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Site-specific design of sustainable cropping systems: Linking agronomic structure to long-term performance

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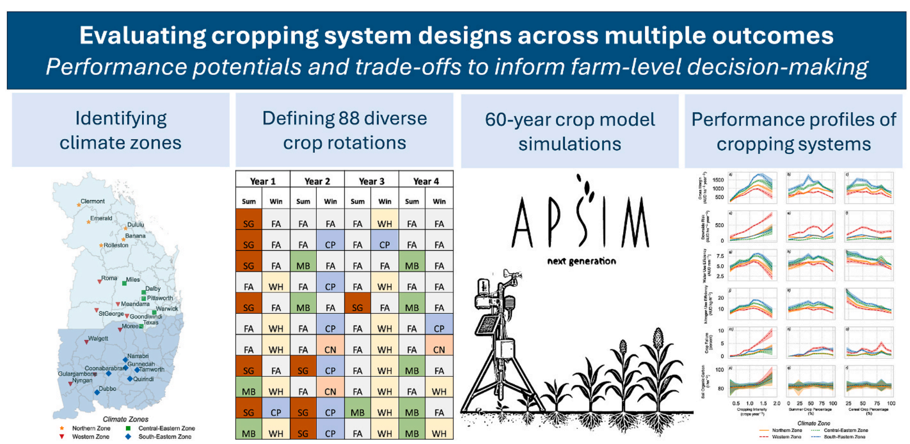
HIGHLIGHTS

- We simulate the performance, risks and trade-offs of diverse crop rotations across financial and environmental outcomes.
- Cropping intensities between 1.2 and 1.4 crops per year provide the highest financial returns and resource use efficiency.
- Winter crops provide higher but also more variable financial returns than summer crops.
- Trade-offs prevail between financial return and resilience-focussed cropping strategies.
- Flexibility to shift between scheduled crops and fallow based on seasonal conditions is crucial to high performance.

GRAPHICAL ABSTRACT



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ABSTRACT

Designing high-performing cropping systems requires agricultural producers to balance complex trade-offs among financial returns, resource use efficiency, and production risks. Quantitative data on the performance of specific cropping strategies can aid decisions on cropping system design, yet such performance profiles remain unavailable.

Here we quantify the financial and environmental performance of diverse cropping systems in a major cropping region of eastern Australia. Using daily gridded weather data, we identify homogeneous climate zones and employ the Agricultural Production Systems Simulator (APSIM) to model 88 crop rotations across 24 locations over a 60-year period of recent climate data.

Our results show that site-specific climate patterns strongly predetermine achievable outcomes, with gross margins differing by up to 34 percent between climate zones. Cropping intensities averaging 1.2 to 1.4 crops per year provided the highest gross margins and water and nitrogen use efficiency, but also amplified downside risk

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and crop failure, particularly in drier regions. Winter crops achieved higher average gross margins than summer crops, but also resulted in greater interannual variability. Cropping systems emphasising sorghum-chickpea or wheat-mungbean consistently performed well across all indicators. A clear trade-off was identified between cropping strategies that performed best in gross margin and nitrogen use efficiency, versus downside risk, crop failure, and water use efficiency.

This study demonstrates how cropping systems modelling can generate quantitative performance profiles to support the data-driven design of sustainable cropping strategies. The proposed framework integrates qualitative system design concepts with quantitative crop modelling and is transferable to other regions where calibrated crop models are available.

1. Introduction

Adjusting crop choice and fallow timing based on seasonal weather conditions, as well as past and planned field occupancy, is a key aspect of cropping systems design for agricultural producers. In rainfed cropping systems within water-limited production environments, the sequencing of crops and fallows centrally determines the intensity and timing of water and nutrient availability during crop growth (Kluger et al., 2022; Zhao et al., 2022). Grain growers' short-term decisions on optimal crop allocation for the upcoming season need to consider intertemporal carryover effects to optimise the medium- and long-term farm performance from a cropping systems perspective (Baumhardt and Anderson, 2006; Martin et al., 2013). This commonly involves deliberately sacrificing some yield potential of selected crops to prioritise water and nutrient availability for higher-priority crops within the system. Production environments capable of supporting crop growth across both summer and winter seasons typically offer a vast array of crop sequencing options. As a further aspect of cropping system design, agricultural producers aim to achieve multiple objectives simultaneously. Depending on their personal circumstances, this commonly includes achieving a high level of profitability, a low risk of severe income declines in unfavourable seasons, a high use efficiency of major production resources such as water and fertiliser, and the conservation or improvement of soil fertility (Grewer and Rodriguez, 2019; Groot et al., 2012; Liang et al., 2018). Given this complexity of cropping system design and the lack of clear decision support for producers, it is important to investigate which structural characteristics and design principles of cropping systems consistently perform well across specific metrics.

Using the highly diverse cropping systems in eastern Australia as an example, this analysis demonstrates how to use biophysical crop modelling to inform farmers' decision-making on selecting specific structural characteristics of cropping systems. We investigate how a system's cropping intensity, the proportion of summer versus winter crops, and the proportion of cereal crops determine overall system performance. We evaluate cropping systems in terms of six financial and environmental metrics, namely gross margin, downside risk, water and nitrogen use efficiency, crop failure, and soil organic carbon. We analyse which cropping strategies are best for each individual metric, as well as for the joint achievement of all six metrics. Our spatially explicit analysis characterises and compares individual locations as well as homogeneous climate zones regarding their performance potential in summer and winter seasons. Further, we investigate how strongly the highest-performing cropping strategies vary spatially. For this purpose, we employ biophysical crop simulation modelling across 24 locations over a 60-year timeframe across a major broadacre cropping region in eastern Australia.

Positive mathematical programming approaches have been developed to assess decisions on cropping system design at the farm level (Heckelei and Britz, 2005; Howitt, 1995). Some applications have coupled mathematical programming and biophysical models to allow for the multi-dimensional assessment of crop designs beyond typical disciplinary boundaries, simultaneously evaluating financial, environmental, and social outcomes (Antle, 2011; Antle and Stoorvogel, 2006). However, both model types require highly comprehensive, empirical farm survey data and have therefore typically been limited to analysing a narrower range of specific farm management decisions – such as erosion management or pesticide leaching (Stoorvogel et al., 2004). Similarly, econometric analyses of cropping system design choices are usually limited to single farm management decisions due to data constraints (Grewer et al., 2024). Other contributions that explicitly focus holistically on all aspects of cropping systems design are typically more qualitative and conceptual in nature, while not providing a quantitative evaluation of crop design choices (Meynard et al., 2012).

Existing biophysical crop simulation modelling has commonly focused on a limited spatial or temporal scale: Analyses covering a large spatial scale through gridded crop simulation modelling typically conduct single-year simulations that reset soil parameters annually (Grewer et al., 2025; Müller et al., 2019). As carryover effects of soil water and nutrients between growing seasons are central to cropping system design, the annual resetting of soil parameters is inappropriate for the analysis of long-term system performance. Studies that instead conducted continuous APSIM simulations across large time periods of up to 100 years, while implementing classical crop model calibration and evaluation procedures, were limited to a few individual plot locations due to the large input data requirements from agricultural field trials (Godde et al., 2016; Teixeira et al., 2015, 2018; Zhao et al., 2013). Crop simulation studies that comprehensively analysed diverse cropping strategies either focused on a few case study farms (Rodriguez et al., 2011) or only considered a smaller number of possible crop rotation choices (Hochman et al., 2020, 2021). The work presented here aims to address these existing gaps in the literature by simultaneously covering a comprehensive spatial and temporal scope as part of the analysis of cropping strategies. Specifically, this study analyses a comprehensive set of 88 diverse crop rotations across multiple decades and various contrasting environments. Instead of conducting site-specific calibration and evaluation for the individual locations analysed, the modelling framework employs standard APSIM parameterisations that have been calibrated and validated across a broad range of agro-environmental conditions using the APSIM test-suite database, supporting their application in large-scale comparative analyses.

The remainder of this article is structured as follows. We first describe the methodology, data sources, and scenario definitions of crop model simulations. This includes the definition of all outcome metrics and the method used to cluster study locations into homogeneous climate zones. The results section presents the main characteristics of the simulated cropping systems and how cropping patterns varied spatially. This is followed by an analysis of how key structural characteristics of cropping systems performed across the different result metrics. Finally, the discussion evaluates the broader implications of these findings.

2. Materials and methods

This study employs biophysical crop simulation modelling to evaluate the long-term performance of diverse crop rotations using a comprehensive set of result indicators in eastern Australia.

2.1. Data

The crop simulation modelling and subsequent analysis utilise diverse input datasets, including meteorological, soil, and agricultural cost-benefit data.

2.1.1. Meteorological data

Daily data on precipitation, minimum and maximum temperature, solar radiation, vapour pressure, and reference evapotranspiration was retrieved from the gridded Scientific Information for Land Owners (SILO) database with a spatial resolution of 0.05 decimal degrees (Jeffrey et al., 2001; QGOV, 2024). The gridded SILO database was developed through interpolation of long-term weather station data from approximately 4600 locations across Australia.

2.1.2. Soils data

We utilised a generic soil profile from the cropping systems platform Agricultural Risk Management Online (ARM Online; www.armonline.com.au; UniSQ and QGOV (2016)) which aims to represent general soil conditions across the target regions characterised by soils with varying ranges of plant available water holding capacity – usually determined by soil depth or the presence of a sub-soil constraint (Lai et al., 2020). We used a shallow (0.9 m), average (1.3 m), and deep (1.8 m) variant of this generic soil profile, which differed in their plant available water capacities (Table C. 3, Table C. 4).

2.1.3. Financial cost-benefit data

Data on the costs of variable inputs and crop sales prices were used from the Queensland Government agricultural gross margin database (AgMargins; https://agmargins.net.au; QGOV (2021)). All financial data is converted from nominal to real prices using the Australian Consumer Price Index for food and beverages, which uses the financial year 2011-12 as its base period (ABS, 2023). For all input prices, we used the last reported prices in AgMargins. For crop sales prices, we considered the average of all reported values from 2015 to 2021.

For variable costs, we considered expenses for fallow management, sowing, fertilisation (products and application), crop protection (products and application), harvesting, post-harvest management, industry levy fees, advisory services, and crop insurance. Instead of using the default fertiliser quantities reported in AgMargins, fertiliser costs were calculated using the specific quantities considered in the crop simulation scenarios.

2.2. Cropping systems modelling

This study used the Agricultural Production Systems sIMulator (APSIM Next Generation, version 2023.5.7225.0; Holzworth et al. (2018)) to systematically simulate all possible combinations of a set of locations (24), soil profile types (3), and crop rotations (88) across 60 years. Cropping system models are mathematical representations of crop growth and development processes that consider soil-plant-atmosphere interactions on a daily time step. They build on established theoretical principles of crop physiology and bio-geo-chemical processes as the basis of equation systems that quantify the conversion of mass and energy in response to environmental conditions and crop management. In contrast to empirical approaches that infer relationships directly from observational data, process-based models encode mechanistic assumptions about crop physiology and soil processes. Consequently, model outcomes are normative in the sense that simulated responses emerge from the parameterisation and process representations embedded in the model structure. While this approach enables systematic scenario analysis and extrapolation beyond observed conditions, it necessarily relies on simplified representations of complex agroecosystem processes and on the accuracy of input data and parameter values. Model outputs should therefore be interpreted as internally consistent simulations of cropping system behaviour under specified assumptions rather than direct empirical observations. As a result, this analysis focuses primarily on comparative differences among simulated systems under consistent modelling assumptions, rather than on exact quantitative prediction of crop yields or system performance.

