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Crop models as decision support tools in digital agriculture: The APSIM-based RotationARM tool in Australia

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ABSTRACT

Designing cropping systems that are simultaneously profitable, resilient, and sustainable remains a key challenge for agricultural producers, particularly under increased climate variability. While digital agriculture tools have advanced rapidly, most applications remain limited to single-season, sub-field precision management rather than supporting multi-year, system-level decisions. Here we present RotationARM, an interactive, simulation-based tool that assists growers and advisors in evaluating and comparing multi-year cropping strategies. The tool is underpinned by a database of 22.9 million crop simulations using the Agricultural Production Systems sIMulator (APSIM) integrated with financial cost-benefit data, spanning 24 sites across Queensland and New South Wales in Australia, 60 years of weather records, three soil profile depths, 88 rotations, nine sowing rules, and three fertiliser intensity levels. It provides an accessible user interface requiring minimal input data. A core novelty is the representation of inter-seasonal water and nutrient carryover, enabling users to evaluate the performance of continuous cropping trajectories rather than single-year outcomes. Multi-criteria outputs – covering agronomic performance, financial returns, risk metrics, and resource-use efficiency – are communicated through intuitive visualisations tailored for non-scientific audiences. Twelve participatory workshops with 65 farmers, industry and government stakeholders informed the tool's design, prioritising iterative reflection over prescriptive recommendations. Scenario analyses demonstrate how adjustments to cropping strategies, such as changes in sowing rules or cropping intensity, can improve agronomic, financial, and environmental outcomes while mitigating risk. RotationARM fills a critical gap in decision support for cropping system design. The tool represents a practical step toward applying dynamic crop models in farm-level tactical and strategic decision making. The APSIM tool has been validated using extensive observed field trial datasets, with strong representation of eastern Australia.

1. Introduction

Designing profitable, resilient, and sustainable cropping systems remains a core challenge for agricultural producers in the face of a variable and changing climate, uncertain market conditions, and growing societal expectations to generate sustainable co-benefits (Moss, 2010; Thornton et al., 2014; Wilson, 2007). Crop choice and management decisions across adjacent seasons interact to result in highly uncertain outcomes across multiple dimensions, including productivity, profitability, resilience, and sustainability.

Owing to this multi-dimensional and multi-causal nature of cropping systems and the embedded seasonal uncertainty, traditional farm planning tools – such as crop budgets, labour calendars, and machinery usage schedules – are commonly ill-prepared to provide realistic estimates of the likely progression and outcomes of a specific cropping strategy. Instead, digital agriculture tools can more readily accommodate complex, multi-causal processes within integrated computational frameworks and synthesise knowledge embedded in extended spatial and temporal data (Basso & Antle, 2020). Drawing on prevailing usage in research and practice (Finger, 2023; MacPherson et al., 2022; Walter et al., 2017), we define digital agriculture as the integration of: (i) the collection and use of high-resolution spatial and temporal data, (ii) the application of advanced data-processing algorithms and modelling frameworks, and (iii) their translation into precision, semi-automated

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crop management. In contrast to this prevailing focus on generating prescriptive rules for sub-field precision management (e.g., variable-rate maps), less attention has been directed toward the potential of digital agriculture to inform cropping system design to satisfy multi-dimensional objectives.

To support cropping system design, digital agriculture tools must go beyond a narrow focus on data and algorithms for isolated production aspects and instead provide a comprehensive representation of the multiple interacting components that define a cropping system. In digital agriculture, data processing methods that translate big data into decision support include machine learning, deep learning, frequentist and Bayesian statistical models, mathematical programming models, expert-based decision algorithms, and process-based crop simulation models (Kamilaris et al., 2017; Kamilaris & Prenafeta-Boldú, 2018). Among these, the purely empirical, data-driven approaches – namely, machine learning, deep learning, and statistical models – are currently unable to represent cropping systems in a holistic and structural manner due to their excessively comprehensive data requirements and are limited to reduced-form representations (Angrist & Pischke, 2009; Nevo & Whinston, 2010). Digital Twins of research farms have recently emerged as the only notable exception capable of generating the requisite, system-wide datasets (Hawkins et al., 2023; Purcell & Neubauer, 2023; Pylianidis et al., 2021). Accordingly, mathematical programming models and process-based crop simulation models represent the principal data processing methods currently available to capture cropping system dynamics as part of digital agriculture applications beyond pure research farms. Both methodologies can be combined in bio-economic models (Britz et al., 2012; Janssen & van Ittersum, 2007).

More specifically, mathematical programming models are constrained optimisation problems comprising an objective function and a system of constraints that represent farmer-resource endowments, regulatory limits, and technical and biological relationships of the production process (Fei & McCarl, 2023).

Crop simulation models represent the cycling of water and nutrients as part of crop growth and development using predefined physiological and biogeochemical equations, rather than estimating relationships ad hoc from data (Wallach et al., 2019). This normative nature of crop simulation models allows them to represent cropping system components comprehensively and mechanistically, even under data limitations, but it also makes their results more reliant on the underlying model structure and parameters. Process-based models are strongly data-driven in their use of high-resolution temporal input data, but not in their representation of mechanistic processes and relationships. Intertemporal, season-to-season dynamics of soil nutrient and water resources, as well as of organic matter pools, are explicitly represented through state variables.

Today, a wide variety of advanced crop simulation models are available, capable of representing multi-year crop growth and management at the field-scale, including APSIM (Holzworth et al., 2018), DSSAT (Jones et al., 2003), EPIC/APEX (Wang et al., 2012), STICS (Beaudoin et al., 2022), and WOFOST (de Wit et al., 2019). Their usage includes investigating crop response to weather, soil types and constraints, and management (Grewer et al., 2025); investigating trade-offs between field-level outcomes such as crop yield, profitability and sustainability (Giller et al., 2011); assessing climate change impacts (Jägermeyr et al., 2021; Kim et al., 2025); yield gap analysis (van Ittersum et al., 2013); and yield forecasting (Kivi et al., 2022). As crop simulation models predate the emergence of digital agriculture, their use as a decision support tool has conventionally focused on their ad-hoc application for limited locations and specific use cases (Rodriguez et al., 2011).

More recently, cropping system models have been integrated within digital decision support tools that cover larger geographic domains, time periods, and research issues. The Graincast mobile App uses the Agricultural Production Systems sIMulator (APSIM) to forecast soil moisture and grain crop yields in Australia (Lawes et al., 2023). The Yield Prophet website provides farmers with the ability to run APSIM simulations using their own soil data and meteorological records from an Australian weather station in proximity to their farm (Hochman et al., 2009). The Crop Analysis for Risk Management (CropARM) website allows users to compare cropping scenarios based on an APSIM simulation database containing a wide range of crop management scenarios for predefined production locations across Australia (Nelson et al., 2002) UniSQ & QGOV (2016) the FACTS website employs APSIM to guide users on choices regarding maize harvesting dates as well as soybean planting dates and maturity choices across Iowa, USA, and selected adjacent states (ISU, 2025). The Agricultural Digital Twin website (NASA, 2025) plans to provide farmers across the USA with the ability to generate yield forecasts for various crop management scenarios based on a modelling framework involving the Decision Support System for Agrotechnology Transfer (DSSAT). The System Approach to Land Use Sustainability (SALUS) maize model is used by the SALUS Online website to allow users across nine states in the USA to evaluate the performance of management practices in terms of nitrogen use efficiency (MSU, 2025).

While a range of digital decision support tools thus exist that leverage cropping system models, they all exclusively focus on the performance of individual crops in a single year. Decision support tools that instead rely on mathematical programming models can explicitly analyse cropping system performance across multiple years, while more comprehensively representing non-biological aspects of the production process, such as labour and capital constraints. For example, Pahmeyer et al. (2021) provide a highly data-driven decision support tool that provides recommendations on multi-year crop choice and manure fertilisation management. However, mathematical programming models do not represent crop growth processes in a mechanistic manner, but use predetermined input–output coefficients embedded within reduced-form production relationships that typically operate at an aggregated, season-level time step. This differentiates them from the here considered core focus of digital agriculture tools that comprise a detailed representation of crop growth processes throughout the season.

