Australian Government
Department of Agriculture, Fisheries and Forestry

ABARES

Australian Gridded Farm Data

Version 1.5

Methods and metadata

Research by the Australian Bureau of Agricultural and Resource Economics and Sciences, supported by the National Australia Bank.

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Cataloguing data

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Acknowledgements

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Acknowledgement of Country

We acknowledge the Traditional Custodians of Australia and their continuing connection to land and sea, waters, environment and community. We pay our respects to the Traditional Custodians of the lands we live and work on, their culture, and their Elders past and present.

Contents

Summary

The Australian Gridded Farm Data (AGFD) are a set of national simulated farm business data produced by ABARES. The development of *Version 1.5* of the AGFD was supported by the National Australia Bank.

As with the initial AGFD, *Version 1.5* contains a set of national maps containing simulated data on historical broadacre farm business outcomes including farm profitability on an 0.05-degree (approximately 5 km) grid. The maps have been derived using ABARES *farmpredict* model (Hughes et al. 2022), which is based on ABARES Agricultural and Grazing Industries Survey (AAGIS) data and historical gridded climate data. The maps do not represent actual observed data – they model predicted outcomes for representative or 'typical' broadacre farm businesses at each location with assumed climate and commodity prices scenarios.

Key updates included in *Version 1.5* of the AGFD include:

- New climate projection scenarios based on an ensemble of CMIP5 climate projections for 3 emission scenarios (RCP 2.5, RCP 4.5 and RCP 8.5) at 2050 and 2070
- Extended historical climate scenario covering the period 1950-51 to 2022-23
- Inclusion of a farm land value layer, based on interpolated farm survey data (Appendix A).

The climate projection scenarios adopt the same methodology as previous ABARES analysis (Hughes et al. 2022c), except that here results are provided on a high-resolution grid. As with previous research, these projections do not account for the offsetting effects of farm adaptation or technological improvement. As such, these results are to be interpreted as estimates of 'adaptation pressure': identifying which farm locations are likely to be under more pressure to adapt to climate change.

These data and the models used to derive them remain under active development, and as such should be considered experimental. ABARES intends to release future updates to allow for improvements to the methods to increase accuracy and coverage of data.

1 Potential applications

While the Australian gridded farm data have been developed specifically to support the AADI project, they have a range of other potential applications as summarised below.

1.1 Farm business risk analysis

1.1.1 Annual climate variability and price risk

The data provide historical sequences of farm profitability, which can be used to estimate the effects of climate and commodity price volatility. As such the data can be used to characterise the levels of climate and financial risk faced by broadacre farmers at different locations across Australia. A demonstration of this type of analysis is provided below (Figure 1 and 2). In this example risk is measured as change in profit between a good (90th percentile) and bad (10th percentile) year (following Hughes et al. 2020).

1.1.2 Long-term climate change projections

A new addition in *Version 1.5* of the AGFD are climate projection scenarios, following the methodology applied previously by ABARES (see Hughes et al. 2022c, and methodology section). These scenarios simulate farm profitability under future projected climate holding farm technology and prices fixed. Importantly, this analysis does not account for the offsetting positive effects of farm adaptation or technological improvement (or any changes in global commodity prices).

As in prior studies (see Hughes et al. 2022c) the results can be used to provide an indication of climate change ‘adaption pressure’ on farm businesses and how this varies across Australia (Figure 3). Compared with prior research, these gridded projections allow for more customised analysis to be undertaken focused on specific regions or locations.

Figure 1a: Farm risk due to climate variability. 1989-90 to 2022-23 climate *(percentage change in profit between 90th percentile and 10th percentile year)*