2.2.1. Geographic and temporal scope

This study covers 24 locations (Fig. A. 1) in south-eastern Queensland and northern New South Wales, which represent a major rainfed broadacre cropping region of Australia (ABARES, 2021; ABS, 2021). The study locations range across temperate, subtropical, and grassland climate classes of the Koeppen classification system modified to Australian conditions (Stern et al., 2000). The analysis focuses on the recent 60-year timeframe from July 1962 to June 2022, which captures the typical pattern and intensity of climate variability at each site. While climatological studies commonly utilise 30-year periods for defining Climatological Standard Normals (WMO, 2017), a 60-year period was adopted here to ensure a better representation of extreme seasonal conditions and rare climate events. Crop model simulations were extended to an additional 11 years prior to this period (July 1951 to June 1962), whose results subsequently have been discarded and served to reduce the impact of initial parameters of soil nitrogen stocks and soil water availability on simulation results.

As part of the continuous simulation of a 60-year period, even minor systematic biases in the annual carryover effects of soil water and nutrients can accumulate to large incorrect trends in long-term simulation results. Therefore, we used an alternative strategy of repeatedly simulating 12-year periods (i.e., three consecutive 4-year rotation cycles), while subsequently restarting our model initialisation routine (see section 2.2.5 *Phasing of crop rotations*). Considering such a continuous period of 12 years constitutes a compromise between allowing for some carryover of soil water and nutrients to occur while avoiding the excessive accumulation of errors when continuously simulating multiple decades of cropping (see Appendix B for a detailed discussion).

2.2.2. Crop model calibration and evaluation

Long-term field trial data for classical crop model calibration and evaluation are unavailable for the exact scenarios simulated in this study, owing to the large scope of crop rotations, locations, and years considered. The APSIM model has been developed and widely calibrated and evaluated for the selected study region (for example: Asseng et al. (2002); Hammer et al. (2019); Hammer et al. (2010); Robertson et al. (2002)). Over the past 30 years of APSIM development, experimental trial data have been collated into evaluation datasets with a strong representation of the study region in south-eastern Queensland and northern New South Wales, as shown for selected crops in Fig. A. 2 and recorded in detail in the APSIM documentation (https://docs.apsim.info/). Each newly released APSIM version is automatically evaluated against these test datasets (Holzworth et al., 2018). This provides a high level of confidence in the ability to utilise APSIM for extrapolative simulation studies across south-eastern Queensland and northern New South Wales.

2.2.3. Crop rotation schedules

Observed data on the consecutive crop occupancy of broadacre fields is not available at a large scale across Australia. Instead, we defined typical crop rotations of rainfed broadacre crops across the study region based on the review of spatially disaggregated commodity production statistics (ABS, 2021), interviews with key informant farmers and agronomists as part of twelve participatory stakeholder workshops, and a review of the literature (Hochman et al., 2020; Whish et al., 2009). Crop rotations were defined as combinations of canola, chickpea, maize, mungbean, sorghum, wheat, and fallow, repeated in four-year sequences. We complemented commonly cultivated crop rotations with rotations of similar crop composition but with marginally lower and higher cropping intensity. We systematically considered rotations that increased the cropping intensity during both summer and winter seasons, as well as by introducing/eliminating cereals, legumes, or oilseeds. We purposefully included some crop rotations that are of lower and higher cropping intensity than what is commonly considered agronomically and economically viable in the study area. This was done with the intention (i) to avoid the exclusion of alternative cropping strategies based on current preconceptions, and (ii) to quantify their (suggested) performance deficit compared to less extreme cropping intensities. A total of 88 crop rotations were defined (Table 1). The crop rotations were considered as a scheduled crop occupancy plan in which the sowing of individual crops was replaced by fallows when sowing conditions were not met. The scheduled cropping intensities ranged from 0.5 to 2 crops per year, corresponding to a time a paddock is in fallow of 0-75 percent. Summer- and winter-dominant crop rotations were considered in roughly equivalent proportions. More specifically the crop rotations contained a mix of: 24 low cropping intensities (<1 crop yr^{-1}), 26 medium cropping intensities (1 crop yr^{-1}), and 38 high cropping intensities (>1 crop yr^{-1}); 37 summer-dominant rotations, 13 rotations with an equal proportion of summer and winter crops, and 38 winter-dominant rotations; 46 cereal-dominant rotations, 20 rotations with an equal proportion of cereal and non-cereal crops, and 22 rotations dominated by non-cereal crops.

2.2.4. Crop management

Our analysis is parameterised to reflect commercially relevant best crop management practices in the study area, representing well-managed farming systems that minimise avoidable agronomic stress while remaining consistent with typical management observed on economically oriented farms. We considered a medium to high level of nitrogen fertiliser application, defined as 25 kg of Nitrogen (N) per hectare (ha) for legumes, 75 kg N ha^{-1} for oilseeds, and 125 kg N ha^{-1} for cereals. These nitrogen application rates broadly reflect the practices of the highest quartile of broadacre farmers in the target region (Norton et al., 2024) and supply sufficient nitrogen to support production without major nitrogen stress (Cox and Strong, 2015; Pandey et al., 2024).

We considered sowing to occur within a predefined crop-specific sowing window (Table C. 1), if precipitation exceeded 25 mm during a consecutive 8-day period and the level of extractable soil water was greater than 25 mm. If these sowing conditions were not met, the respective season was simulated to be left in fallow, thus deviating from the nominally scheduled crop rotation plan. The sowing rule adopted here aligns with approaches widely used in related crop modelling research (Hochman et al., 2020, 2021). Crops were established by sowing into retained stubble from the preceding crop, with minimal soil disturbance, reflecting standard management practices in the study area (Coelli, 2021). We considered a fixed set of early to mid-maturing cultivar types that have widely been used in APSIM calibration and simulation applications (Table C. 2).

2.2.5. Phasing of crop rotations

The performance of any specific crop rotation will differ based on which crop (or fallow) occurs in which year and the associated climatic conditions. Furthermore, simulation results will be influenced by the specific position of any crop within the 12-year simulation period: I.e. crops at the beginning of the 12-year period will always be exposed to soil nutrient and water conditions that are largely determined by default initial simulation conditions, while crops at the end of the 12-year period will always be exposed to soil nutrient conditions that are more strongly co-determined by previous crop choice and management decisions. Besides, a simplistic implementation of 12-year simulation periods would introduce harsh cut-off points, where simulated carryover impacts would be reset to initial conditions.

To eliminate these sources of bias, results for each crop rotation during a given year and season were represented by averaging 12 separate APSIM simulation runs, referred to as simulation phases. The 12 simulation phases were designed in a way to ensure that (i) each crop was exposed to all 60-year weather records by initiating the crop rotation in each possible starting crop or fallow and continuing through the sequence for a fixed number of years, (ii) each scenario was simulated with 12 different initialisation offsets, by discarding 0 to 11 years prior, to vary soil water and nutrient starting conditions, and (iii) there is no time-trend or single cut-off year after 12 years of simulation in the final database of results. A detailed illustration of the crop model phasing procedure is provided in Table C. 5.

2.3. Water balance indicator and climate zones

As an indicator of water deficit or surplus for crop growth, we computed the seasonal water balance as the difference between seasonal precipitation and seasonal reference evapotranspiration (ET_0) of a tall reference crop (0.5 m alfalfa, *syn.* lucerne) using the Penman-Monteith equation (Allen et al., 2005). Specifically, the water balance at location l during year t and season s is defined as:

$$water\ balance_{lts} = precipitation_{lts} - reference\ evapotranspiration_{lts} \quad \text{(Eq. 1)}$$

The water balance is calculated for the summer (15 October to 15 April) and winter (16 April to 14 October) cultivation cycles, which are the most common temporal reference points for farmers in the study area. Throughout this analysis, the water balance indicator is only used for descriptive statistics, but not as input to the identification of climate zones.

We categorised the 24 study locations into four clustered climate zones based on similar patterns in the intensity and timing of precipitation and reference evapotranspiration. Specifically, for each study location, we calculated the long-term averages of precipitation and reference evapotranspiration for six equal intervals during each year – corresponding to the early, mid, and late winter and summer seasons, respectively. Considering the z-score normalised values of the long-term averages of both the sub-seasonal and seasonal total precipitation and reference evapotranspiration (i.e., a total of 16 individual variables), we categorised the 24 study locations into four clusters using the *greedy k-means++* clustering algorithm that we initiated 100 times with different centroid seeds. To ensure the reproducibility of results, we utilised a random state parameter of 2 for centroid initialisation in the function *sklearn.cluster.KMeans* of the *scikit-learn* software package (Pedregosa et al., 2011). Considering both sub-seasonal and seasonal totals of the agro-meteorological variables ensured that the clustering captured the overall seasonal differences between summer and winter conditions as well as their intra-seasonal timing.

The clustering of climate zones relies exclusively on precipitation and evapotranspiration due to their importance as the main environmental drivers of cropping system patterns in the study region. In contrast, the study locations are less constrained by limitations in growing degree days or solar radiation. Soil properties were not included in the classification due to the high variability of in-field soil conditions, which would make it difficult to capture meaningful differences between climate zones without introducing substantial over-simplification (Gladish et al., 2021; Robertson et al., 2007).

2.4. Data analysis

We quantified the performance of cropping systems across financial, resource-use efficiency, and environmental indicators. Specifically, we computed the average long-term performance of cropping systems for the indicators: **(1) Gross margin** (AUD ha^{-1}), given as the revenue from crop sales minus the earlier listed variable costs per year (or per season). The considered variable costs do not include land and labour expenses (i.e., rents, rates, land taxes, wages, as well as the opportunity costs of household-owned land and labour). Gross margins are by definition much higher than net profit levels, as the former does not account for

Table 1
Analysed crop rotation schedules.

