic condition, production scale, and land use of agriculture.[3]

Our results show that weather shocks, measured by changes in water availability and growing degree days, cause fluctuations in agricultural TFP. However, farmers are able to alleviate the weather impacts through two channels. The first is to adjust their outputs (e.g., the mix of crop and livestock) and the second channel is to change input structures (e.g., the capital-labor ratio). Both channels will substantially accelerate the TFP adjustment speed from the short-run to the long-run equilibria. Moreover, differences exist in the adjustment speed across regions, reflecting geographical diversity in natural environment and farmers' adaptive capacities. Farmers in the regions with harsher weather conditions are capable of adapting to weather shocks more rapidly than their counterparts in the regions with more favourable conditions.

This paper contributes to the literature from three perspectives. First, it attempts to empirically uncover potential channels through which farmers adapt to weather shocks. We provide credible evidences suggesting that farmers can mitigate impact of weather shocks through adjusting the mix of crop and livestock and capital-labor ratio. Since we use region-level data, our finding complements the evidence unveiled in the existing literature, which are largely based on analysis of farm level data (Aragón et al., 2021; Jagnani et al., 2021). Second, we analyze the dynamic adjustment path of agricultural productivity to weather shocks. This expands on the knowledge in the existing literature based on cross sectional farm survey data such as Huang et al. (2015) and Wang et al. (2010), which neglects factor reallocation effects within agriculture. Third, we add value to the existing studies (Asche et al., 2008; Yang and Shumway, 2016) by demonstrating how different adaptation capacities across regions may contribute to cross-region productivity differences. All these provide useful insights for government agencies to improve relevant policies to combat weather shocks.

The rest of the paper is organized as follows. Section 2 presents the theoretical model and empirical specifications. Section 3 provides a description on the data used in this study. Section 4 discusses the unit root and co-integration tests. Empirical results are discussed in Section 5. Section 6 shows the results of sensitivity analysis and Section 7 concludes.

2. Theoretical model and empirical specification

2.1. Theoretical model

To analyze the impact of weather shocks on agricultural TFP and farmers' responsive channels, we start with developing a multi-input and multi-output production model to analyze TFP growth and its determinants at a regional level. Assume that representative regions (or farmers) share the same general production technology that takes the following transformation form

$$f(Y_1, \dots, Y_M, X_1, \dots, X_J; t) = exp(v) \tag{1}$$

where Y_1, …, Y_M denote outputs and X_1, …, X_J denote inputs. The variable t indicates time trend and v reflects exogenous production shocks including but not limited to technology progress, weather shocks, etc.

Taking the logarithm on both sides of Eq. (1) and differentiating it totally, we get

$$\sum_m \frac{\partial lnf(X,Y,t)}{\partial lnY_m}\frac{dlnY_m}{dt} + \sum_j \frac{\partial lnf(X,Y,t)}{\partial lnX_j}\frac{dlnX_j}{dt} + \frac{\partial lnf(X,Y,t)}{dt} = \frac{dv}{dt} \tag{2}$$

where $\partial lnf(X,Y,t)/\partial t \equiv \lambda_t$ captures technology progress, weather shocks and/or other exogenous factors. Defining $\frac{\partial lnf(X,Y,t)}{\partial lnY_m} \equiv \lambda_{Y_m}$ and $\frac{\partial lnf(X,Y,t)}{\partial lnX_j} \equiv \lambda_{X_j}$, we re-arrange Eq. (2) into the change form $\sum_m \lambda_{Y_m}\dot{Y}_m + \sum_j \lambda_{X_j}\dot{X}_j + \lambda_t = \frac{dv}{dt}$, where the dot over a variable indicates its rate of change. Agricultural TFP growth (defined as $\dot{TFP} = \sum_m R_m \dot{Y}_m - \sum_j S_j \dot{X}_j$ where $R_m = P_m Y_m / \sum_m P_m Y_m$ and $S_j = w_j X_j / \sum_j w_j X_j$) can thus be written as

$$\dot{TFP} = (RTS - 1)\sum_j S_j \dot{X}_j - \left(\frac{\lambda_t}{\lambda_Y}\right) + \sum_m Q_m \dot{Y}_m + \sum_j D_j \dot{X}_j + \frac{dv}{dt}\Big/\lambda_Y \tag{3}$$

where RTS denote returns to scale, $Q_m = \left[\left(\frac{\lambda_{Y_m}}{\lambda_Y}\right) - R_m\right]$ and $D_j = \left[\left(\frac{\lambda_{X_j}}{\lambda_Y}\right) - \frac{\lambda_X}{\lambda_Y} S_j\right]$. When producers are assumed to maximize profit subject to Eq. (4), we have $Q_m = 0$ and $D_j = 0$, and thus Eq. (3) is reduced to[4]

[2] For example, the annual total rainfall across Australia was 552 mm on average for the period of 2000–2010 — around 3.4% below that of 1980–1990 and 5.5% below that of 1990–2000 (BOM 2015). Over the same time period, average temperature in the growing season increased by 1.9% and 1.4% respectively compared to the periods of 1980–1990 and 1990–2000.

[3] The high-rainfall zone benefits from favorable weather condition and is suitable for grazing and intensive crop growing. Farms in the wheat-sheep zone have a climate that allows regular cropping of grains in addition to grazing of sheep and beef cattle. The pastoral zone includes the arid and semi-arid regions where land use is characterized by extensive grazing of native pastures.

[4] A detailed mathematical derivation for the decomposition of TFP growth is provided in Appendix A.

$$T\dot{F}P = (RTS-1)\sum_j S_j\dot{X}_j - \left(\frac{\lambda_t}{\lambda_Y}\right) + \frac{dv}{dt}\Big/\lambda_Y \tag{4}$$

Eq. (4) decomposes region-level TFP growth into four components: external shocks, scale effects, changes in input mix (such as capital-labor ratio) and output structure. This implies that in addition to technological progress and weather shocks, input mix and output structure also play important roles in affecting TFP growth. Moreover, if farmers choose adjusting their input mix and output structure and scale of operation in response to weather shocks to reduce weather impacts, input mix and output structure will become potential channels through which farmers could make responsive adaptation.

2.2. Empirical specification

We specify a basic empirical model based on Eq. (4) as.

$$lnTFP_{rt} = f_r\left(W_{rt}, T_{rt}, Z_{rt}, C_{rt}, F_t\right) + F_r + \varepsilon_{rt} \tag{5}$$

where $lnTFP_{rt}$ is the logarithm of agriculture TFP index for region $r = (1, \ldots, R)$ and time period $t = (1, \ldots, T)$. W_{rt} and T_{rt} are weather variables denoting regional water availability and temperature respectively. Z_{rt} captures other operating environment represented by human capital, farm size and economic resource in the region, C_{rt} denotes the two channels through which farmers adapt to weather shocks, and a time trend F_t captures technology advancement over time. We use the level form rather than the growth rate, because the accumulated TFP growth will determine the TFP level. A set of region dummies F_r is also included in this equation to eliminate the region-specific effect.

Applying Eq. (5) to investigate farmers' adaptive responses requires distinguishing weather-shock effects in the short term from that in the long term, since farmers are expected to make adaptive responses over time. Fig. 1 illustrates the adjustment process of TFP between the short-term and long-term weather-shock effects. Initially, famers' productivity stays at the level of TFP_0. When weather shocks occur at t_0, farmers' productivity TFP_t will take a dynamic path and gradually converge to the equilibrium response TFP_1. The gap between TFP_1 and TFP_0 captures the long-term effects, while the gap between TFP_t and TFP_0 captures the short-term effects. Thus, the area between TFP_t and TFP_1 represents adjustment costs. Since TFP_t converge more quickly to TFP_1 if the total adjustment costs decline, we can use the adjustment speed to measure adjustment costs associated with the adaptation process. Furthermore, the potential channels can be identified, if they help increase the convergence speed.

