Environmental Modelling & Software 94 (2017) 63–72

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

Realizing modelling outcomes: A synthesis of success factors and their use in a retrospective analysis of 15 Australian water resource projects

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ARTICLE INFO

Article history:
Received 21 March 2017
Accepted 22 March 2017

Keywords:
Decision support
Evaluation
Water resources
Stakeholders
Social learning
Integrated modelling

ABSTRACT

We review several papers that have afforded insights into determinants of positive outcomes (e.g. the adoption of tools, improved learning and/or collaboration) from modelling projects. From a subsequent internet search in the environmental domain we identified 33 such factors that are then invoked in a transferable survey-based method to facilitate structured reflections by model developers on 15 projects. Four factors were considered most necessary to realize overall success for any modelling project. Three factors related to aspects of stakeholder engagement in the modelling process; the other to critical thinking around problem framing and the role(s) of models. The latter factor was considered reasonably well-achieved across the projects. Harder to control were the stakeholder engagement factors which, along with project management considerations, can constrain or enable achievement of other factors. The paper provides further evidence of the critical need to consider non-technical aspects in the design and implementation of modelling projects.

1. Introduction

Effective environmental management can be enhanced with a comprehensive, evidence-based understanding of how complex interactions within the socio-ecological system in question may play out under different settings and policy conditions. Modelling can play a central role in building this understanding and supporting different aspects of management and policy design (Black et al., 2014). Environmental modelling or Decision Support System (DSS) projects, however, often constitute a large investment of time and money, typically involving a team of modellers, software developers, and end users. Evaluation of the beneficial and negative outcomes of modelling projects is therefore critical given this substantial investment.

Furthermore, with what is now a long history of environmental modelling, integrated modelling and construction of decision support tools, it has been recognised that such modelling projects can often fall short in achieving whatever outcomes were expected (e.g. Uran and Janssen, 2003; Voinov and Shugart, 2013). Often-cited reasons include a mismatch in the problem understanding or expectations of model developers and model users, a failure of developers to adequately scope required functionality with intended users, or organisational change within the target user organisation. Crucial, however, to any analysis aimed at understanding the factors influencing successful outcomes of a project is a characterisation of what success entails.

McIntosh et al. (2008) pointed out that success is often informally assessed based on whether the tool was used for the purpose that the developer intended. McIntosh et al. critique this, noting that the implication is that a tool was not a success if it was not applied to solve the target problem. In this paper we consider success to be either the accomplishment of a specified aim or

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http://dx.doi.org/10.1016/j.envsoft.2017.03.021
1364-8152/

purpose (e.g. use of the tool to negotiate aspects of a plan) or an improved learning or collaboration at any of the four levels given by Huz et al. (1997): individual (e.g. positive reaction), group (e.g. increased quality of communication), organisational (e.g. performance improvement), and method (e.g. further use). This broader interpretation reflects in part that integrated environmental models and DSS are developed for a range of purposes including prediction (Guillaume et al., 2015; Robson and Dourdet, 2015), exploration of alternate options through scenario definition and analysis (Liu et al., 2008; Maier et al., 2016), optimisation (Szemis et al., 2014; Tsoukalas and Makropoulos, 2015), or development of system understanding or social learning (El Sawah et al., 2015; Giordano et al., 2007; Lund and Palmer, 1997; Van der Wal et al., 2016; Videira et al., 2009). Often these models are not intended or designed for use on a routine or regular basis by individuals or organisations. In such cases a narrow definition of success will understate the potential benefits gained from a modelling project, for example, individual or group learnings, or enhanced collaborations and networks gained during the development process. Alternatively the intended routine use may not be achieved but the latter measures of success might be realized.

In the next section we provide a brief overview of methodological approaches used in the environmental modelling, operations research and information systems fields to draw insight into the determinants of project success. We then present a synthesis of factors influencing success of environmental modelling projects. The 33 factors identified form the basis of a structured reflection of 15 water resource modelling projects, for which the survey design and evaluation methods are presented in Section 3. The results in Section 4 rank the general importance of the 33 success factors before relating achievement (or not) of the factors to the respondents' views on the client and research outcomes of the 15 projects. Key results are discussed in Section 5, drawing on any identified barriers and enablers to realizing each factor and relating findings back to the modelling literature.

2. Determinants of successful modelling projects

2.1. Overview of methodological approaches to identifying 'success' factors

In the fields of integrated assessment and environmental modelling, several collaborative papers have looked at what had been developed in the past, trying to gain insight into why different model-based tools had, or had not been used, and to derive lessons on key modelling challenges and best model practices (e.g. McIntosh et al., 2011; McIntosh et al., 2008). Other papers have provided in-depth insight into particular case studies or modelling tools (El Sawah et al., 2015; Liu et al., 2008; Maciag and Hepting, 2008; Poch et al., 2004; Ticehurst, 2008; Uran and Janssen, 2003; Welp, 2001). These case study papers are often retrospective and reflective, although formal elicitation processes and workshops have been used to evaluate outcomes and seek feedback from participants throughout the life of a project (Giupponi, 2007; Inman et al., 2011; Matthews et al., 2011). Evaluation approaches have included elicitation from model developers or users using formal structured interviews (Giupponi, 2007; Matthews et al., 2011; Robinson and Pidd, 1998), group discussions including facilitated workshops (Matthews et al., 2011; Sieber et al., 2013), and technical evaluations of (for example) functionality and usability of modelling tools (Uran and Janssen, 2003).