#	Year 1		Year 2		Year 3		Year 4		Scheduled cropping intensity (crops yr^{-1})	Scheduled summer-to-winter crop ratio	Scheduled time in fallow
	S	W	S	W	S	W	S	W			
1	SG	FA	FA	FA	SG	FA	FA	FA	0.5	100% : 0%	75%
2	SG	FA	FA	FA	FA	WH	FA	FA	0.5	50% : 50%	75%
3	FA	WH	FA	FA	FA	WH	FA	FA	0.5	0% : 100%	75%
4	SG	FA	FA	CP	FA	FA	SG	FA	0.75	67% : 33%	63%
5	SG	FA	FA	CN	FA	FA	SG	FA	0.75	67% : 33%	63%
6	SG	FA	MB	FA	SG	FA	FA	FA	0.75	100% : 0%	63%
7	SG	FA	FA	CP	FA	CP	FA	FA	0.75	33% : 67%	63%
8	SG	FA	FA	CN	FA	CN	FA	FA	0.75	33% : 67%	63%
9	SG	FA	MB	FA	FA	FA	MB	FA	0.75	100% : 0%	63%
10	SG	FA	FA	CP	FA	FA	MZ	FA	0.75	67% : 33%	63%
11	SG	FA	SG	FA	SG	FA	FA	FA	0.75	100% : 0%	63%
12	SG	FA	MB	FA	FA	WH	FA	FA	0.75	67% : 33%	63%
13	SG	FA	FA	CP	FA	WH	FA	FA	0.75	33% : 67%	63%
14	SG	FA	FA	CN	FA	WH	FA	FA	0.75	33% : 67%	63%
15	SG	FA	SG	FA	FA	WH	FA	FA	0.75	67% : 33%	63%
16	SG	FA	MZ	FA	FA	WH	FA	FA	0.75	67% : 33%	63%
17	FA	WH	FA	WH	FA	WH	FA	FA	0.75	0% : 100%	63%
18	FA	WH	FA	FA	MB	FA	FA	WH	0.75	33% : 67%	63%
19	FA	WH	FA	CP	FA	WH	FA	FA	0.75	0% : 100%	63%
20	FA	WH	FA	CN	FA	WH	FA	FA	0.75	0% : 100%	63%
21	FA	WH	FA	FA	MB	FA	MB	FA	0.75	67% : 33%	63%
22	FA	WH	FA	CP	FA	CP	FA	FA	0.75	0% : 100%	63%
23	FA	WH	FA	CN	FA	CN	FA	FA	0.75	0% : 100%	63%
24	FA	WH	FA	FA	MZ	FA	FA	WH	0.75	33% : 67%	63%
25	SG	FA	SG	FA	SG	FA	SG	FA	1	100% : 0%	50%
26	SG	FA	MB	FA	SG	FA	SG	FA	1	100% : 0%	50%
27	SG	FA	FA	CP	SG	FA	SG	FA	1	75% : 25%	50%
28	SG	FA	FA	CN	SG	FA	SG	FA	1	75% : 25%	50%
29	SG	FA	MB	FA	SG	FA	MB	FA	1	100% : 0%	50%
30	SG	FA	MB	FA	SG	FA	FA	CN	1	75% : 25%	50%
31	SG	FA	MB	FA	SG	FA	FA	CP	1	75% : 25%	50%
32	SG	FA	MB	FA	MB	FA	FA	CN	1	75% : 25%	50%
33	SG	FA	MB	FA	MB	FA	FA	CP	1	75% : 25%	50%
34	SG	FA	FA	CP	SG	FA	MZ	FA	1	75% : 25%	50%
35	SG	FA	SG	FA	FA	WH	FA	WH	1	50% : 50%	50%
36	SG	FA	MZ	FA	FA	WH	FA	WH	1	50% : 50%	50%
37	SG	FA	SG	FA	FA	WH	MB	FA	1	75% : 25%	50%
38	SG	FA	MB	FA	FA	WH	FA	CP	1	50% : 50%	50%
39	SG	FA	MB	FA	FA	WH	FA	CN	1	50% : 50%	50%
40	FA	WH	FA	WH	FA	WH	FA	WH	1	0% : 100%	50%
41	FA	WH	FA	CP	FA	WH	FA	WH	1	0% : 100%	50%
42	FA	WH	FA	CN	FA	WH	FA	WH	1	0% : 100%	50%
43	FA	WH	FA	CP	FA	WH	FA	CP	1	0% : 100%	50%
44	FA	WH	FA	CN	FA	WH	FA	CN	1	0% : 100%	50%
45	FA	WH	MB	FA	MB	FA	FA	WH	1	50% : 50%	50%
46	FA	WH	SG	FA	FA	WH	FA	WH	1	25% : 75%	50%
47	FA	WH	MB	FA	FA	WH	FA	WH	1	25% : 75%	50%
48	FA	WH	MB	FA	FA	WH	FA	CP	1	25% : 75%	50%
49	FA	WH	MB	FA	FA	WH	FA	CN	1	25% : 75%	50%
50	FA	WH	SG	FA	FA	WH	FA	CP	1	25% : 75%	50%
51	SG	CP	FA	CP	SG	FA	SG	FA	1.25	60% : 40%	38%
52	SG	CN	FA	CP	SG	FA	SG	FA	1.25	60% : 40%	38%
53	SG	CP	FA	CP	SG	FA	MB	FA	1.25	60% : 40%	38%
54	SG	CN	FA	CP	SG	FA	MB	FA	1.25	60% : 40%	38%
55	SG	CP	FA	CP	MZ	FA	MB	FA	1.25	60% : 40%	38%
56	SG	FA	SG	CP	FA	WH	MB	FA	1.25	60% : 40%	38%
57	SG	FA	SG	CN	FA	WH	MB	FA	1.25	60% : 40%	38%
58	SG	FA	MZ	CP	FA	WH	MB	FA	1.25	60% : 40%	38%
59	MB	WH	FA	WH	FA	WH	FA	WH	1.25	20% : 80%	38%
60	MB	WH	FA	FA	MB	WH	FA	WH	1.25	40% : 60%	38%
61	MB	WH	FA	CP	FA	WH	FA	WH	1.25	20% : 80%	38%
62	MB	WH	FA	CN	FA	WH	FA	WH	1.25	20% : 80%	38%
63	MB	WH	FA	CP	FA	WH	FA	CP	1.25	20% : 80%	38%
64	MB	WH	FA	CN	FA	WH	FA	CN	1.25	20% : 80%	38%
65	SG	FA	SG	CP	SG	FA	SG	CP	1.5	67% : 33%	25%
66	SG	FA	SG	CP	SG	FA	SG	CN	1.5	67% : 33%	25%
67	SG	FA	SG	CP	SG	FA	MB	CN	1.5	67% : 33%	25%
68	SG	FA	SG	CP	SG	FA	MB	CP	1.5	67% : 33%	25%
69	SG	FA	SG	CP	MZ	FA	MB	CP	1.5	67% : 33%	25%
70	SG	CP	SG	CP	FA	WH	MB	FA	1.5	50% : 50%	25%
71	SG	CN	SG	CP	FA	WH	MB	FA	1.5	50% : 50%	25%
72	SG	CP	MZ	CP	FA	WH	MB	FA	1.5	50% : 50%	25%
73	MB	WH	MB	CP	FA	WH	FA	WH	1.5	33% : 67%	25%
74	MB	WH	MB	CP	FA	WH	FA	CP	1.5	33% : 67%	25%
75	MB	WH	MB	CP	FA	WH	FA	CN	1.5	33% : 67%	25%
76	SG	CP	SG	CP	SG	CP	FA	CP	1.75	43% : 57%	13%
77	SG	CN	SG	CP	SG	CP	FA	CP	1.75	43% : 57%	13%
78	SG	CP	SG	CP	MB	CP	FA	CP	1.75	43% : 57%	13%
79	SG	CN	SG	CN	SG	CN	FA	CN	1.75	43% : 57%	13%
80	SG	CP	SG	CP	FA	WH	MB	WH	1.75	43% : 57%	13%
81	SG	CP	SG	CP	MB	WH	MB	FA	1.75	57% : 43%	13%
82	SG	CN	SG	CP	MB	WH	MB	FA	1.75	57% : 43%	13%
83	MB	WH	MB	CP	FA	WH	MB	WH	1.75	43% : 57%	13%
84	MB	WH	SG	CP	FA	WH	MB	WH	1.75	43% : 57%	13%
85	SG	CP	SG	CP	SG	CP	SG	CP	2	50% : 50%	0%
86	SG	CN	SG	CN	SG	CN	SG	CN	2	50% : 50%	0%
87	SG	WH	SG	WH	SG	WH	SG	WH	2	50% : 50%	0%
88	MB	WH	MB	WH	MB	WH	MB	WH	2	50% : 50%	0%

Note: Season abbreviations: S – summer, W – winter. Crop abbreviations: CN – canola, CP – chickpea, FA – fallow, MB – Mungbean, MZ – maize, SG – sorghum, WH – wheat.

fixed costs, which typically constitute a large expenditure for Australian agricultural producers (ABARES, 2024). When calculating averages of gross margins over time, we considered fallow seasons as neither generating any crop revenue nor costs (as land preparation and fallow weed control were accounted for as a pre-season cost of cropped seasons). **(2) Downside risk** (AUD ha^{-1}), defined as the average reduction in gross margins below 500 AUD ha^{-1} per year (or 250 AUD ha^{-1} per season) in the 25 percent of cropped years (or seasons) with the lowest gross margins. It is important to note that we calculated the downside risk exclusively for seasons with sown crops while disregarding fallow seasons. Otherwise, all rotations with a high proportion of fallows would have automatically been categorised as "high risk" (as it is evident that fallows do not generate any crop sales, this would not have provided any additional insights). Thus, the downside risk indicator identifies cropping systems that produce frequent and sharp reductions in gross margins below a minimum threshold during cropped seasons. **(3) Water use efficiency** (AUD mm^{-1}), calculated as the gross margin per total crop water uptake. It indicates how efficiently water resources captured by crops are translated into financial gain. **(4) Nitrogen fertiliser use efficiency** (AUD kg^{-1} N), computed as the gross margin per nitrogen applied through fertilisers. It measures the financial return of applied nitrogen fertiliser. **(5) Crop failure frequency** (%) refers to the proportion of sown crops that fail to produce any harvestable yield (e.g., grain, pulses, etc.). This measure of absolute, biophysical crop failure identifies when a cropping system is strongly unsuitable under the given seasonal weather conditions. The indicator instead does not quantify the proportion of very low-yielding crops that do not generate enough revenue to exceed the costs of harvesting and other basic operational costs (i.e., financial crop failure). **(6) Soil organic carbon levels** (t ha^{-1}), calculated as the average level of soil organic carbon during the considered timeframe and considering the full soil profile depth. Soil carbon has multifaceted roles in supporting soil health, structure and functioning, which co-determine, besides others, the fertiliser and water productivity of the cropping system.

We calculated a **composite indicator** (CI) that quantifies which cropping systems provide the most favourable long-term outcomes when simultaneously considering all of the above-listed six indicators. We first averaged the performance for each result indicator across all years and soil profile depths. This aggregation substantially reduces the influence of transient extremes arising from individual years or soil layers, thereby limiting the impact of isolated outlier values. Detailed outlier diagnostics and robustness checks underlying the composite indicator are presented in Appendix D.

We then transformed the values of all six result indicators to a common scale using min-max normalisation, while inverting the sign of selected variables (downside risk, crop failure) to ensure that larger values consistently indicate a more favourable performance. Finally, the composite indicator was calculated as the mean of the six normalised outcome values:

$$CI_{li} = \sum_{d=1}^{D} \left(\frac{o_{lid} - \min\,(o_d)}{\max\,(o_d) - \min\,(o_d)} \right) \times \frac{1}{D} \qquad \text{(Eq. 2)}$$

where:

CI_{li} The composite indicator at the lth location for the ith cropping system.
o_d The dth outcome indicator.
D The number of considered outcome dimensions (=6).

