Agricultural Water Abstraction Behaviour in Response to Policy and Climate Change

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The candidate confirms that the work submitted is his own. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Abstract

This thesis presents an assessment of farmers' behaviour in response to current changes in climate and policy in the UK. At present, many catchments in England are considered as over licensed or over abstracted and although water licence trading is regarded as a potential solution to the problem, and is currently possible, high transaction costs and institutional barriers deter farmers from trading. In response, two new water allocation systems have been proposed to provide farmers with the ability to adapt to climate and demand change pressures (i.e. basic and enhanced systems). A review of the current literature suggested farmers' behaviour very much influences the success of policy interventions. Therefore, this study sought to understand the behavioural intentions of farmers in England, and the underlying factors which drive their decision-making, under different climate and policy scenarios. Furthermore, this study examined whether farmers with different behavioural intentions lead to different patterns of abstraction behaviour at the system level, thus providing a means of assessing the current and proposed water allocation systems.

An empirical survey was conducted within the Great Ouse catchment in eastern England, UK, where freshwater availability for crop irrigation is considered highly vulnerable to climate change. The questionnaire, and subsequent interpretation of behaviours, was developed under the theoretical framework of the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Farmers' preferred behavioural intentions were identified under different strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. Furthermore, the TPB explained between 29-65 % of the variance in intention, based on Nagelkerke's R^2, and was similar to the range found by meta-analytical reviews (i.e. 40-49 % based on R^2). In addition, attitude and subjective norm were found to be significant predictors of intention in three of the four scenarios. Overall, farmers believed they have greater volitional control with regards to decision-making in the long-term but less in the short-term. Furthermore, a behavioural farm typology based on farmers' preferred behavioural intentions was used in the development of an Agent-Based Model (ABM) to simulate system level patterns of abstraction behaviour which emerge from individual farm level decision-making. The scenario simulation results indicated the proposed enhanced water allocation system was likely to provide the greatest utility to balance the needs of licence users, at least farmers, whilst protecting the environment.

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List of Acronyms and Abbreviations

ABM	Agent-Based Model
ANOVA	Analysis of Variance
AP	Assessment Point
CAMS	Catchment Abstraction Management Strategies
CAP	Common Agricultural Policy
CO_2	Carbon Dioxide
DEFRA	Department for Environment, Food and Rural Affairs
EA	Environment Agency
EFI	Environmental Flow Indicator
EU	European Union
FAO	Food and Agricultural Organisation
FL	Fully Licensed scenario
HOF	Hands Off Flow
HWUO	High Water Usage Options
IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile Range
IWN	Irrigation Water Need
LWUO	Low Water Usage Options
NQF	National Qualification Framework
NRW	Natural Resource Wales
ODD	Overview, Design concepts, and Details
Q30	High flow
Q50	Moderate flow
Q70	Below moderate flow
Q95	Low flow
RA	Recent Actual scenario
SPSS	Statistical Package for the Social Sciences
TIB	Theory of Interpersonal Behaviour
TPB	Theory of Planned Behaviour

TRA	Theory of Reasoned Action
UK	United Kingdom
UKIA	United Kingdom Irrigation Association
VIF	Variance Inflation Factor

Chapter 1

Introduction

This thesis presents an empirical investigation into farmer water abstraction behaviour in response to policy and climate change in an area of eastern England, where supplemental irrigation is currently used to safeguard crop quality and to maintain expected yields. The current water allocation system in England is considered by the regulatory authorities as inadequate to provide users with the ability to adapt to climate change whilst providing adequate protection for the environment. In response, the Department for Environment, Food and Rural Affairs (DEFRA), who determine policy in England and Wales, have proposed two new water allocation systems, basic and enhanced, which aim to address the inadequacies of the current system. Despite important differences between the proposed systems, the encouragement of water licence trading underpins both. However, despite groups of stakeholders having been consulted, very little is known whether either of these allocation systems will achieve their intended aims. This thesis aims to address this issue and in doing so aid policy decision-makers in the design and implementation of the proposed systems.

This chapter provides a general introduction to this thesis by discussing the importance of this research within the wider context of water resource management and climate change, with a particular focus on agricultural irrigation. Furthermore, it is argued that the success of the proposed water allocation systems largely depend on the response of users' on the ground. It is this unknown factor which underpins the rationale for this research. Finally, this chapter highlights the main aim and subsequent research questions, including an overview of the methodological approaches used, which together form the main structure of this thesis.

1.1 Rationale of the study

1.1.1 A transition in freshwater resource management

Water is clearly an essential natural resource for life on this planet, yet it is also clear that human activities are directly threatening freshwater systems (Vörösmarty et al., 2010). In one of the first global syntheses investigating human and environmental perspectives on water security, Vörösmarty et al. (2010) reported on the level of impact that large-scale activities such as land cover change, urbanisation, industrialisation, as well as engineering projects such as reservoirs, irrigation and catchment transfers are having on the sustainability of these freshwater systems.

Although these human activities bring considerable benefits to society, they also bring unanticipated social, economical, and ecological costs (Gleick, 2003). For example: the construction of the Three Gorges Dam in China displaced more than one million people (World Commission on Dams, 2000); in 1999 27 % of all North American freshwater fauna populations were considered threatened with extinction (Ricciardi and Rasmussen, 1999); and many rivers around the world such as the Nile; Huang He (Yellow); and the Colorado, no longer maintain adequate environmental flows to their deltas during average years (Gleick, 2003).

Evidence gathered in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) indicates that there is high agreement and robust evidence that freshwater related risks of climate change increase considerably with increasing greenhouse gas concentrations (Cisneros et al., 2014). In particular, for every degree Celsius of global warming approximately 7 % of the global population is projected to be exposed to a 20 % decrease in renewable freshwater resources. Furthermore, by the end of this century, under the Representative Concentration Pathway 8.5 scenario, climate change is likely to increase the frequency of droughts within the agricultural sector, due to less precipitation and increased evapotranspiration, in current dry regions such as southern and central Europe and the Mediterranean. Overall, climate change, coupled with increased demand and non-climatic human activities previously mentioned, are likely to exacerbate local variability within the hydrological system and increase the vulnerability of those areas to floods and droughts (Cisneros et al., 2014).

However, in the last few decades a transition in freshwater resource management has occurred which attempts to tackle these unanticipated issues and potential risks of climate change. This transition complements the large-scale, high-cost, centralised infrastructure projects with low-cost, community-scale, decentralised systems. Largely instigated by major water reform policies prescribed by the International Food Policy Research Institute and the World Bank during the 1990s (Rosegrant and Binswanger, 1994) these transitional approaches include: technological investment at the farm and catchment scale; encouragement of farmer abstraction groups to manage and improve current allocation systems; and to apply economic tools such as water markets and pricing. These water reforms aim to encourage: efficiency; productivity; and equitable distribution with the long-term aim of providing a sustainable allocation system to meet the demands of users without detriment to the environment (Gleick, 2003).

1.1.2 Experiences of water markets

The transition from large-scale, centralised, infrastructure projects to achieve continuous supplies of water to meet demand for small-scale, community based, water market mechanisms has struggled to achieve its intended aim (Garrick et al., 2013). Australia, Chile, South Africa, and the United States have encouraged and permitted water rights trading to improve allocation efficiency (Erfani et al., 2015). However, these mature water markets have experienced major problems ensuring sustainable environmental flows, with governments in Australia and the United States having to buy back water entitlements to protect the environment. In Australia, the government is in the middle of a $3.1 billion programme to buy back water for the environment (Wheeler et al., 2013). As a result of these unanticipated costs, Australia, South Africa and the United States, as well as emerging water markets in countries such as China (Zhang et al., 2014) and parts of the UK (DEFRA, 2016c), are in the process of reforming water allocations to improve efficiency and protect the environment (Young, 2014).

In China, where water is readily available in the south but increasingly scarce in the north, a pilot project in the city of Zhangye found that the main reasons farmers were discouraged from saving water and trading surplus were due to high transaction costs in some areas and where transaction costs were low reasons included: management; legal;

administrative; and fiscal barriers (Zhang, 2007; Zhang et al., 2009, 2014). In parts of the UK similar institutional barriers which have discouraged water trading have been recognised, which restrict the ability to increase water allocation efficiency and also to meet water quality standards set by the European Union (EU) Water Framework Directive (EA, 2008). The same barriers to successful water markets are apparent in many developing countries (Thobani, 1998).

