Living with Less Water:
Development of viable adaptation options for Riverina irrigators

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Donald S. Gaydon

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Abstract

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In Australia, the best use of limited national water resources continues to be a major political and scientific issue. Average water allocations for rice-cereal irrigation farmers in the Riverina region have been drastically reduced since 1998 as a consequence of high rainfall variability and prolonged periods of drought, together with political changes. This has severely impacted regional crop production during the last decade, threatening the livelihoods of many farmers and is in stark contrast to much of this region's 100 year agricultural history, where water resources were available to farmers in steady abundance. The water 'landscape' has changed - bringing with it considerable social, economic and environmental consequences and forcing a rethink of how valuable water resources are best used under such variable, changed and changing conditions. This thesis presents details of investigations into on-farm adaptation options for rice-cereal farmers, using field experimentation, participatory engagement, and farming systems modelling as the major tools of research. Additionally, a major component of this work has been the development and testing of new modelling tools and decision-support structures.

Well-tested cropping systems models that capture interactions between soil water and nutrient dynamics, crop growth, climate and management can assist in the evaluation of new agricultural practices. At the beginning of this research project, all available models were lacking in at least some major element required for simulation of rice-based cropping systems. The capacity to simulate C and N dynamics during transitions between aerobic and anaerobic soil environments was added into the APSIM model, to facilitate our need to model farming system scenarios which involved flooded rice in rotation with other crops and pastures. Thorough testing against international datasets was subsequently conducted. Photosynthetic aquatic biomass (PAB – algae) is a significant source of organic carbon (C) in rice-based cropping systems. A portion of PAB is capable of fixing nitrogen (N), and is hence also a source of N for crops. To account for this phenomenon in long term simulation studies of rice-based cropping systems, the APSIM model was modified to include new descriptions of biological and chemical processes responsible for loss and gain of C and N in rice floodwater.

Using this improved APSIM model as a tool, together with participatory involvement of Riverina case-study farmers, it was demonstrated that the best on-farm cropping and irrigation strategies in years of high water availability were substantially different to those when water supplies were low. The strategies leading to greatest farm returns vary on a season-by-season basis, depending primarily on the water availability level. Significant improvements in average farm profits are possible by modifying irrigation strategies on a season-by-season basis.

The opportunities for Riverina farmers to exploit their irrigation water resources also extend beyond the farm gate. Currently there is considerable confusion amongst farmers on how to evaluate and compare on-farm and off-farm water options. Direct selling of water seasonally on the open market and even permanent sale of irrigation water entitlements are possibilities. In response to this confusion, a new conceptual framework was developed that enables quantitative comparisons between various options. The framework is based on a method regularly employed in the financial world for share portfolio analysis. Simulation modelling provided risk-return characteristics for on-farm options, and helped to elucidate circumstances under which off-farm options were viable.

A modified version of alternate wet-and-dry water management for Australian rice-growing conditions (delayed continuous flooding, DCF) was investigated via a 2 year field experiment – aimed at reducing irrigation water requirement and increasing water productivity (WP). We demonstrated up to a 17% increase in WP, and field data was generated on system performance for a range of discrete irrigation strategies. The APSIM model was then parameterized, calibrated and validated before being used to extrapolate findings from the two year experimental period to a much broader climatic record (55 years), allowing detailed investigation of optimal management strategies and a more realistic estimation of likely long-term gains in water productivity, and associated risks, from this new rice irrigation practice. Best practice guidelines were developed, and the potential impact of a changing climate on both optimal practice and likely benefits was assessed.

This thesis concludes by synthesising the approaches taken - addressing the question of whether improved rice irrigation practices, seasonally-flexible cropping and irrigation strategies and off-farm exploitation options, can in combination address the challenges of reduced irrigation water allocations in Australia’s Riverina region. Evidence is presented that the answer is yes under certain circumstances, but that limits to change exist beyond which the investigated on-farm adaptations are not enough. The thesis also proposes that the concepts and methods developed during this project are globally applicable and useful in the design of farming system adaptation options.

Keywords: irrigation, limited water resources, farming systems modelling, participatory engagement.

Preface

For better or worse, I left my run somewhat late to do this PhD study (44 years of age, as I write). My scientific career has been a chequered one, I guess. After studying agricultural engineering straight after high school, I started work as a professional engineer at age 21 and worked in this capacity for the next seven years, managing to achieve my Masters degree in engineering part-time, concurrently. Soon after reaching this hard-won milestone, I decided that engineering really wasn't my thing after all, and headed off to pursue other possibilities. Three years later, at age 31, I was playing acoustic guitar and singing for my living in Brisbane and Gold Coast pubs. My efforts to make the "big time" continually thwarted, and my pregnant wife no doubt wondering to herself how I was going to support her and our coming first child by singing to drunk people, I concluded that it must be time to get a 'real' job.

My Masters degree had involved development of models for simulating solar air-heating and subsequent drying of agricultural grains. I had always found the concept of modelling fascinating – I think mainly the unexpected and counter-intuitive elements, such as describing several distinct physical processes each with mathematical equations, and then discovering that under certain circumstances their interactions resulted in totally different outcomes to what you expected. Sounds nerdy to non-modellers, but it can be really exciting! So, I poured over the newspapers looking for job adverts that sought modellers. The pickings were very, very few – in fact there were none. I ended up applying for a whole range of relatively boring and menial jobs such as shipping container inspector, grain quality assessor, and even maintenance manager at the Pinkenba sewage treatment plant. What was even more discouraging was that I was passed over for all of them.

It proved to be fortuitous however, because one day I noticed an advertisement from CSIRO, the premier research organisation in Australia, seeking a farming systems modeller. Without being fully sure what that actually was, I put in an application and was delighted to get an interview. The head of the interview panel was someone called Brian Keating, and for me it seemed like I answered every interview question he asked with "Sorry, I don't know anything about that, Brian". He was asking me weird and mysterious things about modelling the water balance, and soil nutrient dynamics, and crop growth, and all I could tell him was how I had simulated the performance of various types of fans under load, and how a hot metal roof warms up under sunlight. I walked out of the interview, straight to my wife Suzanne who was waiting expectedly in the car, and said "Well, we can forget that one." A week later I received a phone call from Neil Huth, also on the interview panel, offering me the job.

I thought it was a cruel joke initially. Then realization set in and I nearly dropped dead on the spot from excitement and pure relief. Maybe I wouldn't have to support my wife and child on a pub guitarist's wage….

Well, twelve years later I am still with CSIRO and it has been a wonderful period of professional growth and opportunity for me within a group of inspiring and dedicated scientists and technical staff. I started in the technical quarter, as part of the APSIM model software engineering group, also acting as an assistant to senior scientists like Brian Keating, Merv Probert and Michael Robertson. This PhD study has given me the opportunity to move into the realm of scientist myself – an opportunity for which I have several people particularly to thank.

Firstly, in chronological order, it all started with Mark Howden, my CSIRO manager during the mid-2000's, who reacted very positively to my vague mutterings about wanting to do a PhD. He took the initiative on my behalf to approach his friend and colleague Herman van Keulen at Wageningen. Everything started from there. Subsequent CSIRO managers of mine such as Peter Thorburn, Zvi Hochman, and currently Christian Roth also deserve particular thanks for their support of my PhD aims. Each of these has taken on extra work themselves at key times, specifically to free me up from CSIRO duties and allow my PhD work to progress. Also particular thanks to more senior CSIRO managers Michael Robertson and Peter Carberry who have at all times given me positive energy, and both organizational and personal support to make this PhD a reality.

Merv Probert (CSIRO) and Roland Buresh (IRRI) were my mentors in coming-to-grips with detailed C and N dynamics in soils – Merv being the expert in the dryland situations, and Roland the man with wet feet. To both of you I extend my greatest thanks – it has been a wonderful privilege to have your guidance. Also to Merv more than anyone else, I attribute my (now ingrained) philosophy to aim for simplicity in modelling - only seeking to complicate process descriptions when model outputs fail to capture observed data dynamics. On this front also, from my first residential period at Wageningen in 2008, I was greatly influenced by one-on-one discussions with Ken Giller, particularly his views relating to Occam's razor and modelling. Achim Dobermann and Bas Bouman from IRRI have always been accommodating in helping me source IRRI datasets and discussing modelling issues.

To Daniel Rodriguez (University of Queensland); Brian Dunn and Geoff Beecher (New South Wales Department of Primary Industries); Tao Li (IRRI, Philippines); Pepijn van Oort (Wageningen) and my colleague Perry Poulton (CSIRO) I express my sincere thanks for interaction on project activities and modelling questions. For logistical and personal support during both my residential periods at Wageningen, I cannot but thank Jan Vos and mention how comforted I have felt to have him 'on my side' during the whole process.

This brings me to my promotor and primary mentor, Prof Holger Meinke. I think a story will help illustrate the nature of my appreciation. The middle of last winter found me in Hobart (quite a climatic challenge for a Queenslander…) resident for a fortnight with Holger's group at the University of Tasmania. He insisted I also stay with him at his home – wouldn't hear of me staying in a hotel room. One evening, I found myself reflecting on the hospitable circumstances, sitting there like a visiting king in Holger's private home office, working on my computer whilst sitting in his comfortable chair looking out the window at the Hobart evening. His lovely wife Julie had just cooked us all a delicious meal, supplemented with a beautiful wine, and I had retired to the office to do some further work. Just as I was reflecting on these generous circumstances, Holger appears at the door with a bowl of ice-cream for my dessert….. How many PhD supervisors bring their students ice-cream? It is not only Holger's immense experience, knowledge and intuitive understanding about cropping systems modelling, adaptation and climate risk which has helped shape this PhD; it has also been the optimism which has pervaded all our interactions, and the unpretentious support I have felt from Holger as a friend, in addition to a PhD supervisor. To him my heartfelt thanks.

To the boys in my running group, Matt Sheerin, Andrew George, Song Sia, Andrew Jennings and Richard Holy – thanks for keeping me sane. But my greatest supporters of all have been my family – my parents and siblings, but mostly my wonderful wife Suzanne and our children Emerald and Heath. They are the core of my life, and have uprooted themselves from their lives and friends to follow me as we shifted home on several occasions (from Brisbane to Canberra to Wageningen to Canberra and back to Brisbane over four years) to enable my completion of this PhD – some of those moves appreciated, others not! Mostly, though, I suspect the biggest load they have all carried is me disappearing into my office of an evening or on weekends to "work on my PhD". To them, all my love and the greatest thanks of all! (I'll probably be a pest to them around the house now…).

I certainly would do it all again – it has been a great experience – however strongly advise anyone wanting a PhD to do it before they have a family.

Donald S. Gaydon
Wageningen, April 2012

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CHAPTER 1

General Introduction

On the driest inhabited continent on earth, availability and access to water has always been a contentious issue. Australia's climate is characterized by high variability and natural boom and bust cycles - consequently streamflow variability is higher than in most parts of the world (Chiew et al, 1998). In dryland rivers the flow regime is influenced by seasonal climatic phenomena such as the Southern Oscillation, so that patterns are highly variable and averages are virtually meaningless (Walker et al., 1997). These cycles of drought and plenty are ingrained in the Australian consciousness – representing dominant themes in many of our best loved bush poems:

"I love a sunburnt country, a land of sweeping plains,
Of ragged mountain ranges, of droughts and flooding rains"
(From "My Country" by Dorothea MacKellar, 1885-1968)
or
"If we don't get three inches, man, or four to break this drought,
'We'll all be rooned', said Hanrahan, before the year is out.
(then later in the poem…..)
And every creek a banker ran, and dams filled overtop;
'We'll all be rooned', said Hanrahan, if this rain doesn't stop."
(From "Said Hanrahan" by John O'Brien, 1878-1952)

Flows in the larger inland rivers supplying Australia's biggest irrigation districts have historically required regulation via large water supply dams to guarantee reliable water supplies to irrigators, but in recent drought-affected years even these reached their limit and irrigation water has been drastically limited (Murray-Darling Basin Authority, 2010). Projected climate change is also likely to impact resource availability (IPCC, 2007). As a result of ongoing changes to global atmospheric and ocean processes, many arid irrigated agricultural regions of the world are expecting a future with decreased and more variable water supplies (Rijsberman, 2006; Christensen et al., 2007). Farmers throughout the world face the challenge of adapting to these new circumstances and confront similar questions: should I adapt by changing crops, investing in more efficient irrigation technology and machinery, or modifying agronomic and/or irrigation strategies? Is it time to leave the land? Universally applicable approaches are required to assess adaptation options for these farmers in the face of changed circumstances (Meinke et al., 2009; Howden et al., 2007). Australia's Riverina is a well-established, irrigated agricultural region, with diverse broad-acre grain cropping traditionally centred around rice production. The region has historically had access to secure irrigation water supplies which are now increasingly under pressure. It provides an ideal opportunity to explore adaptation options, generic principles, and research methodologies using a combination of experimental, modelling, and case-study approaches - particularly due to the ready availability of soil, crop, and farming system information, historical climate data, research facilities, and farmers familiar with research involvement.

The research work detailed in this thesis consists of two primary components:

1. An initial model development phase; necessary to establish a previously unavailable simulation capacity for diverse cropping systems in which flooded (or occasionally-flooded) rice is a component, followed by,

2. Applications of the model (in conjunction with other techniques) for detailed assessment of several key adaptation options for Riverina irrigators.

1.1 Introduction to the region

Australia's Riverina

The Riverina encompasses the irrigated regions of southern NSW and northern Victoria (Figure 1), latitude 34°S–35.5°S; longitude144.5°E–146.5°E. Rice was first commercially grown in Australia in the early 1920's near the townships of Leeton and Yenda, and production is concentrated in this area due to the availability of irrigation infrastructure, historical availability of water, large areas of flat land, suitable clay-based soils and the development of storage and milling infrastructure in or near the regional towns.

Economic and social value of the region

In a year without climate-induced restrictions the Riverina region produces around 1.3 million tonnes of rice. Of this, 85% is exported and 15% services the domestic market. In such a year, the industry earns around A$800 million in revenue, which includes nearly A$500 million from value-added exports. Rice is Australia's third largest cereal grain export, and the ninth largest agricultural export (Sunrice, 2009).

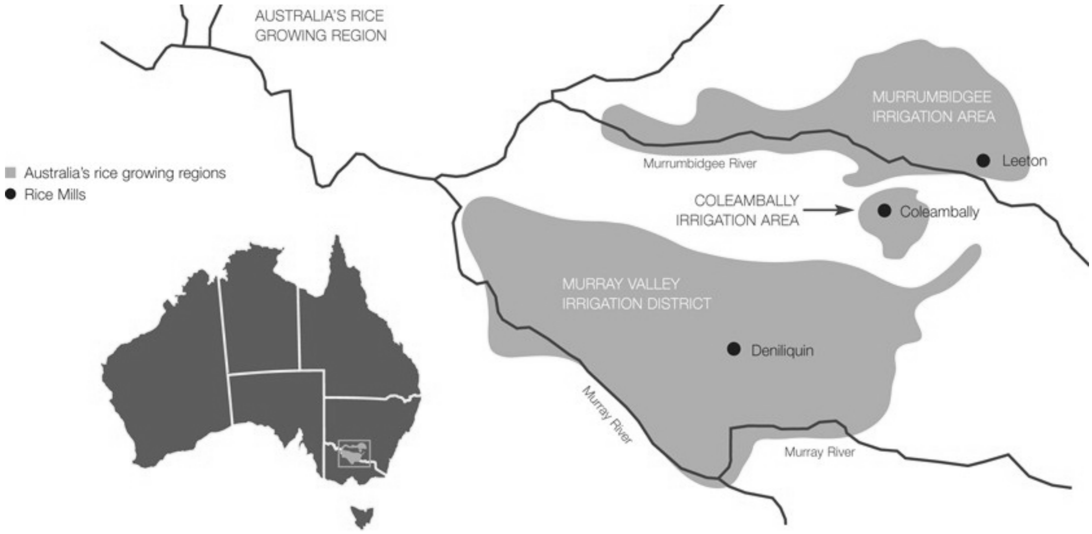

Figure 1. Australia's rice-growing regions (courtesy of the Ricegrowers Association of Australia)

Annual rice production internationally is approximately 650 million tonnes (FAO 2008), making Australia a relatively small player, however Australia grows high quality rice to service specific markets. Also, only 25 million of the 650 million tonnes of world annual rice production is traded outside the country of origin. Therefore, although Australian rice only represents less than 0.2% (0.14%; FAO, 2008) of world rice production, exports represent over 4% of world trade of medium grain rice (Sunrice, 2009). The sustainability of a large number of regional towns and communities in the Riverina is highly-dependant on rice-based farming systems (Linnegar and Woodside 2003).

Climate and Agronomy

Australia's rice-growing region experiences evenly-distributed annual rainfall, with the mean annual average ranging between 350 – 450 mm per annum. It is at the low temperature end of rice producing environments. The consequent long growing seasons, combined with a high radiation environment (long days, clear skies) result in one of the highest yield potentials of any rice-growing region. It is an ideal environment to produce high yielding, good quality rice. Rice is a summer grown crop, sown in windows according to variety from mid-September to mid-November. The crop has a growing season of approximately 6 months, and due to the relatively low rainfall the crop is totally reliant on the supply of irrigation water during this period. Rice costs roughly 1150 $/ha to establish and grow compared with $250 for dryland wheat (NSW Government, 2009), hence farmers are conservative in estimating the total rice area to plant, due to the economic consequences of running out of water. Large yield losses can be expected if ponding cannot be maintained for the required length of time (Heenan and Thomson, 1984). Rice is grown in rotation with a range of other species including cereals (wheat and barley), oilseeds, pulses and pastures, and is only one component in a diverse farming system. It is however the dominant broad-acre crop, in good seasons occupying 25% of the landscape in the major irrigation regions for about 6 months each year, and accounting for 50–70% of the total irrigation water use (Humphreys et al. 2006).

Future Outlook

Recently, Riverina irrigators have experienced unprecedented restrictions in production due to low water allocations resulting from a combination of climatic and political factors. Over the past decade, the volume of available water in the southern Basin has been around 40% less than the long-term average (MDBA, 2010). Average seasonal allocations over the last 15 years were below 50% of entitlement, with high variability. This is in contrast to a prior history of receiving at least 100% every season as far back as 1912 (Figure 2). Recent climate change projections suggest further decreases in regional water supply are likely. The Murray Darling Basin Sustainable Yields Project (CSIRO, 2007) suggested 9–14% reduction in water diversions for irrigation by 2030, whilst a 16–25% reduction in average Murray-Darling stream-flows by 2050 and 16–48% by 2100 has also been predicted (Pittock, 2003; Christensen et al., 2007; Hennessy et al., 2007). Such reductions in stream-flows are likely to have dramatic negative implications for future allocations in the Riverina (Jones and Pittock, 2003). Jones and Page (2002) suggest that a 15% drop in annual rainfall by 2030 could mean a 50% reduction in allocation levels. In Australia the supply of water for irrigation is not affected by climatic factors alone. Environmental policies and the National Competition Policy have also resulted in decreased water availability to irrigators (Adamson et al., 2007; Humphreys and Robinson, 2003; Murray-Darling Basin Authority, 2010). Clearly, the experience of the past is no longer an adequate reference for planning Australia's agricultural future (Jones, 2010).

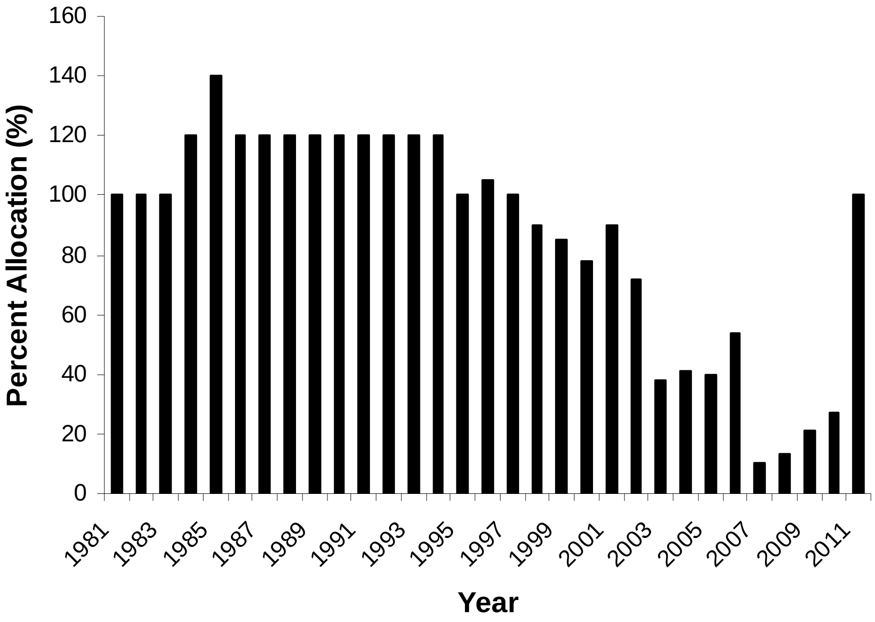

Figure 2. Annual irrigation water allocations (percentage of licensed quota) for Murrumbidgee Irrigation Area (part of the Riverina), 1980/81 – 20010/11 seasons. The trend of 100% or greater allocation extends unbroken from 1998 back to 1912 (Figure 1, Chapter 4).

1.2 Model development

The need

The current water shortages and future outlook for Riverina irrigated farming necessitates research into increased water use efficiency and modified agricultural practices for rice-based cropping systems. Well-tested models that capture interactions between soil water and nutrient dynamics, crop growth, climate and management can assist researchers in the evaluation of new agricultural practices (McCown et al, 1998; Carberry et al., 2002).

Available model options

A range of the most well-tested rice crop models (ORYZA2000 (Bouman and van Laar, 2006); CERES-Rice (Godwin and Singh, 1991); WOFOST (Van Keulen and Wolf, 1986); WARM (Confalonieri et al., 2006); CropSyst (Stöckle et al., 2003)) were designed for simulation of single rice crops only. Although of demonstrable value for certain applications, these was judged to be of limited use for the issues of this research project, which required a cropping systems model capable of simulating options for diverse farming system rotations including numerous crops in addition to rice. These other crops include cereals (wheat, barley, maize), pulses (mungbean, faba beans, navy beans, field peas etc), oilseeds (canola, soybean) and potentially a range of pastures (lucerne, clovers etc.). The RIWER model (Jing et al., 2007, 2010) and the wider DSSAT modelling framework (Jones et al., 2003) offered an additional demonstrated ability to simulate rice in short crop rotations, however both were limited in their flexibility for simulating more varied cropping systems options (other crop species, different sequences, and assorted irrigation, tillage and fallowing practices), which were assumed to be necessary for Riverina applications. The APSIM cropping systems model (Keating et al., 2003) has a proven track record in modelling the performance of diverse cropping systems, rotations, fallowing, crop and environmental dynamics (Whitbread et al., 2010; Carberry et al., 2002; Robertson et al., 2002; Verburg and Bond., 2003; Turpin et al., 1998). The major barrier to modelling rice-based cropping systems in APSIM was the lack of suitable descriptions for soil processes under long-term anaerobic conditions (i.e. flooded conditions such as ponded rice) – a consequence of the model’s heritage in dryland cropping systems. The crop physiology components from the ORYZA2000 model had already been incorporated into the APSIM framework (Zhang et al., 2006; Gaydon et al., 2006), and tested in a number of simplified studies. The inability of APSIM to simulate the complex dynamics of carbon (C) and N in alternately flooded and non-flooded soil environments was identified in these studies as a major future constraint to modelling complex rice-based cropping system scenarios (Zhang et al., 2006). Another vital element missing in all existing models was the ability to simulate additions of C and N to rice-based cropping systems from biological nitrogen fixation (BNF - by cyanobacteria) and growth of other non-N-fixing photosynthetic algal biomass (PAB). These are now considered to be critical for sustaining soil organic C and soil N supplying capacity (Pampolino et al., 2008; Roger and Ladha, 1992), and essential in any model suitable for simulating long-term crop rotations.

The path chosen

Given this assessment of available modelling tools, the decision was made to concentrate effort on improving the existing APSIM framework. The strategy was to address the range of limiting issues and work towards developing a model capable of simulating diverse future adaptation scenarios for rice-based cropping systems. APSIM already possessed the required flexibility and inherent design for specifying an infinite range of different management practices. Enhancements were specifically necessary to achieve:

1. realistic simulation of soil C and N dynamics through cycles of aerobic and anaerobic soil conditions.

2. realistic modelling of PAB influence on nutrient dynamics, and long-term systems sustainability characteristics (soil organic C and grain yield maintenance).

Algorithms and constants from both CERES-Rice and RIWER were used to achieve this, while introducing some new concepts relating to system C and N contributions from PAB. The improved APSIM model was tested against diverse, replicated experimental datasets for rice-based cropping systems, representing a spectrum of geographical locations (Australia, Indonesia and Philippines), soil types, management practices, crop species, varieties and sequences.

1.3 Assessment of adaptation options

The availability of the validated APSIM model provided an essential tool that was subsequently used to explore adaptation options for Riverina farmers. However, the use of modelling was only one element in the research conducted, as is described in the sections following.

Adaptation options

Innovative adaptations in on-farm water management practice are required to keep Riverina irrigators profitable in a future characterized by a reduced and more variable irrigation water supply. There is a range of ways an individual irrigation farmer could potentially adapt. Essentially the challenge is to increase input water productivity, the production per unit of water applied, WP (Zwart and Bastiaanssen, 2004; Cai and Rosegrant, 2003; Seckler et al., 2003). Options such as partial-(deficit) irrigation may increase WP (Fereres and Soriano, 2007); changes in agronomic practices such as rotations, crop species and varieties (Howell, 2001), changes in residue (crop stubble) management practices (Tolk et al., 1999; Schillinger et al., 2010); and changes to proportional sharing of water between winter and summer crops (Lorite et al., 2007), all promise potential increases in WP. More transformational changes such as investing in new irrigation technology and crops (Harris, 2000; Wood and Finger, 2006; Maskey et al., 2006; Hafi et al., 2006) represent further options, as do disposing of water on the free market (Bjornlund, 2003; Crase et al., 2000). All these options are highly context-specific and decisions on suitable adaptations are strongly influenced by locally existing co-limitations (e.g. labour, capital, nutrients (Rodriguez et al., 2007), as well as socio-economic issues (Adger et al., 2009; Crane et al., 2008, 2010).

Massive change - confusion reigns on how best to adapt

The Riverina irrigation district is a region currently experiencing step change. Whereas dryland farmers in Australia have evolved strategies to survive high climatic variability (particularly in rainfall) over a long period of time, Riverina irrigators, prior to the last decade (Figure 2), had never to concern themselves with water supplies which vary drastically from year-to-year. Irrigation water was always available in abundance, and consequently farming practices that conserve water had not developed. Historically potential production was land-limited, not water-limited. During the last decade this all changed, with many farmers experiencing the meaning of water-limited production for the first time. Properties are generally small (average farm size in the Murrumbidgee Irrigation area is around 200 ha), often too small to be viable purely as dryland farming businesses in this geographical region. Hence there are limitations in their capacity to apply the lessons of dryland Australian farmers in managing climate variability - practices which often involved huge land areas to mitigate risk. The drastic recent and projected changes to Riverina irrigators' water supplies necessitate urgent evolution of a whole set of new practice standards. They are thus arguably the farmers hardest hit by climatic change in Australia, even though farmers throughout the country are experiencing some degree of increase in climatic variability. As a result of entering such unprecedented circumstances, the Riverina is abound with numerous ideas on how best farmers should adapt. There has been limited time for research into the evaluation and testing of all these ideas, particularly under potentially changed future climates. Some farmers are in open disagreement about how they should respond to a future with less water. As an example, there is debate regarding the optimal irrigation intensity in the unfamiliar *water-limited* situation. Prior to the mid 1990s, irrigation water was always available in excess, and farmers were *land-limited* in terms of increasing their production. All available fields were fully irrigated, with fertilizer rates and plant populations selected to maximize production per hectare (Hochman et al, 2011). The high-input cropping philosophy of the time (Angus and Lacy, 2002) was never questioned, and rightly so – when land is the limiting resource it makes sense to maximize the returns per hectare. Under water-limited circumstances however, the choice is not intuitively clear (Figure 3). Debate in the Riverina regarding best intensity for irrigation under more variable water supply conditions has remained unresolved, and was one of the issues addressed in this research project.

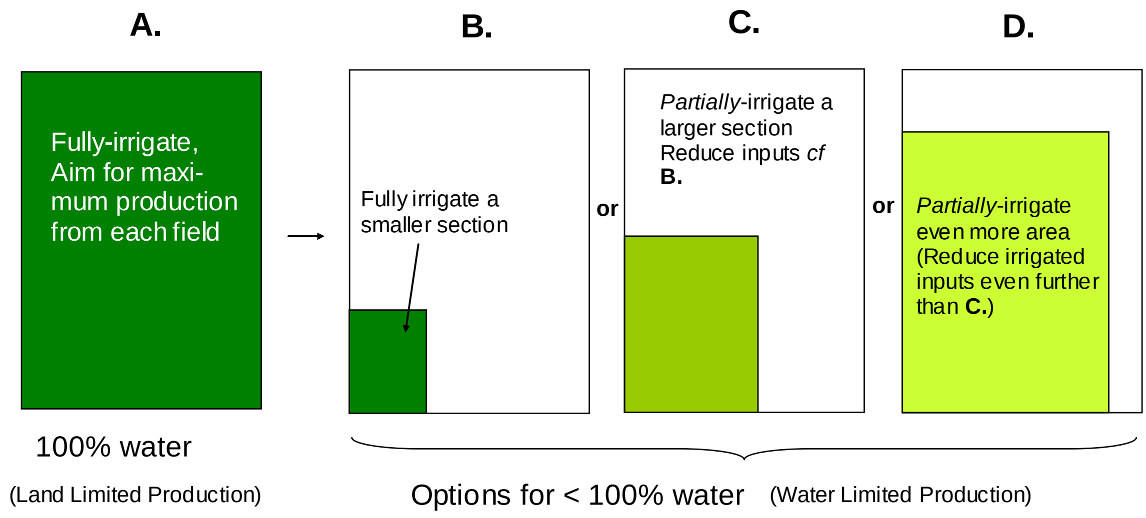

Figure 3. The options which present themselves when changing from *land-limited* to *water-limited* production systems. (A) Represents the historical situation – ample water to irrigate entire farm; (B–D) represent a range of options for using limited irrigation water. Reducing irrigated inputs means partial or supplementary irrigation (rather than full) together with reduced fertilizer inputs as per yield expectations. (C and D) Represent different degrees of input reduction. (Hochman et al., 2011)

Other ideas relate to off-farm options for seeking returns from available water resources. Bjornlund and Rossini (2005) suggest that seasonal water sales to higher value users in the Riverina region are one of the more financially attractive adaptation options for lower-value irrigation farmers in times of low allocations. Producers of high value products with long-term investments in dairy herds and permanent plantings (grapes, citrus, stone-fruits) have demonstrated they will pay high prices during periods of water scarcity to limit potential losses caused by insufficient irrigation (Bjornlund and Rossini, 2005; Brooks and Harris, 2008). Hence some broad-acre farmers suggest they should sell their water on the open market and work in the towns and cities; others suggest they should increase the intensity of their farming practices, investing in higher-efficiency irrigation equipment. Others insist that such capital investment in risky and could lead to economic failure or bankruptcy. Given the rapid changes in circumstances, the answers to questions such as these are unclear.

The role for field experiments and modelling

Field experiments can provide valuable insights and detailed data on cropping system performance - sensitivity and response to changing inputs and management impositions. In this sense they are extremely valuable for calibrating and testing models, in addition to their primary role in testing basic hypotheses. However, field experiments are generally limited to short time periods (< 5 years). In places such as Australia that exhibit extreme seasonal and decadal climate variability (Meinke et al., 2005), this restricts their value in understanding risk associated with practices under investigation. They also provide little insight into the potential impact of a changing climate. If reliable long term climate data (or climate change projections) are available, modelling offers a means to extend experimental findings from a reference period of several years to a much wider climatic record, thereby providing a more thorough assessment of risk and variability associated with the practices under investigation. Well-validated bio-physical models can also assist in understanding the key physical process driving system behaviour. This makes them useful tools in exploring management interventions to overcome system limitations. It has been an underlying premise of this research work that modelling is an essential tool in investigating some of the adaptation options that Riverina irrigators must consider, and in helping inform debate within the community on farming practices (for example, Figure 3).

The role for participatory engagement with farmers

Technical solutions alone rarely address the complexity of the livelihoods of farmers, and there are numerous documented examples were seemingly robust technical solutions to problems have failed to be adopted or made any discernable impact in addressing the focus problem (McCown et al, 2007). The reasons often relate to social, economical and political factors that cannot be ignored if real practice change and increased resilience is the desired outcome. To ensure analysis of realistic adaptation options when using models, participatory research with farmers is far more effective (Robertson et al., 2000; Meinke et al., 2001; Carberry et al., 2002), and has been a fundamental component of research performed during this PhD study. By working closely with farmers in developing detailed scenarios for testing, incorporation of a whole range of farm constraints (labour, machinery, irrigation cycles, etc.) has been possible without actually modelling them, and the cropping and irrigation scenarios investigated have remained realistic and relevant. In line with the concept proposed by Meinke et al. (2009) of ‘adaptation science’ as a truly trans-disciplinary endeavour; only adaptation ideas that are socially acceptable/feasible have been considered.

1.4 Research objectives and methods

Objectives

This thesis has two primary objectives, each with several sub-objectives or research questions. The first primary objective is:

1. Develop new modelling capability that facilitates simulation of adaptation options in diverse rice-based farming systems. Achieve this via enhancement of existing models where possible. Specifically, evolve existing modelling capability from the simulation of single rice crops, to the simulation of rice cropping systems (sequences of rice in rotation with other crops, pastures, and/or fallows etc., under with diverse tillage, irrigation and agronomic management regimes).

   Sub-objective include:

   a. Establish a process for simulating the two-way transition between anaerobic and aerobic soil conditions occurring in crop sequences of flooded rice and other non-flooded crops and fallows, and confirm the subsequent effect on organic matter and nitrogen dynamics. These transitions must be dynamic and driven by modelled hydraulic variables (soil water and floodwater depth), not dependant on arbitrary switching by the user.
   b. Incorporate new descriptions of biological and chemical processes responsible for loss and gain of C and N in rice floodwater, including N-fixation and growth of photosynthetic aquatic biomass (PAB, algae), and confirm veracity of these in simulating the long-term trends in soil organic carbon and low-input yield maintenance in rice cropping systems.

The second objective is:

2. Develop viable on-farm adaptation strategies for irrigation farmers in Australia's Riverina (in response to a reduced and more variable future water supply). Use participatory engagement with farmers, supported by simulation modelling, as the primary tools of research.

   Sub-objectives include:

a. Examine the effect of irrigation intensity on whole farm profit under a range of potential future water supply scenarios
b. Compare potential on-farm water-use strategies for Riverina irrigators, with alternative off-farm options for exploiting their limited irrigation water. Such alternatives include selling irrigation water entitlements to the current Australian Government's Water Buy-back scheme for addressing regional environmental problems.
c. Assess the potential for changed rice irrigation practices to increase input water productivity and profit in the Australian situation.

Hypotheses

The research question at the core of this work can be summarised as: Is it possible to design a future mix of dryland and irrigated cropping options that are profitable, sustainable and socially acceptable for the southern rice-growing areas of Australia, given the future outlook for reduced water availability? To answer this question, this thesis tests the following hypotheses:

1. Current on-farm practices and strategies in Australia's irrigated Riverina must change to remain viable in the face of global change (i.e. climate change and other external forces).

2. Cropping systems simulation capabilities that quantitatively describe soil water, C and N dynamics through alternate anaerobic-aerobic soil phases, together with the addition of C and fixed N from floodwater algae, can be developed and successfully used in scenario analyses of possible adaptation options for rice-based farming systems.

3. Other industries (eg. finance, technology, and communications) have developed frameworks within which to understand human behaviour in response to change and these have direct applicability to feasibility assessment of adaptive change strategies in irrigated agriculture.

4. Most of the concepts and methods that are being developed to assist the rice growers of the Riverina in their transitions are globally applicable and useful in the design of farming system adaptation options.

Research Methods

The research work detailed in this thesis is based around a participatory research paradigm: farmers and scientists jointly engaging in new knowledge generation that stimulates enquiry and enables more resilient management of farming systems. This paradigm explicitly acknowledges that much of the knowledge already exists, but that systems science can play an important, integrative role. Participatory engagement keeps the science relevant and informed, the farmers' ownership level of research findings high, and the synergistic opportunities between farmer and scientist maximised (McCown et al., 1998; Carberry et al., 2002).

A multi-stage research approach was employed, consisting of the following components and their interactions (Figure 4):

1. <u>Review of literature</u> - relevant environmental, agronomic, economic, climatological, and social aspects of the problem were reviewed in the scientific literature, in government and industry body reports, as well as the internet and word of mouth with researchers actively working in the region.
2. <u>Establish basis for feasibility assessments</u> Case-study and advisory farmers within the focus region served as collaborators in participatory development of external scenarios, adaptive strategies and evaluation of adaptive options. The development of a strong sense of co-operation, teamwork and intimacy was a major focus.
3. <u>Visioning</u> - This component posed the question: What are we adapting to? Together with case-study farmers and information from 1, external factor scenarios were developed (for example, potential future changes to water supply regimes, on-farm climate change forecasts, ranges in expected future prices for water, fuel, commodities, fertilizers)
4. <u>Establish sources of information</u> - this component consisted of establishing data for model parameterization, calibration and validation (ie soil physical and chemical parameters, climate files, and crop varietal/phenological information). It also included the establishment of a new experiment at Yanco Agricultural Institute (Chapters 6 and 7) to investigate a specific adaptation option, and also gain further calibration and validation data for the APSIM model.

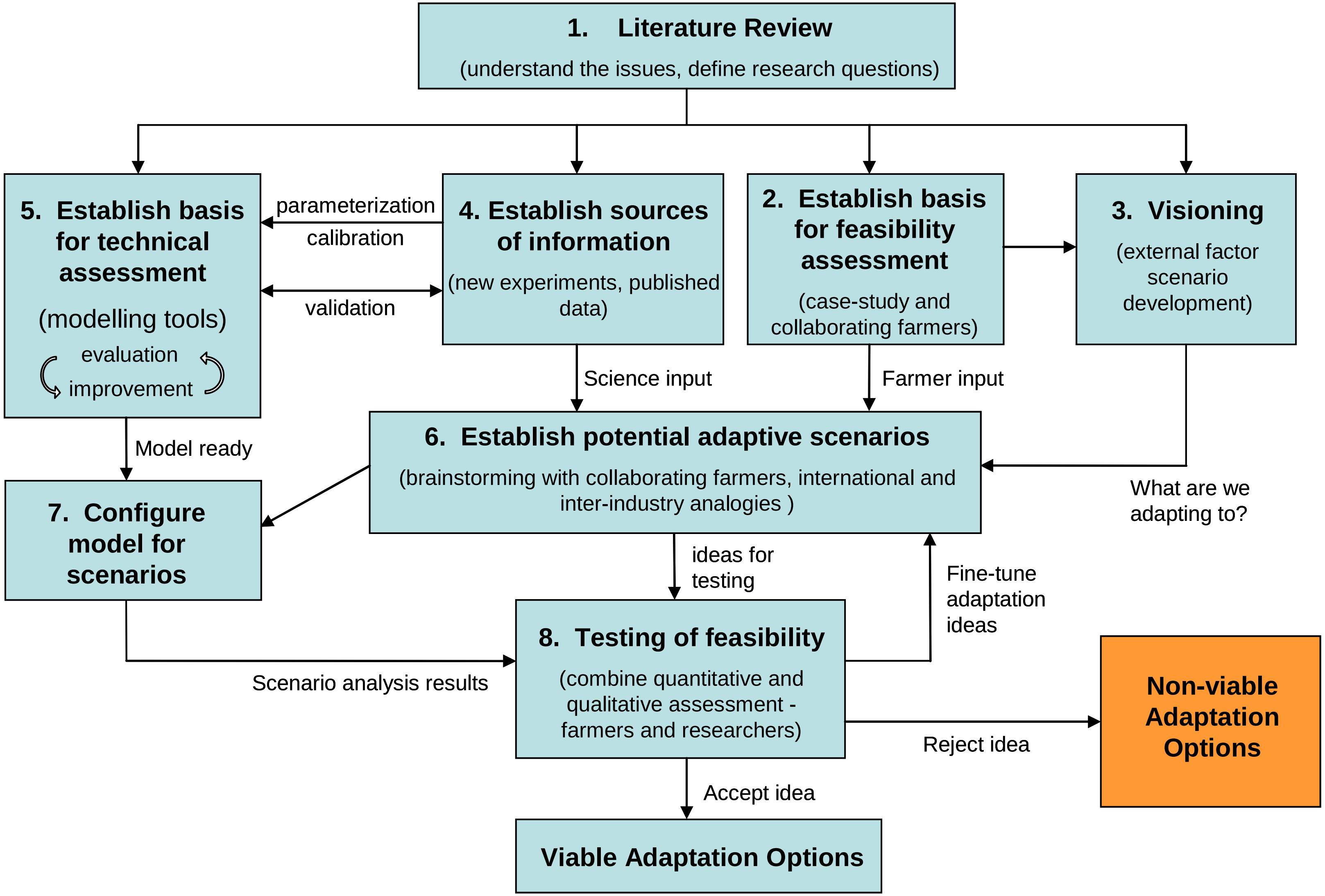

Figure 4. Research methodology used

5. Establish basis for development of technical assessment (modelling tools) Calibration, parameterization and validation of model performance, together with subsequent model enhancement, involved sourcing previous experimental data and published information on soils and crops, conduction of new experiments and on-farm trials, as well as sensibility testing against collaborating farmers' historical production and knowledge of risk. Many of the experimental datasets for implementing the new rice-related modelling functionalities were sourced from international sources. Model improvement is always an iterative process; deficiencies are found during testing against observed data, improvements are made (in calibration, parameterization, algorithms, or incorporation of new process descriptions), testing is re-performed, further improvements made, tested again and so on until acceptable model performance is achieved. A general guideline used in this research work to define 'acceptable' model performance is when Student's t-test indicates no difference between simulated and measured variables of interest at the 95% confidence interval; when the RMSE between observed and simulated data pairs is a similar order of magnitude to the standard deviation of the observed data, and when calculated modelling efficiency (Wilmott, 1981) is between 0 and 1.
6. Establish potential adaptive scenarios - This component synthesized learnings from several earlier components (1, 2, 3 and 4), and involved working with case study farmers, using the assembled information, to develop on testable on-farm adaptation scenarios. These generally involved changes to farm management strategies (irrigation rules and intensities, crop choice, different strategies for deciding what enterprise gets what water etc.) in the face of new circumstances, however some simply involved using different crop varieties and doing everything else the same. Developed scenarios from this component were then subject to feasibility assessments via modelled scenario analyses and subsequent farmer/researcher evaluation. The chief criteria of assessment was generally whole farm gross margins, however other criteria such as the ability to service long-standing supply contracts, and farm workload were also considered.
7. Configure model for scenarios - the improved and validated APSIM model was configured according to the management requirements of each scenario in question, and simulations were performed over long-term periods, producing cumulative probability distributions for the output variables in question. These results were fed directly to component 8.

8. Testing of feasibility based on quantitative and qualitative information and evaluating these through the synthesis of hard-core science inputs from simulation modelling, with the farmers assessment of real factors impinging on a their capacity to change practices. Modelled scenarios were regularly modified after evaluation of outputs (ie back to component 6 for fine-tuning). Eventually, enough information was available to either assign the idea as viable or non-viable.

Many of the scenarios developed for analysis in component 6 have not been fully developed in the course of this PhD study due to time and resource constraints. These have generally been discussed and targeted as future research needs in the subsequent chapters. Also, some developed scenarios were not significantly novel to warrant inclusion in a PhD study (for example, routine analyses of the benefits of residue retention, or sowing date trials for different crop varieties). Many of these analyses were still performed in the interests of the farmer and collaboration, however are not reported here.

1.5 Thesis outline

This thesis consists of a General Introduction (Chapter 1), six research papers (Chapters 2-7), and a General Discussion and Synthesis chapter (Chapter 8). Each of the six research papers focuses on one of the sub-objective (section 1.4).

Chapter 2 (Gaydon et al., 2012, European Journal of Agronomy 39, 9-24) details how enhancements to the APSIM model were implemented to achieve realistic simulation of soil C and N dynamics through cycles of aerobic and anaerobic soil conditions, thereby facilitating sensible modelling of crop nutrient supply in rice-based cropping systems. Evaluation against a diverse range of international experimental datasets is presented, covering a wider spectrum of climates, soil types, crop sequences and management interventions.

Chapter 3 (Gaydon et al., 2012, European Journal of Agronomy 39, 35-43) details how the APSIM model was enhanced to successfully simulate the key inputs from algae (and other pond flora/fauna) to the unique sustainability characteristics of rice-based cropping systems. The performance of long-term simulations, with and without inclusion of these inputs, is shown to be drastically different.

Chapter 4 (Gaydon et al., 2012, Agricultural Water Management 103, 33–42) evaluates a range of on-farm strategies for apportioning limited irrigation water between fields and enterprises using a typical rice-growing case-study farm from the Riverina. These strategies are compared for a range of seasonal water availability levels, on the basis of whole-farm returns and risk levels, leading to conclusions about how management strategies should vary on-farm as a function of the available irrigation water.

In *Chapter 5* (Gaydon et al., 2012. Agricultural Water Management, accepted subject to minor revision),, we demonstrate a method for comparing off-farm (water market) and on-farm (irrigation farming) options for exploiting a farmers' irrigation water, based on their simulated risk-return characteristics. A framework commonly used in the finance sector, Modern Portfolio Theory, is adapted to agricultural water use decisions and illustrated using a case-study farm from Australia's Riverina region.

Chapter 6 (Dunn and Gaydon, 2011. Agricultural Water Management 98, 1799– 1807) details the findings from a two-year replicated field experiment in the Riverina investigating potential input water productivity gains from a new rice irrigation practice known as *delayed continuous flooding* (DCF). Various strategies for imposing DCF management were compared with conventional drill sown treatments. Evaluation criteria included net water input, crop growth, grain yield and ultimately input water productivity. Potential for considerable gains in rice water productivity were demonstrated.

Chapter 7 (Gaydon et al, in preparation for Field Crops Research) uses the improved APSIM model to extend the learnings from Chapter 6. This paper details how the calibrated and validated model, together with 55 years of historical climate data, simulates the long-term risk-return performance of a range of different DCF different strategies, in comparison with traditional water management strategies. The model was used to uncover key environmental limitations constraining DCF system performance, allowing targeting of management interventions to overcome the constraints. Significant water productivity gains from the new practice were demonstrated, and best practice guidelines were suggested for historical and projected future climates.

In *Chapter 8* (General Discussion and Synthesis), learnings from each of the prior chapters are considered in union, leading to an assessment on the degree to which the amalgamation of identified adaptive options is capable of helping Riverina irrigators adapt to potential changes in their future. This chapter concludes with an assessment on the degree to which the original PhD objectives have been met, and suggests further research directions.

CHAPTER 2

Rice in cropping systems – modelling transitions between flooded and non-flooded soil environments

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Abstract

Water shortages in many rice-growing regions, combined with growing global imperatives to increase food production, are driving research into increased water use efficiency and modified agricultural practices in rice-based cropping systems. Well-tested cropping systems models that capture interactions between soil water and nutrient dynamics, crop growth, climate and management can assist in the evaluation of new agricultural practices. The APSIM model was designed to simulate diverse crop sequences, residue/tillage practices and specification of field management options. It was previously unable to simulate processes associated with the long-term flooded or saturated soil conditions encountered in rice-based systems, due to its heritage in dryland cropping applications. To address this shortcoming, the rice crop components of the ORYZA2000 rice model were incorporated and modifications were made to the APSIM soil water and nutrient modules to include descriptions of soil carbon and nitrogen dynamics under anaerobic conditions. We established a process for simulating the two-way transition between anaerobic and aerobic soil conditions occurring in crop sequences of flooded rice and other non-flooded crops, pastures and fallows. These transitions are dynamically simulated and driven by modelled hydraulic variables (soil water and floodwater depth). Descriptions of floodwater biological and chemical processes were also added. Our assumptions included a simplified approach to modelling O_2 transport processes in saturated soils. The improved APSIM model was tested against diverse, replicated experimental datasets for rice-based cropping systems, representing a spectrum of geographical locations (Australia, Indonesia and Philippines), soil types, management practices, crop species, varieties and sequences. The model performed equally well in simulating rice grain yield during multi-season crop sequences as the original validation testing reported for the stand-alone ORYZA2000 model simulating single crops (n = 121, $R^2 = 0.81$ with low bias (slope, $\alpha = 1.02$, intercept, $\beta = -323$ kg/ha), RMSE = 1061 kg ha^{-1} (cf. SD of measured data = 2160 kg ha^{-1})). This suggests robustness in APSIM's simulation of the rice-growing environment and provides evidence on the usefulness of our modifications and practicality of our assumptions. Aspects of particular strength were identified (crop rotations; response to applied fertilizers; the performance of bare fallows), together with areas for further development work (simulation of retained crop stubble

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during fallows, greenhouse gas emissions). APSIM is now suitable to investigate production responses of potential agronomic and management changes in rice-based cropping systems, particularly in response to future imperatives linked to resource availability, climate change, and food security. Further testing is required to evaluate the impact of our simplified assumptions on the model's simulation of greenhouse gas emissions in rice-based cropping systems.

Keywords: APSIM, ORYZA2000, rice, cropping systems, soil nutrient dynamics

INTRODUCTION

Water shortages in agriculture present an increasing problem globally (Rijsberman 2006). Rice-based cropping systems, both irrigated and rainfed, represent the most important cropping system in South Asia (Devendra and Thomas, 2002), and an important system throughout Southeast and East Asia. Various sectors with increasing water demand (urban, industrial, environmental) competing for this limited resource are likely to exacerbate the impact of climate change effects on water supply to rice-growing areas globally (Bouman et al., 2007).

The forthcoming global challenge of producing more food and fibre with limited or reduced future irrigation water has been identified by numerous authors (Keating et al., 2010, Ali and Talukder, 2008; Bouman, 2007; Tuong et al., 2005). Consequently, there is a desire to investigate new practices in rice-growing regions with the aim of enhancing water productivity (WP) (Bouman, 2007), and cropping intensity (Dobermann and Witt, 2000). Suggested pathways include the incorporation of non-flooded crops and pastures into traditional rice rotations (Zeng et al., 2007; Singh et al., 2005; Cho et al., 2003), changed agronomic and/or irrigation practices (Sudhir-Yadav et al., 2011a; Belder et al., 2007; Bouman and Tuong, 2001), reduction of non-productive water loses (Humphreys et al., 2010), and genetic improvement (Bennett, 2003; Sheehy et al., 2000; Peng et al., 1999).

Well-tested simulation models are useful tools to explore opportunities for increasing WP. The APSIM cropping systems model (Keating et al., 2003) has a proven track record in modelling the performance of diverse cropping systems, rotations, fallowing, crop and environmental dynamics (Whitbread et al., 2010; Carberry et al., 2002; Robertson et al., 2002; Verburg and Bond., 2003; Turpin et al., 1998). The major barrier to modelling rice-based cropping systems in APSIM has been the lack of suitable descriptions for soil processes under long-term anaerobic conditions – a consequence of the model's heritage in dryland cropping systems. The ORYZA2000 rice model (Bouman & Van Laar, 2006) was incorporated into the APSIM framework and validated in several studies (Zhang et al., 2006; Gaydon et al., 2006). All soil and water components from the original ORYZA2000 model were removed during this process, retaining only the crop growth routines which now received their water and nutrient supply directly from the APSIM soil and water modules. In each of these studies, soil nitrogen (N) was either assumed to be non-limiting, or calculated for a rice monoculture using a simple N accounting component within ORYZA2000. The inability of APSIM to simulate the complex dynamics of carbon (C) and N in alternately flooded and non-flooded soil environments was identified in these studies as a major future constraint to modelling complex rice-based cropping system scenarios (Zhang et al., 2006).

Jing et al (2007, 2010) addressed this issue of transitional soil environments for rice-wheat rotations in the RIWER model, demonstrating good modelling performance in that specific system. However the flexibility for simulating more varied cropping systems options (other crop species, different sequences, and assorted irrigation and tillage practices) was not present. A range of other published models (such as DNDC (Li et al., 1994); WOFOST (Van Keulen and Wolf, 1986); WARM (Confalonieri et al., 2006); CropSyst (Stöckle et al., 2003); C-Farm (Kemanian and Stöckle, 2010); Chowdary et al., 2004; Jamu and Piedrahita, 2002) are similarly limited when considering flexibility for future adaptation studies in diverse cropping systems.

Another vital element missing in existing models was the ability to simulate additions of C and N to rice-based cropping systems from biological nitrogen fixation (BNF - by cyanobacteria) and growth of other non-N-fixing photosynthetic algal biomass (PAB). These are now considered to be critical for sustaining soil organic C and soil N supplying capacity (Pampolino et al., 2008; Roger and Ladha., 1992). Pampolino et al. (2008) found that soil organic C and total soil N were maintained during 15 years of continuous rice cropping with ample water supply for near continuous soil submergence in four experiments in the Philippines. Soil organic C and anaerobic N mineralization were maintained even with three rice crops per year, zero fertilizer inputs, and complete removal of all above-ground rice biomass at maturity. The ability to simulate this phenomenon is essential for models aiming to examine long-term trends in rice-based cropping systems.

Prior to our work, no existing cropping system model simulated these additions. The impacts of algal *activity* on floodwater pH and partial pressure of ammonia (and consequently on ammonia volatilization) are well simulated in the CERES-Rice model (Godwin and Singh, 1991), however the associated *additions* of C from PAB and *additions* of N through BNF are not simulated. This has not restricted the ability of CERES-Rice to simulate N losses and availability during single rice crops, but has limited its capacity to simulate long-term crop sequences and soil organic C dynamics successfully. Timsina and Humphreys (2006) presented evidence that CERES-Rice did not simulate soil organic C dynamics well.

We concentrated our efforts on improving the existing APSIM framework, with a view to addressing this range of limiting issues and developing a model capable of simulating diverse future adaptation scenarios in rice-based cropping systems. APSIM already possessed the required flexibility and inherent design for specifying an infinite range of different management practices. Enhancements were necessary to achieve realistic simulation of soil C and N dynamics through cycles of aerobic and anaerobic soil conditions. Modelling of PAB influence on nutrient dynamics was also required. We used algorithms and constants from both CERES-Rice and RIWER, whilst introducing some new concepts relating to system C and N contributions from PAB. Up until now, simulation of crop production in diverse rice-based systems has not been possible. Here we report on incorporation of this functionality into the APSIM model and subsequent performance evaluation against key datasets.

MATERIALS AND METHODS

Overview of the APSIM model

APSIM is a dynamic daily time-step model that combines biophysical and management modules within a central engine to simulate cropping systems. The model is capable of simulating soil water, C, N and P dynamics and their interaction within crop/management systems, driven by daily climate data (solar radiation, maximum and minimum temperatures, rainfall). Daily potential production for a range of crop species is calculated using stage-related RUE constrained by climate and available leaf area. The potential production is then limited to actual production on a daily basis by soil water, nitrogen and (for some crop modules) phosphorus availability (Keating et al., 2003). The SOILWAT module uses a multi-layer, cascading approach for the soil water balance following CERES (Jones and Kiniry, 1986). The SURFACEOM module simulates the fate of the above-ground crop residues that can be removed from the system, incorporated into the soil or left to decompose on the soil surface. The SOILN2 module simulates the transformations of C and N in the soil. These include fresh organic matter decomposition, N immobilization, urea hydrolysis, ammonification, nitrification and denitrification. Crop residues tilled into the soil, together with roots from the previous crop, constitute the soil fresh organic matter (FOM) pool. This pool can decompose to form the BIOM (microbial biomass), HUM (humus), and mineral N (NO_3 and NH_4) pools. The BIOM pool notionally represents the more labile soil microbial biomass and microbial products, while the more resistant HUM pool represents the rest of the SOM (Probert et al., 1998). APSIM crop modules seek information regarding water and N availability directly from SOILWAT and SOILN modules, for limitation of crop growth on a daily basis.

Enhancements required to APSIM

The flooded environment

Figure 1 illustrates the broad nutrient and biological processes relevant to simulation of a flooded soil environment. All but one of these processes (denitrification) was originally absent from APSIM. The following is a brief description of the new system elements required:

- *Pond C and N loss and gain mechanisms*. Floodwater introduces a range of C and N loss and gain mechanisms not present in aerobic soil environments. These include significant volatilization of ammonia arising from diurnal elevations in floodwater pH associated with growth of PAB (largely algae, a proportion of which may be N-fixing) (Fillery and Vlek, 1983; Buresh et al., 1980; Roger and Ladha, 1992). They also include separating nitrification into a small volume of the surface soil, overlying floodwater, and crop rhizosphere, together with denitrification into the larger underlying anaerobic soil layer (Buresh et al., 2008).

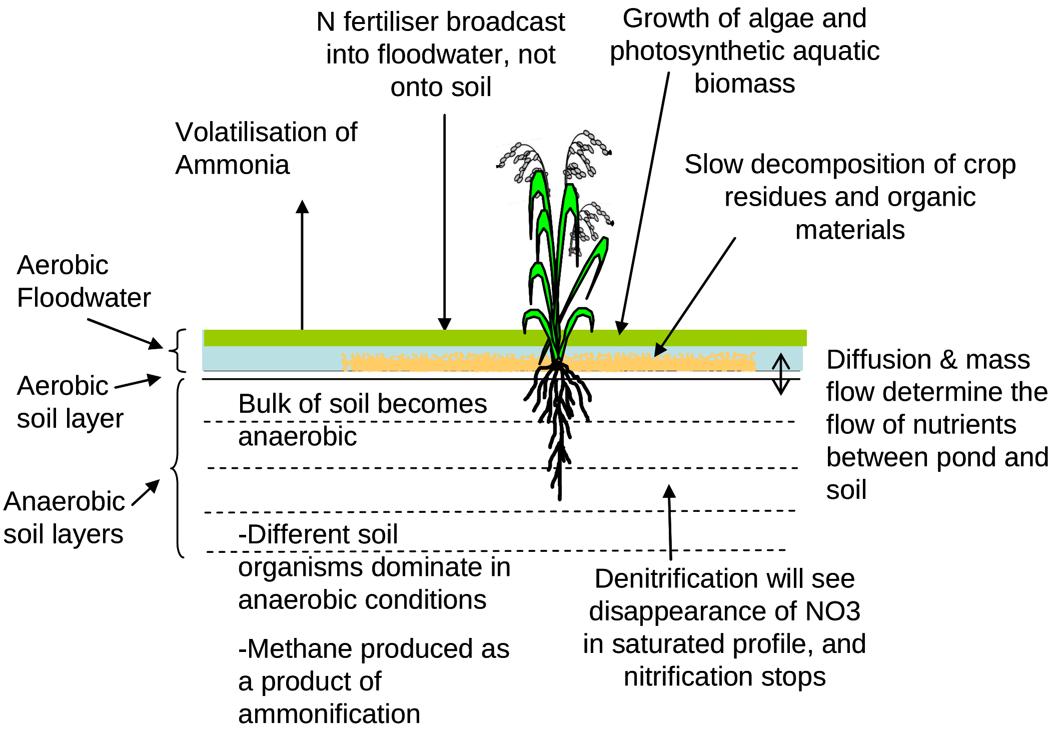


Figure 1. Key processes for system simulation in a flooded rice environment

- *Fertilizer applied into pond.* In rice-based systems, N fertilizer is often broadcast as urea directly into the floodwater. This urea N is then subject to hydrolysis, N loss via ammonia volatilization and nitrification-denitrification, movement into the soil, and ultimately uptake by the rice plant. Previously in APSIM, all applied fertilizer was conceptualized as being applied directly into the soil layers.
- *Surface organic matter decomposition in pond.* Surface organic matter decomposition is comprehensively modelled in APSIM (Probert et al., 1998) for aerobic conditions, however decomposition of organic material in the floodwater is governed by different rate constants reflecting a slower potential rate of decomposition (Acharya, 1935 a-c; Villegas-Pangga et al., 2000)
- *Reduced potential rates of soil organic matter (SOM) decomposition and cycling.* In an anaerobic soil profile saturated for extended periods, reduced potential rates of organic matter decomposition and cycling are likely to be a significant factor in modelling system behaviour (Jing et al., 2007, 2010).

Transitional ability

Changing the aeration status of the soil has significant consequences for nutrient dynamics, movement, and availability to plants. Nitrogen behaves differently in flooded (anaerobic) soil environments compared with non-flooded (aerobic) soil environments (Buresh et al., 2008). In flooded conditions, ammonia volatilization from the floodwater is a major source of N loss (Fillery and Vlek, 1983), hence movement of urea, ammonium and nitrate between the floodwater and the soil, where it is available for plant uptake and protected from atmospheric volatilization, becomes an important process for simulation. Ammonium (NH_4), the major source of mineral N for rice crops, is rapidly nitrified to nitrate (NO_3) when the soil is drained. Nitrate is the major form in which mineral N exists in aerobic soil environments and is used by non-flooded crops such as wheat. When aerobic soil is re-flooded, nitrate present in the system is promptly lost by denitrification to the atmosphere. These cycles of nitrification and denitrification, together with ammonia volatilisation during the flood phase, are major loss mechanisms for N loss in cropping systems which include flooded rice phases (Buresh and De Datta, 1991; Buresh et al., 2008; Shibu et al., 2006; Kirk, 2004; Kirk and Olk, 2000).

The key challenge for incorporating new process descriptions into APSIM was to establish smooth transitions between flooded and non-flooded soil environments within a simulation, capturing the effect of the changed nutrient dynamics on crop growth. It was a design criteria that this transition be contingent on continuous hydraulically-modelled variables (floodwater depth and soil moisture status), rather than an arbitrary switch when one phase had finished and the next begun.

Enhancements implemented

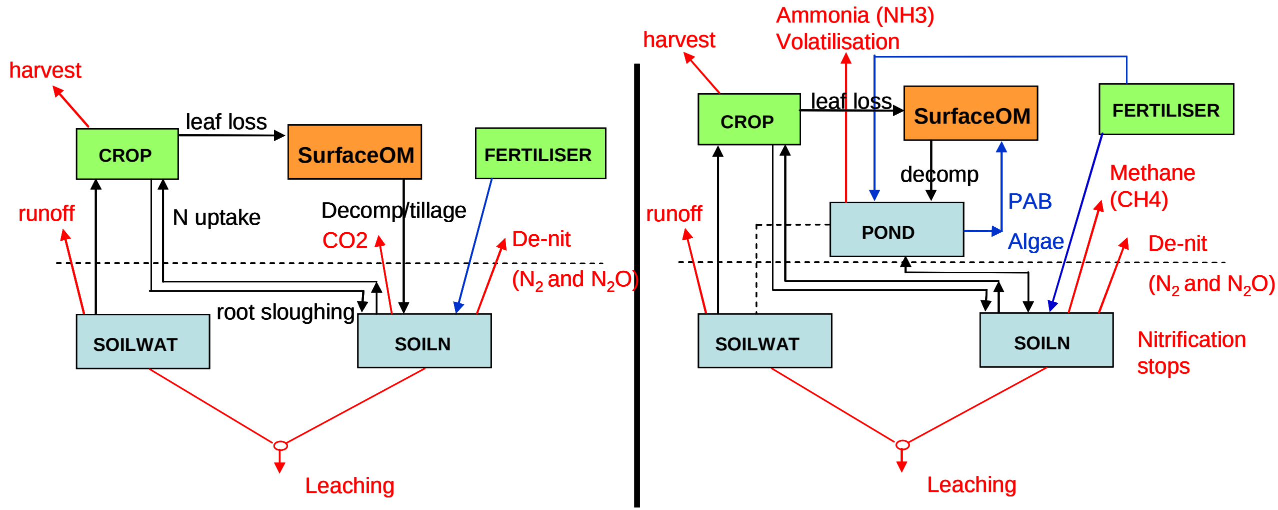
Layering of the system

When a soil is flooded, surface water limits oxygen transfer from the atmosphere to the soil. The imbalance between the high respiration rate of soil organisms and the slow rate of oxygen diffusion through the floodwater (10,000 times less than air (Buresh et al., 2008)) quickly results in the soil layers becoming anaerobic, reduced, or depleted of oxygen (Buresh et al., 2008; Kirk and Olk, 2000). Anaerobic organisms then dominate nutrient and organic matter cycling within the reduced soil. Three distinct layers in the system can be conceptualized: (1) the oxygenated floodwater; (2) a thin (a few millimeters) oxidized layer at the surface of the soil and around rice crop roots; and (3) the vast bulk of the soil mass which is reduced when flooded. CERES-Rice models N transformations within each of these zones (Godwin et al.,1990), the model therefore consisting of a three-layer system with flows calculated between each. Nitrification following urea hydrolysis or ammonification of organic matter can occur in both the floodwater and oxidized soil layer, however any NO_3 subsequently moving into the reduced subsoil is subject to denitrification.

We have used a two layer system (floodwater and soil) on the assumption that the thin oxidized layer at the soil surface is relatively insignificant when modelling larger-scale nutrient processes, as is the oxygenated rhizosphere around rice crop roots. Buresh and De Datta (1990) explained the relative unimportance of nitrification-denitrification in continuously flooded soil. In our modifications, the chemistry of the floodwater is modelled by a new module (APSIM-Pond), and the chemistry of the soil layers by APSIM-SoilN. These two modules communicate with each other on a daily basis to transfer nutrients via a central *engine* according to standard APSIM protocols (Keating et al, 2003). We assume that N is only available for uptake by the rice crop once it is in the soil layers (ie crop uptake from the SoilN module). Figure 2 shows our conceptualization of nutrient flows within APSIM for both flooded and non-flooded soil environments.

New module: APSIM-Pond

The APSIM-Pond module is a transient module in the simulation. It becomes active whenever the APSIM soil water balance module determines that water is ponding on the soil surface. A resettable input parameter for surface water storage capacity (*max_pond* in mm) can be specified to represent the maximum bund height in rice



a) Aerobic system (Traditional APSIM)

b) Anaerobic system (Flooded environment)

Figure 2. Conceptual structure of APSIM module communications and C&N loss (red) and gain (blue) mechanisms in: a) traditional aerobic systems; and b) flooded systems. The black dotted line represents the soil surface.

systems. Runoff only occurs once the surface storage capacity has been exceeded. Daily irrigation or rainfall in excess of infiltration rate can be stored on the surface as floodwater if *max_pond* is greater than zero. The APSIM-Pond module is only concerned with floodwater chemical and biological processes – the soil water balance module simulates the water balance of floodwater and soil alike, as a continuum. When rainfall and/or irrigation cease, the floodwater depth will decrease by infiltration into the soil and evaporation until there is no floodwater remaining. APSIM-Pond checks with the soil water balance module on a daily basis to see whether it should be ‘active’ or not, as well as obtaining information on evaporation and its current depth. The module simulates ‘algal activity’ in the pond using the approach of CERES-Rice (Godwin and Singh, 1991). Additionally, a new innovation of APSIM-Pond is the extension of ‘algal activity’ (via the concept of a potential daily algal growth rate) to simulation of actual algal growth and biomass accumulation, including N uptake and fixation, leading to significant additions of C and N to rice system processes (Gaydon et al., 2012b). The simulated ‘algal activity’ is a function of available light (solar radiation, reduced by canopy cover), floodwater temperature, phosphorus, and mineral N availability, and is used to maintain a dynamic pH balance within the floodwater.