In the results section, we utilise a range of visualisations to summarise the statistical properties of data distributions. Throughout this analysis, Tukey-style boxplots (McGill et al., 1978) are used, with the central box representing the interquartile range, whiskers extending to the most extreme observed values within 1.5 times the interquartile range from the box boundaries, and any points beyond this range plotted individually.

Violin plots display the kernel density estimation of the underlying data, using Scott's Rule for bandwidth selection (Scott, 1979), while their extent is limited to the observed data range. To summarise trends in the relationship between two variables, we compute Locally Weighted Scatterplot Smoothing (LOWESS) functions using 10 regularly spaced x-axis values and considering 30 percent of the overall data for estimating each y-value. We computed 95 percent confidence intervals around the LOWESS estimate using 200 bootstrap samples. To ensure the reproducibility of results, we utilised a random state parameter of 42 in the function *nonparametric.smoothers_lowess.lowess* of the *statsmodels* software package (Seabold and Perktold, 2010).

The data analysed in this study are generated by a deterministic, process-based crop model, rather than representing observational, experimental, or survey data. As a result, statistical inference techniques such as hypothesis testing are not an appropriate form of data analysis for drawing probabilistic or significance-based conclusions about causal drivers. Instead, the observed variability reflects differences in climatic inputs and structural characteristics encoded in the APSIM crop model, rather than stochastic sampling from an underlying data-generating process with random noise.

3. Results

This section reports results from clustering study locations into homogeneous climate zones. Variation between climate zones in average financial and environmental outcomes reveals key differences in their agro-ecological potential. Crop rotation performance is found to be determined systematically by both structural characteristics, such as cropping intensity, and specific crop choices and sequences. The results reveal major synergies and trade-offs between the financial and environmental performance of specific crop rotation choices.

3.1. Characteristics of climate zones

K-means clustering segmented the 24 study sites into four climate zones based on precipitation and evapotranspiration patterns (Fig. 1a). Major characteristics of the climate zones included the scarcity and infrequency of winter rainfall in most zones (except the south-eastern zone), high summer rainfall in the northern zone, and low summer rainfall combined with high evapotranspiration as a driver of summer drought in the western zone.

When analysing each zone in more detail, the **northern climate zone** (delineation: Clermont, Dululu, Rolleston) was characterised by the lowest level of winter and the highest level of summer rainfall (Fig. 1b and c). The extensive **western climate zone** (delineation: Roma, Goondiwindi, Nyngan) had low winter and summer rainfall and, combined with high summer evapotranspiration, was most prone to summer water stress. The **central-eastern climate zone** (delineation: Miles, Warwick, Texas) experienced a longer rainy season and lower summer evapotranspiration, which made it less drought-prone than the northern and western zones. The **south-eastern climate zone** (delineation: Narrabri, Quirindi, Dubbo) observed a largely similar climate pattern than the central-eastern zone but benefitted from higher and more consistent winter rainfall.

3.2. Cropping patterns across climate zones

Each climate zone (Fig. 1a) was characterised by a distinct cropping pattern. This resulted from differences in agro-ecological conditions and the threshold-based sowing rule, which translated into crops being sown at different frequencies across zones (Fig. 2; Table E. 1). Cropping intensity was higher in the south-eastern (0.97 crops yr^{-1}) and central-eastern (0.96) zones than in the northern (0.90) and western (0.88) zones (Table E. 1). It was generally greater in summer than in winter seasons, particularly in the northern zone (summer: 0.53; winter: 0.37

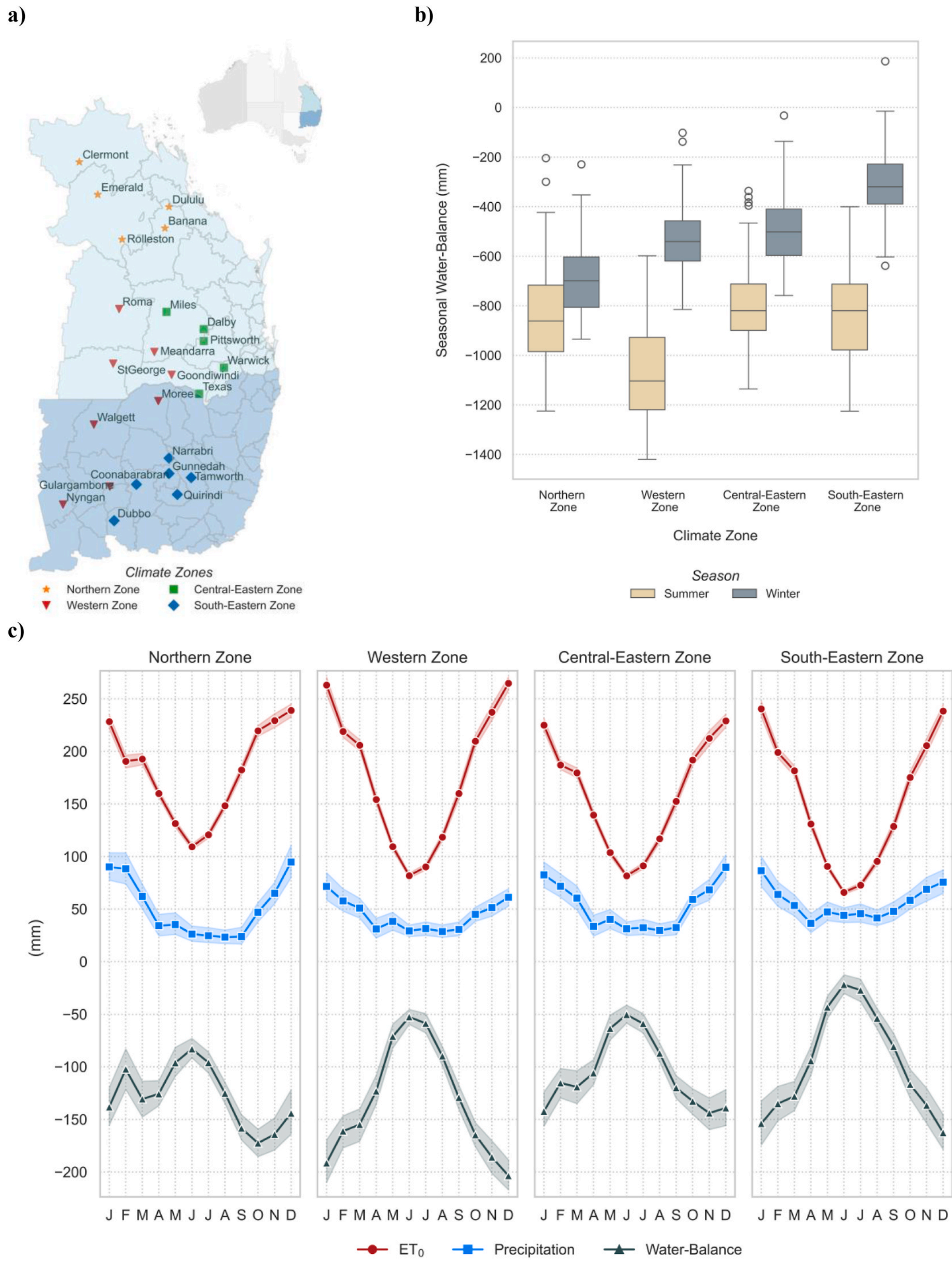

Fig. 1. Climate conditions at study sites

Note: Data covers the 60-year timeframe 1962-2022. a) Clustering of study sites into four distinct climate zones, denoted by different colours and symbols. Boundaries indicate Local Government Areas and shaded areas indicate States. The miniature map indicates the location of the study region within Australian State boundaries. b) Boxplots of the seasonal water balance for the identified climate zones. c) Monthly reference evapotranspiration (ET_0), precipitation, and water balance. Lines identify long-term mean values. Shaded areas identify±one standard deviation across years.

crops yr^{-1}), while the south-eastern zone showed little seasonal difference (summer: 0.50; winter: 0.47 crops yr^{-1}).

Across all zones, cereals comprised about 62 percent of crops, with summer seasons mostly cereal-dominated and winter seasons with a small majority of non-cereal crops (Fig. 2). Summer crops were slightly more prevalent than winter crops across most climate zones, particularly in the northern zone (55.2%).

3.3. Financial and environmental outcomes across climate zones

The differences between climate zones translated into distinct agro-ecological potentials to achieve financial and environmental outcomes. We found substantial differences between climate zones in the ability to achieve gross margins, with the long-term average varying by 34 percent (452 AUD ha^{-1} season^{-1}) between the best (south-eastern) and worst (western) climate zone. In particular, the ability to produce a high-yielding winter crop proved most effective in achieving higher gross

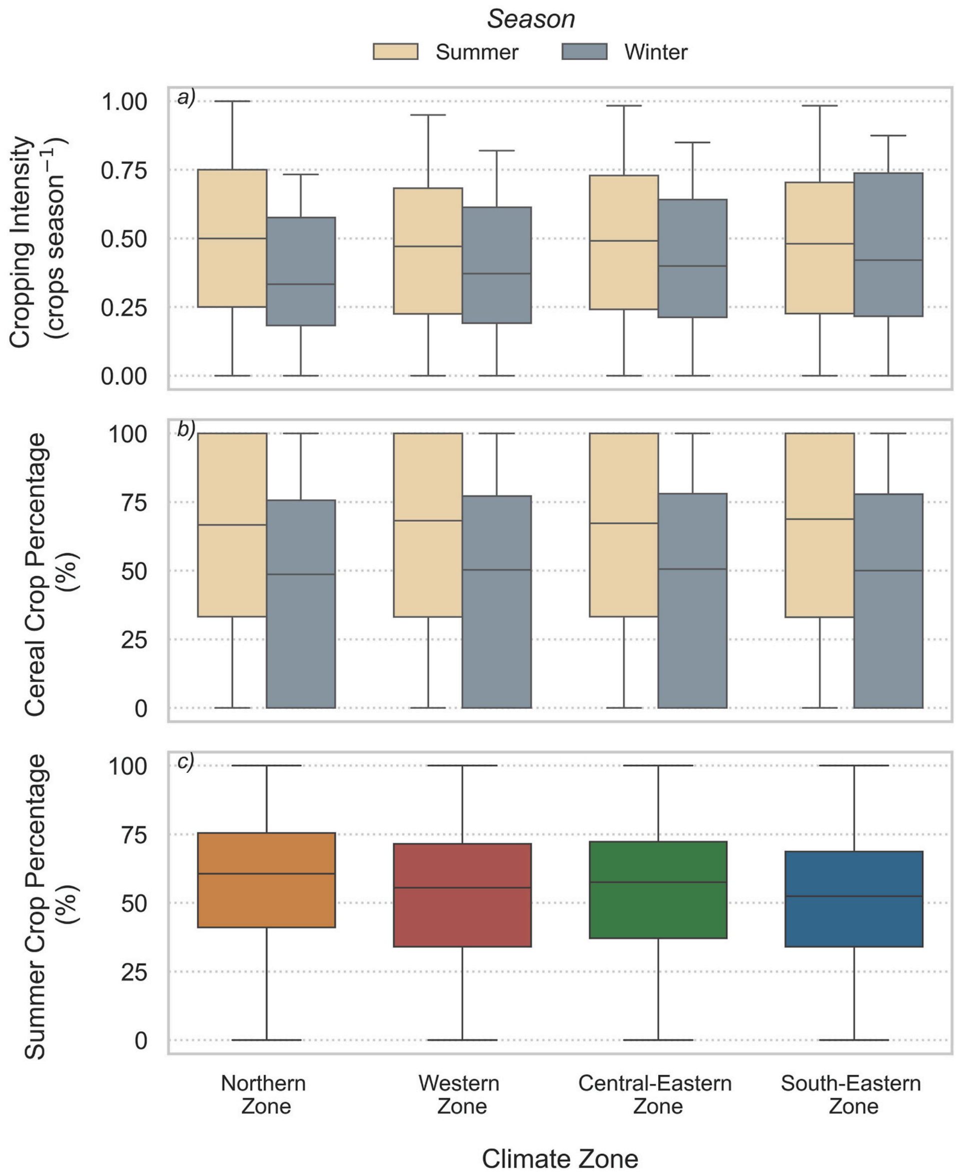

Fig. 2. Boxplots of structural characteristics of cropping systems across climate zones
Note: Boxplots based on data from individual crop rotations for all locations and soil conditions included in this analysis. Data was averaged across seasons (a & b) or years (c) for the 60-year timeframe 1962-2022. All three variables (a, b, c) are defined in terms of crops sown by the simulation analysis, which differed from the nominally scheduled crop rotation plan whenever meteorological conditions did not satisfy sowing rule thresholds.