To decompose the impact of weather shocks on regional TFP into the short-term and long-term effects, we further assume that the adaptation process, $f_{rt}(.)$ is dynamic and evolves in an autoregressive process. If $lnTFP_{rt}$ and any one of its determinants W_{rt}, T_{rt}, Z_{rt} are nonstationary and co-integrated when facing persistent weather shocks, the error term ε_{rt} will be stationary for all regions. The relationship between agricultural TFP and region-level weather variables (W_{rt} and T_{rt}) may thus follow the trans-temporal pattern such that agricultural TFP, in response to weather shocks, will first deviate from and then converge to the long-term level. With these assumptions, Eq. (6) can be re-parameterized into a structural form:

$$\begin{aligned}\Delta \mathrm{lnTFP}_{rt} &= \varnothing[\mathrm{lnTFP}_{rt-1} - \theta \mathrm{f}_{rt-1}(\mathrm{W}_{rt-1}, \mathrm{T}_{rt-1}, \mathrm{Z}_{rt-1}, \mathrm{C}_{rt-1}, \mathrm{F}_{t-1})] \\ &+ \lambda \Delta \mathrm{f}_{rt}(\mathrm{W}_{rt}, \mathrm{T}_{rt}, \mathrm{Z}_{rt}, \mathrm{C}_{rt}) + \varepsilon_{rt}\end{aligned} \tag{6}$$

where θ and λ captures the long-term and short-term direct effects of climate change on agricultural TFP respectively. $\varnothing$ represents the marginal effect of error-correction term, which measures how quickly agricultural TFP converges from the short-term to the long-term level. Specifically, $\varnothing \geq 0$ suggests that regional TFP does not adjust to its long-term trend once it has diverged in the short-term; $\phi < 0$ indicates that TFP tends to return to the long-term trend instead of drifting further apart after weather shocks. The notation of Δ represents changes over time.

Although Eq. (6) is a good representation of the adaptation process, it does not inform the adaptation channels. In particular, it does not tell whether adjusting the output mix and input structure — the two channels as specified in Eq. (5) — will help farmers to alleviate the weather effects on agricultural productivity and its dynamics. This is because that weather shocks are not the only reasons that explains the changes in the output mix and input structure.[5] For example, market conditions usually play a more important role in affecting input and output structure in practice. Thus, it is necessary to eliminate the change in the output and input structures caused by the changing relative prices from our analysis. As in Eq. (7), we first conduct the Granger causality test to examine the relationship of output mix and input structure with weather variables using an autoregressive distributed lag (ARDL) model:

$$C_{rt} = g(W_{rt-k}, T_{rt-k}, P_{rt-k}) + u_{rt} \quad \text{where } k = 0, 1, \ldots\ldots, \tag{7}$$

where C_{rt} denotes the output mix or input quantity ratio, and P_{rt-k} denotes the current and lagged relative prices of outputs or inputs. Then, we predict the impacts of the changing weather conditions on the output mix and input structure ($\widehat{C}_{rt} = g(W_{rt-k}, T_{rt-k}, .)$) using the estimated coefficients of $W_{rt-k}$and T_{rt-k}. These predicted values are then incorporated into (6) to examine the impacts of adaptation on the dynamics of agricultural TFP through the adjustment of the output mix and input structure:

$$\Delta \mathrm{lnTFP}_{rt} = \varnothing'\left[\mathrm{lnTFP}_{rt-1} - \theta' \mathrm{f}_{rt-1}\left(\mathrm{W}_{rt-1}, \mathrm{T}_{rt-1}, \mathrm{Z}_{rt-1}, \widehat{\mathrm{C}}_{rt-1}, \mathrm{F}_{t-1}\right)\right] + \lambda' \Delta \mathrm{f}_{rt}\left(\mathrm{W}_{rt}, \mathrm{T}_{rt}, \mathrm{Z}_{rt}, \widehat{\mathrm{C}}_{rt}\right) + \mathrm{v}_{rt} \tag{8}$$

where $\widehat{C}_{rt}$ contains information on part of the weather effects which captures farmers' adaptation to weather shocks.

Eq. (8) provides the final model specification used to examine the role of farmers' adaptation through adjusting the output mix and input structure on agricultural productivity. The coefficients θ' and λ' represent the long-term and short-term response of TFP to weather shocks. The error-correcting coefficient $\varnothing'$ reflects the adjustment of TFP to its long-run equilibrium when farmers adjust the output mix and input structure in response to weather shocks.

2.3. Estimation strategy

One can estimate Eq. (8) using a fixed effects (FE) estimation approach, which is considered as a suitable procedure to eliminate the series correlation of dependent and independent variables in the long panel data. In the estimation, the time-series data for all the regions are differentiated but the intercepts are allowed to differ across regions. Since weather fluctuations are presumably random which is a standard assumption in the literature, the endogeneity problem in the estimation process is not a concern.

[5] Please refer to the theoretical derivation in Appendix B for the role of market price and its impact on input mix and output structure.

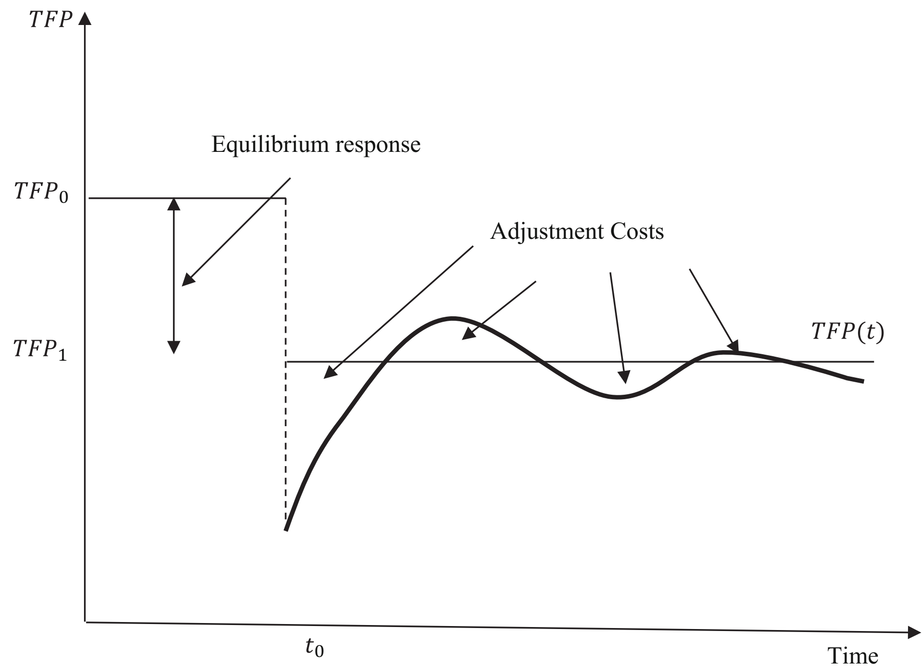

Fig. 1. Dynamic adjustment of TFP in response to weather shocks.

However, there is another econometric problem that needs to be resolved. If the coefficients of slope interact with unobserved regional specific characteristics suggesting that the way weather shocks affecting productivity is not uniform across regions, the FE estimation produces inconsistent and potentially biased results (Blackburne and Frank, 2007). There are two approaches to address this issue. One is the mean group (MG) estimation method (Pesaran and Smith, 1999), which allows the intercepts, slope coefficients (both the short-run and long-run climatic effects), and error variances to vary between regions. The other is the pooled mean group (PMG) method (Pesaran et al., 1999), which allows these coefficients to differ between regions. Following Blackburne and Frank (2007), we apply both the MG and PMG methods in the empirical estimation and use the Hausman test to determine the preferred estimator.

Finally, all the above exercises are also carried out by using the subsamples in the three zones with different ecological conditions (i.e., high rainfall, wheat-sheep and pasture). The results can be used to inform how farmers' adaptive capacities may differ across regions under their own climate and agronomic environments.

3. Data source, variable definition and descriptive statistics

The data used in this paper is in the form of the balanced panel, which covers 32 regions in three climatic zones for the period of 1978–2013 (Fig. 2). They were drawn primarily from three data sources. The Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) annual farm survey of broad-acre industries provided the data on the agricultural inputs and outputs used to construct the cross-regional consistent TFP measure. The same data source is also used to construct the variables to measure farmer's responses (changes in output mix and capital-labor ratio) and to control for the impact of average farm size at the regional level. Regional weather indicators, including water availability and growing season degree days, were constructed by using the data obtained from the Queensland State Government and the University of Queensland (Potgieter et al., 2005, 2006; Carter et al., 2000). Finally, we also use the data from the Australian Bureau of Statistics (ABS) Census of Population and Housing to derive the economic resource index, average education level and farm size for the general economic conditions at the region level.

3.1. *Total factor productivity (TFP) index*

Agricultural TFP is defined as the ratio of the quantity of gross output and total input at the regional level. For each region, the output and input quantities were aggregated using the Törnqvist-Theil index formulas (Diewert, 1976). To allow for the consistent multilateral comparisons across regions and over time, the method proposed by Caves et al. (1982) is applied to achieve transitivity. The results are a series of multilateral indexes with unity being assigned to the base (region 111 in 1995) and other TFP values are expressed relative to this value.