This enables partial pressure of ammonia to be calculated and ultimately daily ammonia volatilization – the major avenue for loss of applied fertilizer N in flooded rice systems (Buresh et al., 2008). We apply a factor, *NH4_loss_fact,* to the calculated partial pressure of ammonia for determination of volatilization. In CERES-Rice (Godwin and Singh, 1991) an empirical factor called *wind* was used, recognizing that wind at a site is a key mechanism by which ammonia is transported away from the floodwater surface, thereby limiting volatilization. Since wind-speed is rarely measured in weather data as input for simulations, APSIM-Pond instead applies NH4_loss_fact together with pan evaporation (either measured or calculated from daily maximum and minimum temperature) as a direct surrogate for wind-speed, modifying the algorithm used in CERES-Rice (Equation 1).

$$amlos = 0.036 \times fnh3p + (NH4\_loss\_fact \times evap) \times (0.0082 + 0.000036 \times fnh3p^2 \times pond\_depth) \quad (1)$$

Where *amlos* is the daily ammonia loss (kg ha^{-1}); *fnh3p* is the partial pressure of ammonia; evap is pan evaporation (mm); and *pond_depth* is the depth of the floodwater (mm). The base value of NH4_loss_fact is varied within the APSIM-Pond module on an intra-daily time-step and as a function of rice crop LAI. This recognizes that wind-speed at pond level is indirectly proportional to crop development and varies during the day (convection effects). NH4_loss_fact is a calibrated constant within APSIM. The APSIM-Pond module may effectively be conceptualized as a filter of nutrients – not allowing all applied N to reach the crop (due to volatilization losses and algal uptake), and simulating loss and gain mechanisms for both C and N. When the floodwater has drained down, the APSIM-Pond module becomes inactive and the nutrient filter is removed. When the floodwater is hydraulically re-established (as determined by the soil water balance module), APSIM-Pond becomes active and once again begins its role filtering N and potentially producing new C and N in the system through algal growth (if conditions are appropriate). A detailed description of pond module processes is provided in Gaydon et al., 2012b.

Changes to APSIM soil carbon and nitrogen module (SoilN)

Under anaerobic conditions, organic matter cycling takes place in the absence of oxygen at a decreased potential rate (Buresh et al, 2008). We assumed different governing rate constants (Table 1) on the basis of various reports in the literature (Jing et al., 2007, 2010; Kirk and Olk 2000). We assumed that anaerobic soil conditions develop rapidly after flooding and there is no lag whilst the micro-organisms adapt to the changed conditions. Each organic matter decomposition rate constant (input parameters to APSIM-SoilN module) now has two values instead of one; a value for aerobic conditions and one for anaerobic conditions. Figure 3 illustrates the logic diagram for the new APSIM-SoilN code structure enabling seamless switching between aerobic and anaerobic soil conditions during a simulation, as a function of soil water content and the presence of floodwater on the surface. If the answer at each of the decision points in Figure 3b is ‘no’ then aerobic conditions prevail and the APSIM-SoilN module operates in aerobic mode, as per normal for any non-flooded crop. If floodwater arises and a subsequent soil layer is saturated (answer ‘yes’ in Figure 3b) then the daily organic matter cycling within that soil layer starts to be governed by the anaerobic rate constants (Table 1). If the floodwater subsequently disappears at some point (dries down or is drained), the system can seamlessly move back to aerobic organic matter cycling as the decision points now answer ‘no’. In this way, seamless transition between aerobic and anaerobic conditions is achieved – a switching process solely governed by the hydraulically-modelled presence (or absence) of floodwater and saturated soil.

Table 1: Constants governing organic matter cycling in APSIM-SoilN, showing values for both aerobic and anaerobic conditions (Jing et al. 2007, 2010; Kirk and Olk 2000).

SoilN2 Constant	**Description**	**Aerobic Value**	**Anaerobic Value**
opt_temp	soil temperature above which there is no further effect on mineralisation and nitrification (oC)	32	32
rd_biom	potential rate of soil biomass mineralization (per day)	0.0081	0.004
rd_hum	potential rate of humus mineralization (per day)	0.00015	0.00007
rd_carb	potential rate for decomposition of FPool1 – carbohydrate (per day)	0.2	0.1
rd_cell	potential rate for decomposition of FPool2 – cellulose (per day)	0.05	0.025
rd_lign	potential rate for decomposition of FPool3 – lignin (per day)	0.0095	0.003

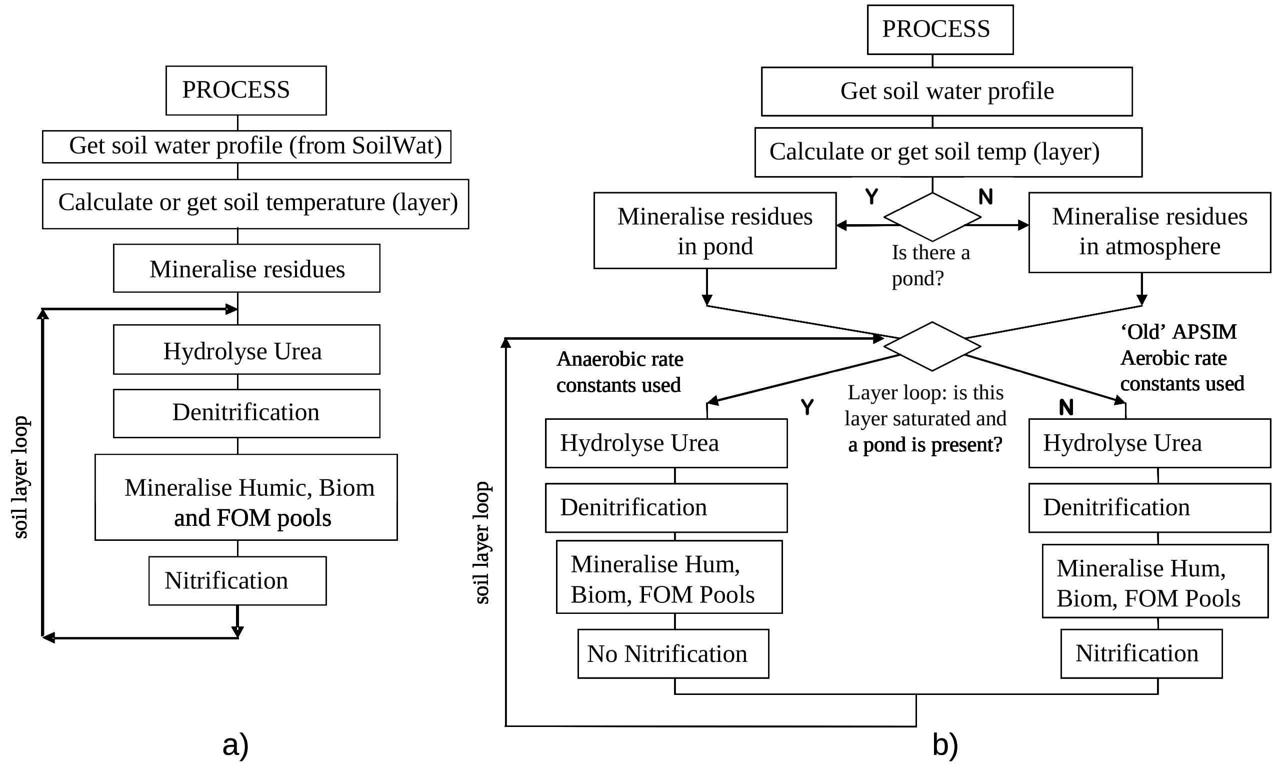


Figure 3. Logic of daily process simulation within APSIM-SoilN illustrating; a) old; and b) new structures. Note that if there is no 'pond', the 'new' is exactly the same as the 'old' process path.

Changes to APSIM Surface Organic Matter Module (SurfaceOM)

The decomposition of surface residues in APSIM is governed by a potential decomposition rate (specific to residue type), modified on a daily basis by several 0-1 limiting factors: - a temperature factor, a moisture factor, a C:N ratio factor, and a contact factor (Probert et al., 1998; Thorburn et al., 2001). When the residue is submerged (as in floodwater) we have assumed a constant moisture factor of 0.5. This recognizes a slower *potential* decomposition rate under submerged conditions, compared with moist, air-exposed conditions (moisture factor = 1.0). We assume the restricted movement of oxygen through floodwater contributes to slower potential decomposition of surface residues. Depending on soil moisture conditions of course, *actual* decomposition rates under submerged conditions may be higher than under non-submerged conditions with moisture limiting. Any immobilisation demand from submerged residues is met from mineral-N pools in APSIM-Pond. Decomposition of surface residues in standing water may therefore be limited by available mineral-N in the floodwater.

Flux of solutes between floodwater and soil

An important component of our modifications to APSIM is the description of transport processes for nutrients between floodwater and soil. The rates of these processes are major determinants of N-use efficiency in rice-based systems (Buresh et al., 2008). APSIM-Pond pools of urea, NH_4^+ and NO_3^- are transferred to/from the soil (APSIM-SoilN module) on a daily basis via the processes of mass flow and diffusion. For diffusion calculations, the concentration of each solute in the floodwater is compared with that in soil solution. When the concentrations are different in the two compartments, a diffusion process is invoked to determine the flux. This is a simple process for the highly soluble NO3 and urea components, as both floodwater and soil pools are assumed to be freely diffusible. The flux of NH4 between floodwater and soil is more complex, and requires determination of the diffusible component of soil NH4 (in other words NH4 that is not adsorped onto clay particles in the soil). A Langmuir isotherm is used to calculate this freely diffusible NH4 proportion as a function of the surface soil cation exchange capacity (CEC), in accordance with the methodology of Godwin & Singh (1991). A concentration gradient is then determined, and a positive or negative flux is calculated for the NH4 in solution, for NO3 and for the urea components. CEC is a new required APSIM-SoilN input parameter. Further details of our conceptualization and implementation of these process descriptions is reported in Gaydon et al., 2012b.

Model Evaluation

Model evaluation was performed in two stages; an initial adjustment of empirical parameters through iteratively comparing simulated and observed data for specific experimental datasets (calibration), followed by testing of the calibrated model against an additional range of independent datasets, designed to evaluate the model’s performance across a range of environments, practices, and seasons (validation). The primary focus of this development exercise was to produce a model capable of simulating *cropping system* performance. Hence the bulk of validation datasets were chosen to provide an insight into system behaviour during crop sequences (rather than individual crops). These calibration and validation datasets included fallow periods, a range of crop types, and varying management practices (Table 2).

Table 2: Details of field experiments used in the calibration and validation of the APSIM model (PTR-puddled transplanted rice; BFR-broadcast flooded rice; DSR-direct-seeded rice; R-rice; S-soybean; W-wheat; B-barley; F-fallow; CS-continually ponded; AWD-alternate wet and dry; I-irrigated; RF-rainfed)

Dataset abbreviation	Reference	Location	Years	Treatments	Crops/varieties	Measurement Details
Calibration						
RB85	Buresh et al. (1988)	Pila, Philippines	1985	0,30,60,90,120 kgN/ha	PTR/ IR58	Pond chemistry, N-uptake, and rice production.
Validation						
Pond-soil chemistry						
SKD88	De Datta et al. (1988)	Muñoz, Philippines	1985	Three (3) N placement methods/timing	PTR, BFR / IR60	Pond chemistry, complete N-balance (uptake, in-situ soil, and loss) and rice production
Crop sequence						
AS09	Suriadi et al. (2009)	Lombok, Indonesia	2007-2009	R-R-S-R-R rotation; two (2) water treatments (CS,AWD). Three (3) N treatments:- 0,69,138 kg N/ha/crop	PTR / cigeulis; soybean/ wilis	Production, water use, pond and soil chemistry
AB04	Boling et al. (2004)	Jakenan, Java, Indonesia	1997-2000	Six (6) consecutive rice crops; three (3) N treatments: 0,120,144 kgN/ha/crop; two (2) water treatments (I,RF)	PTR (dry season) & DSR (wet season)/ IR64	Influence of water table, rice production
SB01	Bucher et al. (2001)	IRRI, Los Banos, Philippines	1996-2000	Seven (7) consecutive rice crops; +/- straw, early/late residue incorporation	PTR / IR72	Production, soil chemistry
GB06	Beecher et al. (2006)	Coleambally, NSW, Australia	2002-2006	Seven (7) crop sequences (combinations of R,W,B,S,F); three (3) irrigation layouts (flat, beds, drippers); four (4) N treatments (0,60,120,180 kgN/ha for rice)	DSR/Amaroo,Quest. Wheat/Chara Barley/Gairdner Soybean/Djakal	Production, water use, soil water and mineral N.

Datasets used

a. Calibration

Calibration of empirical parameters which effect slowly-changing system characteristics (such as soil organic carbon) are impossible from single-crop datasets, however such short-term datasets can be useful in assessing more dynamic characteristics such as ammonia volatilization, provided key driving variables are available in the dataset. We used dataset RB85 (Table 2) to calibrate the APSIM-Pond constant *NH4_loss_fact.* RB85 was particularly suited for this calibration - detailed measurements of pond chemistry were available for floodwater pH, temperature, and ammoniacal-N (ammonium plus ammonia) for the 10 days following each fertilizer application, crop N uptake, crop biomass, and final grain yield. The experiment included a treatment with urea broadcast onto irrigated rice in the Philippines on two occasions at five different total rates of fertilizer N. (0, 30, 60, 90 and 120 kgN $ha^{-1}crop^{-1}$). The fertilizer splits were 2/3 of total amount at 18 days after transplanting, and 1/3 5 days after panicle initiation (PI).

b. Validation

The calibrated model was subsequently validated against a number of independent datasets (Table 2). A single dataset was used to validate pond-soil chemistry and N-balance performance (SKD88). Four subsequent datasets were used to test the model performance in simulation of crop grain yields. These datasets comprised experiments featuring crop sequences (multiple rice crops and other species, separated by fallow periods of varying length and management), a range of biophysical environments (tropical to temperate climates, highly permeable to heavy impermeable soils, influence of shallow water-tables), a range of in-crop management treatments (different irrigation and fertilizer regimes), and of course a spread of variable climatic seasons. Datasets with extensive measurements of soil water, N and C, together with algal activity/biomass/senescence were not available to *directly* test the key new drivers implemented in our APSIM science modifications. Hence we have focused on indirect validation of our changes through examination of more widely availably measures of cropping system performance, namely crop yields. The assumption is that successful simulation of crop yields *within a multi-crop sequence* confirms sensible simulation of soil water and N dynamics. Bellocchi et al (2010) and Sinclair and Seligman (2000) suggest it is desirable for several different output variables to be validated in unison to confirm crop model robustness. They gave the example of using not only crop yields, but also LAI, biomass partitioning between plant components, crop N-uptake etc., to thoroughly demonstrated robust simulation of crops. However we have chosen to focus on crop yields alone in this validation of APSIM, since the simulation of those additional crop components in the ORYZA2000 routines has already been thoroughly developed and tested by Bouman and Van Laar (2006). A few specific notes on the individual datasets used in this validation of APSIM follows:

- ***SKD88*** – This experiment was conducted over a two year period at Muñoz, Philippines to determine the N-use efficiency of three urea application practices in both puddled transplanted rice (PTR) and broadcast-seeded flooded rice (BFR). The treatments imposed consisted of different application methods, timings and splits for fertilizer N. For the BFR, treatments simulated for this validation were a *researchers' split* (T3) applied 2/3 urea basally, and 1/3 at 5-7 days before PI; a *triple split* (T5) applied 1/3 urea basally, 1/3 at 20 days after seeding, and 1/3 at 5-7 days before PI; and a *farmers' split* (T6) applied ½ urea at 15 days after seeding, and ½ at 10 days after PI. For the PTR, a *researchers' split* (T12) and a *farmers' split* (T14) were also imposed according to the same schedule, with 'transplanting date' substituted for 'seeding date'. A complete N balance for all treatments was conducted using ^{15}N, making this dataset particularly valuable for validation testing of APSIM performance in simulating N loss via volatilization. In this experiment N loss was calculated by deduction; the total N recovered at the end of the experiment (in soil, grain, stover, roots) was subtracted from the total N applied (as fertilizer, and in irrigation water) and existing in the soil at the beginning of the experiment to determine the unrecovered N, or N loss. Losses were assumed to have predominantly occurred via ammonia volatilization and to some degree denitrification.
- ***AS09*** **-** This experiment was conducted over a 3 year period in Lombok, Indonesia, and featured an irrigated PTR-soybean rotation on a highly-permeable soil. Crop residues were cut and removed from the field between crops, as per local practice. A key focus of the experiment was evaluating potential gains in water productivity (WP) from alternate wet-and-dry (AWD) irrigation management, compared with continuous flooding. Three N fertilizer regimes were included in sub-plots.
- ***AB04*** **-** This experiment was also conducted in Indonesia (Jakenan, Java) over a 3 year period, but on a heavier soil influenced by a shallow water-table. Six seasons of continuous rice were planted, a mixture of PTR (dry season) and DSR (direct-seeded rice)(wet season). Imposed treatments were two irrigation (irrigated and rainfed), and three effective N fertilizer treatments.

- ***SB01*** – This experiment was conducted over a four year period at IRRI, Los Banõs, Philippines, with seven consecutive PTR rice crops on a heavy clay soil. The primary focus was on management of intercrop fallow periods, with treatments including (i) residues removed at harvest; (ii) residues incorporated 10 days after harvest; and (iii) residues retained throughout fallow period and incorporated during land preparation for next crop. Two fertilizer treatments were overlaid – plus and minus N – with dry season crops receiving 210 kg N ha^{-1} as urea, and wet-season crops receiving 140 kg N ha^{-1} in the plus N treatments. All crops were fully irrigated and flooded. A factorial of plus/minus N and plus/minus residue treatments was used in the validation .
- ***GB06*** – This experiment was conducted over a 4 year period in the temperate rice-growing district of Australia (Coleambally, NSW), and compared a range of crops sequences (including rice, wheat, barley and soybeans) on different layouts (eg beds vs flat) under different irrigation practices and fertilizer regimes.

Statistical evaluation methods used

A linear regression across all crop sequence datasets was used to compare measured and simulated grain yield, for both rice and other crops. We determined the slope (α), intercept (β), and coefficient of correlation (R^2) of the linear regression between simulated and measured values. We also evaluated model performance using the Student's t-test of means assuming unequal variance P(t), and the absolute square root of the mean squared error, RMSE (equation 2).

$$RMSE = \frac{\sqrt{\sum_{i=1,n}(S_i - O_i)^2}}{n} \qquad (2)$$

Where S_i and O_i are simulated and observed values, respectively, and n is the number of pairs. A model reproduces experimental data best when α is 1, β is 0, R^2 is 1, P(t) is larger than 0.05 (indicating observed and simulated data are the same at the 95% confidence level), and the absolute RMSE is similar to standard deviation of experimental measurements. We also calculated the modelling efficiency, EF (Willmott, 1981; Krause et al., 2005) as another recognized measure of fit. The modelling efficiency is defined as:

$$EF = 1 - \frac{\sum_{i=1,n} (O_i - S_i)^2}{\sum_{i=1,n} (O_i - \overline{O}_i)^2} \qquad (3)$$

Where ō is the mean of the observed values. A value of EF = 1 indicates a perfect model (MSE = 0) and a value of 0 indicates a model for which MSE is equal to the original variability in the measured data. Negative values suggest that the average of the measured values is a better predictor than the model in all cases. The term 'model robustness' refers to the model's reliability under a range of experimental conditions (Bellocchi et al., 2010; Confalonieri et al. 2010). Given the broad spread of geographical locations and conditions examined in this model evaluation, we calculated the robustness indicator, I_R, (Confalonieri et al. 2010) as a measure of the transferability of APSIM's performance across varied conditions (Equation 4).

$$I_R = \frac{\sigma_{EF}}{\sigma_{SAM}} \qquad (4)$$

Where σ_{EF} is the standard deviation of the modelling efficiencies, and σ_{SAM} is the the standard deviation of the values of a SAM (Synthetic AgroMeteorological indicator; Confalonieri et al., 2010). I_R has been demonstrated as fairly independent of more traditional statistical metrics and model accuracy measures (such as correlation-based methods detailed earlier), hence we have used it to provide an additional perspective to further appraise model performance. I_R ranges between 0 and $+\infty$, with optimum = 0.

The method outlined by Kobayashi and Salam (2000) was used for a deeper examination of revealed error, via decomposition of the mean squared deviation (MSD) components. This method breaks the MSD (= RMSE^2) into the numeric sum of three parts (Equation 5); the squared bias (SB), the squared difference between standard deviations (SDSD), and the lack of correlation weighted by the standard deviations (LCS). Kobayashi and Salam (2000) demonstrate that:

$$\text{MSD} = \text{SB} + \text{SDSD} + \text{LCS} \qquad (5)$$

The relative sizes of these three components allow attribution of the relative sources of error. A small value for the SDSD indicates that simulated data exhibits a similar sensitivity to changes in conditions as the observed data – a large value indicates differing sensitivities play a large role in observed error; the LCS reflects the contribution of general correlation to the error; and the relative size of SB is a measure of the bias in the simulated data compared with the observed.

Parameterization and calibration

APSIM was parameterized for each experimental site using reported values for the datasets (Table 2). The model requires daily values of rainfall, maximum and minimum temperature and solar radiation. Also required were soil physical parameters including layer-based bulk density, saturated water content, soil water at field capacity and wilting point. Two parameters, U and CONA, which determine first and second stage soil evaporation (Ritchie, 1972) are also required. The latter parameters were set at 6 mm and 3.5 mm day^{-1}, respectively, values accepted for tropical conditions such as those described here (Probert et al., 1998; Keating et al., 2003). The proportion of water in excess of field capacity that drains to the next layer within a day was specified via a coefficient, SWCON, which varies depending on soil texture. Poorly draining clay soils will characteristically have values <0.5 while sandy soils that have high water conductivity can have values >0.8 (Probert et al., 1998). The values for saturated percolation rate (Ks in APSIM, mm day^{-1}) were readily available from the published experimental papers. Soil chemical parameters required by APSIM included soil pH, organic C, the fraction of SOM-C inert and initial BIOM-C, and mineral N. The maximum daily algal growth rate was estimated and assumed to be constant between sites (Gaydon et al., 2012b). Several new constants (Table 1) were employed without calibration, straight from the literature, due to lack of experimental data on which to calibrate. Other parameters required iterative calibration and are described in the following sections:-

a. *Ammonia volatilization*

APSIM was configured to simulate the soil, crop, and imposed management this experiment (RB85) and the value of NH4_loss_fact was incrementally varied until concentrations of urea and ammonium in the pond, together with rice biomass accumulation and final yield, were all simulated well (Figure 4) with R^2 values of greater than 90% for both rice biomass and grain yields (Figure 5). A value for NH4_loss_fact of 0.4 was found to apply, and was used for all subsequent validation simulations at all sites.

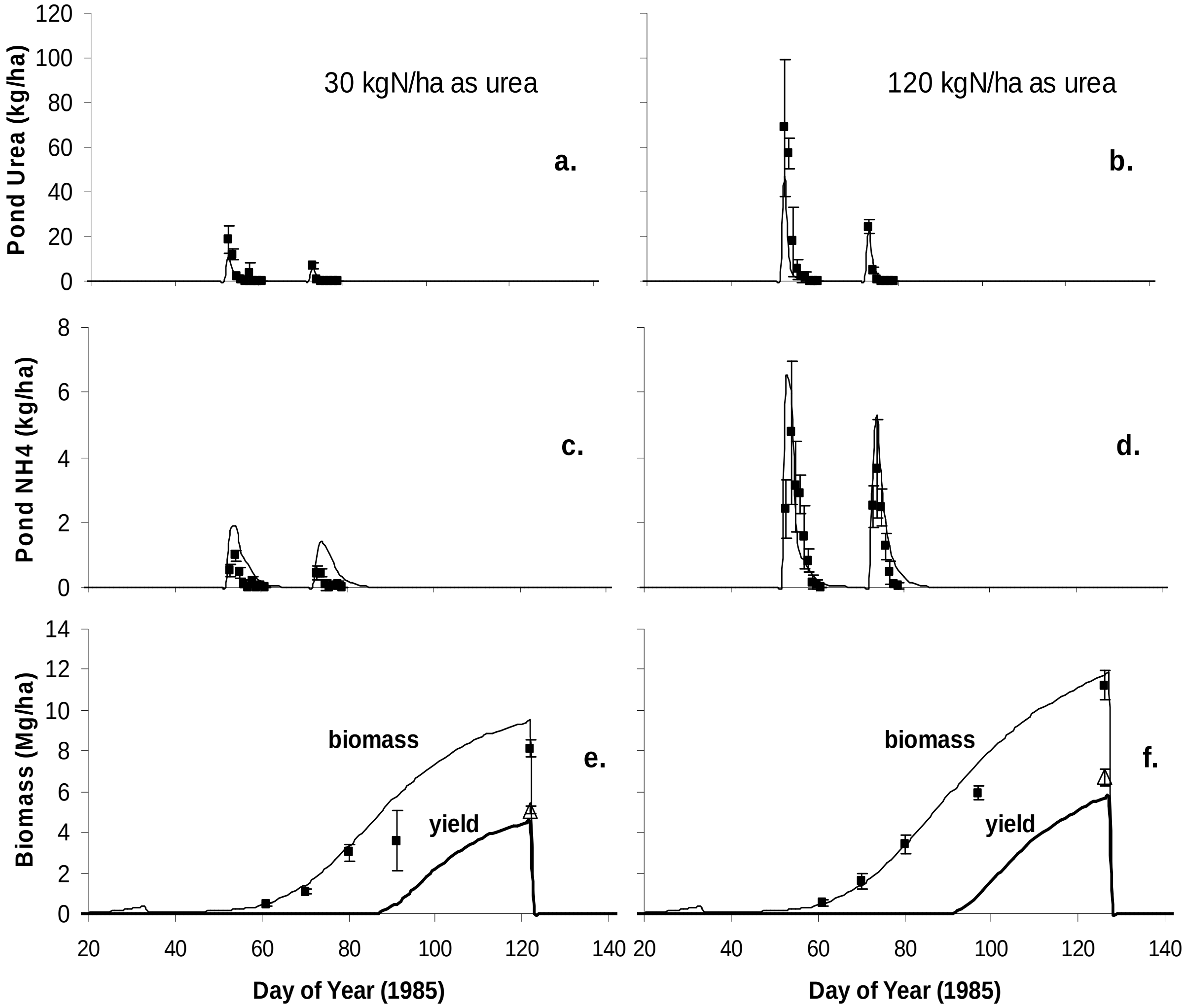


Figure 4. Simulated vs measured data for 30 and 120 kgN ha^{-1} treatments in RB85. Amounts are total N applied, split 2/3 and 1/3. Simulated data is shown as continuous lines, measured data as discrete points with associated error bars representing 1x standard deviation either side of the mean. Graphs a, c, and e are for the 30 kgN ha^{-1} treatment; graphs b,d, and f for the 120 kgN ha^{-1} treatment. The spikes in pond NH_4 coincide with applications of fertilizer (urea) to the experiments.

b. SOM mineralization

Because SOM mineralization capacity varies between locations as a function of soil biota ecology and the proportion of SOM in the resistant or lignin pool (inert fraction), the values of the APSIM parameters *Fbiom* and *Finert* (Probert et al., 1998) were calibrated for each experiment using data from zero-N treatments. A certain amount of plant-available mineral N was assumed to come from rainfall and/or irrigation water, and the remainder from mineralization of organic matter for the simulation of these treatments. The values of Fbiom and Finert were incrementally varied within reasonable bounds (Probert et al., 1998) until the simulated indigenous N supply in the zero-N treatments allowed close simulation of the measured crop yields.

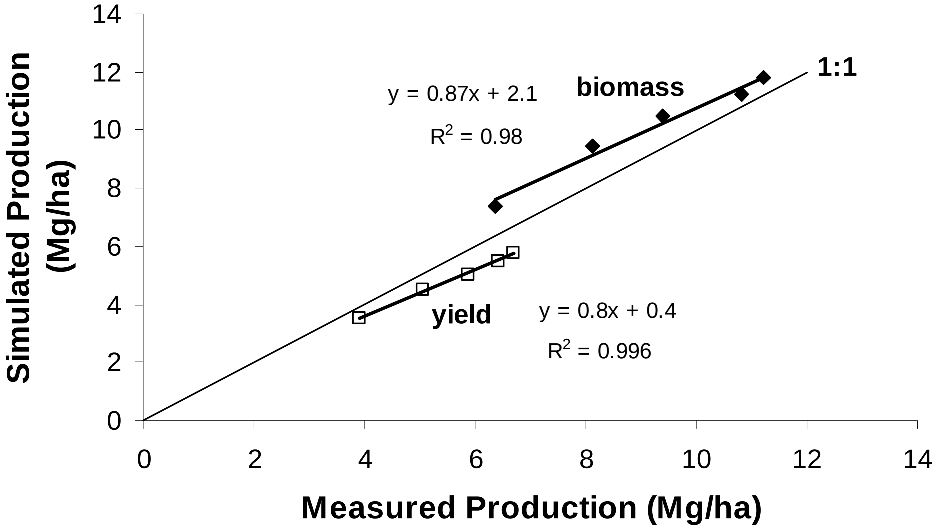


Figure 5. Simulated vs Measured production for calibration experiment RB85; broadcast urea applications rates of 0, 30, 60, 90 and 120 kgN $ha^{-1}crop^{-1}$.

c. *Crop phenology*

In simulation of each experiment, rice crop varieties were calibrated by varying the ORYZA2000 crop phenology parameters until the modelled phenology dates matched the observed dates. The same process was followed with APSIM crops like wheat, barley, and soybean. The primary dates of focus were those associated with sowing, transplanting, panicle initiation, flowering, and physiological maturity.

RESULTS

Validation of floodwater chemistry performance

The model was able to simulate the pattern and magnitude of N-loss characteristics for the various treatments in SKD88 (Figure 6), thereby providing an independent validation for model floodwater chemistry performance resulting from the calibration process detailed in section 2.4.3. N-loss in APSIM was determined by summing the daily simulated ammonia volatilization and denitrification. The comparison between simulated and measured N loss percentages across all treatments gave an r^2 of 0.98 (n = 5 treatments), with an RMSE of 2.98, compared with the average measured standard deviation within treatments of 3.65. This indicates satisfactory model performance, with error of predictions within the bounds of experimental variability. The simulated vs measured grain yields for the same treatments (data not shown) gave an overall RMSE of 453 kg/ha, compared with a range of standard deviations amongst the experimental treatments of 255-577 kg/ha.

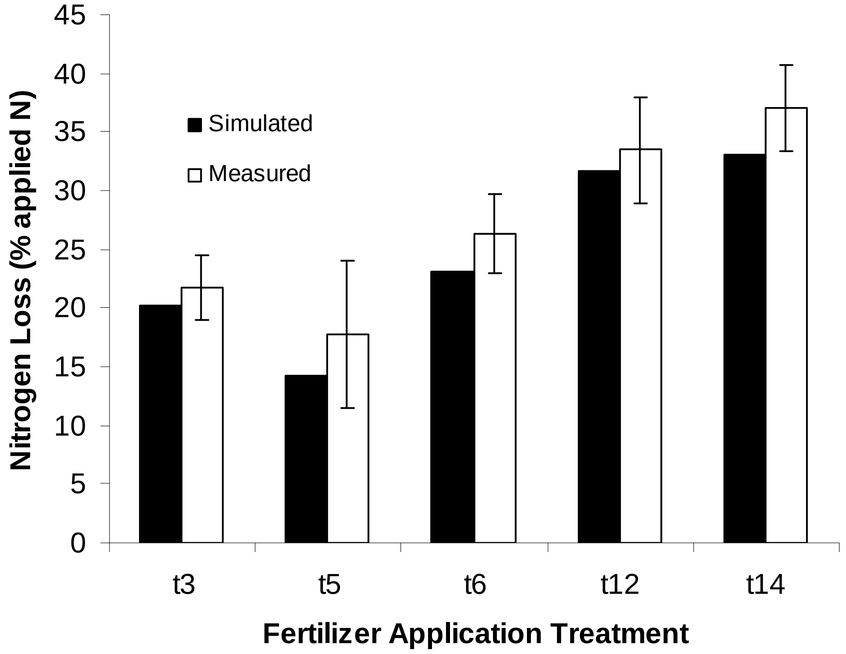


Figure 6. Validation of the calibrated APSIM model in simulating loss of applied N fertilizer for five (5) different N application methods and timings (SKD88). Results for year 1985 are shown. Treatments 3-6 are in broadcast-seeded flooded rice; treatments 12 and 14 are in puddled transplanted rice.

Validation of crop sequence performance

Figure 7 shows simulated versus measured data for two treatments of AS09; zero N and non-limited N. The fallow periods were short (less than 14 days) and four rice crops were separated by a single soybean crop in each treatment. This dataset was chosen to test the performance of the model across fertilizer treatments in a highly permeable soil, for a mix of rice and non-rice crops. Figure 7 demonstrates a good model response to applied fertilizer in the continuously flooded treatments. Model performance for different treatments is illustrated in Figure 8. The model performs best in the continuously submerged treatments (a), with marginal over-prediction of rice yields in the AWD treatments (b). Across individual fertilizer treatments (c), the model performed best for the mid-range fertilizations (69 kg N ha^{-1}), with excessive system sensitivity for zero-N treatments (illustrated by trend-line tending to vertical), and insufficient system sensitivity at the high (138 kg ha^{-1}) N rates. The overall correlation for all treatments (around a 1:1 line through the origin) was $R^2 = 0.82$, indicating good model performance for a 3 year crop-sequence dataset, consisting of 5 crops with no model resets.

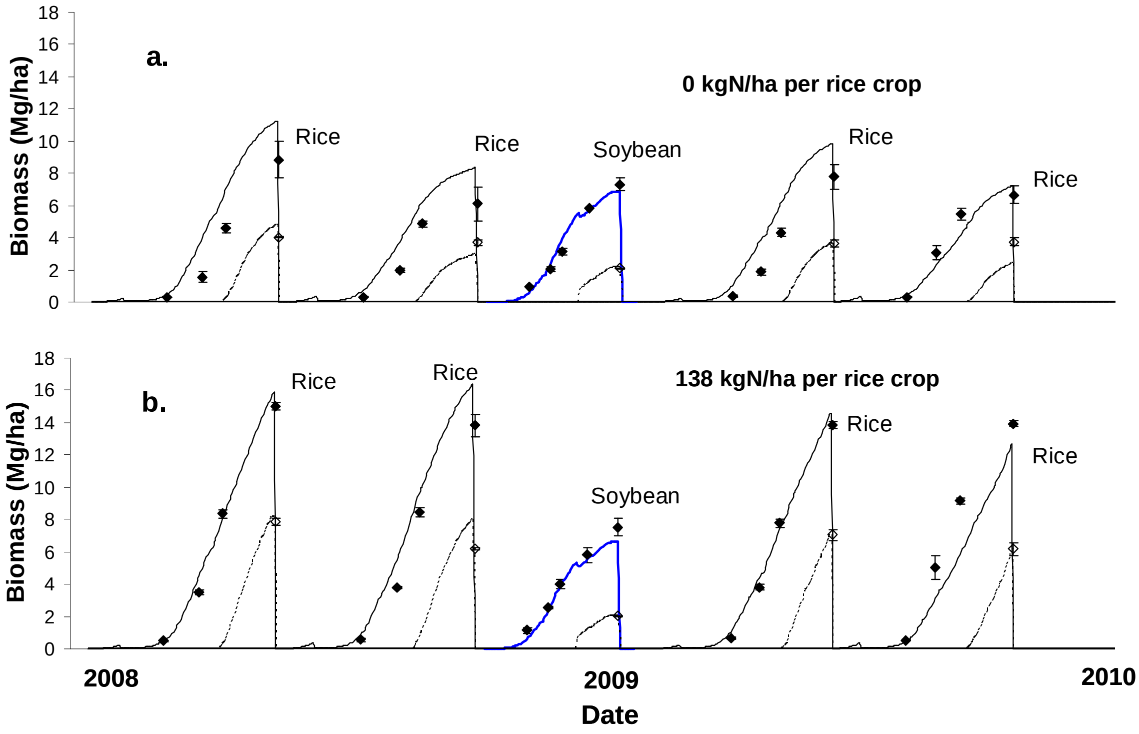


Figure 7. Performance of APSIM in simulating a *rice-rice-soybean-rice-rice* crop sequence (AS09) in Lombok, Indonesia, on a highly permeable soil. Simulated data is shown as solid lines, measured data as discrete points with associated error bars (1 x standard deviation either side of the mean). Graph **a)** shows the biomass and yield for a 0 kgN ha^{-1} application per rice crop; and **b)** a 138 kgN ha^{-1} input, for continuously submerged rice production with partial stubble removal during fallows.

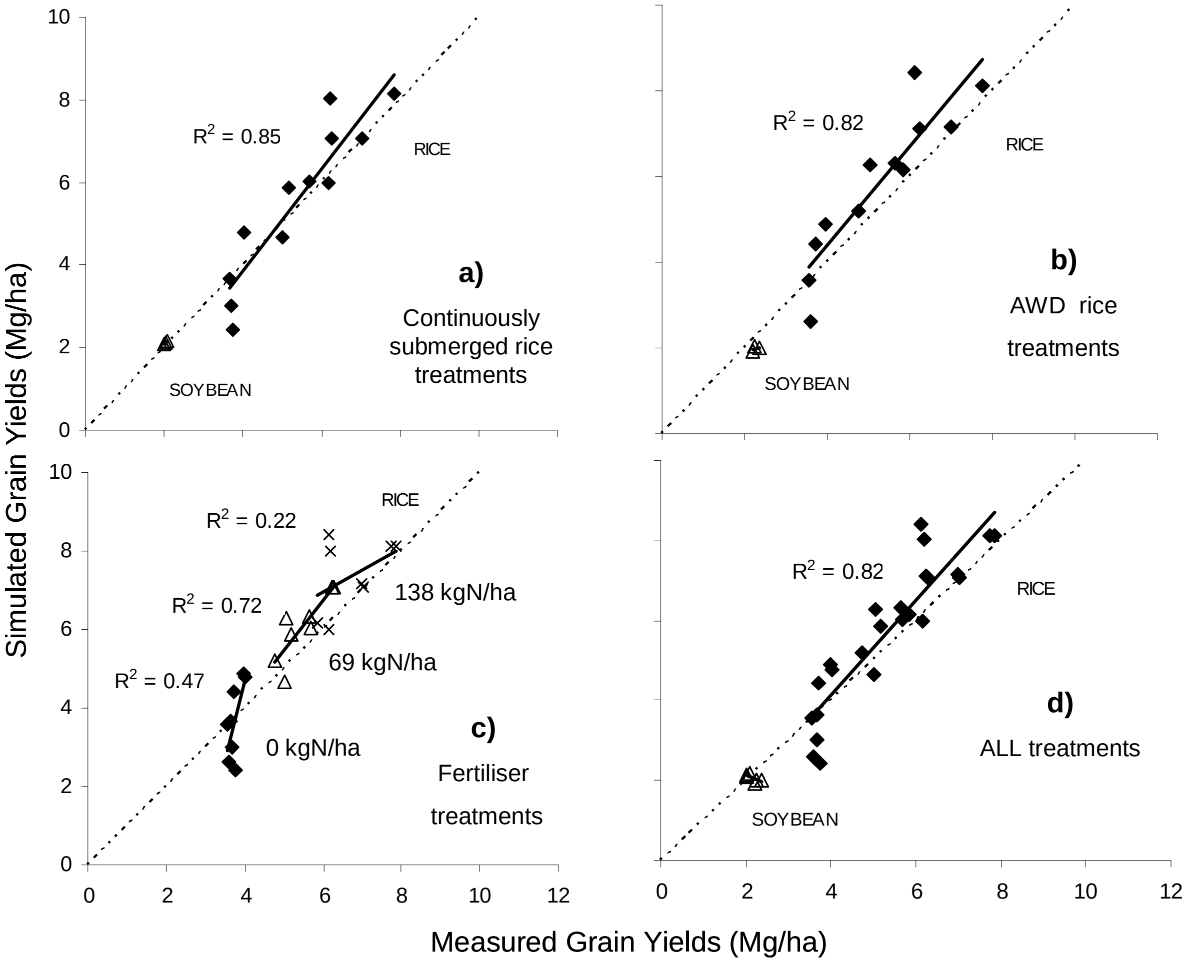


Figure 8. Performance of APSIM in simulating rice and soybean yields during a *rice-rice-soybean-rice-rice* crop sequence (AS09) in Lombok, Indonesia, on a highly permeable soil. Graphs a) and b) show APSIM performance in simulating the two (2) water treatments across a range of fertilizer treatments; Graph c) shows the three (3) fertilizer treatments across water treatments; whilst d) shows APSIM performance across all treatments.

SB01 was included to test APSIM's ability to simulate the effect of different fallow residue management practices (Figure 9 and 10). This experiment was conducted over 4 years at IRRI, Los Banõs, Philippines, comprising 7 consecutive rice crops and a particularly wide variety of season types (Bucher et al., 2001). The fallow periods had either crop residues retained or removed; combined factorially with +/- N. Figures 9 and 10 illustrate the performance of the APSIM model in predicting aboveground biomass and grain yield. Over the period of four (4) years and seven (7) consecutive rice crops for SB01, the comparison between simulated and measured grain yields for the minus-N treatments showed no decreasing trend in accuracy with time. The plus-N treatment yield dynamics are well simulated, indicating our calibration of *NH4_loss_fact* is performing well. Figure 10 illustrates measured vs simulated 1:1 plots for each treatment category, as well as all treatments combined. A tendency to underestimate grain yields is evident overall (Figure 10e), and particularly marked in the *Residue Retained* treatments (Figure 10c), in which total above-ground biomass was also under-predicted. This may indicate APSIM is immobilizing too much N during residue decomposition. Overall the correlation figures are remarkably good for crop production in this experiment, given a diversity of treatments over seven (7) consecutive crops with markedly different season types, employing no model resets of any kind whatsoever.

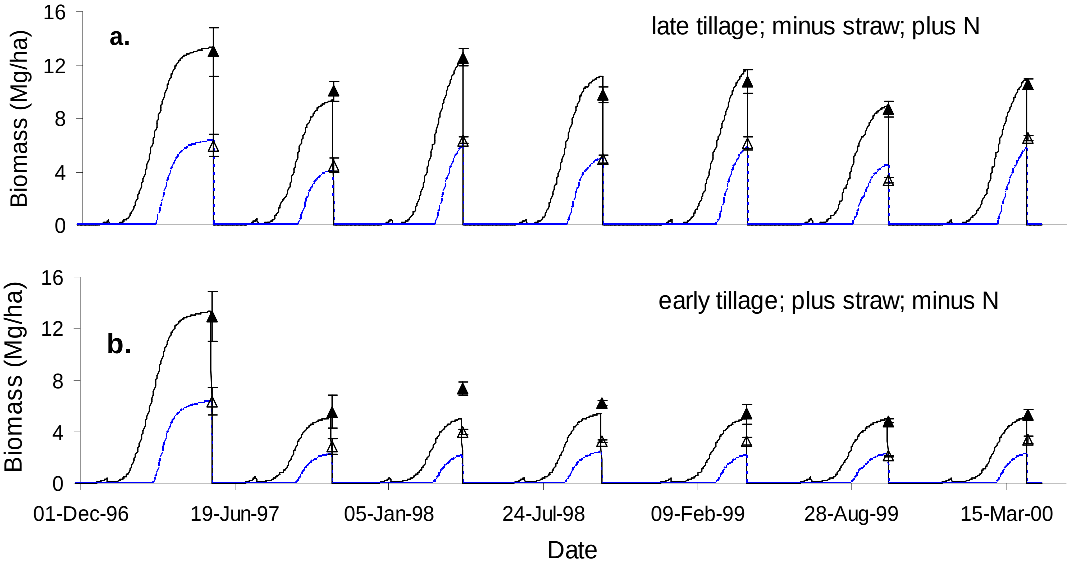


Figure 9. Performance of APSIM in simulating a 4 year continuous sequence of rice crops (SB01) at IRRI, Los Banos, Philippines, with a range of tillage, residue and nitrogen treatments (Two (2) out of six (6) experimental treatments shown). Simulated data is shown as solid lines (biomass - black; grain yields – blue), measured data as discrete points (biomass - ▲; grain yield - Δ) with associated error bars (1 x standard deviation either side of the mean) . A wide variety of season types were encountered over the 4 years of this experiment.

The final validation dataset (GB06) was included specifically to test the performance of the APSIM model in simulating several diverse crop sequences. This experiment also provided testing in a contrasting environment (temperate climate - southern Australia), and included measurements of nitrogen and moisture in the top

90cms of soil. For this reason we have used GB06 to illustrate the full system simulation capabilities of APSIM. Figure 11 shows simulated crop production, together with the dynamics of crop residues, soil NO_3 and NH_4, soil moisture, and ponding depth; presented against measured data where available. Within the bounds of experimental variability and standard uncertainties around model input parameters, APSIM captured the system dynamics well over the four years of the experiment, regardless of the management treatments imposed (Four treatments were simulated, but only one (Treatment 4) is illustrated). No system variable resets were used, suggesting the dynamics of nitrogen, water, crop production and residue decomposition are being sensibly simulated.

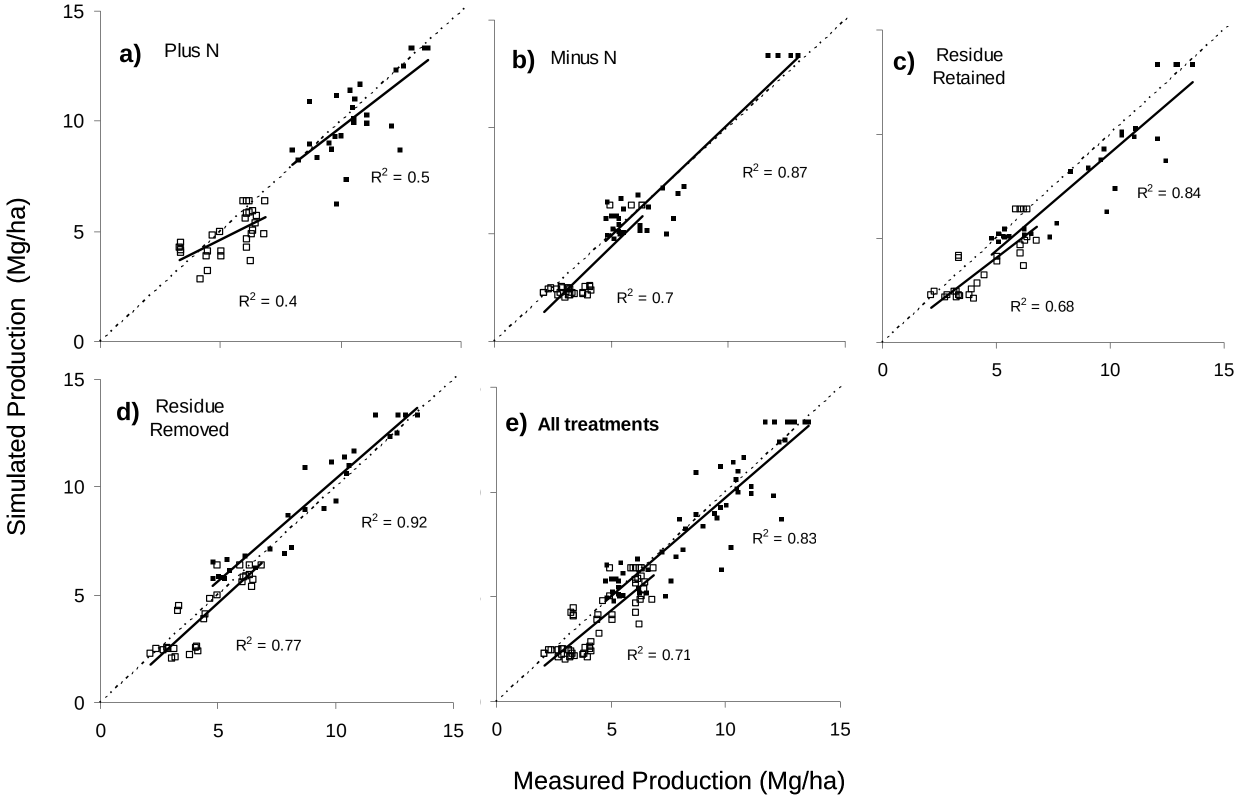


Figure 10. Performance of APSIM-Oryza in simulating a 4 year sequence of rice crops (SB01) at IRRI, Los Banos, Philippines, isolating the model's ability (across all associated treatments) to simulate the effect of **a)** added nitrogen; **b)** no added nitrogen; **c)** crop residues retained in fallows; **d)** crop residues removed in fallows. Graph **e)** shows the collated performance of the model across all treatments. Each graph shows grain yield (open symbols, □) and total biomass (black symbols, ■)

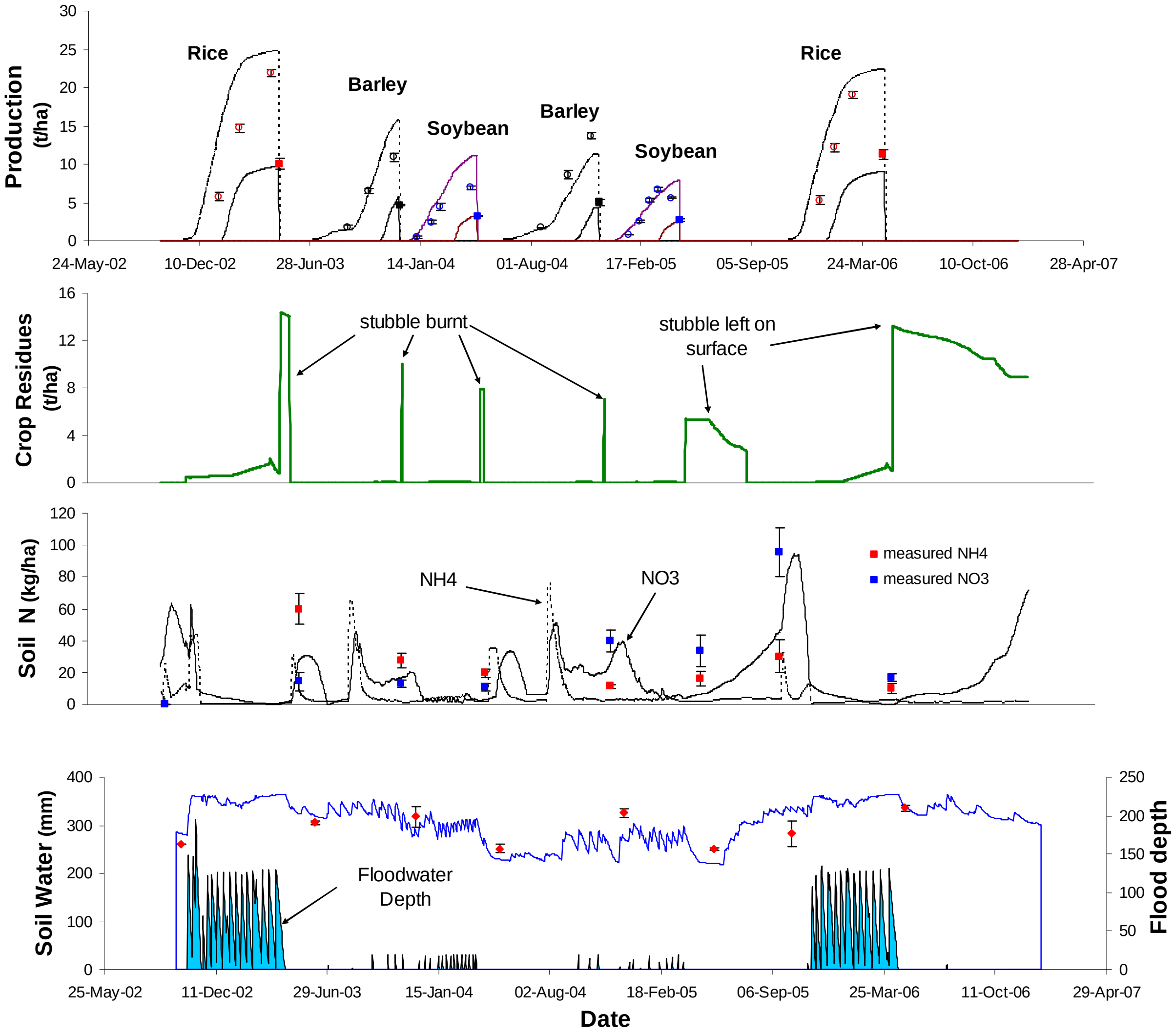


Figure 11. Simulated vs measured system data for GB06, Treatment 4: a rice-barley-soybean experimental rotation on a transitional red brown earth soil at Coleambally, NSW, Australia. Simulated production (t ha^{-1}), crop residues (t ha^{-1}), soil NH_4, NO_3 (kg ha^{-1}) and soil water (mm) in top 90cms soil, and floodwater depth (mm) are shown (Reference: Beecher *et al.* 2006). Ponded depths are less in treatment 4 of this experiment (*cf.* treatments 1 and 2) due to the presence of beds in the rice bays.

Scatter plots (1:1) were produced comparing observed and simulated grain yields across all validation datasets, for both rice and non-rice crops (Figure 12). Table 3 gives associated statistics. We consider that the overall R^2 value of 0.81, with low bias (α = 1.018, β = -323 kg/ha) provides strong evidence that our APSIM modifications are facilitating sensible system simulation over the wide variety of environments, managements, and seasons represented in our validation datasets. The overall RMSE of 1061 kg ha^{-1} is of the same magnitude, but considerably less than the overall standard deviation within the measured data (2160 kg ha^{-1}), suggesting acceptable model performance. The Student's paired T-test (assuming non-equal variances) gave a significance of P(t) = 0.43, indicating that there is no statistical difference between measured and simulated data at the 95% confidence level, whilst the high overall EF of 0.79 indicates the model is performing acceptably.

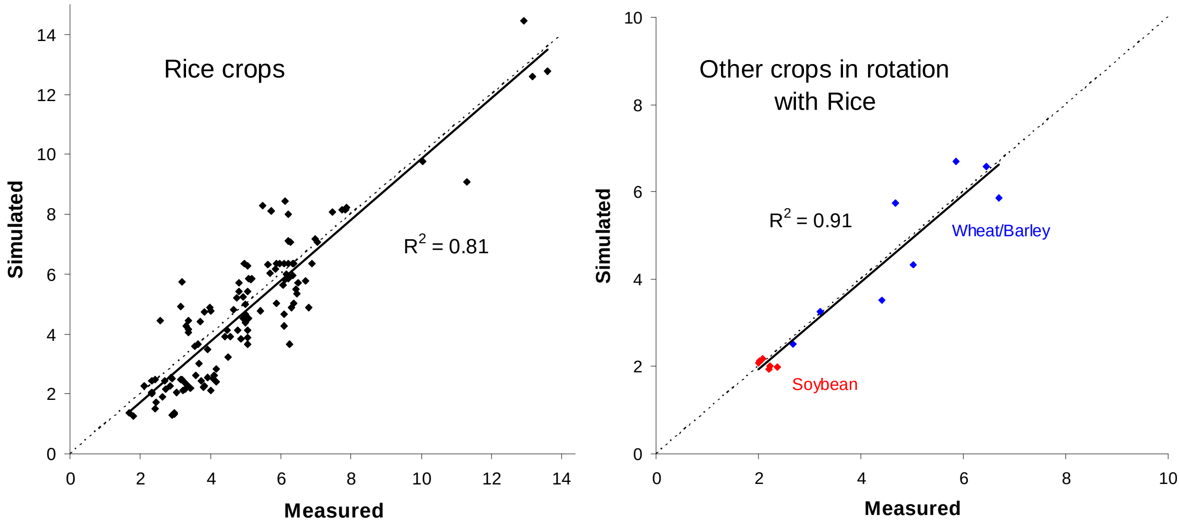


Figure 12 Comparison between measured and simulated grain yields (t ha^{-1}) for all validation crop sequence experiments, for a) *rice crops*; and b) *non-rice crops* in rotation with rice

The diversity of calculated values of the SAM indicates the broad environmental variability of the validation datasets used (Table 4). The values range from positive in the Philippines (0.23 for RB85) indicating less cumulative reference evapotranspiration than rainfall over the March to October reference period, to strongly negative in Australia (-0.564 for GB06) indicating much drier conditions (greater evapotranspiration than rainfall). Simulations gave acceptably high modelling efficiencies (EF) for grain yield across the range, leading to a model robustness (I_R) of 0.27. This compares well with published figures for several modern rice crop models (0.1632 – 0.3719; WARM, CropSyst, and WOFOST, Confalonieri et al., 2010) reporting above-ground rice biomass.

Table 3 Statistics for measured vs simulated rice yield across the datasets

Dataset abbreviation	**N**	**X_{meas}(SD)** (kg ha^{-1})	**X_{sim}(SD)** (kg ha^{-1})	**P(t)**	**α**	**β** (kg ha^{-1})	**R^2**	**RMSE** (kg ha^{-1})	**EF**
AB04	31	4135 (1562)	4227 (2224)	0.85	1.20	-751	0.71	1214	0.38
AS09	24	5319 (1366)	5708 (1798)	0.4	1.19	-644	0.82	874	0.57
SB01	56	4496 (1462)	3885 (1571)	0.04	0.91	-196	0.71	1043	0.48
RB85	5	5599 (1129)	4855 (901)	0.28	0.80	395	0.99	773	0.41
GB06	5	12204 (1487)	11733 (2240)	0.71	1.23	-3317	0.67	1281	0.37
Overall (combined)	121	4931 (2160)	4699 (2423)	0.43	1.02	-323.23	0.82	1061	0.79

N, number of data pairs; X_{meas}, mean of measured values; X_{sim}, mean of simulated values; SD, standard deviation; P(t), significance of Student’s paired t-test assuming non-equal variances; α, slope of linear regression between simulated and measured values; β, y-intercept of linear regression between simulated and measured values; R^2, square of linear correlation coefficient between simulated and measured values; RMSE, absolute root mean squared error; EF, the modelling efficiency.

Table 4. Calculation of Model Robustness index, I_R, using standard deviations of the synthetic agro-meteorological indicator, SAM, and the modelling efficiency, EF. (Equation 4). Rice grain yield was the variable of focus.

Dataset	**Av. SAM**	**EF**
AS09	-0.228	0.573
AB04	-0.225	0.376
SB01	0.093	0.481
RB85	0.244	0.414
GB06	-0.564	0.37
Standard deviation	σ_{SAM} = 0.315	σ_{EF} = 0.085
$I_R = \sigma_{SAM} / \sigma_{EF} = 0.27$		

It is particularly relevant that we have compared observed and simulated grain yields for crops *in sequence*, not *individual* crops with initialized system variables at the commencement of each growing season. For the equivalent validation testing of the original stand-alone ORYZA2000 model, Bouman and Van Laar (2006) recorded an R^2 of 0.79 (with $\alpha = 1.123$, $\beta = -1197$, RMSE = 838 kg ha^{-1}), for an assembled dataset simulated as single crops, with conditions re-set at the start of each growing period. Using the same crop model (ORYZA2000), but with the added complexity of crop sequences involving fallows with no soil variable resets between crops, we have lost little in the performance of the APSIM-Oryza model in simulating grain yields. This provides evidence that our modelling of the rice-growing environment is robust.

The statistics for individual datasets (Table 3) revealed one (SB01) with a $P(t) < 0.05$, denoting a statistical difference between measured and simulated rice grain yields at the 95% confidence level. This dataset contained a variety of treatments relating to fallow residue management over a seven rice crop sequence, several treatments of which were simulated extremely well (Figures 9 and 10). For this reason, we sought to examine the sources of the revealed error more closely using the methods outlined by Kobayashi and Salam (2000). We calculated these three components of MSD for observed versus simulated comparisons in each factorial treatment in SB01 and presented them as a segmented summation of the MSD (Figure 13). This analysis yielded a clear picture of the treatments which exerted the greatest influence over the revealed error, and it also provided an insight into the nature of that error.

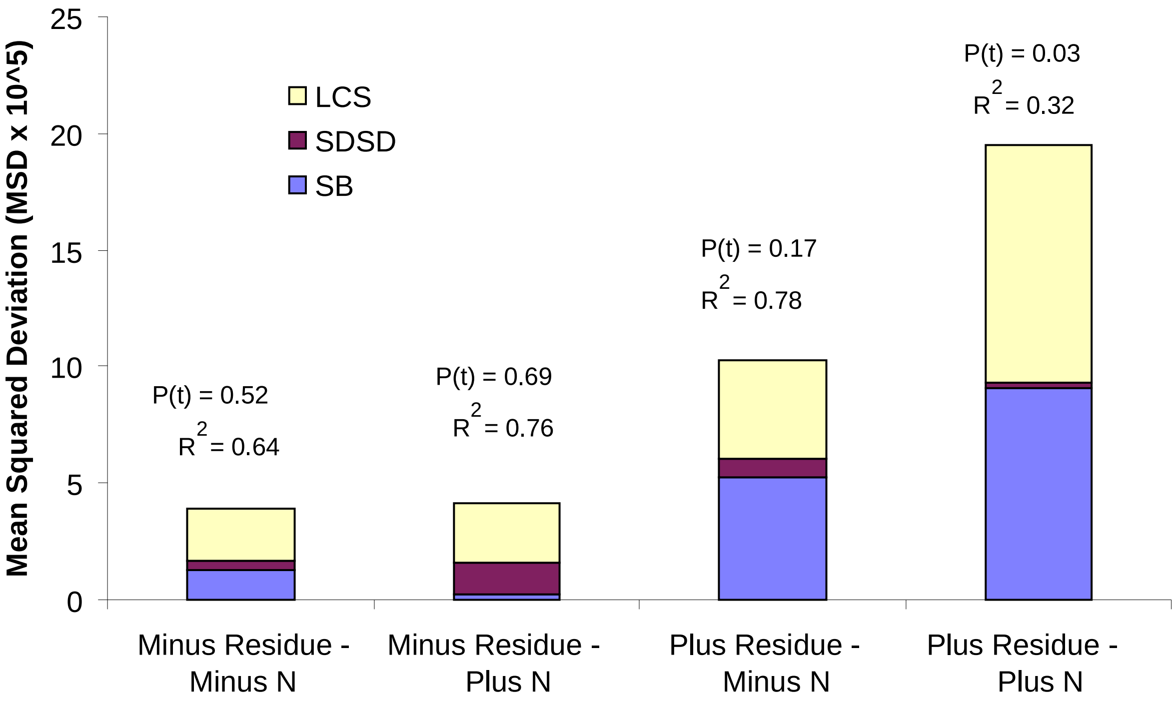


Figure 13. Breakup of the mean squared deviation (MSD) between simulated and measured rice yield data for four (4) treatment categories in SB01. MSD is the sum of the squared bias (SB), the squared difference between standard deviations (SDSD), and the lack of correlation weighted by the standard deviations (LCS) (Kobayashi and Salam 2000); P(t) is the significance of Student’s paired t-test assuming non-equal variances.

Figure 13 shows that the *Minus Residue* treatments were simulated well, with no statistical difference between observed and simulated grain yields for both the +/- N factorials at the 95% confidence level (P(t) > 0.05). The dominant source of error lay in the *Plus Residue* treatments, particularly in the +N factorial. An examination of the components of the MSD tell us that the SDSD was a small component of the error, indicating the modelled grain yields demonstrated similar sensitivity to changes in conditions as the observed grain yields. The largest source of error was the LCS, indicating a general lack of correlation between simulated and measured yields when residue was retained in the fallows, an error which was increased by the addition of N fertilizer. Anecdotal evidence from this experiment indicates that the fallows were often very wet during this four year experiment. This suggests that the simulation of N immobilization by residues during saturated fallows is a current weak point for APSIM, providing at least one direction for further work on improving this modelling framework.

DISCUSSION

The ability to simulate the performance of a *single crop* does not necessarily confirm accurate description of whole-of-system processes in a model. Most models have many empirical input parameters to adjust, and it is possible to achieve the “right results for the wrong reasons”, particularly when simulating a single crop (Bellocchi et al., 2010; Sinclair and Seligman, 2000). However successful simulation of *cropping sequences* (including several consecutive crops, fallows, season types, residue treatments and other management impositions), such as demonstrated in this paper, provides much greater confidence that the model is realistically capturing key system processes in both soil and crop arenas.

The soil environment is a complex ecosystem with numerous interacting physical, chemical and biological processes. This complexity is exemplified by transitions between flooded and non-flooded conditions. Some system elements are complex to model and the relevant variables even more complex to measure, making it difficult to directly confirm correct simulation. In our enhancements to APSIM we have chosen to ignore some well-known system processes (which other models have described at length) on the assumption they do not significantly impact on the key system variables we wish to simulate (crop yields, water-use and N-use efficiency etc.). Examples include the thin oxidized layer which develops at the surface of a submerged soil, and the aerobic rhizosphere which develops within millimetres of the crop roots. Both of these zones have been well studied, exhibiting N-transformational processes such as ammonification, nitrification, and denitrification, however we have assumed the scale of these processes does not warrant inclusion for a cropping systems model focused primarily on simulation of crop production. N transformations within these zones are implicitly captured within other calibrated parameters and constants, and are not modelled independently in our developments. We have also assumed that reduced soil conditions develop instantly following ponding of water on the soil surface, despite knowing in reality there is a lag period. Arah (2000) suggested that a comprehensive treatment of soil organic matter (SOM) transformation in flooded rice requires at least the following: (1) an account of below-ground O_2 transport, occurring primarily through the roots, and (2) an account of the direct influence of O_2 availability on SOM decomposition. Our model development philosophy has been to start with simple process descriptions of what we believe are the key processes driving system performance, only adding further process descriptions (or enhancing detail of existing descriptions) when simulations are not capable of capturing the dynamics of the measured data of interest. Whereas the assertions of Arah (2000) are not questioned, our aim with APSIM is ultimately to model agricultural production, not detailed SOM dynamics. APSIM does not model O_2 transport within the soil. Our simplified assumptions do not represent an alternative understanding of the key drivers of SOM dynamics, rather a basic attempt to simplify description of the system for simulation of crop production.

In this paper we have tested our assumptions and new model modifications against a diverse range of collated experimental rice-based cropping datasets. In the absence of widely available soil N data to directly test our model improvements, we used crop grain yields as an indirect surrogate measure of model performance. Simulations were performed over several years without any variable resets, simulating continuous dynamics of crops, water and soil. The particular focus for the testing has been crop sequences which exhibit alternate anaerobic and aerobic soil conditions, represented by flooded and non-flooded phases in rice-based rotations. The non-flooded phases in our data-sets have consisted of dry fallows between rice crops, in addition to non-rice crops. We have used published, replicated experimental datasets from Indonesia, Philippines, and Australia, capturing varying management impositions, and have used robust statistical methods to help understand the model's strengths and current weaknesses.

The results of comparisons between simulated and observed variables for these datasets have illustrated the strength of APSIM's new capacity to simulate the rice-growing environment for the purposes of modelling crop yields, and therefore the practicality of our modifications. Revealed error between our observed and simulated rice yields (APSIM-Oryza) showed little difference compared with those reported for the stand-alone ORYZA2000 (Bouman and Van Laar, 2006), which were obtained through testing against single crop data sets. This was despite our simulations including *sequences* of crops and fallows over several years with no soil variable resets between crops. This indicates APSIM was able to simulate the starting and finishing soil conditions for each crop as least as well on average as the ORYZA2000 researchers were able to initialize soil variables in each of their single-crop simulations.

The APSIM model showed particular strength in simulating varied crop sequences, response to applied fertilizers and the performance of bare fallows. Continuously submerged rice crops were simulated better than those with periods of mild water stress, however recent developments in ORYZA2000 science have addressed some of these shortcomings (Sudhir-Yadav et al., 2011b; Tao Li, personal communication) and these will soon be implemented within the now outdated APSIM-Oryza code. The model was able to simulate the performance of both PTR and DSR on several soil types and in several different environments. The simulation of retained crop stubble during fallows was identified as an area for improvement, with immobilization N dynamics likely to be a driving feature. Further testing of the model against observed data from AWD and aerobic systems would assist in addressing revealed shortcomings and better position the APSIM framework for future adaptation studies in which these management systems are likely to play a significant role. Further testing is also desirable in the simulation of new/future cropping systems, including newly emerging management options such as no-till direct-seeded rice/conservation agriculture, or a range of potential future nutrient management options. Specifically, datasets with detailed measurements of soil N and water, residues, and crop dynamics would be helpful in fine-tuning APSIM performance in such systems. APSIM is already capable of simulating total gaseous emissions of C and N (Probert et al., 1998), however further development work to segregate greenhouse gas (GHG) emissions into specific pools (N_2, NO_2, N_2O, CO_2, CH_4) would be desirable for adding an additional perspective to future simulation studies on management options in rice-based cropping systems. Further assessment is required on whether our simplifying model assumptions (for example, ignoring the thin oxidized soil layer and oxidized root zone) remain valid when GHG emissions are the output variable of focus.