margins, with winter crops providing a 43 percent (626 AUD ha^{-1} season^{-1}) higher gross margin than summer crops when averaged across climate zones. Similar large differences existed in the level of downside risk, with the western zone facing the largest downside risk (i.e., high reductions in gross margin below a minimum threshold). We found strong fluctuations between seasons of very high and very low resource use efficiency for water and nitrogen, with water use efficiency levels differing markedly across climate zones. Crop failure occurred almost exclusively in summer seasons, with the western (2.6%) and south-eastern zone (1.9%) observing the highest crop failure rates.

When investigating results for each financial and environmental indicator in more detail, the highest average seasonal **gross margin** was achieved in the south-eastern zone (1317 AUD ha^{-1} season^{-1}), followed by the central-eastern zone (1173 AUD ha^{-1} season^{-1}), while substantially lower gross margins were achieved in the northern (961 AUD ha^{-1} season^{-1}), and the western zones (865 AUD ha^{-1} season^{-1}; see Table E. 2 and Fig. E. 2). Across all climate zones, average gross margins were higher in the winter than in the summer growing season, with this difference most pronounced in the south-eastern and western zones (Fig. 3). Very high gross margins were considerably more common in winter than in summer crops. In winter, a few seasons with highly favourable conditions produced very high gross margins, reflected in strongly positively skewed distributions (skewness >0.5) with heavy right tails. In summer, gross margins were more evenly distributed around the mean, resulting in roughly symmetric distributions ($-0.5 <$ skewness <0.5) without heavy tails. Focusing on interannual variability (Fig. 3), most climate zones exhibited relatively stable gross margins in summer seasons, with only occasional poor seasons. In the northern, central-eastern, and south-eastern zones, this can be identified from the negatively skewed gross margin distributions with comparably high medians (922, 910, and 883 AUD ha^{-1} season^{-1}, respectively). The western zone exhibited the opposite pattern, with the bulk of seasonal gross margins clustered around a low median (432 AUD ha^{-1} season^{-1}), and only fewer summer seasons achieving high gross margins – a pattern captured by its positively skewed distribution.

Downside risk (i.e., the average decline in gross margins below a

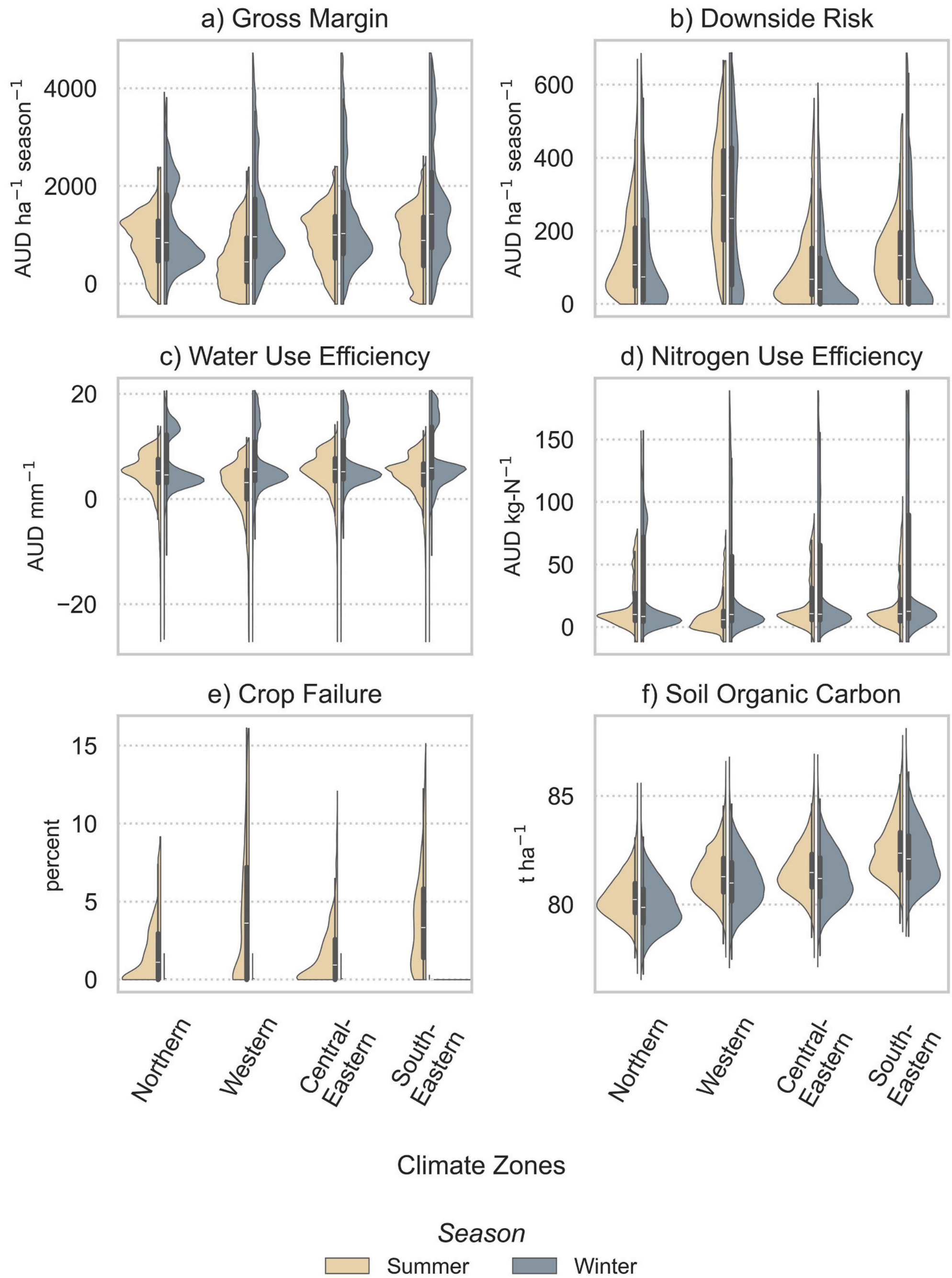

Fig. 3. Seasonal performance of cropping systems across climate zones using multiple metrics
Note: Figure based on seasonal data of individual crop rotations for all locations and soil conditions included in this analysis. The 1st and 99th percentiles have been excluded from the visualised data range to improve readability. Panel (f) shows results for soil profiles with a single identical profile depth (1.3 m) across sites, while results for all soil profile depths are presented in Fig. E. 2.

threshold of 250 AUD ha^{-1} during the worst 25 percent of seasons) varied sharply across climate zones (Fig. 3, Fig. E. 1). Farmers in the western zone faced the highest downside risk of 287 AUD ha^{-1} in the worst 25 percent of seasons. The northern and south-eastern zones experienced moderate downside risks (148 and 146 AUD ha^{-1}, respectively). In contrast, the central-eastern zone stood out for its resilience, with downside risks averaging just 95 AUD ha^{-1} in poor seasons. While summer seasons had a slightly higher median downside risk than winter seasons, the average downside risk and distributional patterns are roughly similar across both seasons (Table E. 2).

The median annual financial **water use efficiency** was similar across most climate zones (Table E. 2), with only the western zone observing consistently lower levels. Across zones, water use efficiency distributions exhibited heavy tails, reflecting frequent seasons with exceptionally high or low values. In winter, differences between zones were minor (Fig. 3), with all zones showing an approximately bimodal distribution, indicating that winter seasons typically fell into two distinct efficiency classes. In summer, the western zone stood out with persistently the lowest water use efficiency. Under unfavourable conditions, the combination of negative gross margins and low water uptake occasionally produced extreme outliers, including highly negative efficiency values.

Average annual financial **nitrogen use efficiency** was larger in the south-eastern (33.8 AUD kg^{-1} N) and central-eastern (29.5 AUD kg^{-1} N) zones than in the northern (23.5 AUD kg^{-1} N) and western (22.1 AUD

kg^{-1} N) zones (Table E. 2). In winter, the south-eastern zone (52.3 AUD kg^{-1} N) achieved by far the highest level of average nitrogen use efficiency. In summer, average nitrogen use efficiency was similar across most zones, with only the western zone (9.8 AUD kg^{-1} N) observing a much lower level. Overall, nitrogen use efficiency was substantially higher in winter than in summer, driven by occasional high-efficiency outliers in winter that were absent during summer.

The average proportion of **crop failure** was larger in the western (2.6 %) and south-eastern (1.9 %) climate zones and lower in the central-eastern (0.8 %) and northern (0.9 %) climate zones. Thereby, nearly all crop failure occurred in the summer season and hardly any crop failure was observed in the winter season.

When using the 1.3m deep soil profile as a reference case, the simulated levels of **soil organic carbon** were slightly higher in the south-eastern zone (84.2 t ha^{-1}). The western (83.0 t ha^{-1}) and central-eastern (82.9 t ha^{-1}) zones had a largely identical average level of soil organic carbon, while the northern zone (81.9 t ha^{-1}) observed the lowest level. Results for all profile depths are provided in Fig. E. 2.