Garrick et al. (2013) supported these findings and summarised water markets as systems which involve two factors: first, a system which balances demand for human requirements and demand for sustainable flows to protect the environment; and second, a system which establishes tradeable water rights to allocate water within and across productive sectors. The experiences of mature water markets in Australia, Chile, South Africa, and the United States indicate that the current policies in these countries do not fully protect the environment and further institutional reforms are required (Bjornlund and McKay, 2002). Therefore, a potential framework for the successful implementation of a water market should include: a multiphase sequencing of reform; strategic investment in institutional tutorial transition costs; and institutional choices that preserve future flexibility to adjust water rights and diversion limits to manage social and environmental externalities (Garrick et al., 2013).

However, institutional barriers are not the only obstacle in successfully implementing a water market or associated allocation mechanisms. The success of any new allocation mechanism is also largely dependent on the actual users whom the allocation reforms will directly affect. Several studies have shown that farmers' behaviour very much influences how and to what success policy proposals are realised on the ground (Moon and Cocklin, 2011; Home et al., 2014; Feola et al., 2015). Furthermore, Feola et al. (2015) suggested that understanding farmers' behaviour is essential to identifying where policy intervention may be required, or should be avoided, as well as where it can be used to inform the design and implementation of reforms.

Bjornlund (2003) examined farmer participation in water markets in southeastern Australia during the first ten years of operation starting in 1989. The main findings of the study indicated that an increasing number of crop irrigation abstractors participated in temporary licence trades (i.e. weekly, monthly, or seasonal) as more farmers increasingly understood the operations and the advantages of a secure, reliable, fast, and cheap water transfer. However, very few farmers participated in permanent water licence trading due to: differential tax treatment; policy uncertainty; institutional barriers such as administrative complexity and cost associated with permanent trades; and crop irrigation abstractors' perception that water rights are an inherent part of their property. The results of this study, and those previously mentioned suggest that institutional barriers and high transaction costs deter farmers from trading; and importantly the success of any new allocation method is largely dependent on the level of participation by the users on the ground.

1.1.3 Agricultural irrigation and climate change

The use of freshwater for crop production by irrigation from rivers, reservoirs, lakes, groundwater aquifers and inter-catchment transfers are all considered sources of blue water; precipitation in regards to crop production is considered a green water source (Rost et al., 2008). Agriculture in general is responsible for approximately 85 % of total global water consumption of both blue and green freshwater resources (Shiklomanov et al., 2003). Crop irrigation accounts for the largest human withdrawal and consumption (i.e. withdrawal minus return flow to the river) of blue water globally, accounting for almost 70 % of this resource (Shiklomanov et al., 2003). However, to put this in perspective, 80 % of global croplands are rainfed, from which 60-70 % of the world's food is produced (Falkenmark and Rockström, 2004). In many places, such as parts of the UK, blue water is used to supplement green water to improve crop quality and not solely to maintain expected yields.

Crop irrigation ultimately relies on freshwater resources being available for abstraction. Whether a farmer abstracts the water and to what extent they use that water for crop irrigation is a human behavioural factor regarding crop management. Nonetheless, crop water requirement is governed by a balance between atmospheric moisture deficit and soil water supply. Therefore, any change in climate (i.e. precipitation, temperature, or radiation) will affect crop water requirements and also the amount of water available for abstraction at the catchment scale (Cisneros et al., 2014).

Although the IPCC Fifth Assessment Report 2008 indicated that global trends in precipitation from several datasets during the last century were statistically insignificant (Bates et al., 2008), regional observations indicate that the most severe floods and droughts since the 1950s have been experienced between 1990 and 2010 (Arndt et al., 2010). The majority of regional changes in precipitation are considered to be attributable to either internal variability regarding atmospheric circulation or to global warming (Lambert et al., 2004; Stott et al., 2010). Despite the uncertainty regarding the climatic drivers Zhang et al. (2007) estimated that twentieth century anthropogenic forcing contributed considerably to observed changes in global and regional precipitation. In addition, there has been a continual decrease in global and regional evapotranspiration since the middle of the last century which has been attributed to changes in precipitation; diurnal temperature range; aerosol concentration; net solar radiation; vapour pressure deficit; and wind speed (Fu et al., 2009; McVicar et al., 2010; Miralles et al., 2011; Wang et al., 2011). All of these factors greatly influence crop water requirements (Allen et al., 1998) particularly as precipitation and evaporation are the main climatic drivers controlling freshwater resources (Cisneros et al., 2014).

A series of different projections regarding changes in irrigation demand and water availability, based on different global climate models and greenhouse gas emission scenarios, report a high confidence that irrigation demand will increase by more than 40 % across Europe, United States, and parts of Asia by 2080 (Cisneros et al., 2014). However, some of these projections also indicate that irrigation demand could decrease in parts of India, Pakistan, and other parts of Asia due to an increase in precipitation. In addition, where poor soil is not a limiting factor, the physiological and structural response of crops to elevated atmospheric carbon dioxide (CO_2) concentration (i.e. CO_2 fertilisation) might alleviate some of the adverse effects of climate change by reducing irrigation demand (Konzmann et al., 2013). Overall, it is projected that irrigation demand will exceed local freshwater availability in many areas (Wada et al., 2013).

1.1.4 The UK transition

In regards to the UK, DEFRA determine policy in England and Wales. These policies are regulated by the Environment Agency (EA) and Natural Resource Wales (NRW) in

Table 1.1: Abstractions licences in England and Wales (2014)

Sector	Licences (%)	Licensed volume (%)	Licensed volume used (%)
Public water supply	8	18	60
Agriculture (spray irrigation only)	48	1	26
Agriculture (excluding spray irrigation)	14	<1	27
Electricity supply industry	3	69	27
Other industry	18	9	40
Fish farming, cress growing, and amenity ponds	3	3	54
Private water supply	5	<1	24
Other	1	<1	13
Total	100	100	35

Source (DEFRA, 2016a)

England and Wales respectively. Anyone wishing to abstract more than 20 m^3 day^{-1} of water requires an abstraction licence. Table 1.1 highlights the percentage of: licences allocated; total volume allocated; and licensed volume abstracted per sector in England and Wales in 2014 (DEFRA, 2016a). Overall, only 35 % of the volume licensed to be abstracted was actually used, but this was dependent on water availability in addition to changes in demand. Furthermore, although the electricity supply industry accounted for the majority of licensed volume, this sector is generally considered as a non-consumptive user as nearly all of the water it abstracts is returned to the catchment. Other non-consumptive sectors include fish farming, cress growing, amenity ponds, and some other industry. Therefore, in regards to consumptive users, the public water supply sector was by far the largest abstractor (i.e. 18 % of licensed volume) with spray irrigation licence users only accounting for 1 % of total licensed volume.

The largest proportion of irrigated agriculture is concentrated in eastern England (i.e. the Anglian region) employing over 50,000 people and contributing £3 billion annually to the region's economy (Leathes et al., 2008). Furthermore, in 1995 50 % of the total irrigated land in England and Wales was located in the Anglian region (Knox et al., 2000) and in 2014 the area accounted for 36 % of all spray irrigation licences and 62 % of estimated spray irrigation abstractions (DEFRA, 2016a). In addition, Knox et al. (2010) reported that since 1990 there has been a marked increase in irrigation of high value crops such as potatoes and field vegetables, largely driven by supermarkets demand for quality; consistency; and continuity of supply, which can only be guaranteed by irrigation. However, this region is one of the driest and most water stressed regions in the UK, with nearly three quarters of the water licensed for irrigation in 2006 located in catchments under severe levels of water stress according to the UK Irrigation Association (UKIA) (i.e. with 47 % over-licensed; 23 % over-abstracted; and 21 % with no water available for further licensing) (UKIA, 2007). Furthermore, several studies have shown that freshwater available for irrigation in this region will be vulnerable to projected changes in climate (Gowing and Ejieji, 2001; Gibbons and Ramsden, 2008; Henriques et al., 2008; Knox et al., 2009).

Therefore, the need to improve efficiency at the farm and catchment scale has become increasingly important as water availability has become increasingly competitive between users and the environment. Several initiatives have previously been implemented towards alleviating some of this pressure such as: restoring sustainable abstractions (EA, 2010); and requiring spray irrigation licence users to demonstrate efficiency as part of their licence application process (Knox et al., 2012). However, DEFRA and the EA consider the current water allocation system in England as inadequate to provide users with the adaptive strategies they require to meet their needs whilst providing sufficient protection to the environment (EA, 2008; DEFRA, 2011).

Consequently, DEFRA have proposed two new water allocation systems, basic and enhanced, which aim to address the inadequacies of the current system, and which are to be implemented by the early 2020s (see Table 1.2). Although both of the proposed systems encourage water licence trading by removing seasonal restrictions (i.e. licences which can only be used during certain months) and time limited licences (i.e. licences which expire after a certain number of years), the enhanced system offers greater incentives for trading. These include access to ‘bonus water’ (i.e. water which is available for abstraction during high flow periods in addition to licensed volumes); gradual implementation of Hands off Flow (HOF) conditions rather than simply on or off as with the current and basic systems (i.e. when the EA stop users from abstracting water during certain low flows in order to protect the environment or other users); and pre-approved trading rules to increase the speed and ease of trading.

