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# Monitoring agricultural and economic drought: the Australian Agricultural Drought Indicators (AADI)

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**Abstract.** Drought events can have significant agricultural and economic impacts, and in many parts of the world their intensity appears to be increasing with climate change. However, drought measurement remains a highly contested space, with a multitude of indicators across both research and operational settings. This article presents a new drought monitoring and forecasting system: the Australian Agricultural Drought Indicators (AADI). Rather than use common meteorological indicators, AADI attempts to estimate specific agricultural and economic drought impacts. An integrated bio-physical and economic modelling system is developed, which translates gridded climate observations and forecasts into outcome-based indicators of crop yields, pasture growth and farm business profits. These indicators are validated against a range of ground-truth data drawn from survey and administrative sources. Results confirm the benefits of the outcome-based approach with the AADI showing higher correlation with both agricultural (crop yield, livestock fertility) and economic outcomes (farm profits, regional incomes) compared with rainfall measures. The novel farm profit indicator also shows promise as a predictor of drought induced financial stress and flow-on socio-economic impacts.

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## 1 Introduction

It is widely accepted that a universal definition of drought is, if not impossible, highly impractical (Wilhite & Glantz 1985, Mishra & Singh 2010, Lloyd-Hughes, 2014). Rather, drought is usually viewed in-terms of its specific impacts: 'agricultural drought' (e.g., crop failure or pasture loss), 'hydrological drought' (e.g., low stream flow or dam storage) or 'economic drought' (e.g., reduced farm profits, income, jobs etc.) (Wilhite & Glantz 1985). While these impacts are all somewhat dependent on rainfall deficit (i.e., 'meteorological drought') each are the product of unique bio-physical and human processes, and as such are imperfectly correlated with each other.

As a result, a multitude of drought indicators have emerged both in the research literature and among operational systems, however, as Bachmair et al. (2016) note: "often with little consideration of which are most meaningful for describing drought impacts". Validation of new indicators against ground-truth data is not common, with research often limited to indicator-indicator comparisons (Bachmair et al. 2016). Further, the selection of indicators for operational systems, often reflects pragmatic factors (such as data availability and common practice) more than systematic assessment (Bachmair et al. 2016).

Among operational systems there has been a trend toward composite or weighted average indicators, typically referred to as "Combined Drought Indicators" (CDIs). Examples include: the US Drought Monitor, the European Drought Observatory (see Cammalleri et al. 2021) and in Australia the NACP Drought Monitor (Guillory et al. 2023) and the NSW Enhanced Drought Information System (EDIS). However, the design and interpretation of composite indicators remains somewhat subjective, and systematic validation is uncommon (Bachmair et al. 2016).

This study presents a new operational drought measurement and forecasting system: the Australian Agricultural Drought Indicators (AADI). This system measures agricultural drought impacts via an integrated bio-physical and economic modelling system. AADI combines existing models including APSIM (Holzworth et al. 2014) to simulate crop yields, AussieGRASS (Carter et al. 2000) and GrassGro (Moore et al. 1997) to simulate pasture growth, with these outputs then linked to the *farmpredict* model (Hughes et.al 2022b) to simulate farm business profits. These models form an operational system, which translates gridded climate observations and forecasts into outcome-based indicators, including: winter and summer crop yields, pasture growth and farm profits.

While the AADI approach differs from most comparable systems, the concept of outcome-based drought indicators is not a new one. In Australia, historical reliance on rainfall percentiles as drought indicators (Gibbs and Maher 1967) has long been criticised given limited correlation with agricultural and economic outcomes in practice (Wilhite & Glantz 1985, Hughes et al. 2022). Economists have frequently argued drought indicators should be developed consistent with policy goals (i.e., economic drought programs should be informed by economic indicators, see Thompson and Powell 1998, Nelson et al., 2007,

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Hughes et al. 2022)[1]. While current operational systems mostly use meteorological indicators (Bachmair et al. 2016) outcome-based measures are not without precedent[2], further within the research literature crop yield indicators are relatively common (see Stephens 1998, Diodato and Bellocchi 2008).

More novel is the inclusion in AADI of a farm profit indicator, as proposed by Hughes et al. (2022). Here the *farmpredict* model is used to simulate sequences of farm profits based on climatic and bio-physical (crop and pasture growth) inputs for representative farms at each location. While AADI does not employ a CDI as such, the farm profit indicator performs a similar role, integrating a diverse range metrological and agricultural data into a single value. In contrast with a CDI farm profit has a clear conceptual basis and can also be easily validated against real-world data.

In Australia, drought indicators have historically been associated with agricultural subsidy programs, leading to a decline in their popularity (see Hughes et al. 2024). This is despite a long-term shift in Australian drought policy away from short-term relief, towards preparedness and resilience, more or less in line with the recommendations of the research community (see Freebairn 1983, Botterill and Hayes 2012, Wilhite et al. 2014). The 2018-2020 Australian drought events led to a re-evaluation however, with subsequent inquiries recognizing the value of indicators in supporting preparedness and encouraging proactive responses from government (see Commonwealth of Australia 2021). AADI has been developed to complement this more modern policy focus, acting as a Drought Early Warning System in the sense of Whittle et al. (2014), albeit with an emphasis on government users (see Hughes et al. 2024).

Forecasting aspects of AADI, including estimates of forecast skill at various lead times, are presented in a separate article (Schepen et al. 2024, in prep). In this article we provide an overview of the AADI system, its component models, input data and key assumptions. We then provide detailed validation results to assess how well these indicators are correlated with observed agricultural (crop yield, livestock fertility) and economic (farm profit, regional income) outcomes, drawing on a range of historical survey and administrative data. For reference, the validation performance of AADI is contrasted with that of rainfall percentiles.

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[1] A recent example of this issue is the operation of the Australian Drought Communities Program during 2018-20., which program provided government funding to drought affected regions, using rainfall percentiles to determine eligibility with mixed success (see Commonwealth of Australia 2021).

[2] In Australia, the former National Agricultural Monitoring System (NAMS) included crop and pasture growth indicators (Sovold et al. 2009), while the NSW EDIS includes a plant growth index in its CDI.

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## 2 Methods

### 2.1 The Australian Agricultural Drought Indicators (AADI) system

The Australian Agricultural Drought Indicator (AADI) system translates spatial climate data and forecasts into predictions of local agricultural outcomes (Figure 1). The AADI system takes gridded historical and forecast climate data as inputs to agricultural simulation models, given other data and assumptions on the types of soil, pasture and agricultural activity prevailing at each grid cell, these models predict agricultural outcomes including: pasture growth via the AussieGRASS system (Carter et al. 2000) and the GrassGro model (Moore et al. 1997, Donnelly et al. 2016); winter and summer crop yields via APSIM (Holzworth et al. 2014) and farm business profits via the *farmpredict* model (Hughes et.al 2022b).

The AADI system operates on a monthly cycle; at the beginning of each month, observed indicators are updated given observed weather data to the end of the previous month and forecast indicators are projected forward using the latest climate forecasts. The indicators are generated across Australia for a defined 'agricultural zone' (visible Figure 1, right), which excludes areas with no agricultural activity (e.g., protected reserves, forests etc., see Hughes et al. 2024).

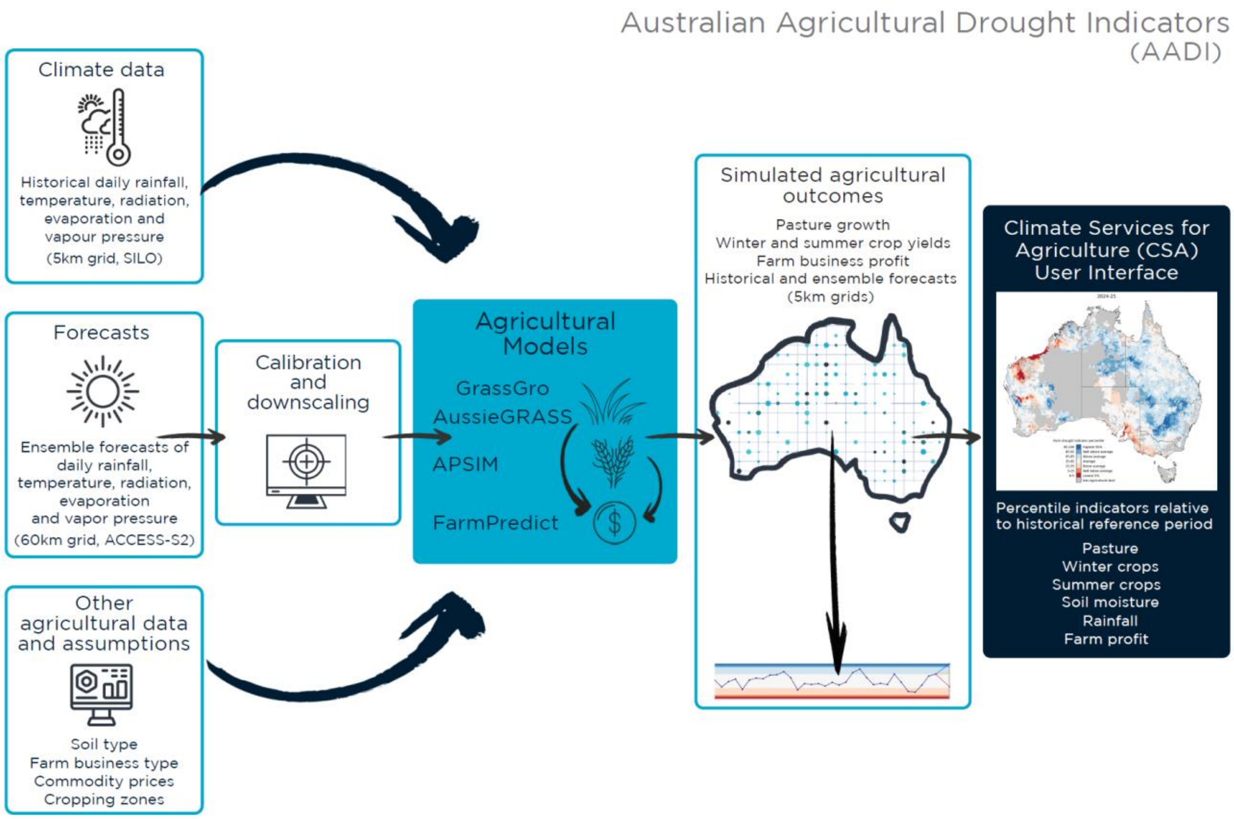


**Figure 1: Overview of the Australian Agriculture Drought Indicators system**

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The final indicators are presented as percentile statistics, comparing current and forecast conditions at each location to a rolling 33-year historical reference period. Given the long-term effects of climate change on Australian temperatures and rainfall (see BoM and CSIRO, 2022), older climate data are now less relevant for benchmarking current conditions or defining drought (see Hughes et al. 2022). This rolling 33-year reference period is intended to strike a pragmatic balance: attempting to represent the present-day climate, while being long enough to characterize climatological variability at each location.

indicators are available for specific grid cells but can also be aggregated to produce regional estimates (at national, state or LGA level), with weightings to account for the relative amount of agricultural activity at each location (see Hughes et al. 2024).