Outside the environmental field, there are valuable studies that have comprehensively assessed factors influencing the failure and success of modelling projects. Tilanus (1985) reviewed 58 different cases across a range of project types (e.g. client-oriented, operational-oriented) and sectors (e.g. agriculture, manufacturing, education). The authors interpreted written reports that they had elicited from sector representatives where they self-evaluated the reasons for success and failure for various projects in which they had been involved. Robinson and Pidd (1998) conducted formal interviews with 20 modellers and customers to explore the varied measures of success and how the level of success can vary throughout a project. Monks et al. (2014) undertook an experimental study to examine the effects of different degrees of stakeholder involvement on the learning outcomes and perceived credibility of the modelling process. To gain insights for the environmental field, Díez and McIntosh (2009) reviewed the non-environment information systems (IS) literature to characterise organisational outcomes of nine IS life cycle processes – design, diffusion, adoption, implementation, acceptance, use, evaluation, assessment and continued use – which they grouped into pre-implementation, implementation and post-implementation phases. The authors identified over 250 factors that could influence these processes and attempted to quantitatively assess the influence of each factor.

2.2. Synthesis of 'success' factors from environmental modelling literature

For the subsequent analyses in this paper, factors or criteria identified as important for maximising the effectiveness of environmental modelling outputs in supporting activities of policy makers and managers were identified from pertinent journal articles, conference papers, and book chapters. To do this, the Google Scholar database was invoked and searched using combinations of the keywords: "critical success factor", "success", "integrated assessment", "integrated model", and "decision support system." Those documents that related to the field of environmental modelling and that included either informal or empirical evidence about success factors were then considered. An initial list of 37 factors was identified from the environmental literature; this was subsequently reduced to 33 factors as four were considered to overlap in their interpretation with other factors. The 33 factors appear in Table 1, classed into seven groups: project management (PM; 7 factors), project actors (PA; 5 factors), stakeholder engagement (SE; 5 factors), model development (MD; 7 factors), model evaluation (ME; 1 factor), contextual factors (CF; 3 factors) and model use (MU; 3 factors).

3. Methods

This section describes the survey-based instrument used, firstly to elicit perceived relative importance of the 'success' factors from the environmental literature, and secondly to retrospectively evaluate 15 water resource modelling projects against the factors. Eleven (the authors of this paper) of the 13 people who were identified as part of the development team of these modelling projects undertook the survey with 1–5 respondents per project. Given the time that had elapsed since completion of some projects and personnel changes within some key partner organisations, it was not considered practicable to conduct an equivalent survey with clients and model users for the 15 projects.

3.1. Survey design

The survey was developed in two parts (Table 2). Part 1 collected information on the role of each respondent for all projects relevant to them. It also aimed to elicit an overall assessment by the respondents of how well research outcomes were met for each project and their perceptions on how well the expectations of

Table 1
Success factors from integrated modelling or decision support literature that focuses on environmental or natural resource management issues.

ID	Description
Project management (PM)	
PM1	Factor time into the schedule to obtain, prepare and review data (van Delden et al., 2011)
PM2	Clearly define roles and responsibilities of end users, stakeholders and clients at the beginning of model/DSS development (Black et al., 2014; McIntosh et al., 2011)
PM3	Develop a business plan that explicitly defines tasks, expected costs and outcomes over the lifetime of the product (McIntosh et al., 2011)
PM4	Create a plan for continuity of the model/DSS support that includes transition from development team to stakeholders and clients for adoption (e.g. maintenance, training, updates) (McIntosh et al., 2011)
PM5	Keep processes and outcomes documented (e.g. stakeholder engagement, model development) (Balci, 2012)
PM6	Manage changes in project personnel (McIntosh et al., 2011)
PM7	Allow flexibility to address unexpected changes in goals and priorities (Voinov and Bousquet, 2010)
Project actors (PA)	
PA1	Model/DSS architect(s) who have the technical and communication skills AND the case study understanding required to integrate knowledge and views of different actors into the model design (van Delden et al., 2011)
PA2	External project champion(s) who can advocate for model development and/or use and who has strong local relationships and knowledge (Ewing et al., 2000; Ticehurst, 2008; van Delden et al., 2011)[a]
PA3	Visionary project leader with a strong project/research record and networks in the research and practitioner communities (Lerner et al., 2011)
PA4	Local scientific knowledge (e.g. researchers, consultants, government or other project partners) (Ticehurst, 2008)
PA5	Model development team are perceived as independent actors, especially in highly contentious situations (Lerner et al., 2011; Voinov and Bousquet, 2010; Voinov and Gaddis, 2008)
Stakeholder engagement (SE)	
SE1	Sufficient interaction between development team (e.g. researchers, software developers) and end users during the model development process (Uran and Janssen, 2003; van Delden et al., 2011; Volk et al., 2010)
SE2	Good relationship and trust between development team and end users (Robinson and Pidd, 1998; Tilanus, 1985; van Delden et al., 2011)
SE3	Open and transparent communication among development team and end users (Parker et al., 2002)
SE4	Use of social science expertise to provide better understanding of the human factors involved in model development (Kalaugher et al., 2013; McIntosh et al., 2011)
SE5	Time taken to obtain stakeholder buy-in from the start and develop a sense of ownership of the model/DSS (Díez and McIntosh, 2009)
Model/DSS development (MD)	
MD1	Effective use of prototypes (van Delden et al., 2011)
MD2	Use of a professional facilitator during model development or use (Franco and Montibeller, 2010; Kasemir et al., 2000; Kelly and Merritt, 2011; Voinov and Bousquet, 2010)
MD3	Use of effective visualisation aids (e.g. graphical user interfaces) that are appropriate for the intended audience (Bishop et al., 2008)
MD4	Keeping the model/DSS simple; utilize existing models and make arrangements to update over time to incorporate new learnings (Boschetti et al., 2012)
MD5	Use of a well-structured modelling process (Liu et al., 2008)
MD6	Use of web-based technologies to facilitate client and stakeholder access to data, information and models (Castelletti and Soncini-Sessa, 2004; Voinov and Bousquet, 2010)
MD7	Critical thinking early during the development process about the problem and the role of modelling in addressing the problem (Hare, 2011; Liu et al., 2008; Sieber et al., 2013; van Delden et al., 2011; Voinov and Shugart, 2013)
Model evaluation (ME)	
ME1	Strong focus on calibration, validation, sensitivity analysis and uncertainty analysis (van Delden et al., 2011)
Expectation management (EM)	
EM1	Do not oversell the model by using flashy technologies (e.g. unnecessary graphical user interface or visualization tools) (McIntosh et al., 2011)
EM2	Engage stakeholders in ongoing discussions regarding problem uncertainty and what the model can and cannot do (Bellamy et al., 1999; Black et al., 2014; Voinov and Gaddis, 2008)
Contextual factors (CF)	
CF1	Recognition of historic conflicts, sensitivities, and external issues that may overshadow the development process (Black et al., 2014; Voinov and Bousquet, 2010)
CF2	Development team is aware of other policy and research initiatives impacting on the case study(Newham et al., 2007)
CF3	Flexible and long term funding arrangements (Newham et al., 2007; Voinov and Bousquet, 2010)
Model use (MU)	
MU1	Ensure sufficient time is given for reflecting on the model's results, and their implications to decision making (Squires and Renn, 2011)
MU2	Gain acceptance of modelling methodology before presenting model results (Voinov and Gaddis, 2008)
MU3	Develop plausible scenarios that stakeholders perceive as useful and relevant (Black et al., 2014; Voinov and Gaddis, 2008)