CONCLUSIONS

Any simulation model aiming to assist in evaluating future adaptation strategies in rice-based cropping systems must be well tested in a range of possible configurations - different geographical locations, soil types, crop mixes and sequences, agronomic managements (fertilizer, sowing criteria, crop establishment and tillage practices), irrigation practices and variation in incident climatic variables such as temperatures and CO_2. In this paper we have described the initial efforts in improving the APSIM model for rice-based systems, and presented evaluation against a range of experimental datasets for cropping sequences involving rice. We have demonstrated the robustness of APSIM's new capacity to simulate the rice-growing environment (as affects crop production), and therefore the practicality of a number of simplifying assumptions and modifications. The validation testing has allowed identification of conditions under which the model is performing well (crop rotations; response to applied fertilizers; the performance of bare fallows) and areas in which to concentrate further work (simulation of N immobilization in retained crop stubble during fallows, greenhouse gas emissions). We will continue to seek datasets which allow further evaluation and enhancement of APSIM's capacity to simulate new and innovative practices, as well as a greater diversity of environmental conditions. The APSIM framework is now a useful tool to investigate the production impacts of future climate and resource scenarios in rice-based cropping systems, as well as potential adaptation options in response to changes. Further testing is required to evaluate the impact of our simplified assumptions on APSIM's simulation of greenhouse gas emissions in rice-based cropping systems.

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CHAPTER 3

Modelling the role of algae in rice crop nutrition and soil organic carbon maintenance

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Abstract

Photosynthetic aquatic biomass (PAB – algae and other floodwater flora) is a significant source of organic carbon (C) in rice-based cropping systems. A portion of PAB is capable of fixing nitrogen (N), and is hence also a source of N for crop nutrition. To account for this phenomenon in long term simulation studies of rice-based cropping systems, the APSIM modelling framework was modified to include new descriptions of biological and chemical processes responsible for loss and gain of C and N in rice floodwater. We used well-tested algorithms from CERES-Rice, together with new conceptualizations for algal dynamics, in modelling the contribution of PAB to maintenance of soil organic C and soil N-supplying capacity in rice-based cropping systems. We demonstrate how our new conceptualization of PAB growth, turnover, and soil incorporation in flooded rice systems facilitates successful simulation of long-term soil fertility trials, such as the IRRI Long Term Continuous Cropping Experiment (35 yrs+), from the perspectives of both soil organic carbon levels and yield maintenance. Previous models have been unable to account for the observed maintenance of soil organic C in these systems, primarily due to ignoring inputs from PAB as a source of C. The performance of long-term rice cropping system simulations, with and without inclusion of these inputs, is shown to be radically different. Details of our modifications to APSIM are presented, together with evidence that the model is now a useful tool to investigate sustainability issues associated with management change in rice-based cropping systems.

Keywords*:* APSIM, ORYZA2000, rice, cropping systems, biological nitrogen fixation, algae

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INTRODUCTION

The need for an enhanced modelling functionality

Gaydon et al (2012a) present an enhanced APSIM modelling framework capable of simulating transitions between flooded and non-flooded soils (in other words, anaerobic and aerobic soil environments). Such a simulation capability is essential for modelling cropping rotations and fallows which involve flooded (or occasionally flooded) rice in rotation with other crops and pastures. An additional element that must be addressed is simulating the substantial system inputs of C and N from photosynthetic aquatic biomass (PAB; algae) in rice-based systems. In addition to being an important source of soil C, certain components of algal communities are also able to fix N from the atmosphere, providing rice systems with special characteristics in sustainability.

Significance of biological nitrogen fixation (BNF) in rice-based systems

De (1939) attributed the natural fertility of tropical rice cropping systems to biological nitrogen fixation (BNF) by algae, and it is now well established that N fixation by blue-green algae or cyanobacteria plays a vital role in the build-up and maintenance of rice system soil fertility. Carbon assimilated by other floodwater flora and fauna also plays an important role in securing sustainability (in the long-term fertility context; on-going maintenance of rice production levels)(Greenland 1997). Lowendorf (1980) noted that the processes by which PAB-fixed N becomes available to the rice crop is largely a mystery. Exudation of nutrients from the living algae is understood to be one mechanism, however it appears that microbial decomposition after the death of the PAB is the principal means by which N is made available to the crop (Roger and Reynaud, 1979). In paddy fields the death of the PAB usually occurs with the end of the crop flooding period, after floodwater dry-down, when surface decomposition and/or subsequent tillage incorporates the PAB C and N contributions into the soil.

PAB growth results in a gradual build-up of soil fertility with a residual effect on, rather than an immediate benefit to, the standing rice crop (Roger and Kulasooria, 1980). In the Philippines, PAB growth did not significantly increase the yield of the standing crop but a build-up of N in the soil at the end of the crop was observed (Alimagno and Yoshida, 1975). In other words, PAB growth during any given rice crop contributes to the nutrition of the following rice crop – a genuine systems issue.

Estimates of fixed N from PAB vary from a few to 80 kilograms per hectare per crop. According to Roger and Kulasooria (1980), the average value of the reported estimates (30 kg N crop^{-1}) seems to constitute a satisfactory reference value. In another summary of extensive N balance studies, the contribution of indigenous BNF to wetland rice has been estimated to be 14-50 kg N ha^{-1} crop^{-1} (Roger and Ladha, 1992), with 20 kg N ha^{-1} crop^{-1} suggested as a mean contribution from cyanobacteria. More recently, four long-term rice experiments in the Philippines indicated indigenous BNF ranging from 19 to 44 kgN ha$^{−1}$ crop$^{−1}$ during a 15-yr period for zero-N treatments (Pampolino et al., 2008). There is evidence that BNF is inhibited by fertilizer N, (Roger and Ladha, 1992), with the mean BNF N contribution dropping from 30 to 4 kgN ha$^{−1}$ crop$^{−1}$ when fertilizer N was applied.

Considerably less fertilizer N is required in flooded rice systems to achieve the same grain yields as (for example) in wheat systems, due to the additional contribution from biologically-fixed nutrients. For example, on irrigated land in most Asian countries, rice farmers typically apply 100 to 150 kg N ha $^{-1}$ to the dry-season rice crop and 60 to 90 kg N ha $^{-1}$ to the wet-season crop (Doberman and Witt, 2000). Corresponding mean grain yields are 6-8 tonnes ha^{-1}. Achieving similar yields in continuous wheat cropping systems requires N fertilizer inputs in the range of 180-250 kg N ha^{-1} (Petrie et al. 2006). The zero-N treatment in the IRRI Long Term Continuous Cropping Experiment (LTCCE; Dobermann et al., 2000; Pampolino et al., 2008) has routinely achieved three rice crops per year, yielding a total of roughly nine tonnes of grain per annum, for 35 consecutive years with no applied N fertilizer. Clearly, it is essential to capture this phenomenon in simulation models designed for long-term yield maintenance studies in rice-based cropping systems.

The community of PAB within rice floodwater is a highly variable and complex mix of species, with the cyanobacteria proportion varying between locations, management practices, and stages of the crop. For example, cyanobacteria in an Italian paddy field comprised 30% of the total algal biomass (Materasi and Balloni, 1965), whereas a 95% figure was measured in Senegal (Roger and Reynaud, 1976). In Japan, PAB was more abundant in fields where the soil was waterlogged throughout the year than in nearby fields with intermittent waterlogging (Okuda and Yamaguchi, 1952). Additionally, alternate drying and wetting of a field throughout the phase of rice germination suppressed a detrimental growth of green algae and favoured cyanobacteria. Roger and Kulasooria (1980) also suggests that the cyanobacteria component changes throughout the crop cycle, with a mean of 2% of total biomass at the start, increasing to a mean of 38% between heading and maturity under dense plant cover. Clearly, the simulation of PAB inputs to rice cropping systems represents a considerable challenge in both process description and parameterization.

Most crop models for rice have focussed on simulating single rice crops rather than sequences of crops. As such, the contribution by PAB to soil C and N is a less significant process, and approaches taken in the past have captured N inputs in a simplified fashion as ‘indigenous soil contribution’ of N, but C is largely ignored (for example, CERES-Rice (Godwin et al., 1990); ORYZA2000 (Bouman and Van Laar, 2006)). Because of the focus of these models on single rice crops, small in-season changes to soil organic C are not significant. This has resulted however in the inability of CERES rice and other crop models to simulate long-term datasets like LTCCE. If a cropping systems model is required to simulate production from long-term sequences of crops and sustainability issues (ie, maintenance of soil organic C and soil N supplying capacity), then simulating the inputs of C and N from PAB become important. PAB inputs will vary with different season types and crop management. The concept of a fixed ‘indigenous contribution’ does not capture these dynamics.

In this paper, we present a simplified, yet responsive method for capturing the contributions from PAB in rice-based cropping systems, enabling realistic long term simulation of cropping sequences involving rice. We present cross-referenced testing of this method against the LTCCE measurements for both grain yield and soil organic C.

MODEL DESCRIPTION: APSIM-POND

A new module, APSIM-Pond, was developed to simulate key chemical and biological processes occurring within a flooded layer of surface water. A dynamic floodwater temperature balance is maintained, calculated daily as an energy balance between atmosphere, floodwater, soil temperature, and incident radiation. The floodwater temperature calculations are from CERES-Rice and are based on SALUS soil temperature routine (Schulthess and Ritchie, 1996):-

$$FT_{\max} = ST(1) + AT_{\max\_diff} \times \left(F_{depth\_t\max} - F_{evap\_effect} - F_{rad\_effect}\right) \tag{1}$$

$$FT_{\min} = ST(1) - AT_{\min\_diff} \times \left(F_{depth\_t\min} + F_{rad\_effect}\right) \tag{2}$$

Where FT_{max} and FT_{min} are the maximum and minimum daily floodwater temperatures, respectively (°C); ST(1) is the soil temperature in layer 1 (°C); AT_{max_diff} and AT_{min_diff} are maximum and minimum atmospheric temperature variations from the average daily temperature (for the current day) (°C); F_{depth_tmax} and F_{depth_tmin} are the floodwater depth effects on FT_{max} and FT_{min} respectively (defined in equations 3 and 4 below); F_{evap_effect} is the cooling effect due to evaporation from the floodwater surface, as calculated below (Equation 5) ; F_{rad_effect} is the warming effect due to incident solar radiation (Equation 6). The floodwater depth effects are calculated as follows:

$$F_{depth\_t\max} = \left(FT_{\max\_diff} \div AT_{\max\_diff}\right) + 0.65 \times \left((40 - FDEPTH) \times 0.025\right) \tag{3}$$

$$F_{depth\_t\min} = \left(FT_{\min\_diff} \div AT_{\min\_diff}\right) + MIN\left(((40 - FDEPTH) \times 0.025) \times 0.9, 1.0\right) \tag{4}$$

Where *FDEPTH* is the floodwater depth in centimeters; and *MIN* is a fortran function for calculating the minimum of two values. The floodwater evaporative cooling effect is calculated as follows:

$$F_{evap\_effect} = MIN\left(1.0, (ET \div FDEPTH) \times 6.0\right) \tag{5}$$

Where *ET* is the evapotranspiration (cm). The floodwater warming effect due to incident solar radiation is calculated by:

$$F_{rad\_effect} = 1.0 - \left[(1.0 - ALBEDO) / (1.0 - WATER\_ALBEDO)\right] \tag{6}$$

Where *WATER_ALBEDO* is assumed to equal 0.05, and the surface albedo (*ALBEDO)* is a function also of the crop leaf area index (*LAI)* as defined below (Equation 7):

$$ALBEDO = 0.23 - (0.23 - WATER\_ALBEDO) \times e^{(-0.75 \times LAI)} \tag{7}$$

Similarly a dynamic floodwater pH balance is maintained, as a function of algal photosynthetic activity (causing a shift in pH; *pH_shift*) and urea hydrolysis activity. The floodwater pH expressed as a function of the intra-daily timestep (i = 1 to 12) and *pH_shift* is:

$$pH_{floodwater} = 7.0 + \left[pH\_shift \times \sin\left(\frac{\pi \times i}{12}\right)\right] \tag{8}$$

Where *pH_shift* (equation 9) is defined by the algal activity factor, *algact* (equation 19).

$$pH\_shift = 0.5 + (2.0 \times a\lg act) \qquad (9)$$

Additionally, the effect of urea hydrolysis on the pH of the floodwater is added whenever FUHYDR (Equation 11) is greater than 0.05 kg N ha^{-1} timestep^{-1}. Equation 10 describes the implementation, as a function of the available light index (*ali* – equation 20) and a factor describing the urea hydrolysis effect on water pH (F_{pH_uhyd}) (Godwin and Singh, 1998):

$$pH_{floodwater} = pH_{floodwater} + \left[\frac{ali \times (10.0 - F_{pH\_uhyd})}{10.0}\right] \qquad (10)$$

We calculate the above balances on a two-hourly time-step basis (by deriving sinusoidal distributions for intra-daily temperature and radiation based on daily measured values from the climate record, and subsequent interpolation on a two-hourly basis) to capture the rapid reaction rates. In doing so, we followed the methods of CERES-Rice (Godwin and Singh, 1998). Both floodwater temperature and pH are important variables in modelling the key chemical and biological processes described below (with reference to Figure 1).

A. *Urea hydrolysis.* The breakdown of applied urea fertilizer to NH_4^+ is described as a daily function of floodwater temperature and a soil-determined hydrolysis rate (a function of organic C in top soil layer) or an algal activity determined rate, whichever is greater (Godwin and Singh 1991) (Equation 11).

$$FUHYDR = \max(pot\_hydrolysis, UALGCT) \times TEMPFU \times pond\_urea \qquad (11)$$

Where *FUDHR* is the floodwater urea hydrolysis rate (kg N ha^{-1} timestep^{-1}); pot_*hydrolysis* is the soil-determined hydrolysis rate (timestep^{-1}) defined below in equation 12; UALGCT is the algal activity factor affecting urea hydrolysis (timestep^{-1}) defined in equation 13; TEMPFU is the temperature effect on floodwater hydrolysis (0-0.9) defined in equation 14; and *pond_urea* is the floodwater urea (kg N ha^{-1} as urea). *Max* is a fortran function returning the largest of two values.

$$pot\_hydrolysis = 0.008 + (0.005 \times OC\%) \qquad (12)$$

$$UALGCT = 0.1 \times algact \tag{13}$$

$$TEMPFU = 0.04 \times (FTEMP + 0.2) \tag{14}$$

Where *OC%* is the organic carbon percentage in the top soil layer; *algact* is the daily algal activity factor (0-1) defined in detail further below (Equation 19); *FTEMP* is the interpolated floodwater temperature for the timestep (^{o}C) defined below (Equation 15).

$$FTEMP = FTMIN + HTMFAC \times (FTMAX + 2.0 - FTMIN) \tag{15}$$

Where *FTMIN* is the daily minimum floodwater temperature (^{o}C); *FTMAX* is the daily maximum floodwater temperature (^{o}C); and *HTMFAC* is a floodwater temperature factor which increases from near zero at the beginning of the day to almost one at midday to zero at the end of the diurnal cycle (Godwin and Singh, 1998).

B. *Ammonia volatilization.* Floodwater ammonia (NH_3) exists in equilibrium with floodwater ammonium (NH_4^+) in proportions calculated using the floodwater temperature (*TK*; in Kelvin) and pH (Godwin and Singh, 1998) (Equation 16):

$$[NH_3]_{floodwater} = \frac{[NH_4^{-}]_{floodwater}}{1.0 + 10^{\left(0.009018 + \frac{2729.92}{TK} - pH_{floodwater}\right)}} \tag{16}$$

The partial pressure of NH_3 is calculated from the overall floodwater NH_3 concentration as a function of floodwater temperature (Freney et al., 1981). This partial pressure of NH_3 provides the potential for NH_3 volatilization and N-loss to the atmosphere. This loss potential is a function of wind and floodwater depth (Godwin and Singh 1991). In the absence of wind data, we use a calibrated surrogate constant *NH4_loss_fact* (Gaydon et al, 2012a). We apply this factor to the calculated partial pressure of ammonia for determination of volatilization according to equation 17.

$$amlos = 0.036 \times fnh3p + (NH4\_loss\_fact \times evap) \times (0.0082 + 0.000036 \times fnh3p^{2} \times FDEPTH) \tag{17}$$

Where *amlos* is the daily ammonia loss (kg ha^{-1}); *fnh3p* is the partial pressure of ammonia; *evap* is pan evaporation (mm); and *FDEPTH* is the depth of the floodwater (mm).

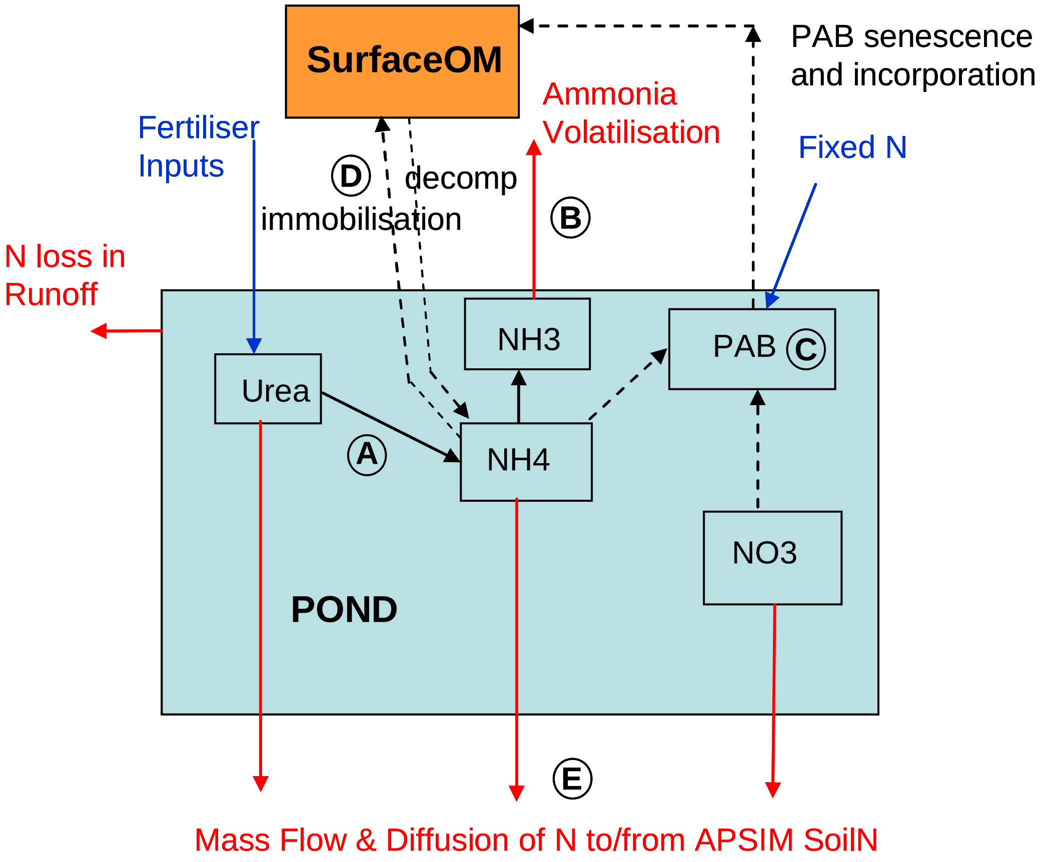


Figure 1. Processes simulated in the APSIM-Pond module; **A** – urea hydrolysis; **B** – NH_3 volatilization; **C** – PAB growth and turnover; **D** – surface residue decomposition; **E** – flux of solutes to and from the soil.

C. *PAB growth and turnover.* Our conceptualized dynamics of PAB growth within a rice crop is illustrated in Figure 2. Godwin and Singh (1991) described the calculation of an algal activity factor which influences urea hydrolysis and floodwater pH. We use this factor but also calculate the daily algal growth and accumulated biomass as follows:

$$dlt\_pab = \max rate\_pab \times a\lg act \qquad (18)$$

Where *dlt_pab* is the daily growth of PAB (kg/ha), *maxrate_pab* is the maximum (unconstrained) daily growth rate of PAB (kg/ha/day). The daily algal activity factor, *algact* (Godwin and Singh 1991), is a function of available light (solar radiation, reduced by canopy cover), floodwater temperature, phosphorus, and mineral N availability (Equation 19).

$$algact = \min[ali, fti, fni, fpi] \tag{19}$$

Each of these potentially limiting components is represented by a 0-1 factor, and on any given day *algact* is assumed to be equal to the minimum (or most limiting) of these (Figure 3). These factors include, a light factor (*ali*), temperature factor (*fti*), nitrogen factor (*fni*), and phosphorus factor (*fpi*), defined as follows: The light factor estimates the fraction of radiant energy (*radiation;* MJ m^{-2} day^{-1}) passing through the crop canopy and reaching the floodwater surface:

$$ali = 1 - e^{\left(\frac{-frad}{5.0}\right)} \tag{20}$$

Where:

$$frad = radiation \times (1 - WATER\_ALBDEDO) \times e^{(-0.65 \times lai)} \tag{21}$$

Godwin and Singh (1991) state that shape of this relationship is rather arbitrary but designed to be asymptotic at 15 MJ m^{-2} day^{-1} to account for light saturation. The effect of changes in floodwater depth and turbidity are not considered. The temperature factor, *fti*, increases linearly from a zero value at 15 ^{o}C to unity at 30 ^{o}C, then decreases linearly again to zero at 45 ^{o}C. The nitrogen factor, *fni*, relates the relative propensity for algal growth to the floodwater N concentration (ppm) (Equation 22):

$$fni = \frac{[NH_4]_{floodwater} + [N0_3]_{floodwater}}{15.0} + 0.1 \tag{22}$$

Godwin and Singh (1991) once again suggest that the shape of the relationship is arbitrary in nature, but becomes asymptotic to a value of unity at around 20 mg N litre^{-1}, at which point algal growth is assumed to be fully supplied with any potential N requirements. The contribution of N-fixation to PAB growth is captured by setting a minimum value of 0.1 for *fni*, which is realized in the absence of floodwater mineral N (Equation 22). Under such circumstances, PAB growth may continue, albeit at this reduced rate. The value (*fni* = 0.1) for the N-fixation-limited growth rate was in accordance with the algal activity calculations of Godwin and Singh (1991) in CERES-Rice, and represents the background activity of N-fixing cyanobacteria in the absence of floodwater mineral N. The addition of fertilizer to the floodwater results temporarily in freely available mineral N, and the subsequent spikes in *fni* reflect the blooms in PAB which often accompany fertilization (Figure 3).

The final limiting factor, *fpi*, is an attempt to accommodate the significant effects of P on algal activity, even though APSIM-Pond does not simulate a P balance. This index has only two possible values which are set at the beginning of each simulation by the user, based on the presence (fpi =1.0) or absence (*fpi* = 0.5) of phosphatic fertilizer. The actual daily growth rate (*dlt_pab*) is then calculated by limiting the potential daily growth rate (*maxrate_pab*) by *algact* as expressed in equation 19. A *net* average PAB growth rate of 20 kg ha^{-1}d^{-1} was suggested by Roger (1996), however there is evidence that maximum potential (non-limited) PAB growth rate is considerably higher (Norsker et al, 2011). Hence, we have treated *maxrate_pab* as a calibrated parameter in APSIM-Pond, due to the potentially complex ecological compositions of PAB species in different environments (see calibration process in section 3.1). Floodwater PAB is constrained to a maximum of 500 kg ha^{-1} (maximum observed in practice; Roger, 1996), with C content of 40% and C:N of approximately 8 (Roger, 1996). As PAB accumulates biomass, N uptake is preferentially from mineral N in the floodwater. When PAB N demand outstrips mineral N supply in the floodwater, *fni* will become a limiting factor to growth, and the PAB production rate is limited to a maximum of ten percent (0.1 x) of the potential daily growth rate to reflect that BNF by cyanobacteria is now driving the growth of PAB in the floodwater. A significant new element of APSIM-Pond is our conceptualization and description of ‘algal turnover’. If the maximum PAB biomass of 500 kg ha^{-1} is reached before full canopy closure, further PAB production is theoretically possible. In this case, we assume that subsequent potential daily PAB growth is matched by PAB senescence, added to the APSIM Surface Organic Matter pool (Probert et al., 1998) on a daily basis. In addition to senesced PAB, which can decompose in the floodwater and enter the soil as mineral N on a daily basis, the total PAB biomass is added to the surface organic matter pool after draining-down of the rice paddy.

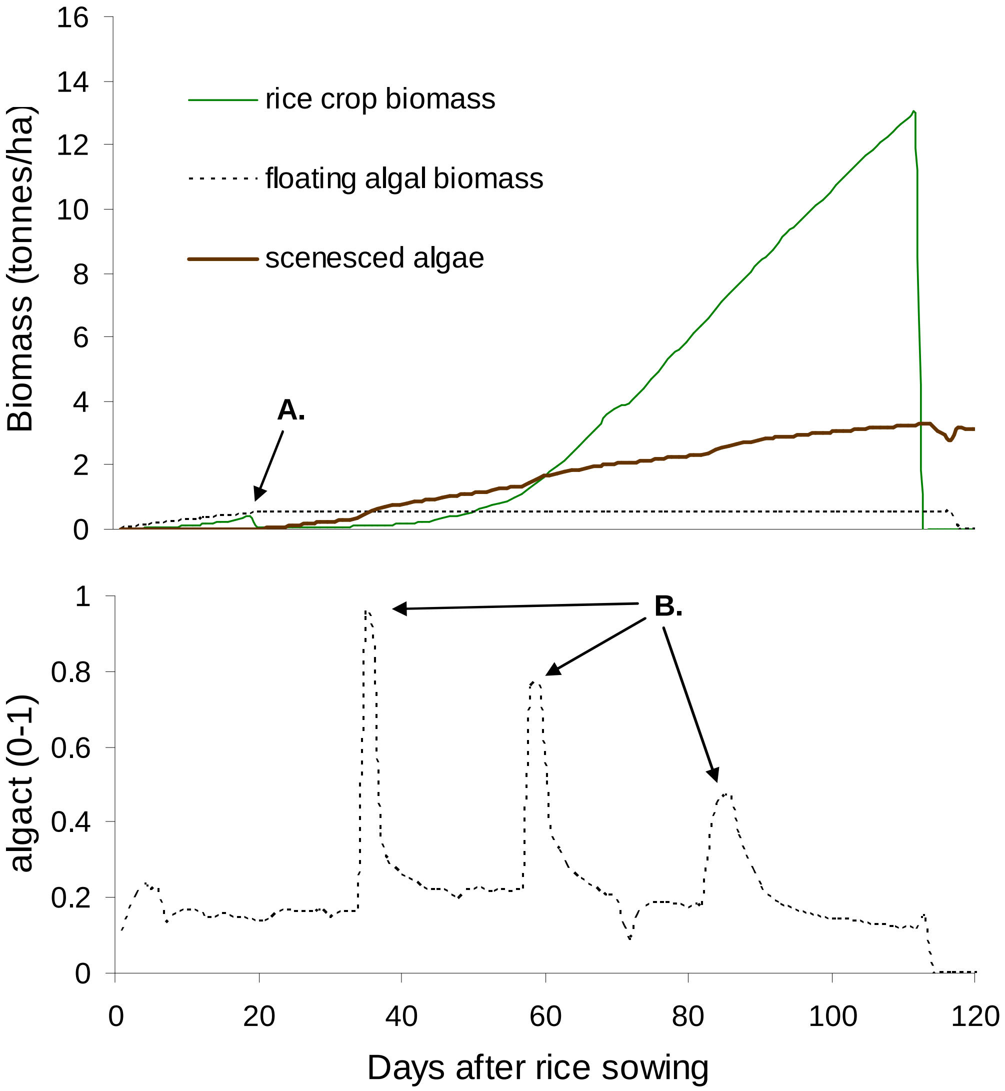
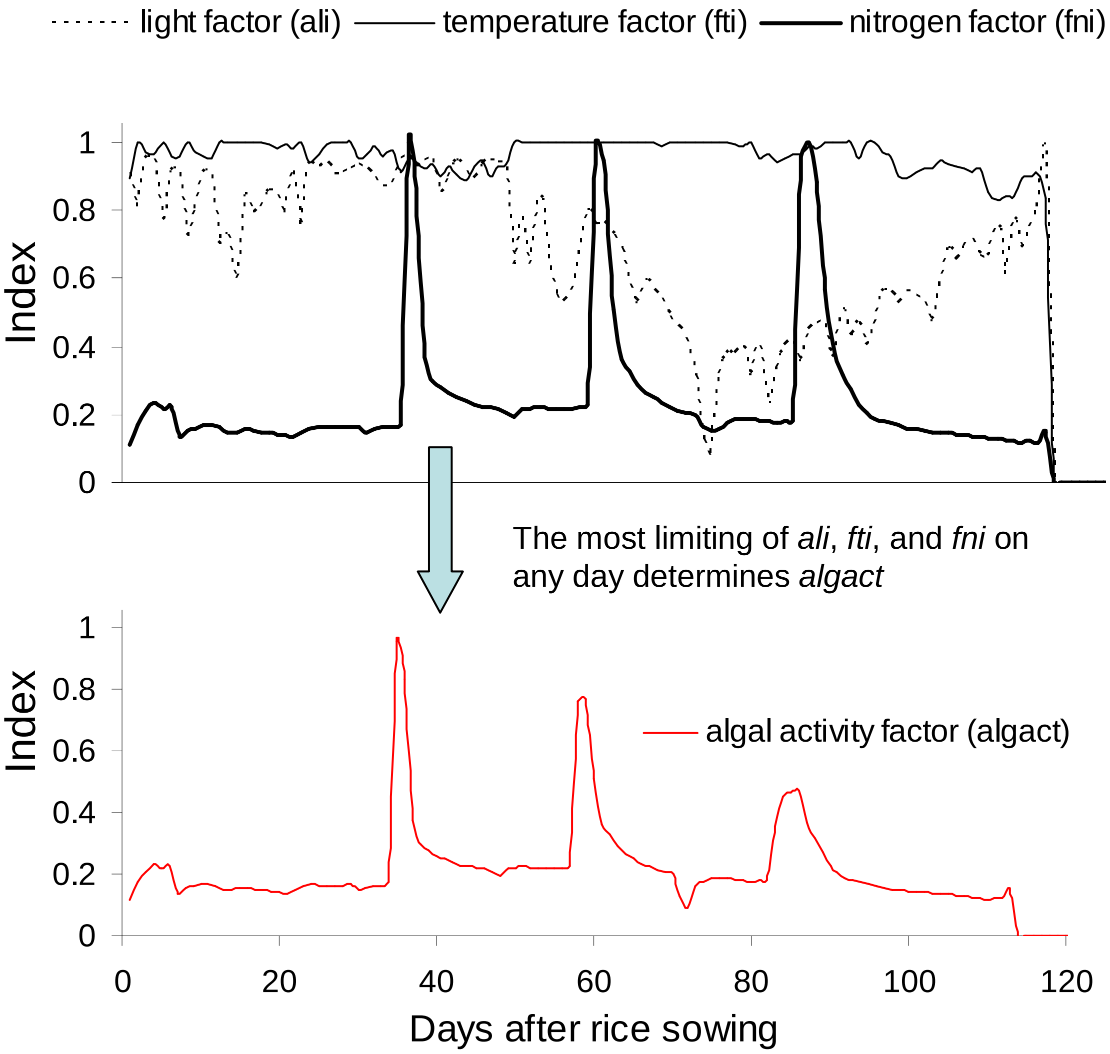


Figure 2. APSIM-Pond conceptualized algal growth dynamics within a rice crop. Floating algal biomass accumulates until the maximum allowable mass is reached (point A; 500 kg/ha (Roger 1996)). If algal growth potential still exists after this point (ie Algal Growth Factor, *algact* > 0), then any further algal production is assumed to be balanced by senescence, leaving the floating mass unchanged. Senesced material is transferred to the APSIM-Surface Organic Matter pool, and can be decomposed. Points B illustrate peaks in algal activity, associated with fertilizer N application.



The most limiting of *ali*, *fti*, and *fni* on any day determines *algact*

Figure 3. The algal activity factor (*algact*) is determined by the most limiting (minimum) of four controlling (0-1) factors; the light factor (*ali*), the temperature factor (*fti*), the nitrogen factor (*fni*), and the phosphorus factor (*fpi* – not shown, assumed to be 1.0 in this example, ie phosphorus not limiting). The minimum value possible for *fni* is 0.1, recognizing the capacity for PAB N-fixation in the absence of floodwater mineral N, yet slowing the potential growth rate of PAB under N-fixing conditions.

There it can decompose *in situ* or be incorporated into the soil (via tillage) as per management specified. To simulate situations where live PAB may sit viably on the wet surface of the soil during intermittent dry-down of floodwater (such as in *alternate wet-and-dry* (AWD) irrigation practice, Bouman et al., 2007) and then revive on re-flooding, we do not add the PAB to the ASPIM surface organic matter pool until a period of 5 days with no floodwater has passed.

D. *Immobilization of floodwater mineral N.* When surface organic matter is decomposed in dryland APSIM simulations, the APSIM-SurfaceOM module creates an N-immobilization demand which it attempts to satisfy from APSIM-SoilN (Probert et al., 1998). Now, when APSIM-Pond is present, this demand is sought from APSIM-Pond mineral N pools. Similarly, mineral N released in decomposition becomes part of the APSIM-Pond mineral N pools. If floodwater is present, the moisture factor for decomposition of residues (Probert et al, 1998; Thorburn et al, 2001) is set to 0.5 to account for lower potential decomposition rates in water.

E. *Flux of solutes to/from soil.* The N pools (urea, NO_3^-, and NH_4^+) represented in APSIM-Pond are transferred to/from the soil on a daily basis via the processes of mass flow and diffusion. For mass flow calculations, the fraction of floodwater infiltrating (*infiltration_frac)* is calculated daily by dividing the depth of water infiltrating (*infiltration*) by the total floodwater depth (*FDEPTH*):

$$\inf iltration\_frac = \left(\frac{\inf iltration}{FDEPTH}\right) \tag{23}$$

This factor is then applied to the mass of each of solute in the floodwater to determine the mass entering soil layer 1 that day. For diffusion calculations, the concentration of each solute in the floodwater is compared with that in soil solution of layer 1. When the concentrations are different in the two compartments, a “diffusion process” is invoked to determine the flux. This is a simple process for the highly soluble NO_3^- and urea components, as both floodwater and soil pools are assumed to be freely diffusible. An effective diffusion coefficient (*DE*) is calculated for each of the urea and NO_3^- pools, as a function of an aqueous diffusion coefficient (*AQDC*), the saturated volumetric moisture content of soil layer 1 (*SAT*), and a *tortuosity* factor (equal to $\sqrt{SAT}$; Nye and Tinker, 1977) (Equation 24):

$$DE = AQDC \times (1.0E-5) \times tortuosity \times SAT \tag{24}$$

The actual diffusion rate (*DIFFN* (kg N ha^{-1} timestep^{-1})) is then calculated as a function of the diffusion coefficient (DE), the difference in the solute concentrations between the floodwater and soil for the solute in question (*DELC*), the diffusion distance (DELX; we assumed half the distance of the top soil layer), and the timestep (Equation 25):

$$DIFFN = \frac{DELC}{DELX} \times DE \times timestep \tag{25}$$

The flux of NH_4^+ between floodwater and soil is more complex, and requires determination of the diffusible component of soil NH_4^+ (in other words NH_4^+ that is not adsorped onto clay particles in the soil). A Langmuir isotherm (Equation 26) is used to calculate this freely diffusible NH_4^+ proportion as a function of the surface soil cation exchange capacity (*CEC*) and the concentration of NH_4^+ in the soil ($[NH_4]_{soil}$), in accordance with the methodology of Godwin and Singh (1998):

$$[NH_4]_{diffusable} = \exp\left((4.1 - 0.07 \times CEC) \times a\log[NH_4]_{soil} - 1.83\right) \tag{26}$$

A concentration gradient is then determined, and a positive or negative flux is calculated for the NH_4^+ in solution, as previously described for the NO_3^- and urea components. The only difference for NH_4^+ is that the calculated *DE* is additionally divided by the soil ammonium buffering power (*BP*), calculated as a function of the surface soil CEC.

$$BP = 30.0 \times \left(1.0 - e^{(-0.065 \times CEC)}\right) \tag{27}$$

CEC is a new required APSIM-Pond input parameter. The source code to all APSIM modules is freely available to the public at http://www.apsim.info under the 'products' tab.

F. *Nitrification and denitrification*

We have simplified the representation of the floodwater environment in APSIM-Pond by neglecting to simulate the processes of nitrification and denitrification in the floodwater, as per the approach of CERES-Rice (Godwin and Singh, 1998). Simulation of both these processes in APSIM is possible and captured as soon as solutes enter the soil profile, depending on degree of soil saturation, temperature and pH conditions, following Michaelis-Menton kinetics as described by Probert et al., 1998.

MODEL EVALUATION

Model evaluation was performed in two stages using field data from the LTCCE (Table 1); an initial adjustment of the empirical parameter *maxrate_PAB* through iteratively comparing simulated and observed data for soil organic C (*calibration),* followed by testing of the calibrated model against the observed grain yield figures (*validation*).

Calibration of empirical parameters

Maximum potential daily growth rate of PAB

Increases in soil organic C measured during the LTCCE are essentially independent of fertilizer treatment, and are believed to have resulted from BNF from PAB in these systems (Figure 4; Pampollino et al., 2008, error bars not available).

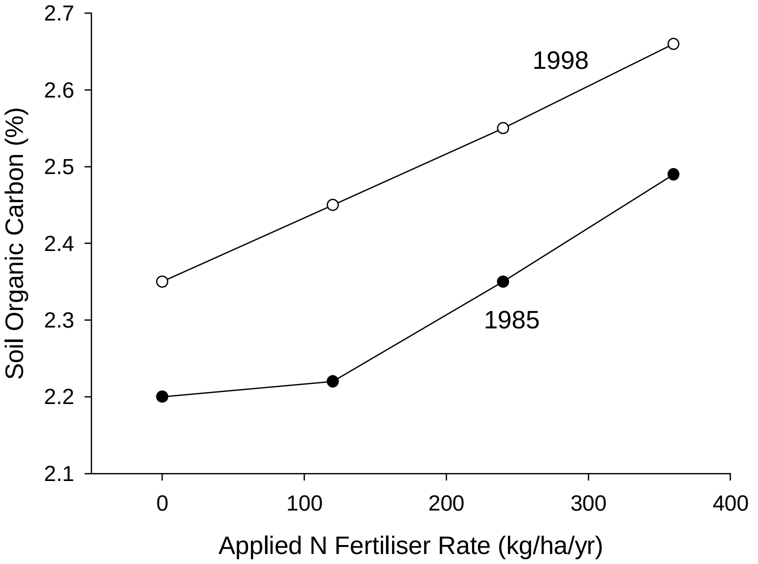


Figure 4. Measured changes in surface soil (0- 20cm) organic carbon during the IRRI Long Term Continuous Cropping Experiment (LTCCE) (Dobermann et al., 2000, Pampolino et al., 2008), as a function of N fertilizer applied to each rice crop. Three rice crops per year were produced between 1985 and 1998; all above-ground crop residues removed from the field. No information on experimental variation between treatment replications was available.

Dataset abbreviation	Reference	Location	Years	Treatments	Crops/varieties	Measurement Details
Calibration and Validation						
LTCCE (IRRI Long Term Continuous Cropping Experiment)	Doberman et al (2000) Pampolino et al (2008)	IRRI, Los Banos, Philippines	1985-1998	0, 150, 240, 360 kgN ha^{-1} per annum. Three (3) rice crops per year	PTR/IR8, various	*Calibration* Changes in surface soil organic carbon (top 20cms) *Validation* Rice production (yield)

Table 1: Details of the field experiment used in the calibration and validation of the APSIM-Pond model (PTR-puddled transplanted rice)

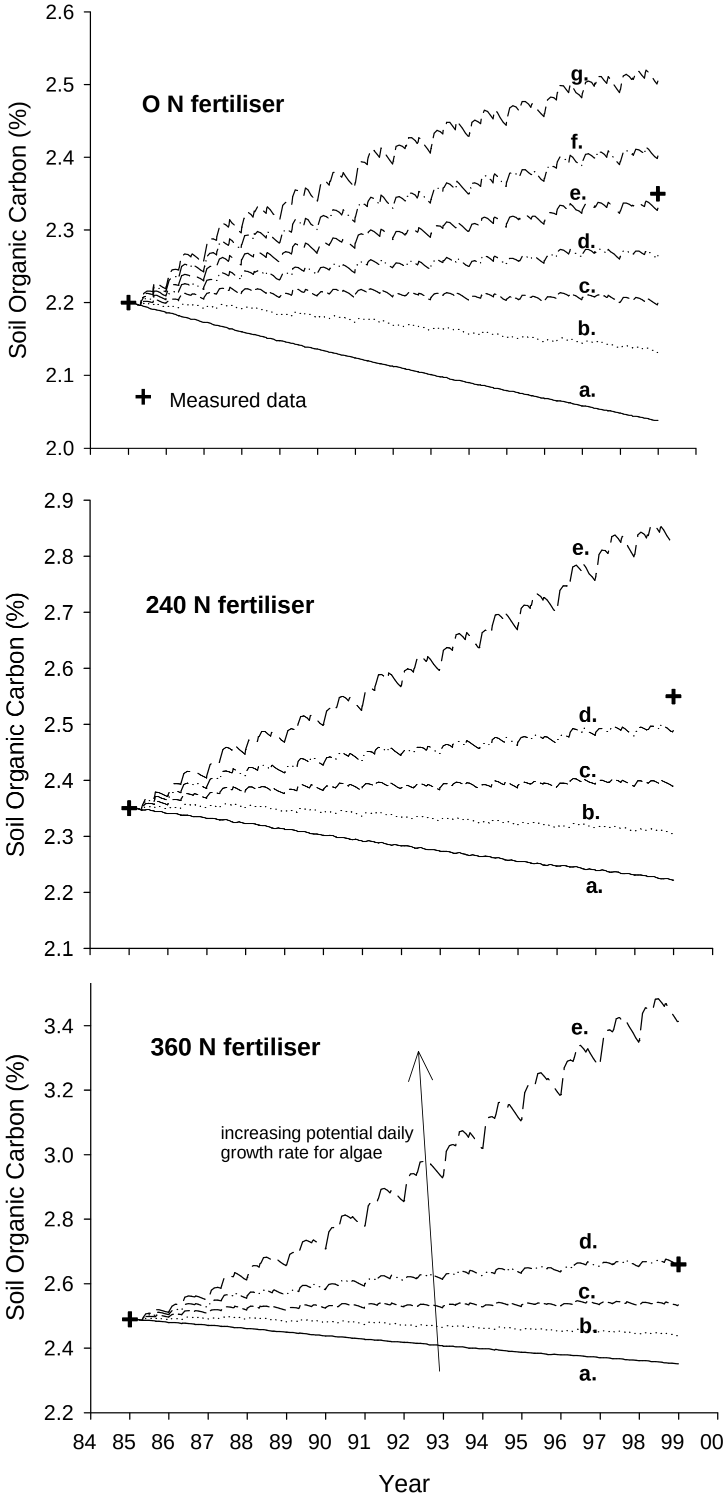


Figure 5. Comparison of APSIM simulations (lines) with measured data (+) for soil organic carbon (0-20 cm) in the IRRI Long Term Continuous Cropping Experiment for three (3) annual fertilizer treatments (0, 240 and 360 kgN ha^{-1}), and a range of values of the APSIM-

Pond parameter *maxrate_pab* (maximum potential daily algal growth rate, kg ha^{-1} day^{-1}). Values of this parameter shown (in kg ha^{-1} day^{-1}) are:- a) 0 – no algal inputs to the system; b) 50; c) 100; d) 150; e) 200; f) 250; g) 300. Note, actual simulated algal inputs to the system are determined by applying limiting factors for light, P, temperature and N, to *maxrate_pab*

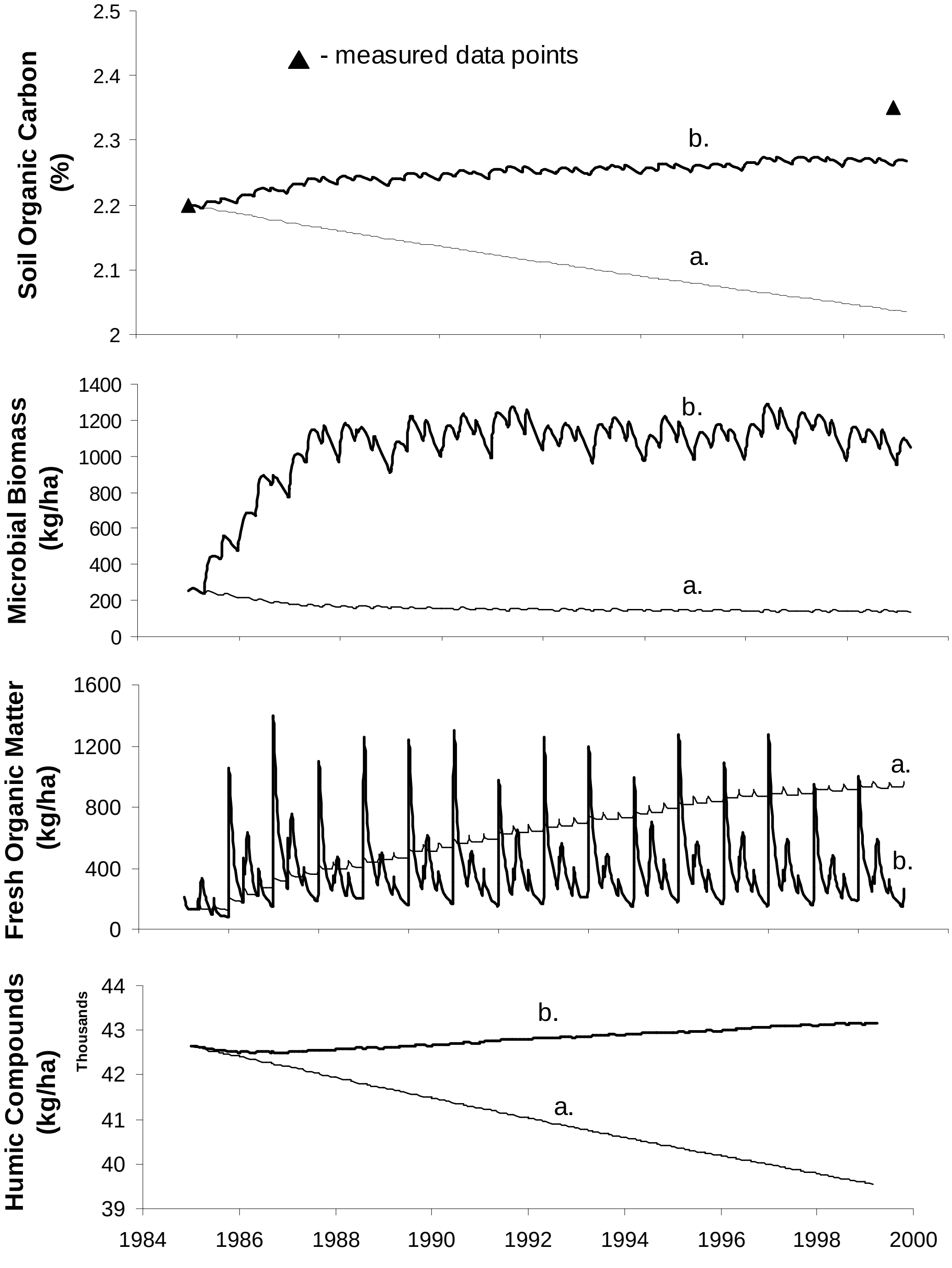


Figure 6. Simulated dynamics of surface soil (0-20 cm), for (**a**-curves**)** no algal inputs into the system, and (**b**-curves**)** algal inputs to the systems at a 150 kg ha^{-1} day^{-1} maximum

potential growth rate, for the zero N treatment in the IRRI Long Term Continuous Cropping Experiment (Doberman et al., 2000; Pampolino et al., 2008)

APSIM-Pond employs a constant, *maxrate_PAB*, to define the potential unlimited growth capacity of PAB on a daily basis. We used the LTCCE to calibrate this constant, by assessing its impact on long-term soil organic C for a range of applied fertilizer rates (0, 120, 240 and 360 kgN ha^{-1} yr^{-1}) over three irrigated lowland rice crops per year for fourteen (14) years. Figure 5 shows APSIM simulation of surface soil (top 20cm) organic C for a range of values of *maxrate_PAB*, plotted against observed soil organic carbon for three different fertilizer rate treatments in the LTCCE. From this calibration process, the best-fitting value for *maxrate_PAB* was judged to be 150 kg ha^{-1} d^{-1}. Using this calibrated value for potential daily PAB growth rate, Figure 6 illustrates how the simulated inclusion of PAB growth and its subsequent incorporation into the soil system compares with a simulation that ignores the C and N contributions from PAB production. It is important to note that the *no algae* curves in figures 5 and 6 still account for the effect of algal activity on NH_3 volatilization (like the approach of CERES-Rice), but they do not incorporate PAB biomass (C and N) into system processes.

Model validation

The calibrated model was subsequently tested by comparing simulated and observed rice yields for the LTCCE using a range of fertilizer treatments over a 15-year period. The addition of PAB C and N to the cropping system results in simulated yields comparable to observed yields (Figure 7). Ignoring these C and N inputs results in severe under-prediction of long-term rice yields, particularly in the zero-N treatment. Comparisons were made between experimentally-estimated (Pampolino et al., 2008) and APSIM-simulated soil C balances from this experiment (Table 2). Simulated C inputs and losses were then further segregated into PAB inputs, rice root inputs, and losses of gaseous C to the atmosphere. Our simulation modelling suggests a significant relative role for PAB inputs, from the perspective of both soil organic C maintenance and production sustainability. Published reports on the LTCCE (Dobermann et al., 2000; Pampolino et al., 2008) provide only long-term average crop yields and changes in soil organic carbon. Individual crop yields over the range of years, together with interspersed measurements of soil organic carbon were not available for use in our analysis. Release of these data in coming years will facilitate further evaluation of our model modifications using more modern methods of validation (for example, Bellocchi et al., 2010; Confalonieri et al., 2010).

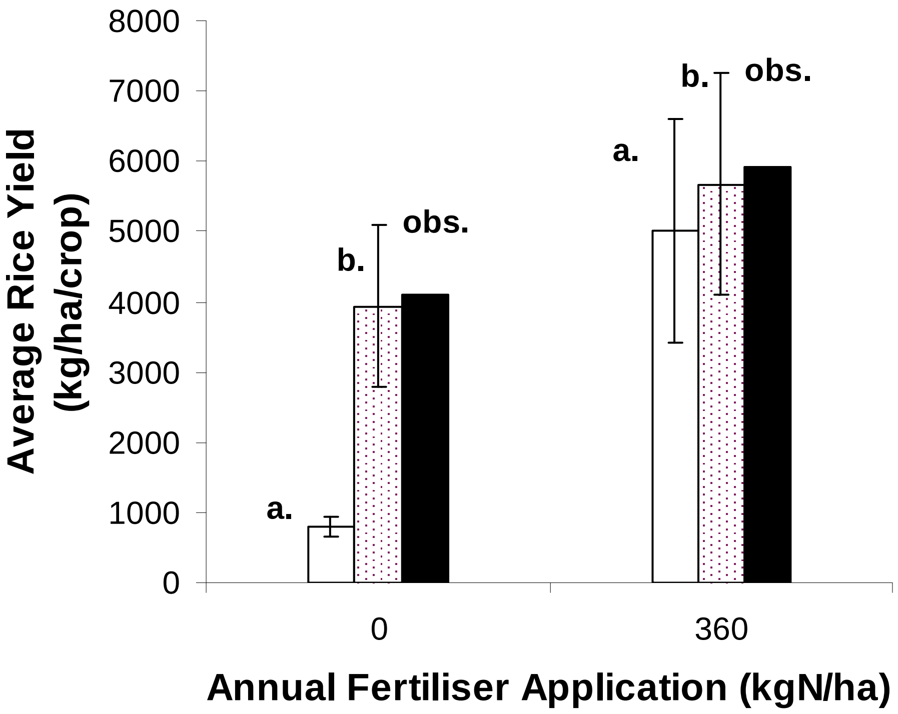


Figure 7. Simulated vs average observed grain yields (over 13 years) for two fertilizer treatments (zero and 360 kgN ha^{-1} yr^{-1}) in the IRRI Long Term Continuous Cropping Experiment (LTCCE). APSIM simulations presented with **a)** no simulated algal inputs to the system; and **b)** algal inputs with 150 kg ha^{-1} day^{-1} potential algal production. No information on observed experimental variation between treatment replications was provided (in Dobermann et al., 2000)

DISCUSSION

As demonstrated by Figures 6 and 7, the simulated dynamics of soil organic C and rice yield only make sense when system inputs of C and N from PAB are included. In theory, simulated organic C could also be maintained without new system inputs by reducing soil mineralization rate parameters, however N supply would decrease and simulated yields would suffer. Figure 6 illustrates APSIM simulated variables Soil Organic Carbon (%), Soil Microbial Biomass (kg ha^{-1}), Fresh Organic Matter (kg ha^{-1}), and Humic Compounds (kg ha^{-1}) for simulation of the LTCCE *with* and *without* inputs of PAB included (for more complete description of how these pools are conceptualized in APSIM, see Probert et al., 1998). Although measured data was only available for

Table 2. Comparison between estimated (Pampolino et al., 2008) and simulated (APSIM) net inputs of carbon to the surface soil from crop roots and PAB incorporation, for low and high fertilizer treatments (kg ha^{-1}) in the IRRI Long Term Continuous Cropping Experiment (LTCCE) over a 15 year period.

Applied N Rate	Net Carbon additions to surface soil per annum (kgC ha^{-1} yr^{-1})					
			Simulated (APSIM)			
	Estimated * **TOTAL**	From Rice roots	**From PAB**		C losses to atmosphere	Simulated **TOTAL**
			Tilled in during puddling[@]	*Decomposition during crops*		
0	1235 – 1863	329	1515	1742	2314	1271
360	1401 - 2113	341	2642	2768	3479	2272

* range is due to assumptions on different rates of annual SOC mineralization (3.5-5.5%)

[@] in the APSIM simulations, algae remaining on soil surface after floodwater dry-down of previous crop was tilled into surface soil during the puddling process for the next crop.

soil organic carbon, it is clear for each of these variables that including PAB is not only logical but also very important. For example, excluding PAB inputs (*a* curves) results in a gradual decline in microbial biomass and corresponding buildup of fresh organic matter in the soil over the simulated period of the LTCCE (Figure 6). This results from a lack of mineral N in the system to facilitate breakdown of old rice roots. This does not occur in practice and would not be sustainable, as illustrated by the run-down in soil humic material. From a *sensibility* perspective (checking for intuitive correctness of simulated variables in the absence of measured data for comparison), incorporating PAB contributions provides a much more logical and sustainable soil system representation, in line with practical experience (*b* curves). There is no run-down in soil organic carbon (supported by measured data), and the pools of microbial biomass, fresh organic matter and humus make intrinsic sense. The fresh organic matter pool is highly dynamic around a low average (as expected), resulting in a strong microbial community and steady soil humus levels. This is what we would anticipate in a proven sustainable cropping system such as the LTCCE. Reichardt et al (1999) suggest that microbial biomass in rice fields represent 2-4% of total C. If we consider the top 20cms of soil, total C in our APSIM simulation was 4.4 x 10^4 kg ha^{-1}, making our simulated microbial biomass (mean of around 1100 kg ha^{-1}) equal to 4%. Hence our assumptions on PAB inputs are also supported by published measured data on soil microbial biomass.

Modelling allows estimates of hard-to-measure components (for example, the relative contribution from rice roots and algae) to be quantified, summed, and then compared with overall net figures from measurements. Net simulated soil C additions compare well with calculations from the field (Table 2). Our simulation analysis particularly allows the segregation of relative C inputs and losses, which indicate that PAB inputs of C to the soil considerably exceed C inputs from rice roots.

After initially validating the model using soil variables, we focused on cross-validation using long-term rice crop yields. The impact of including PAB inputs in simulations of the LTCCE are significant (Figure 7). When no PAB C and N inputs are included, APSIM substantially underestimated the long-term average rice yields in the zero-N treatment. The yields in the 360-N treatment were also underestimated, but by a smaller amount, due to the contributions from fertilizer N and the likely reduced actual contributions from BNF (BNF is inhibited by fertilizer N, (Roger and Ladha, 1992)). When PAB inputs (using maxrate_PAB = 150 kg ha^{-1} day^{-1}) are included, there is a significant increase in the simulated zero-N yields, strongly correlating with measured yields. Simulated yields for the 360-N treatment are similarly enhanced. We believe this dual cross-correlation (comparing simulated and measured variables for above and below ground system dynamics (yields and soil) in the LTCCE) provides strong evidence that our modelling approach captures key system sustainability processes.

Our new assumptions on PAB turnover are critical to this understanding and simulation capacity. For the calibration and subsequent validation presented in this paper, we arrived at a value for maximum potential daily growth rate of algae (*maxrate_PAB;* kg ha^{-1}day^{-1}) of 150 for the LTCCE. This value is considerably higher than the 20 kg ha^{-1}day^{-1} suggested by Roger (1996), however that figure referred to average *net* production and for our purposes we are interested in the daily *gross* algal production. As we have demonstrated, algal senescence (gross minus net production) is a significant component and cannot be ignored. Norsker et al. (2011) found gross PAB production rates in tropical floodwater to exhibit a photosynthetic efficiency of around 2%, approximating 50-60 t/ha dry biomass per year. This corresponds to daily average (unlimited) algal production rates of 137 - 164 kg ha^{-1}day^{-1}, strongly supporting our independently calibrated figure of 150 kg ha^{-1}day^{-1} for *maxrate_PAB.*

There remain several areas of uncertainty which we believe require further investigation so that APSIM can be confidently used in diverse geographical locations and management systems for long-term rice system simulation.

(i) Should *maxrate_PAB* be a constant or a parameter varied for different environments? At this point, without further evidence, we believe it should be a parameter based on accounts from literature. The paddy field ecosystem provides an environment favourable for the growth of N-fixing cyanobacteria; however, the relative occurrence of cyanobacteria varies within large limits. From two extensive studies it appears that they are not always present in rice soils, and if present, can be in varying degrees (Watanabe and Yamamoto, 1971). Reasons for their heterogeneous and sometimes limited distribution are still not well known as no systematic analysis has correlated their presence or absence with environmental factors (Roger and Kulasooria, 1980). For this reason, we suggest that the parameter *maxrate_PAB* should be calibrated or estimated for different sites where possible, assuming 150 kg $ha^{-1}day^{-1}$ in the absence of further information.

(ii) When should simulated algal biomass be ‘killed’ and added to the surface organic matter pools for decomposition? There is some evidence in the literature about PAB persistence after floodwater dry-down (Roger and Kulasooria, 1980). We currently assume that the PAB dies after five (5) days without floodwater, and is transferred to the APSIM-SurfaceOM module where it can begin to decompose. After five days, if floodwater is re-established PAB production must start anew. Due to uncertainty around the appropriate time threshold, we suggest this matter is also worthy of further research.

CONCLUSIONS

We have presented a modelling approach which captures the inputs of C and N from PAB to rice-based cropping systems, in addition to the impact of PAB activity on floodwater processes (e.g. ammonia volatilization). We have described and illustrated why these algae-based C and N inputs are an essential component in a model for long-term simulation of rice-based cropping systems. We have built upon the successful prior work of the CERES-Rice team by using their approach to modelling *algal activity* and expanding it to include actual system inputs of C and N from PAB. In this way we have extended the focus from simulation of single rice crops to the simulation of cropping sequences which include rice. We have obtained strong validation by testing our modelling framework against the best available long-term continuous rice-cropping dataset, from the perspectives of both soil dynamics and crop yield maintenance. This new capacity to simulate system PAB inputs, together with recent developments allowing simulation of transitional anaerobic/aerobic soil environments (Gaydon et al, 2012a), has positioned the APSIM model as a useful tool for future simulations studies evaluating performance and sustainability of changed practices in rice-based cropping systems. Given the model's inherent flexibility in specifying an infinite range of possible management interventions, it is now a functional tool for future research into adaptations related to climate change, reduced water availability and future food production imperatives in rice-based cropping systems.

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CHAPTER 4

The best farm-level irrigation strategy changes seasonally with fluctuating water availability

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Abstract

Around the globe farmers managing irrigated crops face a future with a decreased and more variable water supply. To investigate generic adaptation issues, a range of on-farm strategies were evaluated for apportioning limited water between fields and enterprises using a typical case-study farm from Australia’s Riverina region. These strategies are compared for a range of seasonal water availability levels. The analysis did not address investment in new irrigation technologies or new crops, but focussed on irrigation intensity and crop choice amongst existing enterprises. Participatory engagement and whole-farm simulation modelling were our primary tools of research. The adaptation options found to best suit irrigation farming in years of high water availability were substantially different to those when water supplies were low. This illustrates strategic differences between irrigation farming in land-limited circumstances and water-limited circumstances. Our study indicates that the cropping and irrigation strategy leading to greatest farm returns changes on a season-by-season basis, depending primarily on the water availability level.

Keywords: irrigation, resource allocation, whole farm modelling, farming systems modelling

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INTRODUCTION

Many arid irrigated agricultural regions of the world are expecting a future with decreased and more variable water supplies (Rijsberman 2006; Christensen et al., 2007). Internationally, farmers are faced with similar questions on how to adapt: change crops, invest in more efficient irrigation technology and machinery, or alter agronomic and/or irrigation strategies? Accepting reduced production may be unavoidable but is rarely a desirable option, either from the farmer's perspective or global imperatives (the forecast requirement to increase global food production by 50% over the next 40 years (World Bank, 2008; von Grebmer et al., 2008)). Universally applicable methodologies are required to assess adaptation options for agriculture in the face of changed circumstances (Meinke et al. 2009; Howden et al., 2007). Australia's Riverina is a well-established irrigated region with access to traditionally secure water, now increasingly under pressure. It provides an ideal opportunity to explore adaptation options, generic principles, and research methodologies using a case-study approach, due to the ready availability of soil, crop, and farming system information, historical climate data, and farmers familiar with research involvement.

Irrigated agriculture in this region (latitude 34^{o}S to 35.5^{o}S; longitude 144.5^{o}E to 146.5^{o}E) involves of a variety of crops such as rice, other cereals, pulses and oilseeds, as well as livestock. Farmers possess irrigation water *entitlements* (in ML) which licence them to a proportional share of available water resources in their district or irrigation area. An entitlement applies to either groundwater or surface-water (from rivers or diverted channel schemes) resources and represents the total volume of seasonal water procurable under each licence when the *allocation* is 100%. The *allocation,* expressed as a percentage (%), is a measure of total irrigation water available to the entire district system. It varies from season to season, and is determined and regulated by government. Available water determinations are made at the start of the water year (1 July – 30 June) and allocation percentages are first announced in mid-August. They may then be upgraded on a monthly basis if inflows to storage dams result in increased system water availability (New South Wales Department of Infrastructure, Planning, and Natural Resources, 2004). The seasonal volume of water which an individual irrigation farmer can access is calculated by multiplying their entitlement by the seasonal allocation percentage and dividing by 100. Australian water policy is complex and non-uniform between districts and regions (McKay, 2005; Crase et al., 2000), however Riverina irrigators are able to trade both seasonal allocation and entitlements (Bjornlund, 2003).

Recently, Riverina irrigators have experienced unprecedented restrictions in production due to low allocations brought about by a combination of climatic and political factors. Over the past decade, the volume of available water in the southern Basin has been around 40% less than the long-term average (MDBA, 2010). Average seasonal allocations over the last 15 years have averaged below 50% of entitlement, with high variability. This is in contrast to a prior history of receiving at least 100% every season since as far back as 1912 (depicted in Figure 1, adapted from Gaydon et al., 2008; and McIntyre et al., 2011).

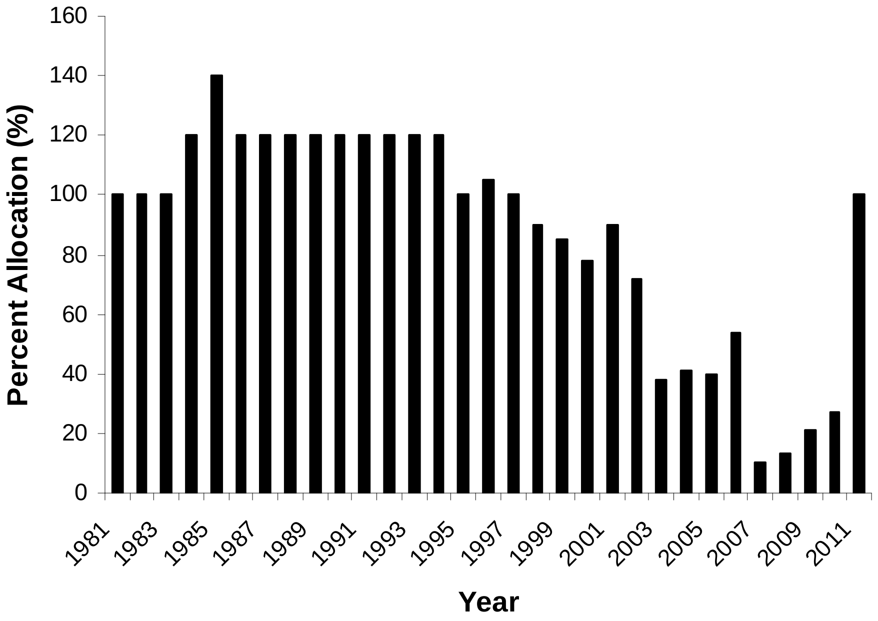

Figure 1. Annual irrigation water allocations (percentage of licensed quota) for Murrumbidgee Irrigation Area, 1980/81 – 20010/11 seasons. The trend of 100% or greater allocation extends unbroken from 1998 back to 1912.

Recent climate change projections suggest further decreases in regional water supply are likely. The Murray Darling Basin Sustainable Yields Project (CSIRO, 2007) suggested 9-14% reduction in water diversions for irrigation by 2030, whilst a 16-25% reduction in average Murray-Darling stream-flows by 2050 and 16-48% by 2100 has also been predicted (Pittock, 2003; Christensen et al., 2007, Hennessy et al., 2007). Such reductions in stream-flows are likely to have dramatic negative implications for future allocations in the Riverina (Jones and Pittock, 2003). Jones and Page (2002) suggest that a 15% drop in annual rainfall by 2030 could mean a 50% reduction in allocation levels. In Australia the supply of water for irrigation is not affected by climatic factors alone. Environmental policies and the National

Competition Policy have also resulted in decreased water availability to irrigators (Adamson et al., 2007; Humphreys and Robinson, 2003; Murray-Darling Basin Authority, 2010). Clearly, the experience of the past is no longer an adequate reference for planning Australia's agricultural future (Jones, 2010), and innovative adaptation in on-farm water management practices are required to keep Riverina irrigators profitable in a future characterized by a reduced and more-variable irrigation water supply.

There is a range of potential ways an individual irrigation farmer could adapt to decreased allocations. Essentially, the aim will be to increase efficiency (Keating et al., 2010) and increase water productivity, the production per unit of water applied, WP (Zwart and Bastiaanssen, 2004; Cai and Rosegrant, 2003; Seckler et al., 2003). Options such as partial- (deficit) irrigation may increase WP (Fereres and Soriano, 2007); changes in agronomic practices such as rotations, crop species and varieties (Howell, 2001), changes in residue (crop stubble) management practices (Tolk et al., 1999; Schillinger et al., 2010); changes to proportional sharing of water between winter and summer crops (Lorite et al., 2007), all promise potential increases in WP. More transformational changes such as investing in new irrigation technology and crops (Harris, 2000; Wood and Finger, 2006; Maskey et al., 2006; Hafi et al., 2006), represent further options, as do disposing of water on the free market (Bjornlund, 2003; Crase et al., 2000). All these options are highly context-specific and decisions on suitable adaptations are strongly influenced by locally existing co-limitations (e.g. labour, capital, nutrients (Rodriguez et al., 2007), as well as socio-economic issues (Adger et al., 2009; Crane et al., 2008; Crane et al., 2010).