A User Interface (Figure 2) was developed to present AADI results, building on the existing Climate Services for Agriculture (CSA) platform, which also hosts the separate MyClimateView app (https://myclimateview.com.au/, see Malakar et al. 2024). The user interface design focused exclusively on government users, particularly staff engaged in the implementation of drought response programs (see Hughes et al. 2024). Key components of the AADI system are summarized below, with further documentation provided in Hughes et al. (2024).

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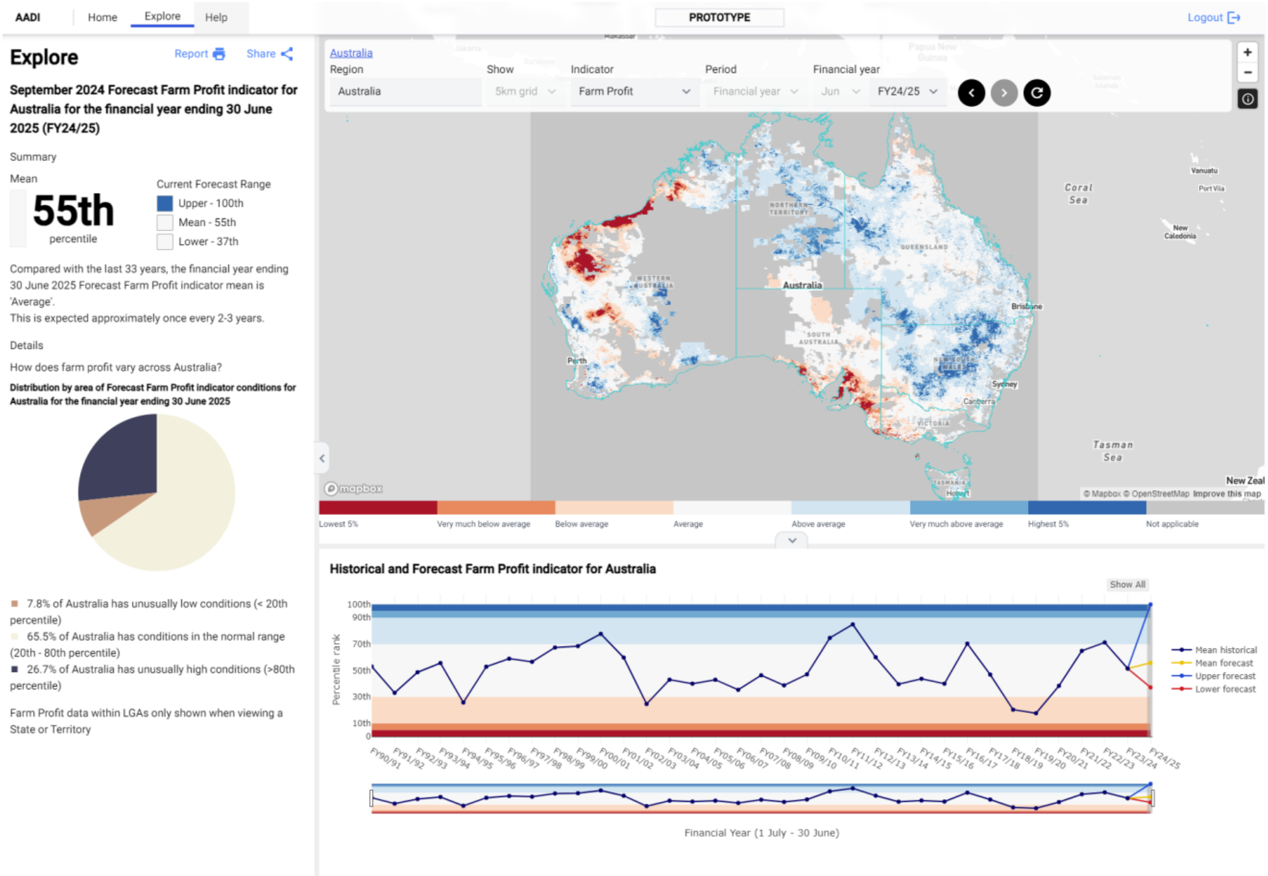


**Figure 2: Australian Agricultural Drought Indicators User Interface (national farm profit indicator forecast for 2024-25, on 1 September 2024)**

### 2.1.1 Climate data

The AADI system operates on an 0.05-degree (approximately 5km) grid drawing on interpolated historical daily weather data from the SILO database (Jeffery et al. 2001). Weather variables used in AADI include: rainfall (mm), minimum and maximum temperature (oC), shortwave radiation (MJ/m2), vapour pressure (hPa) and evaporation (mm).

Seasonal weather forecasts are obtained from the Bureau of Meteorology (BoM) Australian Community Climate and Earth-System Simulator Seasonal (ACCESS-S2) model (Wedd et al. 2022). The ACCESS-S2 is a global climate model operating on coarse 60km to 80km grid. The AADI system includes a custom forecast downscaling and calibration approach (outlined in detail by Schepen at al. 2024).

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### 2.1.2 Soil data

The simulation models require a range of input data in addition to climate observations, including soil types, pasture types, livestock densities, and farm business characteristics (e.g., farm size and enterprise mix). To support the AADI system, several new data layers were developed to provide the required bio-physical, agronomic and economic features at a grid scale.

Available state soil measurement datasets were combined to create new national high-resolution (90 m2) functional soil type maps for Australia (Figure A1). The new soils maps adopt the Soil Generic Groups classification system which divides Australian soils into 18 functional groups each with distinct hydrologic properties that are required for crop and pasture modeling (Bartley et al., 2013).

The development of a national soil type map involved applying Digital Soil Mapping (DSM) (McBratney et al., 2003) methods to data from the National Soil Site Collation (NSSC) (Searle, 2014) along with other spatial environmental data. The approach involved application of machine learning (random forests) to predict the probability of each of the 18 soil types existing at each location.

### 2.1.3 Farm business data

For the AADI a new synthetic dataset of farm business information was developed, to provide inputs for *farmpredict* simulations. This synthetic data was derived from the annual Australian Agricultural and Grazing Industry Survey (AAGIS). AAGIS provides a rotating stratified sample of Australian broadacre (extensive crops and grazing) businesses, of around 1,600 farms per year. For AADI, the most recently available 10 years (2012-13 to 2021-22) of AAGIS data were used.

The new synthetic farm data was developed using a distance weighted gaussian kernel interpolation method. To protect the privacy of survey participants, a degree of random perturbation is applied to AAGIS data prior to interpolation. This process yields a set of synthetic or representative farm businesses data (one farm per grid cell) reflecting the "typical" broadacre farm at a given location, based on AAGIS farm businesses observed in proximity to that location in recent years (see Figure A2).

### 2.1.4 Crop simulations

Cropping simulations make use of The Agricultural Production Systems sIMulator (APSIM) (Holzworth et al. 2014), specifically APSIM Next Generation 2022.12.7128 (Holzworth et al. 2018). Water-limited crop yield simulations are produced for wheat and sorghum: the two most common winter and summer broadacre crops in Australia. Water-limited yield represents yield that can be achieved using current best practices, technology and genetics for rainfed crops.

APSIM simulations are based on daily historical and forecast climate data along with soil type data and management rules. To calibrate initial soil conditions, all APSIM runs begin with a 15 year 'spin-up' period which allow state variables to reach equilibrium. Wheat and sorghum simulations are undertaken for each grid cell within the defined winter and summer cropping zones (see Figure A4). Simulations were conducted for multiple soil types in each grid cell, with results presented as an area-based weighted average. Crop sowing and fertiliser application rules for wheat and sorghum were specified on a regional basis (see Hughes et al. 2024). For wheat, simulations are based on the cultivar with the highest average grain yield at each grid cell, derived from historical (1989-90 to 2021-22) simulations of seven cultivars. All sorghum simulations are based on the 'Buster' cultivar using an historically optimized plant density at each grid cell. Cropping simulations use historical mean CO2 levels (Lan et al., 2022) for each year from 1988 (see NOAA 2023).

#### 2.1.5 Pasture Simulations

AADI pasture simulations make use of both the GrassGro model (Moore et al. 1997, Donnelly et al. 2016) and the AussieGRASS system (Carter et al. 2000). GrassGro is a process-based model that simulates pasture dynamics in response to grazing pressure from sheep or cattle under a specified enterprise type and management scenario. GrassGro is point-based and configured for a specific paddock and runs on a daily time step. AussieGRASS is a spatial implementation of the GRASP model (Rickert et al. 2000) of pasture growth developed to operate on an 0.05-degree grid across Australia. Within AADI, GrassGro was applied to simulate pasture growth for improved pastures across the Australian wheat-sheep and high rainfall zones, while AussieGRASS is used for the Australian pastoral or 'rangelands' zone (Figure A3).

As with APSIM, GrassGro simulations make use of Digital Soil Mapping derived from the NSSC, while AussieGRASS relies on an older soil dataset (Northcote 1988; 1979). Pasture simulations make use of daily-timestep historical and forecast climate data (rainfall, temperature and solar radiation) with AussieGRASS also requiring vapour pressure and potential evaporation. As with APSIM, both models employ a 'spin-up' simulation period to initialize soil and pasture conditions. Other model assumptions including pasture composition, grazing pressure (i.e., stocking rates), tree density and fire scars (in the case of AussieGRASS), are detailed in Hughes et al. (2024).

#### 2.1.6 Farm business simulations

Farm business simulations are derived using *farmpredict* (Hughes et al. 2022b): a statistical micro-simulation model of Australian broadacre farming businesses based on data from the AAGIS. The *farmpredict* model simulates production and financial outcomes at a farm business scale, given each farm's characteristics (e.g., its location, size, industry, capital and livestock holdings), prevailing climate conditions and commodity prices.

The model employs a machine learning approach (a multi-variable xgboost stack, see Hughes et al. 2022b), to develop statistical links between farm production, climate and prices. A sample of around 45,000 observations from the AAGIS over the period 1991-92 to 2021-22 is used to train the model, with each farm linked via geocoding to historical SILO data. The model predicts crop and livestock outputs, input use and stock (inventory) holdings (including livestock on-farm crop and wool storage). These outcomes are then combined within an accounting framework to simulate farm profit (see Hughes et al. 2022b).

For AADI, *farmpredict* was updated to take bio-physical data as inputs alongside existing weather data (i.e., rainfall and temperature), including simulated APSIM wheat and sorghum yields, and simulated pasture variables from AussieGRASS

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(including pasture growth, Total Standing Dry Matter (TSDM), green leaf mass and pasture growth days). For the AADI *farmpredict* is applied to synthetic farm business data (Section 3.1.1), which defines a single farm for each grid cell.