[a] This description is compiled from the van Delden et al. (2011) definition of the project champion as a 'power user' who actively stimulates uptake of the system in their organisation, and the Ticehurst (2008) description of the project champion as a person who is interested in the project and is prepared to promote the project and act as a key local contact.

Table 2
Survey questions used to rank the importance of success factors and to structure reflections of model developers on 15 water resource modelling projects in which they were involved.

Part 1 (asked for each project in which the respondent participated)

1. For this project, please rank your role(s) in delivering the project (if applicable): Model developer, software design, stakeholder engagement, model facilitation, project management, training/capacity building
2. Are there other role(s) you performed that were not included in the previous question?
3. How well did project outcomes meet the expectations of clients or users? (Poorly, Moderately well, Very well, Not applicable/I don't know)
4. How well did project outcomes meet research objectives? (Poorly, Moderately well, Very well, Not applicable/I don't know)

***Part 2 (asked for each factor in* Table 1)**

5. In general, please identify how important you think that each factor listed below is to achieving 'project success' in environmental DSS or integrated modelling projects (Not important, Case-dependent, Essential, Not applicable/I don't know)
6. Are there factors you consider "essential" or "case-dependent" that are not listed in the previous question?

Part 2 (asked for each factor in* Table 1 *and each project in which the respondent participated)

7. Who were the instigator(s) for this project? (purely researcher, mainly researcher, client and researcher, mainly client or purely client)
8. For this project, how well do you think each factor listed below was realised? (1 not at all; 5 fully realised)
9. For this project and each factor, what were the enablers (or barriers) for realising (or failing to) this factor?
10. Are there any other comments that you would like to make with respect to this project?

clients or users were met. Part 2 of the survey was sent to respondents after collation of Part 1 responses. It elicited the general importance and comprehensiveness of the 33 'success' factors synthesised from the environmental literature for modelling projects in addition to reflections on the projects in which they were involved, structured against the achievement (or not) of each factor.

3.2. General importance of success factors

It is reasonable to expect that the 33 factors identified in Table 1 will not equally influence a particular projects success (Díez and McIntosh, 2009). To address this, a survey was developed to allow respondents to qualitatively rank each factor as essential, case dependent or not important (question 5 in Table 2), and identify any other factors not covered in the list (question 6).

3.3. Retrospective evaluation of modelling projects against the success factors

Prior to assessing the project against each success factor, the respondents' overall impression of each project's achievements was elicited. Here, each respondent identified the role(s) they performed for each project to which they contributed, as well as their perspective on how well the project outcomes met both client requirements and research outcomes (questions 1–4 in Table 2). The respondents were then asked how well each project to which they contributed achieved the factor, as well as to identify any relevant enablers or barriers to achieving each factor (questions 7–10 in Table 2).

3.3.1. Case study projects

The 15 projects considered in this paper used one of ten modelling tools developed by the co-authors and their research collaborators (Table 3). The selected projects are those for which the authors have firsthand knowledge and where the modelling approach is published in the scientific literature. The tools were selected as they cover a range of water resources topics, modelling approaches and development rationale (i.e. decision support, scientific understanding, or participatory modelling for social learning). They are considered representative of many of the types of models and DSS used to address water resource problems in the international research and practice community. Projects and tools were also selected on the basis that multiple responses could be elicited per project in an attempt to capture a range of perspectives on what worked well (or not) for a given project as well as start to unpick what key challenges remain within or amongst the developers (e.g. what is not being consistently achieved across projects).