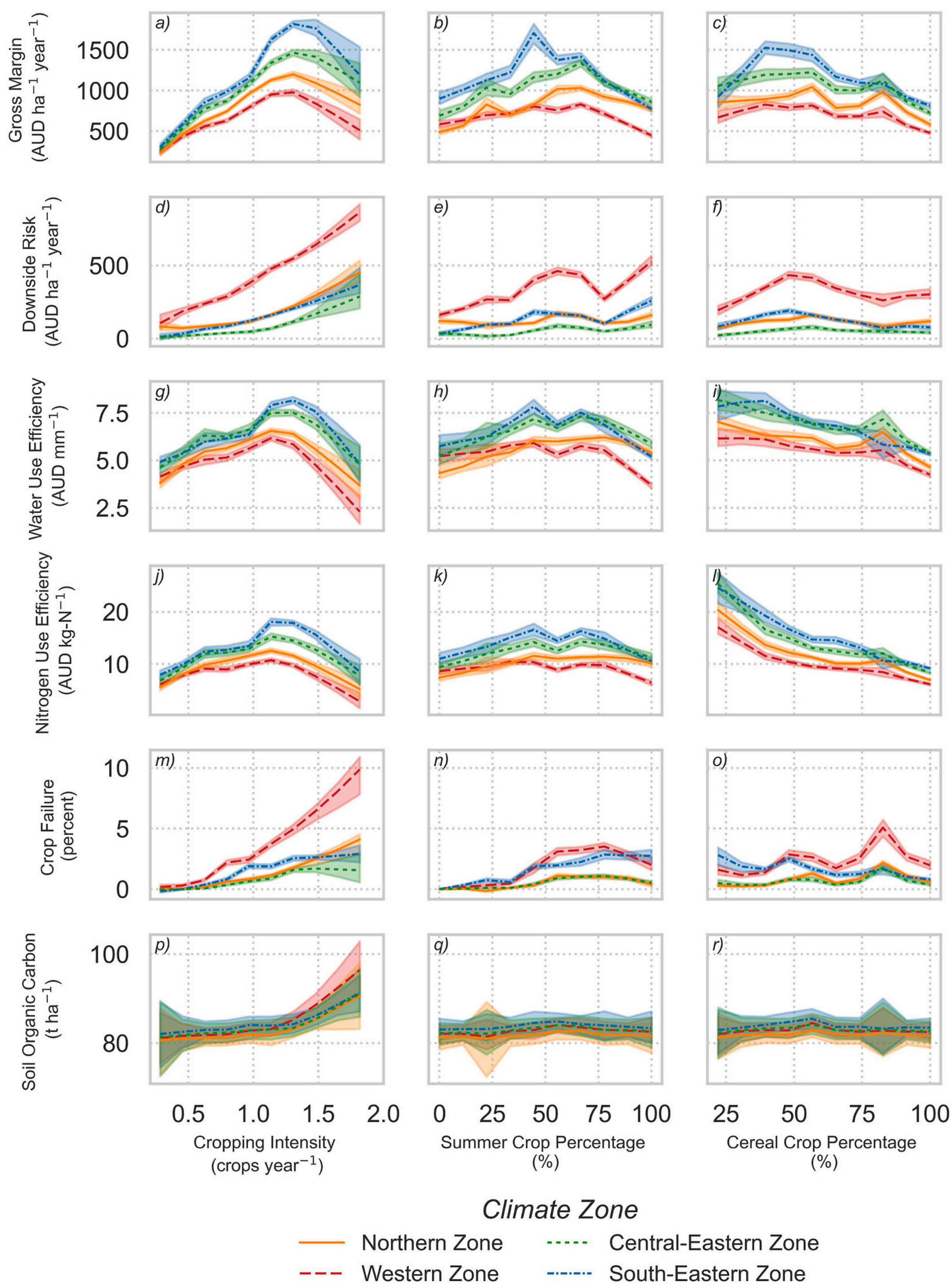

Fig. 4. Long-term average performance of cropping systems for multiple outcome dimensions and across structural cropping system characteristics and climate zones Note: Figure based on the long-term, yearly average across the 60-year timeframe 1962-2022 of individual crop rotations for all locations and soil conditions included in this analysis. Lines represent nonparametric Locally Weighted Scatterplot Smoothing (LOWESS) functions. Shaded areas indicate 95 percent confidence intervals.

3.4. Financial and environmental outcomes across cropping system characteristics

Structural characteristics of cropping systems are key determinants of their financial and environmental performance. Here, we assess how cropping intensity, the proportion of summer versus winter crops, and the proportion of cereal versus non-cereal crops influenced system outcomes, and whether these relationships differed across climate zones.

Very low and very high sown **cropping intensities** performed poorly across all zones in terms of gross margin, water use efficiency, and nitrogen use efficiency (Fig. 4). Across these indicators, optimal cropping intensities were between 1.2 and 1.4 crops per year. Thereby, the largest gains from increasing cropping intensity were achieved in the south-eastern zone, while the western zone benefited least. If cropping intensities were increased beyond approximately 1.2 to 1.4 crops per year, it led to significant reductions in gross margins as well as water and nitrogen use efficiency. High cropping intensities also exacerbated downside risks and crop failure. This relationship was particularly strong in the western zone, while across all other climate zones, a cropping intensity of up to one crop per year could be achieved without pronounced negative effects on downside risk or crop failure. Soil organic carbon levels remained largely unaffected by cropping intensities until a level of about 1.3 crops per year, but increased substantially beyond this level. Gains in soil organic carbon associated with higher cropping intensity are primarily driven by increased inputs of organic matter from crop residues and by shorter periods without soil cover. In the simulations, all cropping systems were assumed to follow typical local management practices, with crops established by direct seeding into retained stubble. This practice minimises soil disturbance and thereby reduces potential losses of soil organic carbon associated with frequent tillage.

Thus, when determining cropping intensity, farmers must balance the benefits of higher gross margins, improved water and nitrogen use efficiency, and increased soil organic carbon against greater downside risk and more frequent crop failure. Typically, high cropping intensities led to high benefits and low trade-offs in the south-eastern zone, while causing low benefits and high trade-offs in the western zone.

A balanced **proportion of summer and winter crops** was found to lead to the highest level of gross margins as well as greater water and nitrogen use efficiency (Fig. 4). In all climate zones except the northern one, highly summer-dominant systems led to pronounced reductions in these metrics. Low proportions of summer crops were consistently associated with reduced downside risk and lower crop failure rates across all zones. A high proportion of summer crops could particularly increase downside risk in the western zone, as well as crop failure in the western and south-eastern zones. There was no strong impact of the proportion of summer and winter crops on soil organic carbon levels.

The **proportion of cereal crops** affected gross margins differently across climate zones. In the south-eastern zone, gross margins peaked at a cereal proportion of 35-45 percent. In all other climate zones, a broad range in the proportion of cereal crops (25-80 %) led to approximately similar levels of gross margin. Across all zones, gross margins declined sharply once cereal proportions exceeded 90 percent. Increasing cereal proportions also led to markedly lower nitrogen use efficiency and moderately lower water use efficiency. Except in the western zone, where a high proportion of cereal crops substantially increased crop failure, the share of cereals had little effect on crop failure rates, downside risk, or soil organic carbon.

In order to examine whether these findings were sensitive to the specific sowing rule employed in this analysis, we compared results with those obtained under three alternative sowing rules in Appendix F. The analysis shows that, despite few expectable differences, the overall pattern of results remained consistent across all four sowing rule scenarios.

3.5. Best-performing crop rotations for diverse criteria

This section presents a comprehensive evaluation of crop rotation performance, identifying rotations that performed best when assessed jointly in terms of gross margin, downside risk, and the composite indicator that equally weights all six individual outcomes considered in this study.

Crop rotations with a high proportion of sorghum and chickpea consistently achieved high gross margins and composite indicator scores in all climate zones (Table 2). A high composite indicator score was also achieved by crop rotations with a high proportion of wheat and chickpea. Generally, we found that a high composite indicator score was achieved by two different performance profiles: Either (i) crop rotations performed well in terms of high gross margin and nitrogen use efficiency, or (ii) crop rotations performed well in terms of low downside risk, infrequent crop failure, and high water use efficiency. This underlines that highly different cropping system design strategies were suitable to deliver highly performant outcomes across multiple criteria.

In the western zone, the highest composite indicator scores were achieved exclusively at lower cropping intensities. In all other climate zones, both low and high cropping intensities delivered high composite indicator scores. Specifically, these include (i) low-intensity, winter-dominant rotations with wheat and chickpea as the main crops, and (ii) high-intensity rotations with a balanced proportion of summer and winter crops, predominantly cultivating sorghum, chickpea, and mungbean. The lowest level of downside risk was achieved by crop rotations with a high proportion of wheat and a low cropping intensity. Many crop rotations with a low level of downside risk were highly winter-dominant, particularly in the western and south-eastern zones.

When broadening the analysis beyond the top three crop rotations (Table 2) to the best-performing 25 percent for each outcome indicator (Table E. 2), crop rotations with a high proportion of wheat and mungbean were among the best-performing rotations in terms of gross margin and the composite indicator score. Across all climate zones, most cropping systems that provided high gross margins had a very high scheduled cropping intensity. This indicates that maintaining a potential crop lined up for sowing if conditions are satisfactory is an important aspect of financially successful crop design. This also held true in the western zone, where the best-performing rotations ultimately skipped many scheduled crops due to unfavourable conditions at the time of sowing.

For a further crop-specific analysis, we quantified at which frequency each crop was sown among the best 25 percent of crop rotations for each result indicator (Fig. 5). Maize and canola were rarely present in systems with the highest performance for the composite indicator, gross margin, or downside risk. Instead, sorghum and chickpea achieved high composite indicator scores in the southern, eastern, and northern zones, while performing less optimally in western locations. The optimal sowing frequencies of wheat and mungbean were relatively consistent across locations. For downside risk minimisation, slightly more frequent wheat cultivation was more favourable in southern production zones.

Analysis of the structural characteristics of the top 25 percent of rotations (Fig. E. 3) reveals that locations further inland achieved the highest composite indicator scores with lower cropping intensities. At all locations, there was a clear trade-off between (i) achieving a high composite indicator score and high gross margins through high cropping intensities, versus (ii) achieving a low level of downside risk through low cropping intensities. The effects of the proportion of cereal crops were spatially consistent with the earlier reported findings for climate zones, showing only minor regional differences. Finally, crop rotations with a high composite indicator score and gross margin but low downside risk were generally summer-dominant in the northern and eastern zones, whereas winter-dominant systems performed better in the southern and western zones.

Table 2
Best three performing crop rotations for selected indicators by climate zone.