Table 1.2: Current and proposed water allocation systems for England

Measure	Current allocation system	Proposed allocation systems	
		Basic	Enhanced
Abstraction >20 m^3 day^{-1}	Licence required	Permit required	Permit required
Daily, annual, and return licence limits	Yes (fixed)	Yes (fixed)	Yes (share)
Seasonal restrictions	Yes	No	No
Time limited licences	Yes	No	No
Hands off Flow (HOF) conditions for some licences	Yes	Yes	Yes
Low flow conditions for those without HOF conditions	No	Yes	Yes
'Bonus water' during high flows in addition to licence	No	No	Yes
Water licence trading	Yes	Yes	Yes
Pre-approved trades	No	No	Yes

Source (DEFRA, 2016c)

These additional incentives for water licence trading, under the enhanced system, are made possible as annual licence limits would not be fixed, as they are with the current and basic systems, but accounted for as shares of available water within a catchment or sub-catchment. The type of proposed system to be implemented depends on whether DEFRA consider a catchment as basic or enhanced. Classification of catchments is still ongoing but the main determining factor is likely to concern the potential for water licence trading related to the cost of implementing an enhanced catchment, as users are required to have smart meters installed in order for the regulatory authorities to calculate water use and availability accurately (DEFRA, 2016c).

Furthermore, licences will become permits under the proposed systems and consist of three parts: water account conditions; site specific conditions; and standard catchment rules. The water account conditions consist of daily, annual, and return licence limits and are stored online to facilitate trading. Site specific conditions relate to any conditions which are unique to a particular licence and for most users will be transferred from their existing licence. Standard catchment rules will apply to everyone and relate to: common HOF conditions; trading rules; and low flow conditions. The latter are restrictions which can be imposed by the regulatory authority for those without HOF conditions, in order to protect the environment and other users.

1.2 The need for further research

England is currently in the process of a major transition in water resource management. The proposed water allocation systems are designed to address the inadequacies of the current system, largely by encouraging water licence trading in order to increase efficiency, whilst providing adequate protection to the environment. These issues are particularly apparent in regards to irrigation within the Anglian region, in eastern England. The success of the proposed water allocation systems, at least in regards to increasing efficiency within the irrigation sector, is very much dependent on how likely users are to engage with the new systems, in particular to trading. Although experiences of water markets elsewhere, and consultations with some users in the UK (DEFRA, 2014b, 2016b), may provide some understanding of potential engagement, no formal scientific approach has been made to attempt to measure, or understand farmers' behaviours with regards to the proposed water allocation systems.

Therefore, further research is required to understand farmers' behaviours, under different scenarios of water shortage and surplus, with regards to the proposed water allocation systems. In addition, an investigation which aims to understand whether a farm typology based on farmers' behaviours, rather than traditional economic or physical descriptors, could provide a valuable tool for policy decision-makers involved with the design and implementation of the proposals. Finally, an understanding of the potential system level patterns of abstraction behaviour which could emerge from individual farm scale decisions under the proposed water allocation systems is essential. This research intends to inform policy decision-makers involved with the proposals and, more generally, assess the potential effectiveness of the transition in freshwater resource management in England by addressing these issues.

1.3 Aim, research questions and methodological overview

The main aim of this thesis was to understand farmers' behavioural intentions under different climate and proposed water allocation system scenarios, in order to assess whether the proposals will achieve their intended aim. Three research questions were formulated to address this main aim.

Research question 1: *What are farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England? And which underlying predictors of intention most influence their decision-making?*

As previously mentioned, and discussed in more depth in the following chapter, there is a clear need to understand farmers' preferred behavioural intentions as this heavily influences the success of the proposals at the ground level. Therefore, an empirical investigation was conducted, in a selected study area in the Anglian region, with the main aim of understanding farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems. The investigation also collected data concerning farm attributes and social demographics. The questionnaire, and subsequent interpretation of behaviours, was developed under the theoretical framework of the Theory of Planned Behaviour (TPB) (Ajzen, 1985).

Research question 2: *If farmers share similar behavioural intentions under different scenarios how can traditional farm typologies incorporate these preferred behaviours?*

Traditional farm typologies tend to concentrate on particular farm attributes such as farm income, size, or output rather than on preferred behavioural intentions. This study presents a farm typology based on the preferred behavioural intentions of farmers identified. Furthermore, statistical analyses were conducted to examine similarities and differences between farm types in regards to: farm attributes; social demographics; licence characteristics; and past abstractions from 2008 to 2012. This study offers one of the first typologies designed for policy decision-makers to understand which farm types are more likely to engage with the proposed water allocation systems and therefore aid in deciding which catchments could be considered basic or enhanced.

Research question 3: *What potential system level patterns of abstraction behaviour emerge from individual farm scale decisions under different policy and climate scenarios?*

This final research question addresses the challenge of developing a model to assess potential patterns of catchment level water abstraction behaviour which emerge from individual farm scale decisions under different water allocation systems (i.e. current and proposed) and climate scenarios. While sophisticated hydrological models (Gosling et al., 2011) and crop models exist (Allen et al., 1998), few successfully integrate farmer decision making (Feola et al., 2015) and none do so in the context of the proposed water allocation systems in England. Therefore, this study presents the development of an Agent-Based Model (ABM) that utilises the farm typology that has been developed. The model is capable of modelling the preferred behaviours of individual farmers and exploring what system level patterns of abstraction behaviour emerge under the different policy and climate scenarios. Furthermore, particular farm indicators are used to present the outputs from the model and measure the system level patterns of abstraction behaviour.

1.4 Thesis structure

This chapter has provided a general introduction outlining the main rationale and areas for further research which this thesis aims to address. Chapter 2 presents a critical review of the main bodies of literature regarding measuring individual behaviour; incorporating preferred behaviours into farm typologies; and modelling individual behaviour at the farm and catchment scales. As a result, Chapter 2 highlights the main research gaps this thesis aims to address. Chapter 3 introduces the study area which was the focus of this investigation. Chapter 4, 5, and 6, are associated with each of the research questions previously discussed and therefore present the methodologies and results of these individual studies. Finally, Chapter 7 presents a discussion of the main results of this research placing the findings within the broader context of agricultural water resource management and climate change in the UK. Furthermore, this final chapter presents the main conclusions and policy applications of this research along with some of the limitations of the methods and potential areas for further research.

Chapter 2

Literature review

The previous chapter discussed the proposed water allocation systems which are to be introduced in England. In particular, Chapter 1 discussed the importance, from a policy decision-making perspective, of understanding how users on the ground (i.e. those who the proposals are going to directly effect) are likely to respond and engage with the proposed water allocation systems. That is, at least with the parts that they will have control over such as deciding whether or not to trade, rather than catchment rules which are enforced to protect the environment from over abstraction. Furthermore, this thesis is particularly interested in how the proposed water allocation systems will effect irrigation farmers, and therefore the term term farmers refers to spray irrigation licence users only, not farmers who abstract for other purposes (see Table 1.1). This chapter critically reviews the main bodies of literature related to each of the three research questions presented previously (see Section 1.3). In particular, this chapter examines: farmers' behaviours with regards to behavioural approaches, limitations, and extensions; farm typologies including limitations and incorporating behaviours; and lastly approaches used to model farmers' behaviours, and how these models can be used to inform policy decision-making. Finally, this chapter highlights the main research gaps this thesis aims to address.

2.1 Farmer behaviour

The behavioural approach within the fields of agricultural and policy decision-making is not a recent concept and is thought to have originally begun with the 'satisficing' concept during the 1950s (Simon, 1957). This concept acknowledged that people do not necessarily indulge in economically optimal decision-making but instead may optimise social, intrinsic, or expressive goals. Despite the growing necessity and increasing application of the behavioural approach over the following decades, particularly in policy driven studies (Wolpert, 1964; Gasson, 1973), it has often been regarded as an additional component of rational, or neo-classical economic models (Beedell and Rehman, 2000), rather than a separate entity partly because the main criticism of it is that it overemphasises the role that attitude has on determining behaviour and partly due to the lack of any real theoretical foundation (Burton, 2004). However, with advancements in the field of social psychology, such as the Theory of Planned Behaviour (TPB) (Ajzen, 1985), the number of studies incorporating farmer decision-making rapidly increased (Burton, 2004; Poppenborg and Koellner, 2013) providing a practical and theoretical basis for the growing amount of research on farmers' attitudes and intentions (Beedell and Rehman, 2000).