The tools can broadly be classified within four thematic issues: hydro-ecological (EXCLAIM, IBIS and CAPER), water quality (CatchMODS, CAPER, NCCARF and Landscape Logic), water allocation (WAdss, Namoi Integrated Model [IM] and Willunga IM), and more holistic integrated assessment issues (CLAM and Namoi IM). Reflecting the different purpose, problem focus and data or knowledge available to the modelling projects these tools were developed using a range of modelling approaches; see Kelly et al. (2013) for guidance. These included Bayesian networks (CLAM, Landscape Logic, EXCLAIM, IBIS, NCCARF and Namoi IM), lumped conceptual models (CatchMODS), coupled component models (WAdss, Namoi IM, Landscape Logic, IBIS, Willunga IM) and metamodels (CAPER).

The tools were designed predominantly for scenario-based decision support or system understanding, with varying focus on social learning. Development of the tools was primarily initiated either by researchers (CatchMODS, Landscape Logic, Namoi IM, NCCARF, WAdss, Willunga IM) or by clients such as government agencies (EXCLAIM, IBIS, CLAM and CAPER). In all cases there was engagement from the outset with end users, and identified stakeholders, to frame the issues and questions that the modelling tools were designed to address. Of the client-instigated projects, CAPER directly informed planning, having benefited from a statutory requirement which obligated the development and use of the DSS to identify and test management options and thereby support negotiation of a specific Water Quality Improvement Plan (WQIP; GLC, 2009). To date, the other client-instigated tools have not had a formal role in planning activities; rather they have been used with clients and other stakeholders to further system understanding and identify opportunities for improving system outcomes. The research-instigated tools and projects typically captured science within decision making frameworks for the purpose of system understanding and scenario analysis of options. The exception to this was the Willunga IM project where the primary role of modelling was to support participatory social learning around how a group of irrigators make strategic and operational vineyard management decisions. The 15 projects considered in the survey included two CAPER, CLAM, and CatchMODS projects and three IBIS projects. All projects considered are Australian case studies although lessons are considered directly relevant to international audiences.

3.3.2. Variable importance measures

In deriving the results in Section 4.2, the variable importance measures of random forest analysis (Strobl et al., 2007) were used to identify which of the 33 'success' factors are most associated with two *response variables*: how well a project met expectations of clients or users (question 3), albeit from the perspective of the model developers, and how well a project met research objectives (question 4). The random forest algorithm (Breiman, 2001) is an ensemble classification method especially suited for analysing high-dimensional data (Boulesteix et al., 2012). In addition, random forests deal well with problems of categorical data, nonlinearity and complex interactions among variables (Knudby et al., 2010; Pino-Mejías et al., 2010). In our case, there are 33 explanatory variables (i.e. the 33 'success' factors), two response variables, and 35 observations (i.e. the number of responses across all modelling projects considered in the survey). One inherent output from the random forest analysis is the variable importance measure which assists in identifying statistically important explanatory variables. It is this variable importance measure that we used for this study; we do not use the random forest algorithm to make predictions. The *cforest()* and *varimp()* functions in the **party** package in R were used to quantify variable importance (Strobl et al., 2007).

4. Results

4.1. General importance of success factors

The radar plot of Fig. 1 maps the number of respondents who ranked the importance of the 33 'success' factors (using data for question 5; see Table 2). Of the 11 respondents, 10 or more believed that four factors were essential in achieving 'project success' in environmental DSS or integrated modelling projects: SE1 (interaction between development team and user), SE2 (good relationship and trust), SE3 (open and transparent communication), and MD7 (critical thinking early about problem and role of model). Some 15 other factors were also considered essential by more than half of the respondents:

- project management factors (PM1 time to collate and review data; PM2 defining roles and responsibilities; PM5 documenting

Table 3
Overview of modelling tools and projects considered in the survey.

Tool	Overview	Modelling projects considered in the evaluation survey		
		Location	Stakeholder involvement[a]	Number of respondents
Primarily research-instigated tools and projects				
WAdss IM Letcher et al. (2004)	Integrated model intended to assist users consider a broad range of changes to water allocation and access conditions	Gwydir and Namoi Rivers, NSW, Australia	Moderate: Project steering committee Low: Irrigators, State government personnel	1
Namoi IM Jakeman et al. (2014)	Integrated model intended to assess groundwater allocation trade-offs associated with policy and climate options	Namoi catchment, NSW, Australia	Moderate: Project steering committee, landholders	5
Willunga IM El Sawah et al. (2015)	Participatory integrated model to support social learning in groundwater management systems and the development and review of water allocation plans	Willunga Basin, SA, Australia	High: Project steering committee Moderate: Landholders, State government agencies Low to moderate: Non-government organisations, Landcare groups and local scientists	2
CatchMODS Newham et al. (2004), Vigiak et al. (2012)	Environmental model to evaluate the water quality and economic trade-offs associated with management activities; identification of sediment sources	Ben Chifley catchment, NSW and Avon-Richardson catchment, Victoria, Australia	High: State government agencies Low to Moderate: North Central Catchment Management Authority (CMA), Landholders	2 per project
Landscape Logic Ticehurst et al. (2012)	Integrated model to support natural resource management (NRM) organisations identify and prioritise catchment management practices and improve target setting	10 catchments and estuaries, Tasmania, Australia	High: Partner NRM bodies Low: State agencies	3
NCCARF Dyer et al. (2014)	Environmental model intended to define relationships between climate change, water quality and ecological response, and so inform climate change adaptation strategies	Upper Murrumbidgee catchment, NSW and Goulburn-Broken catchment, Victoria, Australia	Moderate: ACTEW (now Icon Water) Moderate: ACT Government Low: Goulburn-Broken CMA	2
Primarily client-instigated tools and projects				
EXCLAIM Fu et al. (2015)	DSS for evaluation of the ecological impacts of water management and climate change on response in the rivers and wetlands	Macquarie Marshes, NSW, Australia	High: Central West CMA Moderate: NSW Office of Environment and Heritage (OEH), Indigenous groups CMA	3
IBIS Merritt et al. (2009)	DSS for evaluation of the likely ecological response in inland wetlands to alternate watering regimes or climate scenarios, for use in medium to long term planning	Gwydir Wetlands, Macquarie Marshes, and Narran Lakes in NSW, Australia	High: NSW OEH scientists Low: OEH local water planners	4 per project
CLAM Ticehurst et al. (2007), Ticehurst (2008)	DSS developed to investigate sustainability issues in coastal catchments and support development of management plan	Phase 1: 8 coastal catchments in NSW, Australia Phase 2: 8 coastal catchments in northern NSW, Australia	High: State government, Northern Rivers CMA, Consultants Low: Industry, local government, environment & community groups	3 per phase
CAPER GLC (2009), Kelly and Merritt (2011)	DSS developed to inform development of water quality improvement (WQIP) or protection (WQPP) plans through analysis of catchment land use and management scenarios and their likely estuary impacts	Great Lakes region, NSW, Australia and Darwin Harbour, NT, Australia	High: Local council or state government Moderate to High: Advisory committee Low to Moderate: Industry, local government, environment & community groups	1 per location