Climate Zone	Performance Indicator	Rank	Rotation	Cropping Intensity (crops yr^{-1})	Cereal Percentage	Summer Crop Percentage	Gross Margin (AUD ha^{-1} year^{-1})	Downside Risk (AUD ha^{-1} year^{-1})	Water Use Efficiency (AUD mm^{-1})	Nitrogen Use Efficiency (AUD kg-N^{-1})	Crop Failure Percentage	Soil Organic Carbon (t ha^{-1})
Northern	Composite Indicator	1	FA_WH_FA_CP_FA_CP_FA_FA	0.46	33	0	827	41	10.4	34.4	0	81.1
		2	SG_CP_SG_CP_MB_CP_FA_CP	1.32	36	54	1640	175	8.9	19.7	1.56	83.1
		3	MB_WH_MB_CP_FA_WH_FA_CP	1.1	28	44	1211	106	8	21.1	0	82.4
	Gross Margin	1	SG_CP_SG_CP_MB_CP_FA_CP	1.32	36	54	1640	175	8.9	19.7	1.56	83.1
		2	SG_CP_SG_CP_SG_CP_FA_CP	1.31	54	54	1572	217	8.2	14.8	2.5	83.3
		3	SG_CP_SG_CP_SG_CP_SG_CP	1.54	61	61	1567	352	7.3	11.8	2.99	83.8
	Downside Risk	1	SG_FA_FA_CP_FA_FA_MZ_FA	0.63	76	76	1013	13	8.4	15.6	0.41	81.3
		2	FA_WH_FA_FA_MZ_FA_FA_WH	0.55	100	44	644	24	6.3	9.6	0.08	81.1
		3	FA_WH_FA_CP_FA_CP_FA_FA	0.46	33	0	827	41	10.4	34.4	0	81.1
Western	Composite Indicator	1	FA_WH_FA_CP_FA_CP_FA_FA	0.51	34	0	1069	60	11.7	40.7	0	82.1
		2	SG_FA_FA_CP_FA_CP_FA_FA	0.57	39	39	1109	242	10.8	31.5	0.45	82.3
		3	FA_WH_FA_CP_FA_WH_FA_CP	0.67	51	0	1141	113	9.9	24.7	0.1	82.5
	Gross Margin	1	SG_CP_SG_CP_MB_CP_FA_CP	1.3	32	48	1600	489	9.6	20.9	4.37	84.1
		2	SG_CP_SG_CP_SG_CP_FA_CP	1.3	48	48	1536	560	9	15.8	7.01	84.3
		3	SG_CP_SG_CP_SG_CP_SG_CP	1.5	55	55	1425	724	7.7	11.8	8.73	84.8
	Downside Risk	1	FA_WH_FA_FA_FA_WH_FA_FA	0.33	100	0	323	43	4.8	7.6	0	81.5
		2	FA_WH_FA_CP_FA_CP_FA_FA	0.51	34	0	1069	60	11.7	40.7	0	82.1
		3	FA_WH_FA_FA_MZ_FA_FA_WH	0.55	100	38	620	72	6.2	9.3	0.08	82
Central-Eastern	Composite Indicator	1	FA_WH_FA_CP_FA_CP_FA_FA	0.53	34	0	1279	1	12.5	43	0	82.1
		2	SG_CP_SG_CP_MB_CP_FA_CP	1.43	33	50	2201	100	10.6	25.8	1.71	84.4
		3	SG_FA_FA_CP_FA_CP_FA_FA	0.6	40	40	1413	30	11.8	35.3	0	82.4
	Gross Margin	1	SG_CP_SG_CP_MB_CP_FA_CP	1.43	33	50	2201	100	10.6	25.8	1.71	84.4
		2	SG_CP_SG_CP_SG_CP_FA_CP	1.42	50	50	2104	142	9.9	19.4	2.67	84.6
		3	SG_CP_SG_CP_SG_CP_SG_CP	1.66	57	57	2030	309	8.7	15	3.41	85.1
	Downside Risk	1	FA_WH_FA_FA_MZ_FA_FA_WH	0.59	100	40	814	0	6.9	11.2	0	82.1
		2	FA_WH_FA_CP_FA_CP_FA_FA	0.53	34	0	1279	1	12.5	43	0	82.1
		3	SG_FA_FA_CP_FA_FA_MZ_FA	0.67	73	73	1297	3	9.9	20.7	0.19	82.4
South-Eastern	Composite Indicator	1	SG_CP_SG_CP_MB_CP_FA_CP	1.46	30	45	2895	211	12.1	35.1	2.3	85.5
		2	FA_WH_FA_CP_FA_CP_FA_FA	0.58	34	0	1671	1	12.9	49.4	0	83
		3	SG_FA_FA_CP_FA_CP_FA_FA	0.63	36	36	1717	78	12.6	44.6	0.17	83.1
	Gross Margin	1	SG_CP_SG_CP_MB_CP_FA_CP	1.46	30	45	2895	211	12.1	35.1	2.3	85.5
		2	SG_CP_SG_CP_SG_CP_FA_CP	1.46	45	45	2810	240	11.6	27.1	3.64	85.8
		3	SG_CP_SG_CP_SG_CP_SG_CP	1.68	52	52	2750	341	10.5	21.3	4.73	86.4
	Downside Risk	1	FA_WH_FA_CP_FA_WH_FA_FA	0.58	67	0	1203	0	9.2	22.7	0	83.1
		2	FA_WH_FA_CP_FA_CP_FA_FA	0.58	34	0	1671	1	12.9	49.4	0	83
		3	FA_WH_FA_CP_FA_WH_FA_WH	0.76	76	0	1378	2	8.2	18.5	0	83.6

Best

Worst

Note: Based on data averaged by crop rotation across years, locations, and soil conditions within each climate zone. "Rank" indicates the rank for a given climate zone and performance criterion. Heatmap colouring denotes better/worse performance of cropping systems compared to observations in all climate zones. Crop abbreviations: CN – canola, CP – chickpea, FA – fallow, MB – Mungbean, MZ – maize, SG – sorghum, WH – wheat. Data rounded to the last displayed digit.

4. Discussion

For agricultural producers and agronomists, making decisions on cropping systems design requires understanding which structural cropping system characteristics perform well on key outcomes or carry specific risks. To our knowledge, this is the first study to generate spatially and temporally explicit performance profiles of contrasting cropping systems using long-term simulations across multiple climate zones, and to apply these profiles to inform system design decisions at the farm level. In doing so, we provide a transferable framework that bridges the gap between qualitative cropping system research and quantitative crop modelling.

4.1. *Climate drivers of cropping system performance*

We found substantial evidence of how strongly climate patterns predetermine achievable performance potentials across the study area. The major variation in financial and environmental outcomes across climate zones highlights substantial differences in agro-ecological potentials and constraints and underlines the necessity of zone-specific crop design strategies. This finding is particularly noteworthy given that, within the broader context of Australia's climate diversity, the study locations span only a limited climatic range and share common features such as a summer-dominant rainfall pattern. The large gap in the average gross margin level across climate zones of up to 34 percent (452 AUD ha^{-1} season^{-1}) between the best (south-eastern) and worst (western) performing climate zone highlights the necessity for western producers to operate at larger scales to achieve similar farm-level profits. With producers in the western zone also facing the highest risk of gross margin shocks (i.e., downside risk), as driven by frequent summer droughts, they need to manage the dual challenge of low and highly volatile gross margins. Instead, the south-eastern zone benefits from the most consistent winter rainfall and lower year-round evapotranspiration demand. This supports a more stable and continuous cropping pattern and translates into higher and less volatile gross margins. The comparably more predictable seasonal rainfall patterns of the south-eastern and central-eastern zones allow for more reliable scheduling of crops and better resource planning. Support for the identified geographical pattern can be found in the gridded map of agricultural profits by Marinoni et al. (2012). A large range of related research has analysed the importance of similar agro-climatic zoning schemes on current and future yield potentials and yield gaps (van Wart et al., 2013). Instead, a suitability analysis of specific cropping strategies per agro-climatic zone is generally absent from the literature or limited to qualitative statements without quantitative performance profiles (Dixon et al., 2020). Despite this clear evidence on the central role of climate zones in predetermining production potentials, there is a lack of available zoning schemes to inform crop design decisions in Australia. Specifically, the widely used growing region maps by the Australian Grains and Research Development Cooperation (GRDC, 2025) are spatially coarse and partially follow political boundaries, and the last data-driven agro-ecological zoning scheme for Australia is outdated and spatially coarse (Rickards et al., 2013; Williams et al., 2002). Instead, precipitation zones, temperature-humidity zones, or the adjusted Koeppen classification for Australia (BOM, 2025; Stern et al., 2000) are much more widely utilised, but are not suitable to guide farming systems decisions in a direct manner. Building on the approach presented in this study, e.g. by future studies on different production locations, the definition of climate zones with direct relevance for cropping strategy decisions can provide valuable orientation and guidance to producers and agronomists. In our study area, precipitation and evapotranspiration were the most relevant drivers of cropping system patterns (Hochman et al.,

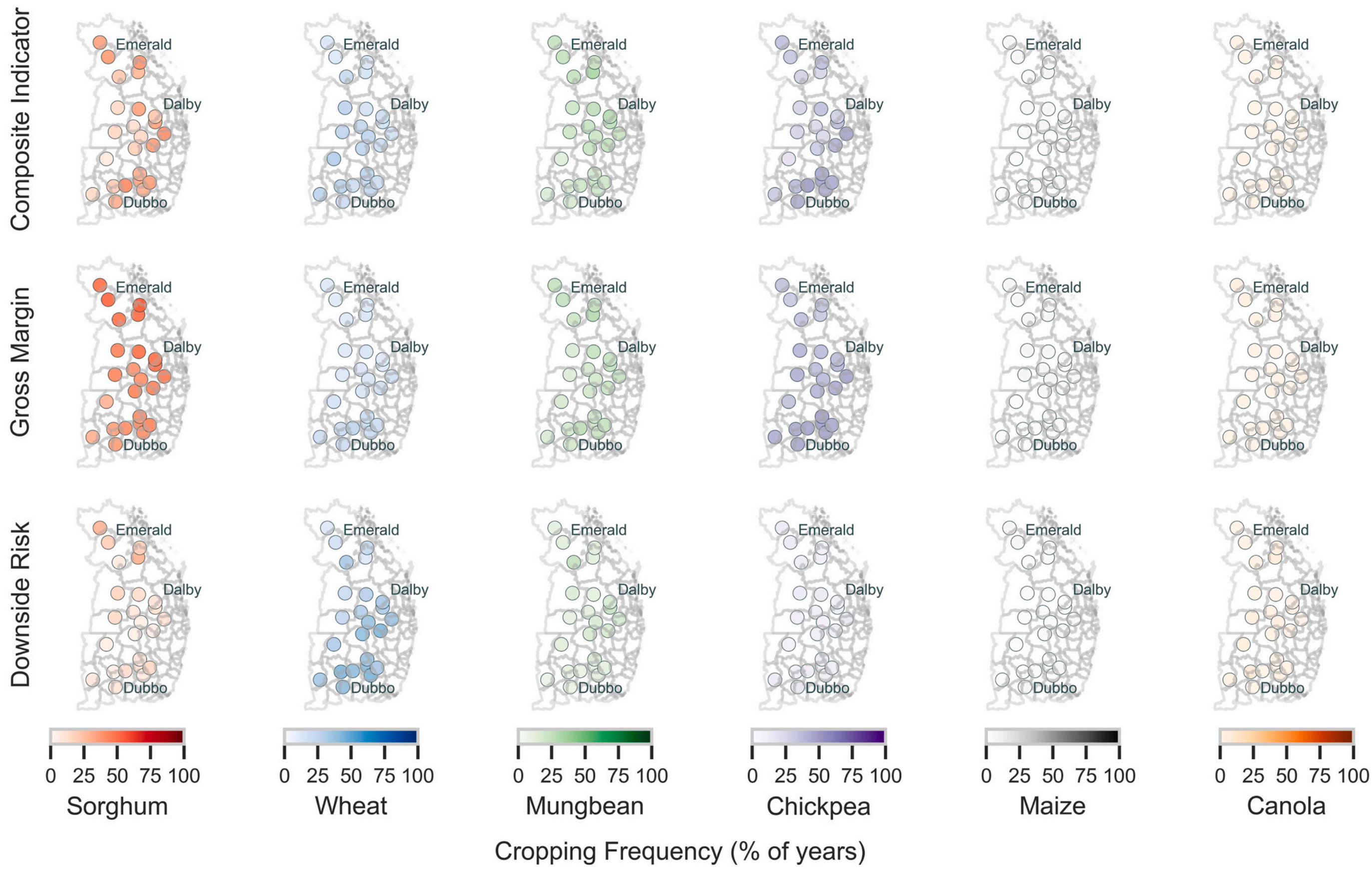

Fig. 5. Cropping frequencies of individual crops in the 25 percent best-performing crop rotations across various indicators
Note: Figure based on data averaged across years, soil conditions, and crop rotations for the highest ranked 25 percent of crop rotations per result indicator at each study site.

