A cognitive decision tool to optimise integrated weed management

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Abstract

Weed management is becoming more complex due to the rise of herbicide resistant weeds. Integrated weed management strategies are recommended to minimize herbicide resistance. However, weed management can be daunting and uncertain leading to biased, avoidant or suboptimal decisions. Existing weed management tools can be insensitive to user needs and changing contexts over time. This paper discusses a proof of concept cognitive tool for integrated weed management decisions.

Our team has taken initial steps into the design of an interactive tool for cotton growers that allows them to explore the impact of individual priorities and strategy preferences (optimistic, pessimistic and risk related) on weed management decisions given uncertainty in temperature and rainfall. Our research tackles the challenge of engaging stakeholders in complex decision making in three ways: 1) recognizing individual cognitive priorities 2) visualising scientific weed management in an appealing mobile interface and 3) representing decision uncertainties and risk weighted against cognitive priorities.

Specifically, our tool communicates personalised barnyard grass weeding management strategies for pre-crop and in-crop cotton weeding decisions. We ranked a set of actions including applications of herbicides: glyphosate, paraquat (shielded and unshielded), group A, trifluralin, diuron, pendimethalin, s-metolachlor, fluometuron, glufosinate; and non-chemical methods such as soil disturbance at various times prior to planting, at planting and in crop. Each action was evaluated against personal priorities including: *saving time/effort*, *health/safety*, *saving money*, *sustainability* and *effectiveness*.

The adoption of decision support in AgTech is improved when users can represent the objective benefits of recommended actions proportionately to their own needs and measures of success. Our interactive decision tool provides individualised decision support and quantifies uncertainty about attributes relevant to decision-makers to optimise integrated weeding management. The framework, however, can be extended to other decision making context where user priorities and decision uncertainties need to be incorporated alongside scientific best-practice.

Background

The evolution of weed populations resistant to key herbicides is now a long-standing, globally-distributed agricultural problem (Thornby, Werth & Charles, 2012). While resistance-conferring genes are rare in wild weed populations, frequent selection in herbicide-intensive industrial agricultural systems has led to the development of resistant populations of over 250 different weed species (Heap 2017). Resistance leads to the loss of efficacy of key management tactics, meaning that farmers must adopt new tactics (and re-adopt old ones), in an environment where the total number of available efficacious options is shrinking, not growing. The commonly-accepted approach to the problem of resistance is to increase the diversity of weed management, within the parameters allowed by the cropping system (Norsworthy et al. 2012). However, increasing diversity implies increasing complexity of decision-making.

In Australian cotton farming, the rapid adoption of glyphosate-resistant crop varieties has meant that growers have spent two decades getting used to minimal complexity in weed management, and the industry must re-learn, to a substantial degree, how to construct and work with more diverse management strategies.

Existing decision support tools (e.g. Thornby, 2016) and information focus generally on empirical studies of best management based on the interface of plant evolutionary dynamics and weed management efficacy, and so far have not explicitly included farmers' personal decision-making drivers.

Methods

The project was set up with a design science methodology to bring together expertise in cognitive science, decision science and interaction design to create a more engaging decision support tool:

1. interaction design to mitigate against cognitive biases that lead to stagnant or myopic decision choices despite existent knowledge of optimisation strategies.
2. accommodates individual differences between users for optimal, personalised decision making
3. explicitly communicates the methodology of decision science

Design science

Design science is a methodology within information systems that allows researchers to tinker and create information systems using top-down theoretical constructs and design principles and processes with bottom-up real-world problems and constraints (Venable, 2006; March & Smith, 1995). The theoretical constructs stem from cognitive science, decision science and interaction design. The constraints included cotton weed resistance management strategies over a single season.

Weeding science

Our tool communicates personalised barnyard grass weeding management strategies for pre-crop and in-crop cotton weeding decisions for a single season incorporating stages and possible actions recommended by cotton weeding expert David Thornby (2016). The team ranked a set of actions including applications of herbicides: glyphosate, paraquat (shielded and unshielded), group A, trifluralin, diuron, pendimethalin, s-metolachlor, fluometuron, glufosinate; and non-chemical methods prior to planting (soil preparation, knock down and early season residual), at planting (sowing method, crop seeding rate) and in crop (weed control and layby). To add personalization and buy-in, each action was evaluated against cognitive priorities including: saving time/effort, health/safety, saving money, sustainability and effectiveness that emerged from cognitive science considerations.