[a] *High:* intensive engagement through the modelling process (scope, conceptual model, model parameterisation, and review and training), also known as co-development or participatory modelling; *Moderate:* engagement during model scoping and training workshops with targeted engagement as required; *Low:* attendance at ≤ 2 workshops (training or scoping, information provision).

progress and outcomes; PM6 management personnel change; PM7 handle change in goals and priority),
- project actor factors (PA1 model/DSS architect; PA4 use local scientific knowledge),
- stakeholder engagement factors (SE5 stakeholder buy-in and ownership),
- model/DSS development (MD3 visualisation; MD4 keep it simple and allow updating; MD5 well-structured model process),
- management expectation (EM2),
- recognising conflicts, sensitivities and external issues (CF1), and
- model use factors (MU1 reflecting upon model results; MU3 developing plausible scenarios).

Factors considered case-dependent by the majority of the respondents were PM3 (business plan), PM4 (adoption plan), PA5 (independent development team), SE4 (human factors in model development), MD1 (prototypes), MD2 (professional facilitator), MD6 (web-based technology), CF2 (other policy and research initiatives), and CF3 (long term funding). The remaining variables where importance is similar (i.e. the difference is ≤ 2 respondents) between essential and case-dependent are PA2 (external project champion), PA3 (visionary project leader), ME1 (strong focus on model evaluation), EM1 (avoid overselling the model) and MU2 (methodology acceptance). No additional factors were identified from the survey (question 6 in Table 1).

4.2. Variable importance measures

The radar plots in Fig. 2 depict the variable importance measures relating the success factors in Table 1 to model developer

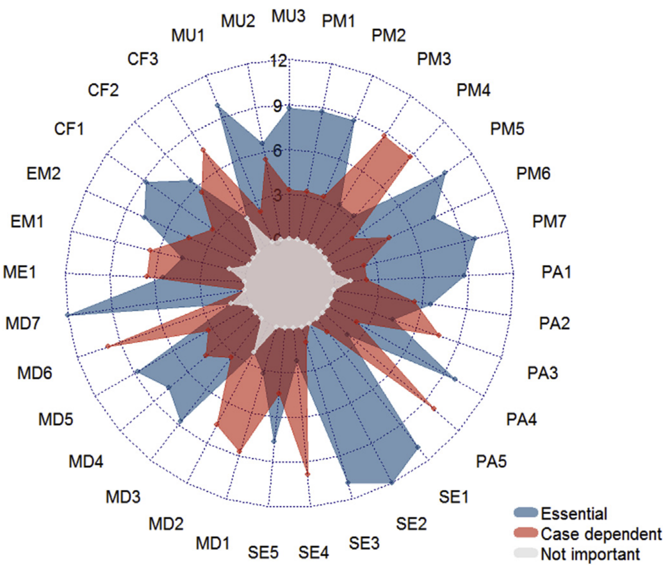

Fig. 1. Radar plot showing the number of respondents that consider the importance of the 'success' factors. The radial axes show the number of respondents. See Table 1 for descriptions of the factors.

perspectives on the research and client outcomes of the 15 surveyed projects. In terms of how well a project meets research objectives, five factors are highlighted: PA4 (local scientific knowledge), SE2 (good relationship and trust), MD5 (well-structured modelling process), ME1 (model evaluation) and MU3 (developing plausible scenarios). From the developers perspective of how well a project meets the expectations of clients/users, the variables with highest variable importance measures are SE2 (good relationship and trust) and MU1 (reflecting upon model results) with a lesser influence from PA1 (model/DSS architect) and ME1 (model evaluation).

5. Discussion

5.1. *Essential factors influencing project success*

From the survey results, it is clear that the respondents' prioritise certain factors as a general rule for environmental modelling and decision support projects. Much emphasis was placed on stakeholder engagement with open and transparent communication (SE3), trust and good relationships (SE2), and the level of interaction (SE1) being assessed as essential by most respondents (10 of 11 for SE1 and SE3 and all 11 for SE2 in Fig. 1). Stakeholder buy-in and ownership (SE5) was also ranked as essential by most respondents. The importance of stakeholder engagement has been consistently noted as being important across the fields of operational research (Monks et al., 2014; Tilanus, 1985), non-environment information systems (Díez and McIntosh, 2009) and environmental decision support (McIntosh et al., 2011). Díez and McIntosh (2009) in particular highlighted the crucial nature of user participation (akin to engagement with end users and other stakeholders; SE1 to SE3). Of the 20 factors Díez and McIntosh identified that could influence the pre-implementation phase of an information system, only user participation was identified as a 'best' predictor (as opposed to 'potential' or 'worst' predictors). User participation was necessary to improve the quality of design decisions and from this 'user satisfaction' also influenced 'success', both through the influence that users could impart on the development of the system and the management of user expectations (Díez and McIntosh, 2009).