Morris and Potter (1995) provided a valuable definition of behavioural approaches in agricultural studies as those that: a) seek to understand the behaviour of individual decision-makers, usually the farmers or land managers, directly responsible for the land; b) focus on psychological constructs such as attitudes, values, and goals but also commonly gather additional relevant data such as farm structure, economic situation, successional status; and c) employ largely quantitative methodologies, in particular psychometric scales such as Likert-type scaling procedures (Likert, 1932), for investigating psychological constructs such as those of the TPB.

2.1.1 The Theory of Planned Behaviour (TPB)

The TPB is an extension of the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975) and was required due to the original model's limitations in dealing with behaviours where individuals fail to have complete volitional control in regards to performing, or not performing, a particular behaviour (Ajzen, 1991). Furthermore, it is one of the most frequently cited and influential models for the prediction of human social behaviour (Ajzen, 2011) and has regularly been supported with empirical evidence (Armitage and Conner, 2001). A central factor in the theory is an individuals' intention to perform a given behaviour. Intentions are assumed to capture the motivational

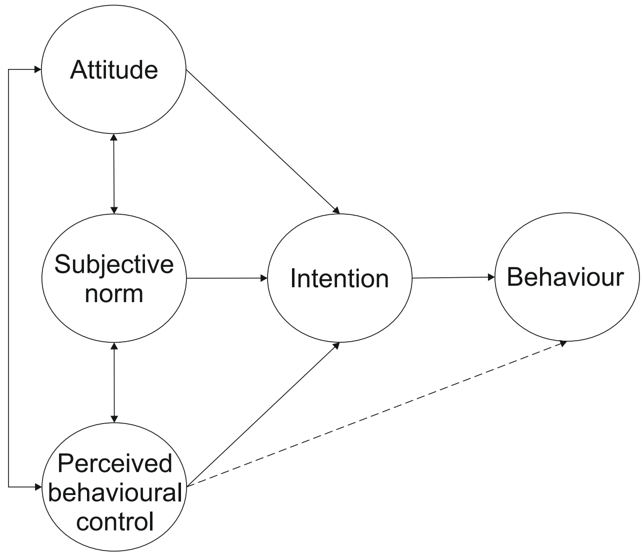

Figure 2.1: The Theory of Planned Behaviour (adapted from Ajzen (1991))

factors that influence a behaviour and therefore the stronger the intention the more likely the behaviour will be performed.

Figure 2.1 illustrates the main constructs of the TPB with the direct antecedents of intention including attitude (i.e. an individuals' overall positive or negative evaluation of performing, or not performing, a particular behaviour); subjective norm (i.e. the social pressure an individual might feel towards performing, or not performing, a particular behaviour); and perceived behavioural control (i.e. the degree of volitional control an individual feels they have over performing, or not performing, a particular behaviour). Consequently, the strength of an individuals' intention to perform, or not perform, a particular behaviour depends on the level, or strength, of that individuals' attitude; subjective norm; and perceived behavioural control (Armitage and Conner, 2001). Furthermore, the constructs of attitude; subjective norm; and perceived behavioural control are based on associated salient behavioural; normative; and control beliefs about the particular behaviour, respectively (Ajzen, 1991).

The relative importance of these three constructs in regards to predicting intention varies depending on the type of behaviours and nature of the situation (Ajzen, 1991). Furthermore, perceived behavioural control is also considered a direct antecedent of behaviour based on the rationale that however strong an individuals' intention is to perform, or not perform, a particular behaviour, the actual performance of said behaviour can depend on personal and environmental barriers. Therefore, this direct relationship between perceived behavioural control and actual behaviour becomes more important as volitional control decreases (Ajzen, 1991), to the extent that perceived behavioural control should be able to directly predict actual behaviour (Armitage and Conner, 2001). Conversely, where an individual has complete volitional control perceived behavioural control should have very little or no influence on their intention to perform, or not perform, a particular behaviour.

Poppenborg and Koellner (2013) investigated whether attitudes toward ecosystem services determine agricultural land use practices. The study examined farmer's decision-making processes, based on the TPB, with respect to land use in a South Korean watershed. Decisions between a variety of cropping patterns and practices were compared among farmers as a function of their attitude towards particular ecosystem services including: biomass production; prevention of soil erosion; improvement of water quality; and conservation of plants and animals. The study found that decisions to plant perennial crops are most often accompanied by positive attitudes toward ecosystem services whereas no differences were found between organic and conventional farming. Furthermore, positive attitudes toward ecosystem services were most likely held by farmers with high income indicating that a farmer's financial means were a key determinant of farmers' environmental attitudes.

Similarly, Wauters et al. (2010) investigated the adoption of soil conservation practices of farmers in Belgium based on the TPB. The results of the study showed that the most important explanatory factor was attitude towards soil conservation practices. They concluded that future interventions directed at promoting erosion control measures should be directed towards changing farmers attitudes, although further investigation was required to understand the negative attitudes of farmers.

2.1.2 Limitations of the TPB

Despite the popularity of the TPB, particularly within the health sciences (Sniehotta et al., 2014), it has also had considerable criticism most notably concerning efficacy (i.e. the predictive ability of the model) and sufficiency (i.e. the assumption that the effect of all other biological, social, environmental, economic, cultural, and unconscious influences are hypothesised to be accounted for by the TPB constructs) (McCarty, 1981; Hardeman et al., 2002; Chatzisarantis et al., 2005; Sniehotta et al., 2014).

In regards to efficacy, several meta-analytical reviews reported that although the TPB explained between 40-49 % of the variance in intention, it only explained between 26-36 % of the variance in actual behaviour (Sheeran et al., 1999; Armitage and Conner, 2001; Hagger et al., 2002; Trafimow et al., 2002; Schulze and Wittmann, 2003; McEachan et al., 2011). This common occurrence has been described as the intention-behaviour gap (Sniehotta et al., 2005), or the issue of inclined abstainers (i.e. despite an individual's intention they fail to act out the behaviour) (Orbell and Sheeran, 1998). The intention-behaviour gap indicates low correlations between the TPB constructs and therefore a failure to account for the majority of variability in behaviour (Sniehotta et al., 2014).

Ajzen (2011) argued that even with carefully considered measures (i.e. well designed salient beliefs), the most one can reasonably expect in regards to correlations between constructs are coefficients of approximately .60 (i.e. the weaker the correlation the less the constructs can explain the variance in intention and therefore behaviour). This statement corresponds with several meta-analytical reviews, for example, multiple mean correlations between attitudes, subjective norms, and perceived behavioural control with intention ranged from .59 to .66 (Cheung and Chan, 2000; Armitage and Conner, 2001; Schulze and Wittmann, 2003); and .53 between intention and behaviour (Sheeran, 2002). Furthermore, several studies have shown that the predictive ability of the TPB model is often reduced depending on: the length of the study (i.e. the predictive ability of the model decreased as the length of the study increased due to external events intervening and changing individuals' salient beliefs) (Sheeran et al., 1999; Conner et al., 2000); and whether measures were taken objectively or self reported (i.e. the predictive ability of the model decreased where outcome measures were measured objectively) (Ajzen, 2011; McEachan et al., 2011). Finally, Ajzen (2011) suggested that where studies which occurred over a short time period reported a large intention-behaviour gap (Kor and Mullan, 2011), the cause was often due to actual control not being accurately represented by perceived behavioural control. In addition, intention-behaviour gap has also been attributed to behaviours which require different social or psychological drivers, such as efficiency and curtailment behaviours (i.e. behaviours which are one-off or occur regularly respectively) (Gardner and Stern, 1996; Russell and Fielding, 2010). However, beyond methodological failures and different types of behaviours being assessed, a low intention-behaviour relation could simply indicate the limits of this particular behavioural approach (Ajzen, 2011).

In regards to sufficiency, several studies have criticised the TPB model for its exclusive focus on rational reasoning (Sniehotta et al., 2013) and ignoring unconscious influences such as habits (Conner and Armitage, 1998; Abraham and Sheeran, 2003; Gardner et al., 2011); affects; emotions; and irrationality (Sutton, 1994; Conner and Armitage, 1998; Richard et al., 1998; Rapaport and Orbell, 2000; McEachan et al., 2011; Wolff et al., 2011; Carraro and Gaudreau, 2013; Conner et al., 2013; Sheeran et al., 2013). However, Ajzen (2011) argued that there is no assumption in the TPB that the salient beliefs are formed in a rational or unbiased fashion, and in fact are more likely to be irrational or inaccurate as the individual beliefs about a behaviour are often incomplete or self serving. Therefore, regardless of being rational or irrational, attitudes, subjective norms, and perceived behavioural control follow on from beliefs and it is only in this sense that behaviour is said to be planned (Geraerts and McNally, 2008).

