Agricultural Systems 105 (2012) 7–20

Contents lists available at SciVerse ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

A cognitive systems framework to inform delivery of analytic support for farmers' intuitive management under seasonal climatic variability

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ARTICLE INFO

Article history:
Received 20 October 2010
Received in revised form 16 August 2011
Accepted 17 August 2011
Available online 4 November 2011

Keywords:
Decision support
Simulation
Information system
Cognitive system
Intuition
Climatic risk

ABSTRACT

The idea of the decision support system (DSS) for farmers remains an enigma. Clever technology to bridge the gap between agricultural science and farming practice still seems appropriate. Many more of the conditions for success appear to exist today than ever before. Yet the DSS has yet to significantly colonise farm decision making practice. This paper comes late in a long program of research conducted to see if, and under what conditions, computer simulation of farming scenarios, on which a DSS generally depends, can be valued by farmers.

The research approach used an unconventional prototypic information system (IS), comprising local measurements, models, and facilitated discussions that evolved in an action research program. The aim has been to elucidate the means by which successful simulation-based decision support intervention can take place and why it usually does not. This required a significant expansion of the researchers' concept of the farm as a system to include the farmer's internal system of practical knowing and learning. This paper reports on a cognitive framework model with transactions at interfaces with both the production system and the analytical IS. Its coarse structure is the classical perception–action cycle influenced by goals and outcome feedback. In the highly uncertain production environment of Australian dryland farming, personal judgement plays a significant mediating role between perception and action, and theory of a continuum between the judgement modes of intuition and analysis adds to framework structure. Further structure comes from the theoretical distinctions between holistic and arbitrary intuition, and between causal and probabilistic analysis. Analytic interventions influence: (a) awareness of current situation conditions and (b) expectations of future conditions and action outcomes, and these serve as primary cognitive resources for evaluation of possible actions in planning and decision making. A theory that matches our research experience in bridging the gap between analytic intervention and intuitive practice posits that virtual situations simulated with analytic models and outputs represented graphically can facilitate vicarious experiential learning. This dovetails with theory concerning the education of intuition.

The paper concludes by applying criteria from the field of cognitive engineering to test whether the framework presents a concept of mind that is workable for informing practical model-based research and development aimed at supporting farmers' judgments and decisions.

> …our theories are very practical because they frame not just the ways we act, but also…the ways we justify our actions to ourselves and to each other (Wenger, 1998, p. 11).

1. Introduction

A recent series of papers reports a 17-year program of research on a type of decision support in Australian dryland cropping that is radically different from the familiar decision support system (DSS) (McCown et al., 2009; Dalgliesh et al., 2009; Carberry et al., 2009; Hochman et al., 2009). The program began in response to: (a) a mandated task of making an existing capability for simulating cropping systems useful to farmers[1] and their advisers and (b) the researchers' growing awareness of persistent low interest in DSS software among farmers. The research strategy has been to deconstruct the DSS and to configure decision support functions as a prototypic researcher-delivered service. This minimised the barriers to farmers receiving the value envisaged by the scientists and derived

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[1] Unless qualified, 'farmer' will refer to the owner–manager of a "family farm" where the farmer has the discretion and agency of an entrepreneur, in contrast to a salaried manager of a corporate farm.

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doi:10.1016/j.agsy.2011.08.005

from improved judgements and decision making. A farmer's need for a computer and competence in use of the decision supporting software was by-passed; researchers got involved in farmers' planning in conditions of high climatic risk, and the scenarios simulated in response to farmers' "what if…?" enquiries were situated using local weather data and paddock-specific soil data.

The central research question was whether the historically-notorious IS 'problem of implementation' (Ackoff, 1960; Huysmans, 1970; McCown, 2002) could be avoided? Our intervention methodology, i.e. participatory action research (PAR) enhanced by soft systems thinking (Checkland, 1981; Checkland and Howell, 1998; McCown et al., 2009), was well-suited to keeping focus on participants' experience with the IS content rather than the technology. Evidence that the content of such IS was highly valued by farmers and consultants (Carberry et al., 2002; Dalgliesh et al., 2009) provided the impetus for commercial delivery of a service based on this approach to decision support (Hochman et al., 2009).

This opportunity to design a delivery platform brought to the fore a limitation of the action research methodology. Although it enabled participating farmers to discover usefulness in our IS offerings, this practical, commonsense approach poorly serves development of understanding that might enable explanation of our experiences and prediction in different circumstances, e.g. explaining changes in a farmer's use over time, anticipating effects of design modifications in the interest of more efficient delivery or designing for users in other environments. How farmers actually use IS outputs in their judgment and decision processes is obscured by a "black box" cognitive model that assumes merely that an IS will be used when it is judged to be sufficiently useful and easy to use (Davis, 1989). The importance of this deficiency was highlighted by Kirlik (2006) for engineering cognitive tools, among which are DSSs/ISs (Zachary, 1988, p. 997).

> … research in fields such as…cognitive engineering…should begin with a qualitative naturalistic phase to identify and distil the central features of a target problem to be solved or phenomenon to be investigated. Yet if attention then turns directly to creating an intuitive solution or qualitative account (regardless of how well received by stakeholders), without bringing the central features to an *abstract level*, it is often impossible to know the conditions in which that same solution will prove useful. As such, each cognitive engineering problem will have to be solved largely from scratch (Kirlik, 2006, p. 6; emphasis and interjection added).

Having practiced the particular action research methodology advocated by Checkland and Howell (1998) in which conceptualisation of "what we think we are doing" precedes each research phase, we had a succession of abstract models of our IS implementation activity (McCown et al., 2009), and this led to an elementary cognitive model (McCown et al., 2009, Fig. 9). A stimulus for investing more in the cognitive framework was provided by surprises experienced by researchers' in narrative interviews of farmers and advisers about their earlier experience with the Farmers', Advisers', Researchers' Monitoring, Simulation, And Performance Evaluation (FARMSCAPE) approach and its influence on their practice (Dalgliesh et al., 2009). It was evident that many farmers and advisers had "re-invented" the technologies that they had earlier adopted. But even when the reported change for a particular technology was outwardly indistinguishable from disadoption, the personal stories were of ongoing learning and adaptation, building on concepts and techniques gained from earlier FARMSCAPE experiences (McCown et al., in press).

This present paper describes an eclectic cognitive systems framework (hereafter referred to as the "Framework"), which has drawn on literature from several fields, including cognitive science, philosophy of mind, judgement and decision making, cognitive engineering, and naturalistic decision making, using our research experiences to direct attention and guide selection of relevant theory elements. At a practical level, a primary test of its value is its power in explaining patterns of adoption and disadoption of FARMSCAPE technologies in Australia's subtropical grain-growing region using longitudinal evaluation data collected mainly as narrative interviews of FARMSCAPE participants (McCown et al., in press). Another practical test will be explaining and giving guidance to model-based intervention in other farming settings, e.g. the Yield Prophet project (Hochman et al., 2009). At a philosophical level, a test is whether the Framework significantly contributes to bridging the gulf between model-based farming systems research and farming practice (McCown, 2001) by reducing conceptual tensions around subjective vs. objective knowledge, intuitive vs. analytical judgement, and causal vs. statistical explanations and predictions.

After describing the overall framework in Section 2, the subsequent sections elaborate on various aspects of the framework. Section 3 considers intuition and analysis, and shows how analysis can lead to rules of thumb and eventually to background expectations as a basis for intuition. Then Section 4 further elaborates on this issue to show how the analytical mode when used by farmers can be expensive and that this can induce the development of an approximate replacement method that becomes a highly accessible mode of situation category recognition. Manager expectations are central in the overall framework, and Section 5 views the construction of expectations from several different perspectives. Then in recognition of the mediating role between desires and the actions of planning and decision making, Section 6 focuses on risk. The final section of the paper brings these threads together and points to an improved paradigm for future DSS.

2. The framework

Fig. 1 is a heuristic representation of a system comprised of three subsystems: 'the internal system of a farmer's cognition',[2] a 'production system', and an 'information system' (IS). The role of Fig. 1 is to aid researchers' thinking about the ways in which the IS can contribute to a farmer's: (a) learning that reduces uncertainty about states of the 'production system' and (b) thinking about acting on the uncertain 'production system'…

> In the systems view there are two independent uncertain systems – the objective ("outside") system and the subjective ("inside") system. Uncertainty in the world outside the observer generates uncertainty in the observer's *cognitive system* – the judgments and predictions – of laypersons and experts alike (Hammond, 1996, p. 17).

Fig. 1 draws on the distinction between two strategies available for reducing uncertainty in the cognitive system, i.e. *intervention* in and *representation* of the uncertain world (Hacking, 1983). A farmer's thinking about the 'production system' is aided by experiential knowledge gained in physical *intervention* in actual fields. It can also be aided by *representation* in a simulation model of a field influenced by both actions on it in an uncertain climate, *represented* by historical weather records.

When in Fig. 1 the 'production system' is represented as a model of an actual (or hypothetical) field provided in the IS, the farmer "acts" on a *virtual* field and can conduct virtual experiments quickly and cheaply. A simulation model of a field specified for soil conditions and an 'action' of "what-if" significance to a farmer can

[2] Throughout the rest of the paper, single quotes are used exclusively to indicate that the term is an element of the figure being discussed.