To ensure analysis of realistic adaptation options, participatory research with farmers is preferred (Robertson et al., 2000; Meinke et al., 2001; Carberry et al., 2002). Questions relating to use of limited water over numerous fields and enterprises on an individual farm necessarily requires a *whole-of-farm* modelling approach (Rodriguez et al., 2007). By working closely with farmers in developing detailed scenarios for testing, it is possible to incorporate a range of whole farm constraints (labour, machinery, irrigation cycles etc) without actually modelling them.

In this paper, we present a case-study approach using participatory research and the APSIM model (Keating et al., 2003) to compare a range of farmer-identified strategies for using limited irrigation water on a typical Riverina grain-cropping farm. The strategies encompass various irrigation intensities and different philosophies for apportioning water between existing on-farm enterprises, under a range of allocation scenarios. We did not consider new investment options (efficient irrigation technology) or new crops in this analysis. We believe this case study approach demonstrates some generic principles and a methodology applicable to on-farm analysis in any region facing the contentious issues of how to use limited irrigation water resources on-farm across a range of allocations.

MATERIALS AND METHODS

Choice of case-study farm

The farm chosen for this analysis was an irrigated rice-cereal-soybean operation in the Murrumbidgee Irrigation Area (MIA), NSW. This dry region experiences a mean annual rainfall of 405mm with an annual potential evaporation of 1780mm. The 600ha farm has 3265 ML of water entitlement (equivalent to approximately 544mm ha^{-1}). The dominant soil type is a Gogeldrie Clay (Blackmore et al., 1956) with smaller areas of sandy-loam (Taylor and Hooper, 1938). The farm is typical of the region, and has been established to use a mixture of flood and furrow irrigation. Irrigation water is supplied via the channel network of Murrumbidgee Irrigation Ltd., and there is no on-farm water storage capacity.

Validating APSIM performance

The APSIM model was parameterized using relevant soil, crop and climate data, and subsequently tested against experimental data, average regional figures, and farmer historical records for both crop production and water-use variables. Satisfactory performance was achieved, with details provided in Appendix A.

Development of Adaptation Scenarios

Together with the case-study farmer, we envisaged a range of potential strategies for apportioning available water to different fields on his farm with varying levels of irrigation intensity. The options considered in this study consisted of changes in agronomic/irrigation practice and subsequent modifications to cropping areas and winter/summer crop proportions.

Adaptation option scenarios identified

AO1 *Control (historical management – full irrigation, residues removed)*

- For seasonal allocations below 15%, concentrate solely on a winter-cropping programme with fully-irrigated barley (variety ‘Gairdner’) at 220mm row spacing, irrigated on an 80mm soil water deficit. Barley is sown starting 20th May and immediately irrigated. Dryland barley is also sown as conditions dictate, depending on soil water availability and planting rainfall of at least

15mm over a 3-day period. All crop residues are removed two weeks prior to sowing of next barley crop.

- For seasonal allocations greater than 15% but less than 50%, introduce soybean summer cropping in rotation with the barley. Soybean (variety 'Djakal') is sown from 26th November, 25 plants/m^2, 900mm row spacing, and immediately irrigated. All barley crop residues are removed prior to sowing, and irrigations are applied at 60mm soil water deficit.
- For seasonal allocations greater than 50%, flooded rice is introduced in rotation with barley (Rice-Rice-Barley) on suitable soils. Several varieties of rice are sown starting in mid September (at 150 kg seed per hectare), and finishing in mid-November. Rice crop residues are removed prior to next crop (barley or rice) by burning.

AO2 *Control + retain barley residues through subsequent soybean crop*

- Management is the same as AO1 (control), except that barley row spacing is increased from 220mm to 400mm. This allows soybean to be sown directly in between rows of barley residues, maintaining the stubble throughout the soybean crop to help limit soil water evaporation and reduce the number of irrigations required. The land area sown to both irrigated barley and soybean is increased due to the irrigation water saved by this evaporation suppression (0.5 Ml ha^{-1} (or 50 mm ha^{-1}) in barley crops; 1.0 ML ha^{-1} (or 100 mm ha^{-1}) in soybean crops).

AO3 *Partially irrigate winter crop (increase irrigated winter crop area)*

- As per AO2, but reduce inputs on the irrigated barley crops (irrigation water and fertilizer). The barley crops are watered on a 100mm soil water deficit (rather than 80mm), resulting in a decreased total water requirement per crop (1.5 ML ha^{-1} (or 150 mm ha^{-1}) rather than 2.5 ML ha^{-1} (or 250 mm ha^{-1}), on average (Table 1)). The water savings are used to increase the irrigated barley crop area.

AO4 *Partially irrigate winter crop (increase summer crop area)*

- As per AO3, however the water savings are used to increase the soybean cropping area, rather than the irrigated barley area.

AO5 *Rainfall-based sowing for winter crop (increase summer crop)*

- As per AO4, however the inputs on the irrigated barley crops are decreased even further, by avoiding the initial irrigation and sowing instead on a suitable rainfall event. Sowing occurs when more than 15mm rainfall occurs over a period of 3 days, in between the dates of 5th May and 30th June. This adaptation results in a further average irrigation saving of 1 ML ha^{-1} (or 100 mm ha^{-1}), but also results in occasional sowing of barley outside the optimal sowing window, resulting in potential yield decline.

AO6 *All winter crop (fully irrigated)*

- As per AO2, however no summer crops planted regardless of seasonal allocation. If total barley area reaches maximum available, then any outstanding water is sold on the open market.

AO7 *All winter crop (partially irrigated)*

- As per AO3, however no summer crops planted regardless of seasonal allocation. As per AO6, excess water sold on open market.

AO8 *All summer crop (fully-irrigated)*

- As per AO1, however no irrigated barley sown. All available water is devoted to a combination of soybean or rice. Below 50% allocation – all soybean; above 50% - rice is proportionately introduced.

AO9 *Maximum areas for summer and winter crops (within constraints), buy water as required (fully irrigate winter crop)*

- As per AO2, however the farm is fully sown, within limits imposed by land areas, rotational requirements, labour and machinery. If the water required to meet the irrigation demand is above the season's allocation, then the outstanding water is purchased on the open market.

AO10 *Maximum areas for summer and winter crops (within constraints), buy water as required (partially irrigate winter crop)*

- As per AO9, however the barley is partially-irrigated, aiming to reduce the total water requirement.

Allocation scenarios considered

To compare the performance of the 10 adaptation options across a range of potential future water-supply scenarios, seasonal allocations of 80%, 50%, and 20% of entitlement were simulated.

Simulation of crop water use

Farmers routinely determine annual sowing areas for different crops by making an assumption on required irrigation water per hectare of production for each crop, and then applying this factor to the water volume they have decided to apportion to that crop. This calculation results in a sow-able area. For the range of adaptation options considered in this analysis, the required water use per hectare of production varies considerably and was simulated using APSIM (Table 1).

Table 1. Simulated crop water-use (ML/ha) for each adaptation option, used in planning of cropping areas.

Crop/crop-sequence	Adaptation Option number									
	1 (control)	2	3	4	5	6	7	8	9	10
Barley	3	2.5	1.5	1.5	1	3	1.5	n/a	2.5	1.5
Barley (w/soy)	3	3	1.5	1.5	1	n/a	n/a	n/a	3	1.5
Barley (after/rice)	2.5	1.5	0.5	0.5	0.5	n/a	n/a	n/a	1.5	0.5
Soybean	8	7	7	7	7	n/a	n/a	8	7	7
Rice	13	13	13	13	13	n/a	n/a	13	13	13

Determination of cropping and irrigation area for each AO

The water-use factors from Table 1 were then used in conjunction with farmer-suggested apportioning of water (Table 2) to determine cropping areas associated with each adaptation option and seasonal allocation scenario. The resulting land areas sown are shown in brackets in Table 2. If the adaptation scenario called for buying or selling of water on the open market, the deficit/surplus is also shown in the table.

Whole Farm Analysis

Traditional modelling studies in agriculture have focussed on field-scale issues, however evaluating options for apportioning a limited resource (in this case, irrigation water) between different fields on a farm necessarily requires a *whole-of-farm* analysis approach. We began by conducting APSIM field-scale simulations, generating gross margin (GM) cumulative probability distributions (CDFs) for the various adaptation options on the case-study farm fields. These distributions were then combined in a spreadsheet to represent the distribution of GM's for the whole farm, using farmer-determined cropping areas (section 2.3.4). By including the farmer's input in this way, a range of whole-of-farm constraints were implicitly included into the analysis. These

Table 2. Farmer-estimated water allocation percentages (of licensed amount, 3265 ML/annum) for each adaptation scenario option, for the three (3) irrigation water allocation scenarios (80%, 50% and 20%). Land areas allocated (in hectares, out of total 530) are shown in brackets

Crop/crop-sequence	**Adaptation Option number**									
	1 (control)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Irrigation Allocation = 80%										
Sole barley	5 (54)	5 (65)	13 (283)	2 (44)	1 (33)	49 (530)	25 (530)	0	16.5 (216)	10 (211)
Barley-Soybean	30 (89)	30 (98)	25 (96)	30 (115)	31 (127)	0	0	33 (133)	60 (196)	52 (200)
Rice-barley	15 (32)	15 (34)	14 (34)	16 (39)	16 (39)	0	0	0	16.5 (37)	16 (39)
Sole rice	30 (75)	30 (75)	28 (70)	32 (80)	32 (80)	0	0	47 (119)	33 (83)	32 (80)
Dryland barley	n/a (95)	n/a (95)	n/a (45)	n/a (95)	n/a (95)	n/a (0)	n/a (0)	n/a (95)	n/a (0)	n/a (0)
Water for sale	0	0	0	0	0	31	55	0	0	0
Water to buy	0	0	0	0	0	0	0	0	46	30
TOTAL	**80** (345)	**80** (367)	**80** (530)	**80** (373)	**80** (373)	**80** (530)	**80** (530)	**80** (530	**126** (530)	**110** (530)
Irrigation Allocation = 50%										
Sole barley	5 (54)	5 (65)	11 (239)	2 (33)	1 (33)	49 (530)	24 (530)	0	16.5 (216)	10 (211)
Barley-Soybean	45 (134)	45 (147)	39 (150)	48 (186)	49 (200)	0	0	50 (204)	60 (196)	52 (200)
Rice-barley	0	0	0	0	0	0	0	0	16.5 (37)	16 (39)
Sole rice	0	0	0	0	0	0	0	0	33 (83)	32 (80)
Dryland barley	n/a (95)	n/a (95)	n/a (45)	n/a (95)	n/a (95)	n/a (0)	n/a (0)	n/a (95)	n/a (0)	n/a (0)
Water for sale	0	0	0	0	0	1	26	0	0	0
Water to buy	0	0	0	0	0	0	0	0	76	60
TOTAL	**50** (283)	**50** (307)	**50** (434)	**50** (314)	**50** (328)	**50** (530)	**50** (530)	**50** (299)	**126** (530)	**110** (530)
Irrigation Allocation = 20%										
Sole barley	15 (163)	15 (196)	16 (348)	7 (152)	4 (131)	20 (218)	20 (435)	0	16.5 (216)	10 (211)
Barley-Soybean	5 (15)	5 (16)	4 (15)	13 (50)	16 (65)	0	0	20 (82)	60 (196)	52 (200)
Rice-barley	0	0	0	0	0	0	0	0 ()	16.5 (37)	16 (39)
Sole rice	0	0	0	0	0	0	0	0 ()	33 (83)	32 (80)
Dryland barley	n/a (95)	n/a (95)	n/a (45)	n/a (95)	n/a (95)	n/a (95)	n/a (0)	n/a (95)	n/a (0)	n/a (0)
Water for sale	0	0	0	0	0	0	0	0	0	0
Water to buy	0	0	0	0	0	0	0	0	106	90
TOTAL	**20** (273)	**20** (307)	**20** (408)	**20** (297)	**20** (291)	**20** (313)	**20** (435)	**20** (177)	**126** (530)	**110** (530)

constraints included: total land area available for sowing to different crops (taking into account rotational requirements); labour and machinery limitations; maximum allowable percentage of land under rice (the Australian rice industry has self-imposed restrictions, aimed at minimizing risk of irrigated salinity problems (Humphreys et al., 2006)); and constraints resulting from limited markets for certain crops.

We used $/farm rather than $/ML as the basic variable of comparison between adaptation scenarios to avoid confusion about how to account for the dryland crop component. Scenarios were compared as CDFs ($/farm), over the range of seasonal allocation scenarios. This aimed to assess whether certain adaptation options were more favourable under high or low water supply. Specific methodologies used in each of these steps are outlined below.

Field-scale simulations

The APSIM model was configured (as per Appendix A) for individual fields on the case-study farm and simulations performed using 52 years of historical climate data (1957-2009) to provide a realistic measure of seasonal climatic variability for the modelled scenarios. The primary APSIM outputs used in subsequent GM calculations were crop yields (kg ha^{-1}) and irrigation water use (mm ha^{-1}).

Calculation of Gross Margins (GMs)

GMs were calculated at a field-scale using detailed costs and prices from the NSW “Farm Enterprise Budget Series” 2009/2010 (NSW Government, 2009), widely used by local farmers in their own calculations. General assumptions on variable costs and prices are provided in Table 3. Variable costs of production include: field operations (sowing, cultivation, harvesting, spraying); consumables (seeds, fertilizer, herbicide, insecticide); cartage; and insurances/levies.

Some of the adaptation options analysed required either buying or selling of water on the open market. The market price varies markedly as a function of seasonal allocations. For example, when allocations are low, available water in the district is scarce, and the market price is high. Vice versa, the price is low when seasonal allocations are high. Using historical data from an online water-trading service (Murrumbidgee Water Exchange, 2010), an algorithm describing the assumed relationship between market price and seasonal allocation was fitted (data not presented). The generalized response function is detailed below in Eq. 1, and illustrated in Figure 2.

$$\boldsymbol{P} = 420 \times e^{-0.025Q} \qquad (1)$$

Where ***P*** is the market water price ($\$\ \mathrm{ML}^{-1}$); ***Q*** is the seasonal allocation (%)

Table 3. Baseline costs and prices used in scenario analyses. (note: variable costs of crop production listed do not include irrigation costs, because these vary based on scenario)

Crop	*Variable Costs of Production* ($\$\ \mathrm{ha}^{-1}$)	*Assumed control Grain Price* ($\$\ \mathrm{tonne}^{-1}$)
Barley		
▪ Fully irrigated (AO 1,2,6,9)	524	200
▪ Partially irrigated (AO 3-5,7, 10)	394	
▪ Dryland	332	
Soybean	582	800
Rice	949	300
Water (includes fixed and variable components)	35 ($\$\ \mathrm{ML}^{-1}$)	n/a

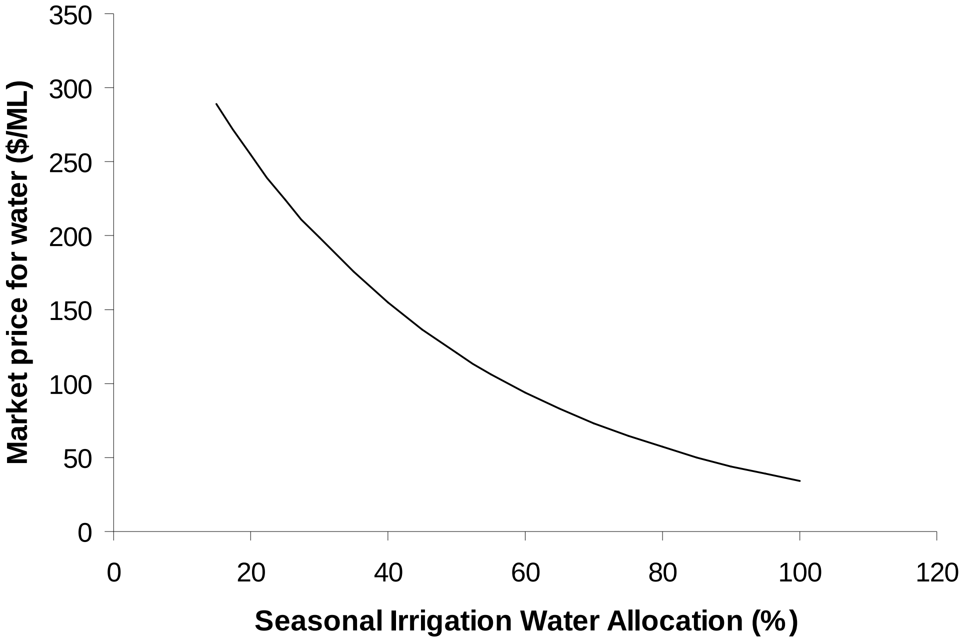

Figure 2. The assumed relationship between water price on the open market and the seasonal water allocation.

Scaling-up field GMs to Whole Farm GMs

Field-scale GMs were scaled up to whole-farm level on an annual basis, using the enterprise area determinations (Table 2). For example, if irrigated barley occupied 3 ha, soybean 2 ha, rice 2 ha, and dryland barley 1ha, then the overall farm GM for that year would be calculated by: (3 x Irrigated barley GM (for that year)) + (2 x Soybean GM) + (2 x Rice GM) + (1 x Dryland Barley GM). The whole-of-farm GMs were expressed in $/farm, and were calculated for each of the simulated 52 years, for each adaptation option.

RESULTS

Evaluation of adaptation scenarios

Irrigation and "The law of diminishing returns"

Graphs were produced using simulated output from the validated APSIM model (Appendix A) to illustrate the relationship between irrigation water applied, and subsequent grain yield for barley on the case-study farm (Figures 3 and 4) The greatest gain per ML of applied water is below 1.5-2 ML ha^{-1} (150-200 mm ha^{-1}) (Figure 4). Above this, increases in yield are still possible but at a reduced rate of return (decreased slope). The relationship between crop production and transpiration is effectively linear (Perry et al., 2009), hence this decreased slope results from increased non-productive losses such as deep drainage below crop roots at higher irrigation applications (Figure 1 in Fereres and Soriano, 2007). This 'law of diminishing returns' leads to the assumption that there may be value in 'spreading out the water' when allocations are low, to extract higher value (extra yield/ML) from less irrigations, sowing greater area and aiming for sub-maximum yields.

The effect of irrigation water allocation

Figure 5 shows the cumulative frequency distribution of whole farm returns, over a 52 year period (1957-2009), for adaptation options 1-10. The allocation level has a large effect on whole-farm returns, however we also found a strong effect on the relative value of the different adaptation options. Figure 5 a-c shows the relative performance of the adaptation options analyzed, for allocations of 80, 50 and 20% respectively.

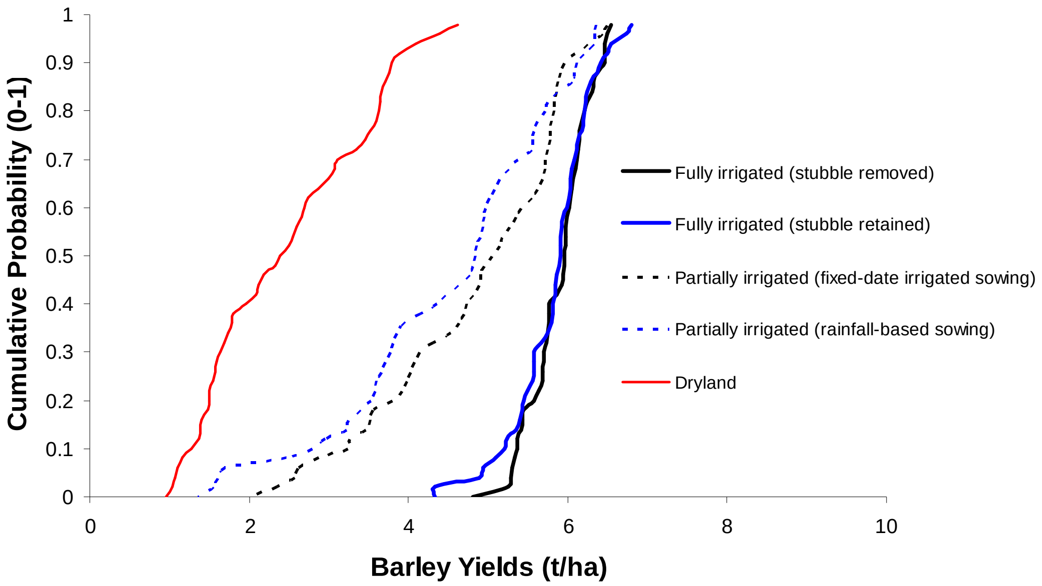

Figure 3. Cumulative probability distributions for barley grain yield as a function of irrigation strategy for the case-study farm.

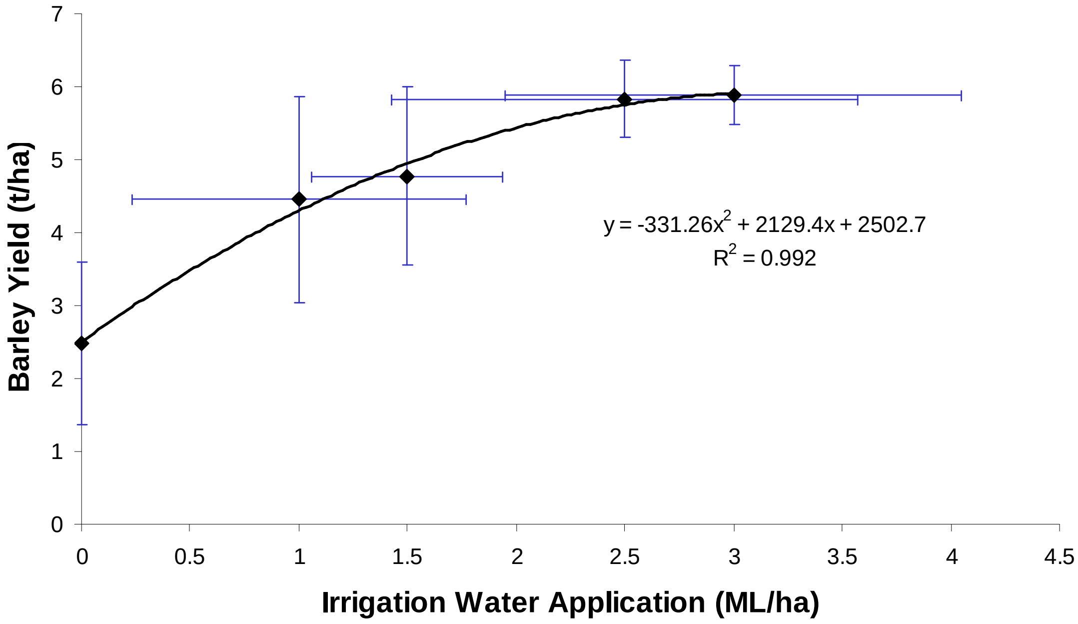

Figure 4. Simulated response of barley yield to applied irrigation amount for the case-study farm. Each point represents the average of 52 years of production under each irrigation strategy. The error bars indicate simulated variability (1 standard deviation) around that average.

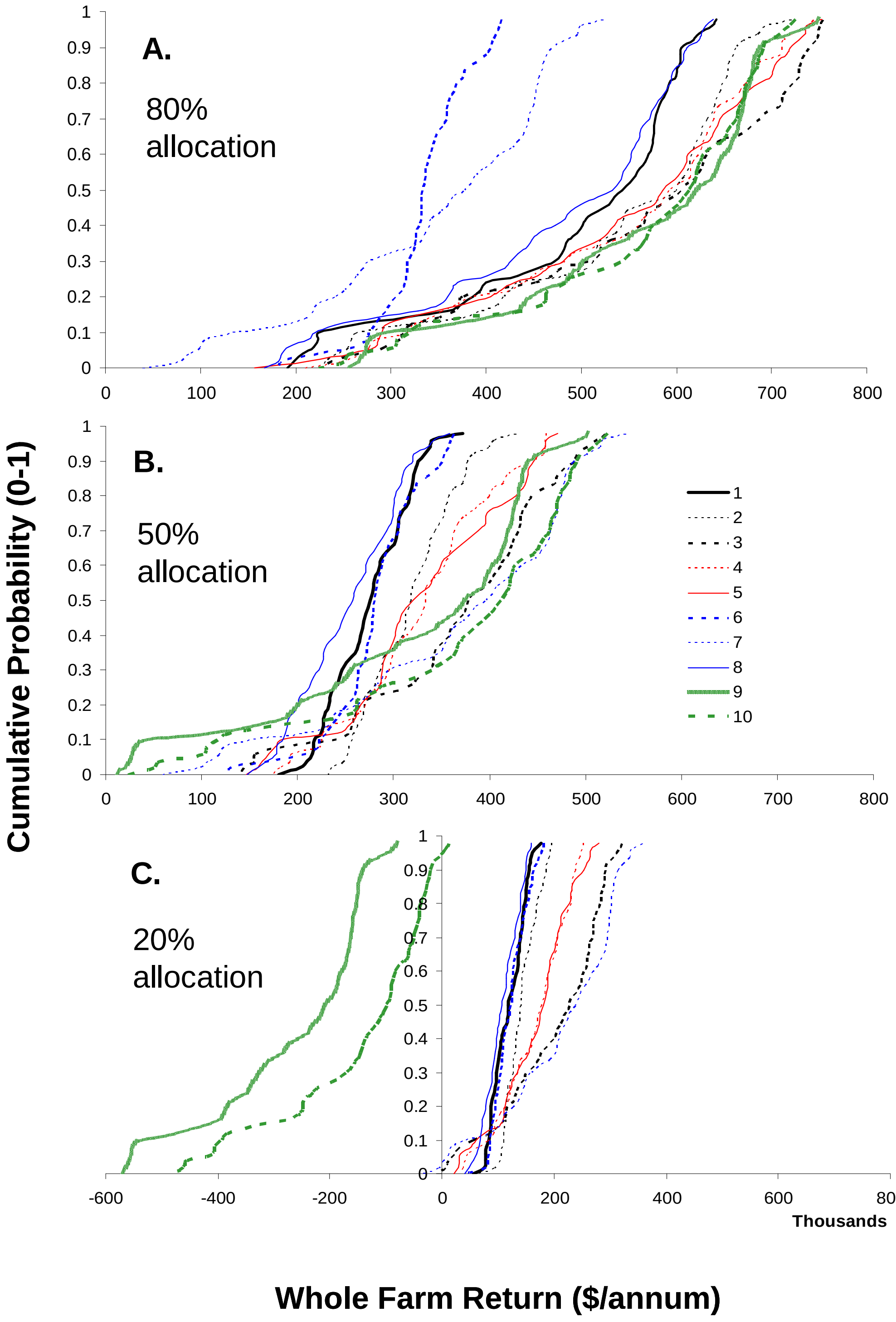

Figure 5. Simulated cumulative probability distributions (1957-2009) for analyzed adaptation options, presented for three (3) different irrigation water allocations

- The solid black curve represents the performance of the traditional (control) management system (**AO1**) on the case study farm. The relative strength of

- this management strategy decreases as allocations decrease, indicating that what was a good strategy for fully-allocated, land-limited irrigated production, is a less adapted strategy under limited water conditions.
- Adaptation option 2 (**AO2**) resulted in a small uniform improvement in returns through limitation of non-productive soil evaporation losses, and use of that water for extra planted/irrigated area.
- Adaptation option 3 (**AO3**) showed significant advantages, particularly at lower allocation amounts when available land was in abundance (Figure 6). The benefits from this strategy reduced as allocation increased, however advantages were still possible, right up to 100% allocation for this case-study farm.
- Adaptation option 4 (**AO4**) was also successful in increasing returns over AO1 at all allocation scenarios examined, however presented a reduced advantage compared to AO3, particularly for the lower allocations.
- Adaptation option 5 (**AO5**) provided minimal benefits over AO4 even with the increased sown area, due to occasionally pushing the barley sowing dates (and hence growing period) into sub-optimal times of the year, resulting in decreased yields and water productivity. Increased risk of a downside result is also evident in Figure 5 (b and c) with a more pronounced tail on the CDF.
- Adaptation option 6 (**AO6**) was clearly a sub-optimal option at higher allocations (Figure 5a), illustrating why in past decades irrigators did not engage in this strategy. It became more and more comparable with AO1 as the allocations decreased. For this case-study farm, it still fell well short of the partial irrigation strategies (AO3, AO4) at lower allocations.
- Adaptation option 7 (**AO7**) is sub-optimal at higher allocations (Figure 5a), however significant advantage accrued as irrigation allocation decreased (Figures 5 and 6). At 20% allocation, there was little to differentiate AO3 and AO7 as the best adaptation options examined.
- Adaptation option 8 (**AO8**) yielded no advantage over AO1 for the case-study farm at any irrigation water allocation level.
- Adaptation option 9 (**AO9**) ranged from *very good* at higher allocations (Figure 5 a, market water is relatively cheap) to *spectacularly bad* at low allocations (Figure 5c, market water is very expensive). Figure 6 depicts this range of outcomes and indicates that above allocations of 50% for the case-study farm, this adaptation option is among the best examined.
- Adaptation option 10 (**AO10**) similarly yielded good results at high allocations, was the best option examined at 50% allocation, and was completely ineffective (but less spectacularly bad than AO9) at 20% allocation.

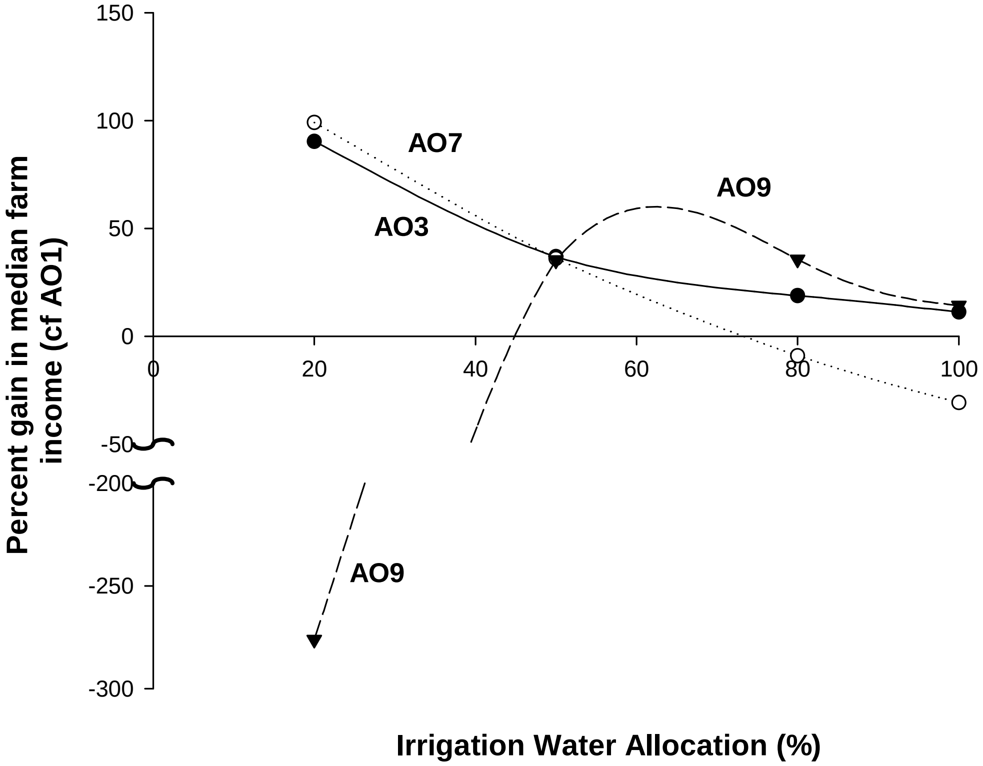

Figure 6. Simulated whole-farm income gains (compared with control, AO1) available from adaptation options 3, 7 and 9 (AO3, AO7 and AO9) as a function of irrigation water allocation.

DISCUSSION

The best whole-farm strategy depends on seasonal water allocation

The whole-farm adaptation options considered in this analysis revealed varying performance across a range of allocations. This variation in performance served to illustrate the profound difference between irrigation farming in *land-limited* circumstances, as compared to *water-limited* circumstances. For the vast majority of the MIA's history (1914 up to mid 1990's), irrigation water was available in excess (100% allocations and greater, Figure 1.) and land-limited conditions prevailed. Not surprisingly, the dominant philosophy which developed in the region's irrigated agricultural community was a fully-irrigated, fully-fertilized, high input approach to cropping, achieving maximum yield in all sown fields. The validity of this approach under those circumstances is revealed in our simulation analysis findings, where Figs.

5 and 6 illustrate the success of AO9 and AO10 as irrigation farming strategies at the high end of the irrigation allocation spectrum.

Future years of high allocation could be interspersed with many years of low to medium allocation. Under such circumstances our analysis suggests that a different approach to irrigation farming is needed. Figs. 5 and 6 illustrate that AO3-5 and AO7 (the partially-irrigated winter-crop adaptation options) provide significantly better outcomes over traditional practice (AO1) and the more intensive irrigated farming approaches (AO9-10) under these conditions. Interestingly also, our analysis has indicated that for our case-study farm, water saved through partial irrigation is best deployed on planting additional winter crops, rather than additional summer crops. This may be dependent on relative prices between the two options, which were not considered as part of this analysis.

The *law of diminishing returns* has been described as one of the most famous laws in all of economics (Samuelson and Nordhaus, 2001). The law states that, at some point, less extra output is achieved through additional doses of an input while holding other inputs fixed. In the context of irrigation, this is evident in Figure 4, where the rate of increase in grain yield for barley decreases as water irrigation inputs are linearly increased. The driving mechanism for this changing relationship is an increase in non-productive losses with water application, primarily deep drainage below the crop root zone. (Deep drainage is considered a ‘loss’ from the farmer’s perspective, however at a higher scale the water may be re-used by other consumers and essentially not ‘lost’ (Paydar et al., 2009)). For the farmer, the success of AO3, AO4, AO5 and AO7 lies in taking advantage of this law of diminishing returns from *applied* water and seeking to limit application to the high-productivity left-hand end of the curve, devoting saved water to the sowing of additional land. The benefits of this strategy are obviously not available when land is the limiting factor in production, as was the case in the Riverina for much of its history. However, now that production is likely to become water-limited in a significant proportion of years, the high-input cropping philosophy of the past (e.g. Angus and Lacy, 2002) needs to be questioned as ‘the best’ for all circumstances. This analysis demonstrates water-limited production can be better managed, and average farm returns increased, by ‘spreading the water’ when allocations are low. Cropping area limitations related to labour, machinery and overheads apply. This strategy becomes even more valuable the lower the allocation goes, as illustrated by Figure 6. It follows that seeking to maximize crop yields does not necessarily lead to maximizing whole-farm returns, particularly in seasons of low allocation.

It is important to note that the advantages of partial irrigation can only be gained from winter crops in this region. Other irrigation districts around the globe may be different. Due to high evapotranspiration demands during the Riverina summer, the law of diminishing returns has reduced effect and significant yield gains from summer crops can be achieved with additional irrigation water, right up until maximum yield. This conclusion is strongly supported by local farmers who steadfastly refuse to consider stressing of summer crops, knowing that this could lead to considerable yield reductions.

General comments about the analysis

The analysis was performed using historical climate data. We did not consider climate change scenarios (ie impacts of changes in CO_2, temperatures, rainfall, and climate variability), and consider such an additional analysis worthy of further study.

We did not consider several other possible adaptation options in response to reduced allocations that involved capital investment by the farmer (ie investment in more efficient irrigation technology). Such comparisons would involve a more detailed economic analysis including capital investment, debt levels etc.. We felt that the evaluation of this option, whilst very relevant and timely, would overly complicate this study if included, hence suggest it better suited to a separate analysis. A further analysis comparing farm performance using strategies from this paper with the sale of water entitlements to the Australian Government’s water buy-back scheme has been undertaken (Chapter 5; Gaydon et al., 2012d)

Our case study should be regarded as an assessment of potential low-cost changes to irrigated farming practice at a whole-farm gross margin level (agronomic practices, cropping priorities and irrigation strategies), in response to the threat of reduced irrigation water availability. It is a part of the bigger story. It is also relevant to note that many Riverina broad-acre irrigation farmers have already responded to low water availability over the last decade by implementing residue maintenance (AO2), and partially irrigating winter crops.

Farmer responses to research findings

Responses to the research findings were sought individually from the case study farmer and two other independent advisory farmers. The three farmers were selected to represent a diversity of farm types from the Riverina region, in terms of soils, geographical location, farm size, attitudes to risk, and current farming practices. A large number of comments were collated, and only the common points will be related here.

There was general consensus on the merits of focusing on high-input cropping when water was abundant, and a lower-input approach when water was scarce. There was strong agreement on the value of residue retention (AO2). The degree to which farmers felt comfortable with ‘spreading the water’ in years of low allocation varied. One farmer noted that he would need to spend “a lot more time at church” if he implemented AO3-AO5, indicating he felt uncomfortable about the downside risk associated with planting larger areas of partially-irrigated fields, despite the considerably greater simulated upside gains possible. Each of the farmers expressed this feeling to some degree, which may have been an artefact of having just experienced a decade of drought. However this may also reflect that Riverina farmers generally manage the downside risk on their farms, before they will focus on pursuing high returns. It was noted that despite the possibilities of greater average returns from other adaptation options , the conservative option (AO1 in Figure 5, for all the simulated allocation percentages), still represented a reliable positive profit and was still attractive from that perspective. The looming threat of a changing climate was also mentioned by one farmer as adding additional risk to the partial irrigation strategies depicted in Figure 5 (which were generated from historical climate data).

Each of the farmers noted that annual relative prices between summer and winter grains was a large factor in determining where water and land would be allocated on-farm, yet this was not an aspect considered in the analysis due to added complexity. The interaction between relative crop prices and seasonal allocation was an issue of interest to farmers, and may warrant further research.

CONCLUSIONS

Our results indicated a profound difference between the best strategies for irrigation cropping in water-limited seasons and water-abundant (land-limited) seasons. In circumstances when water is plentiful and land availability becomes the limiting factor in production, it makes economic sense to fully-irrigate and fertilize crops, selecting populations and varieties to maximize crop yields. In this way, farmers maximize their return per ML, per hectare, and per farm. However, when water allocations are low, our analysis demonstrated that the best average returns per farm are obtained through strategies which ‘spread the water’ and focus on maximizing land utilization through partial irrigation of winter crops, capitalizing on the *law of diminishing returns*. These strategies aim for sub-maximal yields per hectare, but maximize returns per ML and per farm when land is not limiting. In the Riverina region, partial irrigation of summer crops is not a viable option due to hot, dry conditions and very high rates of evapotranspiration. Gains were only shown to be possible from partial irrigation of winter cereals. In our analysis, water saved was better devoted to sowing additional winter crop area rather than additional summer crop area; however this finding is likely to be strongly influenced by relative prices between winter and summer grains.

Some of the 'water-spreading' strategies offered up to 90% improvement in average farm returns over traditional practices at low allocation levels, but up to 30% worse performance than traditional practices at high irrigation levels. Similarly, the best high allocation strategies performed extremely poorly at low allocations. This study suggests that maximizing long-term average returns requires farm management strategies which vary on a season-by-season basis based on allocations.

ACKNOWLEDGEMENTS

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APPENDIX A - Testing APSIM performance

A.1 Materials and Methods

A.1.1 Benchmarking APSIM performance

A critical component of the research approach presented is participatory engagement between researchers and the case study farmer. The first steps in this process involves interviewing the case-study farmer to understand details of their operation (land area, paddock sizes, soil types, irrigation and agronomic practices), major decision points, labour and machinery constraints, risk preferences, and their observed long-term averages and variation for crop yields and irrigation water-use. Based on these details, we configured the APSIM model using local soil information (Hornbuckle and Christen 1999), climate data from the SILO database (Jeffrey et al, 2001) for Whitton (Australian Bureau of Meteorology (BoM) Station 074118). We performed simulations of current practices over a 52-year period (1957- 2009) to compare simulated crop production and water-use with the historical observations of the farmer, and any other available district information. We also checked modelled calculations for gross margins against farmer expectations, with detailed economic inputs (NSW Department of Primary Industries, 2009). This initial phase, benchmarking the performance of the model, involved several iterations of interviews and simulation, until mutually acceptable performance was achieved.

A.1.2 Testing of APSIM model in irrigated water deficit situations

The performance of APSIM in simulating crop growth and water-use in response to water deficit irrigation was tested using experimental data of Thompson and Chase (1992). This experiment was conducted at Yanco Agricultural Institute in the Murrumbidgee Irrigation Area in 1980, comparing wheat grain yield, grain protein, and water-use for a range of strategies under flood irrigation (Table A.1). Several management permutations (6), ranging from rain-fed, through partially-irrigated, to fully irrigated, were examined. Replicated experimental data and standard deviations were not available, hence we have used the reported mean values. APSIM was configured using local soil information (Hornbuckle and Christen 1999), climate data from the SILO database (Jeffrey et al, 2001) for Yanco Regulator (BoM Station 074123), and imposed management information as per the experiment. A simulation was performed for each of the six (6) treatments, reporting variables measured by Thompson and Chase (1992). Measured and simulated data were then compared.

Table A.1. Wheat irrigation treatments imposed for APSIM model testing following experiment of Thompson and Chase (1992).

Treatment	*Description*
1 (control)	No irrigation, totally rain-fed
2	Irrigated only during growth wheat growth stage 1*
3	Irrigated only during growth stage 2 *
4	Irrigated only during stages 1 and 2 *
5	Irrigated during growth stages 1 and 3*
6	Fully irrigated :- irrigated during all growth stages (1-3)

* wheat growth stages as defined by Thompson and Chase (1992)

A.2 Results and Discussion

A.2.1 Benchmarking

Comparisons between simulated and estimated grain yields (Table A.2) and water-use figures (Table A.3) are shown below for the case study farm.

Table A.2. Grain Yield comparison for benchmark simulations

Crop	*Simulated ($t\ ha^{-1}$)*			*Farmer's Estimates ($t\ ha^{-1}$)*	*District Averages ($t\ ha^{-1}$)*
	Max.	*Min.*	*Ave.*		
Rice	11.65	0.0	10.7	10+	9[1]
Soybean	3.39	2.4	2.86	1.5 – 3.5	3[1], 2.6[3]
Irrigated Barley	7.03	2.4	4.8	2-7 (average 5)	5.5[1]
Dryland Barley	4.5	1.0	2.7	2.5	1.8[1]

Table A.3. Irrigation water-use comparison for benchmark simulations

Crop	*Simulated ($Ml\ ha^{-1}$)*			*Farmer's Estimates ($Ml\ ha^{-1}$)*	*District Averages ($Ml\ ha^{-1}$)*
	Max.	*Min.*	*Ave.*		
Rice	14.6	8.8	11.4	12	13[1], 14[2]
Soybean	7.5	4.5	6.7	7	8 [1,2]
Irrigated Barley	4.5	1.5	3.3	1.5 – 4.5	2.5[2], 3.5[1]
Dryland Barley	-	-	-	-	-

[1] NSW Department of Primary Industries (2009)
[2] Khan et al. (2004)
[3] CSIRO (2005)

Simulated results indicate satisfactory performance by the APSIM model in reproducing both the average and range of crop yields and water-use on the case study farm.

A.2.2 Performance of APSIM model in water deficit situations

Simulated versus measured data for the experiment of Thompson and Chase (1992) are shown in Figs A.1 and A.2. APSIM was able to capture the system performance over the range of deficit irrigation treatments (Figures A.1 and A.2), within what we have assumed to be the likely bounds of experimental variability. Grain yield was routinely over-predicted, however the trend in experimental observations was captured. Slight over-prediction of yield is expected for several reasons; (1) APSIM utilises small rainfall events (<5mm) in the climate record whereas in reality these are probably non-effective due to canopy/residue interception and subsequent evaporation (Thompson and Chase 1992). In water-stressed treatments (ie 1-5, Fig A.1), these are likely to be

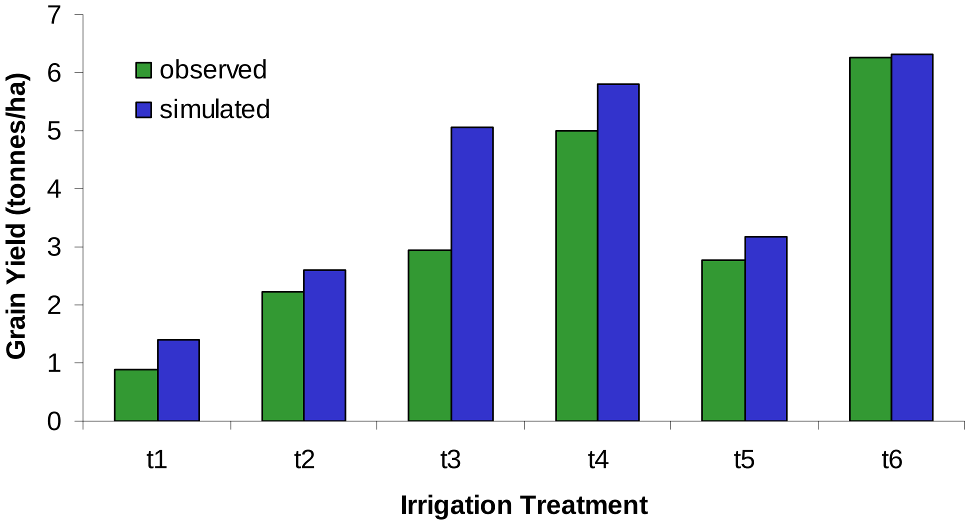

Figure A.1. APSIM simulated vs observed grain yields (dry) for the experiment of Thompson and Chase (1992)

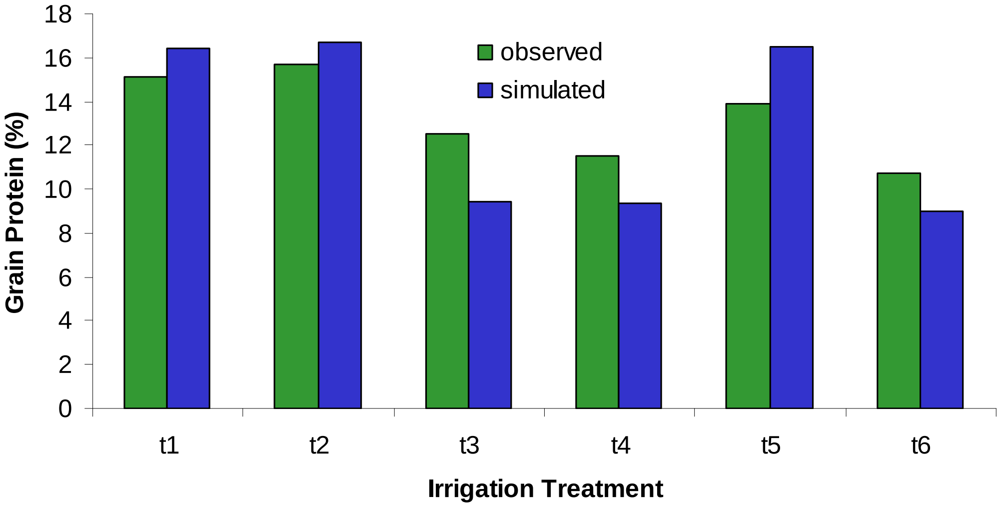

Figure A.2. APSIM simulated vs observed grain proteins for the experiment of Thompson and Chase (1992)

significant. APSIM was not able to satisfactorily simulate the performance of treatment 3, with a yield over-prediction of around 40%. As stated by Thompson and

Chase (1992), T3 (early water stressing with irrigation in middle stages) showed a significantly different physiological response to all the other treatments with significantly more (4.7 vs 3.3) green leaves per shoot at anthesis. This increased partitioning of resources into leaves resulted in reduced grain yield. APSIM was not able to simulate this phenomenon, and consequently substantial over-estimation of grain yield and under-estimation of green leaf biomass occurred. This scenario (T3 - only irrigating in growth stage 2) is not common farming practice, and was not identified as an adaptation option during the adaptation scenario analyses described in this paper, so APSIM's inability to capture the observed physiology did not concern us in assessing suitability for using APSIM in this study. Fig A.2 shows the simulated grain proteins associated with the yields in Fig A.1. Without access to details of treatment variability in Thompson and Chase's experiment, we have assumed that APSIM's performance in both grain yield and protein simulation is within the bounds of experimental variability over the range of applied irrigation stress levels, and hence acceptable for subsequent adaptation scenario analyses.

CHAPTER 5

Using Modern Portfolio Theory to compare options for irrigation farmers to invest water

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Abstract

For irrigation farmers, the deregulation of water markets and consequent emergence of water as a tradeable commodity calls for a method of comparing traditional on-farm water investment options (growing crops) with off-farm market options (selling water). The option to diversify farm income in this way is a desirable future adaptation strategy in response to decreased and more variable water supplies. We demonstrate a method for comparing such options based on their risk-return characteristics. A framework commonly used in the finance sector is adapted to agricultural water investment decisions, and illustrated using a case-study farm from Australia's Riverina region. In our example, a range of potential farm management practices are examined for several future water availability scenarios, and then compared with a fixed-return option (selling water entitlements to the Australian Government's current water buy-back scheme). We demonstrate how the attractiveness of the scheme for farmers depends on future water availability levels. For any future allocation level, the best way to use water on-farm varies with the value of the fixed-return option. The farmer's decision on what portion of their water entitlement to sell provides them with the opportunity to tailor their operation's risk-return performance. This method is universally applicable wherever there is a mix of variable and fixed-return investment options, and offers a framework to assist farmers in conceptualizing comparisons between traditional on-farm uses for water and newer, market-based options.

Keywords: irrigation, farming systems modelling, modern portfolio theory, efficiency frontier

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Agricultural Water Management (2012), accepted subject to minor revision

INTRODUCTION

With deregulation of water markets, irrigation farmers are presented with new options for investing their water. Traditionally farmers gained financial returns from water via production of crops and livestock – today, some farmers can also use water itself as a tradeable entity (Crase et al., 2000; McKay 2006). Forecast reductions and increased variability in water supplies (CSIRO, 2007; Hennessy et al., 2007) compel irrigation farmers to regard such new investment alternatives as potential future adaptation options in response to water scarcity (Bjornlund 2003a; Bjornlund 2006; Howden et al., 2007). In addition to forecast climatic changes, Australia has implemented significant water policy reforms since the mid-1990s. These have additionally imposed uncertainties regarding future supply, passing the risk management burden from water authorities to irrigators. Bjornlund (2006) suggests this has created an increased need for risk management tools to assist irrigators in managing this increased uncertainty amidst an increasing range of exploitation options.

We present a method for assessing water investment options for irrigation farmers, wherever the possibility exists to use their water resources on-farm, to sell them off-farm, or to employ some combination of both. We illustrate this method using a real case-study farm from the Riverina region of Australia - a major irrigation district straddling the Murray and Murrumbidgee Rivers in southern New South Wales and Northern Victoria. (latitude 34^{o}S to 35.5^{o}S; longitude 144.5^{o}E to 146.5^{o}E). For this farm, available water can be used to irrigate various grain crops under a range of potential agronomic and irrigation strategies; it can also be sold seasonally on the open market to other users, or water entitlements could be traded permanently. Various combinations of these options are of course also possible. The farmer possesses a *general security* entitlement - these are characterized by greater risk in annual supply than *high security* entitlements, which are primarily owned by farmers with permanent plantings or infrastructure (crops such as grapes, citrus and stone fruits; dairy). The relative capital values of these entitlement types reflect this (Crean, Jayasuriya and Jones, 2001).

Aspects of the Australian water markets for both seasonal allocation and permanent entitlement have been widely studied and analyzed in the scientific literature (Bjornlund 2003a; Bjornlund 2003b; Bjornlund and Rossini, 2005; Bjornlund 2006; Bjornlund and Rossini, 2007; Bjornlund and Rossini, 2008; Brooks and Harris, 2008; Wheeler et al., 2008). Bjornlund (2006) explains that allocation markets have been used by irrigators to manage risk within and between seasons, whereas entitlement markets are associated with more long-term strategic positioning. The substantial risk in future supply has made irrigators more hesitant to use the entitlement market, and consequently the allocation markets are far more actively used for risk management. Prices therefore fluctuate much more widely than entitlement prices, especially during periods of exceptional drought (such as 2002-03 and 2006-07). The original rationale for introducing markets in permanent water entitlements was to facilitate a move of water from inefficient low-value production, to efficient high-value production (Bjornlund 2003a). Although originally it was assumed this would occur via direct sale of entitlement, Bjornlund and Rossini (2005) suggest that seasonal water sales to higher value users are one of the more financially attractive adaptation options for lower-value irrigation farmers in times of low allocations. Producers of high value products with long-term investments in dairy herds and permanent plantings (grapes, citrus, stone-fruits) have demonstrated they will pay high prices during periods of water scarcity to limit potential losses caused by insufficient irrigation (Bjornlund and Rossini, 2005; Brooks and Harris, 2008). This has been a life-line to growers of lower-valued irrigated cereal crops and grains over recent drought periods, with prices for seasonally-traded water rising above A\$500 ML^{-1} – well beyond the A\$50-100 ML^{-1} which many of them can achieve from using the water to irrigate grain crops (Bjornlund 2006), and substantially offsetting the impact for them of having less water available. The Australian experience therefore is that allocation markets have achieved many of the outcomes expected of the entitlement market (Bjornlund and Rossini, 2007).

Entitlement transfers do occur however (Crase et al., 2000; McKay, 2006; Bjornlund and Rossini, 2007) and prices paid in the market for water entitlements in parts of Australia increased by 15% p.a. over the 10-year period from 1993 to 2003 (Bjornlund and Rossini, 2007). This suggests that retaining ownership of entitlements whilst selling water seasonally made more sense for irrigated grain farmers over that period. Future growth in the value of entitlements however is less certain – Bjornlund and Rossini (2008) suggest it would be strange for entitlement prices keep rising if the seasonal allocations yielded by the entitlements are decreasing.

In Australia, the vast majority of entitlement trading has been rural-to-rural (Turral et al., 2005), unlike the US where trade prices have been significantly influenced by urban expansion and population growth (Person and Michelsen, 1994). More recently a new buyer has entered the Australian market in the form of the Australian Government with its “Water Buy-Back Scheme”, aimed at recouping previously (over-) licensed irrigation water entitlement for environmental purposes (Australian Government, 2010a). Under this scheme, farmers may sell all or part of their entitlement for a tendered price per ML. They can then continue to conduct farming operations (either rain-fed or irrigated using water purchased on the open market), or alternately sell or lease the farm. This is particularly topical because the government is currently offering to buy back up to 100% of the farmer's licensed water (the full *entitlement*), while farmers have received only a fraction of their full entitlement in real water (*allocation*) each year over the past decade due to a combination of climatic and political factors (Gaydon et al., 2012c). Other current initiatives of the Australian Government fund the purchase of efficient irrigation technology for farmers in return for the permanent relinquishment of an equivalent portion of the their licensed allocation (Australian Government, 2010b).

Clearly there are numerous off-farm options for a farmer to consider, each with their own inherent risks and potential returns. The likely future allocation variability, particularly for general security entitlement, is uncertain (CSIRO 2007), and this complicates comparisons between on-farm and such off-farm water investment options. The analytical method we describe in this paper is suitable for comparing any on- and off-farm options providing risk-return estimates are available. For demonstration purposes we have chosen the Australian Government's Water Buyback Scheme as our example for an off-farm water investment option. This does not imply it's the best, or the most important option – it has purely been selected as an example. Here we compare this with a range of on-farm water investment options on the case-study farm (growing different types of crops for sale) using our proposed framework.

Assessing and comparing a range of investment options for water lends itself to methods routinely used in financial and share portfolio analysis, where investments are compared based on their risk-return characteristics. In the agricultural context, water options are rarely conceptualized in this way, largely due to difficulties in defining the risks associated with various on-farm cropping options. We propose that *Modern Portfolio Theory* presents a framework in which to make these comparisons.

Modern Portfolio Theory (MPT)

The Sharpe Ratio (*S)* can be used to express how well the return of an asset compensates the investor for the risk taken (Sharp, 1994). It is defined by Equation 1.

$$S = \frac{R - R_f}{\sigma} = \frac{\lfloor R - R_f \rfloor}{\sqrt{\mathrm{var}\lfloor R - R_f \rfloor}} \qquad (1)$$

Where R is the return from the investment in question, R_f is the 'risk-free' return, and σ is the standard deviation of the excess of the asset return over the 'risk-free' return.

If R_f really is risk-free, then the variance in its returns is zero, hence the standard deviation of the excess is the same as the standard deviation in returns of the asset in question (Equation 2; Scholz, 2007):

$$\sqrt{\mathrm{var}\left[R - R_f\right]} = \sqrt{\mathrm{var}\left[R\right]} \qquad (2)$$

In the irrigated agricultural context, the ‘risk free’ return on a parcel of irrigation water may be considered as the price a farmer would receive for selling this water directly to another user at the start of the irrigation season, or permanently selling their irrigation water entitlement. The return ($/Ml) from the water is then fixed. In the MPT sense ‘risk’ is defined as potential variability in returns – it has no connotations of missed opportunities or potential forgoing of gains from other options which have been forsaken, such as in common language usage. If a farmer decides instead to use the water on-farm to produce saleable products (crops), the risk of achieving a given return from the water increases because of intrinsic production and market risks such as climate variability, pest or disease problems and volatility in commodity price markets. Presumably the decision to use the water for irrigation would be based on the expectation that returns for on-farm water use would potentially be greater than from selling the water. The Sharpe Ratio may be used to assess the reward-to-risk characteristics of a range of possible options, providing that a reliable source for likely outcome distributions is available.

Irrigation farmers from Australia’s Riverina can potentially invest their water in different ways on-farm in an attempt to maximize returns and spread risks; for example, reserving a certain proportion of water for a range of winter crops, some for summer crops, and maybe some for pastures. Within the on-farm options, there exists a myriad of potential strategies to use the water. The crops could be fully- or partially-irrigated with varying land areas. Farmers also have the option to grow different species or varieties of crops, fertilizing and irrigating them in different ways. These different on-farm water investment options can be conceptualized as a spread of potential shares in an investment portfolio. Each of the ‘shares’ will have different risk-return profiles, or Sharpe Ratios. The question is: which combination of ‘shares’ should a farmer invest in, and in what proportion? A method for comparing the risk-return profiles of different investment options is needed. To investigate this, we propose using a financial methodology known as *Modern Portfolio Theory* (MPT; Markowitz, 1952). The fundamental concept of MPT is that individual investments in a portfolio should not be selected on their own merits. Instead, the optimal solution results from a combination of investments (diversification) which present the most desired combination of risks and returns.

If all possible combinations of investments are plotted on risk-return axes, the points define a region in this space bounded by an *Efficient Frontier* (Markowitz, 1952; Merton, 1972; Chamberlain, 1983; Owen and Rabinovitch, 1983). With a specific focus on agriculture, Keating et al. (2010) refer to this as an *Eco-Efficiency Frontier*; in our context we will refer to it as an *Efficiency Frontier*. Combinations of shares (or in the case of irrigation farmers, seasonal on-farm enterprises such as wheat, rice or pastures etc) along the upper edge of this efficiency frontier represent portfolios for which there is lowest risk for a given level of expected return, or the best return for a given risk level (Figure 1).

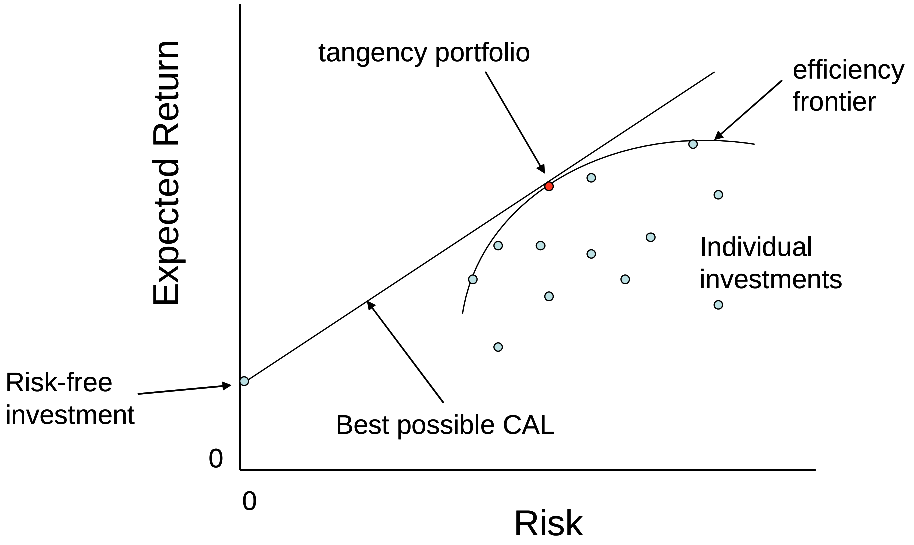

Figure 1. Comparing risk-return profiles for different portfolio options with a risk-free portfolio. Each point on the graph represents a portfolio with a combination of possible investments. CAL is the *Capital Allocation Line.* (Conceptual figure adapted from Merton (1972)).

MPT takes the efficiency frontier idea further. It suggests that combining an investment portfolio which sits on the efficiency frontier with a fixed return (or risk-free) investment can actually increase returns beyond the efficiency frontier for a given risk. When a fixed-return investment possibility is introduced into the mix, the tangential line shown in Figure 1 becomes the *new* efficiency frontier, and is called the *Capital Allocation Line* (CAL). It is tangential to the old efficiency frontier at the risky portfolio point with the highest Sharpe Ratio. In Figure 1, the y-axis intercept of the CAL represents a fixed-return investment portfolio, ie defined as ‘no variability’ in return. The point of tangency with the hyperbola represents the portfolio with the most desirable risk-return profile in relation to the available fixed-return investment. Points in between these two options along the CAL represent the best possible combinations of investments (including fixed-return ones) for each risk level (Merton, 1972).

For an irrigation farmer, selling water on the open market, or selling their water entitlements permanently to the Government represent fixed returns on that water asset. Riskier options, like using the water to produce crops/animals on-farm, are represented by the spectrum of points within the old efficiency frontier. The points along the CAL represent the best combination of risky and fixed-return investments for any given risk level. An alternate conceptualization is that the slope of the CAL illustrates the amount of return (ie returns over and above the fixed-return option) that can be reasonably expected by taking on risk within the system (Figure 2). This is also known as the *risk premium*.

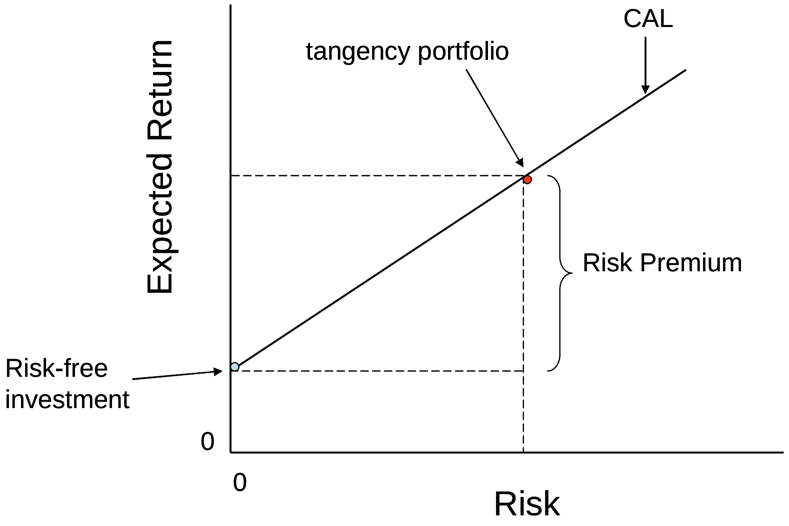

Figure 2. The slope of the CAL in a given system represents the amount of return available for taking on a certain level of risk above a no-risk investment option (or the *risk premium*).

We use this framework to compare traditional agricultural options for using irrigation water with market-based investment options. We use a real farm from Australia’s Riverina to illustrate the approach, comparing on-farm cropping options with the sale of water entitlements to the Australian Government’s water-buyback scheme. This example demonstrates the value of this framework for comparing options with different risk-return profiles, across a range of possible future water allocation scenarios.

MATERIALS AND METHODS

Case-study farm

The farm used in this analysis is described by Gaydon et al. (2012c). It is an irrigated rice-cereal-soybean operation in the Murrumbidgee Irrigation Area (MIA), NSW (latitude 34°S to 35.5°S; longitude 144.5°E to 146.5°E). The 600ha farm has 3265 ML (equivalent to approximately 544mm ha^{-1}) of general security irrigation water entitlement.

Characterizing the on-farm investment options

Ten (10) on-farm water investment options for the case-study farm were considered in this analysis (Table 1). They are described and modelled in detail by Gaydon et al. (2012c), resulting in a population of annual farm returns over a 52 year period for each option. The individual risk-return characteristic for each option is defined by the average annual farm profit in A$ ha^{-1} (the *return*), and the standard deviation of the population (the *risk*). The performance of these on-farm options under fixed seasonal allocations of 80%, 50%, and 20% of entitlement were modelled by Gaydon et al. (2012c) and used in our analysis. In this example, the farmer plans to retain his water entitlement in perpetuity and seek returns from the available water each season by farming.

Characterizing the off-farm investment option

The average sale price for general security water entitlements in the MIA as part of the Australian Federal Government water-buy back scheme was A\$927 ML^{-1} (Jan 2011, Hassall, 2011). The scheme offers to purchase farmers' water entitlements, partially or in their entirety.

We used this average purchase price to calculate the per annum value of the off-farm water investment option for the case-study farm, assuming zero-risk investment returns on cash of 6.5% were possible (Matthew Sheerin, Partner, Deloitte Australia, personal communication regarding Australian Government Treasury Bonds, January

Table 1. Broad outline of on-farm scenarios used in analysis (details in Chapter 4; Gaydon et al., 2012c)

Scenario	Description
AO1	**Control** (historical management: full irrigation, crop residues removed). Crops include barley (winter – mixture of irrigated and dryland), soybean and rice (summer – irrigated).
AO2	AO1 + retain barley residues through subsequent soybean crops instead of removing them (to reduce unproductive soil evaporation).
AO3	AO2 + partially irrigate winter crop (increase irrigated winter crop area with water saved).
AO4	AO2 + partially irrigate winter crop (increase summer crop area)
AO5	AO4 + rainfall-based sowing for winter crops (increase summer crop area).
AO6	All winter crop (fully irrigated) – no summer crops sown
AO7	All winter crop (partially irrigated – ie larger area sown than AO6)
AO8	All summer crop (fully irrigated)
AO9	Maximum areas for summer and winter crops (within constraints), buy water on open market as required (fully irrigate all crops)
AO10	Maximum areas for summer and winter crops (within constraints), buy water as required (partially irrigate winter crop).

2011). For the assumed (January 2011) government buy-back price (A$927 ML^{-1}), and the case-study licensed allocation of 3265ML, we calculated an annual gross return of A$196,733 (A$927 ML^{-1} x 3265 ML x 0.065 year^{-1}) at an assumption of nil risk. We then also used a conservative leased return on the dryland property (without water allocation) of A$124 per ha per annum (Tim Hutchinson, Breed Hutchinson Agents, Leeton, personal communication) to calculate an additional annual property income for the case-study farm of A$74,131. This resulted in a fixed return from the property of A$270,864 per annum.

Representation of options in risk-return space

Each investment option was represented as a point on a graph, with axes representing average farm returns (Y-axis; A$ farm^{-1} year^{-1}) and variability in returns (X-axis; standard deviation of farm returns). This enabled evaluation and comparison of option characteristics in risk-return space, as per the requirements of MPT. The 'risk' for each option results from the expected year-to-year variability in on-farm climate, captured in simulations that use 52 years of historical climate data. Efficiency frontiers were estimated from the spread of points associated with each of the three (3) allocation levels analysed. Each of these frontier curves represents the risk-return performance of the farm for annual water allocations of 20, 50 or 80% respectively.