2.1.3 Adding past behaviour as a predictor variable

Nonetheless, several studies, predominantly within the health sciences, provided evidence to suggest that additional predictor constructs, such as habit which was used within Triandis' Theory of Interpersonal Behaviour (TIB) (Triandis, 1979), can and have been used to address both of the main limitations (Conner and Armitage, 1998). Additional predictor variables have included: past behaviour (Kor and Mullan, 2011; Norman and Cooper, 2011); similarity (Rivis et al., 2011); uncertainty avoidance (Wolff et al., 2011); and self-concept (Hassandra et al., 2011). The possibility of adding additional predictors, or constructs, was in fact originally suggested (Fishbein and Ajzen, 1975; Ajzen, 1991) which led to the updated TPB from the TRA by adding perceived behavioural control. However, Ajzen (2011) argued that the addition of further predictors, or constructs, should be made with caution and after empirical exploration.

Adding past behaviour as a means of improving the predictive measure of intention, has been supported by considerable empirical evidence (Conner and Armitage, 1998; Abraham and Sheeran, 2003; Ajzen, 2011; Kor and Mullan, 2011; Norman and Cooper, 2011). For example, in the study by Abraham and Sheeran (2003), the amount of variance in physical activity explained by the TPB increased from 36 % to 53 % with the addition of past physical activity. However, Ajzen (2011) argued that past behaviour should not be included as an additional construct since it constitutes a causal antecedent of intention, and therefore fails to meet the original criteria for the TPB. In particular, it is difficult to argue that the performance of a behaviour in the past directly causes an individual's current intention; rather it is usually considered a proxy for habit when performed routinely in a stable environment (Ajzen, 2011; Norman and Cooper, 2011).

Nevertheless, in three meta-analytic syntheses the addition of past behaviour raised the proportion of explained variance in intention by between 10 % and 13 % (Albarracin et al., 2001; Sandberg and Conner, 2008; Rise et al., 2010). Ajzen (2011) explained that one possible conclusion to this is that intentions may not only be determined by attitudes, subjective norms, and perceived behavioural control but by one or more additional variables, and these additional variables are captured, at least partly, by measures of past behaviour.

2.2 Farm typologies

The use of farm typologies, particularly with regards to policy decision-making, is not a new concept and has been used for several decades (Kostrowicki, 1977; Whatmore et al., 1987; Landais, 1998; Andreoli and Tellarini, 2000; Daskalopoulou and Petrou, 2002; Köbrich et al., 2003; Tavernier and Tolomeo, 2004). Most commonly they are used to assist policy decision-makers with the design, implementation, or assessment of the performance of agricultural or environmental schemes at the farm and regional scales (Andersen et al., 2007).

Farm typologies are often designed based on some type or combination of farm characteristic, such as: farm size; income; capital; labour; production pattern; soil quality; managerial ability; or output. A farm is the key level at which decisions are made in relation to the management of farmland and natural resources, and a typology offers policy decision-makers a tool to assess farms by these particular criteria or indicators, as well as providing a means to better understand the underlying drivers behind farm management decisions (Andersen et al., 2007).

The EU farm typology, for example, is used to inform policy decision-makers about multiple agricultural issues such as the performance of particular schemes linked with the EU Common Agricultural Policy (CAP) (Andersen et al., 2007). However, the rational behind the EU farm typology is exclusively economic, with the main distribution of farms categorised by farm income. Although farm income can be argued to be one of the main drivers behind farm management decisions and policies, CAP reforms are no longer simply about production and economy; rather they have shifted towards the environment and landscape. Andersen et al. (2007) therefore suggested that the EU farm typology should be updated to include an environmentally based extension, which would classify farms into farm types that are more homogeneous in their environmental performance rather than simply by their income.

2.2.1 Limitations of farm typologies

Although farm typologies clearly offer policy decision-makers a useful tool for categorising farms, and making more informed policy decisions, their main criticism is that they fail to fully capture true farmer behaviour and are therefore of limited value in supporting policy formulation (Guillem et al., 2012). In regards to the EU farm typology, the suggestion proposed by Andersen et al. (2007) to include environmental performance indicators, relied on further statistical measures of environmental pressures caused by farm management practices, rather than any assessment of true farmer behaviour.

Therefore, to address this main criticism, and partly due to the lack of success or changes to such environmental policy schemes (Brotherton, 1991; Morris and Potter, 1995; Wilson, 1996; Winter, 2000; Burton, 2004), policy decision-makers realised they required more sophisticated methods of anticipating farmers motivation to comply with new policy approaches, thus, providing a catalyst for research in this field (Austin et al., 1998; Burton, 2004; Emtage et al., 2006; Guillem et al., 2012). In addition, Emtage et al. (2006) reviewed a number of studies which used landholder typologies in the development of natural resource management programmes in Australia. They concluded that policy decision-makers needed to: better understand the variation in socio-economic circumstances and values of individuals; understand how this variation affects their attitudes and behaviour; and how the differences lead to variation in the impacts of policy reforms across the community or target area.

2.2.2 Incorporating decision-making into farm typologies

As previously discussed, over the last few decades considerable research has focussed on understanding farmer's intentions and behaviours (Austin et al., 1998; Garforth and Rehman, 2006; Gorton et al., 2008; Barnes et al., 2009; Sutherland et al., 2011) by linking behavioural theories from the field of social psychology with the field of agricultural decision-making (Burton, 2004). Guillem et al. (2012) indicated that studies which have incorporated farmer decisions have improved the relevance of policy formulation and have been a major factor in increasing the successful development and use of farmer typologies (Schmitzberger et al., 2005; Emtage et al., 2006, 2007; Gorton et al., 2008; Pike, 2008; Barnes et al., 2011; Poppenborg and Koellner, 2013).

There are two main approaches used to develop farm typologies based on a range of farm characteristics: the data-driven approach; and the conceptual approach. The data-driven approach often utilises multi-variate techniques, such as cluster analysis, to search for patterns in the data which can be identified as farm types (Köbrich et al., 2003; Acosta et al., 2014). The conceptual approach usually pre-defines the types based on a particular research aim and subsequently conducts statistical tests to search for any similarities or differences in farm characteristics (Phillip et al., 2010).

2.3 Modelling farmer behaviour

Traditional neo-classical economic models have for many years been used to model farmer decision-making at different spatial scales (Willock et al., 1999; Edwards-Jones, 2006). Whilst these types of models provided a useful tool for policy decision-making, they have also received criticism for assuming individuals only make rational economic decisions, whilst in reality, individual decisions are often based on a combination of psychological constructs such as attitude, subjective norms, and perceived behavioural control (Ajzen, 1991; Edwards-Jones, 2006). Therefore, the traditional models of farmer decision-making have been increasingly supplemented since the 1990s by simulation models, which integrate theoretical frameworks from psychology in order to fully understand farmer behaviour at the farm or individual scale. Such models include: system dynamic modelling (Guerrin, 2001; Keating et al., 2003; Darnhofer et al., 2011); discrete event modelling (Sokhansanj et al., 2006); and, most commonly, Agent-Based Modelling (ABM) (Railsback, 2001; Janssen, 2002; Strand et al., 2002; Edwards-Jones, 2006; Grimm et al., 2006; Janssen and Ostrom, 2006; Grimm et al., 2010).

2.3.1 Agent-Based Models (ABM)

Janssen and Ostrom (2006) defined ABM as the computational study of social agents, such as farmers, as evolving systems of autonomous interacting agents. The development of ABM can be traced back to early research by Neumann and Burks (1966), who provided a technical methodology for modelling multiple interacting agents during their work on cellular automata. This modelling approach was popularised during the 1970s after a study by Gardner (1970), who illustrated how following simple rules of local interaction could lead to the emergence of complex global patterns. However, cellular automaton models were limited in their ability to model the heterogeneity of agents beyond their specific location and history (Janssen and Ostrom, 2006). Therefore, early studies focussing on ABM, although theoretical, such as work on segregation (Schelling, 1971) and prisoner's dilemma strategies (Axelrod and Hamilton, 1981), showed how simple rules of interaction could explain more complex spatial patterns and levels of cooperation at the larger system scale (Janssen and Ostrom, 2006).