2020; Rickards et al., 2013), and thus formed the basis for defining agro-climatic zones. However, when applying this approach in other production regions, agro-climatic zones should be defined using the environmental variables that are the most locally relevant drivers of cropping patterns.

4.2. *Cropping system characteristics and risk–return trade-offs*

A core question of this analysis was how structural characteristics of cropping systems impact their performance. We found that choosing a high cropping intensity leads to dual consequences: While it enhances gross margin and resource use efficiency, particularly in more favourable environments (e.g., south-eastern zone), it also amplifies downside risk and crop failure, especially in the more climatically constrained western zone. This highlights a fundamental trade-off between pursuing the benefits of opportunistic intensification in favourable seasons and bearing the increased risk of investment losses if seasonal conditions deteriorate beyond expectations. Since cropping intensities of less than one crop per year resulted in distinctly lower gross margins as well as poorer water and nitrogen use efficiency across all climate zones, low-intensity strategies are only desirable for highly risk-averse producers who are willing to accept substantial reductions in gross margin in exchange for moderate reductions in downside risk. Instead, when voluntarily foregoing gross margins is not an acceptable option, cropping intensities of about 1.2 to 1.4 crops per year provide the highest financial benefits and resource use efficiencies across all climate zones. Thereby, the central-eastern and southern-eastern zones benefited much more from higher cropping intensities than the northern and western zones. Importantly, the most performant cropping strategies all relied on a high scheduled cropping intensity, which ensures that a potential crop is lined up for sowing if seasonal conditions are satisfactory. The ability to flexibly adapt crop design decisions in response to seasonal conditions is accordingly a core driver of financially successful farms. This finding is consistent with Rodriguez et al. (2011), who found for case study farms in Australia that the ability to continuously adapt farm management decisions in response to signals from the climate and market environment is a core requirement for maximising profits and minimising risks. Similarly, Sadras and Roget (2004) reported high potential production and environmental benefits from opportunistic intensification in the Mallee region of Australia, provided that unintentional intensification into dry seasons was effectively avoided.

4.3. *Seasonality effects and the role of summer–winter crop balance*

The achievement of the various target outcomes is substantially influenced by seasonality. A noteworthy finding is that winter crops across all climate zones achieved on average higher levels of gross margin than summer crops. This suggests that – even though the study area is characterised by a summer-dominant rainfall pattern and is a major summer growing region of Australia – there is value in rigorously identifying suitable winter cropping opportunities. However, most benefits from winter crops were realised by a small number of highly favourable winter seasons, whereas the bulk of winter crops generated gross margins that were broadly comparable to, or slightly lower than, those of summer crops. Thereby, some of the identified patterns are complex and challenging to communicate as part of advice to farmers and agronomists. For example, on the one hand, summer crops across all zones exhibit a much lower level of overall variability in gross margins. On the other hand, summer crops more frequently observe extreme reductions in gross margins and high downside risk, compared with winter crops. Consequently, summer-dominant cropping systems need to be embedded within farm business strategies capable of absorbing infrequent but severe financial losses, whereas winter cropping systems require strategies that can manage a continuous flux of high gross margin variability, though rarely involving severe losses. Our findings underline that neither extremely (>80%) summer-dominant nor winter-dominant cropping strategies are beneficial in any climate zone within the study area, or with respect to most of the evaluated outcome indicators.

In terms of geographic differences, the northern zone benefits the least, while the south-eastern zone benefits the most from a greater reliance on winter crops. However, the seasonality differences between zones were found to translate less drastically into corresponding differences in summer- and winter-dominant cropping patterns than could have been anticipated. Specifically, sowing crops based on a systematic threshold of precipitation and soil water availability (as simulated throughout this study) resulted in small differences between sowing patterns across the climate zones. This shows that prevailing rainfall patterns do not automatically translate into corresponding differences in cropping patterns, due to rainfall being stored as soil moisture during fallows. Deciding whether to utilise rainfall resources in the season they occur or in the subsequent season is a cropping system design choice that agricultural producers must make actively. Our findings emphasise that, beyond the generic reference points of more summer-dominant cropping in Queensland and more winter-dominant cropping in New South Wales, as emphasised by the GRDC growing regions definition (GRDC, 2025), opposite cropping patterns are also agro-climatically feasible. In recent decades, the sown area to winter crops has increased in both Queensland (moderately) and New South Wales (substantially), while the summer crop area has moderately decreased in both states (Fig. G. 1, ABARES (2025)), indicating that growers already actively try to capitalise on the high gross margin potential of winter crops. Thereby, the practice of flexibly transitioning between periods of summer and winter dominant cropping, appears to be widely practised in the study area – as evidenced by the marked year-to-year fluctuation in total sown area of summer and winter crops between 2010 and 2019 in Queensland (QGOV, 2023). When aggregating across Queensland, the cultivated area of summer and winter crops is relatively balanced, averaging 46% and 54% of the total area, respectively, over the 2010 to 2019 period (QGOV, 2023).

4.4. Crop rotation choice

Agronomic guidelines consistently highlight the benefits of diversifying away from cereal monocultures, citing reasons such as improved weed, disease, and pest management – including control of root lesion nematodes and wheat crown rot (GRDC, 2011). The crop modelling results of this study, which do not consider the impacts from pests and diseases but are predominantly driven by water and nutrient dynamics, further underline the importance of avoiding cereal monocultures. Particularly, crop rotations with a proportion of cereals above 90 percent were found to consistently lead to unfavourable outcomes, specifically regarding gross margin as well as water and nitrogen use efficiency. However, excluding such extreme cases, crop rotations with a wide range of cereal proportions exhibited a similar performance potential, suggesting that this structural characteristic is little decisive in isolation.

As the crop rotations that consistently provided high outcomes across all climate zones and all six considered financial and environmental indicators, two dominant combinations emerged: cropping systems with a high proportion of sorghum and chickpea, or crop rotations with a high proportion of wheat and mungbean. Thereby, western production locations were less suitable for high cropping frequencies of sorghum and chickpea than all other climate zones. While we presented a range of differences in the most performant cropping system designs across climate zones, these differences were often gradual and of a moderate impact strength. The specific crop types that we identified as being most beneficial across a wide range of rotations can also be found in the single, most beneficial rotation identified by Hochman et al. (2020) who found in a comparison of 26 crop rotations that revenue was maximised by a rotation of *Sorghum-Fallow-Mungbean--Wheat-Fallow-Chickpea* across most of the here analysed study locations.

4.5. Implications for cropping system design and future research

Our results highlight that when farmers aim to achieve a balanced performance across multiple financial and environmental outcomes, a range of very diverse cropping strategies can be applied. In particular, two distinct performance profiles emerged: cropping systems that performed well in terms of either (i) gross margin and nitrogen use efficiency or (ii) downside risk, crop failure, and water use efficiency. This underscores, first, the importance for agronomists and consultants to closely co-identify with producers which outcomes they consider most critical to their long-term farming strategy. Second, it highlights that diverse cropping strategies can deliver similarly high performance, offering no empirical basis for promoting a fixed set of crop rotations or a narrow collection of cropping system design principles. The composite indicator used throughout this study equally weights all six considered indicators. Instead, as part of participatory research activities, local stakeholder groups could be directly surveyed to inform customised indicator weightings, providing a stakeholder-specific metric of cropping system performance.

As a further extension of the current study, future analyses could enlarge the study scope beyond indicators of relevance for agricultural producers and further focus on public policy objectives, such as the reduction of greenhouse gas emission intensity (Grewer et al., 2018) and the promotion of agro-biodiversity.

As the temporal scope, our analysis considered a 60-year period, rather than the minimum 30-year period to characterise Climatological Standard Normals (WMO, 2017), in order to be more inclusive of rare and extreme climatic events. A limitation of this approach is that older climate records may be less representative if recent climate patterns have shifted due to climate change. Depending on research objectives, future studies could instead employ stochastic weather generators parameterised from historical climate records (Ailliot et al., 2015; Jones and Thornton, 2013). Such methods allow the generation of an arbitrary number of synthetic weather sequences, encompassing rare climatic events for past, present, or projected future climate conditions, although they introduce their own sources of uncertainty and rely on a set of underlying assumptions. While the results of this study provide insight into the relative performance of cropping systems, the findings are inherently normative, emerging from the mechanistic process representations encoded in APSIM rather than directly from field observations. Empirical research could complement these findings by validating key patterns of cropping system performance.

5. Conclusion

Decisions on cropping systems design are among the most complex and consequential choices by agricultural producers. This study provides a comprehensive, climate zone-sensitive assessment of how structural features of cropping systems influence performance across key financial and environmental indicators. The results demonstrate that climatic constraints fundamentally shape the potential and risk profile of cropping strategies, underscoring the need for zone-specific guidance in system design. Moderate increases in cropping intensity and in the proportion of winter crops emerged as potential levers for improving gross margins and resource use efficiency, particularly in more favourable climate zones. However, these strategies also carry drawbacks, such as increased interannual variability associated with more winter crops and higher downside risk linked to intensified cropping. Rather than promoting a narrow set of cropping strategies, our findings highlight that diverse cropping systems deliver viable outcomes, each involving specific trade-offs that will appeal to different farmers depending on their risk tolerance and strategic objectives.

We demonstrated how biophysical crop modelling can be leveraged to systematically quantify the typical performance profiles of cropping system design decisions across diverse financial and environmental dimensions. Crop modelling is particularly suitable for quantifying the variability across long-term seasonal weather records and contrasting production locations. In this way, it offers valuable guidance to agricultural producers and agronomists in understanding the strengths, weaknesses and trade-offs of specific cropping strategies. In particular, the results highlight the potential and risk profiles linked to specific cropping intensities, summer versus winter season dominance, and specific crop rotation choices. The presented research framework can readily be scaled to other agricultural production regions. As its main limitation, it requires the availability of calibrated crop models for major crop types as well as data on local climatic conditions and soils.

CRediT authorship contribution statement

Uwe Grewer: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Andrew Zull:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Keith G. Pembleton:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Code availability

The code used in this study is available from the corresponding author upon reasonable request.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.148007.

Data availability

The majority of data has been made available in the supplementary material. The simulation database generated by this study can be freely accessed via the website: www.armonline.com.au/ra.

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