Stakeholder engagement was a feature of all the case study projects considered in this paper, although its extent and nature did vary. The approach used to develop the Willunga IM placed a strong emphasis on participatory model development although most projects had at least one stakeholder group that was highly engaged throughout the project (see Table 3). The CLAM projects highlighted the implications of the process for selecting study catchments in achieving effective stakeholder involvement. The involvement of local stakeholders in Phase 2 of the project included selecting the case study catchments. From the researchers' perspective, this involvement increased the buy-in of these stakeholders to the model development process and ownership of the final product (SE5), relative to Phase 1 where study catchments were selected by the state government.

All respondents identified that 'critical thinking about the problem and the role of modelling' (MD7) was essential for environmental DSS and integrated modelling projects. Although this seems an obvious requirement, and is well recognised in the literature (e.g. Black et al., 2014; Voinov and Bousquet, 2010), this factor was not fully realised in some of the projects considered in this paper (albeit it was achieved to a higher level and more

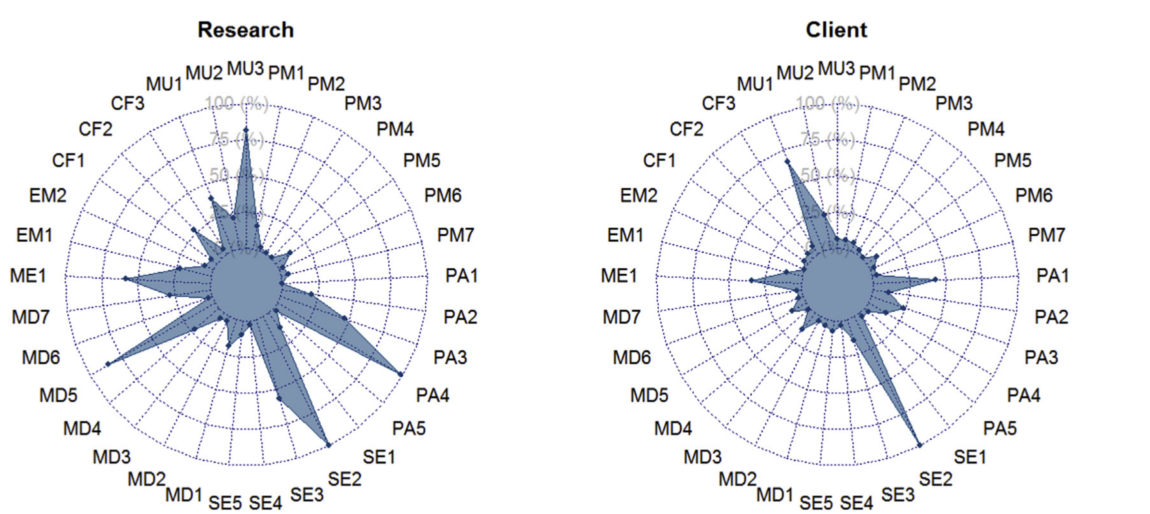

Fig. 2. Radar plots showing the variable importance (up to 100%) of 'success' factors in relation to the research and client outcomes of the surveyed projects. See Table 1 for descriptions of the factors.

consistently than some other factors) and indeed in the wider literature. Sojda et al. (2012) reviewed 100 environmental modelling papers in an investigation that aimed to assist in developing more effective systems and tools, and found that 40% of papers did not directly identify a decision to be addressed. With respect to our 15 projects, critical thinking about the role of the modelling was linked through the respondents' reflections to the effectiveness of the engagement processes and relationship development with all partner organisations (research, government or NRM organisations).

5.2. Association of factors with research outcomes

Rating the achievement of each factor across all projects (if relevant) helped identify which factors in Table 1 were not consistently realised by the developers. The variable importance measures in Section 4.2 provided an indication of which of these factors were most related to achievement of research outcomes for the examined cases. The following variables were identified as being most related to achieving research outcomes: PA4, SE2, MD5, MU3 and ME1. For the general ranking of ME1 (model evaluation) in Section 4.1, five respondents identified it as essential with six classing it as case-dependent. All of the other variables were considered essential by the majority of respondents ($\geq$9). The use of a well-structured modelling process (MD5) and a strong focus on model evaluation (ME1) was unsurprisingly highlighted as important for achieving research outcomes. Without either of these factors, the implications are that model development will be weakened and so will the chances of the work being accepted as quality peer-reviewed publications.

Good relationship and trust between developers and end users (SE2) was the equally most frequently considered ‘essential’ factor for any modelling project and also emerges as the most important factor in highlighting variation in research outcomes from our survey projects. Stakeholders, particularly those with domain expertise and/or local knowledge, can be of critical importance in problem formulation and model scoping (related to MD7), as well as challenging and strengthening model assumptions and performance (MU1 and MU2). In turn this should make a model more defensible and improve research outcomes and metrics such as via scientific publications, especially with the scientific community's increasing recognition of the role of stakeholder engagement and expectation that it be given sincere consideration in environmental and integrated modelling (Hamilton et al., 2015; Voinov and Bousquet, 2010). The development of plausible scenarios that stakeholders perceive as useful and relevant (MU3) was considered by one author as a relatively easy task. In the few cases where a respondent considered that this factor was poorly realised, they ranked the achievement of overall research outcomes of that project to be poor or moderate. On a matter related to both SE2 and MU3, the use of local scientific knowledge (PA4) was reported by the majority of respondents as essential to project success, was typically well realized across the projects and was also associated with achieving research outcomes. Involving local scientists or consultants in the project, with appropriate capacity building in model development as needed, will enhance engagement and model development processes on the proviso that they have effective working relationships with the other stakeholders (Ticehurst, 2008).