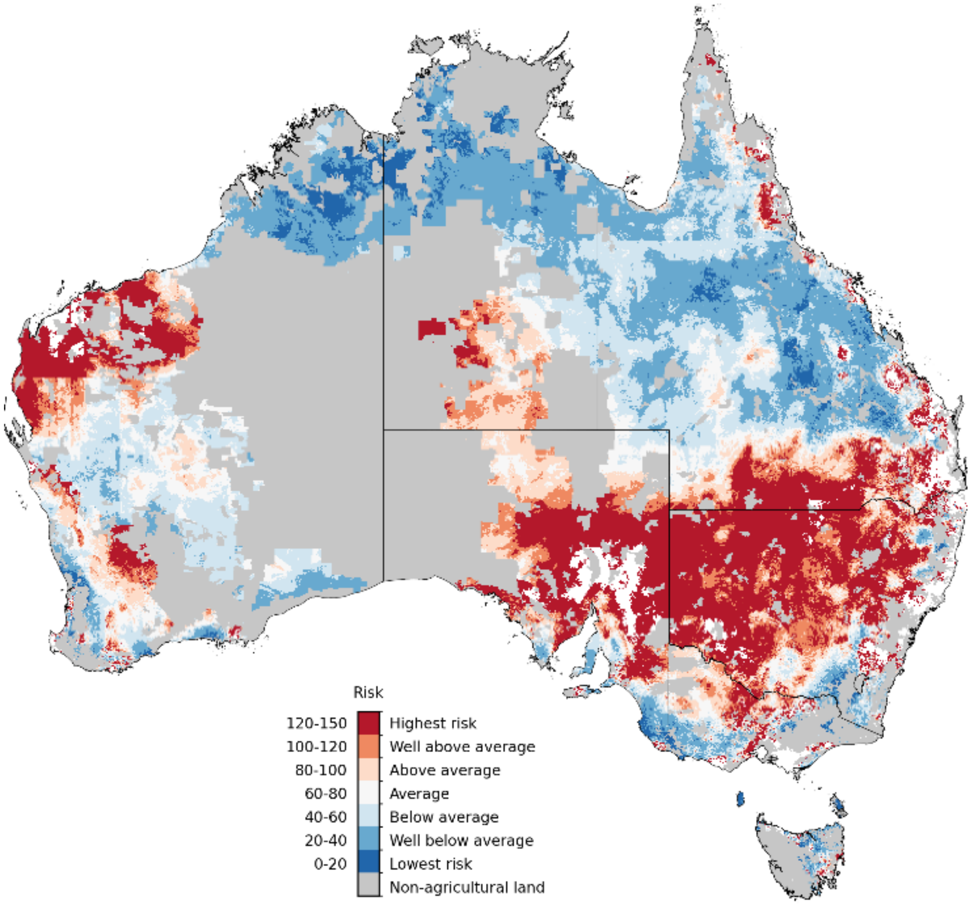


Figure 1b: National mean annual farm profit per hectare, 1989-90 to 2022-23 climate

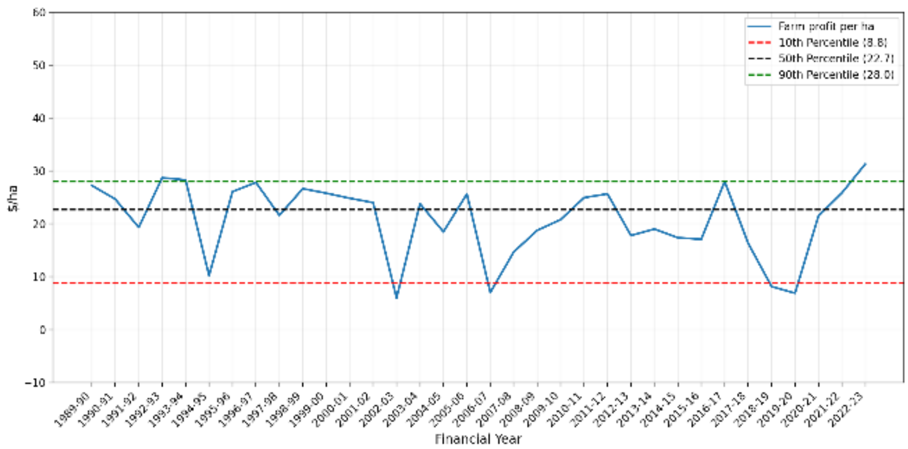


Figure 2a: Farm risk due to climate and price variability. 1989-90 to 2022-23 climate and prices (percentage change in profit between 90th percentile and 10th percentile year)

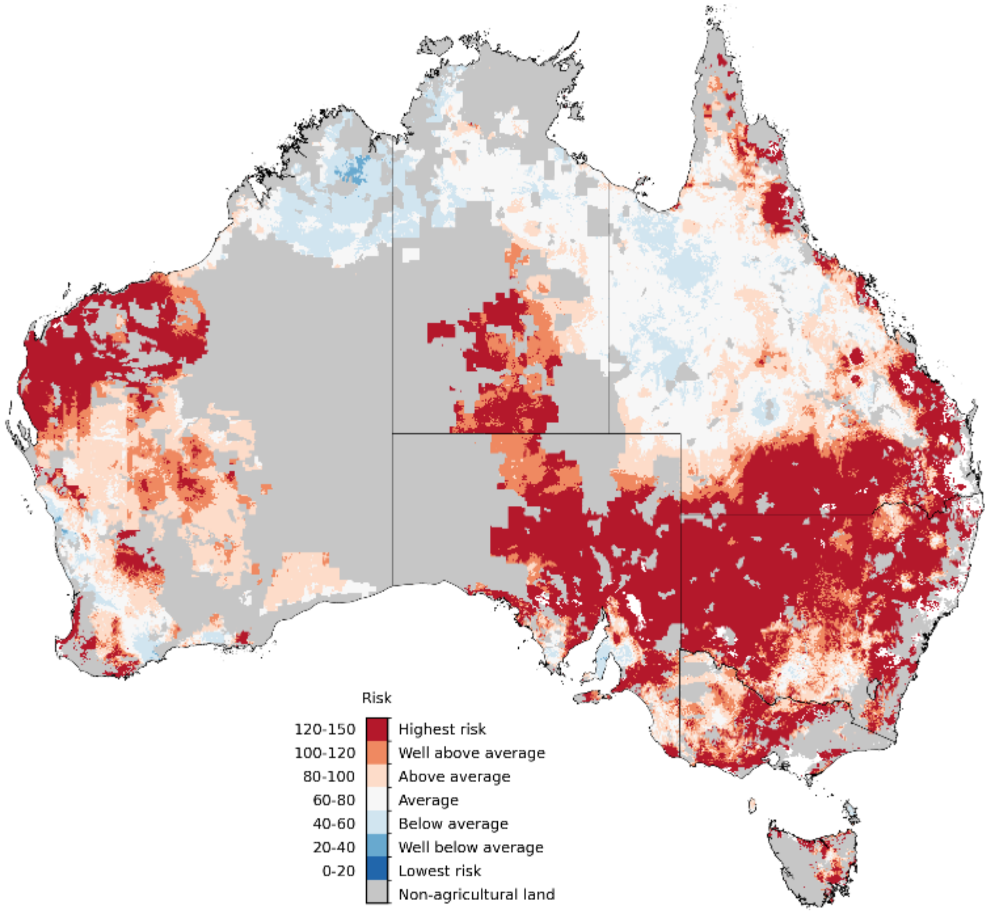


Figure 2b: National mean annual farm profit per hectare, 1989-90 to 2022-23 climate and prices