Cognitive science

Cognitive science is the study of how humans perceive, think, consider and remember. The way information is represented to decision makers affects how they assign likelihoods and can result in either a) cognitive biases or b) rational responses to options. The emotional resonance, vivacity, and perceived risk of options affects both the number of genuine options decision makers consider and the probabilistic breadth they assign to those options.

One concern with complex weeding decisions is that decision makers' judgement of uncertainty may be spurious. That is to say, reflecting on past weeding practices and imagining future weeding actions involves assigning probabilities to events based on emotional priorities and biased risk assessment rather than the rationality and consistency desiderata of probability theory (Jaynes, 2003). Positivity, optimism and narrative bias have all been shown pervade thinking about the past. Because the same cognitive mechanisms of memory are used during strategizing and planning the future; past perceptions can adversely affect future thinking (Betsch, Haase, Renkewitz, & Schmid, 2015; De Brigard et al., 2013). In particular, decision makers may avoid considering positive outcomes that could have occurred if they had made different decisions. People avoid thinking too much about alternatives that devalue their actual decisions and make them feel worse. But, considering alternative paths of action is crucial for better future decisions (Markman, McMullen, Elizaga, & Mizoguchi, 2006).

The team hypothesised that making unfamiliar, yet potentially transformative weeding strategies more salient, personalized, interactive and memorable might improve strategic weeding management decisions to manage herbicide resistance.

Interaction design

The design team (Polson, Quagliata & Taylor, 2017) adopts game development technologies and techniques to deliver interactive scenario-based data simulations to create meaningful engagement with contextually-sensitive practices. The design process results in an interactive interface that allows users to experiment with complex scenarios and options based on data and processes verified through expert collaborations with researchers and practitioners. This approach has been developed over a number of scenario-based data simulation projects with similar objectives such as Scape, FarmIt and ECOS (Polson & Selin 2012). Each project has resulted in the production of interactive simulations designed to promote more efficient practices in urban design, sheep farming and green energy management.

To successfully design a simulation that allows improved decision making requires an interaction designer to coordinate and translate multiple discipline theories and practices with the principal determination to synthesize them into a system that best represents the context and an interface that allows stakeholders to access and experiment with the attributes and variables of that context.

Key attributes of a scenario-based simulation:

- Presents a limited scenario (weeding strategies) within a defined context (cotton farming) to allow for deep exploration while promoting an appreciation of broader contextual implications
- Identifies the who, where, when and why within the scenario. In this case farmers/agronomists, cotton farm, a cotton crop season, improve strategy for weeding
- Offers a variety of interactive controls for experimenting with the options within the scenario that impact and inform decisions
- Presents immediate statistical and visual feedback to interaction:
    - Statistical feedback includes textual and diagrammatic information demonstrating the consequences of certain decision
    - Visual feedback provides an illustration of the situation and consequences of decisions

Decision science

Each decision situation has a decision maker, a decision problem and a context in which a decision is to be made. A decision context can be altered internally (e.g. a decision maker adopts a new approach to farm management) or driven externally (e.g. adverse weather events, increasing herbicide resistance or reduced water allocations). Changes in context affect how the grower (decision maker) addresses the same weeding decision problem from year to year.

Our tool considers a weeding strategy to be made of a sequence of decisions across the growing season and addresses the decision problem associated with each stage as an independent component; that is, we disregard the interaction among outcomes at the different stages. Under this assumption, the decision problems considered are multi-objective single-stage decisions made by a single decision maker or decision making unit (grower and agronomist).

Such a decision problem is characterised by the following components:

- The set of feasible actions that can be taken;
- The set of attributes that influence the outcome of the decision and are outside the control of the decision maker;
- The quantification of the consequences of the different outcomes;
- The decision strategy used to choose the best action from the set of actions considered.

The set of actions considered is $A=[a_1,a_2,\ldots,a_m]$. . In this paper, these represent the possible use of different weeding actions (chemical, mechanical and no action). We also considered the set of states of nature $S=[s_1,s_2,\ldots s_n]$, which are attributes that influence the outcome of the decision that are outside the control of the decision maker. In the proof of concept, a state of nature is defined as the combination of temperature (high, medium) and rainfall (high, medium, low) to make six possible states of nature at each stage of the season. Only one of these states can be true, but the decision maker does not know the state when planning weeding actions.

The decision consists of choosing the best action in the face of uncertainty associated with the states of nature. To do this, note that if the action a_i is taken and the true state of nature is s_j, this results in outcome o_{ij} to which we can associate a consequence c_{ij} through a function C() that measures the consequences (higher values represents more adverse consequences), namely,

$$(a_i,s_j) \rightarrow o_{ij} \rightarrow c_{ij} = C(a_i,s_j).$$

This provides a set of scenarios that the decision maker should consider. Note that the consequences should be quantifiable in a scale allowing their comparison.