The farm profit indicator presented in the current AADI UI is based on a 'climate only' scenario which, consistent with Hughes et al. 2022, isolates the effects of climate variability on farm profits. In these simulations, global output and input prices are held fixed (although the spread between domestic and global grain prices can vary in response to climate data, to capture domestic price increases in drought years, see Hughes et al. 2022). A second scenario ("with prices") was also developed which allows for annual variation in output and input prices along with climate variability. For this scenario, historical prices were de-trended, to account for long-term trends in real output and input prices (particularly increases in sheep and lamb output prices).

As shown in Figure 3 the inclusion of commodity price effects has a significant influence on the results. While both indicators identify the similar drought years at a national scale (2002-03, 2006-07, 2018-19 and 2019-20) the relative rankings vary: price effect lessens the severity of the 2018-19 drought (as commodity prices were favourable) and increases the severity of the 2006-07 drought (which coincided with low commodity prices). More recently 2023-24 was an adverse year for farm businesses due to a dramatic fall in Australian livestock prices (compounded by below average climate conditions).

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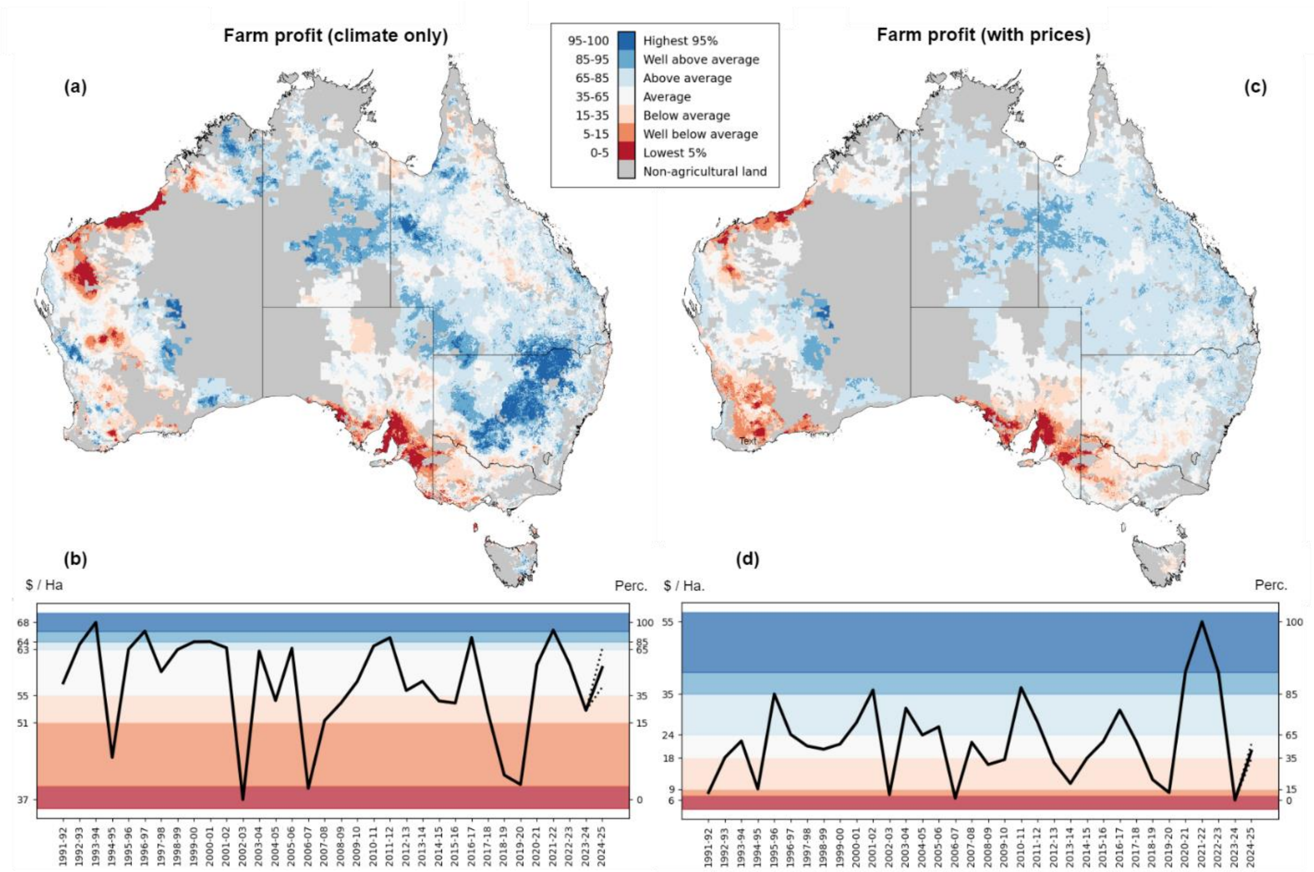


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**Figure 3. (a) AADI farm profit (climate only) indicator forecast for 2024-25 as at October 2024. (b) AADI national average farm profit (climate only) indicator timeseries 1991-92 to 2024-25. (c) AADI farm profit (with prices) indicator forecast for 2024-25 as at October 2024. (d) AADI national average farm profit (with prices) indicator timeseries 1991-92 to 2024-25.**

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### 2.2 Validation

The accuracy of the AADI can be assessed along two main dimensions: 'forecast skill' and 'indicator skill'. Here forecast skill refers to ability of forecasts at various lead times to reflect end-of-period (i.e., crop season or financial year) values, which depends on both weather forecast skill and the effects of antecedent conditions. AADI forecast skill is considered in detail in Schepen et al. (2024). Here the focus is on indicator skill: the extent to which end-of period indicators (derived from observed climate data) are correlated with real-world outcomes.

In the absence of forecast error, indicators will still differ from on-the-ground outcomes (e.g., crop yields, farm profits) due to a combination of model error and input data error. Each of the simulation models used in the AADI system (APSIM, AussieGRASS, GrassGro, and *farmpredict*) have been previously calibrated and validated against specific site data. However, simulating models on a grid introduces additional error, since gridded agricultural data (such as soil type and farm business details) need be interpolated from a limited number of site observations (Richetti et al., 2024). Weather data are also subject to interpolation error given a limited number of weather station sites.

#### 2.2.1 Data sources

In this study, we validate AADI against a range of public small-region observational data drawn from a range of sources (Table 1). These observational data are compared with historical AADI percentile values (for the period 1990-91 to 2021-22) aggregated to match the same regional scales. In addition to the four indicators in the current AADI UI ("climate only" farm profit, pasture growth, winter crop yield and summer crop yield) we also consider the "with prices" farm profit indicator, the AussieGRASS pasture biomass (Total Standing Dry Matter) indicator and rainfall percentiles. In Appendix A, we also present correlation maps at the grid scale comparing AADI data against interpolated AAGIS variables.

Agricultural production data are obtained from annual ABS and ABARES surveys, including a range of regional data from AAGIS (Figure 9) over the period 1990-91 to 2022-23 (Table 1).

To test whether these indicators have predictive power beyond the farm level, we also consider a socio-economic data at the Local Government Area (LGA) taken from the ABS "Data by region" product (see Table 1). The ABS "data by region" is relatively new dataset derived largely from administrative data, and offers small region estimates for a selection of recent years. Administrative data is also obtained on the number of claims made by Australian farmers under the Farm Household Allowance (FHA) program (https://www.agriculture.gov.au/agriculture-land/farm-food-drought/drought/farm-household-allowance) at the LGA level since 2014-15.

Annual LGA level socio-economic data are subject to regression analysis to estimate the marginal effect of low (below 10th percentile) indicator values on socio-economic outcomes. Here, for each indicator and socio-economic measure, a fixed-effects regression is estimated, including a binary variable for percentile values less than 10, along with regional identifiers (fixed effects) and a linear time trend. An additional control variable is included for the mortality regression model: state level covid death rates (with data obtained from the Australian Government NINDSS 2024).

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Table 1. Regional observation data, sources and summary statistics

| Variable | Source | Units | Year range | Region | Sample | Mean | S.D. |
|---|---|---|---|---|---|---|---|
| Annual FHA claims lodged (per total number of agricultural businesses) | DAFF | No. | 2014-15 to 2022-23 | LGA | 3,789 | 0.03 | 0.14 |
| House transfers per 1000 population | ABS | No. / 1000 | 2015-16 to 2020-21 | LGA | 2,322 | 15.13 | 5.97 |
| Dwelling transfers | ABS | No. / 1000 | 2015-16 to 2020-21 | LGA | 1,402 | 2.92 | 2.42 |
| Personal insolvencies | ABS | No. / 1000 | 2016-17 to 2020-21 | LGA | 1,561 | 1.21 | 0.86 |
| Job numbers per capita | ABS | No. | 2015-16 to 2019-20 | LGA | 2,123 | 0.72 | 0.15 |
| Agricultural job numbers per capita | ABS | No. | 2015-16 to 2019-20 | LGA | 2,095 | 0.07 | 0.06 |
| Total employee income per capita | ABS | $'000 | 2015-16 to 2019-20 | LGA | 2,052 | 23.59 | 7.30 |
| Total unincorporated business income per capita | ABS | $'000 | 2015-16 to 2019-20 | LGA | 2,010 | 3.79 | 4.42 |
| Total income per capita | ABS | $'000 | 2015-16 to 2019-20 | LGA | 2,043 | 29.19 | 8.10 |
| Small business exits (turnover < 200,000) | ABS | No. / 1000 | 2018-19 to 2021-22 | LGA | 1,468 | 21.16 | 31.27 |
| Births per 1000 population[a] | ABS | No. / 1000 | 2016 to 2021 | LGA | 2,513 | 11.89 | 3.86 |
| Deaths per 1000 population[a] | ABS | No. / 1000 | 2016 to 2021 | LGA | 2,426 | 8.09 | 3.09 |
| Net internal migration | ABS | No. / 1000 | 2016 to 2021 | LGA | 2,522 | 10.86 | 10.32 |
| Wheat yield | AAGIS | t / ha | 1990-91 to 2021-22 | AAGIS | 602 | 1.99 | 1.00 |
| Sorghum yield | AAGIS | t / ha | 1990-91 to 2021-22 | AAGIS | 129 | 2.87 | 2.06 |
| Farm business profit | AAGIS | $'000 | 1990-91 to 2021-22 | AAGIS | 919 | 145 | 383 |
| Farmer seasonal conditions assessment | AAGIS | 0-4 | 1990-91 to 2021-22 | AAGIS | 961 | 2.34 | 0.91 |
| Farmer drought assessment | AAGIS | 0-1 | 1990-91 to 2021-22 | AAGIS | 961 | 0.20 | 0.27 |
| Livestock fertility (net birth rates)[b] | AAGIS | No. | 1990-91 to 2021-22 | AAGIS | 961 | 0.32 | 0.09 |

ABS: Australian Bureau of Statistics (2023) Data by region https://dbr.abs.gov.au/; AAGIS: Australian Agricultural and Grazing Industry Survey (AAGIS) https://www.agriculture.gov.au/abares/research-topics/surveys/farm-definitions-methods; DAFF: Australian Government Department of Agriculture, Fisheries and Forestry;

[a] Demographic variables are calendar years 01 Jan. to 31 Dec. All other data are financial years 01 July to 30 June. Demographic data are linked to financial year data (ending 30 June in that year), allowing for some lag between drought impacts and demographic changes.