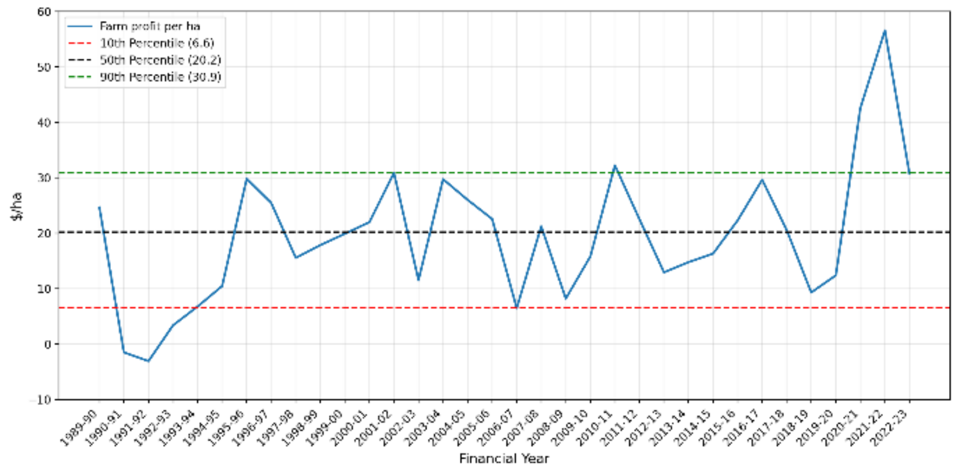
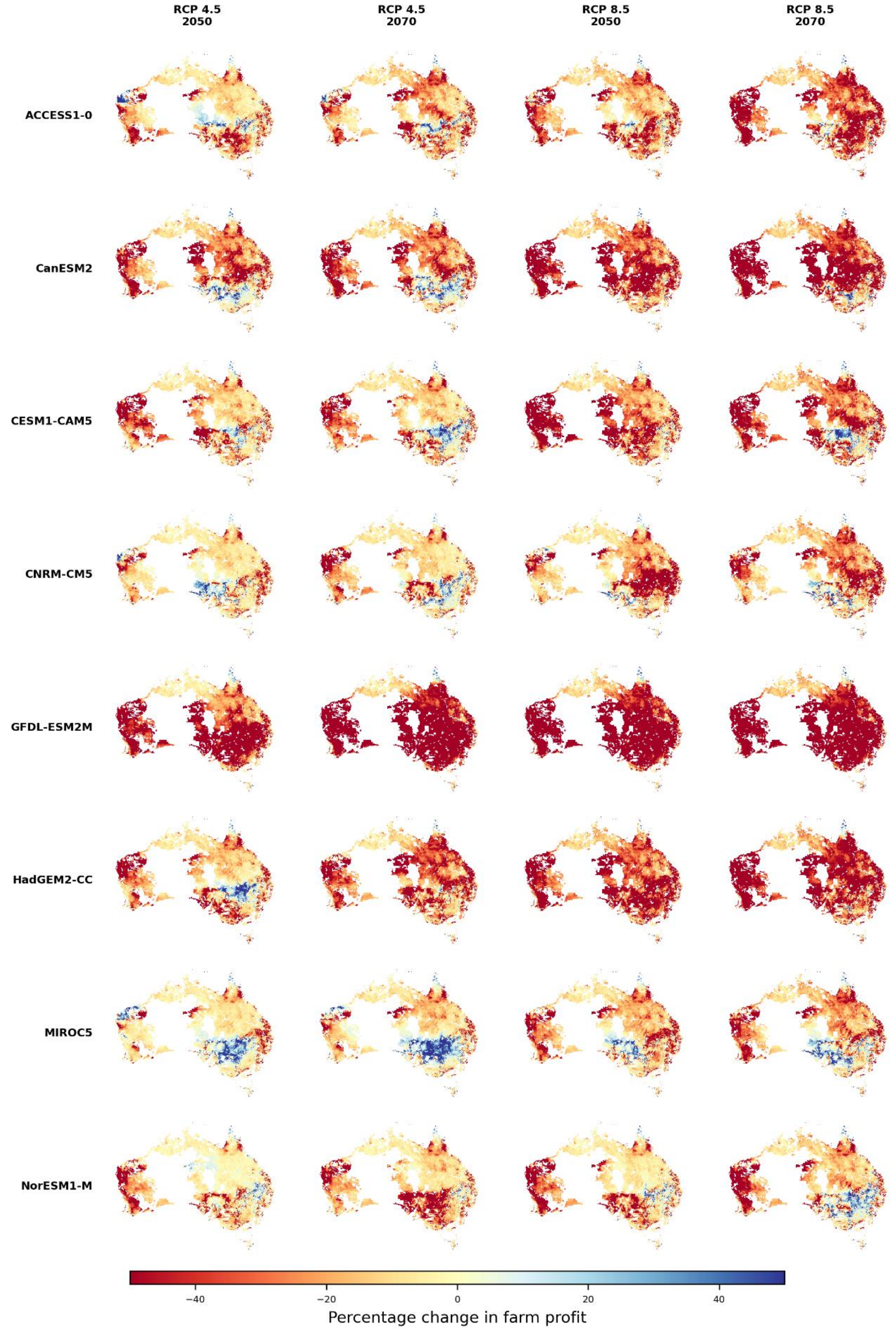


Figure 2: Climate change adaptation pressure

% change in mean farm profit under projected climate scenarios (RCP4.5 and RCP8.5 at 2050 and 2070) versus historical climate (1983-84 to 2009-10)