The ability to simulate cropping systems across multiple years, including the dynamic and mechanistic representation of nutrient and water carryover effects across adjacent seasons, is a major prevailing gap in the literature. Farmers thus face a lack of digital agriculture tools that support the decision making on cropping systems design. Other core aspects of decision support tools are their ability to quantify multiple outcomes – including production, resource-use efficiency, and sustainability metrics – as well as their capacity to present quantitative results and visual figures in a manner that is relevant and intuitive for farmers and agronomists.

This article presents the online decision support tool Agricultural Risk Management of Crop Rotations (RotationARM). The tool assists growers in selecting a multi-year cropping system strategy that is most suitable for their circumstances and long-term objectives. It aids long-term strategic decision making at the cropping system level, rather than just short-term tactical decisions for individual crops. The tool provides users with a guided, stepwise process to compare alternative cropping strategies. Tool results are presented by a variety of visualisations through a Graphical User Interface (GUI) that aims at communicating multi-criteria, system-level outcomes to a non-scientific audience. RotationARM (https://armonline.com.au/ra) is based on an APSIM simulation database and is a companion tool to CropARM as part of the online platform Agricultural Risk Management Online (ARM-Online; UniSQ & QGOV (2016)).

2. Materials and methods

The RotationARM decision support tool has been conceptualised through a multi-stakeholder consultation process. Tool objectives and components were iteratively designed and revised by a steering committee involving researchers, government, industry representatives, and farmers. Informed by the consultation process, we generated a database of diverse cropping system simulations using APSIM, which forms the main quantitative basis of the tool. We then designed the online graphical user interface that presents various simulation results via user-friendly figures. The tool includes a guided, multi-step process for comparing alternative cropping strategies. Finally, the RotationARM tool has been utilised as part of 12 capacity-building workshops from central Queensland to northern New South Wales with farmers, agronomists, consultants, financial advisors, researchers, and students. The tool has been extensively revised based on user feedback from these workshops.

2.1. Site selection

As the study region, we chose one of the major rainfed broadacre cropping regions of Australia that extends across temperate and sub-tropical climates in central and south-eastern Queensland and northern New South Wales (ABARES, 2024; ABS, 2021; Stern et al., 2000). It is characterised by agro-climatological conditions that permit cropping during two distinct crop growing seasons per year (summer/winter), while limited water resources make permanent continuous cropping infeasible. This combination of versatile but constrained growing conditions gives rise to highly diverse cropping systems – differing in crop choice, seasonal timing, and cropping intensities – as farmers experiment with various cropping strategies to make the best use of limited water resources. This makes the study area particularly suitable and relevant for decision support on cropping system design. As specific study sites, we selected 24 locations in proximity to regional towns across the study area to provide easily recognisable geographic reference points for tool users (Fig. 1). As specific geocoordinates of the study sites, we used coordinates from the APSOIL database where available,

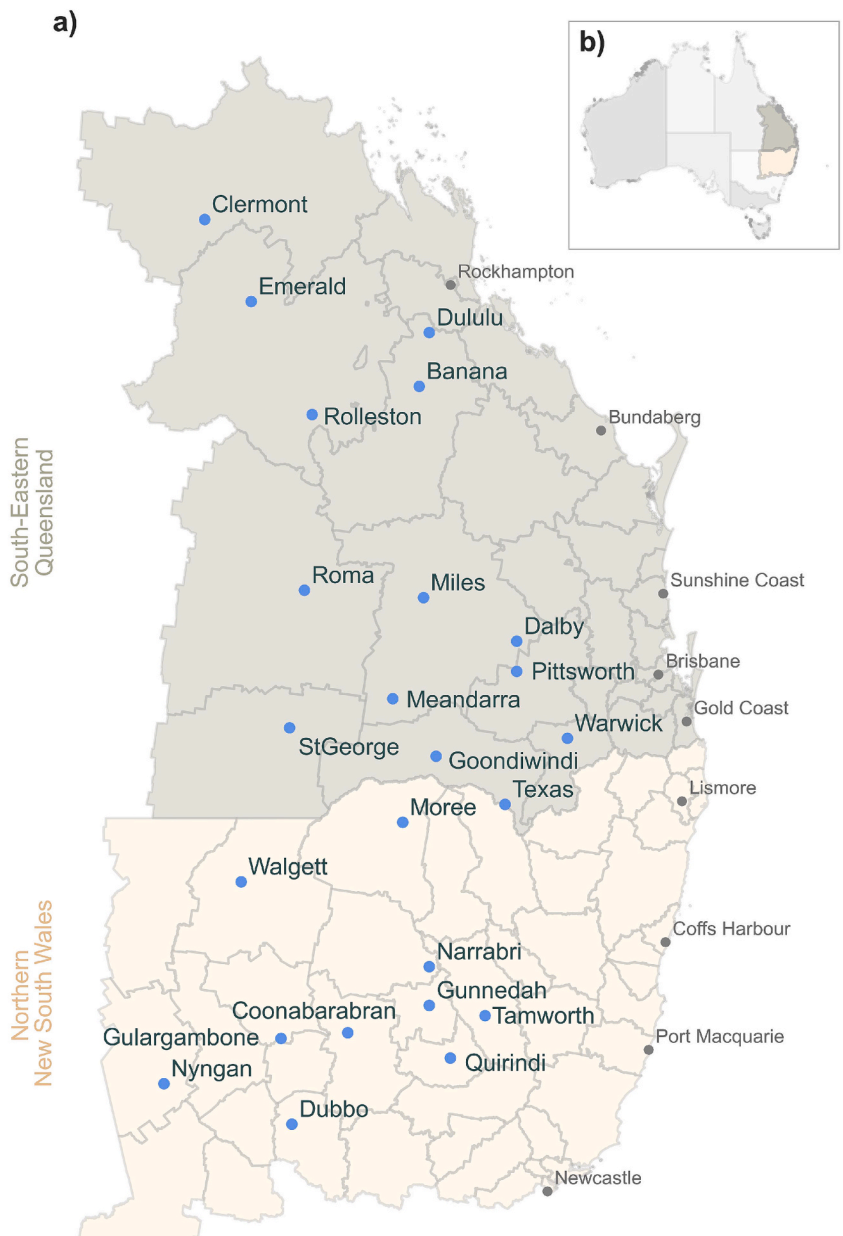

Fig. 1. Study sites in proximity to regional towns across central and south-eastern Queensland and northern New South Wales in Australia. Note: a) The point markers represent APSIM simulation sites (blue) situated in proximity to the labelled towns and locations of major cities (grey); boundaries delineate Local Government Areas (second-level administrative divisions); and coloured areas indicate State affiliation (first-level administrative divisions) according to ABS (2022). b) The inset map shows the geographic position of the main map within Australia, with boundaries identifying States.

which provide indicative reference points for cropland areas rather than built-up townships (Dalgliesh et al., 2012).

2.2. Data sources

Input data for the crop simulation modelling include weather, soil, and financial datasets. The following subsections describe each data source in detail.

2.2.1. Weather data

Daily weather data from 1951 to 2022 at a resolution of 0.05 decimal degrees (~5.6 km at the equator) on precipitation, minimum and maximum temperature, solar radiation, vapour pressure, and reference evapotranspiration based on the Penman-Monteith equation (Allen et al., 2005) were obtained from the gridded version of the Scientific Information for Land Owners (SILO) database (Jeffrey et al., 2001; QGOV, 2024).

2.2.2. Soils data

The RotationARM tool represents soil conditions by three generic soil profiles as opposed to the use of soil profile data from gridded soil databases such as APSoil (Dalgliesh et al., 2012) or the Soil and Landscape Grid of Australia (Grundy et al., 2015). As the tool operates at a limited number of predefined locations rather than at user-selected plots, we considered it more appropriate to use generic, representative soil profiles. Single-point records from gridded databases may not adequately reflect the general soil characteristics of a study area, given the substantial variability in soil conditions both between and within fields. The generic soil profiles were sourced from the companion CropARM tool (UniSQ & QGOV, 2016), which ensures a consistent user experience across the ARM-Online decision support platform. The generic soil profiles represent three contrasting levels of plant available water holding capacity that commonly arise in the study area due to varying soil depth or sub-soil constraints (Lai et al., 2020). Details on the soil depth structure and plant available water holding capacity of the shallow, medium, and deep soil profiles are provided in Table S 1. The transparent use of predetermined generic soil profiles within RotationARM clearly communicates that the tool does not attempt to represent plot-specific soil constraints or soil property characteristics. Extending the RotationARM tool to further locations will require the specification of typical soil profiles for the target regions. Soil types and characteristics are typically very variable within individual fields, let alone at the regional scale. Therefore, all field-level management decisions – with or without decision support tools – necessarily involve a degree of generalisation.