[b] Beef cattle and sheep births less deaths relative to total opening stock, with beef cattle converted to Dry Sheep Equivalents (DSE).

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## 3 Results

### 3.1 Indicator skill

Correlation between the drought indicators and relevant agricultural outcomes is summarised in Tables 2 to 3 and Figures 6 to 8. It is important to note that AADI historical percentiles are based on model scenarios which hold technology and management practices fixed and simulate historical climate (and price) variability. Further, outcome data have not been subject to de-trending or any other calibration. As such these correlation scores are intended purely for measuring the relative performance of the indicators (rather than an absolute assessment of the AADI system).

As shown in Table 2 and Figure 9, the farm profit (with prices) indicator has by far the strongest correlation with historical farm profit data with a mean correlation of 0.67 at a regional scale. The inclusion of commodity price variability leads to a significant improvement in skill, relative to the farm profit (climate only) indicator (mean regional correlation of 0.43), although the climate-only indicator still yields a non-trivial improvement over a simple rainfall percentile (mean regional correlation of 0.25).The inclusion of commodity price effects tends to yield a larger gain in skill in livestock dominant regions (coastal, high-rainfall zones and inland, pastoral zones) given the greater relative exposure of these farms to price risk.

Correlation maps (Figure 9) show that the skill of the profit indicators tends to be higher in eastern Australia, with lower correlation observed in parts of South Australia (SA) and Western Australia (WA) along with far north Queensland. Appendix A presents higher resolution correlation maps using interpolated observational data (Figure A3 and A4). These maps highlight some more specific areas of low correlation including the SA Yorke peninsula (Figure A4)

Table 2 presents correlation against agricultural production outcomes including, wheat yields, sorghum yields and livestock fertility (net birth rates). Assessments of pasture indicators are difficult, given the lack of ground truth data (pasture observations). Here we rely on two proxies: livestock fertility and farm profits. The results show better skill for the AussieGRASS TSDM indicator compared with the AADI pasture indicator, with higher correlations for both livestock fertility and farm profit data. The TSDM measure shows larger gains in parts of NSW, Vic. and WA (Figure 7). While correlation with livestock fertility rates is relatively low (especially in cropping regions) both pasture indicators offer gains compared with rainfall percentiles.

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Table 2. Correlation with observed farm profit 1990-91 to 2022-23 at regional, state and national scales

| | | Farm profit (AADI) | Farm profit (with prices) | Pasture (AADI) | Pasture (TSDM) | Rainfall (Jul-Jun.) |
|---|---|---|---|---|---|---|
| Regional (AAGIS) | 25th | 0.30 | 0.57* | 0.19 | 0.34 | 0.08 |
| | 50th | 0.47 | 0.69* | 0.30 | 0.47 | 0.24 |
| | 75th | 0.55 | 0.76* | 0.46 | 0.53 | 0.46 |
| | Mean | 0.43 | 0.67* | 0.30 | 0.44 | 0.25 |
| State | NSW | 0.63 | 0.76* | 0.51 | 0.71 | 0.57 |
| | Vic. | 0.37 | 0.80* | 0.41 | 0.60 | 0.29 |
| | QLD | 0.44 | 0.80* | 0.35 | 0.34 | 0.46 |
| | SA | 0.29 | 0.58* | 0.21 | 0.24 | 0.18 |
| | WA | 0.18 | 0.47* | 0.06 | 0.40 | -0.04 |
| | Tas. | 0.45 | 0.76* | 0.26 | 0.31 | 0.12 |
| | NT | 0.31 | 0.66* | 0.38 | 0.31 | 0.06 |
| National | | 0.31 | 0.69* | 0.25 | 0.48 | 0.25 |

* Indicator with highest correlation

Table 3. Correlation with observed crop and livestock productivity 1990-91 to 2022-23 at regional, state and national scale

| | | Wheat yield | | Sorghum yield | | Livestock fertility | | |
|---|---|---|---|---|---|---|---|---|
| | | Wheat (AADI) | Apr.-Oct. rainfall | Sorghum (AADI) | Apr.-Mar. rainfall | Pasture (AADI) | Pasture (TSDM) | Jun.-Jul rainfall |
| Regional (AAGIS) | 25th | 0.39 | 0.43* | 0.55* | 0.45 | -0.07 | 0.10* | -0.09 |
| | 50th | 0.64* | 0.60 | 0.59* | 0.50 | 0.10 | 0.21* | 0.11 |
| | 75th | 0.77* | 0.76 | 0.64* | 0.58 | 0.30 | 0.46* | 0.30 |
| | Mean | 0.55 | 0.60* | 0.59* | 0.52 | 0.14 | 0.24* | 0.13 |
| State | NSW | 0.83 | 0.85* | 0.74 | 0.79* | 0.32 | 0.67* | 0.44 |
| | Vic. | 0.69 | 0.78* | | | -0.09 | 0.18* | -0.09 |
| | QLD | 0.79* | 0.67 | 0.74* | 0.55 | 0.50 | 0.50* | 0.60 |
| | SA | 0.81 | 0.84* | | | 0.10 | 0.04 | 0.16* |
| | WA | 0.76 | 0.80* | | | 0.07 | 0.21* | 0.00 |
| | Tas. | 0.40* | 0.17 | | | -0.02 | 0.02* | -0.02 |
| | NT | | | | | 0.12 | 0.28* | -0.11 |
| National | | 0.85* | 0.76 | 0.81* | 0.71 | 0.20 | 0.49* | 0.31 |

*Indicator with highest correlation

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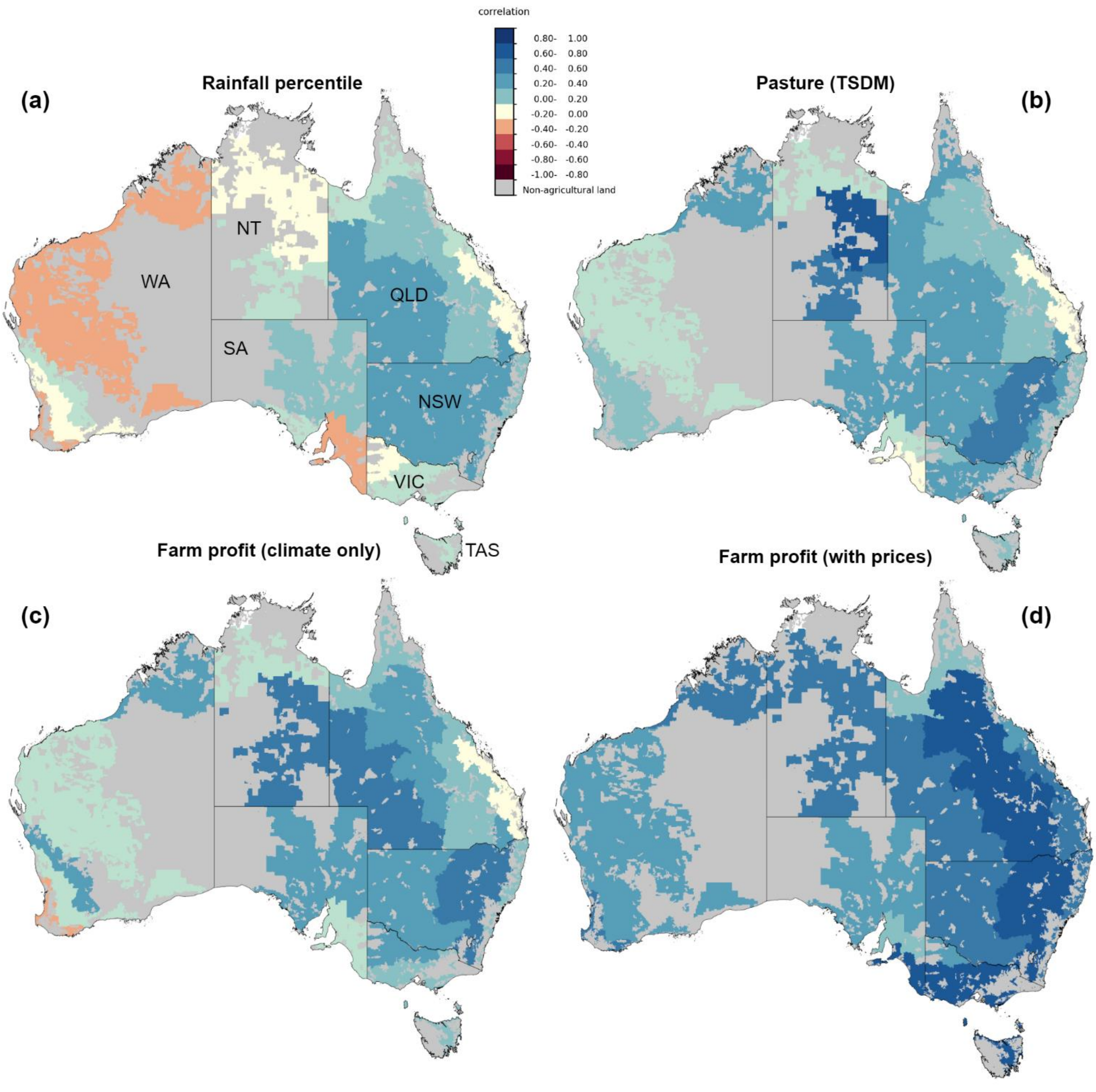


**Figure 4. (a) Regional correlation with observed annual farm profit (AAGIS) 1990-91 to 2021-22 (a) Annual rainfall percentile (b) Pasture growth indicator (AussieGRASS) (c) Farm profit indicator (climate only) (d) Farm profit indicator (with prices)**