5.3. Association of factors with the modeller's perception of meeting client's expectations

As with the research outcomes, variable importance measures were used to highlight factors that were most related to the developers' perception around the project meeting client expectations. For client outcomes, the variable importance measures identified the following variables as being most associated with achieving client outcomes: SE2 and MU1, followed by PA1 and ME1.

Some barriers and enablers to successful stakeholder engagement were identified by the authors from their project-specific experiences. In one client-commissioned project, the client imposed a limited stakeholder engagement process upon the developers of a strategic level DSS. The development team felt that better outcomes could have been gained – in terms of managing expectations about what the tool could do, how it could be useful and who were (and were not) its intended users – had they engaged more in terms of both time and effectiveness with local water managers and other stakeholders. This was supported by the identification that, for other projects, local meetings were an enabler to clarify roles, manage expectations and gain trust (i.e. SE1 and SE3 are necessary to achieve SE2). This is in accordance with the literature where communicating data limitations and implications for models (Díez and McIntosh, 2009), enabling stakeholders to challenge model assumptions and develop relevant scenarios (Voinov and Gaddis, 2008), or eliciting feedback on prototypes from end users (Sieber et al., 2013; van Delden et al., 2011) throughout the model development can help in several ways. Such enablers are to create a sense of ownership of the process amongst stakeholders, ensure model development remains focused on the project requirements, and increase confidence in model results and their use in the management of, or communication about, an issue.

Although allowing sufficient time for reflecting on a model's results and their implications for decision makers (MU1) was highlighted as influencing client outcomes, a common issue raised by respondents was that the project ran out of time to realize this factor to their satisfaction. This was particularly relevant to client-commissioned projects where methodological frameworks, the models and the software all had to be delivered within a short timeframe (e.g. CLAM [Phase 1], EXCLAIM, IBIS). Although partly an issue for the Great Lakes CAPER projects, discussions were had with the highly engaged and committed advisory committee on how modelling results could be used to support the negotiation of actions in the Water Quality Improvement Plan (WQIP). The model developer for this project noted that it was the one project in which they had been involved that directly contributed to a legislatively required planning process. The use of the CAPER DSS was an intensive process, due in part to the high engagement and involvement with the client, advisory committee and technical committees, but the respondent highlighted the contribution of the modelling to support the negotiation process for the WQIP, despite the short timeframes.

The role of the model architect (PA1) appeared to be quite consistently realized across the project cases with most respondents ranking this factor as 4 or better (where 1 is not realized and 5 is fully realized). Although constrained by the sample size, the more this factor was realized the higher the rank of the client outcome by the respondents. The survey respondents noted that it is difficult for one person to have all these characteristics and, even if they do, for that person to have time to engage with the project. Time constraints of the model architect(s) were noted for a number of both client-driven and researcher-driven projects. Practical alternatives were to have multiple people working well together in this role or to draw on external project champions and local stakeholders to develop case study understanding. One respondent stated that technical skills of the architect can be the least required as communication skills and case study understanding, together with good networking, can enable that person to source the required technical help. This viewpoint supports the definition of the project architect from van Delden et al. (2011) as ‘the person who bridges methodological and knowledge gaps between and within groups of policy makers, scientists and IT specialists, and who thus needs to have a sound understanding of the problem domain and the purpose of the modelling system and highly developed communication skills'.

In Section 4.1, a strong focus on calibration, validation, sensitivity analysis and uncertainty analysis (ME1) was considered to be of case-dependent importance. This was reflected in the varying roles of models in the 15 project cases, which ranged from their use as participatory tools for social learning, to develop system understanding, or as a formal tool for planning activities. As indicated by the variable importance measure in Fig. 2, the influence of ME1 on developers' ranking of client outcomes was muted. When this factor was 'not at all' realized (rank = 1 in Table 2, question 8), all respondents considered that the expectations of the clients were poorly met for that project. However, where the client outcomes were considered to be moderately met or well met, there was no strong relationship with the ME1 rank. Time and data constraints were noted as a key barrier to assessing the plausibility of model results within the project timelines for a number of the tools and projects, including three of the four client-commissioned tools (EXCLAIM, CLAM and IBIS). This suggests a mismatch in the time or resources to develop the tools or manage the project. The project management (PM) factors were consistently rated as essential by more than 50% of the respondents (Section 4.1) and, although their influence on project outcomes was not indicated by variable importance measures (Section 4.2), they undoubtedly influence the extent to which other factors are achieved.

5.4. Methodological contribution and limitations

Our 33 success factors were identified from the international environmental DSS and integrated modelling literature. We did, however, omit factors that have been identified in the operational research literature as particularly important for client-oriented work: improved savings and profits, and improved decision making (Tilanus, 1985). These are questions that are arguably best answered by clients or end users and the former may also be less demonstrable for many integrated assessment and environmental management issues.