2.2.3. Financial data

For each location, variable input costs and commodity prices were sourced from the closest available subregion within the Queensland AgMargins agricultural gross margin database (QGOV, 2021). Financial figures were adjusted for inflation to reflect real prices using the Australian Consumer Price Index for food and beverages, with the 2011–12 financial year as the reference base (ABS, 2023). For input costs, the most recent data available in AgMargins was used, while crop sale prices were calculated as the average of values reported between 2015 and 2021. Crop production costs include land preparation, seeds, fertiliser (products and application), crop protection (products and application), harvesting, post-harvest operations, industry levy fees, advisory services, and crop insurance. We deliberately did not include expenses for land and labour as these costs vary significantly between farms, and including them would have reduced the relevance of the tool's results for farming households whose actual expenses differ substantially from the assumed default values. Fertiliser expenses were computed based on the specific nutrient requirements defined in the simulation setup, rather than using the default application rates from AgMargins.

2.3. Crop simulation modelling

Using the APSIM Next Generation cropping systems model (Holzworth et al., 2018; Holzworth et al., 2014), we simulated 88 crop rotations under a wide range of crop management scenarios over 60 years (1962–2022), constituting a total of 22.9 million separate APSIM simulations. While 30-year periods are commonly utilised to characterise Climatological Standard Normals (WMO, 2017), we deliberately utilise a longer 60-year period to capture a higher degree of rare seasonal conditions and variability. Our crop model simulations do not consider impacts from pests and diseases or field-specific factors limiting yield, such as waterlogging or chemical soil constraints. Simulated crop yields should therefore be interpreted as maximum attainable yields under the specified crop management scenarios (i.e., given water and nutrient limitations), rather than as estimates of the yields most likely to be achieved in practice under field conditions. However, this approach can still assist in evaluating the difference in outcomes for alternative cropping designs and strategies.

2.3.1. Scheduled crop rotations

We defined 88 crop rotations composed of repeated four-year sequences of different combinations of canola, chickpea, maize, mungbean, sorghum, wheat, and fallow (Table S 2). To determine the list of considered crop rotations, we first identified crop rotations that are typical for the study area based on key informant interviews with 65 farmers, agronomists and other industry stakeholders (see section 3.4), the consideration of local agricultural commodity statistics (ABS, 2021), and a review of the existing literature (Hochman et al., 2020). The key informant interviews were conducted with both the primary target audience of farmers and agronomists, as well as secondary support stakeholders such as agricultural financial advisors. We then added further crop rotations by systematically modifying typical crop rotations through increasing/decreasing the cropping intensity, dominance of summer and winter cropping, and proportion of cereal versus non-cereal crops. Crop rotations are treated as scheduled crop occupancy plans, while any specific crop is omitted in the APSIM simulation when sowing conditions are not met. For this reason, we purposefully included crop rotations with a high scheduled cropping intensity (e.g., two crops per year), while the actual cropping intensity realised by climate-dependent APSIM simulations may be lower. Further, we purposefully included crop rotations that are currently not grown in the study area, due to being considered agronomically or financially non-viable. This procedure avoids the prior exclusion of crop rotation options due to established beliefs. Lastly, the list of considered crop rotations was extensively modified based on feedback from 12 capacity-building workshops with farmers, agronomists, and industry stakeholders.

The final list of crop rotation schedules includes cropping intensities ranging from 0.5 to 2 crops per year, including low cropping intensities (<1 crops/year, n = 24), medium cropping intensities (1 crops/year, n = 26 rotations), and high cropping intensities (>1 crops/year, n = 38 rotations). Crop rotations with a dominance of either summer or winter cropping were included in similar proportions, including summer-dominant (n = 37), winter-dominant (n = 38), and balanced systems (n = 13). Further, we particularly considered cereal-dominant rotations (n = 46), while fewer rotations were dominated by non-cereal crops (n = 22), or featured an equal share of cereal and non-cereal crops (n = 20).

2.3.2. Crop management scenarios

APSIM simulations were completed for a variety of crop management scenarios with regard to nitrogen fertiliser application rates and sowing rules. Three levels of nitrogen fertiliser application rates were considered that applied varying rates to different crop types: low *(cereals: 75 kg N/ha; oilseeds: 50 kg N/ha; pulses: 0 kg N/ha)*, medium *(cereals: 125 kg N/ha; oilseeds: 75 kg N/ha; pulses: 25 kg N/ha)*, and high *(cereals: 175 kg N/ha; oilseeds: 125 kg N/ha; pulses: 50 kg N/ha)*.

Sowing was restricted to take place within a predefined, crop-specific date window (Table S 3). We simulated a total of nine different sowing rules (Table S 4). Three sowing rules initiate crop sowing on a fixed date (the central day of the first, second, or third tercile of the sowing window), irrespective of seasonal conditions. All other sowing rules require a minimum of 25 mm of precipitation over an 8-day period and, additionally, specify soil water thresholds that must be met for a sowing event to be simulated. If the respective conditions are never fulfilled during the sowing window, no crop is sown in the given season, but instead a fallow is simulated. This approach investigated riskier sowing practices (sowing with less soil moisture) against more conservative sowing practices (sowing with more soil moisture). Specifically, sowing rules 4 and 5 require plant-available soil water to exceed 25 mm and 50 mm, respectively. Sowing rules 6 and 7 require soil water to exceed 40% and 75% of its full capacity. For sowing rules 8 and 9, the combined total of plant-available soil water and average in-season precipitation must exceed 200 mm and 400 mm, respectively. A predefined group of early to mid-maturing cultivar types, frequently used in prior APSIM modelling and calibration efforts (UniSQ & QGOV, 2016), was used in this study (Table S 5).

2.3.3. Setup of long-term crop simulations

The full 60-year analysis was conducted for each rotation and location by repeatedly simulating 12-year periods of continuous crop growth (i.e., three consecutive crop rotations of four years duration each), while subsequently restarting simulations with the initial soil water and nutrient parameters. By using continuous 12-year simulation blocks, we aim to capture some season-to-season carryover impacts of soil water and nutrient dynamics within a cropping system. Since no time series data on soil conditions at the 24 simulation locations is available for model evaluation, we considered that the continuous simulation of the full 60-year period would likely have produced misleading results. Even minor systematic biases in the representation of seasonal carryover effects will accumulate over time, resulting in substantial errors by the end of a 60-year simulation period. Considering such 12-year simulation blocks is a compromise between the annual resetting of soil parameters as part of large-scale, gridded crop model applications (Grewer et al., 2025; Müller et al., 2019), and the continuous simulation over long-term time series that is typically limited to a few experimental locations (Godde et al., 2016; Teixeira et al., 2015).

For each combination of a specific crop rotation and specific seasonal weather record, we simulate a total of 12 separate APSIM simulation runs, referred to as simulation phases in the following. The 12 simulation phases ensure that every crop in a given rotation is simulated under each of the 60-year weather records (even if a given crop only occurs every second or third year in the rotation) by starting the crop rotation in each possible crop or fallow and continuing through the crop sequence thereafter. The simulation phases were further structured to implement 12 different initialisation offsets (ranging from 0 to 11 years) prior to the onset of the actual season of interest, thereby varying the initial soil water and nutrient conditions. Lastly, this simulation structure prevented the existence of any time trends or single cut-off year after 12 years of simulation in the final results database. Final simulation results for a given season were calculated by averaging and scaling the phased simulation outputs for each crop. The crop model phasing is illustrated in detail in Table S 6.