ABM are now widely used within the fields of ecology (DeAngelis et al., 1992; Shugart et al., 1992; Van Winkle et al., 1993; Grimm, 1999; Gimblett, 2002; Huse et al., 2002; DeAngelis and Mooij, 2005; Grimm and Railsback, 2013); social sciences (Epstein and Axtell, 1996; Gilbert and Troitzsch, 2005; Epstein, 2006; Gilbert, 2007; Billari and Prskawetz, 2012); economics (Tesfatsion, 2002; Fagiolo et al., 2007); and geography, particularly land use change, (dAquino et al., 2002; Parker et al., 2003; Evans and Kelley, 2004; Brown et al., 2005; Matthews et al., 2007). The increase in popularity of these models has partly been due to the advancements in computer science over the last two decades, but also in their ability to consider aspects often ignored in analytical, or neo-classical economic models, such as variability among individuals; local interactions; complete life cycles; and individual behaviour adapting to the individual's changing internal and external environment (Grimm et al., 2006).

2.3.2 Limitations of ABM

The main limitation of ABM lies within their development, largely criticised for being far more complex in structure than typical analytical models (Grimm et al., 2006). Furthermore, ABM are also often more difficult to analyse, understand and communicate than traditional analytical models (Grimm, 1999). In regards to communication, Grimm et al. (2006) argues that analytical models are easier to communicate as they are formulated in the general language of mathematics; the description is often complete, unambiguous and accessible to the reader, unlike ABM descriptions which are often difficult to understand, incomplete, ambiguous, and therefore less accessible. As a consequence of this, the results are often very difficult to reproduce, which largely undermines ABM as a suitable modelling approach since science is based on reproducible observations (Hales et al., 2003). As a potential solution to this limitation, Grimm and Railsback (2005) suggested a standardised protocol for describing ABMs which was successfully applied by several leading researchers in this field (Grimm et al., 2006) and later revised after considerable use (Grimm et al., 2010).

The Overview, Design concepts, and Details (ODD) protocol was suggested as a means of standardising the way researchers communicate their ABM to one another to overcome one of the main criticisms of this modelling approach (Grimm et al., 2010).

The ODD protocol is subdivided into seven elements: purpose; entities, state variables, and scale; process overview and scheduling; design concepts (further divided into several elements); initialisation; input data; and sub-models. Although the number of studies using the ODD protocol has increased rapidly since it was first published, it has also received criticism since some elements may be redundant for particular or simple models. However, Grimm et al. (2010) argued that although this can be the case, it is the price of having a hierarchical structure and the majority of times redundancy can be avoided by keeping detail short and precise and any detail provided in the design concept element can be left out of the sub-model element. Overall, ODD provides a method of reviewing and categorising different types of ABM in a systematic approach and has increasingly been used by researchers within the field of ABM (Grimm et al., 2010).

2.3.3 Use of ABM within the field of farmer decision-making

In addition, although ABM has often been considered a promising quantitative methodology for social science research (Parker et al., 2003), it is only in the last few years that researchers are combining ABM with empirical methods (Janssen and Ostrom, 2006). For example, Acosta et al. (2014) developed an ABM to understand the influence of global environmental change drivers and land manager decisions on the future of the Montado, a multifunctional semi-wooded area used for grazing and cereal cultivation in Portugal. The model description followed the standardised ODD protocol suggested by Grimm et al. (2010). A farm typology, based on cluster analysis of empirically derived farm attributes represented the different agents, along with particular behavioural strategies which were driven by global economic and climatic parameters. Overall, the ABM developed indicated that farmers would continue to abandon their land if the future global economic environment, characterised by rapid industrialisation and urbanisation, should persist. However, agriculture remained the dominant land use, indicating some resilience to change from local farmers.

Similarly, other studies have applied ABM to deal with complex human-environmental systems such as Galán et al. (2009). In this study an ABM was used to integrate different social sub-models: models of urban dynamics; water consumption; and technological and opinion diffusion, which together were linked with a geographical information system. The completed ABM represented a computational environment which was able to simulate and compare different water demand scenarios for different agent types. In another study, Schlüter and Pahl-Wostl (2007) developed an ABM which was designed to compare the resilience of different institutional settings of water management to changes in the variability and uncertainty of water availability for irrigation and environmental water requirements. The results of this study indicated that under fluctuating inflows and compliance with restrictions, a centralised management approach provided more sustained levels of water availability when irrigation was the only user. However, as demands from other sectors were introduced a decentralised management approach to water allocation provided a more sustained level of water availability. Therefore, this study highlights the ability of ABM to explore system level patterns of water use and behaviour based on individual decision making at the farm scale.

2.4 Further remarks and research gaps

This chapter has presented a critical review of the main bodies of literature highlighting three important research gaps pertaining to the methods which are to be used to address the three research questions presented in Section 1.3. Firstly, despite the number of studies addressing the issue of understanding farmers' behaviours having increased, it appears no studies have attempted to understand farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed new water allocation systems in England. The TPB demonstrated its ability to provide a reliable method of successfully measuring intention and its predictors, particularly with the addition of past behaviour. Therefore, Chapter 4 presents an empirical investigation in a case study catchment in England, under the theoretical framework of the TPB, aimed at addressing this research gap.

Secondly, traditional farm typologies fail to incorporate true farmer behaviour and are therefore of limited value in supporting policy formulations (Guillem et al., 2012). Furthermore, where studies have measured farmers' behaviours, relatively few have used this data to develop farm typologies (Beedell and Rehman, 2000; Wauters et al., 2010; Poppenborg and Koellner, 2013). In addition, it appears no studies have developed a farm typology based on farmers' preferred behavioural intentions' under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England. Therefore, Chapter 5 presents a farm typology aimed at addressing this research gap.

Finally, although several studies have used ABM to simulate farmer decision-making in regards to irrigation and land use (Bousquet et al., 1999; Barreteau et al., 2001; Berger, 2001; Becu et al., 2003; Hare and Deadman, 2004; Janssen and Ostrom, 2006; Matthews et al., 2007; Schreinemachers and Berger, 2011), no studies have explicitly used ABM as a method of simulating farmers' behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England. Furthermore, an ABM which incorporated a farm typology based on farmers' preferred behavioural intentions could be used to: a) see what patterns of abstraction behaviour emerge at the system level based on decisions made at the farm level; b) see how different climate and proposed water allocation system scenarios affect decisions made at the farm level; and c) see how the results of an ABM can be used to inform policy-decision makers involved in the process of implementing the proposed water allocation systems. Therefore, Chapter 6 presents the development and simulation scenario results of an ABM aimed at addressing these issues.

Chapter 3

The Great Ouse catchment, Anglian region, UK

The Great Ouse catchment represents approximately a third of the Anglian region in eastern England, UK, and was selected as the study area due to two important factors including: the importance of available freshwater resources for agricultural spray irrigation (see Section 1.1.4); and the fact that the Anglian region, although representing more than 50 % of total irrigated land (Knox et al., 2000), and 62 % of estimated spray irrigation abstractions in England and Wales (DEFRA, 2016a), is one of the most water-stressed regions in the UK (Knox et al., 2009) (see Figure 3.1).

3.1 Biophysical environment

The Great Ouse catchment is approximately 8,596 km^2 with elevation in the range of -2 and 241 metres above mean sea level (m.a.s.l.). On average, the area received 655 mm of precipitation annually, and 51 mm monthly, between 1973 and 2012 (MetOffice, 2016). This was 499 mm less annually, and 42 mm less monthly, than the UK in general. In addition, 2011 was the driest year and 2012 was the wettest with annual rainfalls of 454 mm and 810 mm respectively. Furthermore, on average, the area has been 1 ^{o}C warmer than the UK in general with 1986 being the coldest year whilst 2011 was the hottest year with mean temperatures of 9 ^{o}C and 11 ^{o}C respectively (see Figure 3.2).