RESULTS AND DISCUSSION

One of the challenges facing Riverina irrigators when assessing the merits of the Australian Government's water buy-back offer is how to compare a one-off cash payment with a range of possible on-farm water investment options in an uncertain future water-supply environment. Given forecast trends suggesting decreased and more variable allocations into the future, this comparison becomes increasingly difficult to conceptualize without a suitable framework. We have sought to investigate this issue by adapting some methods from the finance world, where such comparisons between investment options with different risk levels are more common.

Figure 3 illustrates the simulated adaption options for the case-study farm, presented within the efficiency framework on risk-return axes. Because the analysis of Gaydon et al. (2012c) generated details for only 10 potential on-farm management options for each allocation level (out of potentially thousands), the graph is intrinsically underpopulated and the red, blue and black 'frontier' curves are approximations only. It would be possible to generate a much more complete population using the methods of Power et al. (2011), or a Monte Carlo-based technique to assess combinations (Markowitz, 1991). For these conceptual estimations, point **A** represents the fixed return option (sell all water entitlement to government buy-back scheme); point **B** represents the optimal portfolio with 80% allocation (highest Sharpe Ratio; the highest return-to-risk ratio in relation to the specified fixed return option, **A**); while point **C** represents the optimal portfolio with 50% allocation. Not surprisingly, the lower the allocation the lower the risk premium (the potential benefit gained by taking that risk, *d* cf *e*). For the approximated frontier curves in Figure 3, AO3 (Adaptation Option 3; Gaydon et al. 2012c) is very close to the optimal adaptive option for years with 50% allocation. Modern Portfolio Theory implies that the risk-return relationship for a scenario of 50% water allocation each year on the case-study farm can be optimized for any desired risk level by combining various proportions of the fixed-return investment (**A**) and the risky investment represented by point **C**. The CAL that connects these two points represents the *new efficiency frontier*, now that a fixed-return option like the water buy-back is ‘in the equation’. By selecting a point on the CAL that provides comfort in terms of risk exposure (defined as variability in returns), farmers can specify their preferred combination of risky and fixed-return investments under the circumstances. This is equivalent to selling a certain proportion of their entitlement back to the government, investing the cash payment, and managing the remaining entitlement on-farm according to the AO3 strategy. The location of that ‘comfort’ point will vary from farmer to farmer, from 100% sell-back (for someone who might be ready to leave the land or retire), to 100% retain (for a farmer keen to explore the full farming potential of their water assets). Regardless of where the farmer’s personal risk preference lies, this approach allows for the definition of a new efficiency frontier.

The effect of future water supply variability

Obviously in reality farmers do not expect to receive 50% allocation every year (or 80% or 20%). It is impossible to know what the future variability in water allocations will be, as large uncertainties exist around both of the key drivers: climate change and politics. Our approach is to present farmers with an operational framework that incorporates their own estimations for future allocation variability and subsequently assesses the impact on comparisons between available options for using their water. We have not attempted to prescribe what will happen with future allocations. For example, if a farmer believes that future seasonal allocations will range between 80% and 20%, then clearly the estimated efficiency frontier for their business will lie somewhere between these two simulated curves on the risk-return diagram (Figure 3). The question is “precisely where?”

To provide some insights, we considered an example with three future allocation scenarios over a 10-year period. The three allocation scenarios each had an average seasonal allocation of 50%, yet exhibited different annual variability around that average. The scenarios were (% allocation each year):

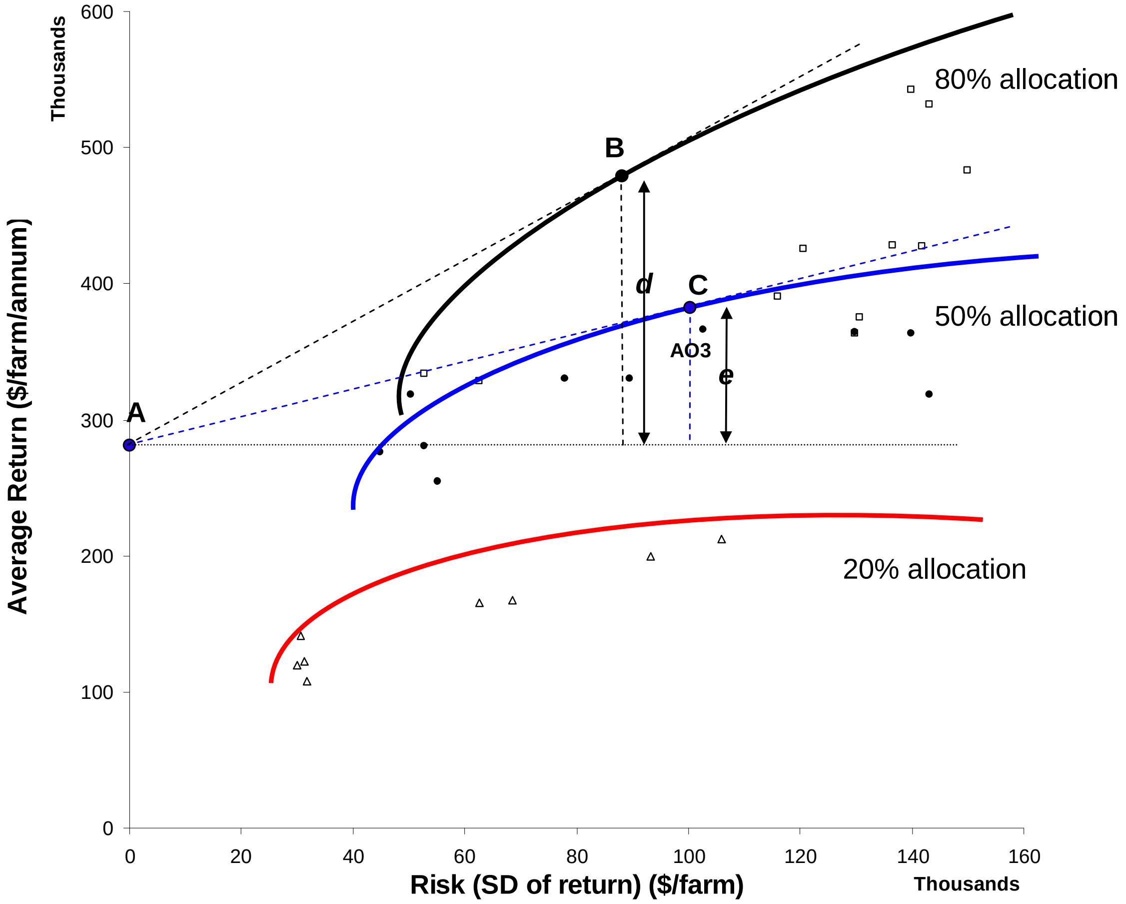

Figure 3. Simulated adaptation options for the case-study farm presented as points on efficiency framework axes, for three (3) potential future allocation amounts. Each point represents 52 years simulated farm performance. The envelope curves (red, blue and black) are estimates, based on a limited population. The x-axis is the standard deviation of population for each average return point.

SCENARIO 1: 50, 50, 50, 50, 50, 50, 50, 50, 50, 50 (average 50)
SCENARIO 2: 80, 20, 80, 20, 80, 20, 80, 20, 80, 20 (average 50)
SCENARIO 3: 90, 90, 10, 90, 10, 10, 90, 10, 10, 90 (average 50)

The risk-return performance for each of the 10 adaptation options was reassessed using the APSIM model for each of the scenarios, as per the original analysis (Gaydon et al., 2012c). The resulting risk-return characteristic for each adaptation option was plotted, and efficiency frontiers for each scenario of allocation estimated (Figure 4).

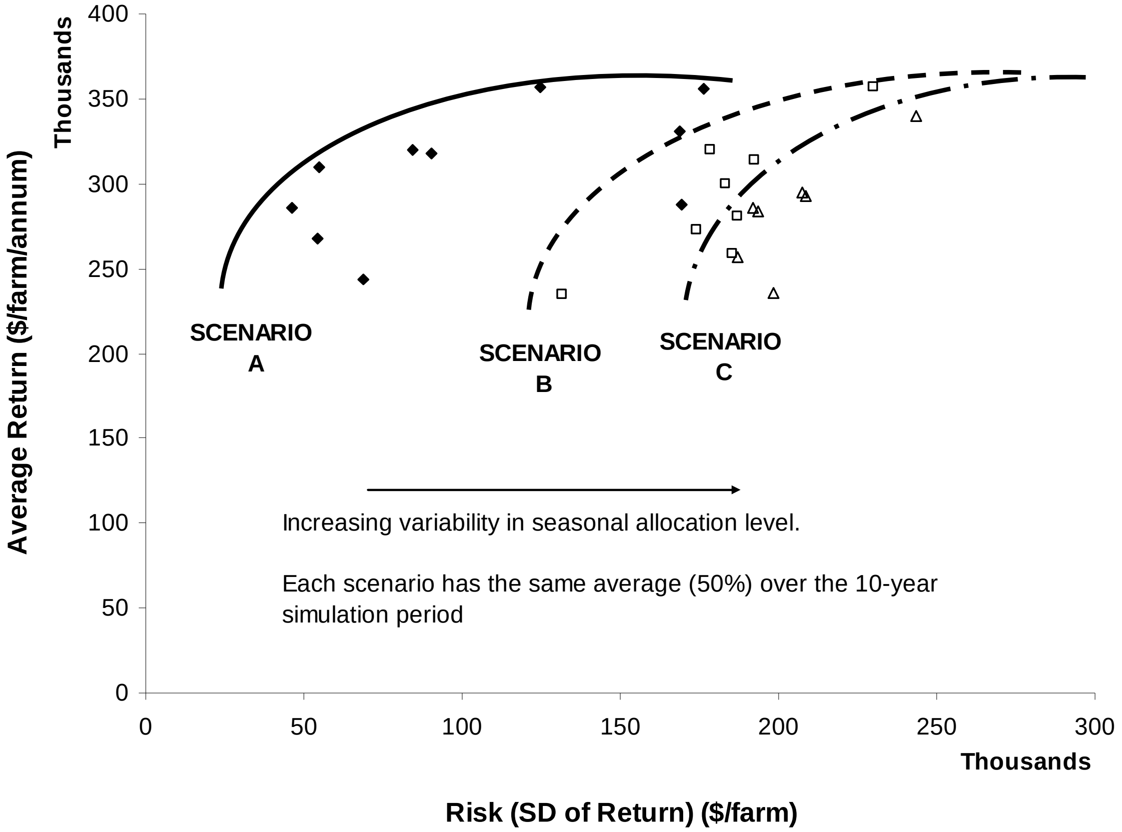

Figure 4. The effect of increasing variability in seasonal water allocation – showing simulated points for the 10 adaptation options (Gaydon et al., 2012c) and estimated efficiency frontiers for three imposed scenarios of increasing allocation variability; SCENARIO A – 50% allocation (constant each year); SCENARIO B – 50% average allocation (ranging between 80% and 20%); and SCENARIO C – 50% average allocation (ranging between 90% and 10%). Each point represents 10 years simulated farm performance with varying seasonal allocations as per each scenario.

Increasing variability in allocation (illustrated by moving from Scenario 1 to Scenario 3), results in greater risk in returns, yet notably the average returns over the period do not vary significantly. It appears likely therefore that there will be a family of efficiency frontier curves for each average future allocation level, spreading horizontally to the right with increasingly variability of supply.

A method for incorporating farmers' own estimate about future allocation variability

Farmers will have their own individual perspectives on the likely range of future water allocations, based on their past experiences and expectations regarding future changes in climate and the political landscape. We postulate that these expectations can be quantified and used to define a sensible location of their business's efficiency frontier. Our proposed method initially requires the definition of four (4) key curves (Figure 5). These can be derived via simulation (as previously demonstrated) after the farmer has specified their expected future allocation *range* e.g. let us assume the farmers predicts a future seasonal range between 80% and 20%. In this case, the required curves to define are (as numbered in Figure 5):

1. The constant-allocation curve for the top of the range (80% allocation)
2. The constant-allocation curve for the bottom of the range (20% allocation)
3. The constant-allocation curve for the middle of the range (50% allocation)
4. The maximum variability curve for the mid-range average (ie a sequence of allocations comprising random years of 80% and 20% allocation, with an average of 50%; like scenario 3 in Figure 4.)

Once these curves are defined, two critical assumptions can logically be made:-

a. The maximum potential variability must occur in the middle of the expected allocation range (in this case, 50%) - a mathematical reality resulting from the possibility for random sequences of years with allocations composed only of the upper and lower bounds (80% and 20%).
b. By the same logic, the variability for an average allocation at both the top and bottom of the estimated range (80% and 20%) is necessarily zero – for example, if the average allocation is 80% and the maximum allocation also is 80%, then every season must be 80% to achieve this – in other words, zero variability).

This allows definition of a *Maximum Variability Envelope* (Figure 5) as a function of the farmer's expected range in future allocations. The final critical step is for farmers to provide their estimation on their expected *average* future allocation within their specified range. This then defines the horizontally-aligned family of curves representing the possible variation for that average allocation, ranging between the constant-allocation curve and the envelope. For example, a sensible location for the efficiency frontier curve could be indicated by the dashed blue line in Figure 5, if this farmer estimated an average future allocation of 65% and expected mid-range season-to-season variability (halfway between a constant allocation and the most extreme variability possible).

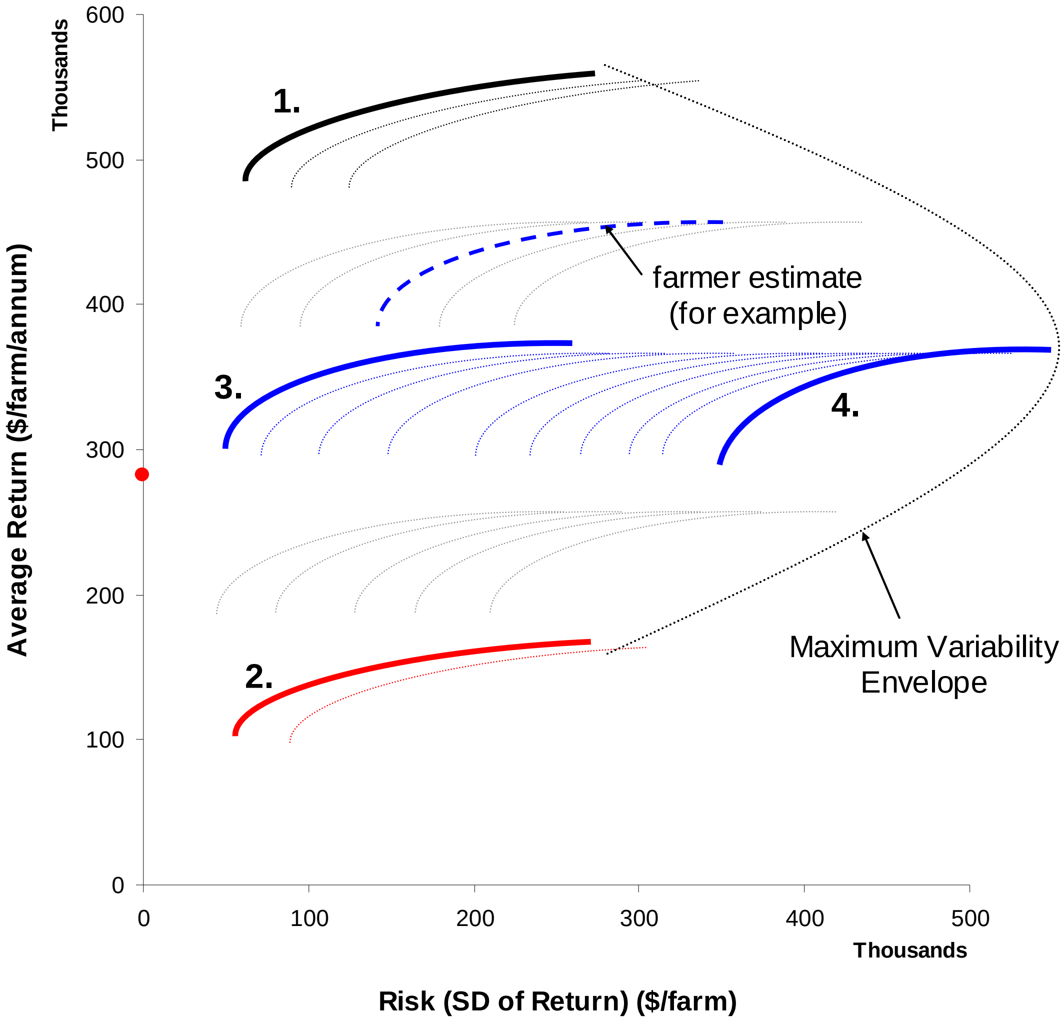

Figure 5. The proposed method for positioning the efficiency frontier associated with a farmer's own estimate of average future water-supply and its associated variability. Four (4) curves are necessary to define the space, and can be established by simulation – **1.** constant allocation at upper estimate of future range (in this example, 80%); **2.** constant allocation at lower estimate of range (20%); **3.** constant allocation in middle of range (50%); and **4.** maximum variability allocation for a 50% average. By definition, the possible spread of efficiency frontiers will always be greatest in the middle of the estimated future range, and zero at maximum and minimum of the range – thereby defining a "Maximum Variability Envelope". This figure shows how a farmer's estimate (in this case, a 'mid-range' variability around an average allocation of 65%) could be located half-way between '65% fixed' curve and envelope (shown as a blue dashed line in this example)

Translating scientific information into real life action requires attention to salience, credibility and legitimacy of the approach (Cash et al., 2003; Meinke et al., 2009). Both saliency and credibility are enhanced when decision-makers, in our case farmers, are able to integrate their own expectations about future water supplies, critical farm cash-flows, and risk preferences. Our framework assists such integration at the individual level. We are therefore confident the analytical approach demonstrated in this paper is well-placed to assist farmers and their advisors in decisions related to investment of water resources. We have consciously avoided being too prescriptive, as there is ample evidence of the failure of such decision-support tools (McCown, 2002). There may be value in additional research building on the concepts presented in this paper to further refine methods for interpolating farmer expectations within simulated efficiency frontiers.

What happens when the value of the fixed-return option is varied?

Once the appropriate efficiency frontier has been defined as described above, variations in the value of the fixed-return investment (in this case, changes to the federal government water buy-back price) can be conceptualized. When the value is varied, the optimal adaptation option for the given irrigation water allocation scenario also changes (Figure 6). In the figure, points **A**, **B**, and **C** represent adaptation options with the highest Sharpe Ratios for buy-back offers of \$766/ML, \$927/ML and \$1100/ML respectively. As the buy-back price for water entitlement increases, competitive on-farm options become fewer and riskier. In our example these on-farm alternatives are adaptation options 4, 3 and 10 respectively (Gaydon et al. 2012c). The current buy-back offer would suggest AO3 (partially irrigate and increase winter crop area) as the best of the analyzed on-farm strategies, whereas a fall in the buy-back offer price would suggest an optimal on-farm strategy closer to AO4 (partially irrigate, then increase fully-irrigated summer crop) which presents reduced average farm returns, but at less risk than AO3. Conversely, an increase in the buy-back price above the current offer sends the optimal farming strategy to higher average returns from riskier practices. Because the curves in Figs. 3 and 6 are estimates, it is pointless to attempt any conclusive statements on the exact position of the *new efficiency frontier* or CAL line for each of the water allocation amounts, or about the optimal farm strategies for different buy-back prices. A more accurate definition of these curves would provide greater confidence in making assertions on these matters.

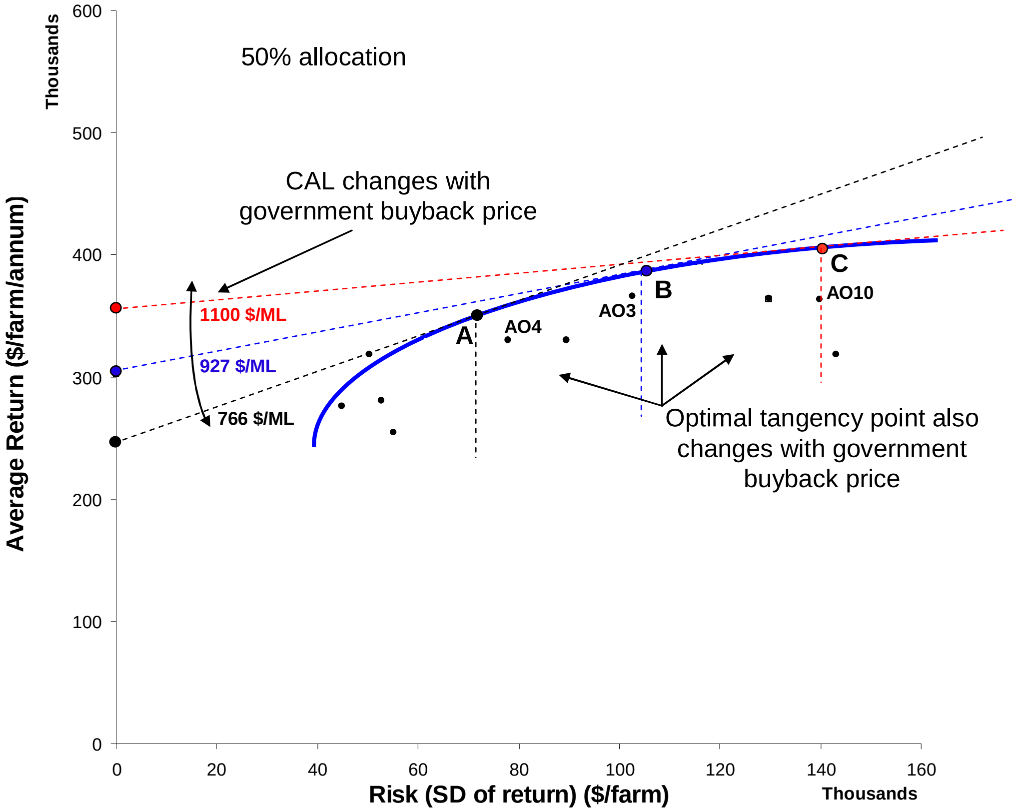

Figure 6. Simulated adaptation options for the case-study farm presented as points on efficiency framework axes (for a future allocation of 50%), illustrating the effect of varying the 'no-risk' investment value on the optimal adaptation option. The x-axis is the standard deviation of population for each average return point.

If the Government buy-back price is incrementally increased, at some point a level is reached at which no on-farm cropping strategy is competitive and risk premiums become negative. For example, Figure 3 implies that this point has already been reached with the current buy-back price, if the future allocations for the case-study farm were to be in the vicinity of 20%. Someone in the financial world might respond to this situation by making a clear judgement to "sell" while the offer stands.

Farmer response to research findings

Responses to the research findings were sought individually from the case study farmer and two other independent advisory farmers. The three farmers were selected to represent a diversity of farm types from the Riverina region, in terms of soils, geographical location, farm size, attitudes to risk, and current farming practices. A large number of comments were collated, and we only report the most pertinent points.

Our MPT analysis comparing on-farm water-use options with the Australian Government's current water buy-back scheme engendered considerable interest amongst the farmers. All commented that this was the first attempt they had seen to relate these options in a quantitative or graphical way. The concept of defining 'risk' as the standard deviation of a population of returns was not an intuitive concept for any of the farmers interviewed. The general consensus was that risk would be better expressed as a 'down-side risk', or as a percentage of years in which returns were below a defined threshold. The substitution of downside risk for variance in return-risk trade-off analyses has considerable precedence in the literature (McCown et al., 1992; Carberry et al., 2000; Keating et al., 2010 and many more). Frequently, anecdotal evidence suggests that the adaptation options with greatest down-side risks are also the ones with the greatest standard deviations; hence the analyses may not be greatly affected. Ultimately this debate over the definition of 'risk' is a communication issue and does not invalidate our approach. It does stress, however, that participatory engagement is required when developing an operational version of our MPT approach to farm-level water management. The farmers were comfortable with the approach, and could see this was a framework for them to incorporate their own estimates of how future variability in water supplies might unfold, and to subsequently define where their business frontier would be positioned on the framework in relation to fixed-return investment options.

There was consensus that the MPT analyses and comparison between Government water buy-back and on-farm adaptation options could be "vastly different" between individual farms; largely due to different ratios between entitlement and land area. Land ownership and water entitlement are not inextricably linked in the Riverina region, and both land and water entitlement can be sold separately resulting in a range of farms exhibiting high to low 'concentrations' of entitlement. In summary, our specific case study findings on the economics of the comparison apply to the case study farm only, and further investigation on how this varies with a farm's 'water to land' ratio may be warranted. An operational version (e.g. spreadsheet-based) of our MPT approach could be developed in partnership with interested farmers and their financial advisors. Such co-development would overcome some of the communication and perception issues discussed earlier.

Comparing other water market options

Obviously the example we have provided comparing on-farm options with the sale of entitlement to the Australian Government's Water Buy-Back Scheme does not provide a comprehensive picture of the wide range of water market options available to irrigation farmers. Several authors (Bjornlund 2003a; Bjornlund and Rossini 2005; Bjornlund 2006) identify retaining entitlements and trading allocation seasonally as a more desirable option, taking advantage of capital growth in value of entitlements (15% per annum increase between 1993 and 2003; Bjornlund and Rossini, 2007) and high seasonal water prices when possible. A further financial analysis showed that investment in a water entitlement over a 5 year holding period, including annual sale of allocation and subsequent sale of the entitlement, was in excess of returns from the Australian share market (Bjornlund and Rossini, 2008). A key element is that entitlements must be liquidated before any capital gains can be realized. Given the reported capital increases in entitlement value, we suggest analyzing further scenarios where the farmer retains the entitlements for a further 5 or 10 years, farming with the water over that period, and then selling the entitlement on the open market to realize the associated capital gain. A scenario of this nature takes the analysis into "real options space" (Trigeorgis, 1996; Black and Scholes, 1973), and is beyond the scope of this current paper, yet once the corresponding volatility of future capital gains is estimated and the risk-returns are quantified, the results could still be represented as operational points on MPT risk-return axes and compared with our current examples. A particular challenge in characterizing the risk-returns associated with this type of "hold then sell" scenario would be deriving reasonable estimates of future capital gains for the water entitlement asset, given that yields from that asset (ie the allocations) are forecast to reduce (CSIRO, 2007; Hennessy et al., 2007) and that Bjornlund and Rossini (2007) suggest "it would seem strange that entitlement prices keep increasing while the seasonal allocations yielded by the entitlements are decreasing"

Bjornlund and Rossini (2008) also suggest the Australian water market is showing signs of becoming a *maturing market*. Derivative products such as 'put and call' options, together with futures contracts/trading in water are market instruments which may be expected to emerge. These products may help future farmers manage risk and variability in water supply and protect them against unforeseen fluctuations in prices, in the same way as in financial markets.

There are clearly many potential future options for irrigation farmers to evaluate, in addition to their traditional decisions about what crops to plant to what area. All of these options can be simultaneously represented on the MPT framework as individual points, providing individual risk-return characteristics can be estimated. If maximising return is the sole aim, the highest average return will clearly identify the best option. However the MPT framework we have demonstrated becomes particularly useful when there is some degree of risk-aversion, and the definition of the efficiency frontier from the range of assembled options can help provide assessment of the best possible of combinations of investments (diversification) to maximise returns for any desired risk level.

Ultimately, different farmers will have different aspirations and therefore different criteria on which to evaluate available options. Turral et al., (2005) explained that buyers of entitlement are principally interested in increasing the reliability of supply and intensification, whereas the majority of sellers have excess water, are reducing irrigated area or need to raise finance. We suggest that further research using this MPT approach is warranted, to assess a more comprehensive range of potential off-farm water market options for farmers, comparing them with traditional on-farm water use options under a range of potential future circumstances (commodity prices, operating costs, allocations). Consideration of prospects for a decision-support tool could follow.

CONCLUSIONS

For irrigation farmers, the deregulation of water markets and consequent emergence of water as a tradeable commodity calls for a method of comparing traditional on-farm water investment options (growing crops) with off-farm market options (selling water). Here we have demonstrated a new approach, adapted from the financial world, for making this comparison. This method uses the concept of an *efficiency frontier*, recognizing that options cannot be compared based on their average returns alone, but also on their risk levels. We used a case-study farm from Australia’s Riverina region, however the method is universally applicable wherever farmers have co-existing investment options to either sell or use (irrigate with) their water, or a mixture of both. Under these circumstances, the method we have presented allows identification of the on-farm strategy with the highest return-to-risk (Sharpe) ratio in comparison with a fixed-return option. Once this identification is made, farmers can conceptualize how the risk-return characteristics of their businesses would be impacted by selling and using various proportions of their water entitlement. We also demonstrated how the best on-farm water use strategy changes with the value of the sale option. The method relies on sensible definition of risk-return characteristics for on-farm water use options, and this may be facilitated by well-tested farming systems models. The method does not intrinsically include any assumptions about future water-supply variability. Instead, it provides a framework for farmers to impose their own expectations. Further research may assist farmers in more accurately estimating a position for their business efficiency frontier which captures their own estimations of future allocation variability, and also making comparisons with a more comprehensive range of off-farm water market options.

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CHAPTER 6

Rice growth, yield and water productivity responses to irrigation scheduling prior to the delayed application of continuous flooding in south-east Australia

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Abstract

The majority of rice grown in south-east Australia is continuously flooded for much of its growing season, but reduced irrigation water availability brought about by a combination of drought and environmental flow legislation has presented a need to maintain (or even increase) rice production with less irrigation water. Delaying the application of continuous flooding until prior to panicle initiation can increase input water productivity by reducing non-beneficial evaporation losses from free water and the soil. A field experiment was conducted over two growing seasons, 2008/9 and 2009/10, comparing a conventional dry seeded treatment (the control – continuous flooding from the 3 leaf stage) with delayed continuous flooding (10–20 days prior to panicle initiation) with several irrigation scheduling treatments prior to flooding commencement. In the first year, the delayed water treatments were irrigated at intervals of 40, 80 and 160 mm of cumulative reference evapotranspiration (ETo) prior to delayed continuous flooding, thereby imposing differing degrees of crop water stress. In year 2, the 80 and 160 mm treatments were modified by use of a crop factor (Kc) when the plants were small and the 40 mm treatment was replaced with a continuously flooded treatment throughout the crop duration. Decreases in net water input (irrigation + rain−surface drainage) and increases in input water productivity were achieved by reducing the flush irrigation frequency during the pre-flood period. Savings of 150 and 230 mm (10 and 15%) were achieved in Year 1 from the 80 and 160 mm cumulative ETo irrigation frequency treatments, respectively, in comparison to the control. In the second year, net water input savings of 230 and 330 mm (15 and 22%) were achieved with the 80/Kc and 160/Kc mm treatments, respectively. Input water productivity of the 160 mm treatment was 0.06 kg/m3 (8%) higher than the control in Year 1, while in Year 2 a 0.15 kg/m3 (17%) increase in input water productivity above the control was achieved by the 160/Kc mm treatment. Delaying the application of continuous flooding in the second year greatly extended the period of crop growth suggesting the need for earlier sowing (by 7–10 days) to ensure pollen microspore still occurs at the best time to minimise yield loss due to cold damage. Nitrogen fertilizer management is an important issue when delaying continuous flooding, and nitrogen losses appeared to increase with the frequency of irrigation prior to continuous flooding. This was likely due to increased denitrification from alternate wetting and drying of the soil. Further research is required to determine the most appropriate nitrogen management strategies, and to also better define the optimal pre-flood irrigation frequency.

Keywords: Rice, input water productivity, irrigation, delayed continuous flooding

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INTRODUCTION

Over the past twenty years the average field input water productivity (WP) of the total NSW rice crop has almost doubled (Humphreys et al., 2006). This has been largely due to increased yields with the introduction of semi-dwarf cultivars, and partly due to reduced rice field water use. Through a combination of the implementation of rice field water use limit policy and the adoption of electromagnetic induction soil surveys to identify more suitable low permeability areas (Beecher et al., 2002), there has been a reduction in rice production on soils where substantial amounts of water is lost through percolation past the root zone, resulting in reduced average rice crop water use for the region (Humphreys and Robinson, 2003).

In recent years rice producers in south-eastern Australia have experienced an unprecedented restriction in production due to water shortages brought about by a combination of drought and environmental flow legislation. Over the period since 1997, irrigators have received only a fraction of their water allocations (Gaydon et al., 2010). Given recent climate change projections, which suggest a 16–25% reduction in average Murray-Darling streamflows by 2050 and 16–48% reduction by 2100 (Pittock, 2003; Christensen et al., 2007; CSIRO, 2008), there is likely to be further downward pressure on irrigation water allocations in the future. This reduced water availability presents a challenge to maintain (or even increase) rice production with less irrigation water. To increase water productivity, either unproductive water losses(evaporation, percolation, seepage, transpiration from weeds) must be reduced, or the efficiency of productive water use (transpiration) must be increased (Haefele et al., 2009), or a combination of both. The majority of rice grown in south east Australia is flooded for much of its growing season, providing favourable water and nutrient supply under anaerobic conditions. There is little opportunity to increase water productivity from the current flooded rice growing practice (Humphreys et al., 2006), so farmers must adopt innovative water management practices to meet the challenge of increasing rice water productivity. One opportunity to save water may be to reduce the length of time the crop is flooded. The period from the start of continuous flooding (which commences prior to seeding for aerial water seeded crops and at the 3 leaf stage for drill sown crops), to the time when the crop reaches full canopy cover, is a period of opportunity for reducing water use. During this period the plant canopy is small and evaporation from the free water surface makes up 40% of total evaporation loss in continuously flooded aerial sown rice (Simpson et al., 1992).

Technologies such as alternate wetting and drying, saturated soil culture (Tuong et al., 2004), aerobic rice culture (Kato et al., 2009) and sprinkler irrigation (Muirhead et al., 1989) have been found to be effective in reducing water use, mainly from a reduction in deep percolation and excessive evaporative losses (Humphreys et al., 2005), but often involve reduced yield, increased costs and more precise irrigation water control. Changing from continuously flooded to a more aerobic rice culture also has implications for other aspects of the rice production system, including nutrients and weed control.

The period when flooding of rice may not be required in south-east Australia, is limited because of the need for cold-temperature protection during the reproductive period. The potential for dramatic yield reductions from low temperature is very high during early pollen microspore development (Williams and Angus, 1994). The application of deep water (20–25 cm) during this period is a recommended method adopted by farmers to protect the pollen against low temperature (Humphreys et al., 2006). Flooding is also required during the reproductive period to meet the crop water requirements during the very high crop growth rates (250–300 kg/ha/d) that occur between panicle initiation (PI) and flowering. The high potential evapotranspiration demand during this period necessitates flooding, and could result in crop water deficit stress if a non-ponded culture was used (Humphreys et al., 2005).

However, delaying the onset of continuous flooding until about 2 weeks before panicle initiation has shown promise in south east Australia. Heenan and Thompson (1984) obtained input water savings of 23% through intermittent irrigation every seven days prior to the establishment of continuous flooding at PI, compared with conventional practice. Equivalent grain yields were achieved in both cases. This research was conducted in a field with considerable deep percolation loss of water which would have inflated the water saving benefit. Thompson and Griffin (2006) undertook further experiments to explore potential irrigation water savings on a less leaky site in 2001–2004. Grain yield from the intermittent irrigation treatment was generally similar to yield of the conventional treatment resulting in an increase of water productivity ranging from 0.06 to 0.23 kg/m3 compared to the normal flooding regime. The research conducted on delayed continuous flooding by Heenan and Thompson (1984) and Thompson and Griffin (2006) involved regular irrigation intervals with little moisture stress on the crop during the unflooded period. Larger water savings may be achieved with less frequent irrigations, but the optimal level of moisture stress between irrigation is currently unknown. Cumulative transpiration is linearly related to total dry matter production (Haefele et al., 2009) hence moisture stress often results in reduced dry matter production and grain yield. Determination of a water stress level threshold to maximize water productivity is therefore important.

In this paper, we present the findings of field experiments to investigate potential input water savings from a range of treatments, irrigated at different cumulative evapotranspiration frequencies prior to the start of continuous flooding which was delayed until 10–20 days before panicle initiation. These were compared with a conventional drill sown treatment with continuous flooding applied at the three leaf stage. The experiment was repeated in 2009. Net water input, crop growth, grain yield and input water productivity from each treatment were compared.

MATERIALS AND METHODS

Site description

The experiment was conducted over the 2008/9 and 2009/10 rice growing seasons (October–April) at the Yanco Agricultural Institute (34◦36’56”S, 146◦25’06”E) on a red-brown earth soil (Alfisols, Soil Survey Staff, 1975). The soil was a Birganbigal clay loam with a clay loam surface horizon 0.15–0.20 m deep and heavy clay subsoil (van Dijk, 1961). The Yanco Agricultural Institute is located in the Murrumbidgee Irrigation Area in south east Australia. The soil properties of the experimental field are presented in Table 1.

Table 1. Initial soil characteristics of the field experimental site (mean of 3 replicates)

Parameters	0-10cm	10-20cm	20-30cm	30-40cm
pH (1:5) ($CaCl_2$)	6.0	6.1	6.5	6.8
EC (1:5) ($\mu S\ cm^{-1}$)	35	37	94	64
P- Colwell (mg kg^{-1})	72	31	21	11
CEC (meq $100g^{-1}$)	15	16	18	21
Ca:Mg ratio	1.8	1.6	1.4	1.2
ESP (%)	3.9	6.2	9.1	12.0
Organic C (%)	1.6	1.1	0.8	0.5
Silt (%)	15	17	18	21
Clay (%)	26	28	35	28
Course Sand (%)	13	9	6	7
Fine Sand (%)	46	46	41	44

The experimental site has a temperate climate characterized by hot dry summers with low humidity. One-third monthly mean (49 years) temperatures and reference evapotranspiration (ETo) for Griffith (49 km from the experimental site) together with values recorded during the experiment are presented in Figure 1. The ETo is calculated for Griffith using a locally calibrated modified Penman equation (Meyer, 1999) and available at http://www.clw.csiro.au/services/weather/#data . Total in-crop rainfall received during the experimental period was 104 and 219 mm for the 2008/9 and 2009/10 seasons, respectively. Rainfall received between sowing and application of continuous flooding to the delayed treatments was 94 mm in 2008/9 and 61 mm in 2009/10.

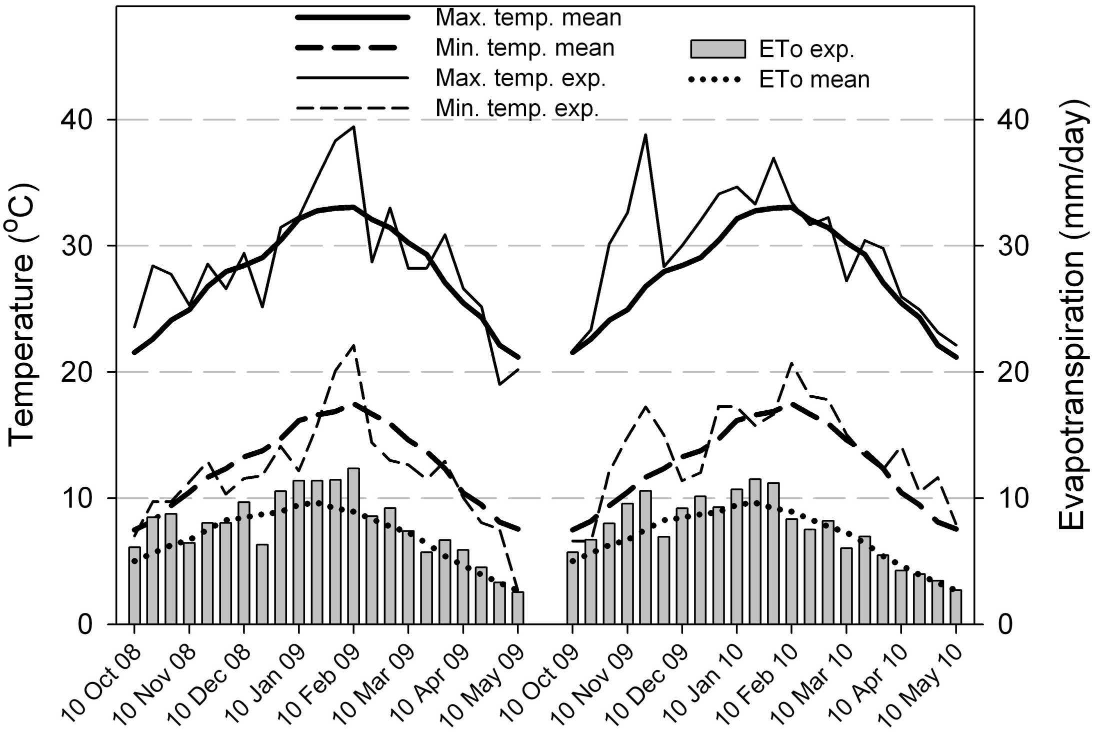

Figure 1. Long term mean (49 years) minimum and maximum temperature and evapotranspiration (ETo) and values recorded during the experiment (one-third month means) for Griffith, NSW.

Treatments and design

The experiment was established in twelve individual bays (12 m x 36 m) each separated by 40 cm high earthen banks. Each bay was independently connected to water supply and drainage channels. The experimental design was a randomized split-plot with four water management treatments as the main treatment, three nitrogen rates as the subplot and three replications. Subplot size was 72 m2. In each year all treatments were dry seeded using a combine seed drill except for one broadcast seeded treatment in 2009/10.

The water management treatments used irrigation scheduling based on cumulative net reference evapotranspiration (ETo-minus rain) until continuous flood was applied

10-20 days prior to panicle initiation, compared to the control where continuous flood was applied at the three leaf stage of crop development.

In Year 1 (2008/9) the water management treatments included:

1. *Control* - permanent water (PW) i.e. continuous flood applied at the three leaf stage;
2. *40ETo* - flush irrigations at 40 mm cumulative net reference evapotranspiration (ETo-minus rain) intervals until PW applied 10 days prior to panicle initiation (PI);
3. *80ETo* - flush irrigations at 80 mm cumulative ETo minus rain intervals until PW applied 10 days prior to PI;
4. *160ETo* - flush irrigations at 160 mm cumulative ETo minus rain intervals until PW applied 10 days prior to PI.

The irrigation scheduling thresholds were chosen with 80 mm being considered suitable for this soil type for other cereal crops and the 40 and 160 mm treatments being half and double this respectively. Flush irrigations involved filling the bays with 5 cm depth of water then leaving them ponded for 3 hours before draining the water from the bays. This is normal practice for drill sown rice in Australia where flush irrigation water is drained through into the next (lower) bays. Surface drainage water was measured and subtracted from the amount of irrigation water added to calculate net irrigation input.

The medium grain short season semi-dwarf variety, *Quest* (Smith et al., 2010) was drill sown into a cultivated seedbed at 150 kg/ha and the first flush irrigation applied to all plots on 23 October 2008. All treatments received a second flush irrigation to ensure good establishment before the irrigation frequency treatments commenced. The Control treatment received 3 flush irrigations (water ponded for 3 hours then drained) in total before permanent water on the 18 Nov 2008, while the 40ETo, 80ETo and 160ETo treatments received 11, 6 and 4 flush irrigations respectively before permanent water was applied on the 1 Jan 2009 (Figure 2a). All irrigation treatments received three split-plot N rate treatments, 0, 135 and 200 kg N ha^{-1} in the form of urea. The nitrogen rates were selected based on an amount normally required to achieve 10 t/ha yields for this soil type in this region (135 kg N ha^{-1}) and a higher rate near the maximum of what would commercially be applied (200 kg N ha^{-1}). The Control treatment received 2/3 of the nitrogen applied to dry soil prior to permanent water and the remaining 1/3 into water at PI. The 40ETo, 80ETo and 160ETo treatments received nitrogen in three equal splits, i.e., 1/3 at 3 leaf stage, 1/3 at mid-tillering and

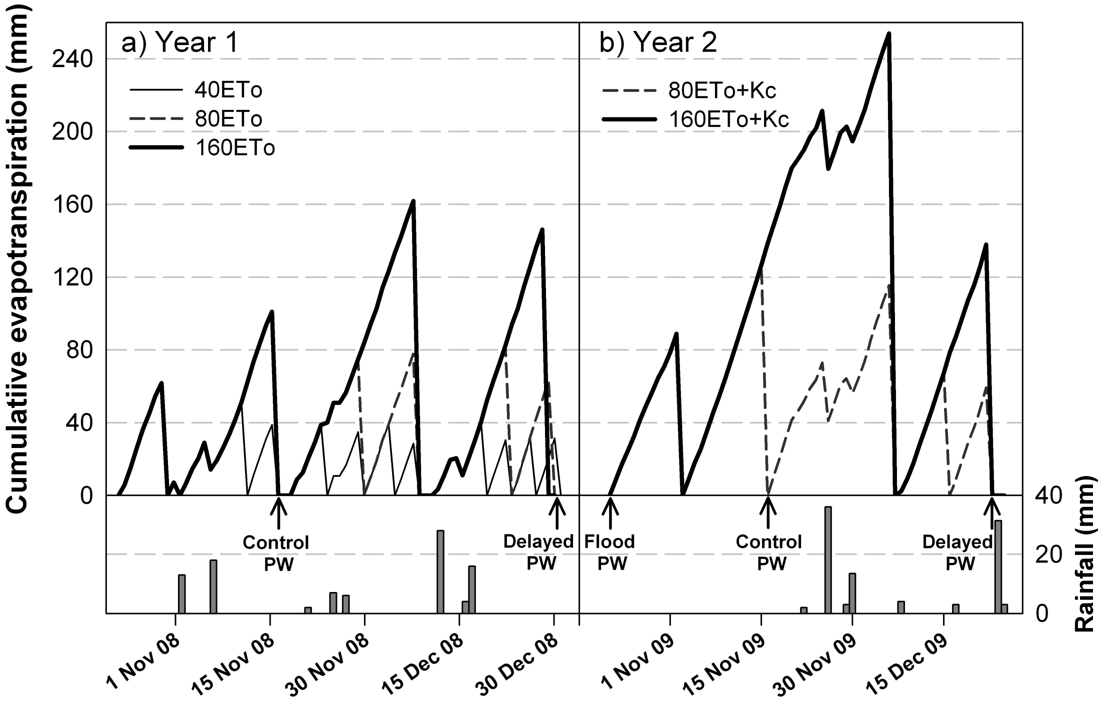

Figure 2. Cumulative reference evapotranspiration for each delayed permanent water treatment and daily rainfall (vertical bars) for a) Year 1 and b) Year 2 of the experiment.

1/3 prior to permanent water (10 days prior to PI). All nitrogen was applied to the dry soil before a 48 hour period of ponding then drained except at the time when permanent water was applied.

In Year 2 (2009/10) the irrigation regimes were similar to year 1 for the Control, 80ETo and 160ETo treatments. Crop factors (Kc) of 0.6 and 0.8 were applied between 1-15 Nov and 16-30 Nov respectively to the 80ETo and 160ETo treatments to create the 80ETo+Kc and 160ETo+Kc treatments respectively. As crop factors for non-ponded rice are not available crop factors from other cereal crops at similar growth stages were applied to increase irrigation water savings as the small plants were being irrigated more often than necessary when using only cumulative ETo. The 40ETo treatment was replaced with a broadcast dry seeded treatment which was continuously flooded from one day after sowing until shortly before maturity. After spreading the seed the continuously flooded bays (Flood) were covered with 15 mm diamond mesh bird netting to prevent ducks from eating the seed. The netting was removed on the 1 Dec 09.

The Control, 80ETo +Kc and 160ETo +Kc treatments were all drill seeded into a cultivated seedbed (Quest at 150 kg ha^{-1}) and received their first flush irrigation on 21 Oct 09. All treatments received a second flush irrigation to ensure good establishment before the irrigation frequency treatments commenced. The Control treatment received 2 flush irrigations before permanent water on the 16 Nov 09, while the 80ETo +Kc and 160ETo +Kc treatments received 5 and 3 flush irrigation treatments in total before permanent water was applied on the 23 Dec 09 (Figure 2b), 20 days prior to panicle initiation. Permanent water was applied a few days earlier than planned due to imminent rainfall which occurred on the 24th Dec 09. All irrigation treatments received three rates of N (urea), 0, 150 and 225 kg N/ha, which was an increase on the nitrogen applied in year 1 due to this being the second rice crop (local practice). The Flood and Control treatments both received 2/3 of the nitrogen applied prior to permanent water, sown into the soil (10 cm depth) for the Flood treatment and onto the dry soil surface for the Control treatment, with the remaining 1/3 applied into the water at PI. The 80ETo +Kc and 160ETo +Kc treatments received nitrogen in two splits, i.e., 1/3 at mid tillering and 2/3 prior to permanent water, 20 days prior to PI.

In all treatments and in both years the weeds were successfully controlled using commercially available herbicides. Post sowing and pre-rice emergence a combination of glyphosate 360 g L^{-1} (1 L ha^{-1}), Clomazone 480 g L^{-1} (0.3 L ha^{-1}) and Pendimethalin 330 g L^{-1} (1.6 L ha^{-1}) was applied to all treatments to control already emerged weeds and provide some residual grass weed control. In the Control and Flood treatments molinate 960 g L^{-1} (3.7 L ha^{-1}) was used to control grass weeds and bensulfuron methyl 600 g L^{-1} (86g ha^{-1}) used to control broadleaf weeds. In Year 1 the delayed permanent water treatments received two applications of propanil 480 g L^{-1} (8 L ha^{-1}) and in Year 2 one application of propanil 480 g L^{-1} (8 L ha^{-1}) was applied during mid-tillering to control grass weeds.

Crop measurements

Crop samples for biomass, tiller number and N uptake were taken five times during the growing season. Above ground plant samples (1 m2) were collected at mid tillering, late tillering (pre-permanent water of delayed PW treatments), panicle initiation, anthesis and physiological maturity. A 100 g subsample was removed from each sample and dried in a microwave before being dried in an oven overnight at 60°C. This subsample was ground and analysed for N by Dumas combustion. A fifty tiller subsample was also removed and separated into leaves and stems. The leaf, stem and remaining samples were dried at 80 °C until a constant weight was achieved.

Grain yield was measured from a 10 m2 area harvested using a Kingaroy small plot harvester and reported at 14% moisture. Two 1 m2 samples were collected from each plot after physiological maturity and dried at 80 °C until a constant weight to determine total dry matter. These samples were threshed through a stationary thresher and the grain weighed to determine harvest index. A separate 50 tiller sample was collected and separated into panicles and stems. The panicles were manually threshed and the filled and unfilled spikelets separated by aspirator and counted to determine percent filled florets. The grain and straw samples were ground and analysed by Dumas combustion to determined N content and total N uptake calculated.

Crop phenology measurements were taken from each plot to accurately determine the timing of PI, anthesis and physiological maturity. Prior to PI, 10 main tillers were removed every second or third day. The tillers were sliced in half and visually assessed for the presence of a panicle. The plot was considered to be at PI when the panicle could be identified with the naked eye (i.e. 1 – 2 mm long) in 5 of the 10 tillers. Pollen microspore was identified by measuring the panicle length of 10 main tillers every 2 - 3 days. When the average panicle length had reached 100 mm it was considered to be at pollen microspore. To identify anthesis, a representative 1 m section of row was pegged in each plot. Every second or third day the number of panicles that had reached mid-anthesis was recorded. Sampling to determine when plots had reached physiological maturity involved taking a sample of heads from a representative section of each plot every second day. The grain was removed from the heads and dried at 100°C until a constant weight to determine moisture content. Physiological maturity was determined as the day that grain moisture had declined to 28%.

Water measurements

Water applications were measured into individual bays using RBC flumes (Clemmens et al., 1984) equipped with water depth loggers. The drainage from each bay was measured with circular flumes (Samani et al., 1991) and water depth loggers. Water use was calculated as the total water applied minus the total drainage plus rainfall. Water productivity was calculated using grain yield at 14% moisture from the highest nitrogen rate plot in each treatment divided by the water use (mm) for each bay.

Statistical analysis

Statistical analysis consisted of analysis of variance (ANOVA), with water regime the main plot and nitrogen the subplot (GenStat Release 10.2, Lawes Agricultural Trust, Rothamsted Experimental Station). Differences between means were compared by least-significant difference (LSD) tests at 5% probability level.

RESULTS

The 2008/9 rice season was characterised by very high temperatures during the plant establishment period in late October and also the reproductive period in late January/early February (Figure 1). Evapotranspiration was also much higher than average during these periods. In 2009/10 extremely high temperatures occurred during late October/early November and evapotranspiration rates were well above average during this period (Figure 1). In both seasons the minimum temperatures were average or above during the critical reproductive period when cold temperature can cause grain sterility.

Plant establishment and growth

Plant establishment was excellent in all plots in Year 1 with an average 325 plants m^{-2} and no significant difference between treatments. In Year 2 of the experiment the three drill sown treatments (Control, 80ETo and 160ETo) all had excellent establishment with an average 351 plants m^{-2}. The Flood sown treatment had a lower level of establishment with 180 plants m^{-2} and a uniform plant distribution. The reduced number of plants established in the Flood treatment may have been caused by soil covering the dry seed when the permanent water was applied.

In Year 1, when permanent water was applied to the delayed PW treatments (69 days after the first irrigation) the interaction between water treatment and nitrogen rate was significant for dry matter sampled at this time. The Control treatment accumulated significantly more dry matter than all of the delayed PW treatments at the 135 and 200 kg N ha^{-1} nitrogen rates (Figure 3a). By panicle initiation, plant dry matter accumulation in the delayed PW treatments had greatly increased after the application of nitrogen and permanent water 10 days earlier. At panicle initiation the water treatment and nitrogen rate interaction was significant with the Control treatment having a significantly higher dry matter than the 40ETo treatment at the 135 kg N ha^{-1} nitrogen rate and the 160ETo treatment at the 200 kg N ha^{-1} nitrogen rate (Figure 3b).

At physiological maturity the water treatment and nitrogen rate interaction was not significant for total dry matter. The Control treatment (averaged across nitrogen rates) accumulated the largest amount of dry matter which was significantly higher than the 80ETo and 160ETo treatments which were both significantly higher than the 40ETo treatment (Table 2).

Table 2. Physiological maturity dry matter, total nitrogen uptake, grain yield at 14% moisture and yield components for four water treatments and three nitrogen rates for year 1 and 2 experiments.

	PM Dry matter (g/m^2	Total N uptake (kg N/ha)	Grain yield (t/ha)	Harvest Index	Panicles /m^2	Florets/ panicle	1000 grain wt. (g)	Filled florets (%)
Year 1								
Water treatment (W)								
Control	2148	179	9.5	0.42	666	83	24.4	72.6
40ETo	1787	125	6.9	0.35	654	64	23.6	72.2
80ETo	1987	147	8.1	0.38	694	67	24.1	73.9
160ETo	1946	154	8.4	0.41	618	74	23.4	80.0
LSD (P<0.05)	144	24	0.5		NS	10	0.5	
Nitrogen Rate (N)								
0 kg N/ha	1502	106	5.7	0.36	560	65	24.3	69.2
135 kg N/ha	2057	155	8.7	0.40	691	71	24.0	77.2
200 kg N/ha	2343	194	10.1	0.41	724	81	23.4	77.8
LSD (P<0.05)	114	11	0.5		52	6	0.5	
Interaction (W x N)								
LSD (P<0.05)	NS	NS	NS	0.04	NS	NS	NS	9.9
Year 2								
Water treatment (W)								
Control	2313	211	10.9	0.44	693	89	23.9	76.9
Flood	2108	183	9.4	0.43	672	78	23.6	75.4
80ETo+Kc	2106	190	10.8	0.48	598	92	23.8	83.6
160ETo+Kc	2182	198	10.7	0.46	618	93	23.6	80.6
LSD (P<0.05)			0.7		NS	9	NS	4.6
Nitrogen Rate (N)								
0 kg N/ha	1508	110	7.0	0.45	540	67	24.3	84.6
150 kg N/ha	2431	213	11.9	0.46	671	94	24.0	80.0
225 kg N/ha	2593	264	12.3	0.45	724	102	22.9	73.9
LSD (P<0.05)			0.6		68	6	0.6	4.0
Interaction (W x N)								
LSD (P<0.05)	315	30	NS	0.05	NS	NS	NS	NS

NS: non-significant

In Year 2 all treatments were sampled prior to when permanent water was applied to the delayed PW treatments (63 days after the first irrigation) and the water treatment and nitrogen rate interaction for dry matter was significant. At the 150 kg N/ha and

225 kg N ha^{-1} nitrogen rates the Control and Flood treatments both produced significantly more dry matter than both of the delayed permanent water treatments which were not significantly different (Figure 3d). At this time both the Control and

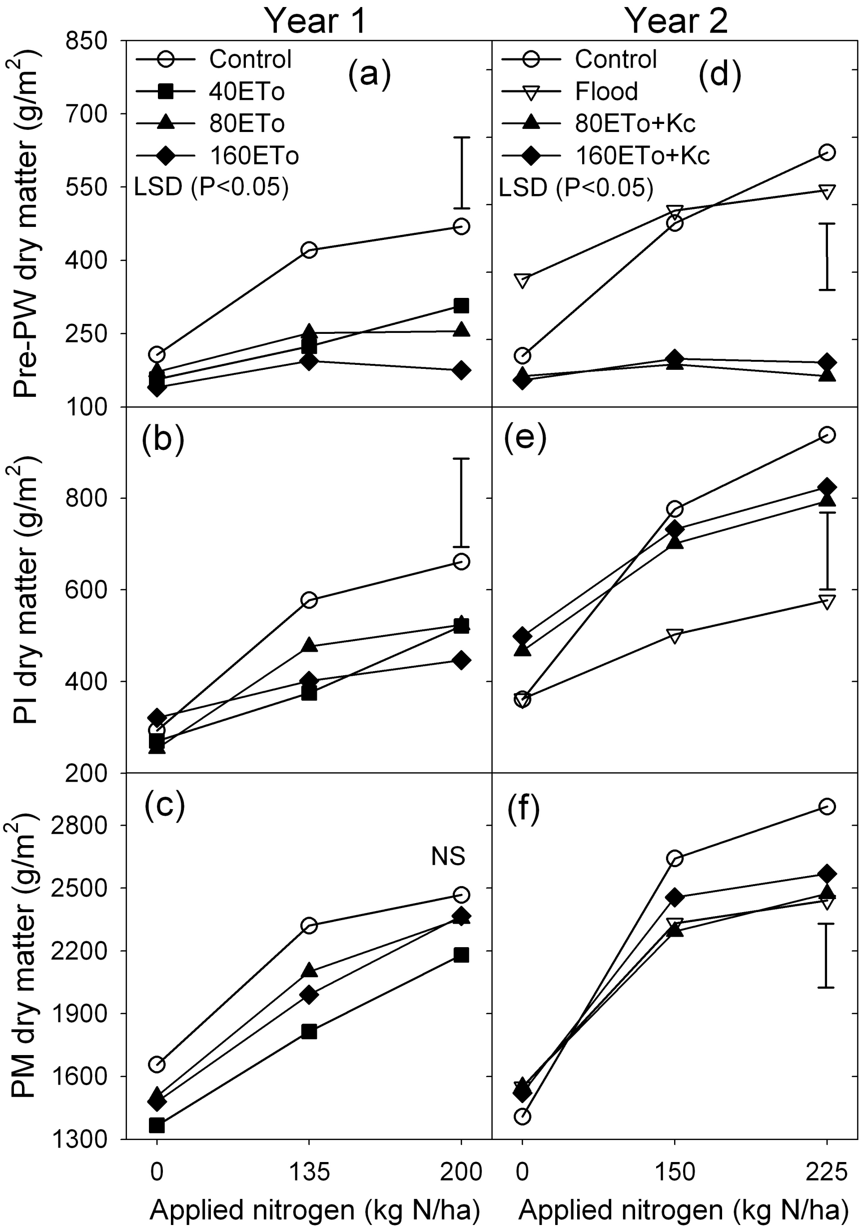

Figure 3. Dry matter for Year 1 and Year 2. For plant growth stages Pre-PW – prior to application of delayed permanent water (a and d), PI - panicle initiation (b and e), PM - physiological maturity (c and f). Bars indicate the least significant difference ($P<0.05$), NS: non-significant.

Flood treatments had already received two thirds of the treatments total applied nitrogen while the 80ETo+Kc and 160ETo+Kc treatments had only received one third of the treatments total nitrogen. The Flood treatment had reached panicle initiation at this sampling time so the Flood treatment dry matter data results from this sampling time are also used for the Flood treatment in the panicle initiation graph (Figure 3e). By panicle initiation the plant dry matter accumulation in the delayed PW treatments had greatly increased after the application of two thirds their nitrogen and permanent water. The water treatment by nitrogen rate interaction for dry matter at panicle initiation was significant with the Flood treatment producing less dry matter than all other treatments at the 150 and 225 kg N ha^{-1} nitrogen rates (Figure 3e).At physiological maturity the irrigation treatment by nitrogen rate interaction was significant and the Control treatment at 225 kg N ha^{-1} produced significantly more dry matter than the other three treatments which were all similar at the same nitrogen rate (Figure 3f).

Total nitrogen uptake was higher in Year 2 of the experiment, with a mean of 196 kg N/ha, compared to Year 1 with a mean of 151 kg N ha^{-1}. This is due to a combination of higher applied N rates in Year 2 and changed nitrogen application timings of the delayed PW treatments between years. In Year 1 the Control treatment had a total N uptake of 179 kg N ha^{-1} which was significantly higher than the 80mm+Kc and 160mm+Kc treatments with 147 and 153 kg N ha^{-1} respectively which were significantly higher than the 40mm treatment with 125 kg N ha^{-1} (Table 2). In Year 2 however the Control treatment had the highest N uptake with 211 kg N ha^{-1} and there was no significant difference between any of the other water treatments (Table 2).

Grain Yield

The interaction between water treatment and nitrogen for grain yield was not significant in either year. In both years there were significant effects of irrigation scheduling, with the highest yield achieved by the Control treatment (Table 2). In Year 1 when averaged across nitrogen rates the Control treatment yielded significantly more than the 80ETo and 160ETo treatments which were both significantly higher than the 40mm treatment with yields of 9.5, 8.0, 8.4 and 6.9 t ha^{-1} respectively. The lower grain yield of the 40ETo water treatment was due to a combination of lower dry matter and lower number of florets per panicle.

In Year 2 there was no significant difference in grain yield when averaged across nitrogen rates between the Control, 80ETo +Kc and 160ETo +Kc treatments (Table 2). The Flood treatment yielded significantly less due to a combination of factors including reduced plant numbers and a lower number of florets per panicle than all other treatments. Total dry matter for the Flood treatment was similar to the delayed PW treatments but lower than the Control, while floret sterility of the Flood treatment was similar to the Control and lower than the delayed PW treatments resulting in the lowest yield of all water treatments. The Flood treatment was earliest to reach pollen microspore which placed it at a time of lower minimum temperatures which increased floret sterility compared to the delayed PW treatments which matured later. Year 2 was an exceptionally good season for rice growing with very high temperatures during tillering and higher than average minimum temperatures during the mid to late part of the reproductive period (Figure 1).

Crop phenology

The delaying of permanent water and the amount of nitrogen applied both had a significant impact on the development of the rice crop (Figure 4). In Year 1, the Control treatment reached PI 3 days earlier than the delayed PW treatments and this difference in development was still present at anthesis. The 40ETo treatment was the first of the delayed permanent water treatments to reach maturity. In all treatments increased nitrogen application extended the time taken to reach anthesis and physiological maturity (Figure 4). The 40mm treatment was the first of the treatments with 200 kg N ha^{-1} applied nitrogen to reach physiological maturity due to its lower fertility level caused by nitrogen losses during the flush irrigations. At physiological maturity the water treatment by nitrogen interaction was significant.

In Year 2 water treatment had a much larger influence on crop phenology than in Year 1 (Figure 4). The Flood treatment was much faster in development reaching all growth stages before any other treatment, followed by the Control treatment which was significantly faster than both the delayed PW treatments in reaching all growth stages. The 80ETo +Kc and 160ETo +Kc treatments, at the highest nitrogen rate, took 15 and 18 days longer respectively than the Control treatment to reach physiological maturity (Figure 4). The higher rates of nitrogen applied in Year 2 combined with 2/3 of the nitrogen applied pre-PW compared to only 1/3 in Year 1 had a large impact on crop development of the delayed PW treatments.

Water use and water productivity

In Year 1 water use (irrigation supply, minus bay drainage, plus rainfall) for the Control treatment (1561 mm) was significantly higher than the other three treatments with 1397, 1411 and 1327 mm for the 40ETo, 80ETo and 160ETo treatments respectively (Table 3). In Year 1 the 160ETo treatment had 0.06 kg m^{-3} higher water productivity than the Control treatment however there was no significant difference between any water treatments (Table 3).

The use of crop factors in irrigation calculations during Year 2 extended the period between irrigations and increased the water savings of the delayed PW treatments. The Flood treatment had the highest water use with 1707 mm which was significantly higher than the Control treatment with 1503 mm. There was no significant difference between the 80ETo +Kc and 160ETo +Kc treatments with 1276 and 1175 mm respectively, both significantly lower than the Control treatment (Table 3). The 160ETo +Kc treatment had the highest water productivity (1.04 kg m^{-3}) which was similar to the 80ETo +Kc (0.97 kg m^{-3}) treatment but significantly higher than the Control treatment (0.89 kg m^{-3}). The Flood treatment had the lowest water productivity (0.67 kg m^{-3}).

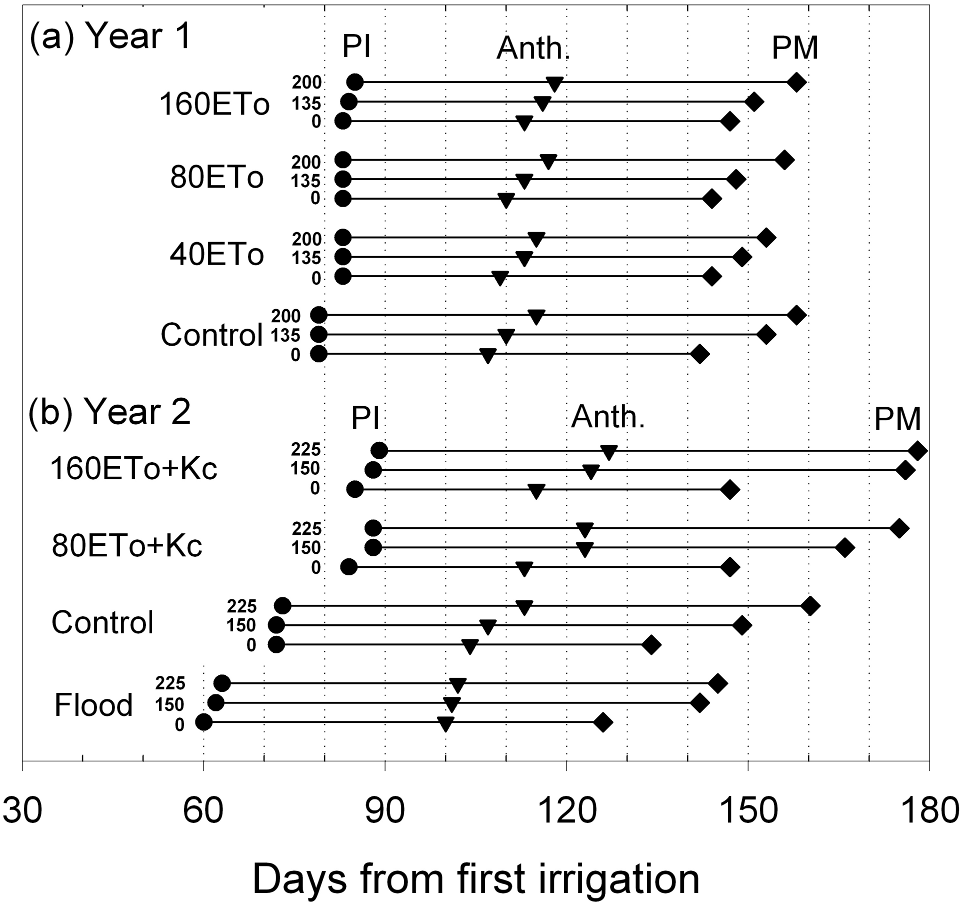

Figure 4. Days after first flush irrigation that the treatments reached panicle initiation (●), anthesis (▼) and physiological maturity (♦) for (a) Year 1 and (b) Year 2 experiments.