1.2 Land use change modelling

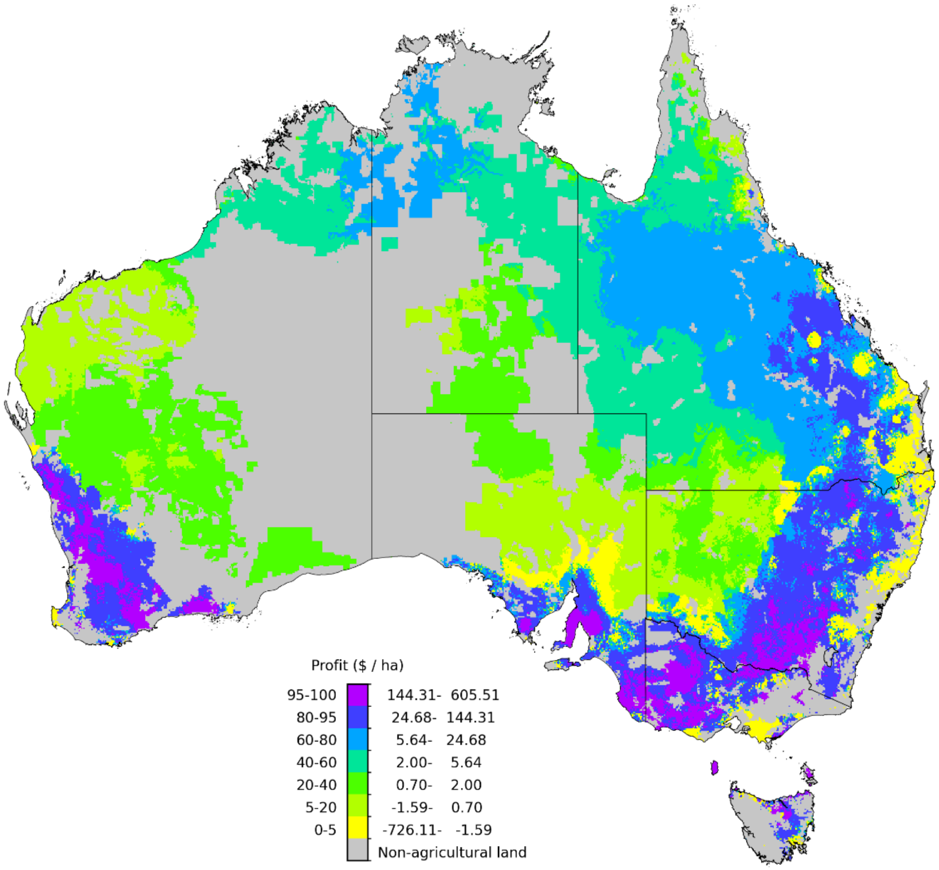
Many research organisations are engaged in land use change modeling, which seeks to simulate potential changes in future Australian land-uses in response to changes in climate or policy drivers. Examples include carbon abatement or biodiversity payments. For example, past research at the CSIRO for the Australian National Outlook applied the Land-Use Trade-Offs (LUTO) model (Bryan et al. 2016) to assess potential land-use changes in Australia to 2050.

One key input for such models is an estimate of the profitability of existing land-uses such as broadacre farming, which is necessary to establish the opportunity cost of any alternative forms of land use (such as carbon farming or plantation forestry etc.). The Australian Gridded Farm data (particularly the *Historical climate* scenario, see Section 2.2.3) provides a baseline estimate of the profitability of existing Australian broadacre farming activity based on recent (last 33 years) climate conditions, and recent (2022) commodity prices. The 0.05-degree gridded results provided here are better suited to high-resolution land use change models than existing public regional scale data.

1.3 Downscaling agricultural statistics

Public agricultural statistics including those published by the ABS and ABARES rely on coarse regional geographies. This limits the data's utility, especially for researchers undertaking higher resolution spatial analysis, or for data users seeking information for specific custom regional boundaries. While the Australian gridded farm data are derived from model scenarios rather than observations, they could be applied to downscale other observational data sets, such as ABARES or ABS agricultural production statistics. For example, crop area and yield predictions in the Australian gridded farm data could be applied to disaggregate regional crop production data. To date ABARES has not undertaken any assessments of the performance of this type of downscaling approach, but it remains a subject for future research.

Figure 3: Australian gridded farm data: mean simulated farm profit ($ / ha) with historical climate (1983-84 to 2009-10), 2024-25 prices and 2021-22 farm technology.



Note: Legend left values are percentile ranges.

2 Methods

An overview of the methods is provided below. For further detail see the AADI: Progress report.