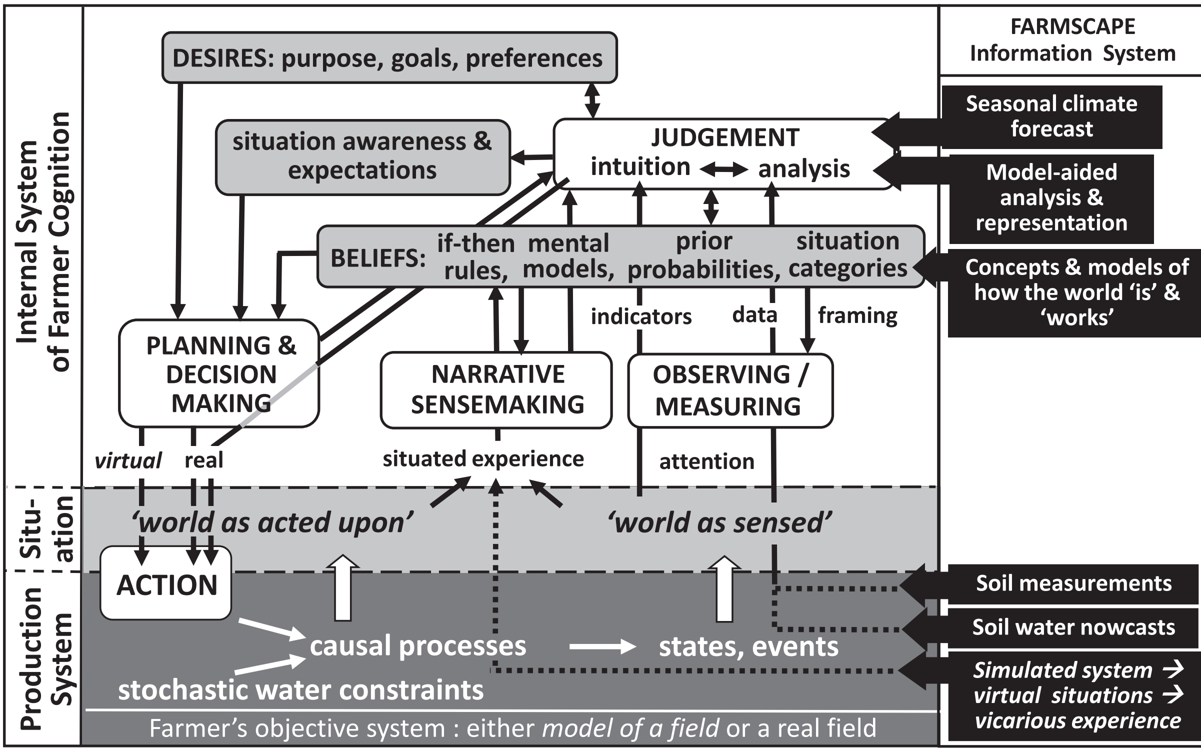

Fig. 1. A theoretical Framework for a farmer's adaptive cognitive system to aid scientists' thinking about intervention with an information system (IS) to support farmers' management of uncertainty in dryland cropping situations. (Shaded elements of 'Internal system' are cognitive structures, unshaded are processes. Default entry at 'world as sensed'; follow arrows up and counter-clockwise.)

be run for many seasons for which rainfall records exist, mimicking 'stochastic water constraints' and generating a probabilistic graph of virtual yields. Fig. 1 contributes the first stage of a Framework to aid thinking about how an IS might moderate uncertainty in the "inside" system through manipulation of historical variability in the "outside system".

At the centre of Fig. 1 is the 'situation' which can be visualised as a metaphorical "overlap" between the inside subjective system and outside objective system. From the objectivist perspective, this is the delimiting of the objective system by what is subjectively meaningful. As the pioneering cognitive scientist, Herbert Simon, saw it,

> We [cognitive scientists] are not interested in describing some physically objective world in its totality, but only those aspects of the totality that have relevance as the "life space" of the organism considered. Hence, what we call the "environment" ['situation' of Fig. 1] will depend upon the "needs," "drives," or "goals" of the organism, and upon its perceptual apparatus (Simon, 1956, p. 130; interjections added).

These days it is scientifically acceptable to augment this by a subjectivist perspective.

> The central idea…is the co specification hypothesis: that an experiencing self and experienced objects are simultaneously specified in the information available to perception [i.e., the 'situation'] (Carlson, 1997, p. vii).

The sequence of cognitive activity that eventually leads to meaningful 'action' in the 'production system' begins with experience of the 'situation' in either of two modalities of meaning that Simon (1996, p. 210) termed the 'world as sensed' and the 'world as acted upon' (Fig. 1). Thinking about the differences between the *existing* state and the desired, or *goal*, state is at the heart of practical management of situations. As Simon, saw it,

> The distinction between the *world as sensed* and the *world as acted upon* defines the basic condition for the survival of adaptive organisms. The organism must develop correlations between goals in the sensed world and actions in the world of process.[ ] Given a desired state of affairs and an existing state of affairs, the task of an adaptive organism is to find the difference between these two states and then to find the correlating process that will erase the difference. Thus problem-solving requires continual translation between the state and process descriptions of the same complex reality (Simon, 1996, p. 210, emphasis added).

The "translating" cognitive activity between *observation of* the world and *action in* the world uses the processes of 'judgment' and 'planning and decision making' to close the gap between desired and existing states observed by Simon (1996). Planning and action are driven by the cognitive structures[3] of 'desires' and constrained by the structures of 'beliefs'.

Drawing on Beach (1992), "what-to-expect" uncertainty exists in the 'world as sensed' and "what-to-do" uncertainty in the 'world as acted upon'. Two of the types of 'belief' (Fig. 1) concern what to expect, and two concern what to do. 'Situation categories' and 'prior probabilities' are related to what to expect, and 'if-then rules' and 'mental models' relate to what to do. First, the mind needs a simplified structure for reducing the boundless variety of the world's structure. 'Situation categories' aid engagement with the 'world as sensed' by 'framing' that pre-shapes perceptual experience (Bruner, 1986, p. 46). Second, 'Prior probabilities' represent a person's experience-based assumptions about 'states' and 'events' in an uncertain 'production system'.

[3] "Cognitive structures store information: cognitive processes are the mental operations that transform, elaborate, and reduce this information during decision making or problem solving" (Doyle and Ford, 1998, p. 19).

The IS interventions in Fig. 1 influence a farmer's risk management in two ways. The first enhances analytic judgment through measurement and computation, providing more realistic 'situation awareness' and 'expectations'. The second uses simulation and analysis to provide vicarious experience in computed virtual systems. The first analytical pathway requires new understandings of 'how the world is and works' and new 'mental models'. A changed concept of soil water storage and availability to a crop precedes farmers' adoption of the interventions of 'soil measurements', 'soil water nowcasts' and 'simulation-aided analysis' (Carberry et al., 2002; Dalgliesh et al., 2009). In the second pathway, much of the analytical information is contained in the model. Learning takes place through virtual 'experience' in simulated 'situations', leading to processes of 'narrative sensemaking' with consequences for 'belief' structures, particularly 'if-then rules'.

3. Intuition, analysis and the cognitive continuum

The scope of the previous section encompassed the contents of three intersecting systems, i.e. the 'production system', the 'cognitive system', and the 'information system'. This section focuses on the key point of system intersection, 'judgment'. In Fig. 1, 'judgement' is needed to interpret uncertain production 'situations'.

> Traditionally, two forms of cognition – *analysis* and *intuition* – have been distinguished. …almost every study of human judgment employs these concepts, implicitly or explicitly. [ ] The meaning of analysis or analytical thought in ordinary language is clear; it signifies a step-by-step, cautious, logically defensible process. The ordinary meaning of intuition signifies the opposite – a cognitive process that somehow produces answer, solution, or idea without the use of a conscious, logically defensible, step-by-step process [and] has acquired powerful claims to efficacy despite its ineffable, undefinable character (Hammond, 1996, p. 60).

Hammond further theorised that although these modes of 'judgement are "rivals" they occur as opposing poles of a continuum containing various mixes and intermediate forms indicated in Fig. 1 by the double arrow connecting 'intuition' and 'analysis' in 'judgment'. Fig. 2 elaborates 'judgement' as a suite of interrelated cognitive operations organised on the horizontal axis by Hammond's concept of the *cognitive continuum* between 'intuition' and 'analysis'.