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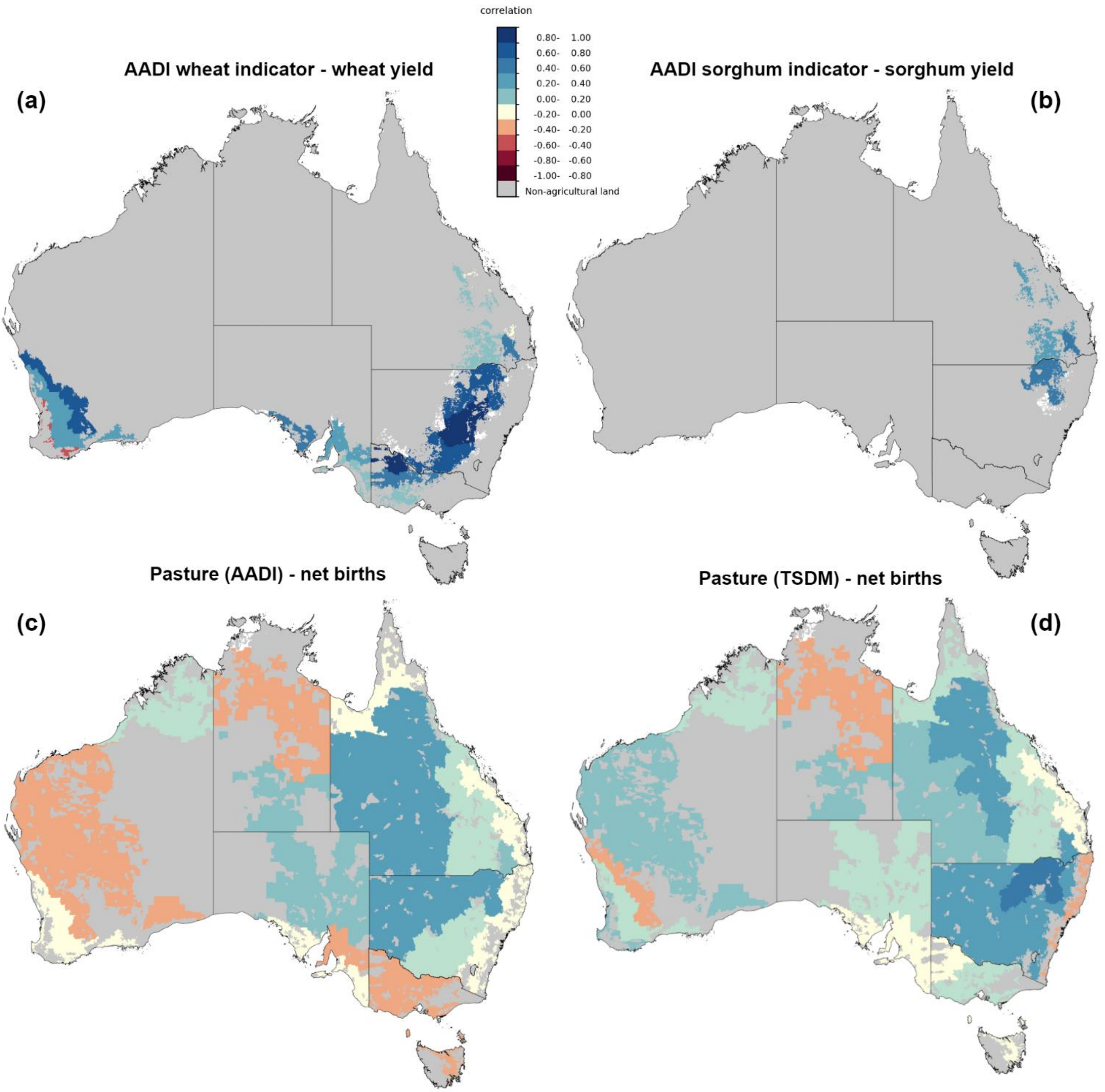


**Figure 5. (a) Regional correlation with observed annual crop and livestock productivity data 1990-91 to 2021-22 (a) AADI wheat yield indictor - wheat yields (b) AADI sorghum yield indicator – sorghum yields (c) AADI pasture growth indicator - livestock fertility (d) Pasture growth indicator (TSDM) – livestock fertility**

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As shown in Table 2 and Figure 8, both APSIM based crop indicators are well correlated with historical crop yield data (mean regional correlation of 0.55 for wheat and 0.59 for sorghum). In a majority of the AAGIS regions (11 of 17), the AADI wheat yield indicator outperforms growing season (Apr.-Oct.) rainfall percentiles, with the largest gains in northern NSW and QLD. But in a number southern and western cropping regions (e.g., southern VIC, SA and WA) growing season rainfall shows higher correlation. More detailed assessments of crop indicator skill using interpolated gridded data are presented in Appendix A. Figure A5 shows the AADI wheat indicator is weaker along the coastal fringe of the winter cropping zone. In contrast, the APSIM sorghum yield indicator generally outperforms rainfall across the summer cropping zone.

### 3.2 Farm household allowance

Data on the number of claims under the Australian Government's Farm Household Allowance (FHA) program show a high level of correlation with AADI data, particularly the Farm profit "with prices" indicator (Table 4, Figure 12 and 13).

Given the nature of the FHA program (income support for farms in financial hardship), it is logical that claims are better correlated with financial than climatic indicators. Further, as would be expected, FHA claims associated with severely adverse (e.g., less than 10th percentile) outcomes for farm profitability (see Figure 13). Figure 13 demonstrates the large improvement in predictive power between the Farm profit "with prices" indicator, with an effect size around double that of the "climate only" version (a result confirmed with regression analysis in Section 3.3).

The level of correlation is particularly strong in eastern Australia (-0.78 NSW, -0.84 VIC and -0.83 QLD), with lower correlation observed in WA (-0.42; Table 4, Figure A1). This may be partly a result of sample size, since the number of claims during this period was lower in WA (and the period 2014-15- 2022-23 included fewer <10th percentile values for the farm profit indicator in these regions).

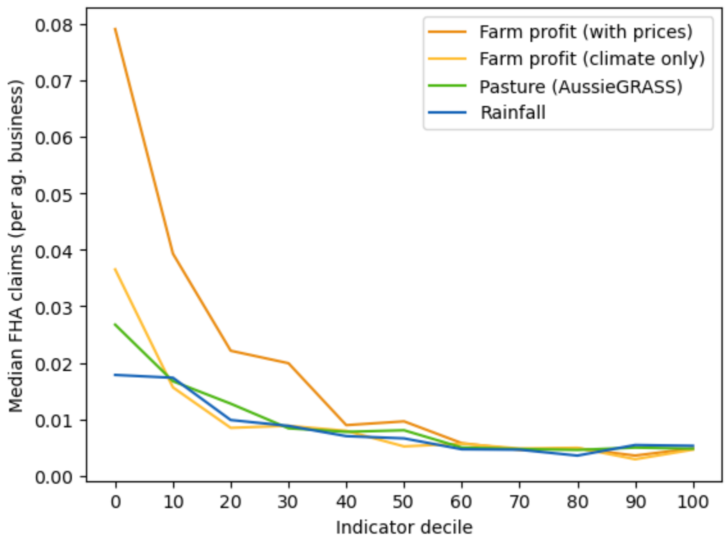


**Figure 6. Median regional FHA claims per total number of ag. Businesses, by indicator decile (2014-15 to 2022-23)**

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Table 4. Correlation with Farm Household Allowance claims 2014-15 to 2022-23 at regional, state and national scales

| | | Farm profit (AADI) | Farm profit (with prices) | Pasture (AADI) | Pasture (TSDM) | Rainfall (Jul-Jun.) |
|---|---|---|---|---|---|---|
| Regional (AAGIS) | 25th | -0.63 | -0.75* | -0.53 | -0.61 | -0.56 |
| | 50th | -0.46 | -0.55* | -0.31 | -0.41 | -0.39 |
| | 75th | -0.11 | -0.14* | -0.01 | -0.09 | -0.08 |
| | Mean | -0.35 | -0.41* | -0.24 | -0.33 | -0.29 |
| State | NSW | -0.69 | -0.78* | -0.51 | -0.70 | -0.65 |
| | Vic. | -0.69 | -0.84* | -0.55 | -0.54 | -0.6 |
| | QLD | -0.78 | -0.83* | -0.26 | -0.65 | -0.68 |
| | SA | -0.51 | -0.51 | -0.26 | -0.55* | -0.63 |
| | WA | -0.17 | -0.42 | 0.20 | -0.58* | -0.37 |
| | Tas. | -0.19 | -0.08 | 0.38 | -0.10 | -0.20* |
| | NT | -0.34 | -0.41* | -0.39 | -0.39 | -0.38 |
| National | | -0.60 | -0.78* | -0.42 | -0.74 | -0.73 |

***** Indicator with highest correlation

**Farmer drought self-assessments**

Following Hughes et al. (2022) we also consider how the AADI indicators correlate with farmer subjective self-assessments of drought (as reported by farmers participating in the annual AAGIS). These self-assessments are based on survey questions asking farmers to assess conditions over the preceding financial year (based on a 5-point scale ranging from drought to flood). These data have then been aggregated to AAGIS region level to estimate proportion of farmers self-assessing as drought affected in each year.

As might be expected, the farm profit "climate only" indicator shows better correlation than the "with prices" version, consistent with the common perception of drought as deriving from adverse weather conditions (rather than adverse economic conditions) (Table 5). Overall, the Pasture (TSDM) indicator shows the highest correlation with farmer self-assessments of drought, with both the Pasture (TSDM) and Farm profit (climate only) both offering gains compared with annual rainfall percentiles (Table 5).

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Table 5. Correlation with farmer drought self-assessments (AAGIS) 1990-91 to 2022-23 at regional, state and national scales

| | | Farm profit (AADI) | Farm profit (with prices) | Pasture (AADI) | Pasture (TSDM) | Rainfall (Jul-Jun.) |
|---|---|---|---|---|---|---|
| Regional (AAGIS) | 25th | -0.68 | -0.53 | -0.64 | -0.73* | -0.68 |
| | 50th | -0.63 | -0.38 | -0.56 | -0.66* | -0.59 |
| | 75th | -0.51* | -0.22 | -0.38 | -0.50 | -0.38 |
| | Mean | -0.56 | -0.37 | -0.50 | -0.59* | -0.54 |
| State | NSW | -0.79* | -0.64 | -0.67 | -0.77 | -0.67 |
| | Vic. | -0.71 | -0.57 | -0.59 | -0.78* | -0.66 |
| | QLD | -0.72 | -0.44 | -0.65 | -0.73* | -0.66 |
| | SA | -0.68 | -0.46 | -0.40 | -0.75* | -0.43 |
| | WA | -0.59* | -0.31 | -0.34 | -0.48 | -0.08 |
| | Tas. | -0.68* | -0.32 | -0.54 | -0.50 | -0.63 |
| | NT | -0.30 | -0.03 | -0.39 | -0.39* | -0.31 |
| National | | -0.70 | -0.56 | -0.61 | -0.78* | -0.53 |

* Indicator with highest correlation

### 3.3 Socio-economic outcomes

Tables 6 and 7 and Figure 10 present regression results estimating the marginal effect of low (<10th percentile) indicator values on a range of socio-economic indicators. These results show that farm profit is a superior indicator of socio-economic outcomes in regional areas. Across most of the variables considered, farm profit indicators show the largest and most statistically significant effects. Further, these responses are broadly consistent with prior expectations. For example, droughts (indicators < 10th percentile) are associated with; declines in regional income, house sales, job numbers and birth rates; and increases in FHA claims, personal insolvencies, small business exits and mortality.

As would be expected the farm profit (with prices) indicator typically shows the largest effects on economic outcomes (Table 6). Farm profit shocks are associated with significant declines in business income (-54%), total income (-11%), jobs (-3%) and house sales (-17%) and significant increases in personal insolvencies (+15%) and small business exists (+7.2%). As shown earlier, the farm profit with prices indicator is also strongly correlated with FHA claims, which increase from an average of 0.03 per agricultural business (in an above 10th percentile year) to 0.11 (in a below 10th percentile year).