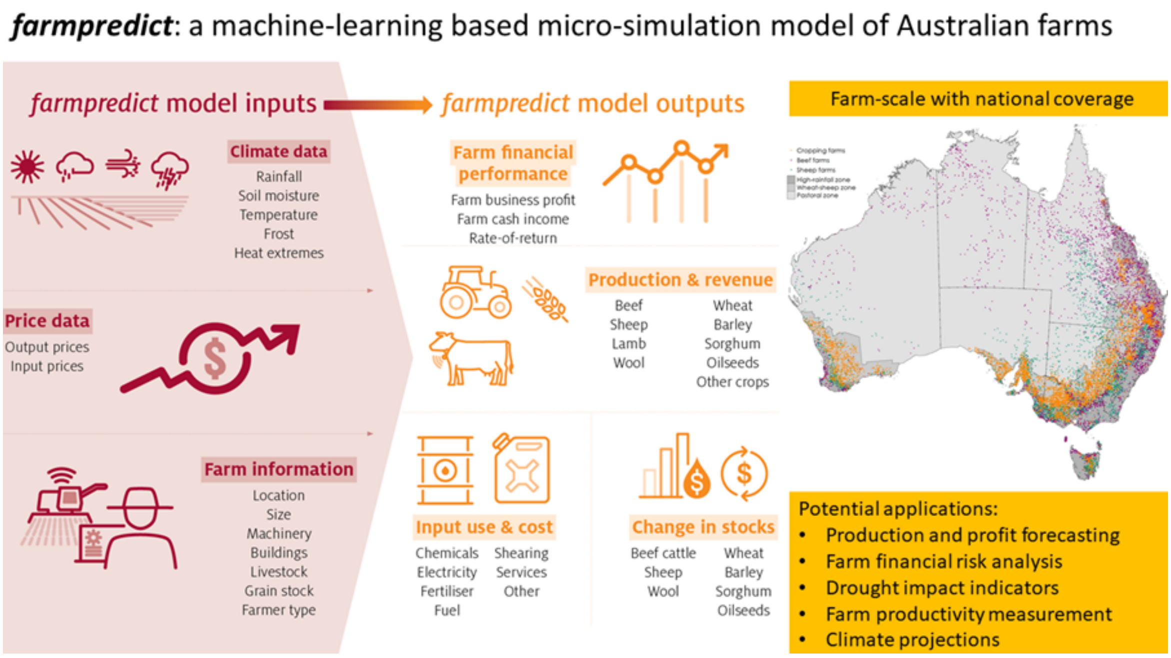
2.1 ABARES *farmpredict* model

ABARES *farmpredict* (Hughes et al. 2022b) is a statistical model of Australian broadacre farming businesses based on ABARES' Australian Agricultural and Grazing Industries Survey (AAGIS). AAGIS collects detailed physical and financial information for around 1,600 broadacre farms across Australia each financial year. The data provides representative coverage of Australian broadacre farming regions and industries, including extensive cropping, livestock (beef and sheep) and mixed farming types.

A sample of around 45,000 farm observations (drawn from AAGIS over the period 1991-92 to 2021-22) is used to develop the model, with each farm linked via point location geocoding to spatial climate data and bio-physical data (simulated pasture growth and crop yields). The statistical model is fitted using a nonparametric machine learning-based method, and verified with out-of-sample validation tests.

farmpredict simulates—at a farm business level—six crop outputs, four livestock outputs and seven stock (inventory) holdings including livestock numbers and on-farm crop and wool storage. These production outcomes are then used to simulate farm financial results, including various measures of profit. In this publication, we are releasing simulated outputs for 13 farm production variables and 5 financial performance measures (farm cash costs, farm cash revenues, farm cash income, farm business profit and farm profit at full equity, see Table 2).

The *farmpredict* model and related data accounts for a wide range of relationships between climate and farm performance. This includes crop planting and storage decisions, input usage (particularly fertiliser and fodder), crop yields, livestock turn-off, birth and death rates, and farm prices received (via quality effects on livestock and crop outputs).



2.2 AADI gridded simulations

2.2.1 Farm business input data

ABARES *farmpredict* model requires detailed data on farm business characteristics. In previous applications this data has been obtained directly from ABARES farm surveys (specifically AAGIS) and then aggregated to regional or national scale in public outputs to maintain the privacy of survey participants.

For the Australian Agricultural Drought Indicators (AADI), a new approach was necessary to allow for the simulation to occur on high-resolution grids, while maintaining the privacy of ABARES farm survey participants. As outlined further in the AADI progress report (Hughes et al. 2024) a, a new synthetic dataset of farm business data set was developed to provide the necessary farm business input data required for *farmpredict* simulations on a grid across Australia.

This synthetic dataset was constructed by applying a “data smearing” approach, which uses actual data from ABARES AAGIS then adds a degree of random perturbation (“noise”) before applying spatial interpolation to generate synthetic farm businesses for each grid cell. These synthetic businesses represent a “typical” or “average” broadacre farm at a given location (reflecting the AAGIS farm businesses observed in proximity to that location in recent years), while still preserving the privacy of farm survey participants.

The smearing process is managed so that the “typical farm” at any given location is always a composite of several different farms, and AADI predictions apply to this composite farm rather than to the actual farm present at that location. ABARES conducted a Privacy Threshold Assessment on this method, concluding that the risk of re-identification of any sensitive individual data was very low.

The datasets developed for AADI draw on 10 recent years of AAGIS data (2012-13 to 2022-23) with higher weightings applied to more recent years. At this stage, only model simulation results have been included in this data release. The synthetic farm business input data used to derive these results could potentially be included in future releases, which would increase the range of variables available.