The explanatory value of the Continuum Theory is realised in conjunction with his Task Structure Theory (Hammond, 1996, p. 180). The structure of a situation, task, or information structured around a action induces an appropriate, i.e. adaptive, cognitive strategy on the continuum between 'intuition' and 'analysis'. Routine, "automatic", tasks induce 'intuitive' judgement operations, e.g. 'recognition of situation categories', 'prior expectations' and 'action propensities' (Fig. 2). (The direct controlling influence of these on action is indicated in Fig. 1 as a dotted arrow from 'judgement' to 'action', by-passing 'planning and decision making.') For example, a farmer's intuitive operations (Fig. 2) concerning planting a crop is induced by 'soil water indicators' experienced in a situation, e.g. when rainfall is received at a time of year recognised from past experience as favourable for planting a crop that yields well when ensuing rainfall is adequate. To the farmer with highly developed 'holistic intuition' about planting and crop establishment, action is triggered by the timing and quantity of rain on the situation. This is implicit and relatively automatic. However, because rainfall is so uncertain, past experience provides little predictive skill for crop performance beyond *establishment*, and such judgements and decision depend on 'arbitrary intuition', i.e. 'guessing' about ensuing rainfall (Fig. 2), informed only by vague 'prior expectations'. (Although there are good theoretical reasons for distinguishing 'arbitrary' intuition from 'holistic', in interviews, farmers tend to self-report *all* intuitive decision making as "gut feel" (Lisa Brennan, pers.comm.).'Analytic' judgement operations at the other end of the cognitive continuum (Fig. 2) can be expected to be induced by a combination of dissatisfaction with variable performance of intuitive practices combined with the availability of external support for an analytic approach (Hammond, 1996). This is evidenced by comments made by an interviewee 10 years after participating in practice-changing analysis activities (McCown et al., in press).

> Consultant: Fifteen years ago most decisions made here were based on planting rainfall events. If it rains you plant and then if you have a crop failure, bad luck. That's what it was like. But now we're saying we can't afford crop failures, how do we stop crop failures, and we start by relating crop failures to starting *subsoil* moisture. Back then we didn't have a strong appreciation of water use efficiency as in "so much soil water means this much yield". Because of that we didn't go after subsoil water. There's no point having one without the other. Then we got onto the "so many millimetres mean this amount of yield", what's a break-even yield that's worth having a dabble at, and putting some things like that into perspective. For that we needed to determine what your soil moisture holding capacities are, and that's where it all started from.

Further structure is provided to Fig. 2 by the dichotomy between 'causal analysis' and 'probabilistic analysis'. 'Causal analysis' depends primarily on the deterministic models of the simulator together with measurements that provide information for specifying boundary conditions and initial conditions, e.g. available water capacity and current available water status for soil water balance simulation. 'Probabilistic analysis' always involves the ordering of random seasonal variation, i.e. ranking, classifying, and tabulating in the process of calculating relative frequencies and probabilities. Causal and probabilistic analysis merge with great advantage to 'expectations' (Fig. 1) when probability distributions of yields are calculated *conditional on* soil water status as discussed in Section 5.3.

The centre "column" of Fig. 2 contains five judgement operations intermediate to 'intuition' and 'analysis', what Hammond broadly referred to as 'commonsense'. "Any commonsense heuristic, any rule-of-thumb, used implicitly or explicitly, is a compromise between analysis and intuition" (Hammond, 1996, p. 175). In Fig. 2, farmers who initially invested in drying and weighing facilities for measuring soil water learned through experience that sensing soil wetness either with a steel probe or squeezing core segments in the hand provided an estimate of soil water that was adequate and cheap (Fig. 2). Farmers' explanations of these practical adaptations, along with other learnings from both real and virtual situations, are reported in interviews (Dalgliesh et al., 2009; McCown et al., in press) as stories about experiences of actions and events ('narrative sensemaking'[4]) (Figs. 1 and 2).

> The importance of the causal narrative can hardly be overstated. To construct a causal narrative is what it means to understand something. [ ] Until there is a causal narrative, there can be no

[4] Hammond (1996, p. 200) flagged this addition himself. In a discussion of cognitive structure in relation to task structure, Hammond included a short section entitled "The Narrative", and commented, "My primary reason for introducing this topic is to encourage others to pursue the matter of the narrative as a judgment process on equal footing with that of the more familiar kinds." Parallel support for inclusion of narrative in this way includes the typology of knowledge of Boisot et al. (2007) embodied, narrative and abstract symbolic [a typology that nicely overlays the Cognitive Continuum of Fig. 2].

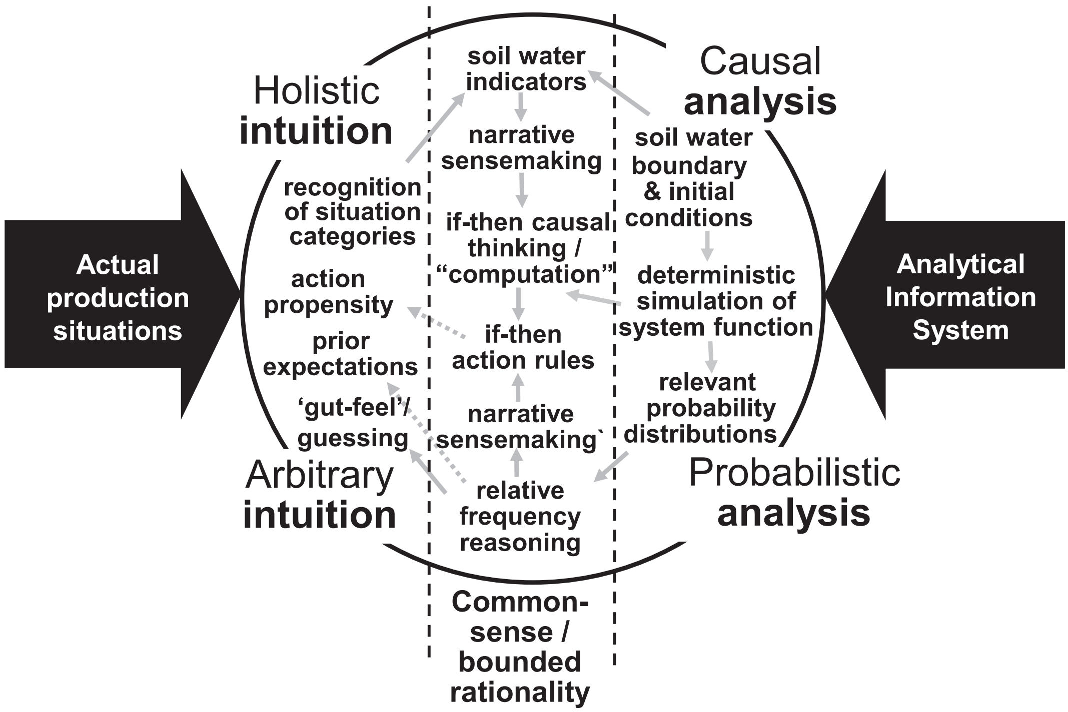

Fig. 2. A map of cognitive operations inside 'judgment' in Fig. 1 on a continuum between intuition and analysis (Hammond, 1996). Differentiating two intuition types follows Endsley (1997).

> comprehension of how things work. [ ] The framework of the causal narrative is what provides its ability to anticipate the outcome [formulate expectations]. This is ultimately how inferences about past events and predictions of future ones are constructed from causal propositions (Vick, 2002, p. 187; interjection added).

Farmers and consultants welcomed insights to models underpinning 'deterministic simulation of system function' that enhanced their commonsense 'if-then causal thinking' (Fig. 2) and construction of 'mental models' of how things work (Fig. 1).

In the main, farmers valued 'relevant probability distributions' based on simulations as a basis for long-term yield expectations (Carberry et al., 2002; McCown et al., in press). Many farmers developed more fluent 'relative frequency reasoning' (Fig. 2) in planning discussions and engaged enthusiastically in What if Analyses and Discussions (WifADs) which provided relevant distributions (Carberry et al., 2009; McCown et al., in press). An important innovation by some farmers was construction of 'if-then action rules' (Fig. 2, centre) based on graphical comparison of conditional probability distributions of simulated yield for scenarios of varying conditions and actions (McCown et al., in press). Formulation of rules is shown in Fig. 2 as part of 'commonsense' judgement operations; once formulated, they become 'belief' structures to guide judgment and 'planning and decision making' (Fig. 1). From farmer interviews, there were signs that, in time, with repeated use, rules tended to transition to new 'prior expectations' and 'action propensities' (Fig. 2, left).

Fig. 1 shows the primary outputs of the 'judgement' operations in Fig. 2 as 'situation awareness' and 'expectations', which serve to update cognitive resources for 'planning and decision making'. Intervention with an IS (Figs. 1 and 2) aims at reducing uncertainties inherent in both here-and-now awareness (Section 4) and future expectations (Section 5). This what-to-expect focus contrasts with the what-to-do strategy prevalent in past model-based intervention efforts oriented to "best practice" (McCown and Parton, 2006).

4. Situation awareness and its external support

In the field of cognitive engineering, the general descriptive term, "situation awareness" has been appropriated for the phenomenon of "knowing what is going on" in the activities of competent human beings acting in conditions of complexity and uncertainty (Endsley, 2000, p. 1). This can be facilitated by what Beach and Mitchell (1978) called an "aided-analytic strategy", as indicated in Fig. 2, right. However, the benefits of better knowledge of "what matters" have to be weighed up against the cost and accessibility of information.

> ...most people, most of the time, cannot afford the luxury of accuracy. Instead, their goal is to establish some sort of stability and predictability under conditions that work against this goal (Weick, 1995, p. 153).