The Great Ouse meanders from the uplands in the south west to the tidal reaches near Earith where it continues to the mouth of the river (i.e. the Wash) at King's

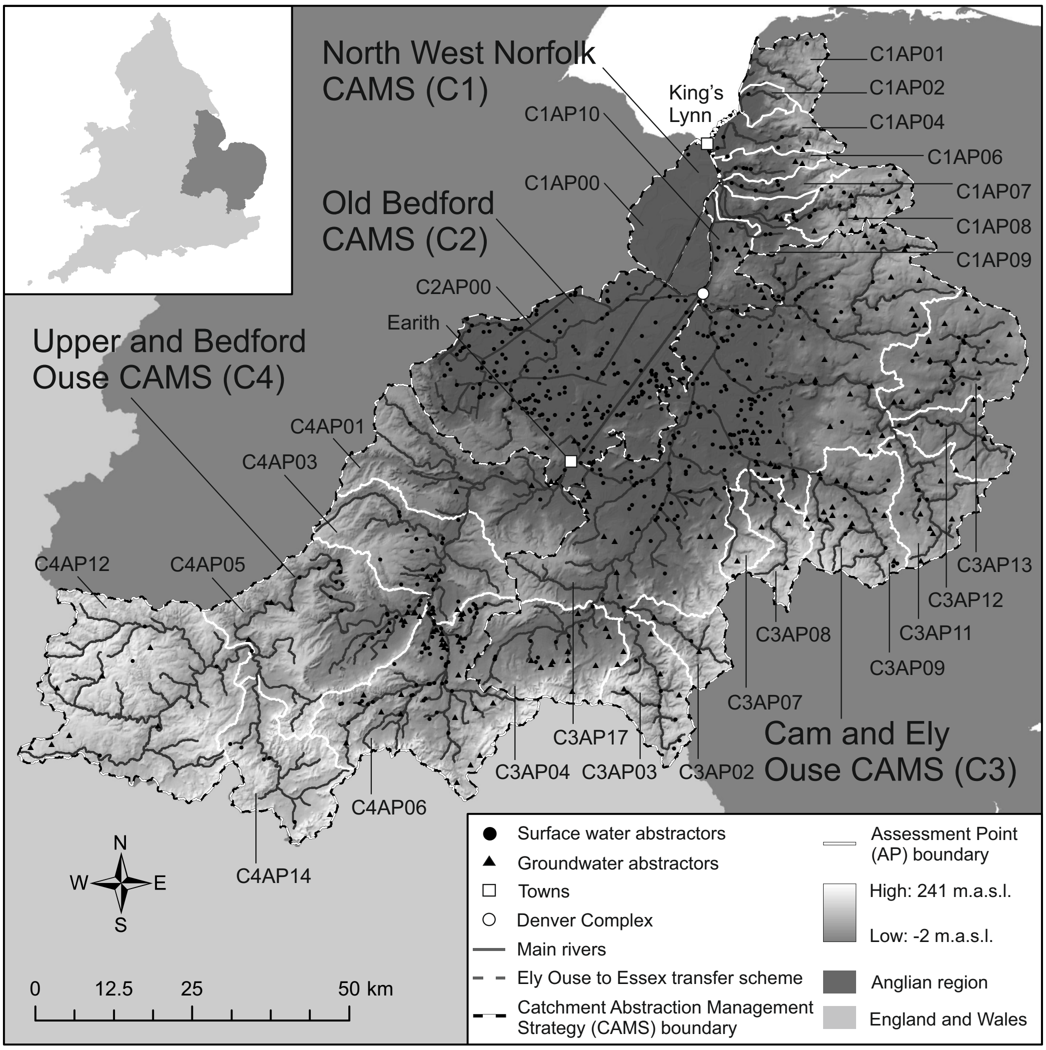

Figure 3.1: The Great Ouse catchment, Anglian region, UK

Lynn. Several major tributaries join the tidal river between Earith and King's Lynn, most notably the Ely Ouse in the south east. Much of the catchment in the north west is below sea level and consists of irrigation drainage channels (i.e. the Fens). The main aquifers in the study area include: the Great Oolite aquifer in the south west; the Woburn Sands aquifer in the south; the Chalk aquifer in the south and east of the catchment; and the Sandringham Sands aquifer in the north east (EA, 2013b,c,a,d).

The catchment is predominantly used for crop production, with 39 % classified as grade one or two agricultural land and a further 40 % classified as grade three (EA, 2011). There are currently 836 spray irrigation farmers operating in the study area

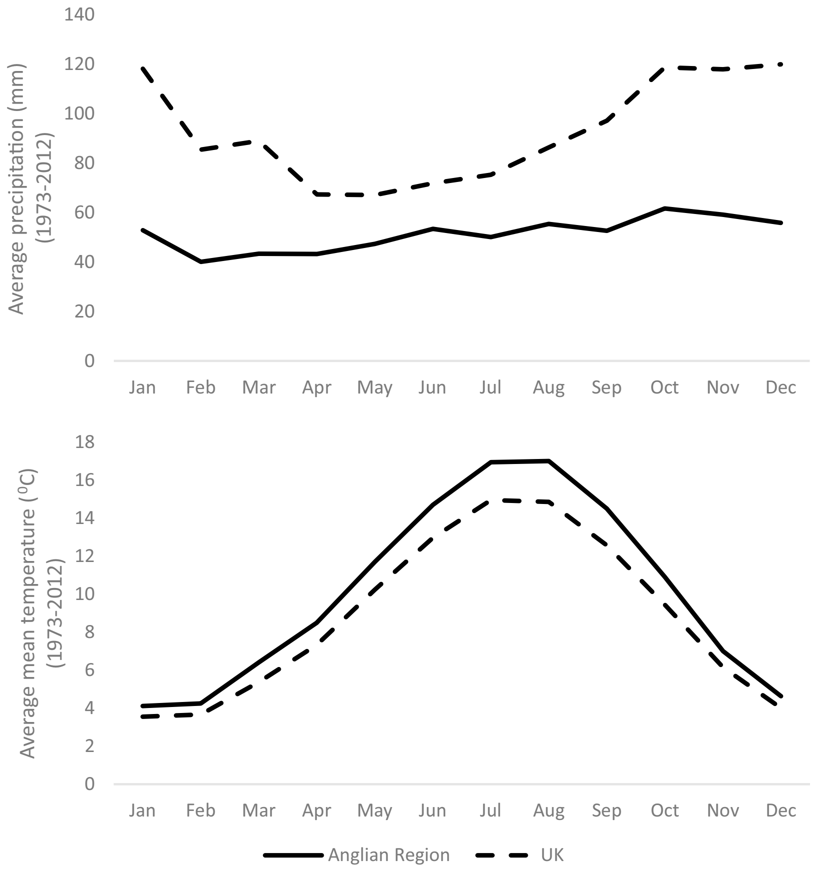

Figure 3.2: Difference in average monthly precipitation and mean temperature between the study area and the UK (1973 to 2012). (Top) Line graph indicating the difference in average monthly precipitation between the study area and the UK. (Bottom) Line graph indicating the difference in average monthly mean temperature between the study area and the UK

who, along with the remaining spray irrigation farmers in the larger Anglian region, rely on available freshwater for supplemental irrigation in order to supply high quality produce, including over 30 % of potatoes and 25 % of all fruit and vegetables, to UK supermarkets (UKIA, 2007). However, water available for spray irrigation in the study area is increasingly under pressure from climate change (see Section 1.1.4), demand from other sectors, most notably public water supply, and growing protection for the environment (Knox et al., 2009). Despite this increasing pressure, Weatherhead and Rivas Casado (2007) found that the total water applied each year for spray irrigation in England is increasing by 2.1 % per annum, as is the total area being irrigated (i.e. 0.9 %).

3.2 Water management

Water availability in England is managed by the Environment Agency (EA) who, through their Catchment Abstraction Management Strategies (CAMS), determine water availability for further licensed abstractions. The study area is divided into four CAMS areas: North West Norfolk (EA, 2013b); Old Bedford (EA, 2013c); Cam and Ely Ouse (EA, 2013a); and Upper and Bedford Ouse (EA, 2013d), which are further divided into 50 Assessment Point (AP) areas. However, for reasons discussed in Section 3.3 only 26 AP areas were used in this study.

Three factors are used to determine water availability within an AP area: an Environmental Flow Indicator (EFI) which refers to a proportion of natural flow allocated to the environment; a Fully Licensed (FL) scenario which refers to the quantity of water which could be abstracted (i.e. a hypothetical scenario); and a Recent Actual (RA) scenario which refers to the quantity of water abstracted over the previous six years. A flow deficit occurs when water available after a RA scenario is below the EFI and therefore no water is available and the AP area is considered over abstracted. A risk of a flow deficit occurs when water available after a FL scenario is below the EFI and therefore restricted water is available and the AP area is considered over licensed. If there is no risk of a flow deficit then the AP area is considered as having water available (EA, 2010). However, the EA also use four flow levels, derived from flow duration curves which show the percentage of time that a particular flow level is equalled or exceeded, to account for natural annual flow variation including: Q30 (i.e. high flow); Q50; Q70; and Q95 (i.e. low flow). Therefore, despite the risk of a flow deficit water may still be available for further licensing but only during high flows.

In regards to the Great Ouse catchment, AP areas within the low lying fens are assessed differently by the EA with water available for further licensing in the Winter and not in the Summer, as river flows are largely controlled by a system of pumps and drains, most notably at the Denver Complex, managed by the Internal Drainage Board and the Middle Level Commissioners (EA, 2010). The Denver Complex controls inundation by the sea for much of the low lying fens in the Winter and provides water for spray irrigation in the Summer by using a large combination of sluices. In addition, the Ely Ouse to Essex transfer scheme augments river flows and reservoir levels in south Essex by transferring excess water from the Ely Ouse during high flow conditions (i.e. inter-catchment transfer).