2.3.4. APSIM calibration and evaluation

The wide range of crop rotations, locations, and years considered in this study means that long-term field experiments are not available for direct calibration and evaluation of the exact simulation scenarios. The APSIM model has been developed, calibrated, and evaluated for the target study region (e.g., Asseng et al. (2002); Hammer et al. (2019); Hammer et al. (2010); Robertson et al. (2002)). During the development of APSIM, over more than three decades, experimental field trial data have been systematically compiled into evaluation datasets that strongly represent south-eastern Queensland and northern New South Wales (Figure S 1). Each release of APSIM is routinely evaluated against these datasets through automated testing procedures (Holzworth et al., 2018), providing a strong basis for its use in extrapolative simulation studies across the region.

2.4. Indicator of water availability

In order to quantify the intensity of water stress or abundance, we computed the water balance ratio (*WBR*) as the ratio of precipitation (*Prcp*) to reference evapotranspiration (Et_0). The *WBR* at location *l* in year *t* and season *s* is defined as:

$$WBR_{lts} = Prcp_{lts}/ET_{0_{lts}} \tag{1}$$

Thereby, the Et_0 data are based on the Penman-Monteith equation (Allen et al., 2005), using alfalfa (syn. lucerne) as the reference crop. The *WBR* is calculated for static seasonal boundaries for the summer (15 October to 15 April) and winter (16 April to 14 October) growing season. Each growing season is then categorised into one of six seasonal climate categories: extremely dry ($WBR \leq 0.15$), moderately dry ($0.15 < WBR \leq 0.3$), mildly dry ($0.3 < WBR \leq 0.45$), mildly wet ($0.45 < WBR \leq 0.6$), moderately wet ($0.6 < WBR \leq 0.75$), extremely wet ($0.75 < WBR$).

2.5. Performance indicators

APSIM simulation outputs were complemented by the calculation of various further performance indicators. We calculated **gross margins** (AUD/ha) as the difference between crop revenue and variable costs, either per season or per year. Thereby, all costs from fallow management were attributed to the subsequent crop as part of land preparation. We calculated **downside risk** (AUD/ha) as the mean gross margin reduction below a threshold of 500 AUD per year (or 250 AUD per season) during the 25 percent of cropped years (or seasons) with the lowest gross margins. Downside risk was calculated only for seasons in which crops were sown, excluding fallow periods. Including fallows would have disproportionately classified all rotations of low cropping intensity as high-risk. This would not have provided meaningful insights, as it is self-evident that no crop revenue is generated during fallow seasons. Downside risk therefore identifies cropping systems that are susceptible to frequent and substantial reductions in gross margin below the specified threshold during cropped seasons. Financial and biophysical **water use efficiency** (AUD/mm and kg/mm, respectively) were calculated as gross margin or crop yield per unit of crop water uptake. **Nitrogen fertiliser use efficiency** (AUD/kg-N) was calculated as gross margin per applied nitrogen fertiliser. **Crop failure frequency** (%) was defined as the percentage of crops sown that do not produce any harvestable yield. Further core performance indicators used throughout the RotationARM tool are **grain/seed/pod yield** (kg/ha), **biomass yield** (kg/ha), **revenue** (AUD/ha), **revenue-cost ratio** (unitless), **soil organic nitrogen** (kg/ha), **soil organic carbon** (kg/ha), **surface organic matter** (kg/ha), **crop nitrogen uptake** (kg/ha), **crop water uptake** (mm/ha), **in-crop rainfall** (mm/ha), and **in-crop water loss** (mm/ha) to runoff, leaching and evaporation.

2.6. Software implementation and management

Crop model simulations were conducted with the Next Generation edition of the APSIM cropping systems model (version 2023.5.7225.0; build 5496) on the “Fawkes” High Performance Computing (HPC) cluster operated by the University of Southern Queensland. The HPC runs the Red Hat Enterprise Linux 8.10 operating system and employs the Portable Batch System PRO (version 2024.1.2) for workload management and scheduling. To ensure a portable and reproducible computing environment, the Apptainer (version 1.3.2) container platform was used (Kurtzer et al., 2017). Software workflows were organised and executed sequentially using Bash, with specific subscripts implemented in Python (version 3.11.4) within a Conda (version 23.3.1) environment (Anaconda Inc., 2020).

The crop model simulation data were stored in Structured Query Language (SQL) database tables. The RotationARM website was developed as a web application using React, a JavaScript library for building user interfaces. The application programming interface (API) was implemented in JavaScript using the NodeJS Express framework to provide access to the SQL database. Some API endpoints provide direct access to specific database tables, while others perform pre-processing before returning data to the web application. User selections and API responses are managed using the Redux Toolkit state management library, which reduces the frequency of repeated database queries by maintaining relevant data in the client-side application state. Data visualisations were generated using the JavaScript package Highcharts.

The RotationARM tool is part of the platform Agriculture Risk Management Online, established in 2017, and receives long-term support under projects from the University of Southern Queensland and the Queensland Department of Primary Industries. To ensure that all data ownership remains with the user and to avoid any privacy concerns, the platform does not retain any user data in persistent storage. An online help desk provides users with timely guidance and support on tool handling and facilitates discussion among users.

3. Results

The above methodology generated the RotationARM tool that can be accessed free-of-charge at https://www.armonline.com.au/ra. The following section presents a case study demonstrating the application of the RotationARM tool.

3.1. Tool user input

The RotationARM tool requires users to specify a cropping system in a simple three-step process using a user-friendly point-and-click graphical user interface (Fig. 2). First, users define site characteristics by selecting one of 24 locations in eastern Australia and specifying the amount of plant available water that the site's soil can store at full capacity. Second, users select a reference crop rotation that either reflects their current practice, represents a planned future rotation, or corresponds to any other rotation of particular interest. Third, users specify crop management decisions by selecting the threshold rule that determines crop sowing and the application intensity of nitrogen fertilisers.

Here, we select "Demo" as the study location, a soil with 210 mm of plant available water capacity, the crop rotation "Sorghum-Fallow, Mungbean-Fallow, Sorghum-Fallow, Sorghum-Fallow" (rotation-ID #26), the sowing rule that requires soil water to exceed 40% of the soil's water holding capacity plus a rainfall event, and a medium application level of nitrogen fertilisers. The "Demo" site reflects simulation outputs for Dalby (Queensland) at the time of publication and will remain unchanged in future RotationARM updates (e.g., for readers who wish to follow along the case study presented here).

3.2. Reference results

Users are presented with the simulation results for each sown crop in the specified rotation (Fig. 3). Results can be displayed for the indicators: crop yield, gross margin, revenue, revenue-cost ratio, financial water-use efficiency, bio-physical water-use efficiency, crop water uptake, crop nitrogen uptake, in-crop rainfall, in-crop water loss, and biomass. Detailed variable definitions, including units of measurement, are accessible via information buttons. All figures are interactive, whereby hovering over elements allows querying specific values (here: yield in a specific year), and clicking on legend items allows including/excluding the item from the figure (here: specific crops). As specified in detail within the methodology, all crops are simulated in every year, even if they occur less frequently in the reference crop rotation. This ensures that crops are not only simulated under an arbitrary subset of years but are exposed systematically to all 60 years of weather records. Long-term average results shown in other figures are scaled to accurately reflect the relative share of each crop in the specified crop rotation. In Fig. 3, years without any displayed result value indicate that the sowing rule conditions were not met, and no crop was sown. Failed crops are indicated by a yield value of zero as opposed to being represented as a missing value. The pink background highlighting indicates seasons with user-specified conditions of water availability (see definition in Section 2.4), here referring to moderately and extremely dry conditions. Fig. 3 shows that for both crops, Sorghum and Mungbean, there is a strong inter-annual variability of crop yields. The figure also allows practitioners to query yield values for specific years.