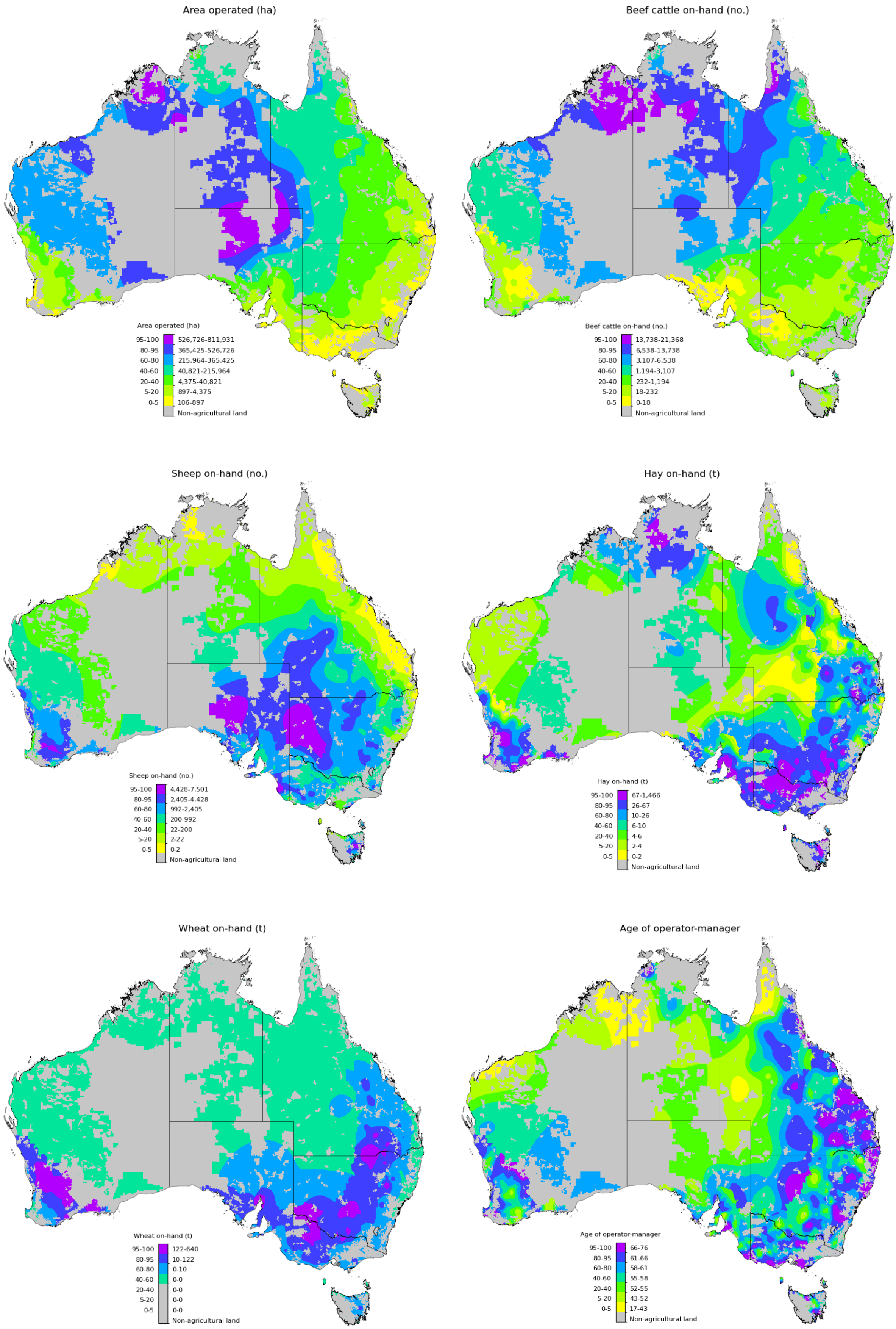
For more information see Hughes et al. (2024) and Hughes et al. (2025).

2.2.2 Agricultural zones and weights

Indicators presented in the AADI prototype are available across a defined 'Agricultural zone', derived from data from the Australian Collaborative Land Use Mapping Program (ACLUMP) maintained by ABARES (as shown in Figure 1 and 2). Gridded data within this agricultural zone can be aggregated to higher regional scales (e.g., state, national etc.) by combining per hectare data for each grid cell with a weight variable (*farmland_per_cell* see Table 3). This weighting variable was derived for the AADI project using ABS 2021-22 Agricultural census data, such that aggregations of the ABARES gridded data (at SA2, state and national level) match ABS estimates of total area of broadacre farm area.

It is important to note that although this weight variable is notionally an estimate of the amount of broadacre farm-land present in each grid cell, it has been designed to aggregate gridded data to large regional scales and is not expected to provide an accurate reflection of actual farming land present within specific grid cells. Higher resolution land use maps are maintained by ABARES as part of Australian Collaborative Land Use Management Program (ACLUMP) and can be used to obtain a more precise classification of farming and non-farming land types present within each grid cell.

Figure 4: Synthetic farm data, selected variables. Legend left values are percentile ranges.



2.2.3 Historical model scenarios

Historical climate (fixed prices)

The *Historical climate (fixed prices)* scenario is similar to that described in Hughes et al. (2022b) and is intended to isolate the effects of climate variability on financial incomes for broadacre farm businesses. In these simulations, global output and input price indexes are fixed at 2024-25 values. However, in these scenarios the spread between domestic and global grain (wheat, barley and sorghum) prices, along with Australian fodder prices, are allowed to vary in response to climate data (to capture domestic increases in grain and fodder prices in drought years, see Hughes et al. 2022b). A 75-year historical climate sequence (including historical simulated crop and pasture data from the AADI project) is simulated for each grid cell (1950-51 to 2022-23).

Historical climate and prices

As part of the AADI project an additional scenario was developed accounting for changes in both climate conditions and output and input prices (i.e., global commodity market variability). This *Historical climate and prices* scenario allows for variation in both historical climate conditions and historical prices. For this scenario, historical price indexes were de-trended, to account for consistent long-term trends in some real commodity prices (particularly sheep and lamb). The resulting simulation results and percentile indicators are intended to reflect the combined impacts of annual climate and commodity price variability. Given limited historical price data this scenario covers the period 1990-91 to 2022-23.

Projected climate

For this version of the AGFD long-term climate projection scenarios were also included. These scenarios are based on CMIP5 climate projections, specifically "Application Ready" 0.05-degree scale rainfall and temperature projections obtained from the CSIRO. These projections include 8 Global Circulation Models (GCMs), and three Representative Concentration Pathways (RCPs) 2.5, 4.5 and 8.5. Results are provided for two future time periods: 2038-39 to 2064-65 (2050 climate) and 2058-59 to 2084-85 (2070 climate). For more detail see Climate Change in Australia: (https://www.climatechangeinaustralia.gov.au/en/obtain-data/application-ready-data/).