Table 3. Grain yield at 14% moisture for Year 1 (200 kg N/ha) and Year 2 (225 kg N/ha), water use including rainfall and water productivity for the water treatments in the Year 1 and Year 2 experiments.

	Grain yield ($t\ ha^{-1}$)	Water use (mm)	Water productivity ($kg\ m^{-3}$)
Year 1			
Control	10.9	1560	0.70
40ETo	9.2	1400	0.66
80ETo	10.2	1410	0.72
160ETo	10.1	1330	0.76
LSD (P<0.05)	0.9	90	NS
Year 2			
Control	13.4	1500	0.89
Flood	11.4	1710	0.67
80ETo +Kc	12.3	1280	0.97
160ETo +Kc	12.2	1180	1.04
LSD (P<0.05)	0.9	160	0.10

NS: non-significant

DISCUSSION

The research presented in this paper resulted from the need to improve water productivity of rice growing in south-east Australia. Drought and reduced water availability has already seen some commercial rice growers delaying the application of permanent water on their drill sown rice crops (Whitworth and Lacy, 2008). These growers sowed their crops and relied on rainfall with minimal irrigation, severely moisture stressing the crop during tillering in order to reduce water use. Some of these growers achieved good grain yields and were claiming very high levels of water productivity from the practice. A potential benefit of delaying the application of permanent water is that the crop can be established with minimal irrigation, fertilizer and herbicide input. Once water allocation announcements are released and potential water availability more accurately defined, the farmer can decide whether nitrogen and water resources should be applied to the crop or it be abandoned if the water resource is not available. This is a better option than farmers waiting until water allocation announcements are released and then sowing a late crop well outside the recommended sowing period and risking severe yield loss due to cold temperature damage.

In this experiment, delaying the application of permanent water reduced the period the crop was ponded by 42 and 37 days in Years 1 and 2 respectively, providing potential water savings from reduced evaporation and seepage losses. The necessity to flood current rice varieties during the reproductive period (Humphreys et al. 2006) prevents further potential water savings from non-flooded rice culture. Irrigating the rice crop during the non-flooded period at different cumulative evapotranspiration intervals provides the opportunity for increased water savings, but the level of moisture stress a rice crop can experience without significant yield loss was unknown in the south-east Australian rice growing environment (Humphreys et al. 2006). In both years the rice plants in the 160ETo and 160ETo +Kc treatments showed visual symptoms of severe moisture stress prior to the application of permanent water but the rice crop recovered quickly from the moisture stress after the application of permanent water to achieve good levels of total dry matter and high grain yields. This supports the findings of Muirhead et al (1989) who noted that rice crops were able to adapt to an improved soil water status when permanent flooding was introduced after drought, up to a late stage of development (PI). Bouman and Tuong (2001) noted that the degree of yield reduction depends on both the severity and frequency of drought, but that in general soil matric potentials of -10 to -30 kPa (at 10-20 cm soil depth) resulted in grain yield reductions of 10-40%. In Year 1 soil moisture tension levels measured by gypsum blocks in our experiment reached 25 kPa, 57 kPa and 200 kPa at 15 cm depth between flush irrigations for the 40ETo, 80ETo and 160ETo treatments respectively but insufficient reliable data restricts reporting soil moisture tensions in any more detail or for Year 2. That final grain yields were only slightly reduced (less than 10%; Table 3) under much higher soil matric potentials in our experiment, suggests the crop stages exposed to drought stress were less sensitive than in the assembled datasets of Bouman and Tuong (2001). Sudhir-Yadav et al (2011) found that reducing drought stress during more sensitive stages (PI and Flowering) reduced yield loss from 9% down to 5% for a -10 to -20 kPa alternate wet-and-dry irrigation regime.

In our experiment water savings of 150 and 230 mm (10 and 15%) for the 80ETo and 160ETo treatments in Year 1 and 230 and 330 mm (15 and 22%) for the 80ETo +Kc and 160ETo +Kc treatments respectively in Year 2 were achieved, compared to the Control. This compares to savings between 8 and 18% found in earlier studies (Thompson and Griffin 2006) with intermittent irrigations at 50 to 60 mm of cumulative evapotranspiration. Although the grain yields were a little lower for the delayed permanent water treatments compared to the conventional treatment a benefit in water productivity was achieved. In Year 1 the water productivity of the 160ETo treatment was 0.06 kg m^{-3} (8%) higher than the conventional treatment and in Year 2 the 0.15 kg m^{-3} (17%) advantage of the 160ETo +Kc treatment was significantly better than the conventional drill sown treatment. In Year 2 the 80ETo + Kc treatment also achieved a significant (but reduced) gain in water productivity over the conventional treatment (0.08 kg m^{-3}; 9%). Thompson and Griffin (2006) reported increased water productivity ranging from 0.06 to 0.23 kg m^{-3} compared to the normal flooded regime. Because our experiments indicated water productivity increased with decreasing frequency of pre-flood irrigations, further research is suggested to better define the optimal irrigation deficit level. The point of maximal water productivity (in kg/m3) may not necessarily correspond with the point of optimal gross margins (in $/m2) from the field, because some treatments will likely have additional costs associated with increased weed control measures. A subsequent validated modelling study may assist in defining the most practical pre-flood irrigation frequency for farmers.

The timing of nitrogen application is very important when delaying permanent water and the most efficient nitrogen application timing without reducing yield is yet to be determined. In Year 1 of the experiment a three way split was used, with 1/3 of the total N applied at both the 3 leaf and mid-tillering stages and the last 1/3 applied prior to the delayed permanent water. Soil nitrate measurements from the 0-10cm soil samples collected on 10 Dec 08 (after the 40ETo treatment had received 8 flush irrigations and the 160ETo treatment 4 flushes) are presented in Table 4. They suggest higher nitrogen losses from the more frequently irrigated treatments, likely due to nitrification and subsequent denitrification when the soil dries then becomes waterlogged as was found by Humphreys et al. (1987). The nitrogen losses are also evidenced by the significantly lower total crop nitrogen uptake in the 40ETo treatment compared to the 160ETo treatment (Table 3). The more flush irrigations a delayed permanent water treatment received, the higher the losses that occurred. Grigg et al. (2000) found reduced N uptake from flush irrigated compared to flooded rice and suggested N losses from denitrification as a result of alternate wetting and drying may be partly responsible. In Year 2, 1/3 of the total N was applied at mid-tillering and the remaining 2/3 applied prior to delayed PW in an effort to improve nitrogen use efficiency. In Year 2, the 80ETo +Kc and 160ETo +Kc treatments had 10% and 8% lower total N uptake respectively than the Control treatment compared to 18% and 14% respectively in Year 1 when only 1/3 of the total nitrogen was applied prior to permanent water.

Delaying permanent water had a significant impact on crop development. In Year 2 of the experiment the 80ETo +Kc and 160ETo +Kc treatments were delayed in reaching pollen microspore by 12 and 16 days respectively compared to the Control treatment. In Year 1 the delay in crop development wasn’t as pronounced as in Year 2 when more nitrogen was applied prior to the application of the delayed permanent water. This greatly increased plant dry matter and total N uptake in Year 2 compared to Year 1 and resulted in extended crop development. The extension of the growth period is important in relation to water use, as the crop needs to be irrigated for a longer period, and also for management, as harvest will then occur during potentially unfavourable conditions. The delay in crop development may also move the critical pollen microspore stage, when the developing pollen is susceptible to cold temperatures, to outside the window of highest probability of safe minimum temperatures. This could be critical for grain yield considering how quickly the mean minimum temperature decreases after mid-February (Figure 1). The delay in crop development that occurs with delayed application of permanent water may necessitate sowing 7 to 10 days earlier compared to conventional drill sown crops to ensure the sensitive pollen microspore stage still occurs when minimum temperatures are likely to be highest.

The results of our field experiments may be characteristic of many rice growing areas in south-eastern Australia which grow rice on a red-brown earth soil. However, large areas of rice are also grown on self-mulching and non self-mulching clay soils. Further research is required into potential water productivity gains on these soils, which have higher plant available water content, in response to delayed permanent water practices. The suitability of the 80ETo and 160ETo cumulative evapotranspiration levels for these soil types and potential crop factors also requires investigation. Further research into nitrogen application timing for both the red-brown earth and clay soils needs to be conducted to determine efficient nitrogen use while not compromising grain yield and excessively extending the growing period of the crop.

CONCLUSIONS

Two seasons of field experiments confirm that water savings can be achieved by delaying the application of permanent water until just before PI in drill sown rice on red-brown earth soils in south east Australia. Additionally, the experiments demonstrated increased water productivity from higher levels of imposed crop water stress during the initial non-flooded period. Irrigating at intervals of 160 mm cumulative ET (plus crop factors) prior to permanent water significantly improved water productivity above that of the conventional drill sown treatment (by 17% in year 2). Irrigating at 80mm intervals resulted in a significant but lesser (9%) water productivity increase over the control in the same year. Non-significant gains in water productivity were also achieved in year 1, before crop factors were added to evapotranspiration calculations. Because increases in water productivity were achieved with higher crop water stress during the non-flooded period, we suggest further research to better define optimal pre-flood irrigation deficit levels for different soils and environments. Validated modelling studies may assist in this process.

Delaying the application of permanent water extended the period of crop growth and it may be necessary to move sowing forward 7-10 days so pollen microspore still occurs at the safest time in regards to cold temperature damage. Nitrogen losses were shown to increase with the frequency of irrigations prior to permanent water, illustrating that N management is an important issue in this practice. Further research is required to determine the most appropriate quantities, timing and splits for nitrogen applications.

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CHAPTER 7

Maximizing water productivity through model-aided design of delayed continuous flood irrigation in Australian rice production

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Abstract

For south-east Australian rice production, delayed continuous flooding (DCF; i.e. irrigation scheduling while delaying the application of continuous floodwater) can reduce non-productive water losses and increase input water productivity (WP), compared with traditional fully-flooded cultivation. Several authors have reported corroborative experimental findings, yet there has been no previous effort to assess long-term risk associated with the practice, or to define best-practice guidelines. In this paper we compare the trade-offs between input water-requirement and grain yield for a range of DCF strategies with different early irrigation intervals in the early non-flooded period, aiming to define best-practice guidelines. We use an experimentally-validated cropping systems model (APSIM) together with 55 years of historical climate data to simulate the performance of the different strategies, and to help understand the key drivers of system behaviour. DCF was shown to provide better long-term WP and gross margin outcomes than conventional fully-flooded practices (both aerial and drill sowing) with benefits increasing as a function of the pre-flood irrigation interval, up until an interval of approximately 200mm cumulative (ETo - rain). Phenological delay caused by the early water stress results in delayed crop maturity, however earlier sowing of DCF crops has the potential to increase WP further by moving the sensitive floral development stage into a time period with lower risk of cold temperatures. Our study suggests that best-practice DCF in rice can achieve a long term average WP of 0.84 kg grain ML-1, representing gains of 0.17 (25%) and 0.13 (17%) kg grain ML-1 over aerially-sown and conventional-drill crops, respectively. We demonstrate that climate change has the potential to change best practice guidelines, however suggest a further analysis using more sophisticated climate projections. DCF seems destined to play a prominent future role in south-east Australian rice production, however further research is required into efficiently synchronising the practice with other crop production enterprises on farm.

Keywords: rice, irrigation, water productivity, modelling, APSIM, Australia

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INTRODUCTION

The international challenge of increasing global food and fibre production with limited or reduced future irrigation water supplies has been identified by numerous authors (Keating et al., 2010, Cribb, 2010; Ali and Talukder, 2008; Bouman, 2007; Tuong et al., 2005). One avenue to achieve this aim is increasing input water productivity, WP (tonnes grain/ML irrigation water applied), through reduction of non-productive water loses (evaporation and percolation/seepage; Humphreys et al., 2010) via improved agronomic and/or irrigation practices (Sudhir-Yadav et al., 2011a; Belder et al., 2007; Bouman and Tuong, 2001).

In flooded rice production, water-use can be reduced in a number of ways. Deep percolation losses can be limited by reducing the hydraulic head; through ponded depth reduction (Kukal and Agarwaal, 2002); or by saturated soil culture (Borrell et al., 1997). Alternate wet-and-dry irrigation (AWD; Bouman and Tuong, 2001) offers reductions in both evaporation and deep percolation losses, particularly on more permeable soils. AWD involves flooding the soil, then allowing the pond to dry-down before re-flooding again and repeating the process after some specified interval. AWD is now a proven technology throughout much of the rice-growing world (Bouman et al., 2007; Li and Barker, 2004; Sudhir-Yadav et al., 2011a) however environmental conditions in Australia's temperate rice-growing districts (southern NSW; latitude 34^{o}S to 35.5^{o}S; longitude 144.5^{o}E to 146.5^{o}E) preclude the full use of AWD as practiced in other areas for several reasons. Firstly, rice production in the region is primarily on heavy clay soils so the opportunities to reduce percolation losses are relatively low (Humphreys et al, 2006). The Australian rice industry also has policies in place to define regions with higher permeability soils and limit flooded rice production in these areas (Humphreys et al., 1994; Beecher et al., 2002). Secondly, the growing Australian rice crops require maintenance of continuous floodwater throughout the reproductive stages of growth for two main reasons: - a.) to limit the high natural risk (>40%) of low temperature damage to the developing rice floret at early microspore (protection is provided by submersion of the developing floret to a depth of 200-250 mm - the floodwater buffers low night-time temperatures by 5-7 ^{o}C; Williams and Angus, 1994), and b.) to satisfy the very high crop transpiration rates encountered during the latter stages of crop growth (resulting from up to 250-300 kg ha^{-1} day^{-1} dry matter production in a very dry, high radiation environment) (Humphreys et al., 2005). So for the Australian context, a modified version of typical AWD practice must be sought.

The majority of non-productive water losses in Australian flooded rice production occur early in the season during the vegetative stages prior to canopy closure.

Simpson et al (1992) suggest that up to 40% of total non-productive water losses occur during this period, primarily through evaporation from the free water surface. This is also a time when the growing rice crop is not as susceptible to low temperature damage, and transpiration demand is relatively low, suggesting the possibility for AWD techniques to limit both evaporative and deep percolation losses during this early period. Heenan and Thompson (1984) investigated potential increases in WP using AWD during this early vegetative stage, under Australian conditions. Their promising results showed water savings of 23% without yield penalties over conventional fully-flooded practice through intermittent irrigation every seven days prior to the establishment of continuous flooding at PI. Equivalent grain yields were achieved in both cases, hence significant increases in WP were calculated. However water savings were judged as inflated compared with typical rice growing conditions from the region, due to use of an experimental field with relatively high percolation rates. To address this issue, Thompson and Griffin (2006) conducted further similar experiments on a less-leaky site between 2001 and 2004. Once again, grain yield from the intermittent irrigation in the early crop stages was generally similar to the yield resulting from fully-flooded management. The increase in WP reported ranged between 0.06 to 0.23 kg m^{-3} over the period of the trials. Although the clear promise of this early AWD practice was now demonstrated for Australian conditions, neither of these early studies sought to examine the effect of different irrigation intervals (hence crop water stress levels) on WP – a necessary next step in defining best-practice guidelines.

Dunn and Gaydon (2011) took this line of investigation one step further by examining the yield and water-use trade-offs (ie WP implications) for a range of early AWD irrigation intervals, seeking to define best-practice. They found that WP increased with the length of the early AWD irrigation interval for all treatments considered. Significantly, crop phenology was impacted leading to later maturity in the early AWD crops compared with continuously-flooded crops. The greater the imposed water stress level, the longer the phenology delay. The implication was that the highly temperature-sensitive rice microspore period for the early AWD treatments could be pushed back into colder time periods, potentially resulting in much riskier practice. They suggested further research into defining the best irrigation interval (to maximize WP), given that WP increased with irrigation interval for all the treatments examined in their trials. They also suggested further research into the possibility that earlier sowing in early AWD management may reduce the risk of cold temperature damage resulting from delayed phenological development. Throughout the text of this paper we will refer to this practice of AWD water management in the period prior to continuous flooding as delayed continuous flooding (DCF).

Modelling offers a way to extend experimental findings from a reference period of several years (the experimental period) to a much wider climatic record, thereby providing a better assessment of risk associated with the practices in question. Providing they are well-validated and tested, bio-physical models can also assist researchers to understand the key physical process driving system behaviour, and can hence be useful tools in defining best management practice. Sudhir-Yadav et al (2011b) applied this approach to extend experimental AWD findings in Punjab, resulting in successful definition of best-management practice for that environment, coupled with an in-depth understanding of climatic risk. Achieving such a system understanding from experiments alone would have taken decades.

In this paper, we use the APSIM cropping systems model (Keating et al, 2003; Gaydon et al., 2012a, 2012b) to extend the learnings from Dunn and Gaydon (2011) and more thoroughly evaluate the practice of irrigation scheduling during DCF for south-eastern Australian rice production. We firstly parameterize, calibrate and validate the model using the experimental data of Dunn and Gaydon (2011), testing against observed grain yields and biomass production, irrigation water use, WP, and soil water/nitrogen dynamics. We then use the validated model to explore long-term trends and variability associated with different DCF strategies (varying irrigation intervals), and compare them with conventional practices from the perspective of WP and gross margins (\$ profit ML^{-1}). This includes a detailed exploration of key underlying processes that govern overall system performance in order to define the best operational strategies. To overcome some of the identified environmental limitations, we explored a wide range of agronomic and irrigation management options. We finish by presenting an analysis on how projected future climate change may affect the performance of DCF in the Australian environment, and how it may potentially change best-practice guidelines.

MATERIALS AND METHODS

Overview of the APSIM model

APSIM is a dynamic daily time-step model that combines biophysical and management modules within a central engine to simulate cropping systems. The model is capable of simulating soil water, C, N and P dynamics and their interaction within crop/management systems, driven by daily climate data (solar radiation, maximum and minimum temperatures, rainfall). Daily potential production for a range of crop species is calculated using stage-related RUE constrained by climate and available leaf area. The potential production is then limited to actual production on a daily basis by soil water, nitrogen and (for some crop modules) phosphorus availability (Keating et al., 2003). The SOILWAT module uses a multi-layer, cascading approach for the soil water balance following CERES (Jones and Kiniry, 1986). The SURFACEOM module simulates the fate of the above-ground crop residues that can be removed from the system, incorporated into the soil or left to decompose on the soil surface. The SOILN2 module simulates the transformations of C and N in the soil. These include fresh organic matter decomposition, N immobilization, urea hydrolysis, ammonification, nitrification and denitrification. Crop residues tilled into the soil, together with roots from the previous crop, constitute the soil fresh organic matter (FOM) pool. This pool can decompose to form the BIOM (microbial biomass), HUM (humus), and mineral N (NO3 and NH4) pools. The BIOM pool notionally represents the more labile soil microbial biomass and microbial products, while the more resistant HUM pool represents the rest of the SOM (Probert et al., 1998). APSIM crop modules seek information regarding water and N availability directly from SOILWAT and SOILN modules, whereby insufficient water or N availability limits crop growth. More recently, APSIM has been enhanced to simulate processes specific to rice-based cropping systems (Gaydon et al., 2012a, 2012b), such as transitions between flooded and non-flooded soil environments, together with floodwater C, N, and water dynamics. Modelled floodwater processes include the growth and senescence of photosynthetic aquatic biomass (PAB; algae and other pond flora), a portion of which may be capable of fixing atmospheric N, ultimately contributing to rice crop nutrition, and to soil organic carbon. Gaydon et al. (2012b) demonstrated that simulation of the unique sustainability characteristics of rice-based cropping systems (maintenance of both grain yield and soil organic carbon levels with little fertilizer inputs) is reliant on simulating inputs of C and N from PAB. APSIM is the only model capable of simulating rice-based cropping systems which includes this feature. The crop physiology routines from the ORYZA2000 rice model (Bouman and van Laar, 2006) have also been incorporated into the APSIM framework (APSIM-Oryza; Zhang et al., 2007), and use the APSIM soil water and nutrient models for simulation of resource supply to the growing rice crop. The version of the ORYZA2000 present within APSIM is referred to as APSIM-Oryza. The APSIM model was therefore chosen for this modelling study on the basis of demonstrated performance in simulating key features of long-term crop sequences rice-based cropping systems.

Model validation

The model was validated using the field experiment of Dunn and Gaydon (2011), comparing key measured and simulated variables for above and below-ground processes (crop growth; soil water and N dynamics) and irrigation water demand. References to WP imply input water productivity – the mass of grain produced per ML of water applied to the crop (irrigation + rainfall).

Field Experiment

Data from the randomized replicated split-plot field experiment of Dunn and Gaydon (2011) was used to parameterize, calibrate, and evaluate the performance of the APSIM model for DCF water management. The experiment was conducted over the 2008/9 and 2009/10 rice growing seasons (October–April) at the Yanco Agricultural Institute (34o 36’ 56’’ S, 146o 25’ 06’’ E) on a red-brown earth soil (Alfisols, Soil Survey Staff, 1975). The soil was a Birganbigal clay loam with a clay loam surface horizon 0.15–0.20m deep and heavy clay subsoil (van Dijk, 1961; Hornbuckle and Christen, 1999). The Yanco Agricultural Institute is located in the Murrumbidgee Irrigation Area in south eastern Australia, near the townships of Yanco and Leeton.

In addition to the two years data provided by Dunn and Gaydon (2011), data from a third year (unpublished) was also used in this validation exercise. The soil properties, crop management, and crop and water monitoring methods are fully described in Dunn and Gaydon (2011), with only details pertinent to the model parameterization summarized here. The experimental treatments were slightly different between year 1 and years 2 and 3. The DCF water management treatments used irrigation scheduling based on cumulative net reference evapotranspiration (ETo−rain) until continuous flooding was applied 10–20 days prior to PI (roughly 70 days after sowing), compared to the control where continuous flooding was applied at the three leaf stage of crop development (roughly 25 days after sowing).

In Year 1 (2008/9) the 4 water management treatments (3 replications) were: (i) Control; (ii) DCF 40 mm – flush irrigations at 40 mm cumulative ETo−rain intervals until continuous flooding applied 10 days prior to panicle initiation (PI); (iii) DCF 80 mm; and (iv) DCF 160mm. In years 2 and 3 the irrigation thresholds were increased through use of a crop factor (0.6 and 0.8 between 1–15 Nov and 16–30 Nov, respectively), to increase the imposed DCF water stress due to limited treatment effect in Year 1. For the same reason, the 40 mm treatment was replaced with a Flood treatment designed to replicate traditional aerial sowing (initiated particularly by farmer interest in this comparison). This treatment was established by broadcast dry seeding, on the same day as the other treatments, and continuously flooded from one day after sowing until shortly before maturity. The treatments for years 2 and 3 were: (i) Control; (ii) Flood; (iii) 80/Kc mm (effective to roughly 120 mm); and (iv) 160/Kc mm (effective to roughly 240 mm). The medium grain short season semi-dwarf rice variety, Quest, was used for all three years of experimentation, and sub-plot treatments of N fertilizer rate were imposed (High (200 kg N ha^{-1}); Medium (135 kg N ha^{-1}); and Low (zero, 0 kg N ha^{-1})) to test the N-response performance of the model. The Control treatment received 2/3 of the nitrogen applied to dry soil prior to the application of continuous flooding and the remaining 1/3 into the floodwater at PI. The 40 mm, 80 mm and 160 mm treatments received nitrogen in three equal splits, i.e., 1/3 at 3 leaf stage, 1/3 at mid-tillering and 1/3 prior to continuous flooding. Further information on techniques used for measuring crop, irrigation, and soil variables are detailed in Chapter 6 (Dunn and Gaydon, 2011).

Model parameterization

a) Soil Physical and Chemical Parameters

Some soil properties of the experimental field are presented Dunn and Gaydon (2011; Table 1, p 1800), however the specific physical soil parameters required for APSIM are provided here (Table 1). They were estimated from Hornbuckle and Christen (1999) for a Birganbigal clay loam.

b) Climate

Measured daily climate data over the period of the field experiment (2008-2011) was obtained from the SILO database (Jeffrey et al., 2001) for Leeton Caravan Park (Australian Bureau of Meteorology (BoM) Station 074062; about 5 km from the experimental site) and used to provide daily maximum/minimum temperatures, and radiation for the APSIM simulations. Rainfall was measured daily at the experimental site and incorporated into the SILO climate file, under the assumption that radiation and temperature is fairly uniform regionally, but rainfall can be extremely variable (hence necessitating on-site measurement).

c) APSIM-Oryza temperature stress parameters

The ORYZA2000 model (and hence APSIM-Oryza) contains separate algorithms to capture the impact of both high and low temperature stresses on spikelet fertility. These have been parameterized for tropical conditions, hence application in the dry, temperate Australian growing environment required re-parameterization.

Table 1. Soil physical parameters (Birganbigal clay loam, Hornbuckle and Christen, 1999) used in parameterizing APSIM for the experimental site at Yanco, NSW.

Soil layer (cms)	**BD ($g\ cm^{-3}$)**	**SAT ($mm\ mm^{-1}$)**	**DUL ($mm\ mm^{-1}$)**	**LL15 ($mm\ mm^{-1}$)**	**AirDry ($mm\ mm^{-1}$)**	**SWCON (day^{-1})**	**K_s ($mm\ day^{-1}$)**	**PAWC (mm)**
0-10	1.41	0.47	0.25	0.14	0.095	0.2	20.8	11.0
10-20	1.55	0.41	0.334	0.2	0.18	0.1	5	13.4
20-30	1.52	0.43	0.38	0.27	0.2	0.1	1.3	11.0
30-40	1.51	0.46	0.41	0.27	0.2	0.1	1.3	14.0
40-70	1.59	0.4	0.38	0.27	0.2	0.1	1.3	33.0
70-100	1.6	0.4	0.38	0.27	0.2	0.1	1.3	33.0
100-130	1.6	0.4	0.38	0.27	0.2	0.1	1.3	33.0
								148.4 (total)

BD, bulk density ($g\ cm^{-3}$); SAT, saturated moisture content (volumetric, mm water / mm soil); DUL, drained upper limit or *Field Capacity*; LL15, 15-bar lower limit or volumetric moisture content at a suction of 1500 KPa; AirDry, air-dried moisture content, the minimum to which the soil can be dried by evaporation; SWCON, APSIM parameter governing moisture drainage between soil layers, defined as the proportion of available water above DUL which can drain into the layer below on a daily basis; K_s, saturated hydraulic conductivity or percolation rate ($mm\ day^{-1}$); PAWC, plant available water content (mm).

(i) *High temperature*. The relationship between average daily maximum temperature (T_{max}) and the fraction of fertile spikelets (S_h) resulting from heat stress is (Equation 1; Bouman et al., 2001, p 61):

$$S_h = \frac{1}{1+e^{(0.853\times(T_{\max}-36.6)}} \qquad (1)$$

This algorithm is applied between crop growth stages 0.96 ≤ DVS ≥1.22, where DVS is the APSIM-Oryza variable for crop development stage, ranging from 0 at sowing to 2.0 at PM. Anthesis occurs at DVS = 1.0, hence the range susceptible to high temperature stress is a period centred on flowering. The value of 36.6 in equation 1 represents the maximum temperature (in oC) above which temperature damage occurs. In a humid tropical environment this is the accepted figure, however in the Australian environment there is evidence that ambient maximum temperatures up to 6-7 ^{o}C higher can be withstood by the crop without damage, due to canopy cooling from the high transpiration rates in the dry air (Matsui et al., 2007). Hence we changed 36.6 to 43.0 for our simulations.

(ii) *Low Temperature*. The percentage floret sterility caused by cold temperature damage (Sc) is calculated over a wider range (0.75 ≤ DVS ≥ 1.2), with DVS = 0.75 representing early microspore. S_c is a function of cumulative cold temperature conditions (Equation 2; Bouman et al., 2001, p 61).

$$S_c = \frac{1-(4.6+0.054\times SQ^{1.56})}{100.0} \qquad (2)$$

Where SQ is the sum of cooling degree-days encountered over the sensitive period. SQ is defined as a function of the average daily temperature (T_{av}) according to Equation 3.

$$SQ = \sum(22-T_{av}) \qquad (3)$$

The value 22 in Equation 3 represents the average daily temperature (^{o}C) corresponding to occurrence of dangerous minimum night-time temperatures of 17 ^{o}C, calibrated for a tropical environment (Uchijima, 1976). We conducted a new parameterization on the assumption that this relationship (ie 17:22) may not necessarily apply in the markedly different Australian rice-growing environment (Figure 1).

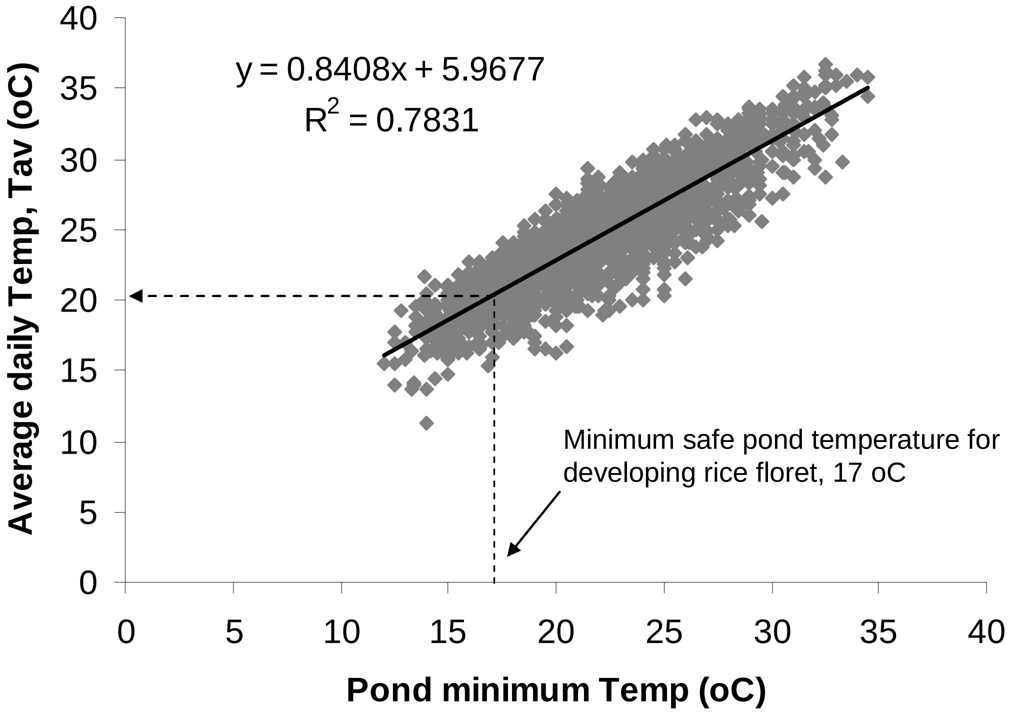

Figure 1. The relationship between dangerous low temperatures for the developing rice florets (submerged in the pond under Australian management) and the average daily temperature for the experimental site at Yanco (1957-2011).

Climate data for the experimental site over a 55-year period was used, plotting daily night-time pond temperature versus average daily temperature between late January and mid February each year (the time associated with the cold sensitive phase in Australian rice crops). Night-time pond temperatures were assumed to equal minimum daily temperature + 5 ^{o}C (the temperature buffering effect of the floodwater; Williams and Angus, 1994). As a result of this analysis, the figure of 22 was changed to 20 for Australian conditions.

Model Calibration

a) Crop variety

Rice crop varieties were calibrated for the simulation of each experimental treatment by varying the APSIM-Oryza crop phenology parameters iteratively until the modelled phenology dates matched the observed dates. The primary dates of focus were those associated with sowing, transplanting, panicle initiation, flowering, and physiological maturity. In APSIM-Oryza, the crop development rates for each growth stage exhibit a G x E x M interaction, hence individual 'varieties' were calibrated for each of the imposed nitrogen-rate x irrigation interval combinations used in the experiment. The critical parameters calibrated were DVRJ, DVRI, DVRP, DVRR, the development rates in juvenile, photoperiod-sensitive, panicle development and reproductive phases respectively (oC d-1).

b) Soil organic matter (SOM) cycling

SOM mineralization capacity varies between locations as a function of soil biota ecology and the proportion of SOM in the resistant or lignin pool (inert fraction). Hence, the values of the APSIM parameters Fbiom and Finert (Probert et al., 1998) were calibrated for each experiment using data from zero-N treatments. A certain amount of plant-available mineral N was assumed to come from rainfall and/or irrigation water, and the remainder from mineralization of organic matter for the simulation of these treatments. The values of Fbiom and Finert were incrementally varied within reasonable bounds (Probert et al., 1998) until the simulated indigenous N supply in the zero-N treatments allowed close simulation of the measured crop yields.

Validation Simulations

a) Variables compared

Simulated APSIM output variables for rice grain yield (wrr, kg dry matter ha-1), above-ground biomass (wagt, kg dry matter ha^{-1}), applied irrigation water (mm), soil mineral N (NH4- and NO3^{-}, kg ha^{-1}) and volumetric soil moisture content (fraction) on a layered soil basis (0-10, 10-20, 20-30, and 30-40cms) were compared with the corresponding measured data.

Statistical evaluation methods used

A linear regression across all treatments was used to compare measured and simulated grain yield, water use, and WP. We determined the slope (α), intercept (β), and coefficient of correlation (R^2) of the linear regression between simulated and measured values. We also evaluated model performance using the Student's t test of means assuming unequal variance P(t), and the absolute square root of the mean squared error, RMSE (Equation 4).

$$RMSE = \frac{\sqrt{\sum_{i=1,n}(S_i - O_i)^2}}{n} \qquad (4)$$

Where S_i and O_i are simulated and observed values, respectively, and n is the number of pairs. A model reproduces experimental data best when α is 1, β is 0, R2 is 1, P(t) is larger than 0.05 (indicating observed and simulated data are the same at the 95% confidence level), and the absolute RMSE is similar to standard deviation of experimental measurements. We also calculated the modelling efficiency, EF (Willmott, 1981) as another recognized measure of fit. The modelling efficiency is defined as (Equation 5):

$$EF = 1 - \frac{\sum_{i=1,n}(O_i - S_i)^2}{\sum_{i=1,n}(O_i - \overline{O}_i)^2} \qquad (5)$$

where ō is the mean of the observed values. A value of EF = 1 indicates a perfect model (MSE = 0) and a value of 0 indicates a model for which MSE is equal to the original variability in the measured data. Negative values suggest that the average of the measured values is a better predictor than the model in all cases.

Scenario Analysis

Using the validated model, a number of operational scenarios were simulated for the experimental site over a much wider climatic period (55 years, 1957-2011) to gain a better understanding of climatic risk associated with DCF at different irrigation intervals. Average gross margins (GMs, A$ ML-1) were calculated for each interval, in addition to WP, recognizing that DCF treatments involve greater weed control costs than conventional fully-flooded treatments. The relative contribution of water and temperature stress to simulated yield decline (cf. control) was evaluated for each of the DCF scenarios, leading to insights into a potential best practice strategy, which was subsequently simulated and evaluated against the original scenarios. The impacts of the most likely projected future climate (for 2030; see section 2.3.6 below) were then evaluated for three selected scenarios and compared with historical performance.

Climate Data used for scenarios

Daily climate data (1957-2011) from the SILO database (Jeffrey et al., 2001) for Leeton Caravan Park (Australian Bureau of Meteorology (BoM) Station 074062) was used for the APSIM simulations.

Scenarios

Detailed descriptions of the scenarios simulated are provided in Table 2. High N rates were used in all scenarios, as these were shown to provide the best WP during experimental investigations (Dunn and Gaydon, 2011) and would be preferred by local farmers.

Gross margin analysis

GMs were calculated at a field-scale using detailed costs and prices from the NSW “Farm Enterprise Budget Series” 2009/2010 (NSW Government, 2011), widely used by local farmers in their own calculations. General assumptions on variable costs and prices are provided in Table 3. Variable costs of production include: field operations (sowing, cultivation, harvesting, spraying); consumables (seeds, fertilizer, herbicide, insecticide); water; cartage; and insurances/levies. Extra costs associated with weed control in the DCF treatments were estimated from experience gained during the experiment of Dunn and Gaydon (2011) and also from the experience of a local farmer (Barry Kirkup, pers. comm. September 2011).

Table 2**.** Description of treatments used in the DCF scenario analysis, extending the experiment of Dunn and Gaydon (2011)

Treatments	**Description**	**Common Elements between treatments**
Flood	Aerially-sown simulation (a historically common practice in the region where pre-soaked rice seed is established directly into floodwater by dropping from airplane). Floodwater established on 14-Oct each year, seeded the following day. Continuously flooded for entire crop duration until PM. The bulk of the fertilizer (150 kg N ha^{-1} (as urea)) sown into the soil (10 cm depth) just before flooding; a top-dressing of 50 kg N ha^{-1} (as urea) applied into floodwater at PI.	- Rice variety *Quest* (medium grain short season semi-dwarf variety; Smith et al. 2010) - Sowing rate: 150 kg seed ha^{-1} (assumed estab. of 300 plants m^{-2}) - Sowing date: 15th October each year - Total applied N : 200kg ha^{-1} - Flush irrigations involved filling the bays with 5 cm depth of water then leaving them ponded for 3 h before draining the water from the bays. - weeds were assumed to be controlled; appropriate costs accounted for each treatment in gross margin analyses (Table 3) - floodwater drained at PM, crops harvested 7 days later
Control	Conventional drill establishment – as per common farmer practice in region. (Drill sowing is more commonly used in the region of recent times, due to reduced water requirement cf. aerial sowing.) Crop sown dry and flush irrigated sporadically (on 80mm cumulative ET_o) until continuous flooding applied at the three leaf stage (approx 30 days after sowing). Sowing fertilizer 150 kg ha^{-1} Di-ammonium Phosphate (DAP; 18% N). Just before continuous flooding is established, 150 kg N ha^{-1} (as urea) is applied to the soil surface and watered in. Top-dressing of a further 50 kg N ha^{-1} (as urea) applied at PI, directly into the floodwater.	
80, 120, 160, 200, 240	*Delayed Continuous Flooding* (DCF) treatments. As per *Control*, however establishment of continuous flooding is delayed until 10 days before PI, aiming to save irrigation water from unproductive evaporative losses. During this pre-flood period flush irrigations are scheduled, applied respectively at 80, 120, 160, 200 and 240 mm cumulative ETo (minus rain) intervals, until continuous flooding applied 10 days prior to PI. Treatments received nitrogen in two splits, i.e., 50 kg N ha^{-1} (as urea) at mid tillering and 150 kg N ha^{-1} (as urea) just prior to continuous flooding, 10 days before PI. Both these urea applications applied to the soil surface and watered in.	

Table 3. Elements used in gross margin calculations for scenario analyses. The flood, control and delayed continuous flood (DCF) treatments (80, 120, 160, 200, 240) are shown below. The rice grain price used is the average over the last ten years (ABARES, 2010). All other cost elements from NSW Government (2011).

Gross Margin Element	**Flood**	**Control**	**DCF**
INCOME			
Rice grain price (A\$ t^{-1})	349	349	349
COSTS			
Cultivation (2x scarify, roterra, grade) (A\$ ha^{-1})	54	54	54
Sowing (A\$ ha^{-1})	88	71	71
Seed (Quest @ 150kg/ha) (A\$ ha^{-1})	73	73	73
Fertilizer (435 kg ha^{-1} urea) (A\$ ha^{-1})	457	457	457
Herbicides & Insecticides (A\$ ha^{-1})	221	221	408
Irrigation water (fixed and variable costs) (A\$ ML^{-1})	35	35	35
Harvest (harvesting + cartage) (\$A t^{-1} grain)	36.5	36.5	36.5
Research Levies (A\$ t^{-1} grain)	3.0	3.0	3.0
Insurance (percentage of estimated crop value) (%)	1.65	1.65	1.65

The relative contributions of water and temperature stress

The major sources of physiological stress expected for the simulated rice crops under DCF management were water and temperature stress, given that high N rates were chosen. Water stress would be expected to occur in the early stages of crop growth (prior to PI, APSIM-Oryza DVS = 0.65), as a function of the imposed AWD irrigation interval. Risk of dangerous temperature stress occurs later in the crop during floral development and early grain filling (APSIM-Oryza DVS; $0.75 > x < 1.2$; Bouman et al., 2001). For the DCF treatments with delayed flowering (due to early water stress on phenological development), local experience suggested that risk of low temperatures would be particularly increased at the critical times. The general simulation of grain yield for each scenario provided the overall net effect of both water and temperature stresses, however to isolate the relative contribution of each, separate simulations were performed alternately with (i) the water stress reduction factor turned off; and then (ii) just the low temperature stress reduction factor turned off. The relative contributions of the two key stresses were then determined by comparison with the control and the general simulation with both stress factors turned on.

Searching for ‘best practice’

System insights gained from examining stress factors (section 2.3.4) were then used to develop new management interventions that reduce these stresses. The additional scenarios were formulated, simulated, and compared with the results of original scenarios to provide insights into ‘best practice’ management.

The impact of climate change

The performance of three selected scenarios (the Control, the best performing original DCF, and the ‘best practice’ DCF strategy) were simulated using 55 years of both (i) historical; and (ii) 2030 climate files. A simple estimate for 2030 climate was obtained by modifying the historical climate file according to statistics forecast by CSIRO (2007b). An average temperature rise of 2.1 ^{o}C was applied to both minimum and maximum temperatures, accompanied by a reduction in rainfall of 10%, and an increase in atmospheric CO2 concentration to 440 ppm. The relative impact on performance of the three selected management scenarios was then examined.

RESULTS

Model validation

Model validation results for grain yield, water use, and WP are illustrated graphically in Figure 2 and summarized in Table 4. Good correlation between observed and simulated grain yield (kg dry matter ha^{-1}) and water use (irrigation water requirement + rainfall; ML ha^{-1}) were achieved. The correlations exhibited high R^2 figures (0.91 and 0.85 respectively), supported by RMSE values of the same order of magnitude as (or less than) the experimental standard deviations. Student’s paired t-test assuming two-tailed distributions with unequal variances gave P(t) values of 0.38 and 0.43 respectively, indicating no statistical difference between simulated and observed populations at the 95% confidence level (ie $P(t) > 0.05$). The Modelling Efficiency, EF, was calculated at 0.83 and 0.81 respectively, demonstrating strong modelling performance. The WP (t grain ML^{-1}) was a calculated variable for both observed and simulated datasets, and exhibited far greater variability within each experimental treatment than either the grain yield or water use. Given this large variability (apparent from the wide error bars in Figure 2, and the high relative standard deviation (20% of the observed WP average), Table 4), the model still performed acceptably well – returning a high R^2 (0.67) in combination with a RMSE smaller than the experimental standard deviation (0.11 cf. 0.14), and high values for both P(t) (0.95) and EF (0.47).

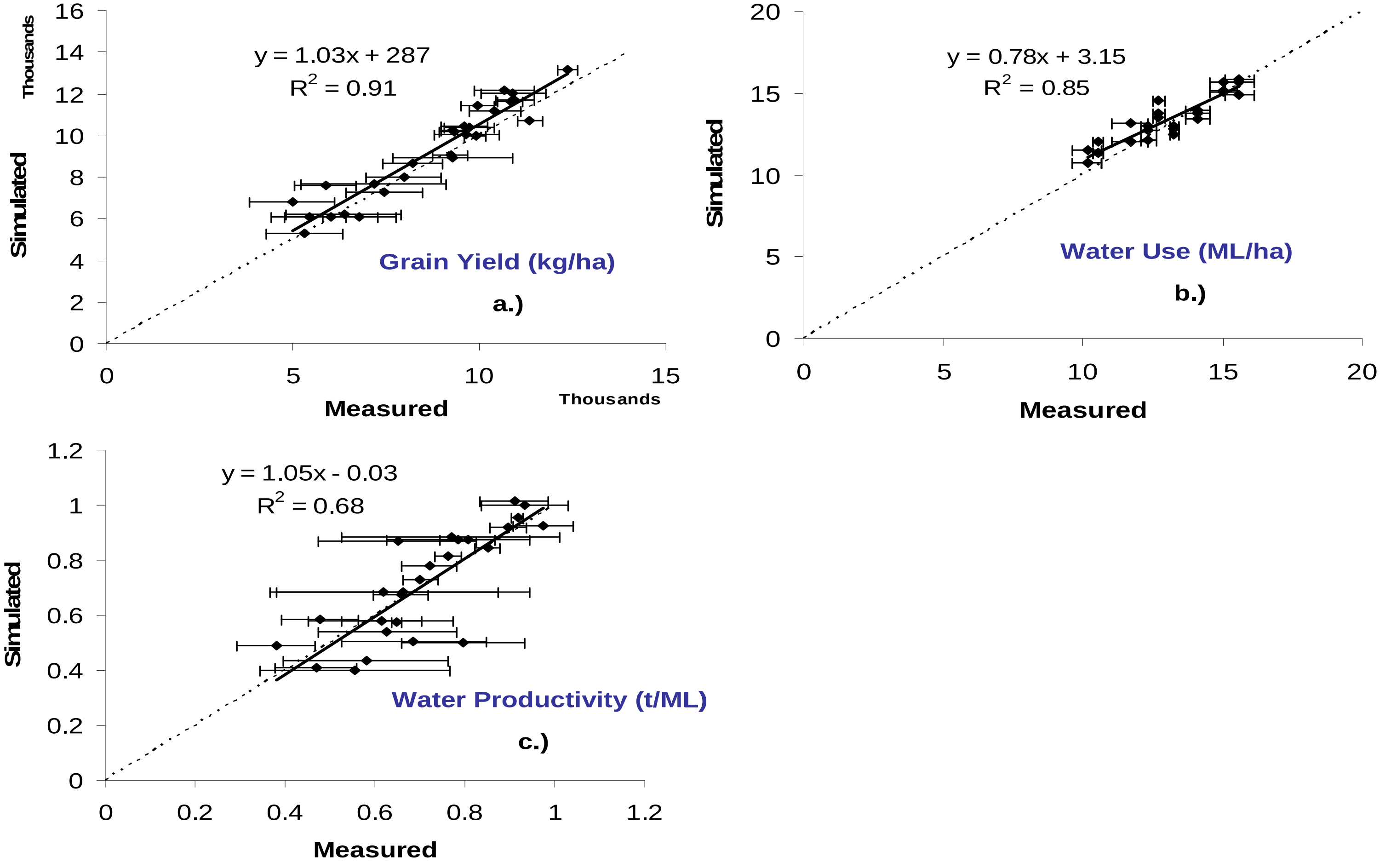

Figure 2. Simulated versus observed variables for validation of APSIM in DCF management against experimental data of Dunn and Gaydon, 2011. Graph (a) shows the correlation for rice grain yield (kg dry matter ha-1); (b) water use (irrigation applied + rain; ML ha-1); and (c) WP (tones grain ML-1). Error bars are shown around the experimental means for each treatement, equal to one standard deviation (over three replications) either side. The dotted line is a linear 1:1 curve through the origin; the heavy solid line is a linear trendline fitted to the plotted points.

Table 4. Model validation statistics for simulated vs measured variables the experiment of Dunn and Gaydon (2011)

Variable		N	X_{meas}(SD)	X_{sim}	P(t)	α	β	R^2	RMSE	EF
Rice grain yield (kg ha^{-1})		**27**	**8706 (918)**	**9229**	**0.38**	**1.03**	**287**	**0.91**	**854**	**0.83**
Water Regime	*Fertilizer*									
Conventional	H	3	10906 (495)	11935						
	M	3	9954 (974)	9575						
	L	3	6043 (1089)	5826						
80mm DCF	H	3	10066 (685)	10748						
	M	3	9520 (726)	10008						
	L	3	5957 (1060)	6731						
160mm DCF	H	3	9843 (584)	10821						
	M	3	9594 (679)	10262	**0.43**	**0.78**	**3.15**	**0.85**	**0.78**	**0.81**
	L	3	6471 (1508)	7152						
Applied water use (ML ha^{-1})		**27**	**12.83 (0.42)**	**13.20**						
Water Regime	*Fertilizer*									
Conventional	H	3	14.33 (0.45)	14.48						
	M	3	14.33 (0.45)	14.84						
	L	3	14.33 (0.45)	14.06						
80mm DCF	H	3	12.46 (0.31)	12.75						
	M	3	12.46 (0.31)	12.94	**0.95**	**1.05**	**-0.03**	**0.67**	**0.11**	**0.47**
	L	3	12.46 (0.31)	13.53						
160mm DCF	H	3	11.71 (0.49)	11.75						
	M	3	11.71 (0.49)	11.86						
	L	3	11.71 (0.49)	12.55						
Water Productivity (t ML^{-1})		**27**	**0.71 (0.14)**	**0.71**						
Water Regime	*Fertilizer*									
Conventional	H	3	0.77 (0.1)	0.83						
	M	3	0.64 (0.22)	0.65						
	L	3	0.54 (0.17)	0.42						
80mm DCF	H	3	0.71 (0.18)	0.84						
	M	3	0.79 (0.06)	0.78						
	L	3	0.62 (0.13)	0.5						
160mm DCF	H	3	0.87 (0.06)	0.92						
	M	3	0.85 (0.07)	0.87						
	L	3	0.57 (0.14)	0.57						

N, number of data pairs; X_{meas}, mean of measured values; X_{sim}, mean of simulated values; SD, combined standard deviation amongst all measured treatment replications; P(t), significance of Student's two-tailed paired t-test assuming non-equal variances; α, slope of linear regression between simulated and measured average values; β, y-intercept of linear regression between simulated and measured values; R^2, square of linear correlation coefficient between simulated and measured values; RMSE, absolute root mean squared error; EF, the modelling efficiency.

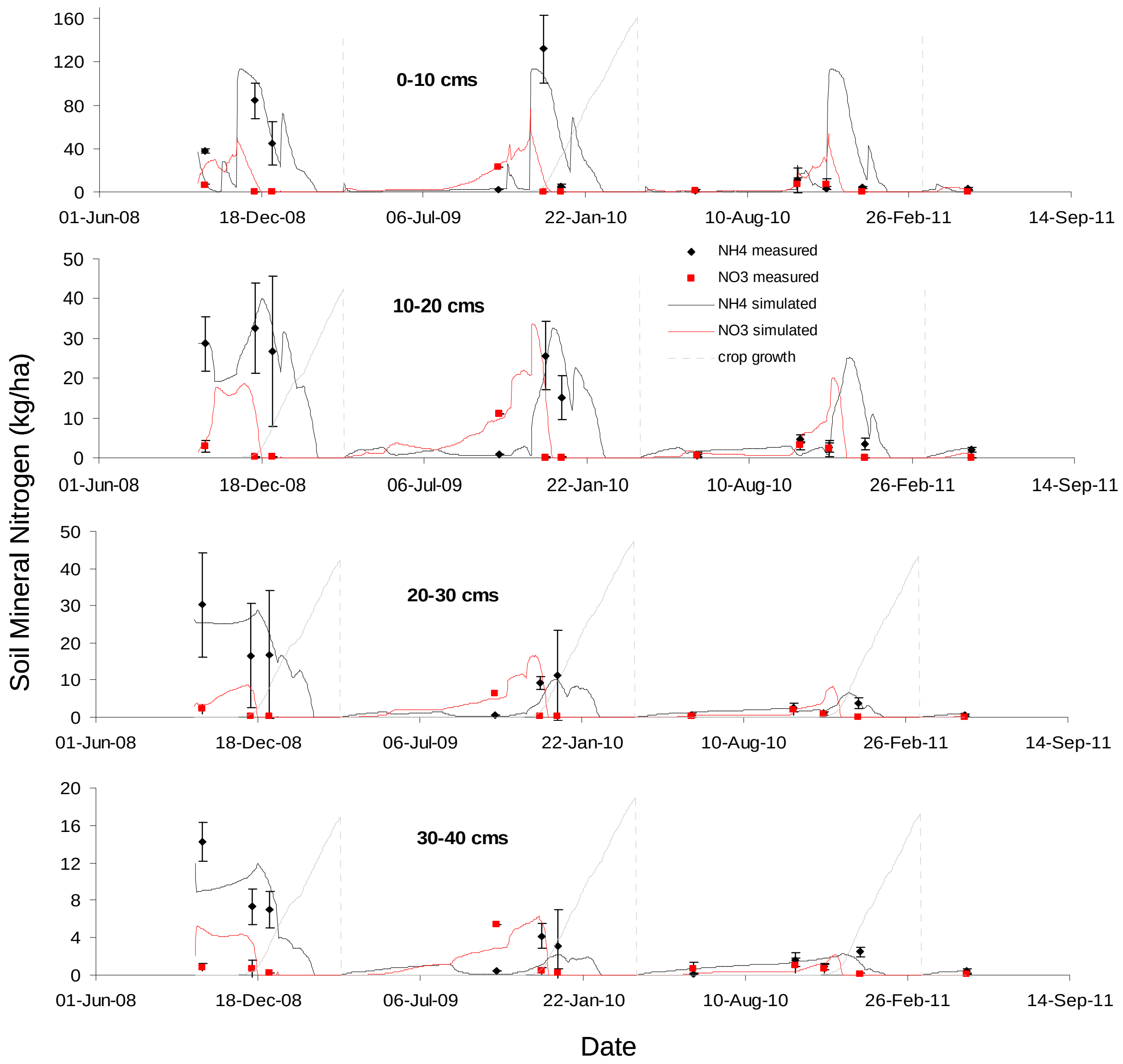

Figure 3. Simulated versus observed soil mineral N pools (NH4- and NO3+; kg N ha-1) for soil layers 1-4 (0-10cm, 10-20cm, 20-30cm, 30-40cm) in the Control high-N treatment. The red lines and points show simulated and observed NO3+ respectively. The black show NH4-. Error bars depict one experimental standard deviation either side of the mean. The dotted grey lines depict the periods when growing rice crops were present in the field (absolute values of production not indicated).

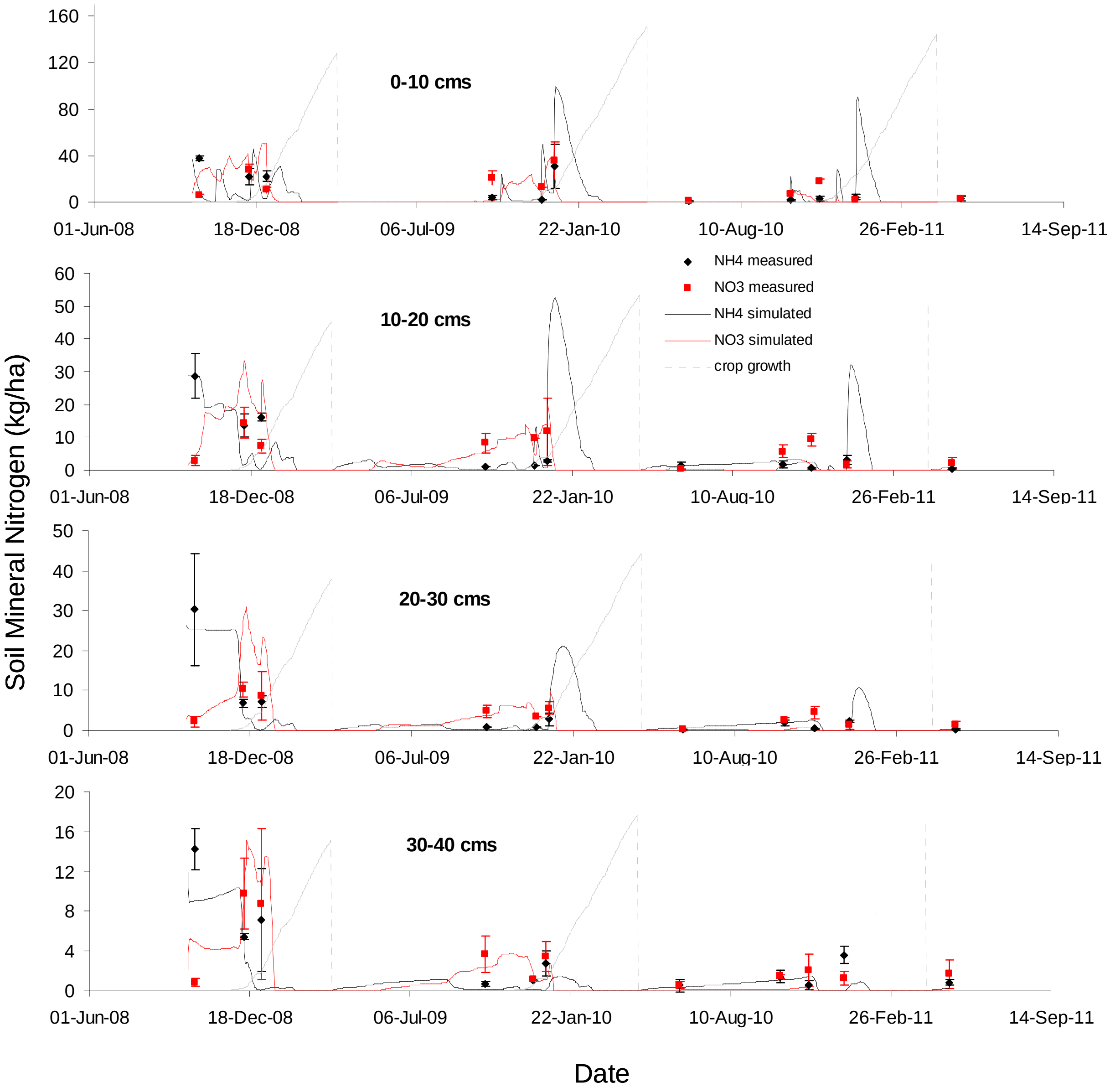

Figure 4. Simulated versus observed soil mineral N pools (NH4- and NO3+; kg N ha-1) for soil layers 1-4 (0-10cm, 10-20cm, 20-30cm, 30-40cm) in the 160mm high-N treatment. The red lines and points show simulated and observed NO3+ respectively. The black show NH4-. Error bars depict one experimental standard deviation either side of the mean. The dotted grey lines depict the periods when growing rice crops were present in the field (absolute values of production not indicated).

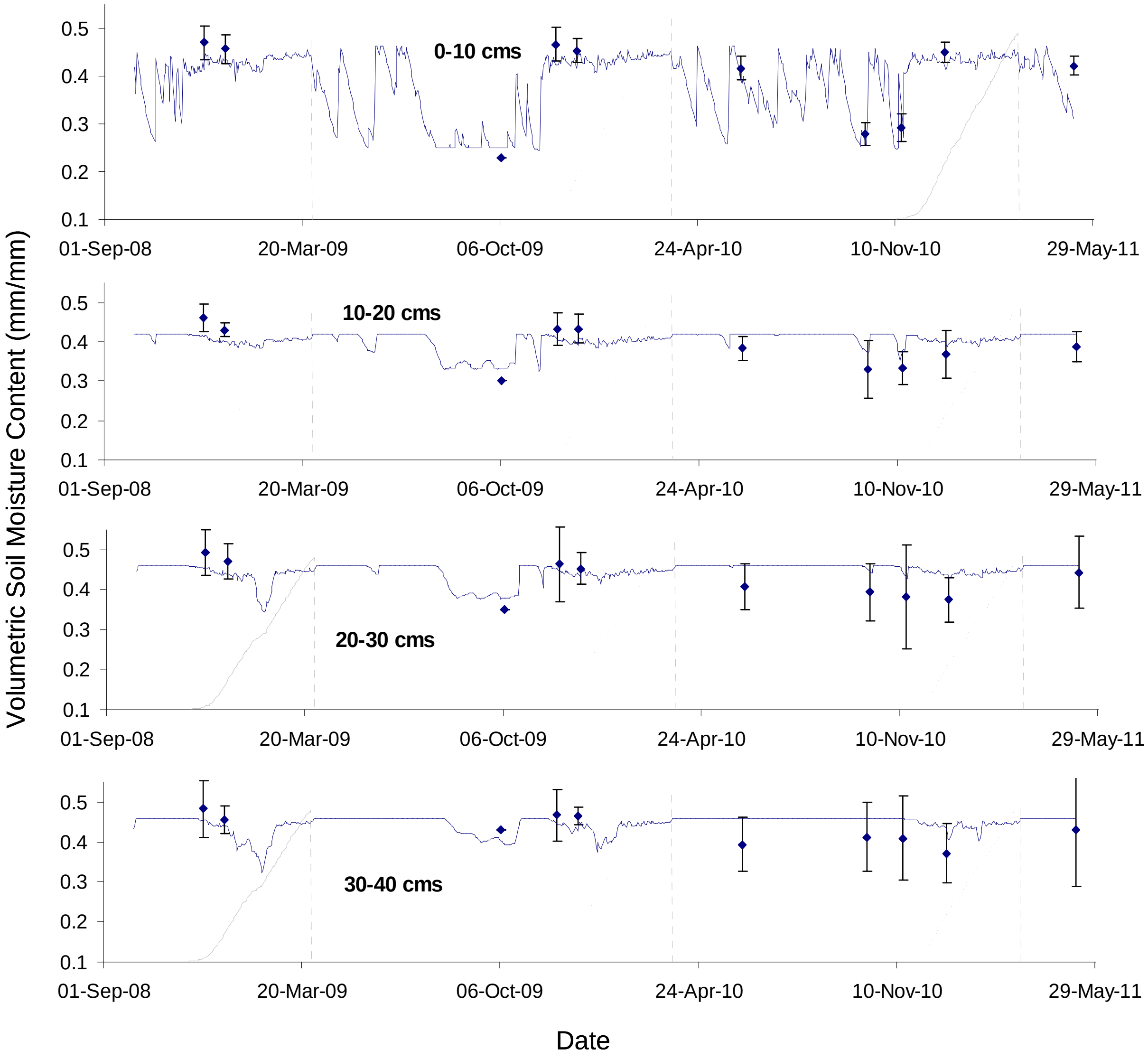

Figure 5. Simulated versus observed volumetric soil water content (mm mm-1) for soil layers 1-4 (0-10cm, 10-20cm, 20-30cm, 30-40cm) in the Control high-N treatment. Error bars depict one experimental standard deviation either side of the mean. The dotted grey lines depict the periods when growing rice crops were present in the field (absolute values of production not indicated).

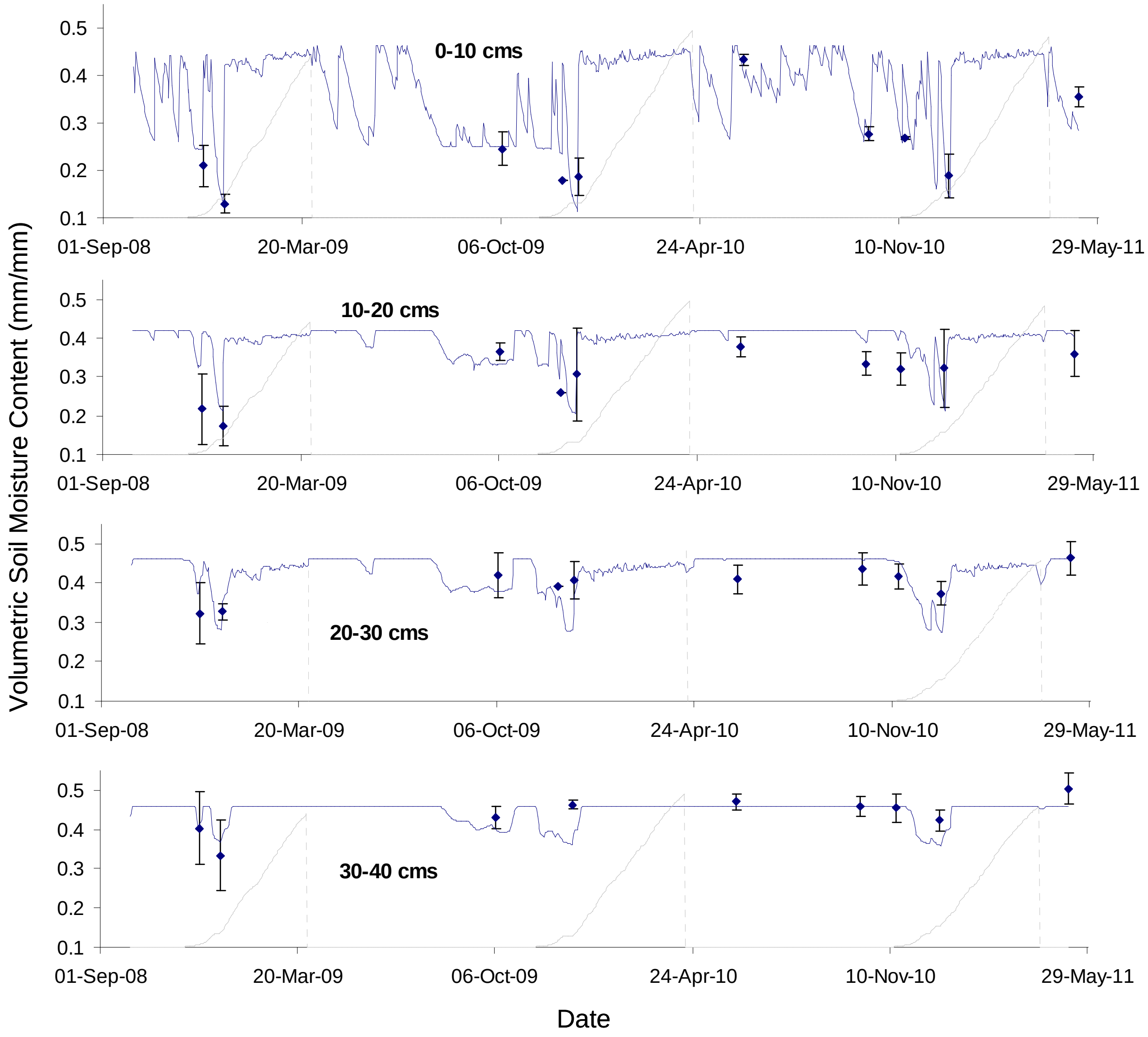

Figure 6. Simulated versus observed volumetric soil water content (mm mm-1) for soil layers 1-4 (0-10cm, 10-20cm, 20-30cm, 30-40cm) in the 160mm high-N treatment. Error bars depict one experimental standard deviation either side of the mean. The dotted grey lines depict the periods when growing rice crops were present in the field (absolute values of production not indicated).

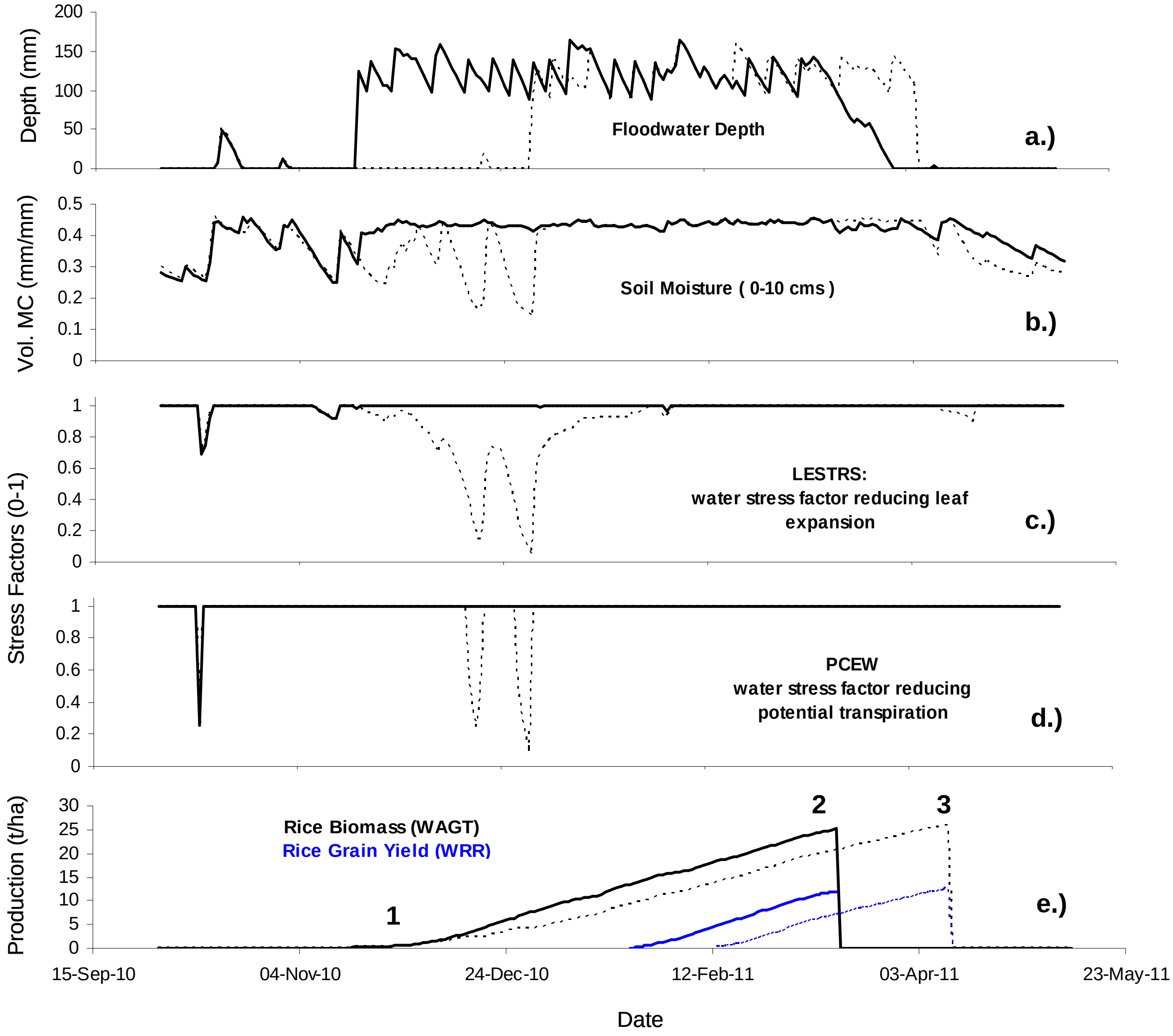

Figure 7. Simulated comparison (for an example year) between the control (solid black and blue lines) and the 160mm DCF (dotted black and blue lines), illustrating differences in the experienced ponding depth, the crop water stress levels, the consequent phenological developments, and the resulting biomass/yield production dynamics. Point 1 is sowing; point 2 is physiological maturity (PM) for the control crop; point 3 is PM for the 160mm DCF crop. Graph c.) and d.) show two APSIM-Oryza water stress factors – a value of 1 indicates no stress; a value of zero indicates severe stress.