Having defined the key ingredients of the decision problem (actions, states of nature, and consequences), we can then consider three different decision strategies—see Table 1.

Table 1. Pessimistic, optimistic and risk minimised decision strategies

Strategy	Encoding
Pessimistic	for each action, identify the largest potential adverse consequence that can result. Then, choose as the action to follow the one that has the minimum largest adverse consequence—this is known as the Min-Max strategy
Optimistic	for each action, identify the minimum potential adverse consequence that can result. Then, choose as the action to follow as the one that has the smallest minimum adverse consequence—this is known as the Min-Min strategy
Risk minimisation (risk related)	encode uncertainty associated with the states of nature in a probability distribution $P(s_j)$. Then, compute the risk of each action as the weighed sum: $R(a_i) = P(s_1)\, C(a_i,s_1) + P(s_2)\, C(a_i,s_2) + \ldots + P(s_m)\, C(a_i,s_m)$, and we choose the action that presents the minimum risk. Note that each term in the sum above is a risk: the compound of a consequence and likelihood of this consequence.

The individual cognitive aspects are embedded into the probabilities representing uncertainty of the states of nature, and the cognitive priorities of the decision maker are embedded into the consequence function C(). Details of this are beyond the scope of this short paper.

Results

The Cognitive Inputs weeding tool make tractable a wide range of possible actions under uncertainty. The team chose a naturalistically modelled and animated growing cotton crop with weather effects (temperature and rainfall) within the interface to trigger memories of past decisions (details, phenomenology, thoughts, emotions), yet allow the user to explore, experiment and remember options they may not have considered, allowing an imaginative resonance to help them weight unfamiliar options more rationally and increase the likelihood that these options are chosen—see *Figure 1*.

Interacting with the interface enables users to visually represent alternate and future scenarios to get more buy-in for speculative possibilities. The more buy-in we can get to possible options, the more likely information will positively influence decision-making behaviour. Exposing decision makers to novel options and complex scenarios, allows them to build on their own experiences, increasing the vivacity and weighting of unfamiliar, yet rationally important options and reducing the negative emotions associated with familiar, yet critical realities.