To estimate the region-level agricultural TFP, an agricultural production account for each region is compiled by aggregating outputs and inputs observed for individual farms. In the process of aggregation, we use the sample structure weights of ABARES' Australian Agricultural and Grazing Survey (AAGIS) to aggregate each output and input to the regional level and make the adjustment using the Agricultural Census data, where weights are assigned to each farm representing farm size, enterprise in production and regional distribution etc. This procedure ensures a good regional representation of the output and input estimates. The sample weights are constructed based on the population of broad-acre farms, stratified by State, industry (cropping and livestock) and size (Zhao et al., 2012). Prices of inputs and outputs are obtained from the relevant ABS publications and the ABARES' Australian Commodity Statistics Database.

The resulting production accounts consist of four broad types of outputs, i.e., crops, livestock, wool and other on-farm output, and five input categories, i.e., land, capital, labor, materials and services. A total of 13 types of output commodities and 26 types of inputs are included.[6] In the calculation of TFP index, prices of outputs and inputs are defined slightly differently. Each output type has a distinct price index, which is assumed to be identical across regions within States but vary over time, as individual farmers are regarded as the price takers in a competitive market. The same assumption is applied to the input prices except, where the appropriate data are available, some prices are allowed to differ between regions within States. Land rents and insurance costs are

[6] Zhao et al. (2012) provides a detailed description of the output and input variables used in this study.

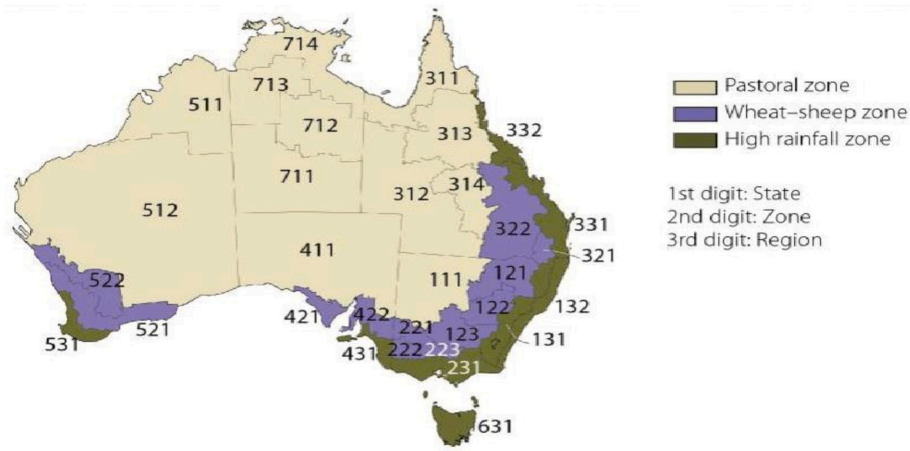

Fig. 2. Geographical distribution of broad-acre agriculture in Australia.

allowed to vary across regions within each state to reflect the regional disparity.

3.2. *Weather variables*

We use two variables to measure weather shocks in this study. One is the water availability index capturing the variation in rainfall and its impact on agriculture, and the other is the growing season degree days capturing the change in the accumulated temperature.

The water availability index takes into account the effects of rainfall, soil quality and water needed for growing crops and pasture. It was constructed based on three agro-climatic indexes, namely the wheat and sorghum water-stress indexes (Potgieter et al., 2005, 2006), and the pasture growth index (Carter et al., 2000), which measures the water availability for broadacre crops and native vegetation across the respective winter and summer growing season.[7] The water availability index was calculated by aggregating these indexes, using the estimates of land areas for winter crops, summer crops and grazing as weights (ABS (various years), 2021a, b). The index ranges from 0 to 1 and a larger index number indicates a higher level of water availability.

We measure the growing degree days for both the summer and winter growing seasons. The variable is defined as the average temperature multiplied by the number of days within the optimal temperature range, i.e., between 8 °C and 32 °C, for plant growth in the summer (1st November to 31st March) and winter seasons (1st April to 31st October), as described by Schlenker et al. (2006) and Deschenes and Greenstone (2007). The land area for agricultural production of each farm in the sample is used as weight to generate the season estimates within a region. We also use the average daily temperature for growing seasons to check the robustness of our results.

3.3. *Control variables*

Apart from weather condition and farm adaptive activities, the previous literature has also identified some other factors that may affect agricultural production and farmers' profits (Schlenker et al., 2006; Deschenes and Greenstone, 2007) and influence a region's trajectory of recovery from a weather shock. In this paper, we have considered endowment of economic resources, human capital and farm size. Specifically, the economic resources index from the ABS socio-economic indexes for areas (SEIFA) (ABS various years) is used to represent regional economic resources. The economic resources index ranks areas in Australia according to relative socio-economic advantage and disadvantage by education and health, business opportunities, infrastructure and natural endowment based on the Population Census data. We use the proportion of farmers in a region with "primary school education or above" as a measure of the stock of human capital. An indicator of average farm size is derived based on the data from AAGIS. Technology advancement may directly affect TFP, especially in the long run. We use a time trend as a proxy for technical change over time as the R&D spending on the regional level are unavailable.[8]

3.4. *Descriptive statistics for all regions and across zones*

Table 1 provides the descriptive statistics of major variables for all regions and for the three climatic zones (namely, the high-rainfall, wheat-sheep and pasture zones) from 1978 to 2013. The average TFP index for all samples is 1.33 with a base of 1 for region 111 in 1995. Among the three zones, the regions located in the wheat-sheep zone have the highest average TFP level (with an index of 1.44) and those from the pastoral zone have the lowest TFP level (with an index of 0.80). Fig. 3 depicts the dynamic changes in TFP across the three zones between 1978 and 2013. TFP increased over the period for all zones, with its growth at an annual average rate of 0.9%, 2.2%, and 1.0% for the high-rainfall, wheat-sheep, and pastoral zone, respectively. The pattern of TFP growth appears to show a divergence in agricultural productivity across zones.

The average water-availability index is 0.40 for all regions. As expected, the pastoral zone has a water-availability index of 0.25, smaller than other two zones, indicating it has the lowest level of soil moisture. A comparison of the growing degree days across zones shows that the high-rainfall zone has the lowest accumulated temperature and the pastoral zone has the highest accumulated temperature over the growing season. In general, farms in the high-rainfall zone tend to benefit from the favorable weather conditions, whereas farms in the wheat-sheep zones experience moderate weather conditions, and farms in the pastoral zone are located mainly in the arid and semi-arid areas. The average economic resource index is 954.30 and the stock of human capital is 0.92 for all samples, varying across zones. Farms in the high-rainfall zone and in the wheat-sheep zone are smaller and farms in the pastoral zones generally operate at a large scale. The average crop-livestock ratio is 2.55 for all regions, which is highest for the wheat-sheep zone (5.58) and lowest for the pastoral zone (0.15), indicating

[7] A detailed discussion on the wheat and sorghum water-stress indexes and the pasture growth index is provided in Appendix B.

[8] The R&D spending system in Australia is at the country level. For example, the research can be done in Canberra (by CSIRO), but it could be applied in Western Australia.

Table 1
Descriptive statistics for panel data during 1978–2013.

Variables	All Samples		High-rainfall Zone		Wheat-sheep Zone		Pastoral Zone	
	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
TFP index	1.33	0.539	1.435	0.389	1.617	0.507	0.794	0.243
Weather variables:								
Water-availability index	0.394	0.138	0.440	0.064	0.462	0.119	0.246	0.100
Growing degree days	5595.415	1435.894	4803.518	1343.811	5033.958	606.169	7229.498	1045.603
Economic variables:								
Economic resources index	954.299	52.420	970.226	37.945	968.722	38.569	916.738	63.122
Operators' education attainment	0.920	0.137	0.921	0.139	0.941	0.099	0.888	0.174
Average farm size (1000 ha)	4.012	8.546	0.315	0.504	0.283	0.223	13.302	11.604
Crop-livestock ratio	2.547	5.336	0.400	0.435	5.579	7.085	0.145	0.290
Capital-labor ratio	1.182	0.529	1.033	0.381	1.184	0.575	1.327	0.544
N	1008		288		432		288	

distinct structures of land use across zones. The capital-labor ratio is 1.18 on average for total samples and does not vary much across zones.

4. Stationarity and co-integration test

To estimate Eq. (8), we need to determine the existence of a structural functional form that approximates the dynamic response of regional TFP to the changes in water availability and the growing degree days (Fig. 4). This involves examining whether region-level agriculture TFP, weather and other control variables are stationary, and if not, whether they are co-integrated through a linear combination.

We first use the test proposed by Hadri (2000) to examine stationarity of each variable in the model, which corrects for the heteroscedasticity across regions — an important condition for the structural relationship between TFP and other variables. The results displayed in Table 2 suggest that most variables are integrated of order 1 (i.e., *I(1)*), except the price ratio of capital and labor, which is of order 2 (i.e., *I(2)*).