At a more aggregate level, the same data is presented using boxplots (Fig. 4). In the RotationARM tool, boxplot whiskers extend to the 10th and 90th percentiles rather than 1.5-times the interquartile range, and outliers beyond this range are not presented to the user. This approach was adopted based on feedback from growers and agronomists to provide a more intuitive reference for non-scientific users than Tukey-style boxplots (McGill et al., 1978). The boxplots provide users with an understanding of the frequency of favourable and unfavourable results. In the displayed example, the large interquartile range (i.e., boxplot height) of sorghum yields indicates that the central 50% of yield observations fluctuate strongly between 3267 and 5511 kg/ha. The bottom whisker of the mungbean boxplot identifies that 25% of mungbean

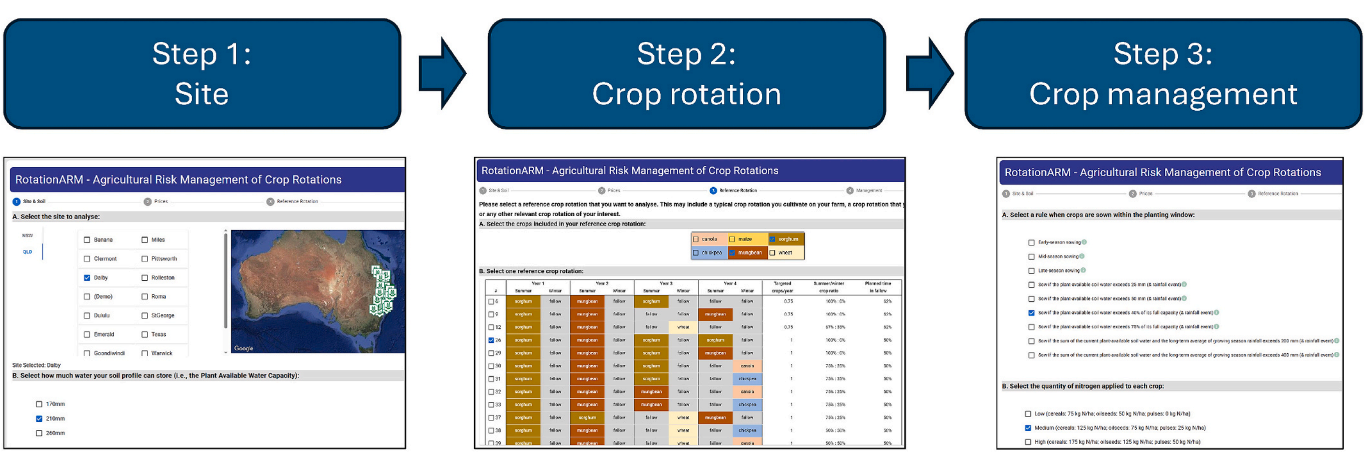

Fig. 2. Three-step user input to the RotationARM tool. Note: Three-step user input consisting of the specification of (i) site characteristics, (ii) focus crop rotation, (iii) crop management.

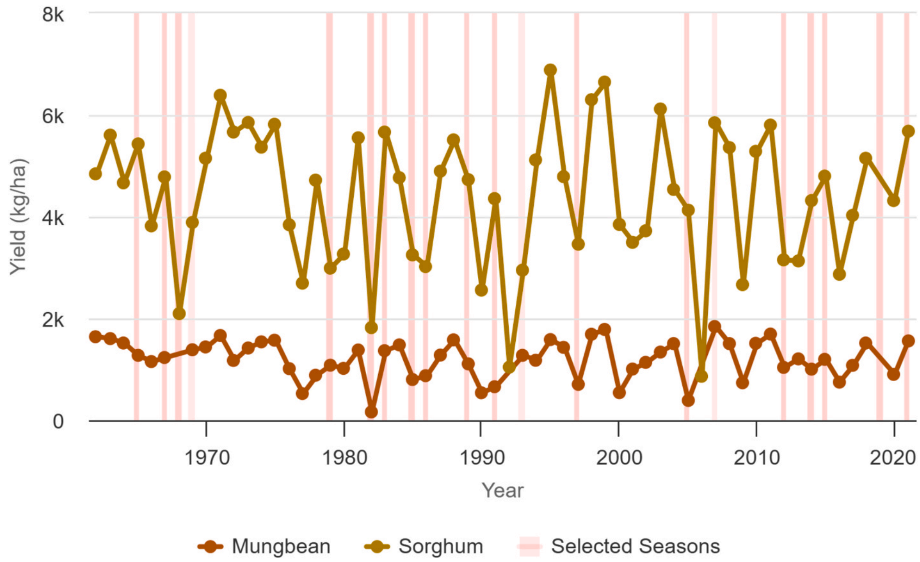

Fig. 3. Time series of simulation results per sown crop: crop yield. Note: Users can toggle between all available results indicators using menu buttons. “Selected Seasons” identify seasons with a specific water balance ratio as selected by the user (here: moderately or extremely dry seasons).

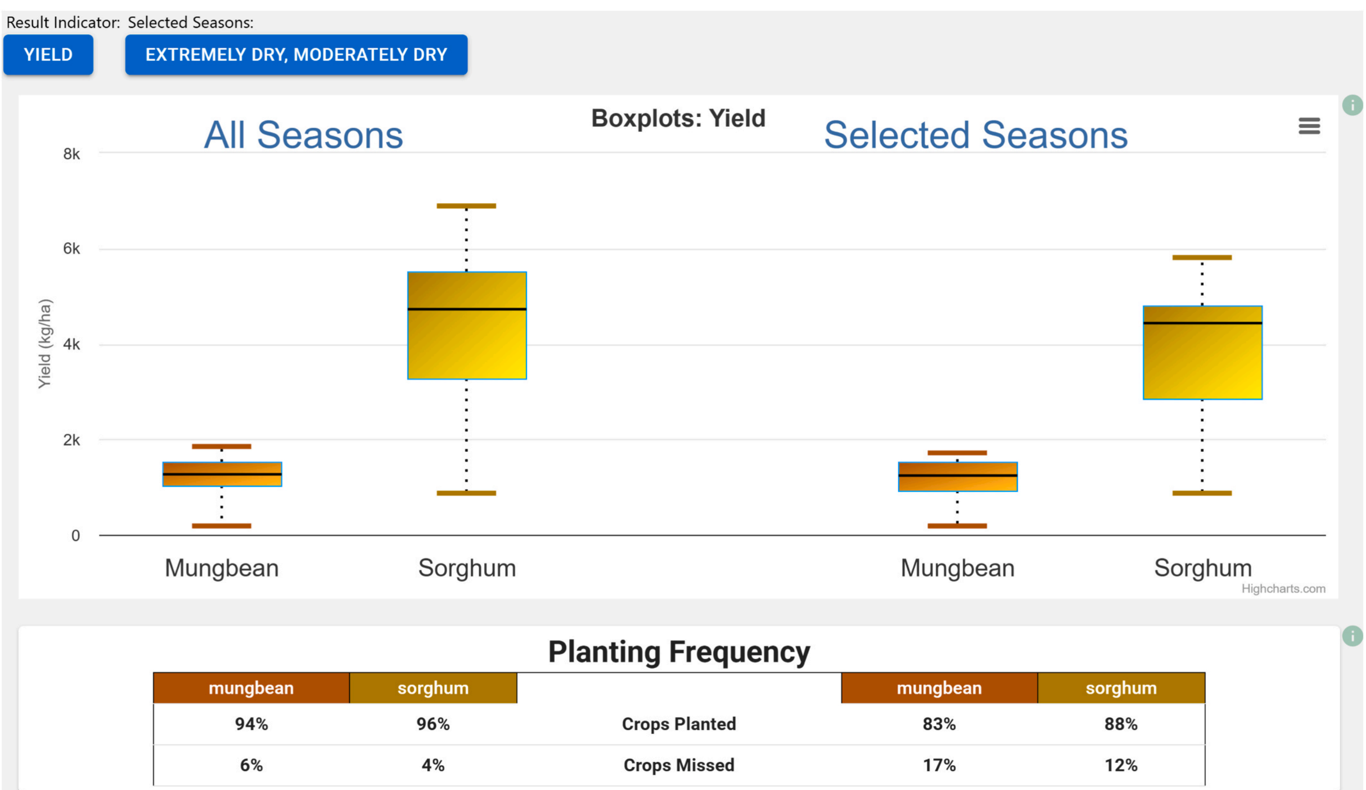

Fig. 4. Boxplots of simulation results per crop: crop yield. Note: Boxplot whiskers represent the 10th and 90th percentiles. “All Seasons” represents results from all seasons in the database, whereas “Selected Seasons” represents results from seasons classified as experiencing moderately or extremely dry conditions. Users can toggle between all available results indicators using menu buttons.

yields are below 1005 kg/ha, while the lowest 10% of mungbean yields are below 164 kg/ha (i.e., observed once in 20 cultivated seasons). Fig. 4 also allows to compare the performance under different seasonal conditions of water availability. In the given example, we compare all seasonal conditions (“All Seasons”, left section of Fig. 4) to seasons with moderately or extremely dry conditions (“Selected Seasons”, right section of Fig. 4). While yields are lower in dry seasons, the specified cropping strategy is comparably drought-resilient, as indicated by median yields for sorghum and mungbean declining by only 292 kg/ha and 21 kg/ha, respectively, compared to all seasons. Fig. 4 further identifies the frequency with which crops were sown. Both crops were sown considerably less in dry seasons, which is a consequence of the chosen sowing rule that requires the soil water profile to be filled at 40% of its capacity. This flexible sowing rule reflects typical farmer behaviour and reduces the occurrence of extremely low yields and crop failure.