While the correlations are generally weaker for demographic variables, significant effects are still observed for births, deaths and net migration. For births and deaths, the climate only version of the farm profit indicator shows the most significant

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and strongest effects: with a -3% effect on regional births and a +3% effect on deaths. Net regional migration is also negatively affected by drought with the strongest indicator being the pasture (TSDM) measure (+16%).

Overall, the relative performance of the indicators is largely consistent with prior expectations. Economic impacts of drought within Australian regional areas are expected to be transmitted mostly via declines in farm business incomes and subsequent flow-on impacts across the local economy (see Fleming-Muñoz, Whitten and Bonnett 2023). As such, the farm profit with prices indicator tends to dominate in this context. In contrast, impacts on fertility, mortality and migration will depend on a wider set of casual factors beyond farm incomes, including, for example, direct weather effects on human physical and mental health (see Hanigan, Schirmer, Niyonsenga 2018, Hanigan et al. 2012, Fleming-Muñoz, Whitten and Bonnett 2023).

Table 6. Percentage effect of drought (indicator below $10^{th}$ percentile) on selected regional socio-economic outcomes

| | Farm profit (AADI) | Farm profit (with prices) | Pasture (AADI) | Pasture (TSDM) | Annual rainfall |
|---|---|---|---|---|---|
| Annual FHA claims lodged | +158.1 | +326.4* | +69.3 | +120.7 | +90.9 |
| House transfers | -12.3 | -16.9* | -12.6 | -10.5 | -12.7 |
| Dwelling transfers | -14.1* | -10.5 | -10.6 | -6.5 | -10.3 |
| Personal insolvencies | +7.7 | +15.0* | +4.7 | +9.3 | +8.1 |
| Job numbers | -3.0 | -3.0* | -0.8 | -2.0 | -0.0 |
| Agricultural job numbers | -8.2* | -7.4 | -2.2 | -4.0 | +1.6 |
| Total employee income | -1.0 | -1.6 | -1.7 | -1.9* | -1.8 |
| Total business income | -28.1 | -53.5* | -22.7 | -39.8 | -26.7 |
| Total income | -5.8 | -11.3* | -5.0 | -7.1 | -4.4 |
| Small business exits | +9.2* | +7.2 | +4.3 | +1.3 | +3.5 |
| Births | -3.1* | -1.2 | -1.2 | -2.2 | +0.1 |
| Deaths | +2.6* | +1.1 | +0.0 | -0.2 | -0.1 |
| Net internal migration | -8.3 | -4.7 | +1.7 | -15.5* | -8.5 |

* Largest effect and statistically significant at 1% level

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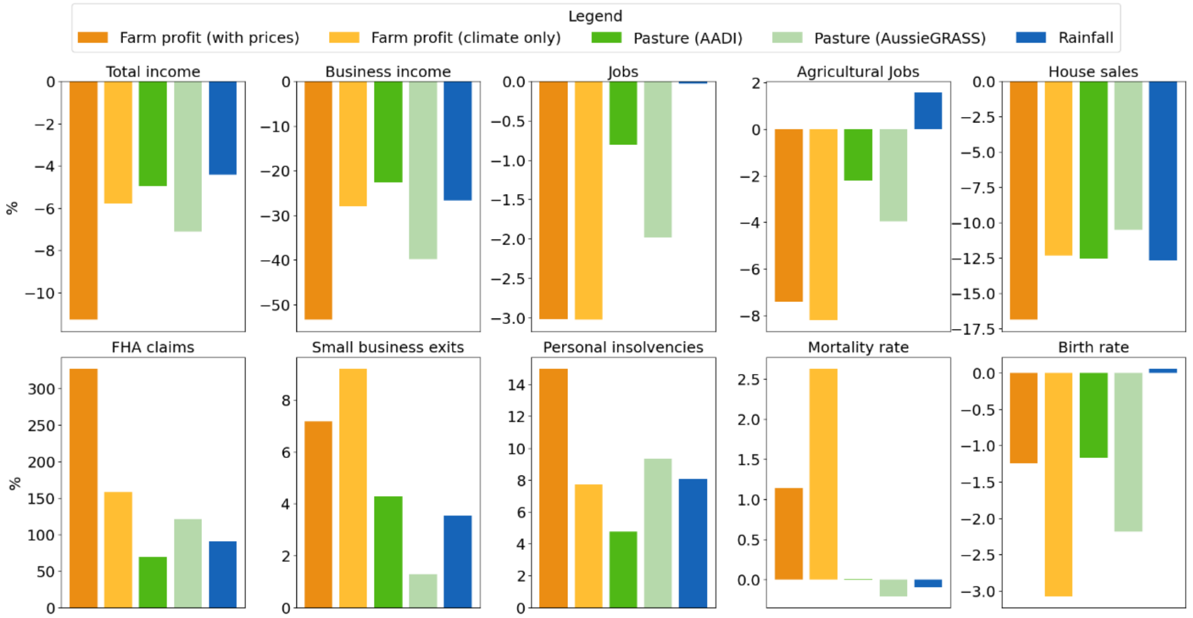


**Figure 7. Percentage effect of drought (indicator below 10th percentile) on selected regional socio-economic outcomes**

Table 7. Marginal effect of drought (indicator below 10th percentile) on selected regional outcomes

| | Indicators | | | | |
|---|---|---|---|---|---|
| **Variable** | Farm profit (AADI) | Farm profit (with prices) | Pasture (AADI) | Pasture (TSDM) | Annual rainfall |
| Annual FHA claims lodged (per ag. bus.) | 0.041* | 0.088* | 0.024* | 0.035* | 0.027* |
| House transfers (per 1000 population) | -1.922* | -2.601* | -1.949* | -1.614* | -1.958* |
| Dwelling transfers (per 1000 population) | -0.429* | -0.31* | -0.317* | -0.193 | -0.306* |
| Personal insolvencies (per 1000 pop.) | 0.091* | 0.178* | 0.057 | 0.111* | 0.096* |
| Job numbers (per capita) | -0.022* | -0.022* | -0.006 | -0.014* | 0 |
| Agricultural job numbers (per capita) | -0.006* | -0.005* | -0.001 | -0.003 | 0.001 |
| Total employee income (per capita) | -0.242* | -0.386* | -0.406* | -0.44* | -0.428* |
| Total business income (per capita) | -1.15* | -2.171* | -0.908* | -1.616* | -1.066* |
| Total income (per capita) | -1.712* | -3.346* | -1.464* | -2.102* | -1.3* |
| Small business exits (per 1000 bus.) | 1.897* | 1.504* | 0.853 | 0.27 | 0.746 |
| Births (per 1000 population) | -0.368* | -0.148 | -0.139 | -0.261 | 0.007 |
| Deaths (per 1000 population) | 0.212* | 0.092 | 0.001 | -0.017 | -0.008 |
| Net internal migration (per 1000) | -0.914 | -0.515 | 0.186 | -1.721* | -0.933 |

* Statistically significant at 1% level

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## 4 Conclusions

The Australian Agricultural Drought Indicators (AADI) are the product of an integrated modelling system which simulates specific agricultural outcomes (i.e., crop yields, pasture growth and farm profits) from gridded climate data. These results are used to derive outcome-based indicators intended to represent different aspects of agricultural drought. The key purpose of this paper was to evaluate these indicators by testing their performance against historical outcome data and contrasting that against a commonly used meteorological indicator (i.e., rainfall percentiles).

Overall, the results demonstrate the value of an outcome-based approach to drought. The AADI indicators have consistently higher correlation with a range of agricultural and economic outcomes. The farm profit (with prices) indicator—which accounts for both climatic and price variability—was found to be a particularly strong predictor of farm outcomes, in many cases offering large gains relative to the climate only indicator.

In line with the findings of Hughes et al. (2022), the AADI farm profit (climate only) and pasture indicators proved more consistent with farmer self-assessments of drought than rainfall and, as would be expected, the farm profit with prices indicator proved less consistent. While an indicator reflecting both price and climate effects is unconventional (at least relative to common perceptions of drought) it is a superior predictor of economic drought impacts and would likely be of use to AADI's intended government audience. For example, the farm profit indicator was able to predict historical demand for a key Australian government drought program: the Farm Household Allowance. Analysis of FHA claim data found an effect size for the farm profit (with prices) indicator around three times that of a rainfall percentile (and around twice that of the farm profit climate only indicator, Table 5).

While models can predict outcomes better than climatic data alone: measurement errors (i.e., differences between indicators and on-ground outcomes) are unavoidable given the limits of the underlying models, and the approximations required to simulate on national grids. This study provides a detailed picture the skill of each of the AADI indicators and how this varies spatially. In future, estimates of indicator skill could be added to the operational system to inform end-users, while also being used to guide system enhancements. While current performance may be adequate for the intended government use case, future improvements in skill could make other farm-level applications—such as index-based insurance or farmer decision support—more feasible by reducing 'basis risk' (see Hughes et al 2022).

At a regional level, the performance of the farm profit indicators is weaker in some livestock dominant regions, particularly the remote rangelands of Western Australia, far northern Australia, and parts of coastal Queensland. To some extent this reflects the limitations of the *farmpredict* model which currently performs better for cropping than for livestock farms (Hughes et al. 2022b). Higher resolution maps also identify specific areas of weaker performance in southern Australia (Appendix A3) which warrant further consideration.

The APSIM based crop yield indicators show good correlation with observed yields in most regions; however, the performance is lower along the coastal fringe of the cropping zone. In these areas, and in much of the South Australian cropping zone, the AADI wheat indicator is outperformed by growing season rainfall. Future research could consider alternative

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specifications of APSIM or simpler statistical models as an alternative (for example Potgieter et al. 2022; Pang et al. 2022; Stephens 1998). The current AADI pasture indicator is a composite of two models: GrassGro and AussieGRASS. In areas where both models overlap, AussieGRASS (particularly the Total Standing Dry Matter TSDM measure) appears to have greater predictive power. Given GrassGro is computationally intensive, there may be value in adopting an AussieGRASS only indicator for AADI in future.

Perhaps the most surprising result from this study is the ability of AADI to generalise beyond agriculture and predict broader socio-economic drought impacts. The AADI farm profit indicators were found to have superior correlation with a range of regional economic impacts, predicting drought related decreases in regional incomes, jobs and house sales and increases in personal insolvencies and business exits. This study also found some correlation between the indicators and demographic outcomes, with drought linked to lower birth rates, higher mortality and negative net migration. While there has been some research measuring the effects of drought (as opposed to extreme heat) on mortality in the US (Berman et al. 2017; Salvador et al. 2023; Lynch et al; 2020) the findings have been mixed. In Australia research has been limited to mental health effects and suicide risk (Hanigan et al. 2012; Hanigan et al. 2018; Edwards et al. 2015); while fertility and migration have received limited attention in general. This study makes use of a relatively new dataset derived from administrative records. While beyond the scope of this study, future research could use this data to examine the transmission of socio-economic drought impacts in more detail.