All other assumptions are identical to the historical climate (fixed prices) scenario above (global output and input prices are fixed at 2024-25 values; farm characteristics are based on the last 10 years of observed AAGIS data). As with previous research (see Hughes et al. 2022c) these projections do not account for the offsetting positive effects of farm adaptation, technological improvement or CO2 fertilisation.

Table 1: *Model scenarios*

	Historical climate	**Historical climate and prices**
Description	Simulated farm outcomes over the historical reference period, holding commodity prices fixed.	Simulated farm outcomes over the historical reference period, allowing for commodity price variation
Simulation period	75-year historical sequence 1950-51 to 2022-23	35-year historical sequence 1989-90 to 2022-23
Farm business data	Gridded farm business data derived from survey data for the period 2012-13 to 2021-22	
Price data	Commodity price data from ABARES, prices fixed to last year of the reference period.	Historical commodity price data from ABARES (de-trended)
Climate data	Historical climate data from the Australian Gridded Climate Data (AGCD) (see https://www.bom.gov.au/climate/austmaps/about-agcd-maps.shtml)	
	2050 climate projections	**2070 climate projections**
Description	Simulated farm outcomes over the projection period, holding commodity prices fixed.	
Simulation period	27-year historical sequence 2038-39 to 2064-65	27-year historical sequence 2058-59 to 2084-85
Farm business data	Gridded farm business data derived from survey data for the period 2012-13 to 2021-22	
Price data	Commodity price data from ABARES, prices fixed to last year of the reference period.	
Climate data	CSIRO CIMP5 data using quantile-quantile downscaling, for three RCPs (2.5, 4.5 & 8.5) and eight GCMs (*ACCESS1-0*, *CanESM2*, *CESM1-CAM5*, *CNRM-CM5*, *GFDL-ESM2M*, *HadGEM2-CC*, *MIROC5*, *NorESM1-M*)	

Table 2: National average simulated farm profit ($ / ha), projected climate (RCP 4.5 and RCP8.5, 2050 and 2070) relative to historical climate (1984 to 2010)

		Farm profit ($ / ha)				**Change from historical (%)**			
Global Circulation Model (GCM)	Historical (1984 - 2010)	RCP 4.5		RCP 8.5		RCP 4.5		RCP 8.5	
		2050	2070	2050	2070	2050	2070	2050	2070
ACCESS1-0	22.3	18.1	18.2	17.2	14.4	-18.7%	-18.1%	-22.6%	-35.3%
CESM1-CAM5	22.3	19.5	19.6	16.5	17.1	-12.3%	-11.9%	-25.6%	-23.2%
CNRM-CM5	22.3	19.9	20.2	18.4	18.8	-10.6%	-9.3%	-17.4%	-15.7%
CanESM2	22.3	18.7	17.9	15.4	15.2	-16%	-19.4%	-30.9%	-31.5%
GFDL-ESM2M	22.3	12.4	5.1	6.4	4.4	-44.3%	-76.9%	-71.4%	-80.1%
HadGEM2-CC	22.3	18.3	16.9	14	13.3	-17.7%	-24%	-37.2%	-40.2%
MIROC5	22.3	20.7	20.8	18.2	18.9	-6.9%	-6.4%	-18.2%	-14.9%
NorESM1-M	22.3	19.2	18.7	18	19.4	-13.7%	-15.8%	-19.1%	-12.7%

3 File formats and metadata

3.1 Data files

Simulation output data are saved as multilayer NetCDF files, which are named as follows:

f<farm year>.c<climate year>.p<price year>.t<technology year>.nc

where:

- *<farm year>* = Financial year of farm business data is used in simulations.
- *<climate year>* = Financial year of climate data is used in simulations.
- *<price year>* = Financial year of output and input prices used in simulations.
- *<technology year>* = Financial year of farm ‘technology’ (equal to farm year in all simulations)

Here financial years are referred to by the closing calendar year (e.g., 2022 = 1 July 2021 to 30 June 2022).

3.2 File format

Each of the layers in simulation output data is represented as a 2D raster in NETCDF files, with the following grid format:

CRS	EPSG:4326 - WGS 84 – Geographic
Extent	111.975, -44.525: 156.275, -9.975
Unit	Degrees
Width	886
Height	691
Cell size	0.05 degree x 0.05 degree

3.3 Metadata

There are 41 layers in NETCDF files, as outlined in Table 2 below. These variables are each available on a per hectare of farm land area basis (e.g., simulated farm business profit / total farm-land area operated), except for crop yields which are provided on a per hectare of crop area planted basis.

Table 3 Data layers

Layer	Unit	Description
farmno	-	Row index and column index of the grid cell in the form of YYYXXX
A_barley_hat_ha	-	Proportion of total farm area planted to barley
A_oilseeds_hat_ha	-	Proportion of total farm area planted to canola
A_sorghum_hat_ha	-	Proportion of total farm area planted to sorghum
A_total_cropped_ha	-	Proportion of total farm area planted to crops
A_wheat_hat_ha	-	Proportion of total farm area planted to wheat
C_chem_hat_ha	$/ha	Expenditure on crop and pasture chemicals per hectare
C_fert_hat_ha	$/ha	Expenditure on fertiliser per hectare
C_fodder_hat_ha	$/ha	Expenditure on fodder per hectare
C_fuel_hat_ha	$/ha	Expenditure on fuel, oil and grease per hectare
C_total_hat_ha	$/ha	Total cash costs per hectare
FBP_fci_hat_ha	$/ha	Farm cash income per hectare
FBP_fbp_hat_ha	$/ha	Farm business profit per hectare, cash income adjusted for family labour, depreciation, and changes in stocks
FBP_pfe_hat_ha	$/ha	Profit at full equity per hectare
H_barley_dot_hat	t/ha	Barley yield (production per hectare planted)
H_oilseeds_dot_hat	t/ha	Oilseeds yield (production per hectare planted)
H_sorghum_dot_hat	t/ha	Sorghum yield (production per hectare planted)
H_wheat_dot_hat	t/ha	Wheat yield (production per hectare planted)
Q_barley_hat_ha	t/ha	Barley sold per hectare (total farm area)
Q_beef_hat_ha	Number/ha	Beef number sold per hectare
Q_lamb_hat_ha	Number/ha	Prime lamb number sold per hectare
Q_oilseeds_hat_ha	t/ha	Canola sold per hectare (total farm area)
Q_sheep_hat_ha	Number/ha	Sheep number sold per hectare