While the previous results provide users with a good understanding of the disaggregated performance by crop type, Fig. 5 shows the annual average results at the cropping system level across all years. In addition to the results for the reference cropping system (blue line), the tool displays the results for the best- (green line) and worst-performing (red line) cropping systems based on a user-selected indicator (here: gross margin) under the specified site conditions (location and plant available water capacity). The here analysed reference cropping system effectively achieves a cropping intensity of 0.95 crops per year and an annual gross margin of 1010 AUD/ha, which is roughly at an equal distance between the lowest (246 AUD/ha) and highest (2271 AUD/ha) gross margin achievable at the selected site conditions (Table S 7). The reference cropping system outperforms the system with the highest average gross margin in terms of crop failure rate (0% vs. 6.7%) and downside risk (145 AUD/ha vs. 202 AUD/ha), highlighting clear trade-offs between maximising average financial returns and minimising year-to-year variability. By providing this wide range of indicators, farmers and agronomists can prioritise the performance across those dimensions that are judged most important within the socio-economic context of their farm, while actively considering trade-offs and synergies.

The reference results section of the RotationARM tool further includes figures on the cumulative distribution function per crop and the multi-criteria performance per crop, which are excluded here for brevity.

3.3. Scenario analysis of alternative cropping strategies

After analysing the reference cropping strategy, tool users are guided to define an alternative cropping strategy and compare their performance. Specifically, users define the alternative cropping strategy by repeating Step 2 (crop rotation) and Step 3 (sowing rule and nitrogen application rate) from the earlier user input (Fig. 2).

3.3.1. Scenario 1: Inclusion of winter cropping

For the first alternative cropping strategy, the reference rotation of exclusively summer crops is replaced by a rotation that incorporates wheat as a winter crop: “Sorghum-Fallow, Sorghum-Fallow, Fallow-Wheat, Mungbean-Fallow” (#37). The targeted cropping intensity remains one crop per year. The sowing rule (plant available water > 40%) and nitrogen application rate (“medium”) are kept unchanged. The RotationARM tool subsequently provides all previously mentioned result figures comparing the reference and alternative cropping strategies, of which only a selection is presented here.

The simulation results identify that both cropping strategies have a rather similar performance across most results indicators (Fig. 6b, Table S 8). However, the shift towards occasionally sowing a winter crop in this case decreased the average annual gross margin by 150 AUD/ha (from 1010 AUD/ha to 860 AUD/ha). At the same time, the annual downside risk was reduced by 130 AUD/ha (from 145 AUD/ha to 15 AUD/ha). Shifting to a rotation with a winter crop reduced the proportion of water that was utilised via crop uptake by 16% (from 176 mm/ha to 148 mm/ha) while increasing water loss via runoff, drainage, and evaporation. Examining the disaggregated results by crop can provide some more mechanistic understanding of these outcomes (Fig. 6c). Specifically, the mungbean yield of the alternative cropping strategy is much lower and more variable than for the reference cropping strategy. In the alternative cropping strategy, mungbean is double-cropped, being sown directly after wheat (while mungbean is instead preceded by a full season of fallow in the reference cropping strategy). Consequently, under the alternative cropping strategy, mungbean experiences more frequent water stress and achieves lower yields.

The results highlight that growers should not anticipate massive but more subtle differences when shifting between these two cropping strategies. At the example location, farmers who prioritise high gross margins are likely to benefit from the pure summer cropping strategy, while farmers who aim at minimising risk would more likely benefit from introducing the winter crop into their cropping system.

3.3.2. Scenario 2: Opportunistic increase in cropping intensity

After comparing two cropping strategies, RotationARM users are provided with guidance on how to interpret results and conduct further reflections about cropping systems design. A unique feature of the tool is its capacity to support iterative comparisons of cropping strategies, allowing users to evaluate any previously defined strategy against further alternative scenarios. In doing so, the RotationARM tool supports farmers and agronomists in critically assessing the relative strengths and weaknesses of a broader range of strategies as part of a comprehensive reflection about cropping system design options. Users are prompted to iteratively explore multiple scenarios tailored to their specific objectives

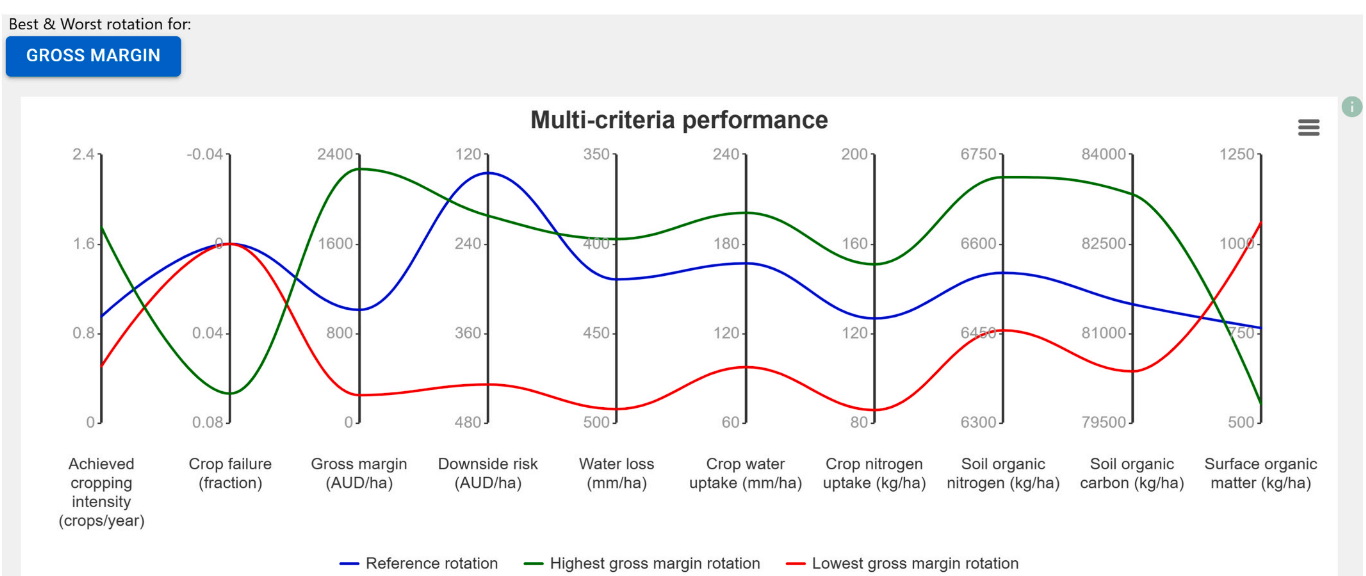

Fig. 5. Long-term performance of the reference cropping strategy across multiple criteria. Note: Parallel axes chart displaying the performance of the reference crop rotation (blue line) across ten performance dimensions. Each axis represents a single performance indicator, with values towards the top of the axis indicating more favourable performance and values towards the bottom indicating less favourable performance. The green and red lines indicate the best- and worst-performing cropping strategies at the chosen site conditions for a user-selected indicator (here: gross margin).