Following Westerlund (2007), we then conduct the co-integration test which is carried out for the variables in the original form for I(1) series and in the form of first differences for I(2). The variables will be co-integrated, if the error correction relationship exists among the variables for our sample regions. Results shown in Table 3 suggest that the null hypothesis of non-existence of co-integration is rejected at the 1% level.

In sum, the results obtained from the unit root and the co-integration tests confirm that the dynamic response of regional TFP to weather shocks and other explanatory variables can be approximated by an error correction process. This provides the basis for our analysis of farmers' adaptation and its impact on the dynamics of agricultural productivity in response to weather shocks.

5. Weather shocks and TFP adjustment: The role of farm adaptation

Based on the unit root and co-integration test results, we are ready to apply the panel error correction model to address three issues. First, we will test whether farmers change the output mix and capital-labor ratio in response to weather shocks, which are considered as the important channels for adaptation using Eq. (7). Second, we will examine how changes in the output and input structures affect the dynamic path of agricultural TFP from the short-term to its long-term level by using Eq. (8). Third, we investigate whether farmers' adaptation behaviors differ across regions, and if it is different, what are its implications for the cross-regional productivity difference by using both Eqs. (7, 8) for the three zones.

5.1. Granger causality between weather shocks and farmers' adaptation

To determine the output-mix and capital-labor ratio as effective channels for adaptation, we run an autoregressive distributed lag (ARDL) model for the panel data to examine whether weather shocks will cause farmers to change the crop-livestock mix and the capital-labor ratio.[9] Our model assumes that output-mix and capital-labor ratio are a function of its lags, lags of their relative prices and weather variables. Since the water availability index and the growing degree days are exogenously determined, the estimation is free from the reverse causality and the endogeneity problem. The orders of lag for the dependent and independent variables are determined by minimizing the Akaike information criterion (AIC) with a constraint of maximum 3 periods.[10] We report the results in Table 4. The individual coefficients for lagged water availability and growing degree days collectively comprise the lag distribution and define the pattern (including magnitude and timing) of how weather shocks affect the adaptation channels.

The dynamic marginal effect of water availability on crop-livestock ratio is significantly negative at the two-period lag but turns to be positive at the three-period lag, implying that permanent increases in water availability will lead to temporary decreases but eventually permanent increases in the production of crops relative to livestock. Similarly, the positive marginal effects of water availability on capital-labor ratio at the one-period lag and two-period lag are partially offset by the negative marginal effect at the three-period lag so that the cumulative effect is still positive. Permanent increases in growing degree days will cause permanent increases in the production of crops relative to livestock and in the investment of capital relative to labor. Moreover, a joint test of water availability and growing degree days suggests that weather shocks tend to induce the adjustment of crop-livestock mix and capital-labor ratio. Based on these results, we confirm that weather shocks do influence the farming practices through variations in the output and input structures, and these changes can be used as the indicators of the channels through which farmers adapt to weather shocks.

5.2. Farm adaptation to weather shocks and dynamics of agricultural TFP

We now investigate how farmers' adaptive behaviors affect the dynamics of agricultural TFP through the two proposed channels. The error correction results suggest that the relationships between the regional TFP and the variables representing weather shocks are stable, after controlling for the regional economic conditions, such as the economic resource index, farmers' average education level, and the farm size.

The estimated results for all broadacre regions are shown in the second and third column of Table 5. The impact of the increased water-

[9] We rely on the assumption of the Granger causality test that cause precedes the effect and can help in forecasting the effect. As such, we regard the Granger causality between weather shocks and changes in output-mix and capital-labor ratio as farmers' adaptive behaviors.

[10] Following Lütkepohl (1993, p. 306), maximum lag length was set equal to the integer of $T^{1/3}$, that is, 3 in our dataset.

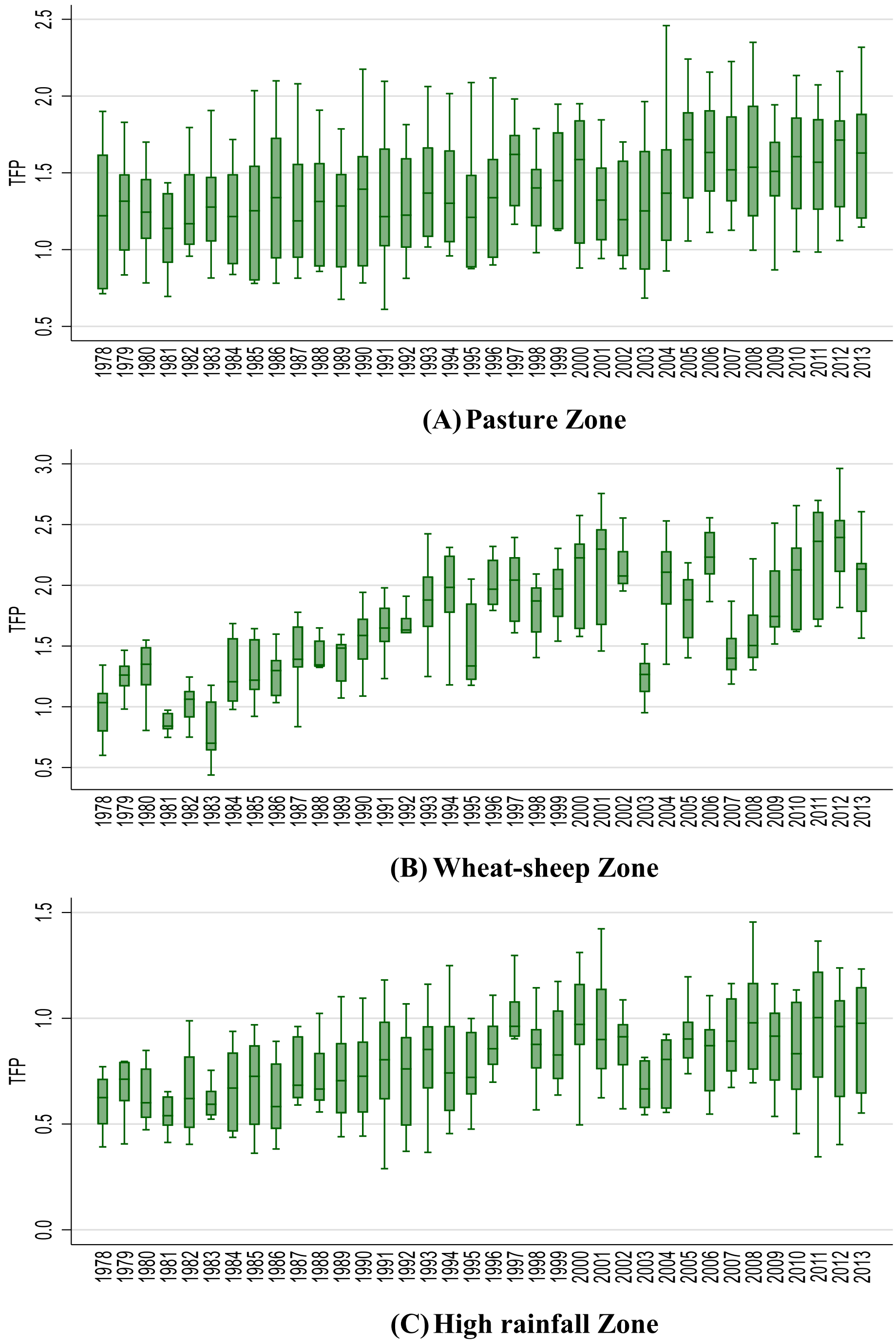

Fig. 3. Changes in TFP across zones over the period 1978–2013.

availability index on TFP is positive and the effect of the increased growing degree days on TFP is negative. Both of the estimated coefficients are significant at the 1% level. The effects of the water availability and the growing degree days are both larger in the long term than in the short term. In particular, a 1% increase in the water availability delivers a 0.31% gain in TFP in the following year, whereas in the long-term equilibrium, a 1% increase in water availability leads to a 0.41% increase in TFP. With a 1% increase in growing degree days, agricultural TFP decreases by 0.65% in the short term and decreases by 1.11% in the long term.[11]

Moreover, farmers can make adaptation to weather shocks through adjusting their input and/or output structures. As discussed in Section

[11] In our exercise, the long-run impact of climate variables on TFP could be larger than the short-run impact. The difference between the long run and the short run depends on whether the impact is on/off equilibrium, which is not only caused by adaptation behaviors but other economic or non-economic factors.