Validation using a combination of above-ground and below-ground variables provides greater confidence in model performance than either alone, and can provide strong evidence that the right model answers are being obtained for the right reasons (Meinke et al., 1997). Modelled mineral N pools (NH4- and NO3+; kg N ha-1) in each of the top 4 soil layers (0-10cm, 10-20cm, 20-30cm, 30-40cm) compared well with observed values (Figures 3 and 4), as did modelled volumetric soil water content (mm mm^{-1}) (Figures 5 and 6). Comparisons for the high-N subplots of the control and 160mm treatments only are shown in Figures 3-6. A graphical comparison of modelled water stress factors and production dynamics for the Control and 160mm DCF treatments in 2009/10 demonstrates why a rice crop which is severely water-stressed in the early stages (160mm DCF treatment) can still produce equivalent grain yield to a less stressed crop (Control) (Figure 7).

With reference to Figure 7, APSIM suggests that the delay in crop phenology induced by early water stress forces the 160mm crop to reach maturity at a later date (Figure 7e, compare points 2 and 3). The 160mm DCF crop (at least in this example year 2009/2010) is thereby still able to reaching the same biomass and yield at its PM as the less-stressed and earlier-finishing control. Several authors have noted the ability of the early-stressed crops to achieve similar yields to the non-stressed crops under experimental conditions (Heenan and Thompson, 1984; Thompson and Griffin, 2006; Gaydon and Dunn, 2011). Figure 7 may illustrate why. From a long-term risk perspective, however, there are several negative implications of delayed phenology, which will be examined later (for example, greater risk of cold temperature damage, and even delayed sowing of the subsequent wheat or barley crop resulting in net overall yield reductions for the farm).

Scenarios

Long-term performance of DCF management

Long-term simulations revealed a slight trend of decreasing average grain yield, as the imposed water stress prior to PI was increased (Figure 8a, Table 5). Of particular relevance was a larger decrease in required irrigation water per crop (Figure 8b, Table 5), leading to a steady increase in WP with increasing early imposed water stress, until the 240mm DCF scenario where there appears to a slight (but non-significant) fall in WP (Figure 8c, Table 5). This suggests that for the range of scenarios examined, input WP can be maximized by using roughly a 200mm cumulative (ETo - rain) irrigation interval during the pre-PI period.

The gross margin comparison is important from the farmers' perspective - the delay in permanent flooding invariably requires increased weed control costs compared with traditional practices. However even when these extra costs are included, the DCF scenarios still outperformed the traditional fully-flooded scenarios (flood and control; Figure 8d, Table 5). The conventional aerially-sown scenario (flood) provided less variable returns than all other scenarios, but with a reduction in overall average return of roughly A$39 per ML.

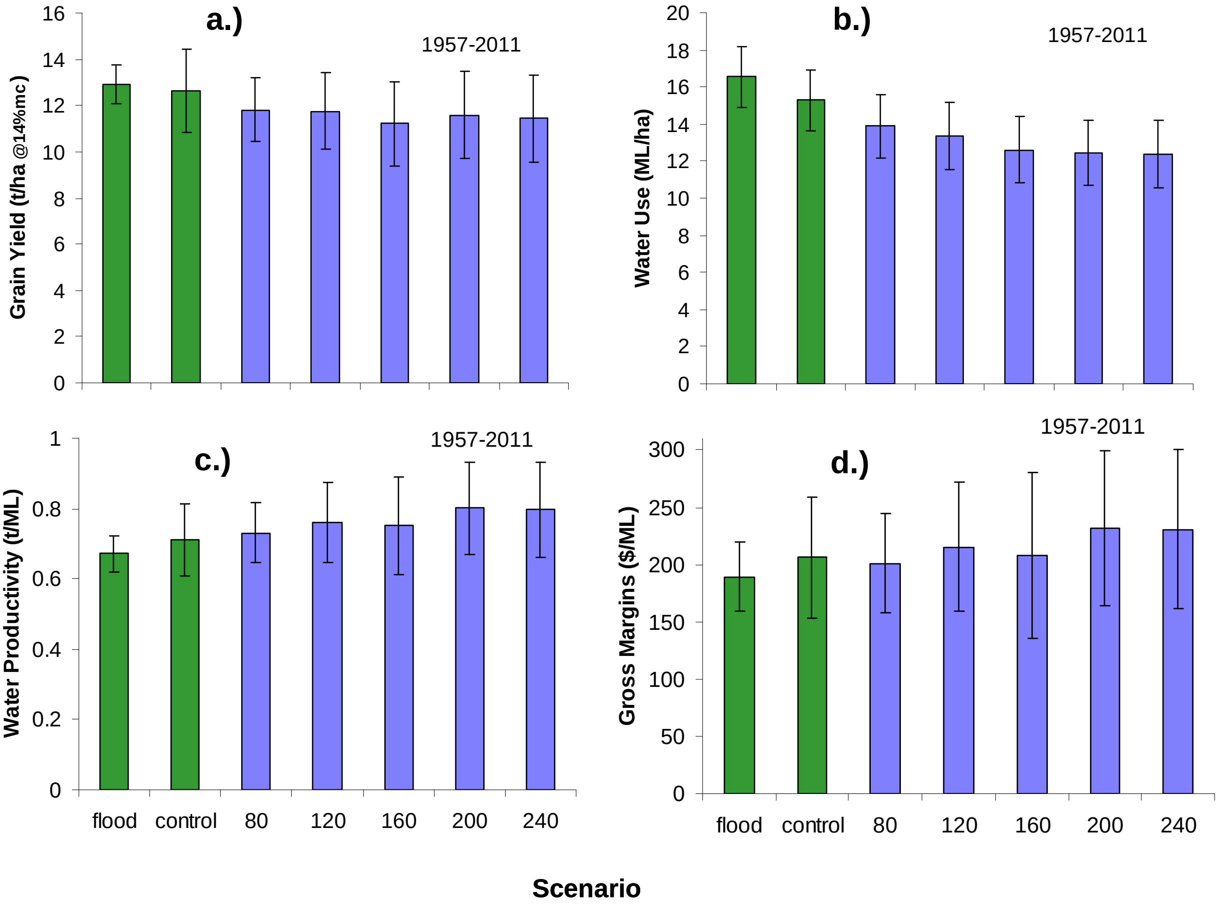

Figure 8. Comparison between the performance of simulated scenarios over a 50-year period (1957-2011):- a.) grain yield (t ha^{-1} at 14% moisture content); b.) water use (applied irrigation + rain; ML ha^{-1}); c.) Input WP (t grain ML^{-1} water applied); and d.) Gross Margins (A$ profit ML^{-1}). The error bars represent one standard deviation about the mean. The first two scenarios (flood and control – currently practiced in the region) are coloured green to differentiate them from 'new' DCF scenarios.

The DCF rice crops all took considerably longer to mature than the control and much longer to mature than the flood crops (Table 6). For example, the 200mm DPF scenario (which maximized gross margins from the applied irrigation water) matured on average 30 days after the control, and 49 days after the flood scenario. This could have significant implications for timing and potential yield of following crops such as wheat and barley. Average time of anthesis for the 200mm DCF crops is delayed by 14 days (cf. control) and 24 days (cf. flood).

Table 5. Simulated performance of the various scenarios over an historical 55 year period (1957-2011), presented as averages (with standard deviation in brackets) for rice grain yields (t ha^{-1} at 14% mc), applied water (irrigation + rain) (ML ha^{-1}), input water productivity, WP (t ML^{-1}), and gross margins, GM (A$ ML^{-1}). Average rainfall for each treatment varied between 175-228mm. Statistical differences between each scenario and the control were evaluated using a two-tailed Student's T-test ($P<0.05$), assuming unequal variances. An asterix (*) indicates a statistical difference at the 95% confidence level.

Irrigation Regime	Grain Yield (t ha^{-1})	Water Applied (ML ha^{-1})	WP (t ML^{-1})	GM (A$ ML^{-1})
Flood	12.9 (0.85)	16.6 (1.64) *	0.67 (0.05) *	189.3 (30.1) *
Control	12.6 (1.81)	15.3 (1.64)	0.71 (0.1)	206.6 (52.8)
80	11.8 (1.39) *	13.9 (1.72) *	0.73 (0.09)	201.2 (43.4)
120	11.7 (1.66) *	13.3 (1.79) *	0.76 (0.11) *	215.4 (56.5)
160	11.2 (1.81) *	12.6 (1.81) *	0.75 (0.14) *	207.7 (72.7)
200	11.5 (1.98) *	12.4 (1.77) *	0.79 (0.14) *	228.5 (70.3) *
240	11.4 (1.90) *	12.4 (1.82) *	0.79 (0.14) *	227.9 (69.7) *

Table 6. Simulated rice crop phenology for each of the scenarios (1957-2011). The data is presented as average 'days after sowing', with the standard deviation in brackets (days), followed by the date for the average, with the simulated sowing date of 15-October.

Treatments Rice sown on 15-Oct	Panicle Initiation, PI		Anthesis		Physiological Maturity, PM	
Flood	74 (4)	28-Dec	112 (4)	04-Feb	158 (7)	22-Mar
Control	78 (4)	01-Jan	122 (5)	14-Feb	172 (9)	05-Apr
80	90 (4)	13-Jan	126 (5)	18-Feb	184 (11)	17-Apr
120	96 (4)	19-Jan	133(5)	25-Feb	199 (15)	02-May
160	97 (4)	20-Jan	133(5)	25-Feb	200 (15)	03-May
200	98 (4)	21-Jan	136 (5)	28-Feb	202 (16)	05-May
240	99 (4)	22-Jan	137 (5)	29-Feb	207 (18)	10-May

Sowing times for rice crops in south-east Australia are traditionally chosen to position the temperature-sensitive floral development period around late January or early February (i.e. mid summer) – historically the period with the least risk of low night-time temperatures (Farrell et al., 2006). The later flowering period for the DCF crops (for the 15 October sowing date used in this scenario analysis) raises the question about the influence of cold temperatures in these crops. A simple analysis counting the number of days with average ambient temperature below 20 oC during the flowering period revealed that the DCF crops were indeed prone to greater risk of more cold days at critical time (Figure 9).

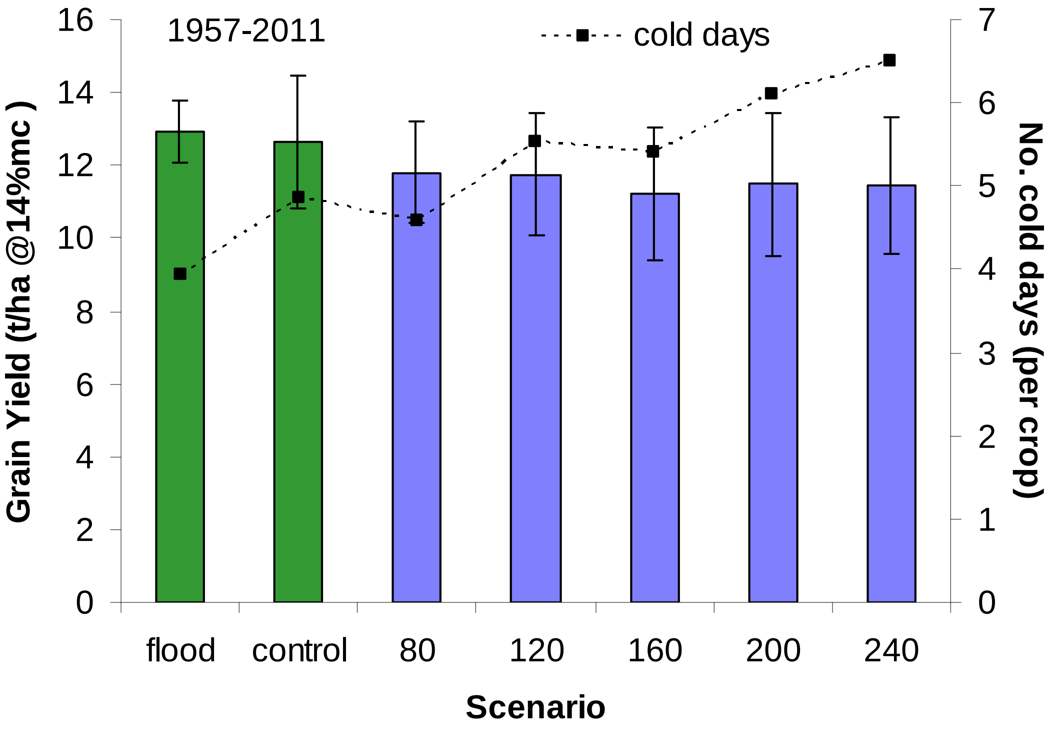

Figure 9. The relationship between simulated rice grain yield in each scenario, and the average number of dangerously cold days (average ambient temperature < 20 oC) encountered during the cold-sensitive period of each crop. The error bars represent one standard deviation about the mean.

The relative contributions of drought and temperature stress

Alternately disabling the APSIM-Oryza water stress and cold-temperature stress factors in the scenario simulations revealed an unexpected behaviour – according to the model, the yield decline from DCF is largely the result of increased cold-temperature damage due to delayed phenology, with only a small role played by the initial imposed water stress (Figure 10). This is evident in Figure 10a by the minimal gains in average grain yield by ignoring the effects of water stress in the model.

Conversely, ignoring the effects of cold temperature stress (Figure 10b) has a drastic effect - the average grain yield for all scenarios becomes close to that of the continuously-flooded scenario and all obvious traces of a yield decline disappear.

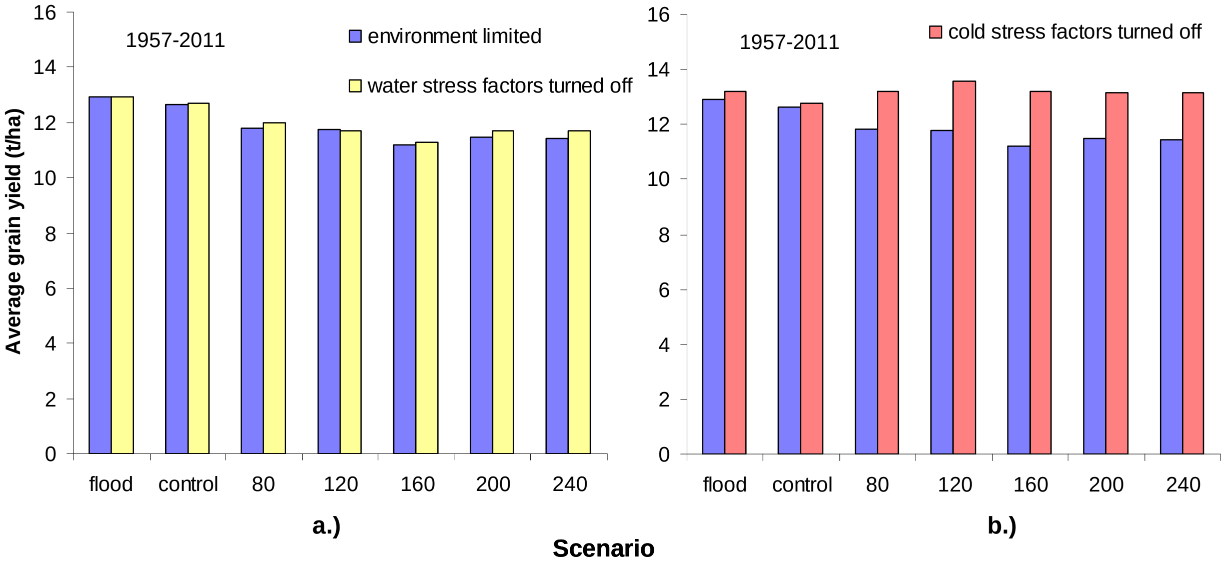

Figure 10. The relative contributions of a.) water stress; and b.) cold-temperature stress, to simulated rice grain yield (1957-2011) in each scenario. The blue environment limited bars illustrate simulated grain yields with drought and temperature stress factors limiting growth in normal operation. The yellow bars (in graph a.) and the red bars (in graph b.) are the simulated average grain yields when drought and cold-temperature stresses, respectively, are turned off – ie not limiting production.

Defining best practice

The revealed dramatic role of cold-temperature damage in the delayed DCF performance suggested the possibility to improve yields by sowing earlier to avoid cold temperatures at the sensitive times. A simulated sowing date trial, using the best performing DCF scenario (200mm), revealed increasing yield performance with sowing back to as early as mid-September (Figure 11). A plateau was then reached and, according to the model, earlier sowing provided no further yield benefits. We have therefore defined our best practice DCF management for this region as sowing 15th September and applying AWD irrigation management with a 200mm cumulative (ETo - rain) trigger, prior to establishing continuous flooding just prior to PI. This strategy provides increased average input WP again over the previous ‘best’ (200mm

DCF at 15 October sowing), but importantly there is also a considerably decreased risk of lower WP indicated by the condensed box plot (Figure 12). The best practice DCF exhibited a long-term average WP of 0.84 kg grain ML-1, representing simulated increases of 0.17, 0.13, and 0.03 kg grain ML-1 over traditional aerial sown (flood), drill sowing (control), and the best 15th October sown DPF treatment (200mm), respectively. The long-term average GM for best-practice DCF was calculated as 256 A$ ML-1, a gain of 67 and 50 A$ ML-1 respectively over aerial and conventional drill sowing.

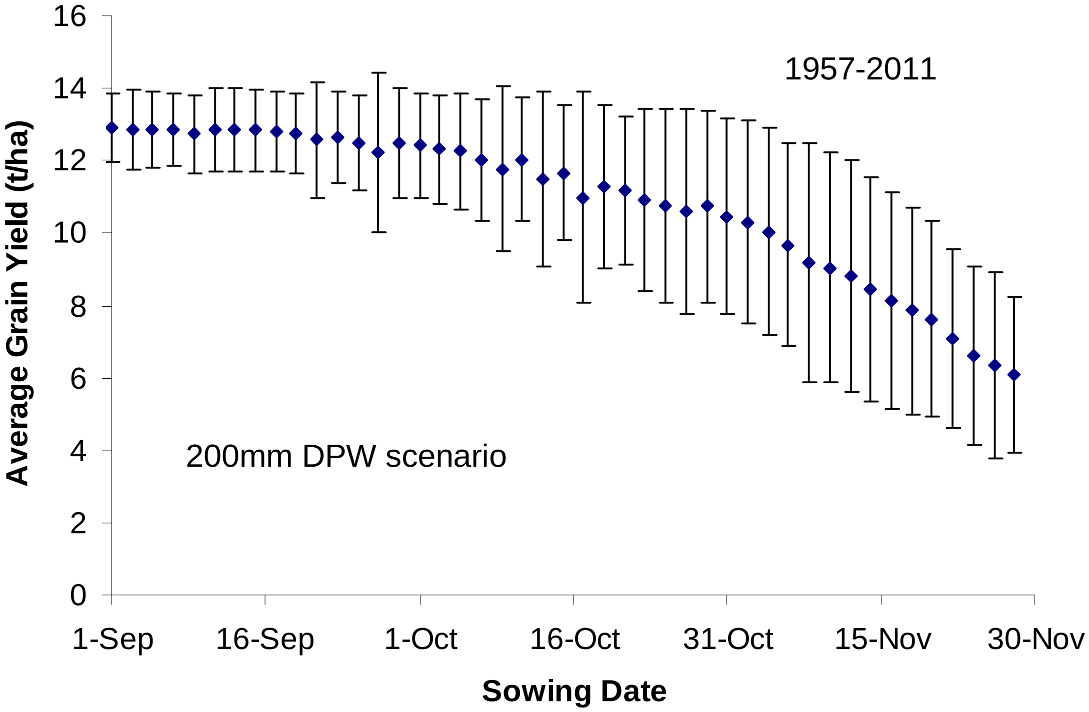

Figure 11. Simulated sowing date (1957-2011) for the 200mm DCF scenario. Average grain yield (over 55 years) from sowing on each of the 45 different days is shown as a single point with error bars either side of the mean representing one standard deviation. Each point is the average of 55 crops.

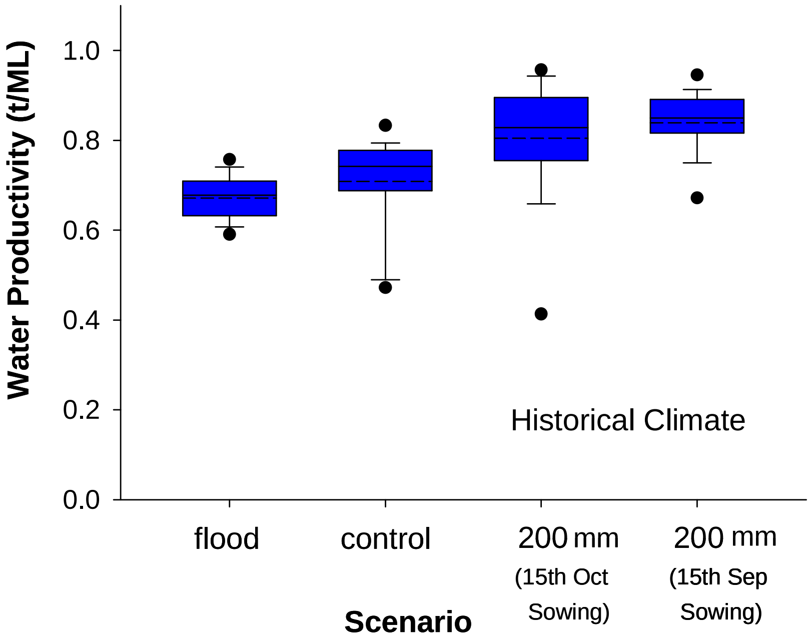

Figure 12. Simulated Input WP under an historical climate (1957-2011, over 55 years; t ML-1) for the two existing conventional treatments from the Murrumbidgee region (flood and control, sown on 15th October); the best of the DCF treatments sown at the same time (200mm DCF sown on 15 October); and the best practice DCF treatment sown earlier (200m DCF sown on 15 September). The bounds of the blue boxes illustrate the 25th and 75th percentiles (top and bottom, respectively); the upper and lower error bars represent the 5th and 95th percentiles; the dots represent outliers; the solid line inside the boxes illustrates the median, the dashed line the mean.

The impact of climate change

The climate change simulations modified the relative performance of the scenarios considerably (and hence the conclusions regarding best practice; Figure 13). The 200mm DCF with 15th October sowing now presents as the best practice option, presumably due to reduced cold-temperature constraints brought about by increasing night-time temperatures. All scenarios achieved higher water productivity than with the historical climate (Figure 12). Of course this result is highly contingent on the assumptions used in modifying the historical temperature records to represent a future 2030-centred climate scenario (max vs min temp etc).

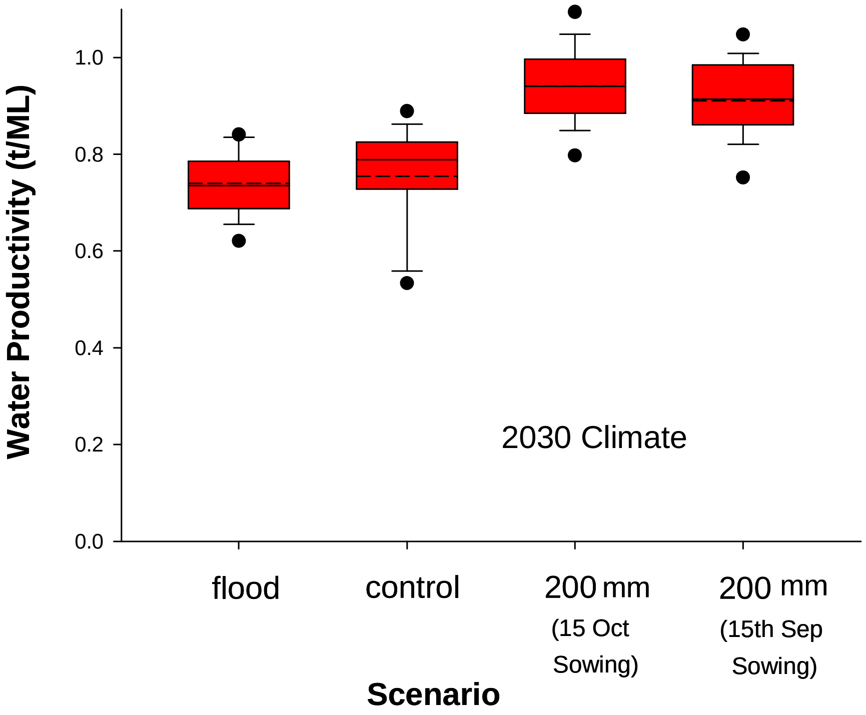

Figure 13. Simulated Input WP under a projected 2030 climate (over 55 years; t ML-1) for the two existing conventional treatments from the Murrumbidgee region (flood and control, sown on 15th October); the best of the DCF treatments sown at the same time (200mm DCF sown on 15 October); and the best practice DCF treatment sown earlier (200m DCF sown on 15 September).

DISCUSSION

Long-term simulations (with 15th October planting) revealed a slight trend of decreasing average grain yield as the imposed water stress prior to PI was increased (Figure 8a). This is consistent with the experimental findings of a number of researchers (Heenan and Thompson, 1984; Thompson and Griffin, 2006; Dunn and Gaydon, 2011), as well as the experience of key local farmers involved in our research (Barry Kirkup, Graeme Menzies; pers. comm.), who noted the ability of young rice crops to “bounce back” strongly from early water stress once continuous flooding was applied. Simulated reductions in crop water use were expected and more intuitive. The simulated presence of an optimum in gross margins (or at least a plateau; Figure 8 and Table 5), suggests that benefits from DCF management do not continue indefinitely with increasing water stress prior to PI. Eventually ongoing severe water deficit would ultimately kill the young rice plants, yet we have simulated an optimum (200mm cumulative ETo between irrigations), which falls within the bounds of experimental experience (years 2 and 3, Dunn and Gaydon, 2011).

Increasing the levels of imposed crop water stress prior to PI results in delayed phenology with a later onset of flowering and physiological maturity. We had anticipated a consequence of this may be increased risk of cold-temperature damage during flowering, however had always assumed that the observed yield declines with increasing DCF irrigation interval were in fact due primarily to the water stress imposed. This modelling study has indicated that the largest factor responsible for the decline in yield is actually the increased cold-temperature damage itself, with the water stress effects being negligible. This suggested the potential to reduce yield decline by management interventions (earlier sowing) – an option which would have been less valuable if the yield decline were related primarily to the imposed water stress. Earlier sowing (1 month earlier, 15th September) of the 200mm DCF crops was shown to result in further increases in yield and hence input WP, with reduced risk in returns. We have defined this as a tentative ‘best practice’ for the conditions simulated, with a long-term average WP of 0.84 kg grain ML-1. This represents simulated increases in long-term average WP’s of 0.17 (25%), 0.13 (17%), and 0.03 (4%) kg grain ML-1 over traditional aerial sown (flood), drill sowing (control), and the best 15th October sown DPF treatment (200mm), respectively.

A final aspect of DCF that requires further research to understand ‘best practice’ is the impact of the delayed rice maturity dates on the establishment timeliness of following crops in the rotation. A common cropping sequence in the region involves a cereal crop (wheat or barley) sown directly after several successive rice crops (referred to as ‘sod-sowing’). The primary reason is to capitalize on the full profile of soil water, but there are additional agronomic reasons also (for example, provision of a disease and pest break). Generally 3-4 weeks is required following harvest of the rice crop until the farmer is able to sow the wheat/barley, due to logistical issues including drying of rice stubbles before burning, and drying of surface soil before actual planting operations are possible. An additional delay of a month or more due to delayed DCF rice harvest could result in the yield potential of the wheat/barley being considerably compromised. Additionally, maturity dates for DCF rice crops show much greater variability than traditional practices (standard deviation of 16 days for 200mm DCF, compared with 7 days (flood) and 9 days (control); Table 6), further complicating farm planning. A reassessment of appropriate wheat/barley varieties may be required in combinations with DCF rice. We suggest a broader-scale study of whole-farm implications of introducing DCF rice water management (along the lines of Power et al., 2011; or Gaydon et al., 2012c).

Our simulations suggest that a warmer, drier future with increased levels of atmospheric CO2 could influence best practice specifications in DCF rice production. The previously cold-limited 15th October sowing of the 200mm DCF scenario performed better than the mid-September sown crops under the climate change scenario envisaged - presumably a result of reduced cold-temperature sterility due to warmer night-time temperatures. Given the simple nature of our climate change assumptions (simple arithmetic increases/decreases applied to historical temperatures and rainfalls, with no change in variability), we suggest further research into this issue using the latest climate projection methods and data.

CONCLUSIONS

We investigated the practice of delayed continuous flooding (DCF) for south-east Australian rice production using a modelling approach. The APSIM cropping systems model was initially parameterized, calibrated, and tested against 3 years of experimental data, before simulating the long-term performance of various conventional and DCF management scenarios over a 55-year historical period. DPF was shown to provide better long-term WP and gross margin outcomes than conventional fully-flooded practices (both aerial and drill sowing) with benefits increasing as a function of the pre-flood irrigation interval, up until an optimal interval of 200mm cumulative (ETo - rain). The WP increases were achieved through limiting non-productive water losses early in the season, but were accompanied by delayed maturity and reduced grain yields. Increased cold-temperature damage due to late maturity was shown as the primary driver of grain yield reductions in the DCF crops. The imposed early water stress caused the phenological delay, yet itself unexpectedly played only a small direct role in the simulated grain yield reductions. Earlier sowing of DCF crops has potential to increase WP further by moving the sensitive floral development stage into a time period with lower risk of cold temperatures. Our study suggests that best-practice DCF in rice can achieve a long term average WP of 0.84 kg grain ML-1, representing gains of 0.17 and 0.13 kg grain ML-1 over aerially-sown and conventional-drill crops, respectively. The long-term average GM for best-practice DCF was calculated as 256 A$ ML-1, a gain of 67 and 50 A$ ML-1 respectively over aerial and conventional drill sowing. Further research is warranted to examine the whole-farm implications of DCF rice management, particularly the effect of delayed harvest upon other crops in rotation with rice. Projected future changes in climate are likely to alter best-practice guidelines for DCF, however we suggest further research using more sophisticated climate projections.

ACKNOWLEDGMENTS

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CHAPTER 8

Synthesis and General Discussion

The research work outlined in this thesis consists of two major, inter-linked components: (i) initial development of modelling tools to facilitate long-term simulation of rice-based cropping systems, and (ii) subsequent use of the tools in a participatory fashion to investigate adaptation options for rice farmers in Australia's Riverina region. This final chapter will review and synthesize the achievements in both elements.

Modelling of rice-based farming systems

Prospects for developed modelling tools

This research project has successfully developed a modelling framework which can assist in adaptation studies for rice-based cropping systems. Its scope is not limited to the Australian Riverina – chapters 2 and 3 demonstrated international applicability, wherever information on climate, soil properties, and crops (including phenology and other physiological parameters) can be obtained. Long-term information on cropping practices (management rules, fertilizer inputs) and associated grain yields are particularly valuable to calibrate soil organic matter cycling parameters and potential algal input rates (given that these are environment specific and difficult to measure directly) - however if not available, they can be estimated. The APSIM model can now be used to evaluate the long-term risk-return performance of a wide range of potential management scenarios which may be under evaluation in rice-based systems, including climate change scenarios. The pre-existing multi-crop, rotational and fallowing capability of APSIM positions the model strongly, while the new components simulating seamlessly the transitions between aerobic and anaerobic soil conditions (Chapter 2), critical floodwater processes, and the inputs of C and N from floodwater algae (Chapter 3) provide functionality essential to modelling rice-based systems. There is growing need for a full *systems* modelling capability, particularly when reduced water supplies and the growing need to produce more food in many parts of the rice-growing world are driving new research into rice-wheat, rice-maize, and rice-legume systems with various modified tillage, irrigation and residue practices (Yadvinder-Singh et al., 2005; Jalota et al., 2002). This includes the further development of water-saving techniques such as aerobic rice and AWD that require the ability to simulate soil water x nitrogen interactions more completely and comprehensively. Experience warns against the use of cropping systems models without including farmer input to scenario development (McCown et al., 2007). Many systems constraints are not obvious to the non-practitioner. The participatory methods we have used in this research project demonstrate that farmer involvement in scenario development includes many of such constraints implicitly.

The new research capability introduced by the model development component of this project has already directly spawned several new international research projects in rice-based cropping systems (worth in excess of A$6M), based around the APSIM model. The model also forms an important component in other informal international collaborative initiatives around rice modelling (Meinke et al., 2009). Detailed APSIM model evaluation and testing by in-country scientists using experimental datasets is currently underway in India, Bangladesh, Pakistan, Sri Lanka, Bhutan, Nepal, Cambodia, and Laos.

- ACIAR project LWR/2010/033, “Developing capacity in cropping systems modelling to promote food security and the sustainable use of water resources in South Asia”, http://www.saarc-sec.org/2011/08/24/news/SAARC-Australia-Project--Developing-capacity-in-cropping-systems-modelling-for-sustainable-use-of-water-resources-to-promote-food-security-in-South-Asia-Dhaka-8th-August-2011/69/ ; http://aciar.gov.au/project/LWR/2010/033 ;
- ACIAR project LWR/2008/019, “Developing multi-scale climate change adaptation strategies for farming communities in Cambodia, Laos, Bangladesh and India”, http://aciar.gov.au/project/LWR/2008/019.

Future challenges

Such ongoing testing by collaborating international scientists in a range of environments and applications will continue to help identify strengths and weaknesses in the existing APSIM framework. The following areas have already been identified for further investigation and improvement during the course of this PhD study:

- simulation of N immobilization in retained crop stubble during wet fallows;
- introduction of algorithms describing greenhouse gas emissions ;
- variation in potential algal growth between environments;
- survival times for algae during floodwater dry-down phases.

Adaptation prospects in the Riverina

Resilience (the ability to change practices and stay economically viable) in the face of reduced water supplies is a function of farm size, the degree of water reductions, and the effectiveness of the practice changes implemented. In this thesis we have closely examined a number of potential adaptation options for rice-based farmers in Australia's Riverina, with the aim of remaining economically viable in a future with decreased and more variable water supplies. Other options were identified during the participatory engagement process, however remained unexplored in this research project due to time and resource constraints. These additional options are detailed in the final section of this chapter, and suggested for further research. The priority order in which investigations were undertaken was determined largely by our farmer advisory group. It is worth noting that there was consensus on the order between our five advisory farmers. Adaptation options which involved little or no capital investment were given higher priority over more capital-intensive possibilities (for example, investing in new, more efficient irrigation machinery), particularly in an environment with a very uncertain water-supply future.

Criteria for assessing the contribution of this research

A stated objective of this PhD study was to develop adaptation ideas to keep farmers viable in a future with decreased and more variable water supplies. Assessing the degree to which this objective has been achieved clearly requires a definition of the word 'viable'. Many Australian farm families continue to remain farming long after a prudent business-person would say the farm has become *non-viable*. There are well-documented psychological reasons for this phenomenon ('psychic income' associated with farming, that is the 'non-monetary attractions' it holds for farmers and their families (Vincent, 1976)), largely related to lifestyle choice and the farmer's sense of self. Therefore we suggest different criteria to assess family farm viability than would usually apply in a purely business-oriented assessment. A shrewd business-person may require a certain threshold return on capital (for example > 4.25%, the current Australian government reserve bank cash rate), whereas a farm family may consider themselves *viable* if they are able to meet all their family expenses and are not spiralling further into debt while only just meeting their living expenses. All of the farmers participating in this research were family men trying to maximize returns from their businesses, however it was explained to me that the final (minimum) criteria for being *viable* was the ability to meet family expenses. Based on this advice, we have set the absolute minimum criteria for viability as a farm operating surplus (gross margins minus overheads) of A$80,000 per year. This figure is debatable and varies between families based on their circumstances (children, age, health, assets and savings etc), however for the purposes of the following assessment, this is the criteria we used.

Synthesis of adaptation options from this study

A scenario analysis involving the case-study farm from Chapters 4 and 5 was conducted for a final synthesis and assessment on how well the learnings from this research project have contributed to increased adaptation in the Riverina. The APSIM model, with 53 years (1957-2009) of historical climate data, was used to evaluate several synthesised scenarios and compare performance with viability criteria under 3 different future water supply conditions (average seasonal allocations of 80%, 50%, and 20% of licensed entitlement). Materials and methods used were as per detailed in Chapter 4. The aim of this analysis was to assess the cumulative contribution from the adaptation options considered in this PhD study. The 4 scenarios were:

1. ***Control*** – unmodified historical farm-management practices (as per the control in Chapter 4);

2. ***Agile*** – changing farm irrigation/cropping strategy as a function of the seasonally-fluctuating allocation (as per best-practice suggestions in Chapter 4);

3. ***Agile + DCF*** – scenario 2 with the addition of delayed continuous flooding (DCF) of rice crops (as per best-practice suggestions of Chapter 4 + 6 + 7);

4. ***Entitlement sale*** – sell water entitlements to the Australian Government Water Buyback Scheme, and lease out the farm (as per Chapter 5);

Table 1 details the assumed financial parameters for the case-study farm. Figures for assets, debts, and overheads are based on published average regional figures (Singh and Lacy, 2004). Average figures for gross margins (GMs), farm cash surpluses (GMs – overheads), and returns on capital were simulated for each scenario, across the three seasonal allocation levels (Table 2). Average figures are presented, along with associated variability (standard deviations in brackets). The relationship between scenario, seasonal allocation level, and farm cash surplus is shown in Figure 1. The minimum viable cash surplus threshold of A$80,000 per year is also illustrated on the same graph (coarse dashed line). The simulated high variability in annual cash surpluses is evident from the wide error bars.

Table 1. Parameters for the example farm in the Murrumbidgee Irrigation District. Total assets, debts and overheads assumed from regional averages (asterisk indicates data source: Singh and Lacy, 2005).

Parameter	**Value**
Land Area (ha)	600
Irrigation entitlement (ML) (at 100% allocation)	3265
Total Assets (A$; @ A$6818 ha^{-1})*	4,090,800
Total Debts (A$; @ A$1364 ha^{-1})*	818,400
Overheads (A$ yr^{-1})*	199,090
Minimum family income acceptable (A$ yr^{-1})	80,000

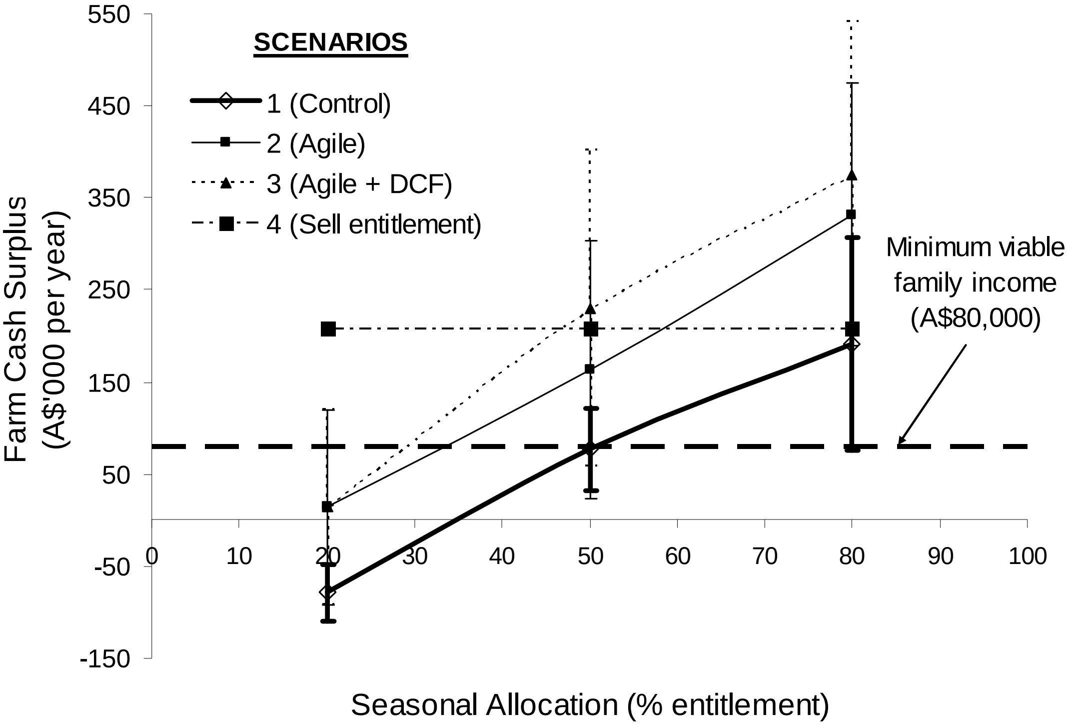

Figure 1. Average farm cash surpluses for the 4 scenarios as a function of seasonal allocation level. Error bars represent one standard deviation either side of the mean. The minimum viable annual income is shown as the coarse dashed line.

Table 2: Returns associated with different adaptation options for the case study farm. Standard deviations give in brackets for the GM; the same exact figures apply to the cash surplus. The average return on capital (%) is also followed by the standard deviation in brackets.

Parameter (average, 1957-2009)	**Av. Annual Allocation (%)**	**Adaptation Scenario**			
		1	**2**	**3**	**4**
Av. Gross margin (A$’000 farm^{-1} yr^{-1})	**80**	391 (116)	531 (143)	574 (166)	271 (0)
	50	276 (45)	363 (140)	429 (172)	271 (0)
	20	120 (30)	213 (106)	213 (106)	271 (0)
Av. Farm cash surplus (A$’000 farm^{-1} yr^{-1})	**80**	191	332	375	209
	50	77	164	230	209
	20	-80	14	14	209
Av. Return on capital (%)	**80**	4.7 (2.9)	8.1 (3.5)	9.2 (4.1)	5.1 (0)
	50	1.9 (1.1)	4.0 (3.4)	5.6 (4.2)	5.1 (0)
	20	-1.9 (0.7)	0.3 (2.3)	0.3 (2.3)	5.1 (0)

Below allocations of 35%, the control scenario is unable to cover overheads and the returns from the farm become negative. The adaptations explored (scenarios 2 and 3) allow the farm to achieve positive returns down to an average allocation below 20% (Figure 1). The returns from scenario 4 are unaffected by allocation level, as water entitlements have been sold, the monies invested, and the farm leased (Chapter 5). The surplus is represented by a horizontal line at a value equal to the annual returns (A$270,864; Chapter 5) minus the bank interest on outstanding loans (Table 1, assuming a business loan interest rate of 7.5% pa). The value of this surplus was calculated at A$209,000 per annum. With the financial parameters we have assumed in this analysis (Table 1), scenario 4 always provides a better financial return than the control, with much lower levels of risk.

Scenario 2 (*agile*) provides substantially improved performance over the control at all allocation levels, and over scenario 4 for average future allocations over 60%. The addition of DCF rice to the agile farming strategy (scenario 3) adds further gains, particularly at allocation levels above 50%. Gains decrease again slightly towards 80% as the farm reaches it’s maximum allowable rice area limit (Industry-imposed limits to control irrigated salinity, Humphreys et al., 2006). The incremental benefits over scenario 2 also tail away at lower allocations, since the proportion of rice in the system becomes zero (Chapter 4). The combined adaptations represented by scenario 3 make irrigation farming a better financial prospect than selling water entitlements (*scenario 4*) for seasonal allocations greater than around 46%.

The value of the allocation at the intercept point between each individual scenario curve and the coarsely-dashed minimum viability line (Figure 1) represents the minimum viable future allocation when the farm is operated under that scenario. The values were read from Figure 1 and then illustrated in Figure 2.

This shows that the adaptation options investigated in this research project are clearly able to assist Riverina irrigators to adapt to reduced levels of irrigation water supply. An unresponsive traditional management strategy (*control*) results in the case-study farm becoming non-viable below average future allocation levels of 50%. This finding supports Singh and Lacy (2005) who derived a similar threshold figure via different means. By adopting the practice of modifying cropping/irrigation strategies in accordance with the seasonal allocation (scenario 2, *agile*, Chapter 4), the farm becomes more resilient to future reductions in irrigation water supply and can stay viable down to an average allocation of 33% (Figure 2). Additionally adopting delayed continuous flooding (scenario 3, *agile + DCF*; Chapters 4, 6 and 7) results in a further resilience gain, with the case-study farm now able to stay viable under future allocations of roughly 30%. Selling the water entitlements, investing the money, and leasing out the farm (scenario 5; Chapter 5) has a 0% survivable threshold – it is a viable option regardless of future allocations because it is essentially independent of future water-supply trends.

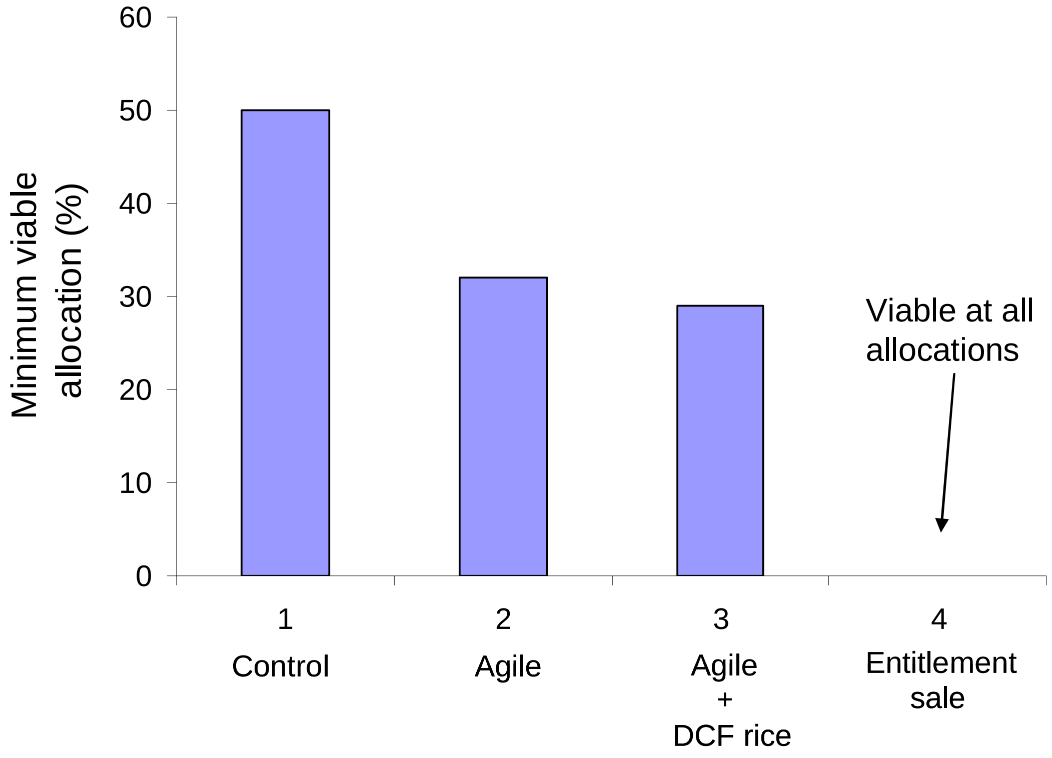

Figure 2. The minimum viable average season allocation (%) for the case study farm, for each of the 4 imposed management scenarios. Below the indicated allocation level, the family farm becomes unsustainable.

Conclusions and recommendations

Singh and Lacy (2005) also determined that an average seasonal allocation under 50% will make family farms non-viable. They evaluated an unchanging traditional management scenario very similar to the *control* scenario used in the analysis just presented. The most severe future forecasts for the Riverina regions include average allocation levels below 50%. A reduction in average Murray-Darling stream-flows of 16–48% by 2100 has been predicted (Pittock, 2003; Christensen et al., 2007; Hennessy et al., 2007). The maximum allocation in the Murrumbidgee Irrigation Areas has been capped at 83% since 1995/96, hence a further reduction of 48% would take the bottom of the predicted range to 35%. Also, the recent Murray Darling Basin Plan (Murray

Darling Basin Authority, 2010) suggested that officially cutting 83% cap by a further 35-40% might be necessary to properly manage the diminished regional water resource into the future. If that were to happen, the cap (maximum allowable seasonal allocation) would reduce to 48%. This plan caused outrage in the irrigation districts, with copies of the new Murray Darling Basin Plan being burned in piles on the streets of farming towns (http://www.abc.net.au/news/2011-11-17/young-men-burn-copies-of-the-guide-to-the-murray/3678418). The Australian government quickly stepped in and ordered the plan to be re-drafted and re-negotiated, yet this still illustrates the gravity of water resource issues for the region, and it may be simply impossible to avoid large cuts to future allocations.

Hence, according to this analysis and also that of Lacy and Singh (2005), many family farms are under threat of becoming non-viable if changes to traditional management practices are not implemented. The research detailed in this thesis demonstrates that simple changes in strategic management, such as agile management (Chapter 4) and delayed continuous flooding in rice production (DCF, Chapters 6 and 7) can reduce survivable future allocation levels by up to 20%, down to a sustainable average level of 30% (Figure 2). Greater annual variability in farm returns should be expected under this type of management (error bars in Figure 1; standard deviations on returns in Table 2), however if these can be managed, then technically the farm families could stay viable down to these levels of future allocations. At average future allocations below 30%, no on-farm adaptation options we considered offer viability to the case-study farm. The option of selling entitlements to the Australian government now and leaving the farm (scenario 4; Chapter 5) is viable regardless of future water supply scenario. In this way, it offers farmer an option to avoid the risk associated with possible future water supply variability, although the substantial gains possible through improved management if better future water supply scenarios unfold (Figure 1) cannot then be realized.

In summary: without changed management strategies the case-study farm would become non-viable if future water allocations were to average below 50%. Implementation of agile management in tandem with delayed continuous flooding in rice production would keep the farm viable down to 30% allocation. If future average allocations fall below 30%, the best choice for farmers (from the options investigated) would be to sell their entitlements and invest the money.

Strengths and weaknesses of methods

The biggest strengths in the methods used for this PhD study lies in a) the incremental development of a widely used modelling framework (APSIM) leading to generic and broad applicability of the newly developed modelling capabilities, and b) the participatory nature of the research philosophy and program. Biophysical models alone can provide interesting information, however it is only when they are combined with real knowledge of system constraints and possibilities (via farmers' involvement) that they become a very powerful element in developing real pragmatic adaptation options.

The biggest methodological weakness in this study may relate to the simplified nature of many of the presented financial analyses. More comprehensive financial analyses may provide additional detail on aspects relating to variability of returns and their impacts on farming families. This, however, was beyond the scope of this PhD. In my experience, Australian farmers have a robust ability to synthesise a wide range of information before making decisions, and it was the belief of my advisory farmers that our simplified financial analyses captured the key elements of the financial system behaviour and told them what they needed to know. Nevertheless, a further detailed economic analysis on these research findings may be valuable and is recommended.

The findings presented are specific to the case-study farm considered, however we believe trends and conclusions will apply universally in the region. Absolute values may be different for other individual farms (larger/smaller, different debt levels, different soils etc.). Further, the tools developed and the approach taken might stimulate the thinking about appropriate water resource management in other parts of the world, beyond the Riverina or even Australia. This might further improve the efficiency of use of one of the most precious commodities: water.

Future challenges

Numerous potential adaptation ideas were developed in this research project, yet remained un-examined due to time and resource constraints. Of particular scientific interest are:

- The potential for using seasonal climate forecasting (for on-farm climate) in conjunction with wider, regional streamflow forecasts (for irrigation water supply) in improving risk management for these types of irrigated farming systems. The two forecasts could be quite different, because major water supply dams for the Murrumbidgee Irrigation Area are up to 500 km distant, experiencing different conditions. The on-farm forecasts could give a good insight into water *demand*, whereas the wider catchment streamflow forecast could predict water supply. The novel aspect would be combining these two disparate pieces of information, and the efficient incorporation of both into on-farm management decisions represents an area worthy of research.

- The risks and potential returns from investing in more efficient irrigation systems, and how this varies as a function of possible climatic and market outcomes (commodity prices and costs).
- The effect of different projected climate change scenarios on on-farm climate.
- The impact of farm size, soil type, and debt level on all the analyses present in this PhD.
- Following from the research point above, extension of learnings using GIS applications to make wider regional proclamations on adaptation in the irrigation districts – specifically for policy considerations.

References

ABARES, 2010. Australian commodity statistics 2010, Canberra. http://adl.brs.gov.au/data/warehouse/pe_abares99001762/ACS_2010.pdf

Acharya, C.N., 1935a. Studies on the anaerobic decomposition of plant materials. I. The anaerobic decomposition of rice straw (*Oryza sativa*). Biochemical Journal 29, 528–541.

Acharya, C.N. 1935b. Studies on the anaerobic decomposition of plant materials. II. Some factors influencing the anaerobic decomposition of rice straw (*Oryza sativa*). Biochemical Journal 29, 953–960.

Acharya, C.N. 1935c. Studies on the anaerobic decomposition of plant materials. III. Comparison of the course of decomposition of rice straw under anaerobic, aerobic, and partially aerobic conditions. Biochemical Journal 29, 1116–1120.

Adger, W. N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D.R., Naess, L.o., Wolf, J., and Wreford, A., 2009. Are there social limits to adaptation to climate change? Climatic Change 93(3-4), 335-354.

Ali, M.H., Talukder, M.S.U., 2008. Increasing water productivity in crop production - a synthesis, Agricultural Water Management 95(11), 1201-1213.

Alimagno, B.V., Yoshida, T. 1975. Growth and yield of rice in Maahas soil inoculated with nitrogen-fixing blue-green algae. Philipp. Agric. 59(3/4), 80-90.

Angus, J., and Lacy, J., 2002. N management for an 8 tonne/ha wheat under irrigation in south-eastern Australia, Farmers Newsletter, no. 161, Spring.

Arah, J.R.M., 2000. Modeling SOM cycling in rice-based production systems. In: G.J.D. Kirk and D.C. Olk (eds.) Carbon and nitrogen dynamics in flooded soils. International Rice Research Institute, Makati City (Philippines), p. 163-179.

Australian Government, 2010a. Water Entitlement Purchasing in the Murray-Darling Basin, Department of Sustainability, Environment, Water, Population, and Communities, Canberra, ACT. http://www.environment.gov.au/water/policy-programs/entitlement-purchasing/index.html

Australian Government, 2010b. On-Farm Irrigation Efficiency Program, Department of Sustainability, Environment, Water, Population, and Communities, Canberra, ACT. http://www.environment.gov.au/water/policy-programs/srwui/irrigation-efficiency/index.html

Beecher H.G., Dunn B.W., Thompson J.A., Humphreys E., Mathews S.K., Timsina J., 2006. Effect of raised beds, irrigation and nitrogen management on growth, water use and yield of rice in south-eastern Australia. Australian Journal of Experimental Agriculture 46, 1363-1372.

Beecher, H.G., Hume, I.H., Dunn, B.W., 2002. Improved method for assessing rice soil suitability to restrict recharge. Australian Journal of Experimental Agriculture 42**,** 297-307.

Belder, P., Bouman, B.A.M. Spiertz, J.H.J., Lu G., 2007. Comparing options for water savings in lowland rice using a modeling approach. Agricultural Systems 92, 91-114.

Bellocchi, G., Rivington, M., Donatelli, M., Matthews, K., 2010. Validation of biophysical models: issues and methodologies. A review. Agron. Sustain. Dev. 30, 109–130.

Bennett, J., 2003. Status of breeding for tolerance of water deficit and prospects for using molecular techniques. In: J.W. Kijne, R. Baker, D. Molden, (Eds.), Water Productivity in Agriculture: Limits and Opportunities for Improvement, CABI Publishing, Wallingford, UK. pp. 103–126.

Bjornlund, H., 2003a. Efficient water market mechanisms to cope with water scarcity, International Journal of Water Resources Development 19(4), 553-567.

Bjornlund, H., 2003b. Farmer participation in markets for temporary and permanent water in southeastern Australia, Agricultural Water Management 3(1),57–76.

Bjornland, H., and Rossini, P., 2005. Fundamentals Determining Prices and Activities in the Market for Water Allocations, Water Resources Development 21(2), 355–369.

Bjornlund, H., 2006. Can water markets assist irrigators Managing Increased Supply Risk? Some Australian experiences, Water International 31(2), 221-232.

Bjornlund, H., Rossini, P., 2007. Fundamentals Determining Prices in the Market for Water Entitlements: An Australian Case Study, International Journal of Water Resources Development 23(3), 537-553.

Bjornlund, H., Rossini, P., 2008. Are the fundamentals emerging for more sophisticated water market instruments? Proceedings from the 14th Annual Conference of the Pacific Rim Real Estate Society, Kuala Lumpur, Malaysia, January 2008.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities, Journal of Political Economy 81, 637-654.

Blackmore, A.V., Talsma, T., Hutton, J.T., 1956. The cumulative effect of rice growing on the two soil types in the Murrumbidgee Irrigation Areas, CSIRO, Australia. Division of Soils, Divisional Report No. 1/56.

Boling, A., Tuong, T.P., Jatmiko, S.Y., Burac, M.A., 2004. Yield constraints of rainfed lowland rice in Central Java, Indonesia, Field Crops Research 90, 351–360.

Borrell, A., Garside, A., Fukai, S., 1997. Improving efficiency of water use for irrigated rice in a semi-arid tropical environment. Field Crops Research 52, 231-248.

Bouman, B.A.M., 2007. A conceptual framework for the improvement of crop water productivity at different spatial scales, Agricultural Systems 93 (1-3), 43-60.

Bouman, B.A.M., Lampayan, R., Tuong, T., 2007. Water Management in Irrigated Rice – coping with water scarcity. International Rice Research Institute publication, Los Banos, Philippines.

Bouman, B.A.M., van Laar, H.H., 2006. Description and evaluation of the rice growth model ORYZA2000 under nitrogen-limited conditions, Agricultural Systems 87, 249–273.

Bouman, B.A.M., Tuong, T.P., 2001. Field water management to save water and increase its productivity in irrigated lowland rice, Agricultural Water Management 49(1), 11-30.

Bouman, B.A.M., Kropff, M.J., Tuong, T.P., Wopereis, M.C.S., ten Berge, H.F.M., Van Laar, H.H., 2001. ORYZA2000: Modelling Lowland Rice. International Rice Research Institute, Wageningen University and Research Centre, Los Baños, Philippines and Wageningen, Netherlands

Brooks, R., Harris, E., 2008. Efficiency gains from water markets: Empirical analysis of Watermove in Australia, Agricultural Water Management 95, 391-399.

Bucher, S., 2001. Nitrogen and phosphorus availability in irrigated rice as influenced by soil drying during the fallow period, straw incorporation, and tillage. PhD dissertation submitted to the Swiss Federal Institute of Technology Zurich, Diss. ETH No. 14017.

Buresh, R.J., Reddy, K.R., van Kessel, C., 2008. Nitrogen transformations in submerged soils. In: Schepers JS, Raun WR (Eds), Nitrogen in agricultural systems. Agronomy Monograph 49. ASA, CSSA, and SSSA, Madison, WI, USA, pp 401–436.

Buresh, R.J., De Datta, S.K., 1991. Nitrogen dynamics and management in rice–legume cropping systems. Advances in Agronomy 45, 1–59.

Buresh, R.J., De Datta, S.K., 1990. Denitrification losses from puddled rice soils in the tropics. Biology and Fertility of Soils 9, 1–13.

Buresh, R.J., De Datta, S.K., Padilla, J.L., Samson, M.I., 1988. Effect of two urease inhibitors on floodwater ammonia following urea application to lowland rice, Soil Science of America Society Journal 52, 856-861.

Buresh, R.J, Casselman, M.E., Patrick W.H. Jr., 1980. Nitrogen fixation in flooded soil systems, a review. Advances in Agronomy 33, 149-192.

Carberry, P. S., Bruce, S.E., Walcott, J. J., and Keating, B.A., 2010. Innovation and productivity in dryland agriculture: a return-risk analysis for Australia, The Journal of Agricultural Science 149, 77-89.

Carberry, P.S., Probert, M.E., Dimes, J.P., Keating, B.A., McCown, R.L., 2002. Role of modelling in improving nutrient efficiency in cropping systems. Plant and Soil 245, 193–203.

Carberry, P.S., Hochman, Z., McCown, R.L., Dalgliesh, N.P., Foale, M.A., Poulton, P.L., Hargreaves, J.N.G., Hargreaves, D.M.G., Cawthray, S., Hillcoat, N., Robertson, M.J., 2002. The FARMSCAPE approach to decision support: farmers', advisers', researchers' monitoring, simulation, communication and performance evaluation. Agricultural Systems 74 (1), 141–177.

Cash, DW., Clark, W.C., Alcock, F., Dickson, N.M., Eckley, N., Guston, D.H., Jaeger, J., and Mitchell, R.B., 2003. Knowledge systems for sustainable development. Proc Natl Acad Sci USA 100, 8086-8091.

Chamberlain, G., 1983. A characterization of the distributions that imply mean-variance utility functions, Journal of Economic Theory 29, 185-201.

Chiew, F.H.S., Piechota, T.C., Dracup, J.A., McMahon, T.A. 1998. El Nino/Southern Oscillation and Australian rainfall, streamflow and drought: links and potential forecasting. Journal of Hydrology 204, 138–149.

Cho, Y.S., Hidaka, K., Mineta, T., 2003. Evaluation of white clover and rye grown in rotation with no-tilled rice, Field Crops Research 83(3), 237-250.

Chowdary, V. M., Rao, N.H., Sarma, P.B.S., 2004. A coupled soil water and nitrogen balance model for flooded rice fields in India. Agriculture, Ecosystems & Environment 103(3), 425-441.

Christensen, J.H., Hewitson, B., et al., 2007. IPCC WG1 Chapter 11. Regional Climate Projections. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K., Tignor, M., Miller, H. (Eds.), Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, pp. 849–926.

Clemmens, A.J., Bos, M.G., Replogle, J.A. 1984. Portable RBC flumes for furrows and earthen channels. Transactions of ASAE 21(4), 1016-1026.

Confalonieri, R., Acutis, M., Bellocchi, G., Cerrani, I., Tarantola, S., Donatelli, M., Genovese, G., 2006. Exploratory sensitivity analysis of CropSyst WARM and WOFOST: a case-study with rice biomass simulations. Ital. J. Agrometeorol. 11, 17–25.

Confalonieri, R., Bregaglio, S., Acutisa, M., 2010. A proposal of an indicator for quantifying model robustness based on the relationship between variability of errors and of explored conditions. Ecological Modelling 221, 960–964.

Crane, T. A., Roncoli, C., Paz, J., Breuer, N., Broad, K., Ingram, K.T., and Hoogenboom, G., 2010. Forecast skill and farmers' skills: Seasonal climate forecasts and risk management among Georgia (U.S.) farmers, Weather, Climate and Society 2, 44-59.

Crane, T. A., Roncoli, C., Paz, J., Breuer, N., Broad, K., Ingram, K.T., and Hoogenboom, G., 2008. Collaborative approaches to the development of climate-based decision support systems: what role for social sciences? Proceedings of the 88th American Meteorological Society annual meetings, New Orleans, Louisiana, USA, 20–24 Jan 2008.

Crase, L., O'Reilly, L., and Dollery, B., 2000. Water markets as a vehicle for water reform: the case of New South Wales, Australian Journal of Agricultural and Resource Economics 44(2), 299-321.

Crean, J., Jayasuriya, R., Jones, R., 2001. Regional agricultural implications of environmental flows in the Murrumbidgee Valley, Australia. In Water Policy Reform: Lessons from Asia and Australia, Proceedings of an International Workshop, Bangkok, Thailand, 8-9 June.

CSIRO, 2008. Water availability in the Murray-Darling Basin. A report to the Australian Government from the CSIRO Murray-Darling Basin Sustainable Yields Project. CSIRO, Australia. 67pp. (www.csiro.au/mdbsy).

CSIRO, 2007. The Murray Darling Basin Sustainable Yields Project, CSIRO Water for a Healthy Country Flagship, Canberra.

http://www.csiro.au/partnerships/MDBSY.html

CSIRO, 2007b. Climate Change in the Murrumbidgee Catchment – a report for the New South Wales Government,

http://www.environment.nsw.gov.au/resources/climatechange/061108MurrumbidgeeDetailedFinal.pdfCSIRO, 2005. Off- and On-farm savings of irrigation water, Report to the Pratt Water Group by CSIRO Water for a Healthy Country Flagship, 16pp

De, P.K., 1939. The role of blue-green algae in nitrogen fixation in rice fields. Proc. R. Soc. Lond. 127 B, 121-139.

De Datta, S.K., Buresh, R.J., Samson, M.I., Wang Kai-Rong., 1988. Nitrogen use efficiency and N-15 balances in broadcast-seeded flooded and transplanted rice, Soil Science Society of America Journal 52, 849-855.

Devendra, C., Thomas, D., 2002. Smallholder farming systems in Asia. Agricultural Systems 71(1-2), 17-25.

Dobermann, A., Witt, C., 2000. The potential impact of crop intensification on carbon and nitrogen cycling in intensive rice systems. In: G.J.D. Kirk and D.C. Olk (Eds), Carbon and Nitrogen Dynamics in Flooded Rice: proceedings of the workshop on Carbon and Nitrogen Dynamics in Flooded Soils, IRRI, Los Banõs, Laguna, Philippines, 19-22 Apr 2000, 188 p.

Dobermann, A., Dawe, D., Roetter, R.P., and Cassman, K.G., 2000. Reversal of Rice Yield Decline in a Long-Term Continuous Cropping Experiment, Agronomy Journal 92, 633-643.

FAO, 2008. FAOSTAT Database, FAO, Rome. 22 Sep 2008 (FAO last access).

Farrell, T.C., Fukai, S., Williams, R.L., 2006. Minimising cold damage during reproductive development among temperate rice genotypes. I. Avoiding low temperature with the use of appropriate sowing time and photoperiod-sensitive varieties, Australian Journal of Agricultural Research 57, 75-88.

Fereres, E. and Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. Journal of Experimental Botany 58, 147–159

Fillery, I.R.P., Vlek, P.L.G., 1983. Reappraisal of the significance of ammonia volatilization as an N loss mechanism in flooded rice fields. In: Nitrogen economy of flooded rice soils, Washington DC, USA, Dordrecht : Martinus Nijhoff, Netherlands.

Freney, J.R., Denmead, O.T., Watanabe, I., Craswell, E.T., 1981. Ammonia and nitrous oxide losses following applications of ammonium sulfate to flooded rice. Australian Journal of Agricultural Research 32, 37–45.