Dalgliesh et al. (2009) reported that farmers and consultants who had adopted an analytical approach to gain accuracy were highly motivated to then make analysis more accessible and less costly as long as the sacrifices of lower accuracy are discovered in practice to be tolerable. This resulted in a trend from measurement to estimation of soil wetness by 'soil water sensory indicators' (Fig. 2). This can be seen as a form of information *satisficing* (Prabha et al., 2007) with retention of the desire to satisfy the requirements for 'if-then computation'. Even greater accessibility of 'situation awareness' is possible in 'holistic intuition' (Fig. 2) as 'recognition of situation categories' (Rottenstreich and Kivetz, 2006, p. 76).

5. Supporting construction of expectations

Planning depends strongly on expectations about an uncertain future and, especially, the uncertain outcomes of actions taken to create an envisioned future. In FARMSCAPE, simulation and analyses generating relevant probability distributions have aided farmers and their consultants in scenario exploration, forecasting yield and tactical planning (Carberry et al., 2009; Hochman et al., 2000). Process models of the 'production system' of Fig. 1 are causal and simulations are deterministic, but random climate variation among seasons means that representations of yield outputs are stochastic. Even though it might be expected that the stochastic nature of annual crop yields would induce 'relative frequency reasoning' (Fig. 2), distributional language is not prominent in farmers' planning discourse, and according to the general management literature, farmers are in good company.

5.1. Competing paradigms for management prediction: causal vs. statistical

Nisbett et al. (1982) concluded that while statistical, or distributional, thinking is evident at some level in a few aspects of everyday of life, e.g. in sport, weather, and games of chance, in general, active use of this mode of expectation formulation is strongly dependent on having received formal training in mathematical statistics. But even people trained in statistics tend to use alternative means of dealing with uncertainty in their everyday lives. Kahneman (2003) noted that 'if-then causal thinking' (Fig. 2) dominates the thinking of most people most of the time—even people well-versed in statistical concepts. This propensity for avoiding 'probability distributions' in favour of 'if-then causal thinking' in spite of accompanying biases and errors of logic became the focus of his laboratory research for over 35 years and for which he received the Nobel Prize. An expansive study by Shapira (1995) with similarly statistically–sophistically professionals also revealed an underlying belief that risk could somehow be controlled most of the time.

Similar behaviour by farmer–managers has been described and discussed in numerous papers on low use by farmers of probabilistic seasonal climate forecasting services (Stone and Meinke, 2006; Hu et al., 2006; Ash et al., 2007). Such "belief that risk can be controlled" implies 'if-then causal thinking' (Fig. 2) that explains and predicts in both the 'world as sensed' and the 'world as acted upon' (Fig. 1)—both what to *expect* and what to *do* (Beach et al., 1986). Farmers' normal approach to explanation and prediction reported by McCown et al., in press is described by Vick (2002) explaining behaviour of geophysical engineers.

> Assigning causal attributions to events is fundamental to inductive reasoning. Through past observations, people posit inductive "if-then" relationships by enumeration. These: are not hard-and-fast rules but loose relations expressed in terms of likelihood: If A occurs, then you can usually expect B because A usually causes B. ...they indicate what to expect if certain conditions are met (Vick, 2002, p. 186).

But the normative view assumed in the FARMSCAPE IS is that at some high level of risk, under conditions when objective probability distributions are available, decision strategy focus should logically shift from *causal* construction of if-then causal scenarios with large safety margins to *frequency* expectations, or probabilities, given the local conditions in question (Kahneman and Tversky, 1982).

A view typically held by participant farmers was that "...it takes your head a long time to get around probabilities" (farmer quoted by Hochman et al., 2009), so that scientists trained in descriptive frequentist probability methods had much to learn about creating value for decision makers from relevant probability distributions of simulated yields. Participatory activities helped farmers improve their probability literacy and develop competence in 'relative frequency reasoning' Carberry et al., 2002; Hansen et al., 2004; Hochman et al., 2009; McCown et al., in press), but both understanding probability and facilitation of learning to value and use probabilistic information are inherently difficult due to the opacity of the concept.

5.2. The prediction problem caused by complexity of the probability concept

Agricultural scientists are introduced to probability in their training in experimental design and statistical analysis. Agricultural economists learn about probability in formal decision analysis. But both are of limited value in assisting farmers in thinking about and managing uncertainty. Hamm (1994) reported a similar problem in the medical field. The best-known difference in meanings is between statistical, or frequency, probability and subjective probability based in personal beliefs. Shafer (1992) more rigorously defines subjective probability and adds a third meaning of high relevance to intervention with an IS to influence farmers expectations. In the Shafer construct, embedded in Fig. 3, at one point of a triangle sits probability as a 'frequency' interpretation of an event, e.g. the long-run frequencies of crop yields in the 'production system'. This constitutes "a fact independent of any person's beliefs". Occupying a second corner is probability as 'degree of support for a belief' by evidence in situations for which frequency information is unknown or is inapplicable, e.g. a single event. The third corner is occupied by 'belief as fair odds for a risky action', classically a bet but applicable to the act of planting a crop—fair in the sense that gains and losses break even in the long run.

Fig. 3 also includes several expressions of personal probabilities that differ from these two in the triangle because they are more intuitive in the 'arbitrary' sense of Fig. 2. They "depend on idiosyncrasies as well as information" (Shafer, 1985, p. 261).

As the locus of support for beliefs and a guide for fair odds in risky singular decisions, 'knowledge of frequency in the long run' is of special significance. The low accessibility of unambiguous frequency information in normal dryland cropping experience provides an opportunity for valuable IS contribution in the form of frequency/probability distributions (Fig. 3). These can often be seen as analysis-derived objective "base rates" of relevant events and outcomes to replace or update subjective 'prior probabilities'.

5.3. Analysing uncertainty in order to predict

In dryland farming the main source of randomness of yield outcomes is the often chaotic nature of rain-providing processes. One perverse aspect of this is that any 'knowledge of frequency in the long run' (Fig. 3) gained from personal experience will be vague and, often, misleading. A second perversity is the inability of the long-run frequency distribution to eliminate the need to *guess* the rainfall deficit for next season (Fig. 1).

> The ideal picture of probability is more subtle than the picture drawn by most physical theories... Probability, in this picture, is known long-run frequency. The picture involves both a sequence of questions and a person. The person does not know the answers to the questions but does know the frequencies with which different answers occur. Moreover, the person knows that nothing else she knows can help guess the answers (Shafer, 1993, p. 4).

But despite the determinism of water deficits in dryland cropping and the perplexing randomness of this constraint, crop production is not simply a matter of placing multiple bets against the climate. Hammond (1996) observed that those up against irreducible uncertainty do not just throw up their hands and say

> "Since its chaos out there, let's just roll the dice." Instead they do just what we all do: They exercise their judgment, some-

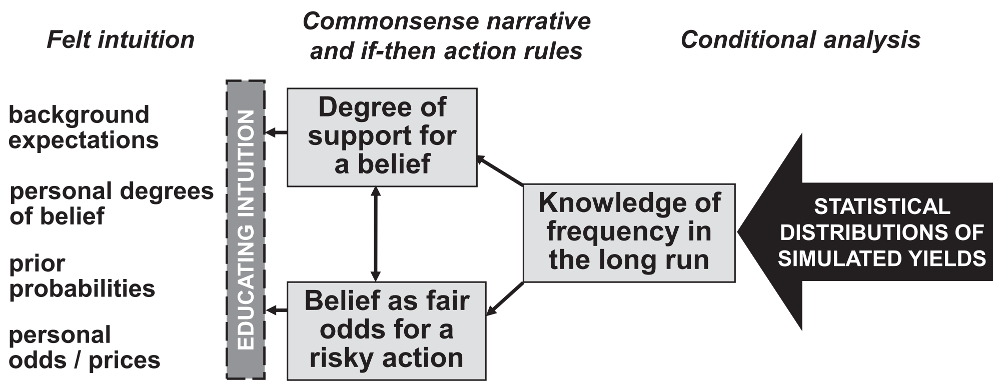

Fig. 3. A cognitive continuum of probability meanings. Shafer's (1992) three modes of probability as two types of commonsense beliefs stemming from knowledge of frequency, with IS as a source of objective conditional long-run frequencies.

> times carefully, sometimes impulsively, and they plan. [ ] Planning under uncertainty demands – and gets – human judgment (Hammond, 1996, p. 13).

Planning in dryland cropping encounters two challenging tasks. The first is to formulate expectations about pending production prospects for the forthcoming season. The second is the judgement of just what threats are amenable to management control. Unaided, the challenge of judging production prospects is formidable, and results in vague expectations that farmers call "gut feelings" and decision researchers call 'prior expectations' or 'prior probabilities'. The most fundamental constraint in this practice of intuitive judgement is the randomness of the rainfall climate and ensuing crop water supply deficits. This absence of regularities that inhibits learning from experience constitutes what Hogarth (2001) termed a "wicked" learning structure. It is largely the result of randomness of relevant events and weak relations between actions and outcomes. This means that management is constrained not only by poor expectation of next season's potential, i.e. simple risk, but by "uncertainty about uncertainty" (Einhorn and Hogarth, 1987), or *ambiguity* (Camerer and Weber, 1992; Aloysius, 2005).