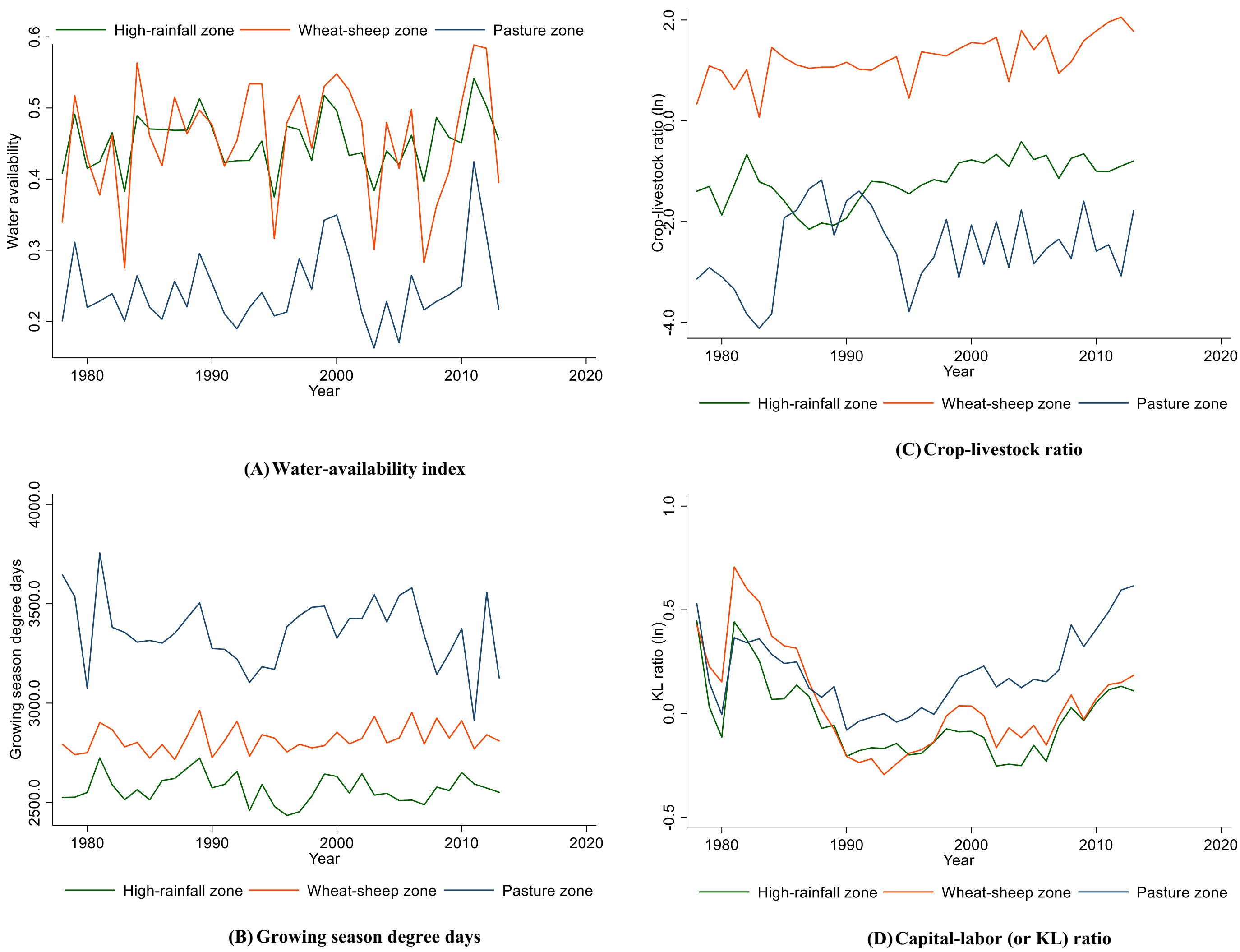

Fig. 4. Changes in weather variables, input and output structures across zones over the period 1978–2013.

2.2, the coefficients of the predicted crop-livestock mix and the predicted capital-labor ratio represent how farmers' adaption activities affect the dynamics of TFP through adjusting the output and input structures. Results show that an increase in capital-labor ratio contributes to TFP in the short term, since the estimated coefficients are positive and significant at the 10% level. This suggests that, in the face of weather shocks, farmers increase capital investment relative to labor in the short run as an attempt to recoup the loss. In this sense, policies that abate the adjustment costs of adaption, i.e., facilitating changes in the input structure, will help to compensate for the loss under weather shocks. Finally, while the estimated coefficients of the predicted crop-livestock mix are insignificant, it does not mean that this adaptation channel is not feasible. Because we model farmers' adaptive capacity using adjustment speed that reflects farmers' adaptation in a symmetric way either through adjusting output or input structures. The direct impact of adjusting output mix on TFP could be absorbed by adjusting input structure, which may not necessarily be significant in our econometric model.

Regarding other control variables, our results show that the availability of regional economic resources is an important determinant of TFP in the short run. This makes sense because generally farmers with more abundant economic resources are in a better position to combat with the unfavorable weather condition. An interesting observation is that farm size is negatively correlated with changes in TFP in the long term, suggesting smaller farms exhibit more flexibility than larger farms in response to weather shocks. The technology progress captured by using the time trend in the long term is positive and significant at the 1% level, indicating TFP growth being spurred by the technical progress — a result consistent with the findings of Chambers and Pieralli (2020) for the US agriculture.

Accounting for farmers' adaptation behaviors, agricultural TFP has a tendency to converge to its long-term level after weather shocks. This is confirmed by the negative error correction coefficient ($\varnothing' = -0.52$), which is statistically significant at the 1% level. This finding means that, after a serious reduction in water availability following a weather shock, the adjustment mechanism will bring agricultural TFP back to its long-term level in around 1.9 years at the adjustment speed of 52% a year.

5.3. *Cross-zone difference in the adaptive capacity*

To investigate whether farmers' adaptation capacities differ across farms in different climatic zones, we re-estimate Eqs. (7, 8) by using the sub-samples for the high rainfall zone, the wheat-sheep zone and the pasture zone respectively. The estimation results are shown in the rest columns of Table 5.

The water availability index has a significant and positive impact on the long term agricultural TFP in all the three zones. It is also true for the short-term impact except in the pasture zone. The growing degree days have a significant and negative impact on TFP across the three zones both in short run and long run. The impacts of both water and

Table 2
Hadri tests for non-stationary I(1) behavior for the panel data.

Data series	Levels		1st differences		2nd differences	
	Statistics	p-value	Statistics	p-value	Statistics	p-value
TFP (log)	15.061	0.000	−4.603	1.000		
Crop-livestock quantity ratio (log)	6.132	0.000	−4.711	1.000		
Crop-livestock price ratio (log)	12.798	0.000	−1.869	0.969		
Capital-labor quantity ratio (log)	46.658	0.000	−1.460	0.928		
Capital-labor price ratio (log)	55.855	0.000	15.672	0.000	−3.796	0.999
Water-availability index (log)	2.445	0.007	−4.964	1.000		
Growing degree days(log)	4.635	0.000	−5.036	1.000		
Economic resources index (log)	35.437	0.000	−0.776	0.781		
Operators' education attainment	26.925	0.000	−2.731	0.997		
Average farm size (log)	19.676	0.000	−2.900	0.998		

Note: Hadri tests examine unit roots accounting for heteroskedasticity across regions. The null hypothesis is that all panels contain unit roots. A time trend was included when testing for stationarity in levels.

Table 3
Co-integration test results.

	Some panels [a]		All panels [b]	
	Statistics	P-value	Statistics	P-value
Variance ratio	6.69	0.00	3.86	0.00

[a] The alternative hypothesis is that the variables are cointegrated in some of the panels.
[b] The alternative hypothesis is that the variables are cointegrated in all panels.

temperature shocks are larger in magnitudes in the long term than in the short term, consistent with the results obtained from using the full sample. The growing degree days have the largest impact on TFP for farms in the pastoral zone, medium impact in the wheat-sheep zone, and the smallest impact in the high-rainfall zone, as the former two zones are more sensitive to the accumulated temperature.

Adaptation through changing the output and input structures has imposed a significant impact on TFP for farms in the pasture zone in the short term, and a significant impact for farms in the high-rainfall zone and in the wheat-sheep zone in the long term. In particular, increasing the production of crop products relative to livestock products raises TFP growth in the long term for the high-rainfall zone, whereas decreasing the production of crops relative to livestock raises TFP growth in the long term for the wheat-sheep zone and in the short run for the pasture zone. This finding makes sense because farmers' typical response to a drought is to reduce the production of crops in favor of livestock (Zhao et al., 2012) and obviously, the wheat-sheep zone and the pasture zone have apparently less rainfall and are more sensitive to temperature than the high-rainfall zone.

Moreover, we also show that the impacts of weather shocks on TFP through the proposed farmers' adaptation channels differ substantially across regions. Decreasing the use of capital relative to labor to combat with the unfavorable weather condition is effective in boosting TFP in the long term for the farms in the high-rainfall and wheat-sheep zones

Table 4
Results of autoregressive distributed lag model.