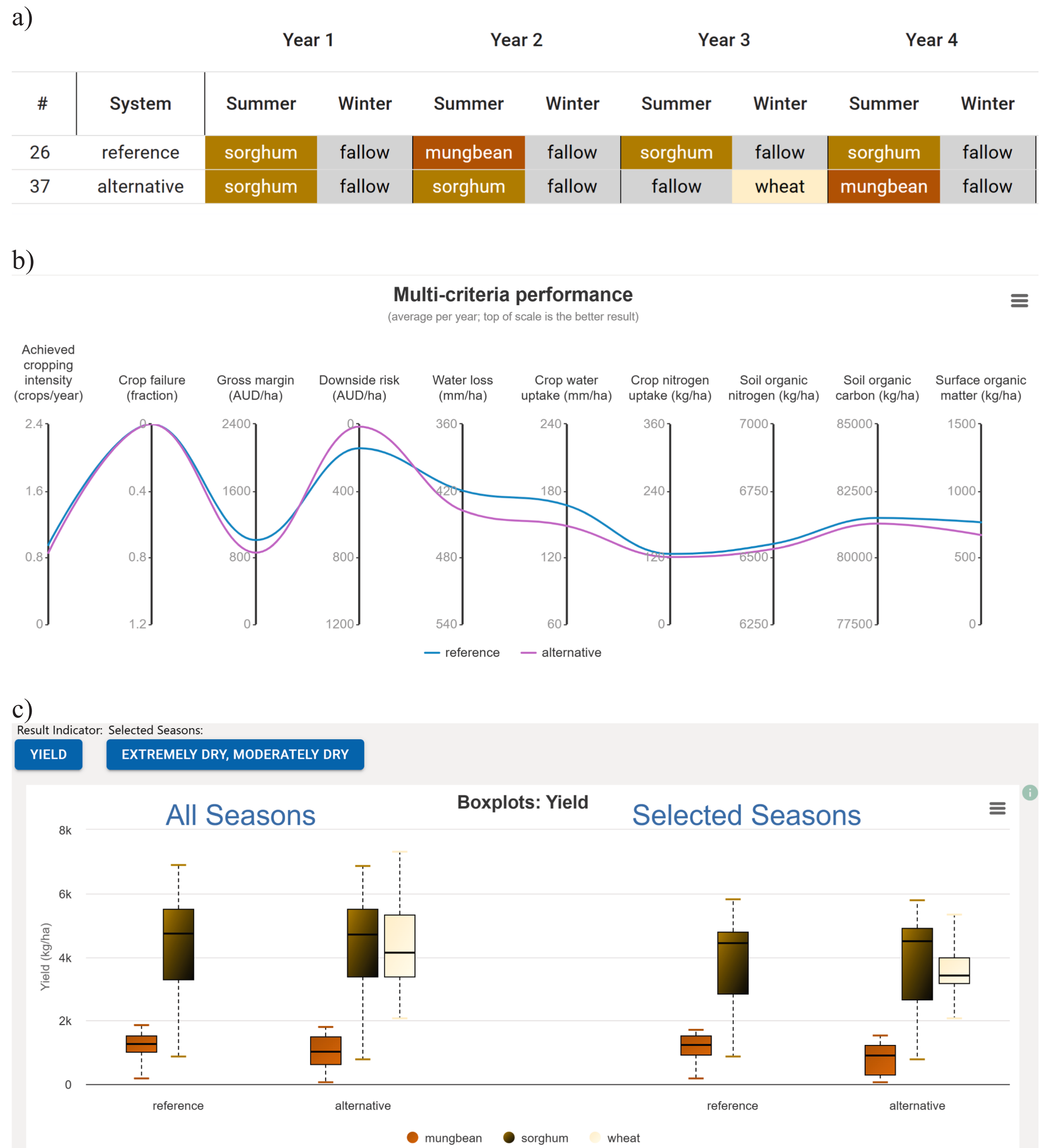

Fig. 6. Performance comparison of cropping strategies: Summer cropping strategy versus summer-winter cropping strategy (scenario 1). Note: a) Crop rotations implemented as part of the reference (top) and alternative (bottom) cropping strategies. b) Long-term performance of the cropping strategies across multiple criteria. Numerical results are provided in Table S 8. c) Boxplots of simulation results per crop (here: crop yield).

and constraints.

As a second scenario, we consider a crop rotation with a much higher scheduled cropping intensity, combined with a sowing rule that requires a greater level of soil water accumulation before sowing can proceed. This reflects a shift toward a more opportunistic cropping strategy that intensifies production when water resources are sufficient and reverts to fallow periods when they are not. Specifically, we consider the crop rotation "Sorghum-Chickpea, Sorghum-Chickpea, Mungbean-Wheat, Mungbean-Fallow" (#81), the sowing rule that requires soil water to exceed 75% of the soil's water holding capacity plus a rainfall event, and a medium application level of nitrogen fertilisers.

The simulation results identify that this second alternative cropping strategy leads to a substantial increase in the average gross margin and a reduction of downside risk, while performing similarly across most other results dimensions (Fig. 7b, Table S8). Specifically, the average annual gross margin increases by 47% (from 1010 AUD/ha to 1482 AUD/ha), while the annual downside risk reduces from 145 AUD/ha to 0 AUD/ha. Thereby, the second alternative cropping strategy does not achieve this better financial performance by growing more crops, as its cropping intensity is even moderately lower than that of the original reference cropping strategy (reference: 0.95 crops/year; alternative 2: 0.87 crops/year). The combination of a more restrictive sowing rule and the permanent scheduling of potential crops across summer and winter seasons led to a marked reduction in low-yielding seasons. This is reflected in the narrower interquartile range and shorter whiskers for sorghum and mungbean under the second alternative strategy (Fig. 7c). Further, there is a notable increase in the median annual gross margin of sorghum (reference: 1078 AUD/ha; alternative 2: 1247 AUD/ha) and mungbean

a)

		Year 1		Year 2		Year 3		Year 4	
#	System	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter
26	reference	sorghum	fallow	mungbean	fallow	sorghum	fallow	sorghum	fallow
81	alternative	sorghum	chickpea	sorghum	chickpea	mungbean	wheat	mungbean	fallow

Fig. 7. Performance comparison of cropping strategies: Summer cropping strategy versus opportunistic intensification (scenario 2). Note: a) Crop rotations implemented as part of the reference (top) and second alternative (bottom) cropping strategies. b) Long-term performance of the cropping strategies across multiple criteria. Numerical results are provided in Table S 8. c) Boxplots of simulation results per crop (here: gross margin). d) Time series and cumulative distribution function of simulation results for the cropping strategy (here: crop water uptake).

(reference: 1265 AUD/ha; alternative 2: 1526 AUD/ha). The introduction of chickpea into the rotation is a further driver of the better financial performance. However, it is important to note that chickpea prices can be highly volatile in Australia, based on export market restrictions and further factors.

When investigating the difference in crop water uptake between the two cropping strategies, which constitutes a key driver of their performance differences, we found that the reference cropping strategy (167 mm/ha) achieves slightly higher average annual crop water uptake than the second alternative strategy (160 mm/ha). However, the more disaggregate analysis of the cumulative distribution of crop water uptake (Fig. 7d) indicates that, in the 53% driest seasons, the reference strategy results in higher water uptake, whereas in the 47% wettest seasons, it results in lower uptake. By shifting water use from dry, low-yield seasons to wetter, higher-yield seasons, the second alternative strategy enhances water-use efficiency, leading to improvements in crop yields and financial performance. The here analysed second alternative cropping strategy is of particular interest, as it (i) offers clear benefits without substantial trade-offs, and (ii) improves average financial returns while simultaneously reducing risk. However, the approach of maintaining year-round readiness to sow a diverse range of crops – while frequently foregoing dry-season planting to accumulate soil moisture – presents significant socio-economic and operational challenges at the farm level. Specifically, it demands continuous and accurate monitoring of soil moisture, the capacity to respond flexibly to seasonal conditions with minimal lead time, and the ability to secure timely access to labour and machinery. These requirements may render the strategy impractical for farmers who rely partially or entirely on contractors for field operations, or who must coordinate on-farm responsibilities with off-farm employment – factors that often cannot be adjusted on short notice. Despite these difficulties, the empirical evidence of planting patterns in Australia points to the wide diffusion of opportunistic cropping strategies across Queensland and New South Wales during the winter cropping season (ABARES, 2025; Sadras et al., 2003).