## Data availability

Data sets used to produce the validation results presented in this paper are available for download in Mendeley Data (https://doi.org/10.17632/8yhcr28wbk.1). These datasets include observed outcome data (as outlined in Table 1) along with AADI indicators aggregated to the same regional scales (LGA and AAGIS regions). FHA claim data is held by DAFF and could not be included in the datasets due to privacy constraints (all other data listed in Table 1 are included). Historical gridded farm simulation data generated from the AADI project are available on via ABARES website as the Australian Gridded Farm Data (https://www.agriculture.gov.au/abares/research-topics/surveys/farm-survey-data/australian-gridded-farm-data). ABARES AAGIS farm survey data are available online here (https://www.agriculture.gov.au/abares/data/farm-data-portal). ABS “Data-by-region” is available online (https://dbr.abs.gov.au/). SILO climate data and a selection of AussieGRASS outputs are available via the Queensland Government “The Long Paddock” site (https://www.longpaddock.qld.gov.au/).

## Author contribution

Neal Hughes, Donald Gaydon and Mihir Gupta provided project leadership for AADI. Andrew Schepen led the climate forecast calibration and downscaling with contributions from Yong Song. Donald Gaydon, Zvi Hochman and Heidi Horan contributed to AADI crop simulation modeling. Ross Searle developed the national soil data. Patrick Mitchel and Yacob Beletse contributed to GrassGro pasture modelling. John Carter and Dorine Bruget undertook AussieGRASS modelling. Neal Hughes, Geoffrey Brent, Andrew Turner, Peter Tan and Mihir Gupta contributed to AADI *farmpredict* modelling. Chris Sharman and Peter Taylor developed operational modeling and data systems for AADI. Laura Guillory developed data ingestion processes for the AADI UI. Jonathon McComb led the design of the AADI UI. Connor Brodie led the development of the AADI UI, with contributions from Ramneek Singh. Neal Hughes, Mihir Gupta and Sean Bellew undertook the validation analysis. Neal Hughes wrote the manuscript with contributions from Donald Gaydon, Andrew Schepen, Zvi Hochman and Mihir Gupta.

## Competing interests

The authors declare that they have no conflict of interest.

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## Appendix A: AADI system

### A.1 Soil data

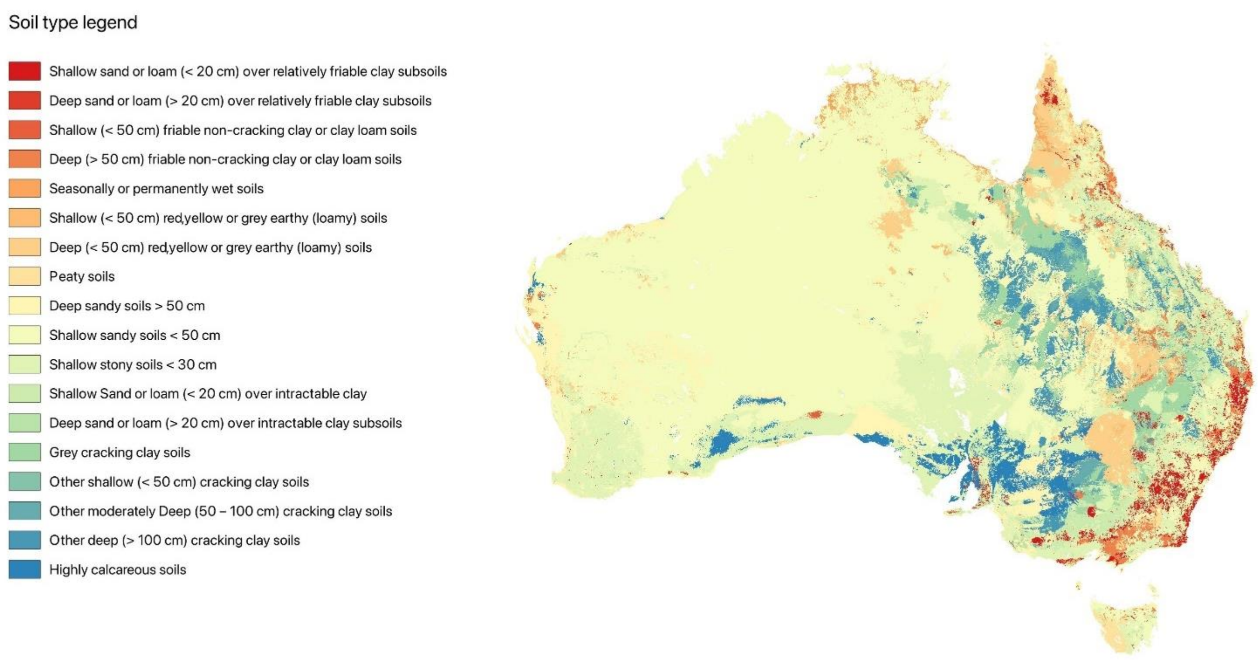


**Figure A1. National Generic Soil Group (GSG) dominant class map**

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## A.2 Farm business data

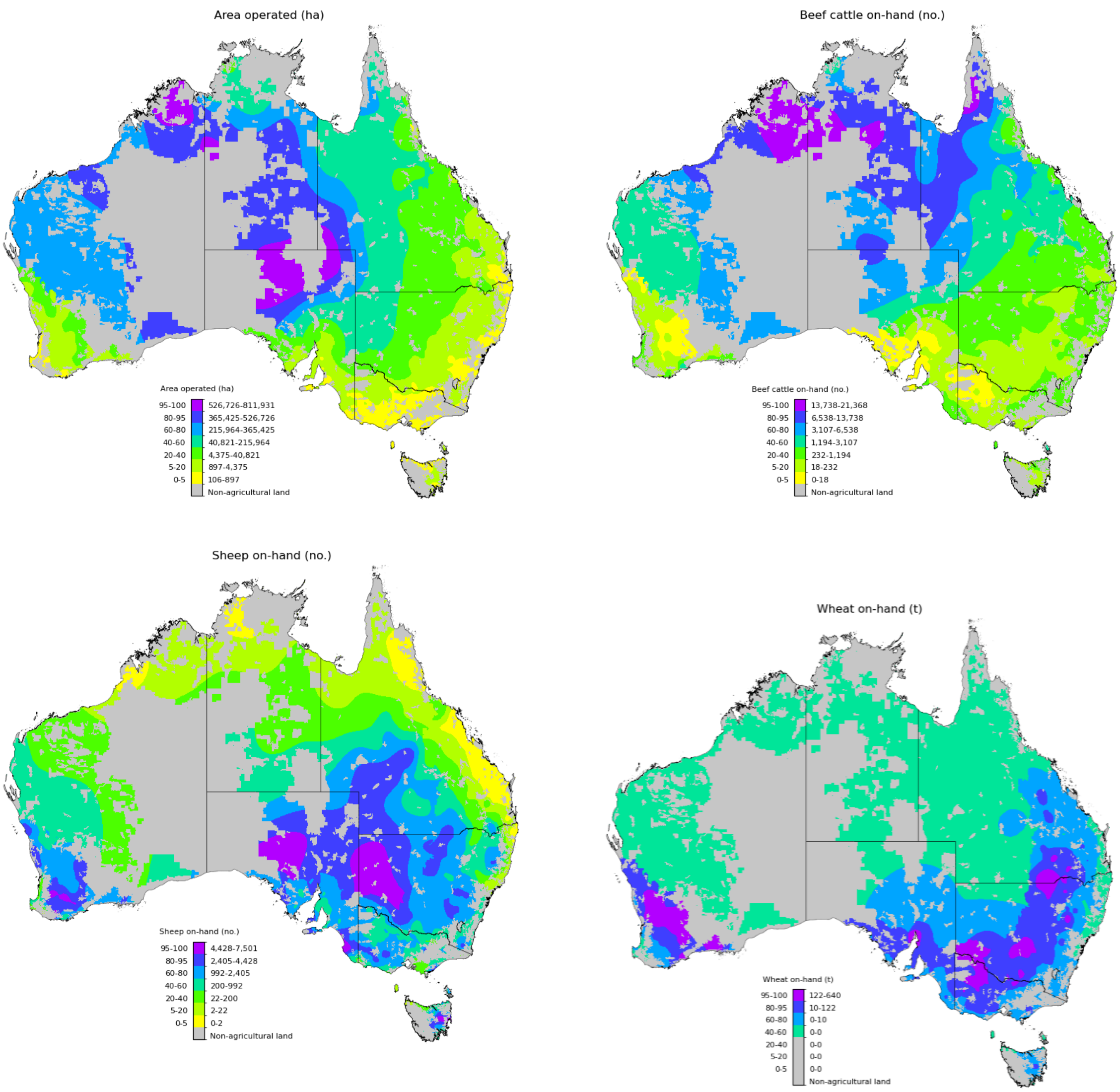


**Figure A2. Synthetic farm business data selected variables**

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### A.3 Pasture simulations

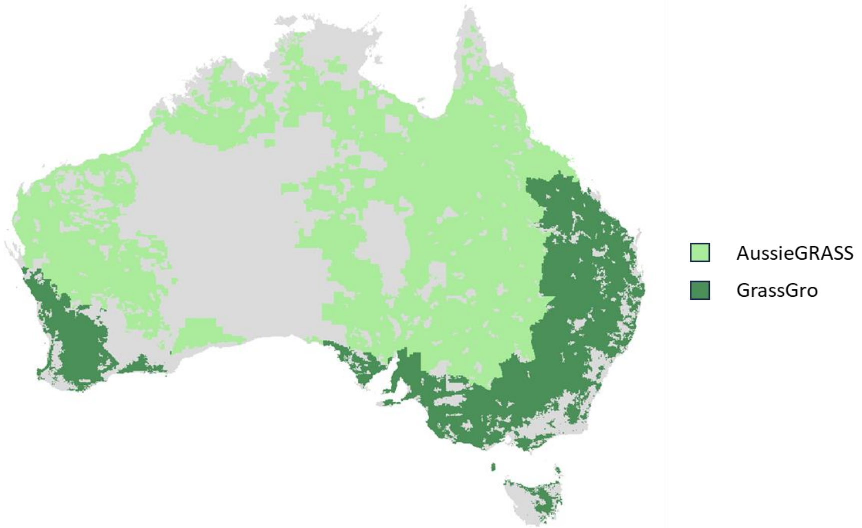


**Figure A3. Extent of AussieGRASS and GrassGro pasture growth data using in AADI pasture indicator**

### A.4 Crop simulations

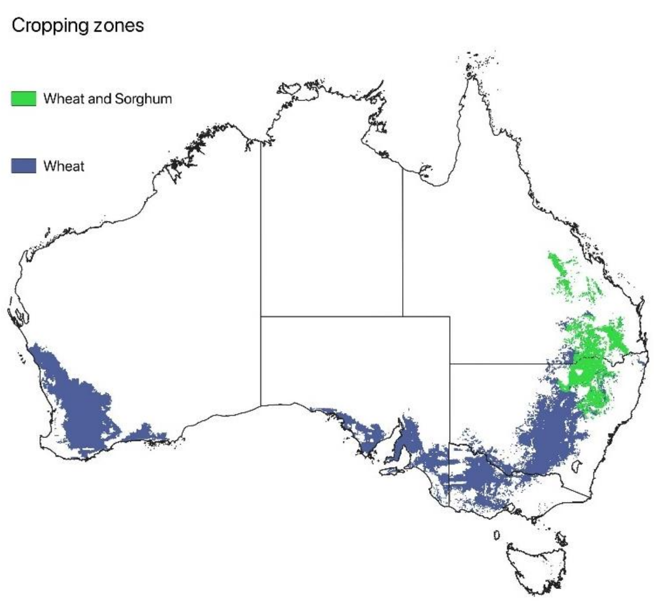


**Figure A4. Extend of AADI cropping simulations for the winter (wheat) and summer (sorghum) crop yield indicators**

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## Appendix B: Additional results

### B.1 AADI correlation with farmer drought self-assessments and FHA claims

As shown in Figure B1, the AADI farm profit (with prices) indicator (b) is better correlated with FHA claims than the climate only version (a), particularly in eastern Australia. While the Farm profit (with climate) indicator shows better correlation with farmer drought self-assessments across most regions (Figure B1, c), compared to the Farm profit (with prices) version (d).