Variables	Crop-Livestock Ratio		Capital-Labor Ratio	
	Coefficient	Standard Error	Coefficient	Standard Error
ln (output/input ratio)$_{t-1}$	0.169***	0.061	0.624***	0.031
ln (output/input ratio)$_{t-2}$	0.217***	0.035	0.207***	0.046
ln (output/input ratio)$_{t-3}$	−0.012	0.041	−0.056	0.035
ln (relative output/ input price)$_{t-1}$	−0.207	0.192	−0.405***	0.080
ln (relative output/ input price)$_{t-2}$	−0.117	0.216	0.073	0.063
ln(relative output/ input price)$_{t-3}$	0.091	0.229	0.102**	0.050
ln(water-availability index)$_{t-1}$	−0.243	0.158	0.047**	0.023
ln(water-availability index)$_{t-2}$	−0.300*	0.177	0.044**	0.019
ln(water-availability index)$_{t-3}$	0.456*	0.258	−0.085***	0.023
ln(growing degree days)$_{t-1}$	0.524	0.740	−0.134	0.164
ln(growing degree days))$_{t-2}$	0.386	0.697	0.255**	0.124
ln(growing degree days))$_{t-3}$	2.804***	0.742	0.394***	0.136
Constant	−32.462***	9.431	−4.421***	1.594

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and in the short run for the farms in the pasture zone. These findings indicate that, depending on the location of farms and their production structure, different adaption mechanisms were at play.

Finally, the speed of TFP recovering from the short-term impact of weather shocks to its long-term level differs across zones. The estimated error correction coefficient is −0.53, −0.65, and − 0.72 for farms in the high-rainfall zone, the wheat-sheep zone, and the pasture zone, respectively. In other words, it will take around 1.9, 1.5, and 1.4 years for farms in the three zones to adjust back to the long-run level. The adjustment speed of agricultural TFP to its long-term level after weather shocks is fastest for the pastoral zone and slowest for the high-rainfall zone, with the wheat-sheep zone ranking in the middle. It implies that farms in this zone are used to having unfavorable weather conditions and are able to adapt to weather shocks more quickly, which is corroborated by Chambers et al. (2020).

6. Robustness check

Our findings in the previous section have provided interesting insights on the impacts of farmers' adaptation on the dynamics of agricultural productivity in response to weather shocks. However, these findings depend on the accuracy of TFP and weather condition measurement. In order to ensure that our findings are sufficiently robust, we conducted a series of sensitivity tests.

The first concern is whether our estimation is sensitive to the method used to construct agricultural TFP. In this study, agricultural TFP was constructed using the Törnqvist-Theil index formula. As a robustness check, we estimate the regional TFP by using an alternative Fisher index and the regression-based method (Hulten, 2001). The empirical results based on the TFP estimates using the Fisher index are shown in Table 6. The direct impacts of weather variables and the identified adaptation channels are similar as what we have obtained before. The coefficients of the error correction for all samples and sub-samples across zones are slightly different in magnitudes but they are in agreement with the discussion reported in the previous sections. In particular, farms in the pastoral zone still adjust more rapidly than those in the wheat-sheep zone and the high-rainfall zone. This suggests that our modelling

Table 5
Farmers' adaptation and its impact on dynamics of agricultural TFP.

	All Samples		High-rainfall Zone		Wheat-sheep Zone		Pastoral Zone	
	LR	SR	LR	SR	LR	SR	LR	SR
Water-availability index (log)	0.413***	0.313***	0.574***	0.209***	0.583***	0.553***	0.265***	0.082
	(0.049)	(0.047)	(0.144)	(0.057)	(0.053)	(0.054)	(0.061)	(0.051)
Growing degree days (log)	−1.106***	−0.645***	−1.272***	−0.348***	−1.286***	−0.821***	−2.091***	−1.197**
	(0.257)	(0.178)	(0.318)	(0.118)	(0.398)	(0.153)	(0.672)	(0.552)
Crop-livestock mix (log)	−0.101	0.023	0.305*	0.102	−0.362***	0.019	−0.081	−0.139*
	(0.064)	(0.046)	(0.168)	(0.099)	(0.075)	(0.043)	(0.125)	(0.081)
Capital-labor ratio (log)	−0.125	0.369*	−1.856**	0.312	−1.398***	0.297	−0.047	−0.750**
	(0.306)	(0.221)	(0.851)	(0.424)	(0.363)	(0.232)	(0.502)	(0.339)
Economic resources index (log)	−0.132	1.773***	0.070	1.249**	−0.929***	1.090***	0.210	1.605**
	(0.190)	(0.326)	(0.263)	(0.600)	(0.273)	(0.348)	(0.307)	(0.785)
Operators' education attainment	−0.136	0.150	−0.228*	0.219**	0.127	0.466	0.037	−0.002
	(0.084)	(0.190)	(0.128)	(0.104)	(0.247)	(0.564)	(0.106)	(0.134)
Average Farm Size (log)	−0.073*	−0.042	−0.126*	−0.055	0.258***	0.152*	−0.110*	−0.115*
	(0.041)	(0.041)	(0.065)	(0.056)	(0.086)	(0.089)	(0.058)	(0.062)
Technical change	0.012***		0.011***		0.017***		0.009***	
	(0.001)		(0.002)		(0.002)		(0.001)	
Error Correction Coefficient		−0.519***		−0.528***		−0.647***		−0.721***
		(0.043)		(0.075)		(0.074)		(0.115)
Constant		8.005***		5.539***		21.629***		15.264***
		(0.673)		(0.789)		(2.473)		(2.421)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. "LR" stands for long-term effects, "SR" for short-term effects. The number of observations for high-rainfall zone, wheat-sheep zone and pasture zone are 240, 330 and 240, respectively.

Table 6
Farmers' adaptation and its impact on dynamics of agricultural TFP: using Fisher index for TFP.

	All Samples		High-rainfall Zone		Wheat-sheep Zone		Pastoral Zone	
	LR	SR	LR	SR	LR	SR	LR	SR
Water-availability index (log)	0.414***	0.313***	0.517***	0.197***	0.586***	0.554***	0.262***	0.081
	(0.049)	(0.047)	(0.141)	(0.057)	(0.054)	(0.053)	(0.061)	(0.051)
Growing Degree Days (log)	−0.984***	−0.616***	−1.082***	−0.326***	−1.229***	−0.793***	−2.119***	−1.217**
	(0.260)	(0.177)	(0.316)	(0.123)	(0.402)	(0.151)	(0.671)	(0.551)
Crop-livestock mix (log)	−0.088	0.027	0.286*	0.106	−0.354***	0.023	−0.087	−0.140*
	(0.065)	(0.046)	(0.164)	(0.097)	(0.076)	(0.043)	(0.125)	(0.081)
Capital-labor ratio (log)	−0.090	0.372*	−1.609*	0.394	−1.390***	0.300	−0.082	−0.754**
	(0.309)	(0.223)	(0.830)	(0.435)	(0.369)	(0.235)	(0.501)	(0.335)
Economic resources index (log)	−0.043	1.811***	0.169	1.280**	−0.924***	1.148***	0.243	1.609**
	(0.189)	(0.328)	(0.259)	(0.580)	(0.275)	(0.373)	(0.305)	(0.784)
Operators' education attainment	−0.105	0.148	−0.219*	0.211**	0.156	0.464	0.058	0.000
	(0.083)	(0.190)	(0.128)	(0.108)	(0.247)	(0.560)	(0.105)	(0.134)
Average Farm Size (log)	−0.076*	0.043	−0.121*	−0.053	0.261***	0.150*	−0.111*	−0.117*
	(0.041)	(0.041)	(0.064)	(0.057)	(0.087)	(0.088)	(0.057)	(0.062)
Technical change	0.011***		0.011***		0.017***		0.009***	
	(0.001)		(0.002)		(0.002)		(0.001)	
Error Correction Coefficient		−0.521***		−0.550***		−0.641***		−0.721***
		(0.043)		(0.073)		(0.074)		(0.116)
Constant		7.050***		4.491***		21.138***		15.621***
		(0.575)		(0.596)		(2.425)		(2.468)

The same notes as Table 5.

results are not sensitive to the index approach used for TFP estimates.

Another concern is whether we measure weather shocks in a proper way. In particular, the construction of growing degree days involves quite a number of assumptions, many of which may affect the estimation results but cannot be tested in this study. For example, we are unable to verify whether our models are sensitive to the setting of the optimal temperature range for plant growth. To deal with this problem, we replace growing degree days with intensity of average temperature over the growing season and re-do the exercise. Table 7 displays the results estimated by using the average temperature. The direct impact of the water-availability index on TFP is similar as the previous results except that the insignificant effect for the farms in the pasture zone in the short term becomes significant. When we use average temperature to replace the growing season degree days, the previously insignificant effect of adjusting the crop-livestock mix on TFP in the long term becomes significant, while the effect of changing the capital-labor ratio becomes insignificant. Still, our finding confirms that the adjustment speed of TFP is higher for the farms in the pastoral zone than those in the wheat-sheep and in the high-rainfall zones.