The intervention with models, e.g. in the FARMSCAPE IS, uses 'analysis' tools to engineer a "*kind*" learning structure, i.e. "where the important connections can be seen" (Hogarth, 2001). This provides a *virtual* experience with new insights to climate-constrained production—a set of "histories of the future". The first step is to simulate crop yields for all years of the climate record, which creates a climate-determined stochastic sequence that approximates what farmers' face over time. Then the chronology, whose randomness is partly responsible for making the learning structure "wicked",[5] is eliminated by ranking and ordering outputs into frequencies. As depicted in Fig. 3, this provides 'knowledge as frequency in the long run' using a computed frequentist "base rate" distribution of crop yields based on long-term weather records. In the Bayesian inference scheme this can replace or update personal 'prior probabilities' formed in a "wicked" learning structure due to a random climate. Access to relevant distributions can benefit planning by greatly reducing ambiguity, i.e. "uncertainty about uncertainty". What remains (irreducibly) uncertain is what will happen in the pending season. The probability distributions on offer are computed from simulated yields rather than from actual yield data. The use of a simulator composed of structural causal models (Pearl, 2000) provides a flexibility that allows for the long-term outcome frequencies of a wide range of hypothetical scenarios to be explored as well as historical ones. Actual use by farmers and consultants of these distributions of yield outcomes to reduce ambiguity as a basis for expectations in planning and decision making is reported by McCown et al., in press.

The second cognitive task in planning under uncertainty in dryland cropping, i.e. the judgement of what is amenable to management control, is no less formidable than formulating expectations.

> The essence of risk management lies in maximizing the areas where we have some control over the outcome while minimizing the areas where we have absolutely no control over the outcome and the linkage between the effect and cause is hidden from us (Bernstein, 1996, p. 197).

Any analysis-based support strategy for enhancing management 'expectation' must deal with this challenge of promoting controllable determinants of yield and minimising random ones. One way of reducing uncertainty of an expectation is by taking advantage of awareness of a specific, current, situational condition that is correlated with future outcome. The degree to which this previously-ignored correlation reduces random variance can be seen by comparing the probability distribution conditional on this determinant with the unconditional base rate distribution. Any difference is due to reduced randomness of outcomes as statistical structure of the situation is more precisely partitioned.

> For the kinds of medium-scale causal systems that people tend to think about in everyday life, randomness is produced by what we *ignore*, not by the fundamental nature of events (Sloman, 2005, p. 43; emphasis added.

Although most randomness of annual yields in dryland cropping is due to the fundamental nature of the climate, nevertheless, randomness is due in part to the ignoring of information about current causal states in the 'production system' and its potential to help predict future outcome states. To experimental scientists, this is reminiscent of the value of maximising "accounted-for" variance in ANOVA. The smaller the "unaccounted-for" variance, or "random error", the greater the predictive power of the analysis. The conditioning of probabilities cannot eliminate the need to guess the answer to the question about next season's rainfall deficit, but it shrinks the range of the answers making the guess less uncertain.

6. Support for planning and decision making under climatic risk

In brief, 'planning and decision making' in Fig. 1 mediates 'desires' and 'actions', constrained by 'beliefs'. It is an activity that instantiates goals and formulates intentions (Carlson, 2002, p. 210). This draws on 'judgement' that updates 'awareness' of present situation conditions and 'expectations' pertaining to future

[5] Another contributor is the one-off nature of the decision.

conditions that are contingent on present conditions and on actions. The arrow in Fig. 1 from 'planning and decision making' back to 'judgement' creates the loop that represents the iterative nature of this relationship between committing to 'action' and 'judgement' of prospects and consequences. The IS supports 'planning and decision making' indirectly via influence on 'beliefs' and 'judgement', but analyses of courses of action take place mainly in the planning contexts of WifADs with farmers and their advisers/consultants.

6.1. Conceptual grounds for using models to reduce uncertainty

At the core of this intervention approach is the facilitation of expectation formation by participants through simulation, analysis and discussion. Support for the 'expectation' focus stemmed from Schultz' (1939) classic critique of intervention in farm management with economic models for planning efficient resources use, recently re-visited by Malcolm (2000), Pannell et al., (2000) and McCown and Parton (2006). As Schultz (a 1979 Nobel Laureate in Economics) saw it,

> The farmer as entrepreneur must do two things. He must formulate the…technical rates that he expects. He must then develop a production plan based on his expectations which will give him optimum use of is resources. Expectations cover the first and the plan covers the second. The more difficult and also the more important of these two categories of decisions, both to farmers and to other entrepreneurs, is the formulation of expectations. For this reason should not research in farm management give major attention to this phase? (p.577)
>
> We know that the…outputs which farmers expect are at best probable, very often nothing more than guesses, and sometimes even only hunches. Economic theory, however, is not able to give us much help. The…output that is realised by the firm is usually something different from what was expected. *The divergence between expectations and realisation is a highly important matter* from a practical point of view. [ ] A farmer's most costly mistakes can usually be traced back to faulty expectations (Schultz, 1939, p. 585, 6; emphasis added).

The reduction of differences between farmers' expectations of future conditions and action outcomes and their respective realisations is the primary aim of the practical engagement with farmers mediated by production models. Significantly, with respect to uncertainties in both environmental conditions and action outcomes, intervention targets what to expect rather than what to do.

A starting point for thinking about the scientific side of the WifAD is to substitute a simulation model for the notional 'production system' in Fig. 1. APSIM is a complex dynamic, functional model of soil and crop processes, driven by historical weather records, with a flexible rule-based controller of management actions and strategies (Keating et al., 2003). This enables the conduct of a virtual "experiment" that is realistic and quick. It does this in support of a farmer's "thought experiment" expressed as a what-if question about the consequences of a condition or an action on the behaviour of the 'production system.' Because the 'virtual situation' is specified with data from the real situation, the "experiment" is uniquely meaningful to the enquiring farmer and contributes to the results of the experiment serving as 'vicarious experience' (Fig. 1, lower right).[6]

Once farmers gained some understanding and appreciation of the simulator (Carberry et al., 2009), they were motivated to participate in a WifAD by the possibility that they would learn something that could make a difference in their planning and decision making, if not immediately, at least "down the track". In a succession of WifAD meetings, farmers discovered various ways that simulation could be valuable to them, e.g. benchmarking, scenario exploration, yield forecasting, and tactical planning (Carberry et al., 2009; Hochman et al., 2000). These practical categories of use are revisited in McCown et al., in press for a closer look under the illumination of the knowledge theories of cause-effect and statistical relationships.

Causal knowledge of soil–crop–weather relations is embedded in crop simulation models. *Distributional* knowledge features use of knowledge of the present and past in future-oriented prediction. In WifADs, experienced farmers come together with scientists and their models to collaborate in testing the value of simulation models driven by historical weather records for reducing uncertainty about the future. Our aim here is to elucidate the theory that makes this sensible, building on the Framework of expectation construction[7] in Figs. 1 and 2. The aim here is to pick up on the connections to model-based support for both causal and distributional judgement (Fig. 2) to elaborate the operations on the science side of this intervention and to examine theory of how the science and the cognitive practice connect.

APSIM output is a chronology – a temporal sequence of virtual yields. Sometimes a chronological histogram is useful in a WifAD, e.g. to facilitate farmers' validation of predictions against their own recalled experience—particularly for extreme seasons. However to be useful for future-directed prediction, an analysis is required. The first step in a probability analysis as *prediction* is simply the provision of a description of the variability of yields in the long term. A base rate probability distribution of yield provides a farmer with knowledge of the behaviour of the production system that not only goes beyond the limited sample of his/her individual experience but provides clarity of event frequency that is obscured in experience by random year-to-year variability. We have found that farmers universally welcome this reduction in "uncertainty about uncertainty", or ambiguity. Managers are averse to risk associated with singular actions even if the risk has been revealed by frequency distributions. Additionally they are averse to the more ambiguous situations in which they do not have access to this long-run distributional information. Ambiguity about probability creates a kind of risk—the risk of having the wrong belief (Camerer and Weber, 1992, p. 326).

A second contribution of probability-based prediction is achieved by narrowing the reference class for a probability distribution through increased specification of the simulated production situation. The analysis is "predictive" to the degree that the restrictions on situation conditions shifts the mean and reduces dispersion of the distribution (Potgieter et al., 2003). A *conditional* probability distribution is the means by which the SOI[8] serves as a forecasting instrument (Stone et al., 1996). Based on the research that shows yields (and rainfall) to be generally lower following the SOI in Phase 1 (Hammer et al., 1996), the population of yields simulated for all years of weather records is filtered for those years in which SOI = Phase 1. This subset of yields entails a conditional probability distribution (a distribution conditional on SOI = Phase 1) with a lower median yield and lower dispersion than the unconditional, base rate, distribution.

[6] Elsewhere, such *counterfactual* simulation activity has been described in terms of microworlds, management games, management flight simulators, Computer-Based Learning Environments, business simulators, and learning laboratories (McCown, 2005).

[7] The terms predictions, forecasts, expectations and expectancies are used interchangeably as outcomes of future-directed judgement.

[8] The Southern Oscillation Index (SOI) is calculated from the monthly or seasonal fluctuations in the air pressure difference between Tahiti and Darwin. Sustained negative values of the SOI often indicate El Niño episodes…and a reduction in rainfall over eastern and northern Australia. Positive values of the SOI…give an increased probability that eastern and northern Australia will be wetter than normal.