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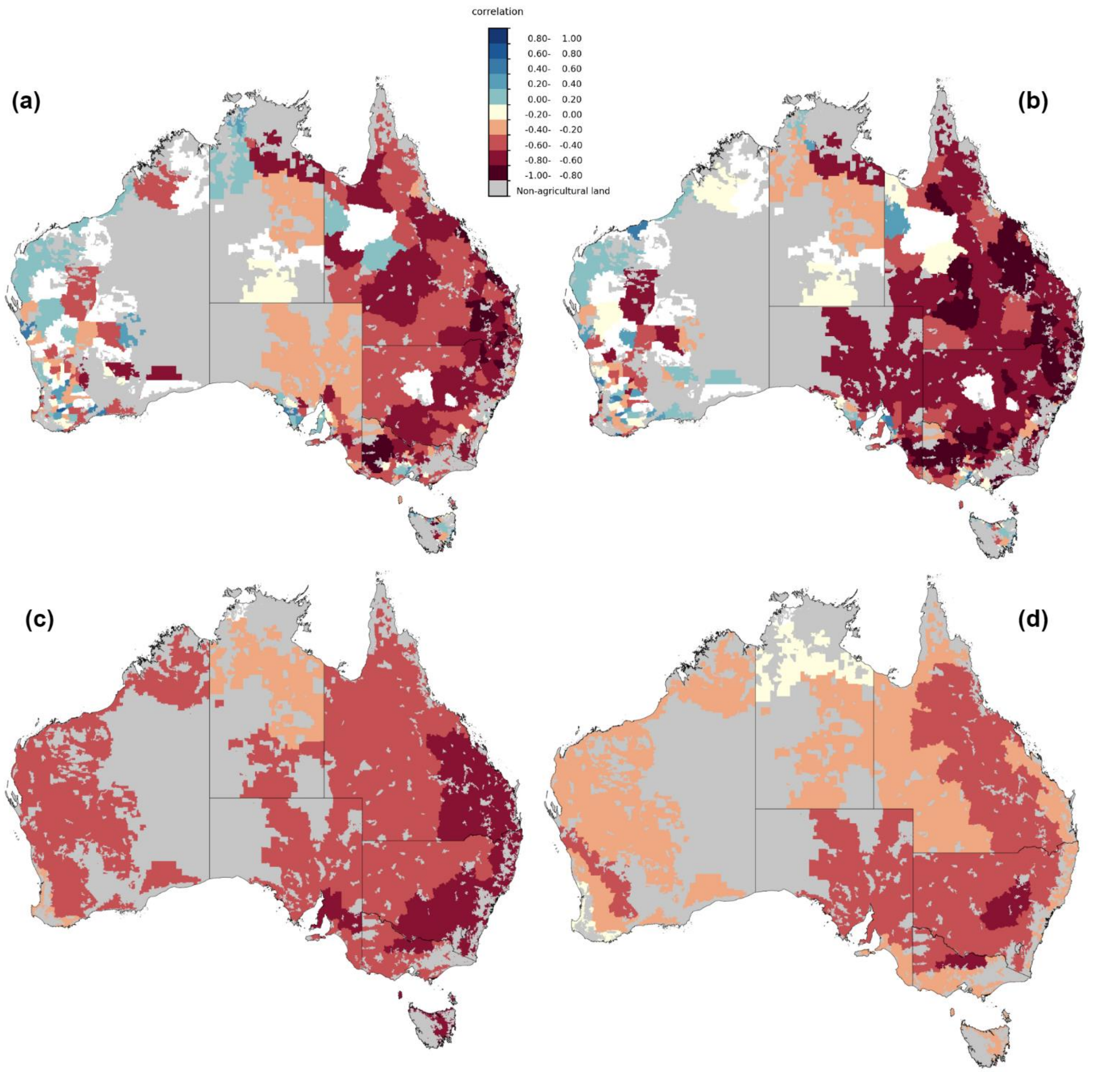


**Figure B1. (a) AADI farm profit (climate only) indicator correlation with FHA claims. (b) AADI farm profit (with prices) indicator correlation with FHA claims. (b) AADI farm profit (climate only) indicator correlation with farmer drought self-assessments. (c) AADI farm profit (with prices) indicator correlation with farmer drought self-assessments.**

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### B2 AADI correlation with interpolated data

In this section AADI indicators are evaluated at the 0.05-degree scale by measuring their correlation with gridded observational data. This gridded observation data is derived from geo-coded unit-record AAGIS data (individual farm survey respondents / farm business locations), which have been interpolated across the 0.05-degree grid using the same distance weighted kernel smoothing method applied to the AADI farm business data (summarised in section 2.1.1 of this article and in the AADI progress report, see Hughes et al. 2024).

Results are shown Figure B2 (a, farm profit climate only, b: farm profit with prices, c: winter crop yield indicator). These maps show comparable high-level patterns to the regional results presented in the main article just with much higher resolution. While these results show more precise patterns they need to be treated with a degree of caution, given the observational data are interpolated.

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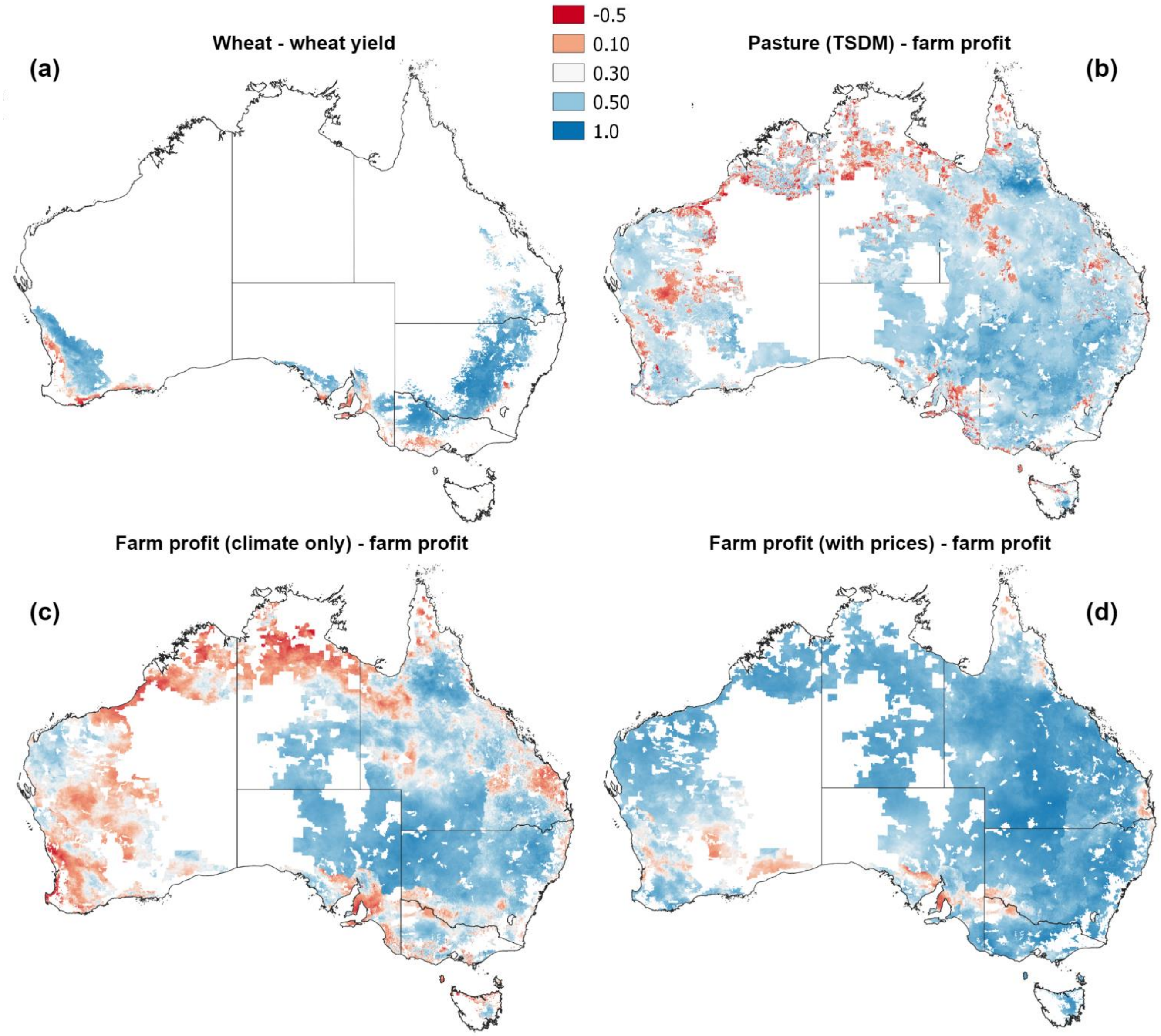


600 **Figure B2. (a) AADI wheat indicator: correlation with interpolated wheat yield (AAGIS) 1990-91 to 2022-23 at 0.05-degree grid scale. (b) Pasture (TSDM) indicator: correlation with interpolated farm profit (AAGIS) 1990-91 to 2022-23 at 0.05-degree grid scale (c) AADI farm profit (climate only) indicator: correlation with interpolated farm profit (AAGIS) 1990-91 to 2022-23 at 0.05-degree grid scale. (d) Farm profit (with prices) indicator: correlation with interpolated farm profit (AAGIS) 1990-91 to 2022-23 at 0.05-degree grid scale**