In sum, although the significance levels of the coefficients estimated using alternative data specifications differ to varying degrees, their signs remained unchanged and magnitudes are similar. These results suggest that our main findings about farmers' adaptation to weather shocks are quite robust.

7. Conclusions

In this paper, we investigate farmers' adaptation behaviors in response to weather shocks and their impact on the productivity of non-irrigated agriculture in Australia. Our main interest is in examining whether and how weather shocks (i.e., changes in water availability and the growing degree days) may cause agricultural TFP growth in the short term to first deviate and then converge to its long-term level. In addition, we have also examined the role of adjustments to the output mix and the

Table 7
Farmers' adaptation and its impact on dynamics of agricultural TFP: using average daily temperature.

	All Samples		High-rainfall Zone		Wheat-sheep Zone		Pastoral Zone	
	LR	SR	LR	SR	LR	SR	LR	SR
Water-availability index (log)	0.425***	0.324***	0.426***	0.198***	0.611***	0.565***	0.324***	0.090**
	(0.047)	(0.047)	(0.144)	(0.061)	(0.049)	(0.049)	(0.067)	(0.044)
Average temperature (log)	−1.246***	−0.569***	−1.522***	−0.234	−1.505***	−0.666***	−1.459	−1.368***
	(0.380)	(0.151)	(0.541)	(0.226)	(0.509)	(0.203)	(0.984)	(0.243)
Crop-livestock mix (log)	−0.136*	0.004	0.090	0.073	−0.357***	−0.015	−0.086	−0.154**
	(0.070)	(0.037)	(0.177)	(0.074)	(0.073)	(0.029)	(0.136)	(0.067)
Capital-labor ratio (log)	−0.198	0.208	−0.747	0.576	−1.556***	0.041	−0.102	−1.032***
	(0.307)	(0.212)	(0.719)	(0.410)	(0.360)	(0.176)	(0.580)	(0.273)
Economic resources index (log)	−0.244	1.700***	0.041	1.227**	−1.002***	0.903**	0.045	1.579**
	(0.193)	(0.333)	(0.276)	(0.549)	(0.261)	(0.445)	(0.331)	(0.623)
Operators' education attainment	−0.145	0.121	−0.204	0.250***	0.14	0.321	0.033	0.109
	(0.088)	(0.147)	(0.135)	(0.083)	(0.240)	(0.466)	(0.116)	(0.114)
Average Farm Size (log)	−0.067	−0.045	−0.146**	−0.051	0.267***	0.144	−0.101	−0.122*
	(0.043)	(0.044)	(0.067)	(0.055)	(0.082)	(0.091)	(0.062)	(0.064)
Technical change	0.012***		0.011***		0.018***		0.009***	
	(0.001)		(0.002)		(0.002)		(0.001)	
Error Correction Coefficient		−0.525***		−0.547***		−0.681***		−0.701***
		(0.041)		(0.070)		(0.071)		(0.109)
Constant		4.702***		3.180***		12.199***		4.960***
		(0.371)		(0.401)		(1.273)		(0.763)

The same notes as Table 5.

input ratio in affecting the dynamics of agricultural TFP. As the analysis is based on a panel data for 32 regions located in 3 climatic zones over 35 years, our findings also shed light on theTFP differences across regions.

We start the investigation by applying a panel error correction model to analyze the response of the aggregate TFP to weather shocks, after taking into account of the region-level heterogeneity in farm characteristics and economic conditions. We show that, in the short term, TFP tends to plunge deviating from its long-term level when an adverse weather condition strikes, but over time the short-term effects are likely to be subsumed into the long-term effects. The convergence was brought forward by farmers' efforts to adjust the input structure (or the capital-labor ratio) and the possibly enterprise choices (or the crop-livestock mix), which helps alleviate the weather-induced loss in productivity. This evidence suggests that farmers' adaptive activities have played an important role in Australia and their efforts to relieve farm businesses from the weather impact can be effective. To this end, government policies can also play a role to influence both the short-term and long-term outcomes (Zhao et al., 2021).[12]

Our finding also adds new insights to the interpretation of the observed differences in agricultural productivity across regions. We find weather conditions, the scale of operation, output mix and capital-labour ratio in the agriculture production are not only important determinants of agricultural productivity but also influence farmers' adaptive capacity. Farms adapt more rapidly to weather shocks in regions frequented by unfavorable climatic conditions than those located under better climate. The differences in the adaptive capacities across regions could widen the cross-region gap in agricultural productivity if weather shocks intensify and strike more frequently.

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Appendix A. A Theoretical Derivation on the Decomposition of Agricultural TFP

We assume that the production technology of a representative farmer takes the following transformation form

$$f(Y_1, \dots, Y_M, X_1, \dots, X_J; t) = exp(v) \tag{1a}$$

Take total differential of (1a) to get

$$\sum_m \frac{\partial lnf(X,Y,t)}{\partial lnY_m}\frac{dlnY_m}{dt} + \sum_{j=1}^{J} \frac{\partial lnf(X,Y,t)}{\partial lnX_j}\frac{dlnX_j}{dt} + \frac{\partial lnf(X,Y,t)}{\partial t} = \partial v \Big/ \partial t \tag{2a}$$

where $\frac{\partial lnf(X,Y,t)}{\partial t} \equiv \lambda_t$.

Rewrite (2a) as

$$\sum_{m=1}^{M} \lambda_{Y_m}\dot{Y}_m + \sum_{j=1}^{J} \lambda_{X_j}\dot{X}_j + \lambda_t = \partial v \Big/ \partial t \tag{3a}$$

[12] According to Zhao et al. (2021), government can influence agricultural productivity performance by directing policies at three areas: strengthening farmers' incentive to participate in market competition; providing a flexible environment to allow farmers to make production decisions without unnecessary impediments; encouraging farmers to build physical, human and financial capabilities.

where the dot over a variable indicates its rates of change. Furthermore, $\frac{\partial lnf(X,Y,t)}{\partial lnY_m} \equiv \lambda_{Y_m}$, $\frac{\partial lnf(X,Y,t)}{\partial lnX_j} \equiv \lambda_{X_j}$. To express (3a) in terms of TFP growth we rewrite (3a) as

$$\begin{aligned}
\lambda_Y\left\{\sum_{m=1}^{M}\left(\frac{\lambda_{Y_m}}{\lambda_Y}\right)\dot{Y}_m+\sum_{j=1}^{J}\left(\frac{\lambda_{X_j}}{\lambda_Y}\right)\dot{X}_j\right\}+\lambda_t &= \frac{\partial v}{\partial t}\Rightarrow\left\{\sum_{m=1}^{M}R_m\dot{Y}_m-\sum_{j=1}^{J}S_j\dot{X}_j\right\}+\left\{\sum_{m=1}^{M}\left[\left(\frac{\lambda_{Y_m}}{\lambda_Y}\right)-R_m\right]\dot{Y}_m+\sum_{j=1}^{J}\left(\frac{\lambda_{X_j}}{\lambda_Y}\right)\dot{X}_j+\sum_{j=1}^{J}S_j\dot{X}_j\right\}+\frac{\lambda_t}{\lambda_Y} \\
&= \frac{\frac{\partial v}{\partial t}}{\lambda_Y}\Rightarrow T\dot{F}P+\sum_{m=1}^{M}\left[\left(\frac{\lambda_{Y_m}}{\lambda_Y}\right)-R_m\right]\dot{Y}_m+\sum_{j=1}^{J}\left[\left(\frac{\lambda_{X_j}}{\lambda_Y}\right)-\left(\frac{\lambda_X}{\lambda_Y}\right)S_j\right]\dot{X}_j+(1-RTS)\sum_{j=1}^{J}S_j\dot{X}_j+\frac{\lambda_t}{\lambda_Y}=\frac{\frac{\partial v}{\partial t}}{\lambda_Y}\Rightarrow T\dot{F}P \\
&= (RTS-1)\sum_{j=1}^{J}S_j\dot{X}_j-(\lambda_t/\lambda_Y)-\sum_m Q_m\dot{Y}_m-\sum_m D_j\dot{X}_j+(\partial v/\partial t)\Big/\lambda_Y
\end{aligned} \tag{4a}$$

where $T\dot{F}P=\sum_m R_m\dot{Y}_m-\sum_j S_j\dot{X}_j$, $R_m=p_mY_m/\sum_m p_mY_m$, $S_j=w_jX_j/\sum_j w_jX_j$,

$$Q_m=\left[(\lambda_{Y_m}/\lambda_Y)-R_m\right], \mathrm{D}_j=\left[\left(\lambda_{X_j}/\lambda_Y\right)-(\lambda_X/\lambda_Y)S_j\right] \tag{5a}$$

This decomposes TFP change into scale effects, technology change, change in structure of output and/or input ratio (determined by their relative prices), and a residual component (which includes weather shocks and other exogenous factors). If output and input markets are competitive and the output and input structure are constant, the structure related components vanish.