With reference to Fig. 1, the classical Bayesian approach, illustrated in the previous paragraph, uses observations of 'production system' outcome 'events' (yields) that are correlated with earlier observations of situational 'conditions' (e.g. SOI values). Hence, in a Bayesian context "analytical" intervention in a WifAD is a potential source of new knowledge about the climate of the site in question, based on simulated yield history as well as a new description of current soil conditions. Moreover functional models of production systems afford a different, and more powerful, Bayesian approach to conditional "prediction". In the functional algorithms of the simulator the associations between conditions and outputs are *causal*, not merely correlated, but the power of this is not utilised by standard Bayes theory because it does not distinguish between correlation and cause. This deficiency has given rise in recent years to a radically revised Bayesian methodology that utilises learning from causal intervention in the 'world as acted upon' (Fig. 1). This new approach, termed "causal Bayes" theory (Pearl, 2000; Sloman, 2005) contributes theoretical rigour to our explanation of "what we are doing" in WifADs in bridging between the deterministic scientific simulation and inductive probabilistic forecasts. It also fits comfortably with the naturalistic "commonsense" of 'if-then causal thinking' and 'narrative sensemaking' of farmer–managers (Fig. 2).

In causal Bayes thinking, the concept that "causes change the probability distributions of their effects" replaces conditional probabilities based on correlated covariates.

> Although standard [Bayesian] logic does not distinguish between the *observation* of an event and the generation of the same event by an *intervention*, the distinction is central to causal Bayes. Causal models have the ability to represent both action (intervention in the world) and imagination (intervention in the mind) (Hagmayer et al. (2007), p. 92).

Indeed, the imagination-dependent "what-if" depends on the applicability of causal Bayes theory to *intervention in the mind* and a simulator of *intervention in the world*. The simulator enables a prediction of the outcome of a what-if enquiry. It does this in the first instance using embedded causal relationships for deterministic, "scientific" prediction of crop yields (Sarewitz et al., 2000). When specified for an actual situation, given soil properties and initial conditions, management actions, and weather inputs, predictive accuracy can be tested using physical measurements of outcomes (Carberry et al., 2009). But when this capability is used for responding to what-if questions about *future* yields for either actual or hypothetical initial conditions and/or actions, simulations using weather inputs for historical seasons generate probability distributions that provide future expectations in terms of "how often" and "on average."

Prediction using "causal conditioning" (Pearl, 1996, 2000) of a yield distribution is achieved by an intervention[9] in the simulation to purposefully manipulate a causal condition at an appropriate time (e.g. amount of soil water at planting) that functionally constrains causal variables, through the course of the simulation, to "cause" a yield. This intervention "screens off" the yield probability distribution from any causal variation "upstream" of the intervention, creating a *causal Markov condition*. An invariant relationship is created by intervening with a rule for setting situation state, e.g. soil water and N. (In practice this is conceptualised as simply "re-setting soil conditions at planting"). The condition created and its relation to "downstream" computation is *invariant* across all simulated years and enables the *generation* of a set that is conditional on the intervention rather than on a value of covariate. Avoiding filtering on the covariate value has the substantial benefit of avoiding reduction in set size. (The SOI Phase I subset in Hammer et al. (1996), cited above, contained only 12 years of the 96 total years.)

6.2. Framing effects on plans and decisions

Although Bayesian conditional probability provides a sound theoretical basis for analytic support of 'planning and decision making' via WifADs, implementation of such an approach has a history of substantial behavioural obstacles in the form of conflicting cognitive *frames*, i.e. a frame of reference, or point of view. Of particular relevance to our focus on facilitating participants' construction of expectations is variation in the framing of risk. Kahneman and Lovallo (1993) make a strong case for the merits of distributional thinking to replace what they term the *narrow decision framing* of an if-then causal approach. This is most clearly visualised as framing each risky choice as a unique gamble in which, above all, loss is to be avoided rather than a risky choice being one of multiple plays of the same gamble that allows "statistical aggregation" of risks into the future (Kahneman and Lovallo, 1993, p. 19).

This issue is of immense importance to support for risky cropping decisions using the FARMSCAPE IS. Farmers differ in their framing of investment in a particular crop between what cognitive researchers have termed "one-shot" and multiple gambles. Central to the issue is variation in the personal experience of risk. It is part of behavioural decision theory that for most people in most decisions, losses are felt more intensely than foregone gains. Hence, choice and investment under uncertainty are often governed by a loss-aversion strategy, which is inevitably accompanied by penalties of foregone aggregate gains. Importantly, this loss aversion tendency has been shown repeatedly to be alleviated by new knowledge of the long run frequencies of losses and gains, as in a study by Benartzi and Thaler (1999) described by Aloysius (2005, p. 636). Such excessive risk aversion that occurs when long-run frequencies are inaccessible and/or when narrow framing results in focus on incremental gain or loss is well documented. Extending the frame into the future using the distribution enables prospects to be visualised as change in *aggregate* returns. This decision frame is important in Australian dryland farming for aggregating variable returns and insuring adequate resources for crop production in the best seasons. Using simulated yields, Egan and Hammer (1995) demonstrated that 70–80% of farm profit may be made in just 30% of years—years that cannot be accurately forecast. Interviews of farmers by Nelson et al. (2002) preliminary to intervention with an IS that forecasts next season's yield potential revealed that, although farmers had some interest in this technology, their greater management concern was for profits aggregated over the longer term.

6.3. Narrative sensemaking from experience in WifADs

The notion of narrative as cognition fits well as 'commonsense' in Hammond's cognitive continuum between 'analysis' and 'intuition' (Fig. 2). A place for 'narrative' here was anticipated by Hammond (footnote 7, above), and in the Boisot et al. (2007) typology *narrative* appears intermediate to *embodied* and *abstract symbolic* knowledge. Narrative, like intuition or embodied knowledge, is subjective, but unlike these, narrative is conscious. In the main, intuition is "educated" automatically by stimuli that produce desired outcomes (Fig. 3) (Hogarth, 2001); narrative learning involves conscious experiencing and produces felt meaning. Narrative has a limited analytical function, framing episodes of experience in terms of purpose and time. Relationships between events are structured by their relevance to purpose and their sequence in time, with an event that precedes another judged on their strength

[9] Key concepts in causal Bayes are *intervention*, *manipulation*, the *causal Markov condition*, *screening off*, and *invariants* (Sloman, 2005; Pearl, 2000).

of association to be causal, diagnostic, indicative, or incidental (Tversky and Kahneman, 1982, p. 118).

> Narratives are analytic constructs that unify a number of past or contemporaneous actions and happenings, which might otherwise have been viewed as discrete or disparate, into a coherent relational whole that gives meaning to and explains each of its elements and is, at the same time, constituted by them. (Griffin, 1993, p. 1097).

The literature on narrative learning is made confusing for the unsuspecting systems scientist by the fact that "narrative" phenomenon has different sides, and the difference makes a difference. On the first, as in the quote above by Polkinghorne (1988), learning is narrative derived from one's own enacted experiences – "presentation of the original story to personal awareness" (p. 21). This is 'narrative sensemaking' in Fig. 1. Polkinghorne's second type of narrative learning is "the reception—including interpretation and understanding—of a story" conveyed by another (p. 22). In what follows, a theoretical case is made that a flexible simulator can contribute to farmers' updating their beliefs about the production system in WifADs in narrative learning that draws on both types of narrative, enabled by a *virtual* production system.

'Narrative sensemaking' of Fig. 1 has important "upstream" and "downstream" connections. Upstream it begins at the outset of 'observation/measurement' with the 'framing' by 'meaningful categories' and 'mental models' of 'the 'world-as-sensed'. These are part of what Carey (1996, p. 190) calls *intuitive theory*—cognitive representation that specifies the meaningful kinds of things there are in the world and provides causal models for interpreting and explaining their relationships. Downstream, learning as 'narrative sensemaking' (Fig. 1) may influence belief structures. But this learning from experience is severely limited as an instrument of change in these structures that (Carey, 1996, p. 204). Replacement of a 'vicarious experience' in planning (Fig. 4) by a model of the production system offers the possibility of narrative learning from *vicarious* experience (Fig. 1). Arie de Geus (1994, quote below) saw this as a way that models help managers "make up their own minds" rather than advise them as to what they *should* do.