Q_sorghum_hat_ha	t/ha	Sorghum sold per hectare (total farm area)
Q_wheat_hat_ha	t/ha	Wheat sold per hectare (total farm area)
R_barley_hat_ha	$/ha	Barley gross receipts per hectare
R_beef_hat_ha	$/ha	Beef cattle receipts per hectare
R_lamb_hat_ha	$/ha	Prime lamb net receipts per hectare
R_oilseeds_hat_ha	$/ha	Receipts for oilseeds this FY for oilseeds sold this FY or in previous FYs per hectare
R_sheep_hat_ha	$/ha	Sheep gross receipts per hectare
R_sorghum_hat_ha	$/ha	Sorghum gross receipts per hectare
R_total_hat_ha	$/ha	Total farm receipts per hectare
R_wheat_hat_ha	$/ha	Wheat gross receipts per hectare
S_beef_births_hat_ha	Number/ha	Beef cattle births per hectare
S_beef_cl_hat_ha	Number/ha	Beef cattle on hand per hectare on 30 June
S_beef_deaths_hat_ha	Number/ha	Beef cattle deaths per hectare
S_sheep_births_hat_ha	Number/ha	Sheep births per hectare
S_sheep_cl_hat_ha	Number/ha	Sheep on hand per hectare on 30 June
S_sheep_deaths_hat_ha	Number/ha	Sheep deaths per hectare
S_wheat_cl_hat_ha	t/ha	Wheat on hand per hectare on 30 June
farmland_per_cell	ha	Indicative area of farm land in the grid cell

References

Bryan, B.A., Nolan, M., McKellar, L., Connor, J.D., Newth, D., Harwood, T., King, D., Navarro, J., Cai, Y., Gao, L. and Grundy, M., 2016. Land-use and sustainability under intersecting global change and domestic policy scenarios: Trajectories for Australia to 2050. Global Environmental Change, 38, pp.130-152.

Hughes, N., Brent, G., Gaydon, D., Schepen, A., Mitchell, P., Hochman, Z. Carter, J., Sharman, C., Taylor, P., McComb, J. and Searle, R. (2024) The Drought Early Warning System (DEWS) [aka Australian Agricultural Drought Indicators, AADI] project, Progress report, https://www.agriculture.gov.au/abares/research-topics/climate/drought/australian-agriculture-drought-indicators-progress-report

Hughes, N., Burns., K., Soh., Wei Ying., and Lawson, K. (2020) Measuring drought risk: The exposure and sensitivity of Australian farms to drought, https://www.agriculture.gov.au/abares/research-topics/climate/measuring-drought-risk

Hughes, N., Gaydon, D., Gupta, M., Schepen, A., Tan, P., Brent, G., ... & Singh, R. (2025). Monitoring agricultural and economic drought: the Australian Agricultural Drought Indicators (AADI). *Natural Hazards and Earth System Sciences*, *25*(9), 3461-3482.

Hughes, N., Soh, W., Lawson, K. and Lu, M. (2022) Improving the performance of micro-simulation models with machine learning: The case of Australian farms, Economic Modelling

Hughes, N., Soh, W., Boult, C., Lawson, K. (2022b) Defining drought from the perspective of Australian farmers, Climate Risk Management

Hughes, N., Lu, M., Soh, W. Y., & Lawson, K. (2022c). Modelling the effects of climate change on the profitability of Australian farms. *Climatic Change*, *172*(1), 12.

Appendix A: Farm land values

In this release of the AGFD an additional layer has been included containing interpolated estimates of farm land values, derived from the ABARES AAGIS farm survey data (based on farmer self-reported estimates of land value). This layer (*K_land_op_ha)* represents the land value (in $ per ha) of a representative farm for each 5km grid cell.

Values of *K_land_op_ha* are calculated as a weighted averaging of *K_land_op_ha* entries AAGIS farm survey data from 2013 to 2022, with weights for years defined as [1.0, 2.0, …, 10.0] (i.e., higher weights for more recent years). A random factor is generated, according to a normal distribution with mean 1 and standard deviation 0.1. Each of the *K_land_op_ha* entries in AAGIS farm survey data is then multiplied by this perturbation factor to protect farm business confidentiality.

Values of *K_land_op_ha* for each grid cell are calculated as weighted average of land values of neighbouring farms specified in the farm survey data. With weights of neighbouring farms defined as $0.5^{\left(\frac{d(g,f)}{r_f}\right)^2}$, where $d(g,f)$ is the distance between grid cell and a farm, r_f is radius of a farm.

There are at least 3 neighbouring farms for each grid cell. It is important to note that neighbouring farms may come from different broadacre farm industries. This means that the land values of cropping and livestock farms are currently mixed together in version 1 of the gridded farm data.

The gridded data is primarily designed to provide spatial distributions of land values across regions, rather than a reflection of the current land values for each region.

For more detail on the methodology see Hughes et al. (2024).