If producers maximize profit subject to (1a), the first-order conditions of profit maximization are:

$$p_m+\frac{\mu\partial f}{\partial Y_m}=0\Rightarrow p_mY_m\Big/f(Y,X,t)=-\mu\lambda_{Y_m}$$

$$w_j+\frac{\mu\partial f}{\partial X_j}=0\Rightarrow w_jX_j\Big/f(Y,X,t)=\mu\lambda_{X_j}$$

Rewrite the above FOCs as

$$p_mY_m\Big/\sum_m p_mY_m\equiv R_m=\lambda_{Y_m}\Big/\sum_m\lambda_{Y_m}\equiv\lambda_{Y_m}\Big/\lambda_Y\Rightarrow Q_m=\lambda_{Y_m}\Big/\lambda_Y-R_m=0$$

$$w_jX_j\Big/\sum_m p_mY_m=-\lambda_{X_j}\Big/\lambda_Y=S_jC\Big/R\Rightarrow C\Big/R=-\lambda_{X_j}\Big/\lambda_Y\Rightarrow D_j=\lambda_{X_j}\Big/\lambda_Y$$

which in turn implies that $D_j=(\lambda_{X_j}/\lambda_Y)-(\lambda_{X_j}/\lambda_Y)S_j=0$ where $C=\sum_j w_jX_j$ and $R=\sum_m p_mY_m$.

This gives the following form of TFP change, viz.,

$$T\dot{F}P=(RTS-1)\sum_{j=1}^{J}S_j\dot{X}_j-\lambda_t\Big/\lambda_Y+\partial v\Big/\partial t\Big/\lambda_Y \tag{6a}$$

This expression shows that the TFP change can be broken down into scale, technical change and a residual component.

We can show that if there are allocative effects in input and output markets, the TFP change formula in (4) can be explicitly derived. If these effects are present in both markets, FOCs can be written as.

$$p_m^s+\mu\partial f/\partial Y_m\Rightarrow p_m^sY_m/f(Y,X,t)=-\mu\lambda_{Y_m}$$

$$w_j^s+\mu\partial f\Big/\partial X_j\Rightarrow w_j^sX_j\Big/f(Y,X,t)=\mu\lambda_{X_j}$$

where $p_m^s$and $w_j^s$are shadow prices for outputs and inputs, respectively. We can rewrite these FOCs as

$$\lambda_{Y_m}/\lambda_Y=R_m\theta_mR/R^s\equiv R_m-Q_m\Rightarrow Q_m=\lambda_{Y_m}/\lambda_Y-R_m\lambda_{X_j}/\lambda_Y=-S_j(C/R)(R/R^s)\kappa_j\equiv-S_j(C/R)+D_j\Rightarrow D_j=\lambda_{X_j}/\lambda_Y+S_j(C/R)=\left(\lambda_{X_j}/\lambda_Y\right)-(\lambda_X/\lambda_Y)S_j$$

where $p_m^s=p_m\theta_m$and $w_j^s=w_j\kappa_j$. If we use these results in the eq. (4a), we get the result

$$T\dot{F}P=(RTS-1)\sum_{j=1}^{J}S_j\dot{X}_j-\lambda_t\Big/\lambda_Y+\sum_m Q_m\dot{Y}_m+\sum_m D_j\dot{X}_j+(\partial v/\partial t)\Big/\lambda_Y$$

Thus, the two additional components $\sum_m Q_m\dot{Y}_m$ and $\sum_m D_j\dot{X}_j$capture the effects of distortions on TFP change.

Appendix B. A Detailed Discussion on Data Source for Weather Variables

Wheat and sorghum water-stress indexes

Wheat and sorghum water-stress indexes are derived from a water-balance model that takes into account soil moisture and crop water requirements. The model considers factors affecting water contained in the soil, including rainfall, evaporation, runoff and relevant attributes of soil quality (Potgieter et al., 2005, 2006). The model also accounts for water requirements for specific crop types during a fallow period, a sowing window, a development phase and a flowing/maturing period.

In aggregating the indexes to the regional level, shire-level agricultural land areas are used as weights. The cropping areas are obtained from the ABS Agriculture Census and Agricultural Surveys (ABS (various years), 2021a, b). The resulting crop water-availability index is an agriculture land area weighted average of the inverse of wheat and sorghum water-stress indexes.

Pasture growth index

We used the pasture growth index (Carter et al., 2000; Rickert et al., 2000) to measure the water availability for growth of native vegetation which is important for livestock grazing. The index is derived from a model of soil moisture and pasture growth that has been parameterised and validated with field data for a wide range of native vegetation across Australia. The model of soil moisture uses data of daily rainfall and evaporation to calculate run-off, soil evaporation, transpiration and drainage. Pasture growth is then modelled by considering growth requirements in terms of soil moisture, temperature and radiation.

Pasture growth index ranges from 0 (no growth) to 1 (maximum growth) and is calculated on a 0.05°x0.05° (approximately 5 × 5 km) grid across Australia on a daily basis. To represent average conditions for each region, we applied a weighted average across grid cells within each region and further averaged across months within the financial year. Each grid cell is assigned weights that reflect the proportion of total agricultural land within the region occupied by the grid cell. For this purpose, agricultural land data was accessed from the Australian Collaboration Land Use and Management Program (ACLUMP).

Temperature and rainfall data

The data used to calculate the daily average temperature and degree-days (and rainfall) at the growing seasons for each region are obtained from 8, 023 weather stations of the Bureau of Meteorology (BOM) (2015), which record rainfall, temperature (maximum and minimum), vapor pressure, solar exposure and NDVI at daily frequency between 1978 and 2013. The calculation of average temperature and degree-days involves two steps. First, each farm is paired with its closest weather station based on latitudinal and longitudinal information. Temperatures observed in the stations are used in the calculation for the farms in the pairs. Second, reginal temperature is estimated as the average across farms within a region, weighted by their total land areas multiplied by the associated AAGIS sample weights (Figure B1). In the calculation of regional level degree-days, this aggregation procedure produces two estimates: winter season degree-days and summer season degree-days. We combine these estimates into one measure – an average weighted by the land areas for summer and winter crops. It is to be noted that this procedure only affects the estimates for 6 out of 22 regions, because the rest are not significant producers of summer crops.

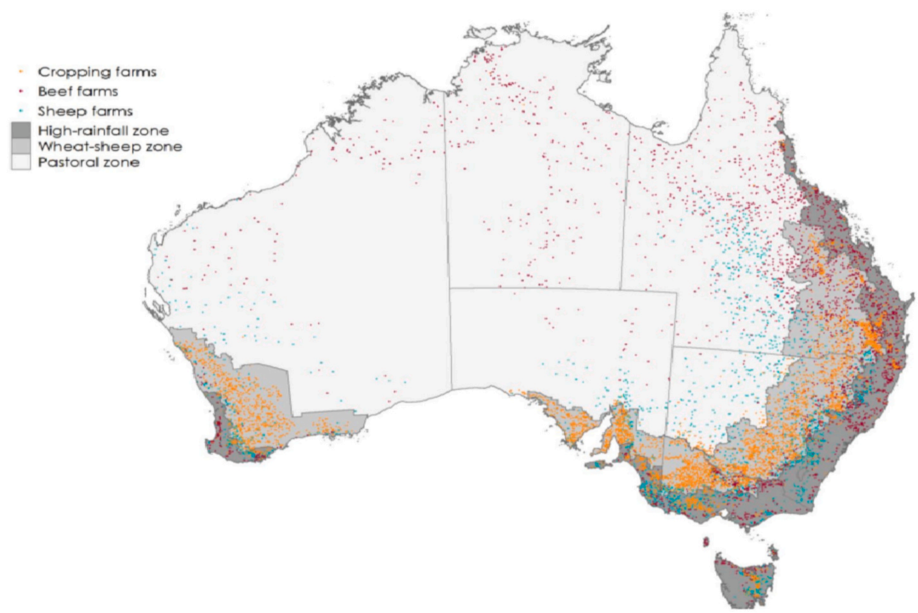

Fig. B1. Geographical distribution of AAGIS farms in Australian broadacre agriculture.
Source: ABARES.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105417.

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