Similarly, but with the addition of a probabilistic dimension, WifADs provide an opportunity for relevant vicarious 'situated experience' and 'narrative sensemaking' that clarifies 'what-to-expect' and 'what-to-do' uncertainties without having to experience the real-world impacts of such uncertainties. A WifAD begins with an enquiry about expected crop yields, given a scenario of relevant

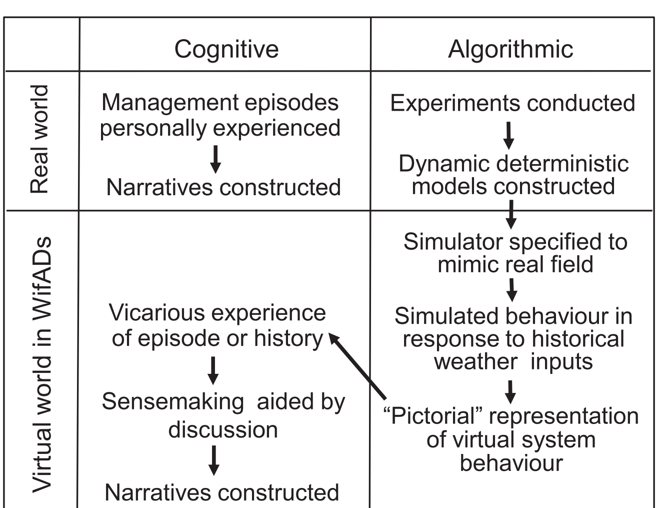

Fig. 4. A map of how algorithms and minds combine to produce meaningful narrative in a What if Analysis and Discussion.

soil conditions and an action taken or alternative plausible actions. Using the historical rainfall records as inputs, the simulator returns yields for all seasons, which are organised as graphical frequency distributions or relative frequency distributions. Ensuing discussion often leads to a logical follow-up enquiry and a continuation of the thread of the discussion. The structure is that of a conversation that facilitates Polkinghorne's (1988) second type of narrative learning.

The contribution of a personally-meaningful what-if enquiry and ensuing discussion to personal narrative construction is self-evident. Less evident is the idea that dynamic simulation itself is structured as narrative and contributes rather seamlessly to the narrative of the WifAD. Guhathakurta (2002) argues that a dynamic deterministic systems model assigned initial conditions generates output that has narrative qualities of time progression as well as causal relation to conditions.

Fig. 4 depicts simulation models as having a role in contributing to narrative learning ancillary to practical experience the real world. Actual data are used to develop abstract models that faithfully represent the real production system.

The first step toward meaning-making in Fig. 4 is specifying the simulator for paddocks that are significant to farmer participants. The second is facilitating WifADs in which farmers try out management actions and strategies in these virtual paddocks in order to learn from consequences that carry no physical hazard. Yet, in evaluation interviews, participants' references to such activity indicated that they felt that they had learned from experience that had meaning and provided rules for action *as if* it had been actual (Dalgliesh et al., 2009; McCown et al., in press).

> ...scientific studies and data generation do not generate meaning. It is the power of the narrative...that substitutes meaning for the straightforward copy of the events recounted (Guhathakurta, 2002, p. 909).

6.4. Connection between what-to-expect support and what-to-do decisions

FARMSCAPE analytical IS intervention targets constraints to 'planning and decision making' posed by uncertainty of the climate and soil environment. While this focus may appear to ignore the connection between uncertainty reduction and better decision making and actions, it, rather, respects the agency and competence of the farmer to make connections, in keeping with the theoretical Framework for the adaptive manager. A "connecting" process was described by Arie de Geus, one-time senior manager in Shell Oil and later "systems" academic.

> Witness the use of flight simulators for pilots, pilot plants for chemical process engineers, or flow models in hydraulic engineering. All are good examples of representations of real worlds with which the pilots and engineers can experiment without having to fear the consequences. In the process they learn – and only then do they go and apply into practice their new, and now confirmed, understanding of this part of their world, accepting the responsibility for their actions (de Geus, 1994, pp. xiv, xv).

One of the aims of this research was to learn about the connection making between what-to-expect and what-to-do judgment of participating farmers and consultants, and it became a central theme of evaluation activity reported by McCown et al., in press.

7. Discussion

This paper revisits an old argument about what we think we are doing in providing "decision support". There has been an economics view that it's about provision of information that is of obvious value if it is true (Llewellyn, 2007; Pannell et al., 2000). But there is another tradition that has been (at times) more aware of the "thinking" aspect of decision making. In a retrospective paper in 1987, a founding father of the DSS enterprise, Peter Keen, lamented the fact that after more than 10 years of enthusiastic development activity, just what was going on inside decision makers was still undefined. The field had failed to get beyond information technological "Systems" to address "Decisions" and "Support". He argued that in spite of an original DSS concept which was about "the intellectual as well computer-related technologies", this had been lost. The reality was that "the mission of DSS [had] attracted individuals from a wide range of backgrounds who saw it as a way of extending the practical application of tools, methods and objectives they believed in". For Keen, the field needed to regain the theoretical interest in decision making that had originally distinguished the field. Over 20 years later it seems that the field's response to this rallying cry has rarely been more than a nod in the direction of "the personal", as typified in a recent, frequently cited, review.

> The *technical* [10] perspective has dominated DSS problem formulation in the past, and involves the development of databases and models. The *organizational* and *personal* perspectives are developed by discussing the problem with all affected stakeholders, at least as resources permit, so as to ensure that all relevant variables are either included in models, or taken into account during the analysis, if they cannot be quantified (Shim et al., 2002; emphasis added).

But the reforms Keen advocated for DSS *are* an established feature of the sister field of Cognitive Systems Engineering (CSE) (e.g. Rasmussen et al., 1994). The link between DSS and CSE is provided by Zachary (1988).

> The approach here is based on the idea that an interactive DSS must be well integrated into the decision process of its human user, i.e., the DSS user must be able to integrate the computer aid into her/his own cognitive process (of decision making). Viewed in this manner, DSS design becomes primarily a problem of cognitive engineering (Zachary, 1988, p. 997).

DSS, or when defined as broadly as by Zachary, IS, had always been about computer systems that interfaced with a human user who valued good information that could be acted upon. Provision of this information depended wholly on the developer's conceptualisation of the client's work system. For Zachary DSS design needed to include the decision maker as part of the work system being analysed and aided. This included

> ... understanding how the human decision maker is cognitively approaching the decision, finding out what is constraining or limiting decision-making performance, and identifying and successfully applying one or more computational techniques to remove the limits and improve performance (Zachary, 1988, p. 1001).

Inclusion of the decision maker in this way needed representations of the relevant world as understood by the decision maker, his/her goals flexibly represented as desired states of the world, and flexible modes of information acquisition and processing in response to an often uncertain and dynamic environment (Zachary, 1988, p. 999).

This cognitive aspect of IS is central to the fields of Cognitive Engineering (and the sub-field, Situation Awareness; Rasmussen et al., 1994, Endsley, 2000) as well as the field of naturalistic decision making (Klein et al., 1995). Focus in these fields has been on intuitive decision making by individuals in situations of considerable moment and great uncertainty, e.g. pilots, air traffic controllers, fire-fighters, and soldiers. This means that research on ways to support such actors is cast in a strongly *personal* perspective (Mitroff and Linstone, 1995). This is a more individualistic managerial tradition than typical in OR/MS, the parent field of the agricultural DSS (McCown, 2002). OR/MS originated in the bureaucratic structure of hierarchical organisations where primary stake holders had an *organisational* perspective. A good case can be made for considering dryland farmers as having more in common with "naturalistic" decision makers than with middle-level corporate managers, the original targets for DSS technology (McCown, 2002). In common with fire-fighting, etc., dryland cropping is conducted under high environmental uncertainty by decision makers with a high degree of discretion and agency who rely heavily on intuitive judgement underpinned by experience.

The FARMSCAPE approach to IS development shares with cognitive engineering an interest in the cognition of the decision maker. But the methodologies for including "mind" are very different. The approach of cognitive systems research has been to carefully analyse the cognitive task environments of practitioners to reduce the chance of omission of a human factor causing a problem of implementation. Information systems designed in this way *should* work if the knowledge underpinning the design is correct. However, in FARMSCAPE we worked with decision makers in their task environment using action research methodology, i.e. disciplined trial and error, to get an IS that *can be observed to* work. In the *design* approach, cognitive theory is used to *infer* IS functionality *before* the development event. In our *action research* approach, cognitive theory is being used to *interpret* IS functionality *after* the development event, giving it a degree of scientific/'hard' systems explanation. The Framework is represented by Figs. 1–3, construed in a particular "nested" fashion. Fig. 2 is an elaboration of the 'judgement' element of Figs. 1 and 3 elaborates the probability strand in the lower half of Fig. 2. An empirical evaluation of the resulting Framework is how well it makes sense of recorded patterns of events and explicates the experiences of participants revealed in narrative interviews (McCown et al., in press). But some assessment of the Framework can be achieved by comparison with standards set by those in research fields whose very identity is concerned with improving cognitive performance in work activities. This is undertaken below.

It seems a safe bet that inattention to cognitive theory has been a contributing factor in the DSS/IS 'problem of implementation' and a reasonable bet that such theory is important to understanding FARMSCAPE action research outcomes. But how deep to delve into voluminous sources of unfamiliar theory for this practical purpose is a practical issue. Cognitive engineering has a history of pragmatic inclusion of "mind" in information system design. Kirlik (2006) quoted the conclusion of the eminent psychologist, Jerome Bruner, that "you cannot properly conceive of managing a complex world of information without a workable concept of mind" (Bruner, 1983, p. 63). To Kirlik (2006, p. 4) this means a description of the "whole" human–technology–environment system and not merely internal cognition, i.e. taking a systems approach. He then proceeds to set out several essential features of a "workable concept of mind" that "provide methods and models that can be fruitfully applied to solving practically relevant problems in human–technology interaction" (Kirlik, 2006, p. 3). In what follows, I apply the three primary criteria of Kirlik's "checklist' to the Framework in this paper. I then add a further feature that is crucial to "workability" of a cognitive model in relation to the FARMSCAPE IS and which distinguishes it from a cognitive engineering approach.