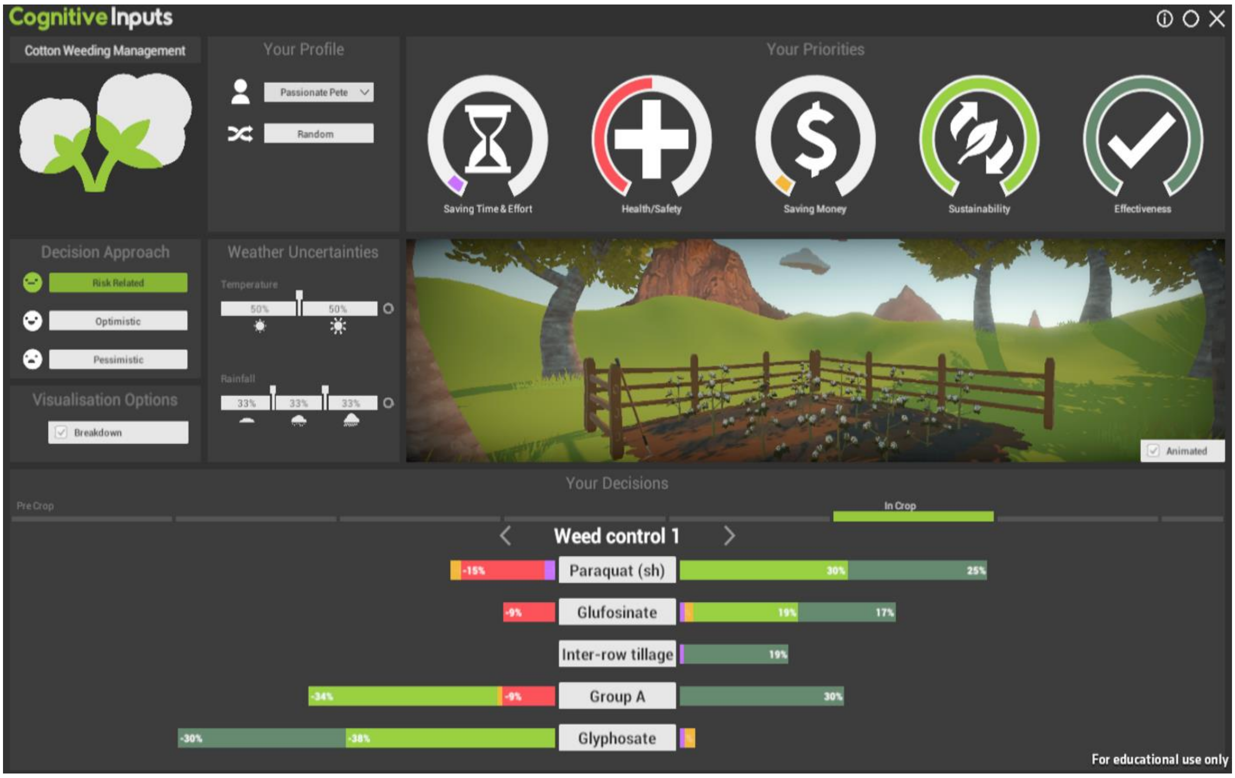

Figure 1. The main control and feedback panels of the Cognitive Inputs user interface. On the top and middle sections there are control panels for setting the farmers priorities, potential weather conditions and crop timeline. Followed by a visual feedback panel of the health and growth of the cotton field and time of day. The bottom panel displays diagrammatic feedback of resulting options with a breakdown of data influencing these results. The top result shows the recommendation aligned with cognitive priorities, uncertainties and decision strategy.

Once users have chosen their weeding actions, results are exported as a simple txt file to be shared by decision makers and stake-holders such as agronomists, farm managers and business partners.

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Cognitive Inputs
Module: Cotton Weeding Management


Your Profile: Passionate Pete

Your Priorities:
Saving Time & Effort: 1/10
Health/Safety: 5/10
Saving Money: 1/10
Sustainability: 10/10
Effectiveness: 10/10

Decision Approach: RiskBased

Uncertainties:
      Temperature:
            Average: 50%
            High: 50%
      Rainfall:
            Low: 33%
            Medium: 33%
            High: 33%
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Results:
      Pre Crop:
            Soil Preparation:
                  Tickle Selected
            Knock-down:
                  Tillage Selected
            Early season residual:
                  Fluometuron & Prometryn Selected
            Sowing method:
                  Min-till seeding Selected
            Crop seeding rate:
                  High Selected
      In Crop:
            Weed control 1:
                  Paraquat (sh) Selected
            Layby weed control 4:
                  Pendimethali Selected

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Discussion

Early feedback from the cotton industry suggests that growers will be interested in a tool similar to our proof of concept, particularly if it can be made suitable for multiple crops over multiple seasons and manage sequential decisions, e.g. decisions made earlier in the season affect later season decisions, also, decisions made one year affect subsequent years. The industry is also interested in regional solutions to deal with a variety of herbicide resistant weeds, i.e. awnless barnyard grass, liverseed grass, sweet summer grass, windmill grass and annual ryegrass, and one broadleaf species, flaxleaf fleabane.

If the sequential version of the tool was created, how would it intersect with existing best-management practices, such as the decision-making heuristic 2 + 2 + 0 (Australian Cotton Industry, 2016)? i.e.

2 non-glyphosate tactics targeting both grasses and broadleaf weeds during the cotton crop

2 non-glyphosate tactics in fallow targeting both grasses and broadleaf weeds

0 glyphosate survivors allowed to set seed

If a tactic is selected that only targets grass weeds, than an additional tactic that targets broadleaf weeds will need to be included

Next steps include validating the tool, building screens with scenarios that show various consequences of chosen actions, e.g. goes into detail on sustainability issues relating to applications of early season residuals. The team will also consider using similar design science methodology to other cotton decisions, e.g. integrated pest management and nutrition.

Conclusion

The Cognitive Inputs weeding tool uses graphical representations of the components of multi-objective single-stage weeding decisions made by a single decision maker or decision making unit (grower and agronomist) over a cotton season. The user can consider different scenarios by adjusting their priorities: saving time/effort, health/safety, saving money, sustainability and effectiveness; the assignment of probabilities to states of nature (temperature, rainfall) and their own decision strategy (optimistic, pessimistic or risk related). Variables are combined with an animated representation of the scenarios that can help triggering positive cognitive experiences to improve retention and use of alternate weeding strategies. The tool uses familiarity triggers to broaden how users will think about alternate futures; predicts how these processes affect rational decision making; and aims to mitigate against cognitive biases by promoting behaviours likely to generate more rational information analysis

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