Gaydon, D.S., Probert, M.E., Buresh, R.J., Meinke, H., Timsina, J., 2012a. Capturing the role of algae in rice crop production and soil organic carbon maintenance, European Journal of Agronomy 39, 9-24.

Gaydon, D.S., Probert, M.E., Buresh, R.J., Meinke, H., Suriadi, A., Dobermann, A., Bouman, B.A.M., Timsina, J., 2012b. Rice in cropping systems - Modelling transitions between flooded and non-flooded soil environments, European Journal of Agronomy 39, 35-43

Gaydon, D.S., Meinke, H., and Rodriguez, D., 2012c. The best farm-level irrigation strategy changes seasonally with fluctuating water availability, Agricultural Water Management 103, 33– 42.

Gaydon, D.S., Meinke, H., Rodriguez, D., and McGrath, D.J., 2012d. Comparing water investment options for irrigation farmers using Modern Portfolio Theory, submitted to Agricultural Water Management

Gaydon, D.S., Beecher, H.G., Reinke, R., Crimp, S., Howden, S.M., 2010. Chapter 5 – *Rice*, In: Adapting Australian Agriculture to Climate Change, CSIRO Publishing 2010, Edited by C.J. Stokes & S.M. Howden.

Gaydon, D., Beecher, H.G., Reinke, R., Crimp, S., Howden, S.M., 2008. Chapter 4 – *Rice*, In: An overview of climate change adaptation in Australian primary industries – impacts, options and priorities. Report prepared by CSIRO for the National Climate Change Research Strategy for Primary Industries, February 2008 (Eds CJ Stokes, SM Howden).

Gaydon D.S., Lisson S.N., Xevi E., 2006. Application of APSIM 'multi-paddock' to estimate whole-of-farm water-use efficiency, system water balance and crop production for a rice-based operation in the Coleambally Irrigation District, NSW, Proceedings of the 13th Australian Society of Agronomy Conference, 10-14 September 2006, Perth, Western Australia.

Godwin, D.C. Singh, U., 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In: Understanding Options for Agricultural Production, Editors Tsuji, G., Hoogenboom, G., Thornton, P.K., Kluwer, Dordrecht, pp 55-77.

Godwin, D.C., Singh, U., Buresh, R.J., De Datta, S.K., 1990. Modeling of nitrogen dynamics in relation to rice growth and yield. Transactions 14th International Congress of Soil Science, Kyoto, Japan. Volume IV, 320-325.

Godwin, D.C., Singh, U., 1991. Modelling nitrogen dynamics in rice cropping systems. In: Deturek and Ponnamperuma (Eds), Rice Production on Acid Soils of the Tropics, Institute of Fundamental Studies, Kandy, Sri Lanka, pp 287-294.

Greenland, D.J., 1997. The sustainability of rice farming. CAB International and International Rice Research Institute, Oxon (UK) and Manila (Philippines).

Grigg, B.C., Beyrouty, C.A., Norman, R.J., Gbur, E.E., Hanson, M.G., Wells, B.R., 2000. Rice responses to changes in floodwater and N timing in southern USA, Field Crops Research 66**,** 73-79.

Haefele, S.M., Siopongco, J.D.L.C., Boling, A.A., Bouman, B.A.M., Tuong, T.P. 2009. Transpiration efficiency of rice (Oryza sativa L.), Field Crops Research 111, 1-10.

Hafi, A., Heaney, A., and Beare, S., 2006. Investment in irreversible irrigation technology under uncertainty - A case study of the Murrumbidgee Irrigation Area, ABARE Conference Paper 06.2, 50th Annual Conference of the Australian Agricultural and Resource Economics Society, Sydney, February 8–10, 2006

Harris, G., 2000. The economics of subsurface drip irrigation. In Proceedings of the Irrigation Association of Australia national conference and exhibition: water — essential for life. (Ed. GJ Connellan) pp. 287–297. (Irrigation Association of Australia: Melbourne)

Hassall, G.H.D., 2011. Murray-Darling Basin Water Entitlements Summary of Market Prices for Approved Transfers, http://www.environment.gov.au/water/policy-programs/entitlement-purchasing/pubs/market-prices-dec10.pdf

Heenan, D.P., Thompson, J.A., 1984. Growth, grain yield and water use of rice grown under restricted water supply in New South Wales. Australian Journal of Experimental Animal Husbandry 24, 104-109.

Hennessy, K., B. Fitzharris, B.C. Bates, N. Harvey, S.M. Howden, L. Hughes, J. Salinger and R. Warrick, 2007. Australia and New Zealand. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 507-540.

Hochman, Z., Carberry, P.S., Robertson, M.J., Gaydon, D.S., Bell, L.W., McIntosh, P.C., 2011, Prospects for ecological intensification of Australian agriculture, European Journal of Agronomy (in press)

Hornbuckle, J., Christen, E., 1999. Physical Properties of Soils in the Murrumbidgee and Coleambally Irrigation Areas, CSIRO Land and Water Technical Report, 17/99.

Howden, S.M., Soussana, J.F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. Proceedings of the National Academy of Sciences of the United States of America 104 (50), 19691–19696.

Howell, T. A., 2001. Enhancing Water Use Efficiency in Irrigated Agriculture, Agronomy Journal 93, 281-289.

Humphreys, E., Kukal, S.S., Christen, E.W., Hira, G.S., Balwinder-Singh, Sudhir-Yadav, Sharma, R.K., 2010. Halting the Groundwater Decline in North-West India—Which Crop Technologies will be Winners? Advances in Agronomy 109, 155-217.

Humphreys, E., Lewin L.G., Khan, S., Beecher, H.G., Lacy, J.M., Thompson, J.A., Batten, G.D., Brown, A., Russell, C.A., Christen, E.W. and Dunn, B.W., 2006. Integration of approaches to increasing water use efficiency in rice-based systems in southeast Australia. Field Crops Research 97, 19-33.

Humphreys, E., Meisner, C., Gupta, R.K., Timsina, J., Beecher, H.G., Lu, T.Y., Singh, Y., Gill, M.A., Masih, I., Gou, Z.J., Thompson, J.A., 2005. Water savings in rice-wheat systems. Plant Production Science 8 (3**)**, 242-258.

Humphreys, E., Robinson, D., 2003. Improving water productivity in rice cropping systems in Australia: institutions and policy. In: 'Rice Science: innovations and impact for livelihood.' Eds T.W. Mew, D.S. Bar, S. Peng, D. Dawe and B. Hardy. Proceedings of the International Rice Research Conference'. 16-19 September 2002, Beijing, China. International Rice Research Institute, Chinese Academy of Engineering and Chinese Academy of Agricultural Sciences. pp. 885-900

Humphreys, E., van der Lelij, A., Muirhead, W.A., Hoey, D., 1994. The development of environmental restrictions for rice growing in New South Wales. Australian Journal of Soil Water Conservation 7, 11-20.

Humphreys, E., Muirhead, W.A., Melhuish, F.M., White, R.J.O., Blackwell, J., 1989. The growth and nitrogen economy of rice under sprinkler and flood irrigation in South East Australia II, Irrigation Science 10, 201—213.

Humphreys, E., Muirhead, W.A., Melhuish, F.M., White, R.J.G., Chalk, P.M., Douglas, L.A., 1987. Effects of time of urea application on combine-sown Calrose rice in South-east Australia. II Mineral nitrogen transformations in the soil-water system. Australian Journal of Agricultural Research 38**,** 113-127.

IPCC, 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.), Cambridge University Press, Cambridge and New York.

Jalota S.K., Arora V.K., 2002. Model-based assessment of water balance components under different cropping systems in north-west India, Agricultural Water Management 57 (1), 75-87.

Jamu, D.M., Piedrahita, R.H., 2002. An organic matter and nitrogen dynamics model for the ecological analysis of integrated aquaculture/agriculture systems: I. model development and calibration. Environmental Modelling and Software 17(6), 571-582.

Jeffrey, S.J., Carter, J.O., Moodie, K.B., Beswick, A.R., 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environmental Modelling and Software 16, 309–330.

Jing, Q., van Keulen, H., Hengsdijk, H. 2010. Modeling biomass, nitrogen and water dynamics in rice–wheat rotations, Agricultural Systems 103, 433–443.

Jing, Q., Hengsdijk, H., van Keulen, H., 2007. Modeling nitrogen and water dynamics in rice-wheat rotations. Proceedings Third IASTED International Conference *Environmental Modelling and Simulation*, Honolulu, Hawaii, USA, pp 121-126. ISBN CD 978-0-88986-682-9.

Jones, C.A., Kiniry, J.R., 1986. CERES-Maize: A Simulation Model of Maize Growth and Development. Texas A&M University Press, College Station, Texas.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U. Gijsman, A.J., Ritchie., J.T., 2003. The DSSAT cropping system model, European Journal of Agronomy 18, 35–265.

Jones, R. and Pittock, B., 2003. Climate change and water resources in an arid continent: Managing uncertainty and risk in Australia., Springer, The Netherlands.

Jones, R., and Page, C., 2002. Climate Change and the Risk to Long-term Water Supply in the Murray Darling Basin. In Synthesis Report of River Symposium on Murray-Darling Basin Dialogue on Water and Climate, Brisbane, September 2002 (compiled and edited by Awadhesh Prasad and Shahbaz Khan).

Kato Y., Okami, M., Katsura, K., 2009. Yield potential and water use efficiency of aerobic rice (Oryza sativa L.) in Japan, Field Crops Research 113: 328-334.

Keating, B.A., Carberry, P.S., Bindraban, P.S., Asseng, S., Meinke, H., Dixon, J. (2010). Eco-efficient Agriculture: Concepts, Challenges, and Opportunities, Crop Science 50, (suppl. 1), S109-S119.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An Overview of APSIM, a model designed for farming systems simulation, European Journal of Agronomy 18, 267-288.

Kemanian, A.R., Stöckle, C.O., 2010. C-Farm: A simple model to evaluate the carbon balance of soil profiles. European Journal of Agronomy 32(1), 22-29.

Khan, S., Robinson, D., Beddek, R., Wang, B., Dassanake, D., Rana, T., 2004. Hydro-climatic and Economic Evaluation of Seasonal Climate Forecasts for Risk Based Irrigation Management, CSIRO Land & Water Technical Report No. 5/04, January 2004.

Kirk G.J.D., 2004. The Biogeochemistry of Submerged Soils, John Wiley & Sons, West Sussex, England.

Kirk G.J.D. and Olk D.C., 2000. Carbon and Nitrogen Dynamics in Flooded Soils. IRRI, Los Banos, Philippines. 250p.

Kobayashi, K., Salam, M.U., 2000. Comparing simulated and measured values using mean squared deviation and its components, Agronomy Journal 92, 345-352.

Krause P., Boyle D.P., Bäse F., 2005. Comparison of different efficiency criteria for hydrological model assessment, Adv. Geosci. 5, 89–97.

Kukal, S.S., Aggarwal, G.C., 2002. Percolation losses of water in relation to puddling intensity and depth in a sandy loam rice (Oryza sativa) field. Agricultural Water Management 57, 49-59.

Li, Y., Barker, R., 2004. Increasing water productivity for paddy irrigation in China. Paddy Water Environ. 2, 187-193.

Li, C., Frolking, S., Harriss, R.C., 1994. Modelling carbon biogeochemistry in agricultural soils. Glob. Biogeochem. Cycle. 8, 237–254.

Linnegar, M., Woodside, D., 2003. Australian Rice: Leaders in Environmental Change. Australian Association of Natural Resource Management, Canberra, Australia.

Lorite, I. J., Mateos, L., Orgaz, F., and Fereres, E., 2007. Assessing deficit irrigation strategies at the level of an irrigation district, Agricultural Water Management 91(1-3), 51-60.

Lowendorf, H.S. 1980. Biological nitrogen fixation in flooded rice. Agron. Paper No. 1305. Dep. Agron., Cornell University., Ithaca, N.Y.

McCown, R.L., Keating, B.A., Probert, M.E., and Jones, R.K. 1992. Strategies for sustainable crop production in semi-arid Africa. Outlook on Agriculture 21, 21-31.

McCown, R.L., 2002. Changing systems for supporting farmers' decisions: problems, paradigms, and prospects, Agricultural Systems 74, 179–220

McCown, R.L., Carberry, P.S., Foale, M.A., Hochman, Z., Coutts, J.A., Dalgliesh, N.P., 1998. The FARMSCAPE approach to farming systems research. In: Michalk, D.L., Pratley, J.E. (Eds.), Proceedings of the Ninth Australian Society of Agronomy Conference, Australian Society of Agronomy, Wagga Wagga, NSW, pp. 633–636.

Mcintyre, S., McGinness, H.M., Gaydon, D.S., and Arthur, A.D., 2011. Introducing irrigation efficiencies: prospects for water-dependent biodiversity in a rice agro-ecosystem, Environmental Conservation, Environmental Conservation 38 (3), 353–365

McKay, J., 2005. Water institutional reforms in Australia, Water Policy 7, 35–52.

Markowitz, H.M., 1952, Portfolio Selection, The Journal of Finance 7(1), 77–91.

Markowitz, H.M., 1991. Portfolio Selection: the Efficient Diversification of Investment. Blackwell, Malden.

Maskey, R., Bethune, M., and Lawler, D., 2006. Landowners perceptions of the benefits and barriers to adopting centre pivot and lateral move irrigators on dairy farms. Australian Journal of Experimental Agriculture 46(11), 1433-1437.

Materasi, R., Balloni, W., 1965. Some observations on the presence of microorganisms and autotrophic nitrogen fixers in rice fields [in French, English summary], Ann. Inst. Pasteur 109, 218-223.

Matsui, T., Kobayashi, K., Yoshimoto, M., Hasegawa, T., 2007. Stability of rice pollination in the field under hot and dry conditions in the Riverina region of New South Wales, Australia. Plant Production Science 10, 57-63.

Meinke, H., Howden, S.M., Struik, P.C., Nelson, R., Rodriguez, D., Chapman, S.C., 2009. Adaptation science for agriculture and natural resource management—urgency and theoretical basis. Current Opinion in Environmental Sustainability 1 (1), 69–76.

Meinke, H., Bastiaans, L., Bouman, B., Dingkuhn, M., Gaydon, D., Hasegawa, T., Heinemann, A.B., Kiepe, P., Lafarge, T., Luquet, D., Masood, A., van Oort, P., Rodenburg, J., Yan, J., Yin, X., 2009. An international collaborative research network helps to design climate robust rice systems, Invited Key Note; In: Hasegawa, T. and Sakai, H. (eds). Crop production under heat stress: Monitoring, impact assessment and adaptation. Proceedings of the MARCO Symposium, 5 - 9 October, 2009, Tsukuba, Japan, p. 1 - 11.

http://www.niaes.affrc.go.jp/marco/marco2009/ws2proc.pdf

Meinke, H., deVoil, P., Hammer, G.L., Power, S., Allan, R., Stone, R.C., Folland, C., Potgieter, A., 2005. Rainfall variability at decadal and longer time scales: signal or noise? Journal of Climate, 18: 89-96.

Meinke, H., Baethgen, W.E., Carberry, P.S., Donatelli, M.m Hammer, G.L., Selvaraju, R., and Stockle, C.O., 2001. Increasing profits and reducing risks in crop production using participatory systems simulation approaches, Agricultural Systems 70(2-3), 493-513.

Meinke, H., Rabbinge, R., Hammer, G.L., van Keulen, H., Jamieson, P.D., 1997. Improving wheat simulation capabilities in Australia from a cropping systems perspective. II. Testing simulation capabilities of wheat growth. European Journal of Agronomy 8, 83-99.

Merton, R., 1972. An analytic derivation of the efficient portfolio frontier, Journal of Financial and Quantitative Analysis 7, 1851-1872.

Meyer, W.S. 1999. Standard reference evaporation calculation for inland, south eastern Australia. CSIRO Land and Water, Adelaide Laboratory, technical report

35/98, September 1999. http://www.clw.csiro.au/publications/technical98/tr35-98.pdf

Muirhead, W.A., Blackwell, J.B., Humphreys, E., White, R.J.K., 1989. The growth and nitrogen economy of rice under sprinkler and flood irrigation in southeast Australia. I. Crop response and N uptake. Irrigation Science 10, 183-199.

Murray–Darling Basin Authority, 2010. Guide to the proposed Basin Plan: overview, Murray–Darling Basin Authority, Canberra, ISBN (online) 978-1-921557-73-6

Murrumbidgee Water Exchange, 2010. Historical temporary trade data, http://www.murrumbidgeewater.com.au/index.php?id=6&no_cache=1 (accessed Jan 2011)

New South Wales Department of Infrastructure, Planning, and Natural Resources, 2004. A guide to the Water Sharing Plan for the Murrumbidgee Regulated River Water Source, September 2004. http://www.water.nsw.gov.au/Water-management/Water-sharing-plans/Plans-commenced/Water-source/Murrumbidgee-Regulated-River/default.aspx (accessed Jan 2011)

Norsker, N.H., Barbosa, M.J., Vermue, M.H., Wijffels, R.H., 2011. Microalgal production - A close look at the economics, Biotechnology Advances 29, 24-27.

NSW Government, 2011. “Farm Enterprise Budget Series” 2011, http://www.dpi.nsw.gov.au/agriculture/farm-business/budgets (accessed December 2011).

NSW Government (2009) “Farm Enterprise Budget Series” 2009/2010, http://www.agric.nsw.gov.au/reader/budget (accessed June 2009)

Nye, P.H., Tinker, P.B., 1977. Solute Movement in the Soil-Root System, Studies in Ecology, Blackwell, Oxford/London/Edinburgh/Melbourne.

Okuda, A., Yamaguchi, M.,1952. Algae and atmospheric nitrogen fixation in paddy soils. II: relation between the growth of blue-green algae and physical or chemical properties of soil and effect of soil treatments and inoculation on the nitrogen fixation. Mem. Res. Inst. Food Sci. 4, 1-11.

Owen, J., and Rabinovitch, R., 1983. On the class of elliptical distributions and their applications to the theory of portfolio choice, Journal of Finance 38, 745-752.

Pampolino, M.F., Laureles, E.V., Gines, H.C., Buresh, R.J., 2008. Soil carbon and nitrogen changes in long-term continuous lowland rice cropping, Soil Science Society of America Journal 72(3), 798-807.

Paydar Z., Gaydon D.S., & Chen Y., 2009. A methodology for up-scaling irrigation losses, Irrigation Science 27(5), 347-356

Peng, S., Cassman, K.G., Virmani, S.S., Sheehy, J., Khush, G.S., 1999. Yield potential trends of tropical rice since the release of IR8 and the challenge of increasing rice yield potential. Crop Science 39, 1552–1559.

Perry, C., Steduto, P., Allen, R.G., and Burt, C.M., 2009. Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities, Agricultural Water Management 96(11), 1517-1524.

Person, P., Michelsen, A., 1994. Determinants and Trends in Water Right Prices: An Econometric Analysis, Laramie, Wyoming, Wyoming Water Resources Centre.

Petrie, S.E., Wysocki, D.W., Horneck, D.A., Lutcher, L.K., Hart, J.M., Corp, M.K., 2006. Winter wheat in continuous cropping systems, FertilizerGuide FG 84, Oregon State University Extension Service, http://extension.oregonstate.edu/catalog/pdf/fg/fg84.pdf (accessed June 2011)

Pittock, B., 2003. Climate Change – An Australian Guide to the Science and Potential Impacts, Australian Greenhouse Office, Canberra.

Power, B., Rodriguez, D., deVoil, P., Harris, H., Payero, J., 2011. A multi-field bio-economic model of irrigated grain-cotton farming systems. Field Crops Research 124(2), 171-179.

Probert, M.E.P., Dimes, J.P., Keating, B.A., Dalal, R.C., Strong, W.M., 1998. APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems, Agricultural Systems 56(1), 1-28.

Reichardt, W., Inubushi, K., Tiedje, J. 1999. Microbial Processes in C and N Dynamics, in: Carbon and nitrogen dynamics in flooded rice: proceedings of the workshop on Carbon and Nitrogen Dynamics in Flooded Soils, ed. by G.J.D. Kirk and D.C. Olk, 19-22 Apr 1999, Los Baños, Philippines, Los Baños, Laguna : IRRI. 188 p.

Rijsberman, F.R., 2006. Water scarcity: fact or fiction? Agricultural Water Management 80, 5–22.

Ritchie, J.T., 1972. Model for predicting evaporation from a row crop with incomplete cover. Water Resources Research 8(5), 1204-1213.

Robertson, M.J., Carberry, P.S., Huth, N.I., Turpin, J.E., Probert, M.E., Poulton, P.L., Bell, M., Wright, G.C., Yeates, S.J., Brinsmead, B.R., 2002. Simulation of growth and development of diverse legume species in APSIM, Australian Journal of Agricultural Research 53 (4), 429 – 446.

Robertson, M. J., Carberry, P.S., and Lucy, M., 2000. Evaluation of a new cropping option using a participatory approach with on-farm monitoring and simulation: a case study of spring-sown Mungbeans, Australian Journal of Agricultural Research 51(1), 1-12.

Rodriguez, D., deVoil, P., and Cox, H. , 2007. Helping practical wisdom: A niche for whole farm systems modelling. International Conference on Farming Systems Design, Catania, Italy (http://www.iemss.org/farmsys07/)

Roger P.A., 1996. Biology and management of the floodwater ecosystem in ricefields. IRRI, Los Banos, Philippines.

Roger P.A., Ladha, J.K., 1992. Biological nitrogen fixation in wetland rice fields: estimation and contribution to nitrogen balance. Plant and Soil 141, 41-55.

Roger, P.A., Kulasooria, S.A., 1980. Blue Green Algae and Rice, International Rice Research Institute. Los Baños. Philippines

Roger, P.A., Reynaud, P.A.,1979. Ecology of blue-green algae in paddy fields. in: International Rice Research Institute. Nitrogen and Rice. Los Baños. Philippines, 289-309.

Roger, P.A., Reynaud, P., 1976. Dynamics of the algal populations during a culture cycle in a Sahel rice field [in French, English summary], Rev. Ecol. Biol. Sol. 13(14), 545-560.

Samani, Z., Jorat, S., Yousaf, M. 1991. Hydraulic characteristics of circular flume. Journal of Irrigation and Drainage Engineering 117(4), 558-566.

Samuelson, P.A. and Nordhaus, W.D., 2001. Macroeconomics (17th ed.), McGraw Hill, New York. (page 110).

Schillinger, W. F., D. L. Young, Kennedy A.C., and Paulitz, T.C., 2010. Diverse no-till irrigated crop rotations instead of burning and plowing continuous wheat. Field Crops Research 115(1), 39-49.

Scholz, H., 2007. Refinements to the Sharpe ratio: Comparing alternatives for bear markets. Journal of Asset Management 7(5), 347–357.

Schulthess, U., Ritchie, J., 1996. Simulation of tillage and crop residue dynamics with the SALUS-model. 26th Annual Crop Simulation Workshop. Fort Collins, 9-11 April, pp. 24-25.

Seckler, D., Molden, D., and Sakthivadivel, R., 2003. The concept of efficiency in water resources management and policy. In: Kijne, J.W., Barker, R., Molden, D. (Eds.), Water productivity in agriculture: Limits and opportunities for improvement. CABI Publishing, UK, (in association with IWMI, Colombo, Sri Lanka), pp. 37–51.

Sharpe, W. F., 1994. The Sharpe Ratio, Journal of Portfolio Management 21(1), 49–58.

Simpson, H.J., Herczeg, A.L. Meyer,W.S., 1992. Stable isotope ratios in irrigation water can estimate rice crop evaporation. Geophysical Research letters 19, 377-380.

Sinclair T.R., Seligman N., 2000. Criteria for publishing papers on crop modelling, Field Crops Research 68, 165–172.

Singh, R.P., Lacy, J., 2004. Effect of different water allocations on rice farm profitability in the Murrumbidgee Irrigation Area, Grains Research Update for irrigation croppers, Irrigation Research and Extension Committee (IREC), Griffith, NSW Australia.

http://www.irec.org.au/reser_f/04_pdf/Water%20allocations%20effects%20on%20rice%20farm%20profitability.pdf

Singh, R.P., Lacy., 2005. The effect of different water allocations on rice farm profitability in the MIA, IREC Farmer's Newsletter, No. 170, Spring 2005

http://www.irec.org.au/farmer_f/pdf_170/The%20effect%20of%20different%20water%20allocations%20on%20rice%20farm%20profitability%20in%20the%20MIA.pdf

Singh, V.K., Dwivedia, B.S., Shuklaa, A.K., Chauhan, Y.S., Yadav, R.L. 2005. Diversification of rice with pigeon pea in a rice–wheat cropping system on a Typic Ustochrept: effect on soil fertility, yield and nutrient use efficiency, Field Crops Research 92(1), 85-105.

Sheehy, J.E., Mitchell, P.L., Hardy, B. (Eds.), 2000. Redesigning Rice Photosynthesis to Increase Yield, Elsevier Science, Amsterdam, Netherlands, p. 293.

Shibu, M.E., Leffelaar, P.A., van Keulen, H., Aggarwal, P.K., 2006. Quantitative description of soil organic matter dynamics - A review of approaches with reference to rice-based cropping systems. Geoderma 137(1-2), 1-18.

Smith, J., Lacy, J., Reinke, R., Snell, P., 2010. Rice variety selection. Primefact 1035, Industry & Investment NSW. http://www.dpi.nsw.gov.au/agriculture/field/field-crops/summer-grains/rice/rice-variety-selection (retrieved 30.09.2010).

Soil Survey Staff, 1975. Soil Taxonomy: a basic system of soil classification for making and interpreting soil surveys. Soil conservation service, US Department of Agriculture, Agriculture Handbook. No. 436.

Stöckle, C.O., Donatelli, M.,Nelson, R., 2003. CropSyst, a cropping systems simulation model. Eur. J. Agron. 18, 289–307.

Sudhir–Yadav, Humphreys, E., Kukal, S.S., Gill, G., Rangarajan, R. 2011a. Effect of water management on dry seeded and puddled transplanted rice: Part 2: Water balance and water productivity, Field Crops Research 120(1), 123-132.

Sudhir–Yadav, Li, T., Humphreys, E., Gill, G., and Kukal, S.S. 2011b. Evaluation and application of ORYZA2000 for irrigation scheduling of puddled transplanted rice in north west India, Field Crops Research 122(2), 104-117.

Sunrice website - http://www.sunrice.com.au (accessed 01/12/09)

Suriadi, A., Misra, R., Gaydon, D.S., Abawi, G.Y., 2009. Performance of rice on a coarse sandy loam soil in response to water-saving irrigation practices in lowland eastern Indonesia, Proceedings of *Farming Systems Design 2009*- International Symposium on Methodologies for Integrated Analysis of Farm Production Systems, Monterey, California, USA, 23-26 August, 2009.

Taylor, J.K., and Hooper, P.D., 1938. A Soil Survey of the Horticultural Soils in the Murrumbidgee Irrigation Areas, New South Wales, CSIRO Bulletin No. 118, Melbourne.

Thompson, J.A., Griffin, D., 2006. Delayed flooding of rice – effect on yields and water. IREC Farmers Newsletter, No 173, Spring 2006, pp 52-53.

Thompson, J.A., and Chase, D.L., 1992. Effect of limited irrigation on growth and yield of a semi-dwarf wheat in southern New South Wales, Australian Journal of Experimental Agriculture 32, 725-730.

Thorburn, P.J., Probert, M.E., Robertson, F.A., 2001. Modelling decomposition of sugar cane surface residues with APSIM–Residue, Field Crops Research 70(3), 223-232.

Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-Wheat models in rice-wheat systems: A review. Agricultural Systems 90 (1-3), 5-31.

Tolk, J.A., Howell, T.A., Evett, S.R., 1999. Effect of mulch, irrigation, and soil type on water use and yield of maize, Soil and Tillage Research 50, 137–147.

Trigeorgis, L., 1996. Real Options: Managerial Flexibility and Strategy in Resource Allocation. Cambridge, The MIT Press. ISBN 0-262-20102-X.

Tuong, T.P., Bouman, B.A.M., Mortimer, M., 2005. More rice, less water - integrated approaches for increasing water productivity in irrigated rice based systems in Asia. Plant Prod. Sci. 8(3), 229-239.

Tuong, T.P., Bouman, B.A.M., Mortimer, M., 2004. More rice, less water – Integrated approaches for increasing water productivity in irrigation rice-based systems in Asia. Paper presented at the 4th International Crop Science Congress on New Directions for a Diverse Planet in Brisbane, Australia, September 26 – October 1, 2004, http://www.cropscience.org.au/icsc2004/symposia/1/2/1148_tuongtp.htm (retrieved 10.07.2010).

Turral, H.N., Etchells, T., Malano, H.M.M., Wijedasa, H.A., Taylor, P., McMahon, T.A.M., Austin, N., 2005. Water trading at the margin: The evolution of water markets in the Murray-Darling Basin, Water Resources Research 41(7), 1-8.

Turpin, J.E., Carberry, P.S., McCown, R.L., Probert, M.E., 1998. Simulation of legume-cereal systems using APSIM, Australian Journal of Agricultural Research 49(3), 317 – 328.

Uchijima, T., 1976. Some aspects of relation between low air temperature and sterile spikelets in rice plants. Journal of Agricultural Meteorology 31, 199-202.

van Dijk, D.C., 1961. Soils of the southern portion of the Murrumbidgee Irrigation Areas. CSIRO Division Soils. Tech. Bull. No. 40 p.16.

van Keulen, H., Wolf, J., 1986. Modelling of agricultural production: weather soils and crops. Simulation Monographs, Pudoc, Wageningen.

Verburg, K., Bond, W.J., 2003. Use of APSIM to simulate water balances of dryland farming systems in south eastern Australia, CSIRO Land and Water, Canberra, Technical Report 50/03.

Villegas-Pangga, G., Blair, G., Lefroy, R., 2000. Measurement of decomposition and associated nutrient release from straw (*Oryza sativa* L.) of different rice varieties using perfusion system. Plant Soil 223, 1–11.

Vincent, D.P., 1976. Economic Aspects of Farm Poverty, Australian Journal of Agricultural Economics 20, 103–18.

von Grebmer, K., Fritschel, H., Nestorova, B., Olofinbiyi, T., Pandya-Lorch, R. and Yohannes, Y., 2008. Global Hunger Index. The Challenge of Hunger 2008. Bonn, Washington D.C., Dublin, October 2008.

Walker, K.F., Puckridge, J.T., Blanch, S.J., 1997. Irrigation development on Cooper Creek, central Australia - prospects for a regulated economy in a boom-and-bust ecology, Aquatic Conservation 7, 63-73.

Watanabe, A., Yamamoto, Y., 1971. Algal nitrogen fixation in the tropics. Plant. Soil (special volume): 403-413, doi:10.1007/BF02661867.

Wheeler, S., Bjornlund, H., Shanahan, M., Zuo, A., 2008. Price elasticity of water allocations demand in the Goulburn–Murray Irrigation District. Australian Journal of Agricultural and Resource Economics 52, 37–56.

Whitbread, A.M., Robertson, M.J., Carberry, P.S., Dimes, J.P., 2010. How farming systems simulation can aid the development of more sustainable smallholder farming systems in southern Africa, European Journal of Agronomy 32(1), 52-58.

Whitworth, R., Lacy, J., 2008. Delaying the application of permanent water to rice – will it improve returns? IREC Farmers Newsletter, No 179, Spring 2008, pp 14-15.

Williams, R.L., Angus, J.F., 1994. Deep floodwater protects high nitrogen rice crops from low temperature damage. Australian Journal of Experimental Agriculture 34, 927-932.

Willmott C.J., 1981. On the validation of models. Phys. Geogr. 2, 184–194.

Wood, M. L. and Finger, L., 2006. Influence of irrigation method on water use and production of perennial pastures in northern Victoria, Australian Journal of Experimental Agriculture 46(12), 1605-1614.

World Bank, 2008. World Development Report 2008: Agriculture for Development. The World Bank, Washington, DC.

Yadvinder-Singh, Bijay-Singh, Timsina, J., 2005. Crop Residue Management for nutrient Cycling and Improving Soil Productivity in Rice-Based Cropping Systems in the Tropics, Advances in Agronomy 85, 269-407.

Zeng, X., Sun, N., Gao, J., Wang, B., Li, L., 2007. Effects of Cropping System Change for Paddy Field with Double Harvest Rice on the Crops Growth and Soil Nutrient, Agricultural Sciences in China 6(9), 1115-1123.

Zhang, X., Jae-Hong Lee, Abawi, Y., Young-ho Kim, Hee-Dong Kim, 2006. Testing the simulation capability of APSIM-ORYZA under different levels of nitrogen fertilizer and transplanting time regimes in Korea. Australian Journal of Experimental Agriculture 47(12), 1446-1454.

Zwart, S.J. and Bastiaanssen, W.G.M., 2004. Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize, Agricultural Water Management 69(2), 115-133.

Summary

Rice-based cropping systems throughout the world are experiencing adaptive pressure from various forces of change. These include changes to water availability and quality, increasing ambient temperatures and CO_2, market imperatives, and the global need to produce more food for a growing population. In Australia's rice-growing Riverina region the biggest driver of change has been drastic reductions in irrigation water availability over the last decade, in contrast to a long history of reliably abundant supply. Droughts, competition for resources in an over-allocated river system, and political changes driven by environmental imperatives have combined to create the current situation. Climate change predictions give no comfort, with an outlook of ongoing water reductions and high variability of supply. Cropping systems in the region have never been rice monocultures – they are traditionally diverse, with rice as the major crop in rotation with other cereals, pulses, oilseeds and pastures. Over the last decade, agricultural production from the region has been decimated with many farming families economically forced to leave the land. This research project investigated on-farm adaptation options in response to reduced irrigation water supplies. The overarching aim was to increase the resilience of farmers via increased water productivity and farm returns.

An essential first component of the work was the further development of required modelling tools. Available rice models and previous rice-modelling efforts had focussed on simulation of agronomic issues within *single rice crops*. This project required a *cropping systems* model capable of simulating the performance of long-term crop rotations involving rice and other crops/pastures, together with fallow periods. Such a model did not exist. The APSIM cropping systems model, already possessing many of the required features (multiple crops, rotations, residue/tillage practices, flexible management specification etc.), was unable to simulate key processes specific to flooded soils and rice floodwater due to its heritage in dryland agricultural applications. We modified APSIM to include descriptions of soil C and N dynamics under anaerobic conditions, and established a process for simulating the two-way transition between anaerobic and aerobic soil conditions occurring in crop sequences of flooded rice and other non-flooded crops, pastures and fallows (Chapter 1). Photosynthetic aquatic biomass (PAB – algae and other floodwater flora, including N-fixing species) was recognized as a significant source of organic C and N in rice-based cropping systems, and judged as an essential component for sensibly simulating long-term rice system performance. The literature revealed that contributions of fixed N from floodwater algae was significant for nutrition of the *following* rice crop (not the

current one), hence explaining why previous rice-modelling efforts around single rice crops had been able to ignore these contributions. Similarly, the impact of small, incremental seasonal additions of organic C from algae can be ignored for a single rice crop, but not for a long-term simulated cropping sequence. Hence, the APSIM model had to be modified to include new descriptions of biological and chemical processes responsible for loss and gain of C and N in rice floodwater (including the growth, senescence, death, and subsequent soil incorporation of algal biomass) (Chapter 3). The improved APSIM model was then tested against a range of diverse, replicated experimental datasets, and acceptable performance was demonstrated.

The improved and validated APSIM model was then used in conjunction with participatory farmer engagement (and a field experiment) to assess a range of identified adaptation options. The question of appropriate irrigation intensity and crop choice under different levels of water availability was investigated using a typical case-study farm from the region. The adaptation options found to best suit irrigation farming in years of high water availability were substantially different to those when water supplies were low. Our study demonstrated that the cropping and irrigation strategy leading to the greatest farm returns changes on a season-by-season basis, depending primarily on water availability (Chapter 4). We refer to this as *agile* management later in the thesis.

Our collaborating farmers were also interested in comparing on-farm options for alternative uses of their water resources (ie irrigating crops and pastures and selling the resulting grain/hay/meat) with off-farm options (such as selling water or entitlements on the open market). A framework (Modern Portfolio Theory, MPT), commonly used in the finance sector for assessing the composition of share portfolios, was adapted for the case study farm and used to compare a range of on-farm irrigation options (from Chapter 4), with an off-farm option to sell water entitlements directly to an external buyer (the Australian Government Water Buy-back Scheme). The framework allows options to be compared based solely on their risk-return characteristics, and we used the MPT framework to demonstrate how the attractiveness of the Australian Government scheme for farmers depends primarily on future water availability levels (Chapter 5). We showed why the MPT method is universally applicable wherever there is a mix of variable and fixed-return investment options, thereby offering a framework to assist farmers in conceptualizing comparisons between traditional on-farm uses for water and newer, market-based options.

Delaying the application of continuous floodwater to young rice crops has shown promise for increasing rice water productivity through decreasing non-productive water losses early in the season (Heenan and Thompson, 1984; Thompson and Griffin, 2006). Previous experiments had demonstrated the principle, but fell short of defining

best-practice guidelines, suggesting that a more detailed investigation may result in a viable adaptation option to reduced water supplies for Riverina rice farmers. We conducted a field experiment over two growing seasons, 2008/9 and 2009/10, comparing traditional fully-flooded rice irrigation methods with delayed continuous flooding (DCF) using a range of irrigation scheduling treatments prior to flooding commencement. The aim was to compare the tradeoffs between water savings (achieved by water stressing the young crop to different degrees) and resulting yield penalties, seeking the degree of water stress which provided optimum water productivity (t grain ML^{-1}). The experiment demonstrated increased water productivity right up to the maximum pre-flooding stress level imposed during the experiment – representing an increase of up to 17% over conventional irrigation practices in the region (Chapter 6). The experiment was also used to collect modelling-specific field data for the purposes of calibrating and validating the APSIM model. The model performed well in simulating observed experimental behaviour (rice grain yield, water use, water productivity, soil water and N dynamics). We subsequently used the improved model for a long-term scenario analysis (55 years) that further explored risk-returns associated with DCF and improved our understanding of the key drivers of system behaviour. Our study defined best-practice guidelines for DCF in rice production, and demonstrated water productivity gains of 25% and 17% over traditional aerially-sown and conventional-drill crops, respectively (Chapter 7).

An overall synthesis of all the investigated adaptation options was performed in Chapter 8, using the case-study farm from Chapters 4 and 5. The aim was to assess the degree to which this PhD study contributes to greater resilience of Riverina rice-farmers facing reduced future water supplies. We demonstrated that without changes to traditional management practices the case-study farm would become non-viable if future water allocations were to average below 50% of entitlement. Implementation of agile management (Chapter 4) in tandem with delayed continuous flooding in rice production (DCF, Chapters 6 and 7) would keep the farm viable down to 30% allocation. If future average allocations fall below 30%, the best choice for farmers (from the options investigated) would be to sell their entitlements and invest the money (Chapter 5).

Samenvatting

Rijst-gebaseerde gewassystemen in de hele wereld ervaren druk tot adaptatie door verschillende krachten voor verandering. Deze omvatten veranderingen in de beschikbaarheid en de kwaliteit van water, de toename in temperatuur en in de CO2 concentratie, eisen van de markt en de wereldwijde noodzaak om meer voedsel te produceren voor een groeiende bevolking. In het Australische rijstteeltgebied Riverina is gedurende de laatste tien jaren een drastische vermindering in de beschikbaarheid van irrigatiewater de belangrijkste motor voor verandering geweest; dit in tegenstelling tot een lange geschiedenis van een betrouwbaar, overvloedig aanbod van water. Droogte, concurrentie om middelen in een over-bevraagd riviersysteem en de politieke veranderingen als gevolg van milieueisen hebben samen de huidige situatie gecreëerd. Voorspellingen van klimaatverandering stellen niet gerust met uitzicht op doorgaande beperkingen in water en grote variabiliteit van het aanbod ervan. Teeltsystemen in de regio zijn nooit monoculturen van rijst geweest - ze zijn van oudsher divers, met rijst als het belangrijkste gewas in rotatie met andere granen, peulvruchten, oliehoudende zaden en graslanden. In de afgelopen tien jaar is de landbouwproductie in de regio gedecimeerd en zijn vele boerenfamilies economisch gedwongen om het land te verlaten. In dit onderzoeksproject zijn adaptatieopties op het boerenbedrijf onderzocht als antwoord op verminderde beschikbaarheid van water voor irrigatie. De overkoepelende doelstelling was om de veerkracht van de boeren te verhogen via een grotere waterproductiviteit met toegenomen rendement van de boerderij.

Een essentiële eerste component van het werk was de verdere ontwikkeling van de benodigde modellen. Beschikbare rijstmodellen en voorgaande rijst-modelleringsinspanningen waren gericht op simulatie van landbouwkundige vraagstukken binnen enkel de rijstgewassen. Dit project vereiste een teeltsystemenmodel dat voorziet in het simuleren van het gedrag op lange termijn van vruchtwisselingssystemen die naast rijst andere gewassen /grasland en ook braakperioden omvatten. Een dergelijk model bestond niet. Het APSIM teeltsystemen model, dat al veel van de vereiste kenmerken bezit (meerdere gewassen, rotaties, gewasresten/grondbewerking, specificatie van flexibel gewasmanagement, enz.), was niet in staat om de belangrijkste processen te simuleren die specifiek zijn voor bevloeide bodems die onder een laag water staan en voor die waterlaag zelf – dit als gevolg van de ontstaangeschiedenis van APSIM voor agrarische toepassingen onder droge omstandigheden. We hebben APSIM uitgebreid met beschrijvingen van de dynamiek in de bodem van C en N onder anaërobe omstandigheden, en er zijn voorzieningen gemaakt voor het simuleren van de twee-weg overgangen tussen anaërobe - en aërobe bodemomstandigheden die zich voordoen bij de op éénvolgende teelt van bevloeide rijst en andere niet-bevloeide gewassen, graslanden en braak (hoofdstuk 1). Fotosynthetisch actieve aquatische biomassa (PAB - algen en andere flora in waterlagen boven bevloeide gronden, stikstofbindende soorten inbegrepen) werd gezien als een belangrijke bron van organische C en N in op rijst gebaseerde gewassystemen, en werd beschouwd als een essentieel onderdeel voor het zinvol kunnen simuleren van het gedrag op lange termijn van het rijstsysteem. Uit de literatuur blijkt dat de bijdragen van vastgelegde N uit algen in de waterlaag belangrijk was voor de voeding van het volgende rijstgewas (niet het huidige gewas), daarmee is tevens verklaard waarom eerdere modellen van enkel het rijstgewas op zich deze bijdrage konden verwaarlozen. Op dezelfde manier kan de invloed van kleine, incrementele toevoegingen van organisch C uit algen buiten beschouwing gelaten worden bij simulatie van een enkel rijstgewas, maar niet bij het simuleren over lange termijn van een reeks van gewassen. Vandaar dat het APSIM model moest worden uitgebreid met nieuwe beschrijvingen van de biologische en chemische processen die verantwoordelijk zijn voor het verlies en de toename van C en N in de waterlaag op rijst (omvattende de groei, veroudering, dood, en de daaropvolgende inwerking in de bodem van algen-biomassa) (Hoofdstuk 3). Het verbeterde APSIM model werd vervolgens getoetst aan een reeks van diverse, herhaalde, experimentele datasets en aanvaardbare resultaten werden verkregen.

Het verbeterde en gevalideerde APSIM model werd vervolgens gebruikt om –in combinatie met participerende boeren (en een veldexperiment) - een bepaalde reeks adaptatieopties te beoordelen. De kwestie van de juiste irrigatie intensiteit en gewaskeuze onder de verschillende niveaus van de beschikbaarheid van water werd onderzocht met behulp van een case-study op een boerderij die typisch was voor de regio. De aanpassingsopties die gevonden werden voor een optimale afstemming van irrigatie in de landbouw waren in jaren van hoge beschikbaarheid van water aanzienlijk verschillend van jaren waarin de watervoorziening laag was. Onze studie toonde aan dat de teelt- en irrigatiestrategie die leidt tot het grootste rendement van de boerderij per seizoen verandert, voornamelijk afhankelijk van de beschikbaarheid van water (hoofdstuk 4). We noemen dit later in het proefschrift behendig management.

Onze samenwerkende boeren waren ook geïnteresseerd in het vergelijken van mogelijkheden voor alternatief gebruik van hun watervoorraden op de bedrijven (dat wil zeggen irrigatie van gewassen en graslanden en de verkoop van de daaruit voortvloeiend graan / hooi / vlees) met ‘off-farm’ opties (zoals de verkoop van water of waterrechten op de open markt). Een rekenkader (‘Modern Portfolio Theory’, MPT), vaak gebruikt in de financiële sector voor de beoordeling van de samenstelling van aandelenportefeuilles, werd aangepast voor de boerderij van de case study en gebruikt om een reeks van irrigatie-opties voor het bedrijf (uit hoofdstuk 4) te vergelijken met een ‘off-farm’ mogelijkheid om waterrechten direct aan een externe koper te verkopen (‘the Australian Government Water Buy-back Scheme’, i.e. het waterterugkoop programma van de Australische overheid). Het rekenkader biedt mogelijkheden om opties te vergelijken alleen op basis van hun risico-rendement kenmerken; wij hebben het MPT-rekenkader gebruikt om aan te tonen hoe de aantrekkelijkheid voor boeren van de regeling van de Australische overheid in de eerste plaats afhankelijk is van de toekomstige beschikbaarheid van water (hoofdstuk 5). We hebben laten zien waarom de MPT-methode universeel toepasbaar is overal waar er sprake is van een mix van investeringsopties met variabele - en vaste rendementen; daarmee bieden we een rekenkader om de boeren te helpen bij het conceptualiseren van vergelijkingen tussen het traditionele gebruik van water op het bedrijf en nieuwere, op de markt gebaseerde opties.

Het uitstellen van de toepassing van continue bevloeiing aan jonge rijstgewassen is veelbelovend gebleken voor het verhogen van de waterproductiviteit van rijst vanwege afname van het niet-productieve waterverlies vroeg in het seizoen (Heenan en Thompson, 1984; Thompson en Griffin, 2006). Eerdere experimenten hadden het principe aangetoond, maar schoten tekort in het definiëren van richtlijnen voor beste praktijken, wat suggereert dat een meer gedetailleerd onderzoek zou kunnen resulteren in een bruikbaar aanpassingsoptie met verminderde watertoevoer voor rijstboeren in Riverina. Wij hebben een veldexperiment uitgevoerd over twee groeiseizoenen, 2008/9 en 2009/10, waarin we de traditionele irrigatiemethode van volledig bevloeide rijst vergeleken met een uitgestelde volledige bevloeiing (‘delayed continuous flooding’, DCF) met daarbij een scala aan behandelingen betreffende de planning van de irrigatie voorafgaand aan de volledige bevloeiing. Het doel was om de uitruil te vergelijken tussen waterbesparingen (bereikt door verschillende mate van water stress op te leggen aan het jonge gewas) en de daaruit voortvloeiende opbrengstreducties, zoekend naar de mate van waterstress die een optimale waterproductiviteit (ton korrel ML-1) bewerkstelligt. Het experiment toonde toenemende waterproductiviteit aan tot het maximale stressniveau in de initiële fase voorafgaand aan volledige bevloeiing- wat neerkomt op een toename tot 17% ten opzichte van conventionele irrigatiepraktijken in de regio (hoofdstuk 6). Het experiment werd ook gebruikt om specifiek ten bate van modellering veldgegevens te verzamelen met als doeleinden het calibreren en valideren van het APSIM model. Het model presteerde goed in het simuleren van het waargenomen experimentele gedrag (korrelopbrengst van rijst, het gebruik van water, waterproductiviteit, bodemwater en N-dynamiek). We hebben vervolgens het verbeterde model gebruikt voor een lange-termijn scenario-analyse (55 jaar), waarmeehet risico-rendement dat samenhangt met DCF verder werd onderzocht en waarmee ons begrip verbeterd werd van de belangrijkste gedragbepalende factoren van het systeem. Onze studie definieerde richtlijnen voor beste praktijken voor het DCF in de productie van rijst, en toonde een toename aan in de waterproductiviteit van 25% en 17% ten opzichte van respectievelijk traditionele vanuit de lucht gezaaide en conventioneel met zaaimachine gezaaide gewassen (hoofdstuk 7).

Een algemene synthese van alle onderzochte adaptatieopties werd uitgevoerd in hoofdstuk 8, met gebruik van de case-studie boerderij van de hoofdstukken 4 en 5. Het doel was om de mate te beoordelen waarin dit promotie-onderzoek bijdraagt aan een grotere veerkracht van rijstboeren in Riverina die geconfronteerd zijn met lagere toekomstige watervoorziening. We hebben aangetoond dat zonder veranderingen in de traditionele beheersvormen de case-studie boerderij niet-levensvatbaar zou worden indien in de toekomst de toewijzing van water gemiddeld zou zakken tot minder dan 50% van het huidige recht. Implementatie van ‘behendig management’ (hoofdstuk 4) in combinatie met een uitgestelde volledige bevloeiing in de productie van rijst (DCF, de hoofdstukken 6 en 7) zou de boerderij levensvatbaar houden tot 30% van de watertoewijzing. Als de toekomstige gemiddelde toewijzingen dalen tot onder 30%, zou de beste keuze voor de landbouwers (uit de onderzochte opties) zijn om hun rechten te verkopen en het geld (hoofdstuk 5) te investeren.

Publications of the author

Peer-reviewed journal papers

Balwinder-Singh, Gaydon, D.S., Humphreys, E., Eberbach, P.L., 2011. The effects of mulch and irrigation management on wheat in Punjab, India—Evaluation of the APSIM model, Field Crops Research 124(1), 1-13.

Brown P.R., Phung, M.T., Gaydon D.S., 2011. Rats in rice: linking crop and pest models to explore management strategies, Wildlife Research 38, 560–567.

Dunn B.W., Gaydon D.S., 2011. Rice growth, yield and water productivity responses to irrigation scheduling prior to the delayed application of continuous flooding in south-east Australia, Agricultural Water Management 98, 1799–1807

Gaydon, D.S., Probert, M.E., Buresh, R.J., Meinke, H., Suriadi, A.., Dobermann, A., Bouman, B.A.M., Timsina, J., 2012. Rice in cropping systems - Modelling transitions between flooded and non-flooded soil environments, European Journal of Agronomy 39, 9-24.

Gaydon, D.S., Probert, M.E., Buresh, R.J., Meinke, H., Timsina, J., 2012. Capturing the role of algae in rice crop production and soil organic carbon maintenance, European Journal of Agronomy 39, 35-43.

Gaydon D.S., Meinke, H., Rodriguez, D., 2011. The best farm-level irrigation strategy changes seasonally with fluctuating water availability, Agricultural Water Management 103, 33– 42.

Hochman, Z., Carberry, P.S., Robertson, M.J., Gaydon, D.S., Bell, L.W., McIntosh, P.C., 2011, Prospects for ecological intensification of Australian agriculture, European Journal of Agronomy (in press)

Keating B.A., Gaydon D.S., Huth N.I., Probert M.E., Verburg K, Smith C.J., Bond W.J., 2002. Use of modelling to explore the water balance of dryland farming systems in the Murray-Darling Basin, Australia, European Journal of Agronomy 18, 159-169.

Mcintyre, S., McGinness, H.M., Gaydon, D.S., Arthur, A.D., 2011. Introducing irrigation efficiencies: prospects for water-dependent biodiversity in a rice agro-ecosystem , Environmental Conservation 38 (3), 353–365.

Park, S.E., Howden, S.M., Crimp, S.J., Gaydon, D.S., Attwood, S.J., Kokic, P.N., 2010. More than eco-efficiency is required to improve food system security, Crop Science 50(2), 132-141.

Paydar, Z., Gaydon, D.S., Chen, Y., 2009. A methodology for up-scaling irrigation losses, Irrigation Science 27(5), 347-356.

Robertson, M.J., Gaydon, D.S., Hall, D.J.M., Hills, A, Penny, S., 2005. Production risks and water-use benefits of summer crop production on the south coast of Western Australia, Australian Journal of Agricultural Research 56, 597-612.

Radajewski W, Gaydon D.S., McGahan E.J., 1990. Optimization of Solar Hay Drying in a Step-Flow Dryer, Transactions of the American Society of Agricultural Engineers 33(5), 1423-1431.

Book Chapters

Gaydon, D.S., Beecher, H.G., Reinke, R., Crimp, S., Howden, S.M., 2010. Chapter 5 – *Rice*, in Adapting Australian Agriculture to Climate Change, Edited by C.J. Stokes & S.M. Howden, CSIRO Publishing, Melbourne.

Peer-reviewed conference papers

Gaydon, D.S., Cattanach, D., Houghton, R., Meinke, H., Rodriguez, D., 2010. Adapting to climate change in broad-acre irrigated farming systems – Case studies from the Riverina region of South East Australia, NCCARF 2010 International Climate Change Adaptation Conference, Climate Adaptation Futures – Preparing for the unavoidable impacts of climate change, Gold Coast Convention Centre, Gold Coast, Queensland, Australia, 29 June – 1 July 2010.

Crimp, S., Laing, A., Gaydon, D., Howden, M., Brown, P., 2010. The challenges of agricultural production in a future variable and changing climate, NCCARF 2010 International Climate Change Adaptation Conference, Climate Adaptation Futures – Preparing for the unavoidable impacts of climate change, Gold Coast Convention Centre, Gold Coast, Queensland, Australia, 29 June – 1 July 2010.

Meinke, H., Bastiaans, L., Bouman, B.A.M., Dingkuhn, M., Gaydon, D.S., Hasegawa, T., Heinemann, A.B., Kiepe, P., Lafarge, T., Luquet, D., Masood, A., Möller, C., van Oort, P., Rodenburg, J., Yan, J., Yin, X., 2009. Adaptation of rice production under climatic constraints, EU-ASEAN Science and Technology Dialogue, Bogor, Indonesia, 11-12 November 2009.

Meinke, H., Bastiaans, L., Bouman, B.A.M., Dingkuhn, M., Gaydon, D.S., Hasegawa, T., Heinemann, A.B., Kiepe, P., Lafarge, T., Luquet, D., Masood, A., Möller, C., van Oort, P., Rodenburg, J., Yan, J., Yin, X., 2009. An international collaborative research network helps to design climate robust rice systems, Keynote Paper from International Workshop on Crop Production under Heat Stress – Monitoring, Impact Assesment, and Adaptation, Tsukuba International Congress Centre, Tsukuba, Ibaraki, Japan, 5-9 October 2009. Published in Hasegawa T. and Sakai H., eds. 2009. Crop Production under Heat Stress: Monitoring, Impact Assessment and Adaptation. Proceedings of the MARCO Symposium 2009 held in Tsukuba, Japan, 5-9 October 2009. Tsukuba (Japan): National Institute for Agro-Environmental Sciences (NIAES). http://www.niaes.affrc.go.jp/marco/marco2009/ws2proc.pdf

Gaydon, D.S., Buresh, R.J., Probert, M.E., Meinke, H., 2009. Simulating rice within broader farming systems using the APSIM framework, Proceedings of Farming Systems Design 2009- International Symposium on Methodologies for Integrated Analysis of Farm Production Systems, Monterey, California, USA, August 23-26 2009.

Suriadi, A., Gaydon, D.S., Abawi, G.Y., Misra, R., 2009. Capability of APSIM-Oryza to simulate lowland rice-based farming systems under nitrogen treatments in a tropical climate, Proceedings of Farming Systems Design 2009- International Symposium on Methodologies for Integrated Analysis of Farm Production Systems, Monterey, California, USA, August 23-26 2009.

Suriadi, A., Gaydon, D.S., Abawi, G.Y., Misra, R., 2009. Yield and Yield Components of Rice on a Coarse Sandy Loam Soil in Response to Water-Saving Irrigation, Proceedings of Farming Systems Design 2009- International Symposium on Methodologies for Integrated Analysis of Farm Production Systems, Monterey, California, USA, August 23-26 2009

Laing, A, Crimp, S., Poulton, P., Gaydon, D.S., Brown, P.R., 2009. Enhancing options to adapt to climate risk at the field scale: an Australian example of integrating expert knowledge, crop and climate science in mixed cropping systems, Proceedings of Farming Systems Design 2009- International Symposium on Methodologies for Integrated Analysis of Farm Production Systems, Monterey, California, USA, August 23-26 2009.

Crimp, S., Howden, S.M., Laing, A., Gaydon, D.S., Gartmann, A., Brown, P., 2009. Managing future agricultural production in a variable and changing climate. Proceedings of Climate Change: Global risks, challenges and decisions. Copenhagen, 10-12 March, 2009.

Gaydon, D.S., Buresh, R.J., Probert, M.E., Meinke, H., 2009. Simulating rice in farming systems – modelling transitions between aerobic and ponded soil environments in APSIM, Proceedings of 18th World IMACS Congress, MODSIM09 -International Congress on Modelling and Simulation, Cairns, Australia 13–17th July 2009.

Laing, A., Crimp, S., Brown, P.R., Gaydon, D.S., Poulton, P., 2009. Modelling the impacts of and adaptation responses to climate variability and change in mixed cropping systems in NSW, Proceedings of 18th World IMACS Congress, MODSIM09 -International Congress on Modelling and Simulation, Cairns, Australia 13–17th July 2009.

Harris, R., Gaydon, D.S., Bellotti, WD., Unkovich, M., Robertson, M.J., 2008. Simulating competition between cereal and lucerne grown in mixture, Global issues – Paddock Action, Proceedings of the 14th Australian Society of Agronomy Conference, Adelaide, 21-25 September 2008.

Crimp, S., Nidumolu, U., Gaydon, D.S., Howden, S.M., Hayman, P., 2008. Examining the value of dynamic seasonal forecasts in managing farm-level production and environmental outcomes in a variable climate, Global issues – Paddock Action, Proceedings of the 14th Australian Society of Agronomy Conference, Adelaide, 21-25 September 2008.

Crimp, S., Howden, S.M., Gaydon, D.S., 2008. Managing water in a changing climate: an agricultural context, CONFARM 08 Farming for today and tomorrow, Conference of the Australian Conservation Farmers Inc., Moree, NSW, 12-13 March 2008.

Crimp, S., Gaydon, D.S., Howden, M., Hall C., Poulton P., Nelson R., Hochman, Z., 2007. Managing farm-level production and environmental outcomes in a variable and changing climate, Farming Systems Design 2007 - an international symposium on Methodologies for Integrated Analysis of Farm Production Systems, Catania, Sicily, Italy, 10-12 September 2007.

Hall,C., Crimp, S., Hochman, Z., Gaydon, D.S., Poulton P., Howden S.M., 2007. Novel combinations: qualitative research and technology, Australasia-Pacific Extension Network (APEN) National Forum 07, Capture, consolidate and communicate - the changing nature of contemporary extension, Canberra, 13-14 November 2007.

Howden, S.M., Nelson, R., Crimp, S., Gaydon, D.S., 2006. Climate change – where are we heading?, International Landcare Conference – Landscapes, Lifestyles, Livelihoods, Melbourne, Oct 8-11th 2006.

Gaydon, D.S., Lisson, S.N., Xevi, E., 2006. Application of APSIM ‘multi-paddock’ to estimate whole-of-farm water-use efficiency, system water balance and crop production for a rice-based operation in the Coleambally Irrigation District, NSW, Ground-breaking Stuff, Proceedings of the 13th Australian Society of Agronomy

Conference, Perth, Western Australia, 10-14 September 2006. (http://www.regional.org.au/au/asa/2006/concurrent/water/4632_gaydond.htm)

Gaydon, D.S., Robertson, M.J., 2006. Are there pre-sowing indicators for choosing in which seasons to crop wheat into existing lucerne?, Ground-breaking Stuff, Proceedings of the 13th Australian Society of Agronomy Conference, Perth, Western Australia, 10-14 September 2006. (http://www.regional.org.au/au/asa/2006/poster/systems/4623_gaydond.htm)

Latta, R., Bellotti, W., Crawford, M., Dolling, P., Fedorenko, D., Fettell, N., Gaydon, D., Harris, R., Hirth, J., Honeysett, B., Lyons, A., Peoples, M., Robertson, M., Ward, P., 2005. Addressing salinity in southern Australia with alfalfa based high water-use farming systems. In: Managing Saline Soils and Water: Science Technology and Social Issues Proceedings International Salinity Forum. California, USA. 25-27 April 2005, pp. 277-342.

Howden, S.M., Seis, C., Bruce, S., Gaydon, D.S., 2005. Can pasture cropping help the management of climate risks?, Grassland conservation and production: Both sides of the fence. Proceedings of 4th Stipa Conference on Management of Native Grasses and Pastures, Burra SA, FLFR University of Melbourne, Dookie Campus, 11-13 October 2005.

Robertson, M.J., Gaydon, D.S., Latta, R., Peoples, M., Swan, A., 2004. Simulating lucerne/crop companion farming systems in Australia, In: New directions for a diverse planet, Proceedings of the 4th International Crop Science Congress, Brisbane, 2004. (http://www.cropscience.org.au/icsc2004/symposia/6/1/926_robertson.htm)

Ward, P.R., Bellotti, W., Butterly, C., Crawford, M.C., Dolling, P., Federenko, D., Fettell, N., Gaydon, D.S., Harris, R., Hirth, J., Honeysett, B., Latta, R., Lyons, A., Peoples, M.B., Robertson, M.J., 2004. High water use farming systems that integrate crops with perennial pastures, Working with Science and Society, Proceedings of the Salinity Solutions Conference, Bendigo, Victoria, 2–5 August 2004.

Hills, A., Robertson, M. J., Gaydon, D.S., Hall, D., Lacey, T., Ryder, A., 2003. Evaluation of sorghum in Western Australia, Solutions for a better environment: Proceedings of the 11th Australian Agronomy Conference Geelong, Victoria, 2003.

Keating, B.A., Verburg, K., Smith, C.J., Probert, ME., Gaydon, D.S., 2001. Analysis of water balance in alternative dryland farming systems in Australia, In: Bindi, M., Donatelli, M, Porter, J. R. and van Ittersum, M. K. (Eds). Book of Proceedings, 2nd

International Symposium Modelling Cropping Systems, Florence, 16-18 July, 2001, Italy. Florence: European Society for Agronomy; 2001, pp 137-138.

Keating, B.A., Verburg, K., Smith, C.J., Probert, M.E., Gaydon, D.S., 2001. Assessing leakiness in Australia's dryland farming systems. In: Proceedings MODSIM 2001, The Australian National University, (Eds F Ghassemi, D White, S Cuddy, T Nakanishi) pp. 1811-1816. (Modelling and Simulation Society of Australia and New Zealand: Canberra, ACT)

Radajewski, W., Gaydon, D.S., 1991. Solar Drying of Agricultural Products – Technical, Eonomic, and Policy-related Issues, Energy for a Sustainable World, Proceedings of the Australian and New Zealand Solar Energy Society Annual Conference, Flinders University, Adelaide, 1991, pp 246-250.

Radajewski, W., Gaydon, D.S., 1991. Solar Heating System for Plant-Research Greenhouses, Energy for a Sustainable World, Proceedings of the Australian and New Zealand Solar Energy Society Annual Conference, Flinders University, Adelaide, 1991, pp 323-327.

PE&RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (6 ECTS)

- Adapting to climate change: potential future water management strategies for Riverina broad-acre irrigators and the impacts on biodiversity and production (2008)

Writing of project proposal (4.5 ECTS)

- Living with less water: designing viable adaption options for Riverina irrigators (2008)

Post-graduate courses (3.3 ECTS)

- Training in SigmaPlot 11: advanced statistics, graphical presentation; IT Training Solutions, Brisbane (2009)
- Greenhouse gas modelling workshop; CSIRO Ecosystem Sciences, Brisbane (2009)
- Greenhouse management fundamentals; CSIRO Learning and Development, Canberra (2009)
- Decagon devices and ICT International Training workshop; ICT International, University of Queensland, Brisbane, Australia (2010)
- Quantifying model uncertainty: Dr. Daniel Wallach (France), CSIRO Ecosystem Sciences, Brisbane (2011)

Laboratory training and working visits (6.3 ECTS)

- Biophysical issues related to modelling rice-based farming systems; IRRI (2007, 2 times 2008 and 2009)

Invited review of (unpublished) journal (4 ECTS)

- Agriculture, Ecosystems and Environment: climate change impact on land capability using MicroLEIS DSS in Ahar soils, Iran (2008)
- Biosystems Engineering: modelling of water and nitrogen balance the ponded water and soil profile of rice fields (2008)
- Journal of Agricultural Science, Cambridge: challenges for weed management in African rice systems in a changing climate (2010)
- Field Crops Research: evaluation and application of ORYZA200 for irrigation scheduling of puddled transplanted rice to optimize yield and water productivity (2011)

Competence strengthening / skills courses (1.5 ECTS)

- Journal paper writing course; CSIRO Land and Water, Canberra, Australia (2008)
- Professional time management; Australian Institute of management, Brisbane, Australia (2010)

4.1 PE&RC Annual meetings, seminars and the PE&RC weekend (1.5 ECTS)

- Rural Industries Research Forum; New South Wales department of Primary Industries, Griffith (2009)
- Sustainable Agriculture Flagship, Developing R&D Priorities for Productivity Growth in Agriculture; CSIRO, Canberra, Australia (2011)

4.1 Discussion groups / local seminars / other scientific meetings (7.5 ECTS)

- CSIRO Ecosystem Sciences Seminar Series, Canberra, Australia (2007-2009)
- CSIRO Ecosystem Sciences Seminar Series; St Lucia, Brisbane, Australia (2010)
- International Rice-modelling consortium group meetings (2007, 2008)

4.1 International symposia, workshops and conferences (11.6 ECTS)

- Ground-breaking Stuff, Proceedings of the 13th Australian Society of Agronomy Conference; Perth, Western Australia (2006)
- Global issues – Paddock Action, Proceedings of the 14th Australian Society of Agronomy Conference; Adelaide Convention Centre, Adelaide, South Australia (2008)
- 18th World IMACS Congress, MODSIM09-International Congress on Modelling and Simulation; Cairns, Australia (2009)
- Farming Systems Design – International Symposium on Methodologies for Integrated Analysis of Farm Production Systems; Monterey, California, USA (2009)
- NCCARF 2010 International Climate Change Adaption Conference Climate Adaption Futures – Preparing for the unavoidable impacts of climate change; Gold Coast Convention Centre, Gold Coast, Queensland, Australia (2010)

4.1 Lecturing / supervision of practical's / tutorials (3 ECTS)

- APSIM Training course at Wageningen University; 4 days (2008)
- APSIM Training course at International Rice research Institute; IRRI, Los Baños, Philippines (2008)
- APSIM Training course at Bangladesh Rice Research Institute / Bangladesh Agricultural research Institute (BRRI/BARI) (2010)

Curriculum Vitae

Donald Gaydon was born in Toowoomba, Queensland, Australia on 17 Spetember 1967. After finishing secondary school at Toowoomba State High School, he commenced a Bachelor of Engineering (Agricultural) degree at the Darling Downs Institute of Advance Education, Toowoomba, graduating with Credit in 1989. He then worked for four years as an agricultural engineer on the Darling Downs with Queensland Department of Primary Industries (QDPI), building solar grain-drying systems and studying for his Masters degree (in engineering) concurrently. After graduating with his M.Eng, he moved to Brisbane to work on mechanisation of wholesale plant nurseries. In this endeavour, he collaborated with Wageningen University (group of Dr Wim Huisman, Landbouwtechniek) and hosted 5 consecutive WUR Masters students at both his work and home in Brisbane. In 1997, feeling the need for a career change, he resigned his job with QDPI and spent the next 3 years playing acoustic guitar and singing in Brisbane and Gold Coast pubs and clubs. By late 1999 he was ready for another career change, and commenced work with the Australian Government research organisation, CSIRO, in Brisbane as part of a group working on farming systems science. He remains with this employer to this date. In 2007, he relocated to Canberra to commence work on this PhD study through Wageningen University, moving back to Brisbane in late 2009. Since 1999 he has worked in farming systems research in numerous environments throughout Australia, and has on-ground professional experience in Philippines, Bangladesh, Fiji, New Zealand, and USA.