The 15 projects from a water resource domain were selected because they covered a broad range of model approaches, modelling roles and problem foci and we had firsthand knowledge of the projects. In relation to the spectrum of views expressed in the survey, there was some consistency between respondents about the success in achieving client and/or research outcomes for a particular project, but there was also some variation for a number of possible reasons. The level of involvement, role and day-to-day dealings with the project could influence a person's opinion of the success of the project as could their personal views and expectations. Whilst we asked questions about each person's role we did not attain enough project-specific data to explore the influence of their role further. Despite an effort to gain multiple perspectives about the projects, the maximum data points for a project was six and most projects had two to three respondents. Additionally, the time elapsed since these projects were completed ranged from <1 year to 11 years. For some of the older projects, memories about the project details may not have been sufficiently fresh in the respondents' minds, and may be moderated by the experience they have accumulated in the interim period. For some of the more recent projects, it may be too early to judge the success of a project.

Our findings are subject to limitations of small sample size, namely different views between members of the same project, and the potential for recall errors. With respect to sample size, 15 modelling projects were assessed against 33 'success' factors. The 35 observations that were available reflect the responses of each person for each of the modelling projects to which they contributed. The variable importance measures were invoked to explore and handle this data set. The approach was able to highlight the relative importance of success factors, particularly where there was variation across the projects in the level to which the factors were realized. However, if there is no variation in a factor (i.e. a task that is consistently well done or consistently missed, or no variation is captured amongst the respondents), then its influence on the overall project outcome may not be captured.

The extent to which the results are specific to the projects considered in the paper, as well as the developers who were surveyed, remains unclear though we hope that our analysis and discussion serve to spark some deeper thinking about realizing project success. Furthermore, the methodology could be readily applied to a wider range of modelling case studies and a larger community of model developers. It could also be adapted to retrospectively elicit reflections from clients, and users of the outputs, of environmental modelling projects. Of potentially more value would be to adapt the survey structure and analyses for use throughout the life of a project to allow model developers and intended users of a modelling tool (or its results) to communicate and manage expectations and evaluate progress towards achieving intended project outcomes.

6. Conclusions

A list of factors affecting the broader success of environmental modelling projects was compiled in this paper from environment modelling and decision support literature. A survey was then used to elicit from 11 model developers a priority ranking of these factors and an assessment of how well each factor was realized across 15 project cases, as well as the extent to which they felt research outcomes and client expectations were met by the end of the project. Analysis of these data was used to structure reflections of model developers on the projects, particularly what they considered was performed well (or not) for a given project, and identify the factors that across the projects were not consistently being achieved, particularly those that were highlighted as being most influential on the extent of project success.

Of the 33 factors identified from the international literature, four factors were considered essential to achieve project success in any environmental DSS or integrated modelling project by all, or all bar one, respondent. Three factors related to stakeholder engagement: namely aiming for open and transparent communication, good relationships and trust, and sufficient interaction between development team and users. The model development factor that emerged as indispensable was that there be critical thought given to problem framing and the role of the modelling early in the project.

The study has also served to initiate a line of quantitative evidence on the influence of these factors regarding the extent to which project outcomes are met. Critical thinking around problem framing and the role(s) of models was considered to be achieved to a good standard for the majority of the study projects and, although considered essential by most respondents, this factor was not shown to be useful as a measure of project 'success' (defined as meeting research objectives or meeting the expectations of clients or users). Factors that were harder to control for across the modelling projects but which were more associated with project outcomes included stakeholder engagement (good relationships and trust), model use (time for reflection upon model results, and development of useful and plausible scenarios) and the level of focus on model evaluation. Reflections elicited from the survey provide an indication of interdependencies between the success factors, namely those relating to the effectiveness of stakeholder engagement processes, project management, and the use and evaluation of models.

While our results are context-specific to the projects and the model developers, their findings can provide a benchmark for further studies. A similar assessment based on client views and an analysis of a larger population of environmental decision support models and their developers would serve to further validate or qualify the outcomes of this study. It would also confirm practical measures and priorities to improve model development and use in future projects. Lastly, the list of factors synthesised from the literature has the potential for use as a communication tool and in relationship-building by model developers, users and other stakeholders throughout the duration of a modelling project.

Acknowledgements

A large number of people have contributed to the DSS and integrated modelling projects discussed in this paper, as clients, stakeholders, collaborating scientist or as part of the model and software development teams. Their input is greatly appreciated as is the funding provided by NRM agencies or state and federal governments to individual projects. A particular mention must be made of the scientific and project management contributions that Dr Rebecca Kelly made during and since her time at the Australian National University (ANU) to many of the projects and modelling tools discussed in this paper. The Australian Government funded the Willunga and Namoi integrated modelling projects through the National Centre for Groundwater Research and Training (NCGRT) (SR0800001), the Great Lakes and Darwin CAPER projects through the Coastal Catchment Initiative and Caring for Country, respectively, and the Tasmanian Water Quality DSS as part of the Landscape Logic Commonwealth Environmental Research Facility. The Great Lakes Council and the Northern Territory NRETAS contributed to the CAPER application for their region. The CLAM projects were funded by the NSW DIPNR (Phase 1) and the Northern Rivers CMA (Phase 2). The development of WAdss and the Namoi integrated model were both co-funded by the Cotton Research and Development Corporation. EXCLAIM was co-funded by Central West CMA and the NSW Office of Environment and Heritage. NSW OEH also funded the development of the IBIS DSS. The Avon-Richardson CATCHMODS work was funded by the Victorian Department of Primary Industries. The NCCARF project was funded by the Australian Government (through the Department of Climate Change and Energy Efficiency and the National Water Commission), the National Climate Change Adaptation Research Facility, ACTEW Water and the Australian Capital Territory Government. We thank the anonymous reviewers for their valuable comments.

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