[10] Mitroff and Linstone (1995) distinguished three perspective from which decision aiding could be viewed: technical, organisational, and personal.

7.1. Ecological, systems, perspective

Fig. 1 frames abstractions of three interacting systems: the agricultural 'production system' (including the climate), the farmer's 'cognitive system', and an external 'information system'. System dynamics include both closed-loop and open-loop types (Rasmussen et al., 1994). The 'cognitive system' (mind) and its interface with the 'production system' is represented as a closed-loop cybernetic system. The 'production system' that contains the targets of farmers' control efforts is represented as an open-loop system that imposes high uncertainty on events in the 'world as sensed', much of it irreducible by management learning and control processes.

The foundations for a systems perspective were laid on p. 7 above by the quote of Herbert Simon (1996). A monitoring function of the 'cognitive system' enables awareness of states of the 'production system' relative to states embodied in the goals of efficient and stable production. Cognitive discrepancies in states drive action to change the production system (and occasionally drive adaptation of goals) (Fig. 1). When an 'information system' is effectively implemented, the 'cognitive system' interacts with the 'information system' to extract value for management. The 'information system' generates "cognitive artefacts", e.g. graphs representing 'production system' behaviour, that provide insight and reduces uncertainty. An *ecological* perspective for "thinking about farmers' thinking about" what-to-expect and what-to-do is a particularly poignant metaphor in dryland crop production. The 'situation' here is not just the information, or cognitive task, environment. It is the risky natural environment of dryland crop production activity. This is "cognition in the wild" (Hutchins, 1999).

7.2. An adaptive, functional perspective

From the adaptive, functional perspective, attention on the Framework centres on representation of adjustment in cognition modality to changes in the external environment. The Framework structures three such functional relations. The first is the determination of the relative role of intuition vs. analysis. The structure used is Hammond's Cognitive Continuum on which 'analysis' and 'intuition' are the extreme modes of an induced adaptation to the 'situation' as regards the cognitive task or the nature of available information. (This adaptive emphasis contrasts with the interpretation of *intuitive* and *analytic* as dispositional "cognitive styles" (Huysmans, 1970; Huber, 1983; Lu et al., 2001). While not denying differences in personalities, an adaptive, functional approach escapes the cul-de-sac that an emphasis on individual differences imposes on intervention with an 'information system'.) The second environment-dependent function is the distinction between 'holistic' and 'arbitrary' intuition (Fig. 2). The nature of the information/task environment determines whether the experience of "gut feeling" is tacit *expertise* or simply *guessing* in a state of irreducible ignorance. The third environment-dependent function is the switch between 'causal if-then thinking' and 'relative frequency reasoning' (Fig. 2). Deviation from narrative causality is observed when the information environment offers a frequency distribution. While the latter is an uncommon resource, it is arguably the most important contribution made by the *FARMSCAPE* 'information system'

While the cognitive continuum represents the key adaptive function of cognitive mode to task/information environment, Hammond's theory is not the only occupant of this spot in the Framework. Hamm (1988) compared and contrasted the Hammonds's cognitive continuum theory (CCT) with the theory of Dreyfus and Dreyfus (1986) concerning holistic intuition, e.g. theory of expertise acquisition (TEA). The latter theory focuses on changes in cognitive mode used in a task as experience accrues over time. Instruction as articulated procedural knowledge enables novices to carry out an operation before they have experience. In this stage, abundant information is obtained from the environment to use in if-then rules. In progressing from "novice" to "expert" (through intermediate stages of "competent" and "proficient"), there is a transition from information gathering and processing to the knowledge, gained in experience, of what to do in a situation and how to do it (Fig. 2). This adaptation results in savings of attention, time, and cognitive work and often with increased accuracy (Hamm, 1988). This fits well with a third theory, the model of the Adaptive Decision Maker (ADM) (Payne and Betteman, 2007). ADM assumes that the decision process is driven by the goals of: (a) attaining decision accuracy and (b) efficient use of cognitive resources and the control of associated personal costs. Emphasis is on adaptation as the trading off, on the cognitive continuum, *benefits of accuracy* (achieved in 'analysis') against *benefits of economy* (achieved in 'intuition').

Combining these three theories in the Framework has proved quite "workable" in analysis of the behaviour of farmers (McCown et al., in press). When soil information and yield frequency distributions were made readily available (and free), participants shifted from 'intuition' to 'analysis' with evident benefit. When accessibility of analysis declined and costs increased, farmers used their new expertise in this domain to shift in the direction of 'intuition' by developing simple soil water estimation techniques. They went further to construct simple if-then decision rules that they judged to be of enduring usefulness—until they encountered "a situation out of the ordinary" (McCown et al., in press; Dalgliesh et al., 2009).

The availability of problem-responsive, quick, and (temporarily) cost-free analysis of risk in WifADs induced a 'distributional' cognitive mode among participants (Fig. 2). Fig. 3 elaborates the subtlety of the *probability* response to uncertainty and what makes it so problematic in intervention in intuitive, naturalistic risk management practice. The early intuition of FARMSCAPE researchers was that farmers could become skilful in using cumulative frequency graphs, and this proved to be the case. We later became aware of theory for such conceptual artefacts enabling and stimulating movement between 'analysis' and 'intuition' in active learning.

> Pictorial (in contrast to numerical) displays allow cognition to oscillate between the intuitive and the analytical poles of the cognitive continuum. [ ] In addition to these intuitive judgements, the model allows us to turn back to analytical cognition, to check, to retrace, for we can now say to ourselves, Is it really true? How credible is the model? How credible is the data that went into it? (Hammond, 1996, p. 259).

7.3. Embracing uncertainty

Any cognitive framework that helps think about aiding decision making in dryland crop production embraces uncertainty. Two types of climate-related uncertainty appear in Fig. 1, i.e. uncertainty about the here-and-now soil water ('situation awareness') and uncertainty about the future season's weather ('expectations'). Provision by the IS of the concept of soil profile water budget and 'soil measurements' and 'soil water nowcasts' (Fig. 1) is significant in reducing the former (Dalgliesh et al., 2009). Probability distributions of yields simulated for historical years are significant in alleviating the 2nd order uncertainty of the latter, i.e. uncertainty about next season's uncertainty (Carberry et al., 2009; McCown et al., in press). Fig. 2 elaborates adaptive shifts between intervention with 'relevant probabilistic distributions' and induced intuitive 'relative frequency reasoning' and further to the 'arbitrary intuition' required at the point of decision even when a frequency distribution is available. A second path from 'relevant probability distributions' leads to the abstraction of 'if-then action rules' enabled by comparing simulated outcome distributions for alternative actions. Its inclusion in Fig. 2 was prompted by the surprising prominence of this adaptation in farmers' narratives in evaluation interviews (McCown et al., in press). Its position there was cemented by the importance of "rules" as intermediate between analytical "action planning" and intuitive physical acts in the typology of cognitive control levels (Rasmussen et al., 1994)—an action control construct analogous to Hammond's judgement continuum construct.

7.4. A perspective of the conscious, experiencing, adaptive actor

This perspective departs from the checklist of Kirlik (2006) that structures the discussion above and marks a paradigm shift from a human–machine systems view that represents the human as a "factor" to a view that represents the human as the "actor". In a participatory action research approach, any perspective of mind that ignores this is of questionable "workability". Such a perspective that includes felt personal agency has long been deemed essential in the philosophy of social science (Rosenberg, 1995), but was deemed by many cognitive scientists to be incompatible with the well-established "information processing" model of mind (Neisser, 1976, p. xii). But with recent recognition of pragmatic "multiparadigm multimethodology" in systems endeavours (Mingers, 2004), inclusion of this perspective of mind in scientific and engineering activity has become more an issue of utility than of scholarly respectability.

Theoretical support for this change is also increasing in cognitive psychology, e.g. Experienced Cognition theory of Carlson (1997, 2002, p. 233). Carlson's theory of mind has three main elements. One is an *ecological* perspective common to Kirlik's design approach, above. The second concerns two functions of *experience*, i.e. consciousness and cognitive skill – "cognition as we experience it and as we become experienced" (Carlson, 1997, p. vii). The third feature is that actions derive from conscious intentions that arise when goals are instantiated in practice. Carlson (2002) concludes that

> Perhaps the most important conclusion of this theoretical effort is that an agentic perspective on human action (Bandura, 2001) is compatible with the computational view of the mind and the general research program based on that view. The conscious agent, or active self, as conceived here is an informational construct, embedded in an understanding of cognition, perception, and action as varieties of information processing (Carlson, 2002, p. 223).

The case has been made here that the Framework includes a "workable concept of mind" by conforming to the key theoretical criteria of Kirlik (2006) and with the addition of theory of consciousness and subjectivity as aspects of human 'mind' that are part of nature (Morgan and Smircich, 1980; Searle, 1995). The remaining test of "workability" is explanation of the puzzling behaviour of farmers and consultants in the northern cropping zone of Australia that included surprising initial enthusiasm for soil measurements followed some time later by surprising disadoption (Dalgliesh et al., 2009). The Framework enables explanation in terms of adaptation and re-invention in which situated simulation in WifADs plays a pivotal role (McCown et al., in press).

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