3.4. Facilitated adult-learning processes

We developed dedicated training material using the two major channels of face-to-face capacity-building workshops and self-paced online video tutorials. We conducted 12 face-to-face capacity-building workshops across nine locations in Queensland and New South Wales, engaging a diverse range of 65 stakeholders, including farmers, private-sector agronomists, government extension officers, agricultural financial advisors, representatives of peak industry bodies and environmental non-governmental organisations (NGOs), soil scientists, and agronomy students. We provided participants with a semi-structured, adult-learning approach (Zull et al., 2023). Following a comprehensive introduction to cropping system design and practical instruction on using the RotationARM tool, we then facilitated participants to undertake self-paced analyses of their own personal circumstances. Subsequently, we guided participants to share the main findings of their personal analyses and discuss potential alternatives as part of a peer-to-peer learning process with other workshop participants. The face-to-face capacity-building workshops underlined the high value of interactive, adult-learning approaches in facilitating the uptake and efficient use of decision support tools.

While face-to-face workshops provide a high learning intensity, they require substantial time and financial resources, which constrain their scalability. To extend access to a broader audience, we developed and published a set of three self-paced online training videos (https://www.armonline.com.au/train). These videos provide users with a guided yet concise introduction to both the practical use of the RotationARM tool and the underlying concepts for comparing cropping system strategies.

4. Discussion

The outcomes of any given rainfed cropping strategy are highly uncertain due to the inherent variability in climatic and financial conditions, making data-driven decision support tools increasingly important in guiding sustainable cropping system design. Crop simulation models constitute a versatile and powerful framework for data-driven ex-ante evaluation of how different cropping strategies perform under realistic environmental and management conditions (Grewer & Rodriguez, 2019; Hochman et al., 2009). To our knowledge, RotationARM is the first available decision support tool designed for farmers and agronomists to guide multi-year cropping systems design decisions based on a dynamic crop simulation model. The tool is easily accessible to non-scientific users via a simple point-and-click graphical user interface and requires minimal data inputs. It actively considers inter-annual carry over impacts of soil water and nitrogen, thus allowing to represent multi-year crop rotations. The tool particularly emphasises the importance of diverse thresholds governing the decision of whether to sow a crop or accumulate soil water during a fallow season.

The RotationARM tool does not claim to prescriptively identify a set of most favourable cropping strategies but rather helps to identify cropping strategies that best align with decision makers' long-term goals. During the participatory tool-design workshops with farmers, industry and government stakeholders, it was deliberately decided not to provide users with a list of the best-performing cropping strategies for given site conditions. Instead, the tool actively stimulates users to engage in their own iterative reflection that focuses on the comparison of cropping strategies, to understand system dynamics over time and identify a cropping system that is meaningful in their own circumstances.

Further, a core novelty of the tool is the focus on a wide range of multiple performance indicators that can support the sustainable intensification of cropping systems (Grewer & Rodriguez, 2019). In their review of decision support tools for supporting crop rotation decisions, Dury et al. (2012) found that multi-criteria assessments beyond the focus on a single financial indicator are one of the major shortcomings of existing tools. A core novelty of the RotationARM tool is the simultaneous focus on multiple performance indicators. This enables users to think beyond a single main objective and instead actively consider a wide range of trade-offs and synergies. These various aspects of the RotationARM tool constitute major innovations in the space of decision support tools for cropping systems design.

Cropping systems are difficult to conceptualise, and the quantification of their performance is typically cumbersome. Weersink et al. (2018, p. 19) identify that one of the major challenges to realising gains from big data and the digitalisation of agriculture is the *"lack of ability to aggregate and interpret data in such a way that it results in useful decision support tools for farmers and the need to train farmers in how to use new tools."* Many decision support tools that are based on crop simulation models present results in a largely unprocessed form, relying on basic transformations or direct visualisations of raw simulation outputs (Hochman et al., 2009). However, such outputs are primarily relevant to scientific audiences and are difficult for practitioners to translate into actionable on-farm decisions. The RotationARM tool addresses these challenges by translating large-scale databases of agricultural simulation output into information of direct relevance for farm-level decision making. The tool leverages additional data beyond crop simulation outputs (particularly on costs and prices) and converts complex numeric results into more easily understandable charts and figures that are aimed at a non-scientific audience.

Besides these major advancements and innovations, the RotationARM tool also faces a number of limitations. As with all crop simulation models, the tool is limited to considering input data that can be represented as mechanistic variables or parameters within the underlying model structure. In contrast, many emerging big data sources that capture in-field variability – such as those obtained via remote sensing or drone-mounted sensors – have not yet been widely integrated into crop simulation frameworks in an operationally robust manner. However, a large diversity of scientific work is currently aiming at advancing the dynamic integration of crop simulation models and multispectral data (Della Nave et al., 2022; Huang et al., 2019). As a tool aiming at cropping system design rather than precision management, RotationARM does not provide machine-readable prescription files suitable for semi-automated in-field operations, such as those used in variable-rate application systems. Dury et al. (2012) suggest that decision support tools should allow users not to select a single cropping strategy, but multiple changing cropping strategies over time to account for the dynamic nature of farm-level decision making. We deliberately decided not to follow this recommendation, as enabling tool users to select multiple changing cropping strategies over time would have greatly increased the complexity of tool usage and strongly reduced the interpretability of scenario results.

The RotationARM tool primarily supports farmers and agronomists by providing a detailed, mechanistic representation of crop growth processes through crop simulation modelling. However, it does not capture the socio-economic dimensions of farm-level decision making, such as constraints related to labour and capital availability and personal goals and objectives. Combining RotationARM and mathematical programming within a bio-economic model could extend the present work, enabling a comprehensive representation of both agronomic processes and socio-economic on-farm decision making. As another avenue for future development, improvements in the coverage and reliability of greenhouse gas emission processes represented by crop simulation models could enable RotationARM to be extended to provide greenhouse gas emission estimates (Grewer et al., 2018).

As with any application of crop simulation modelling beyond the geographic and temporal scales for which it has been calibrated and evaluated, RotationARM is subject to considerable uncertainty arising from inputs, parameters, and model structure (Wallach, 2011). While absolute predictions remain uncertain, the model supports risk-informed decision making by illustrating likely ranges of outcomes from different cropping strategies, identifying conditions under which strategies perform well or poorly, and highlighting trade-offs in water use, productivity, and economic returns. The explicit and transparent communication of these methodological limitations is central to the informed use of such decision support tools.

RotationARM demonstrates how crop simulation models can be operationalised into practical decision support tools for cropping system design. The tool can be readily adapted to additional production regions within Australia. APSIM and other crop models can be used to develop similar tools tailored to additional cropping systems and agro-ecological contexts.

5. Conclusion

This study introduced RotationARM, a simulation-based decision support tool designed to apply crop simulation modelling to the practical challenge of multi-year cropping system design. In contrast to prevailing digital agriculture tools that focus on short-term, field-scale precision management, RotationARM provides a structured, multi-year framework for evaluating the trade-offs and synergies among alternative cropping strategies under realistic seasonal variability and site-specific constraints.

The tool's novel features – such as the dynamic representation of inter-seasonal water and nitrogen carryover, the integration of multiple performance indicators, and the visualisation of results in a farmer-accessible format – address key limitations of previous decision support tools. By encouraging users to iteratively compare user-defined cropping strategies, rather than prescribing optimal solutions, RotationARM promotes critical reflection and learning, aligned with diverse farm-specific goals and constraints.

By supporting structured, data-driven evaluation of cropping system options, RotationARM contributes to a broader shift in digital agriculture – away from isolated precision interventions and toward holistic systems thinking. Its design, implementation, and capacity-building approaches serve as a template for future tools that aim to enhance sustainability, resilience, and profitability in agriculture. Future research and development should explore its extension to additional crops and regions, as well as integration with emerging, multispectral data sources to further enhance its relevance and utility.

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. **Roy Anderson:** Writing – review & editing, Software. **Keith G. Pembleton:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Uwe Grewer reports financial support was provided by Australian Government's Future Drought Fund. Andrew Zull reports financial support was provided by Australian Government's Future Drought Fund. Roy Anderson reports financial support was provided by Australian Government's Future Drought Fund. Keith Pembleton reports financial support was provided by Australian Government's Future Drought Fund. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2026.111725.

Data availability

The simulation database generated by this study can be freely accessed from the website "Agricultural Risk Management of Crop Rotations" (RotationARM; www.armonline.com.au/ra).

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