3.3 River flows

River flow data for each AP area was derived from the National River Flow Archive gauge station network (CEH, 2016). However, only 16 of the 50 AP areas used by the EA corresponded with available gauge station data. Furthermore, river flow data for these 16 AP areas consisted of missing data and were only available from 1973 to 2012. Therefore, where gauge station records were incomplete average values for the AP area were used. For this study, any upstream AP area which did not correspond with available river flow data was amalgamated with the downstream AP area which did have river flow data available. Furthermore, due to the tidal nature of the river, 10 AP areas were essentially all downstream catchments and none had river flow data available. Therefore, for these 10 AP areas the watershed area ratio method was used to derive river flows (Gianfagna et al., 2015) using either an upstream AP area or a similar sized neighbouring AP area:

$$Q_{ungauged} = Q_{gauged}(\frac{A_{ungauged}}{A_{gauged}}) \tag{3.1}$$

where Q equals river flow (i.e. discharge) and A equals AP area (i.e. km^2). Although this method provides a reasonable estimation for river flows in ungauged AP areas for this study, it does assume that river flow is proportional to area which may not always be accurate. In addition, for the purposes of this study, the two AP areas which represent the low lying fens (i.e. C1AP00 and C2AP00) derived their river flows using the watershed area ration method, from C3AP17 in the Cam and Ely Ouse CAMS area. River flow in this AP area largely influences the availability of freshwater at the Denver Complex, and therefore also for the low lying fens. Figures 3.3, 3.4, and 3.5 illustrate, respectively, a schematic of the 26 AP area network used in this study, flow duration curves for each AP area, and average monthly river flows for each AP area. Furthermore, Table 3.1 summarises average river flows for each AP area at the flow exceedence levels used by the EA to determine water availability.

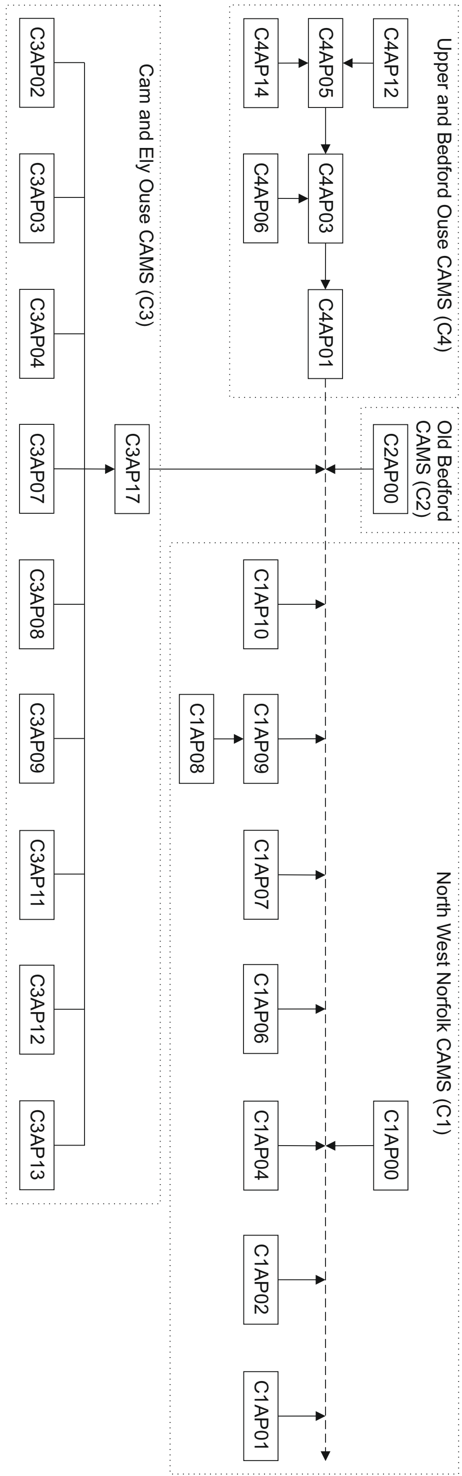

Figure 3.3: Schematic diagram illustrating river flow between Assessment Point (AP) areas within each of the four Catchment Abstraction Management Strategy (CAMS) areas (the dash line relates to the tidal river whilst dotted lines relate to CAMS boundaries)

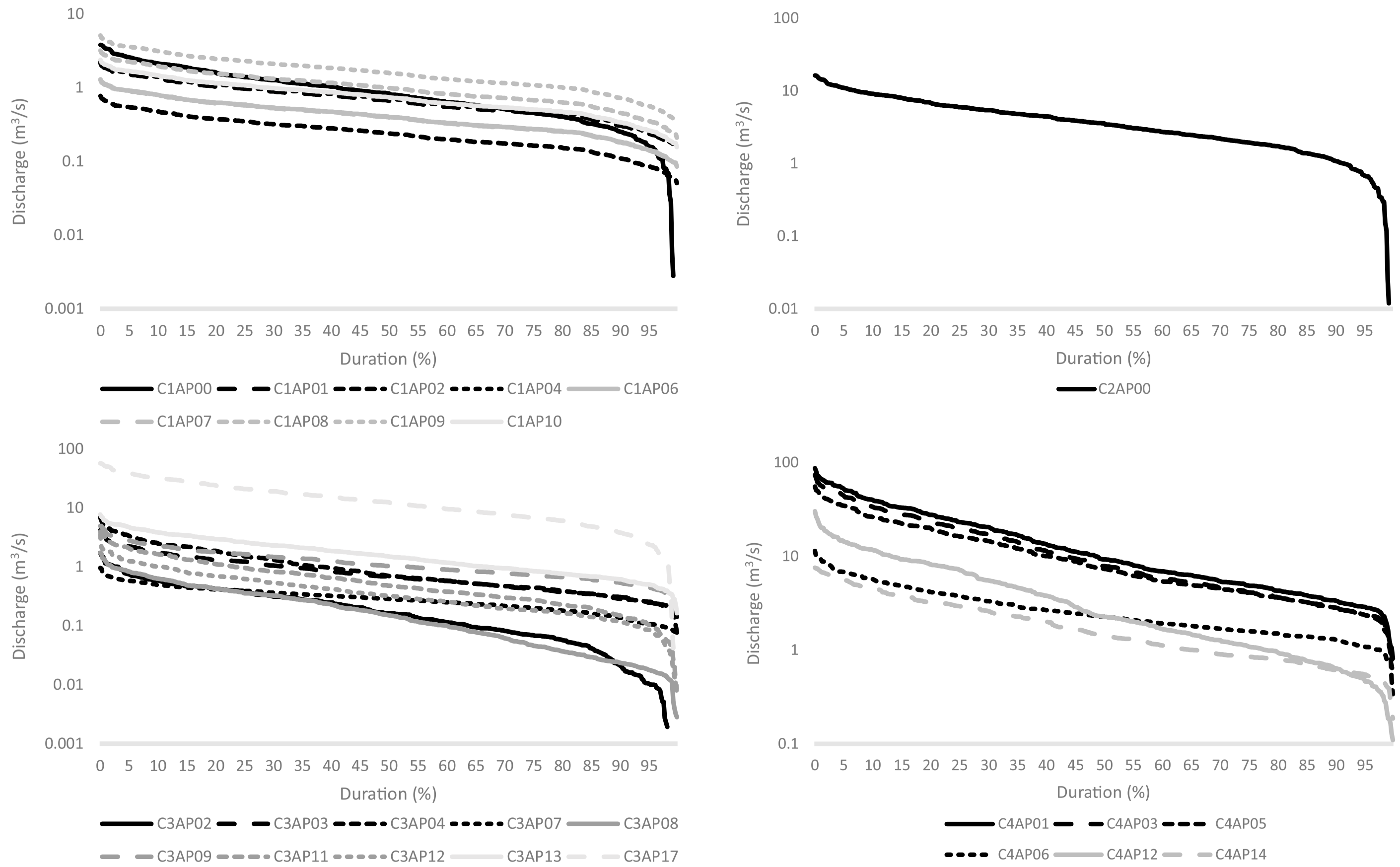

Figure 3.4: Flow duration curves of each AP area within the study area (1973 to 2012). (Top left) Flow duration curves of AP areas within the North West Norfolk CAMS area. (Top right) Flow duration curve of the AP area within the Old Bedford CAMS area. (Bottom left) Flow duration curves of AP areas within the Cam and Ely Ouse CAMS area. (Bottom right) Flow duration curves of AP areas within the Upper and Bedford Ouse CAMS area

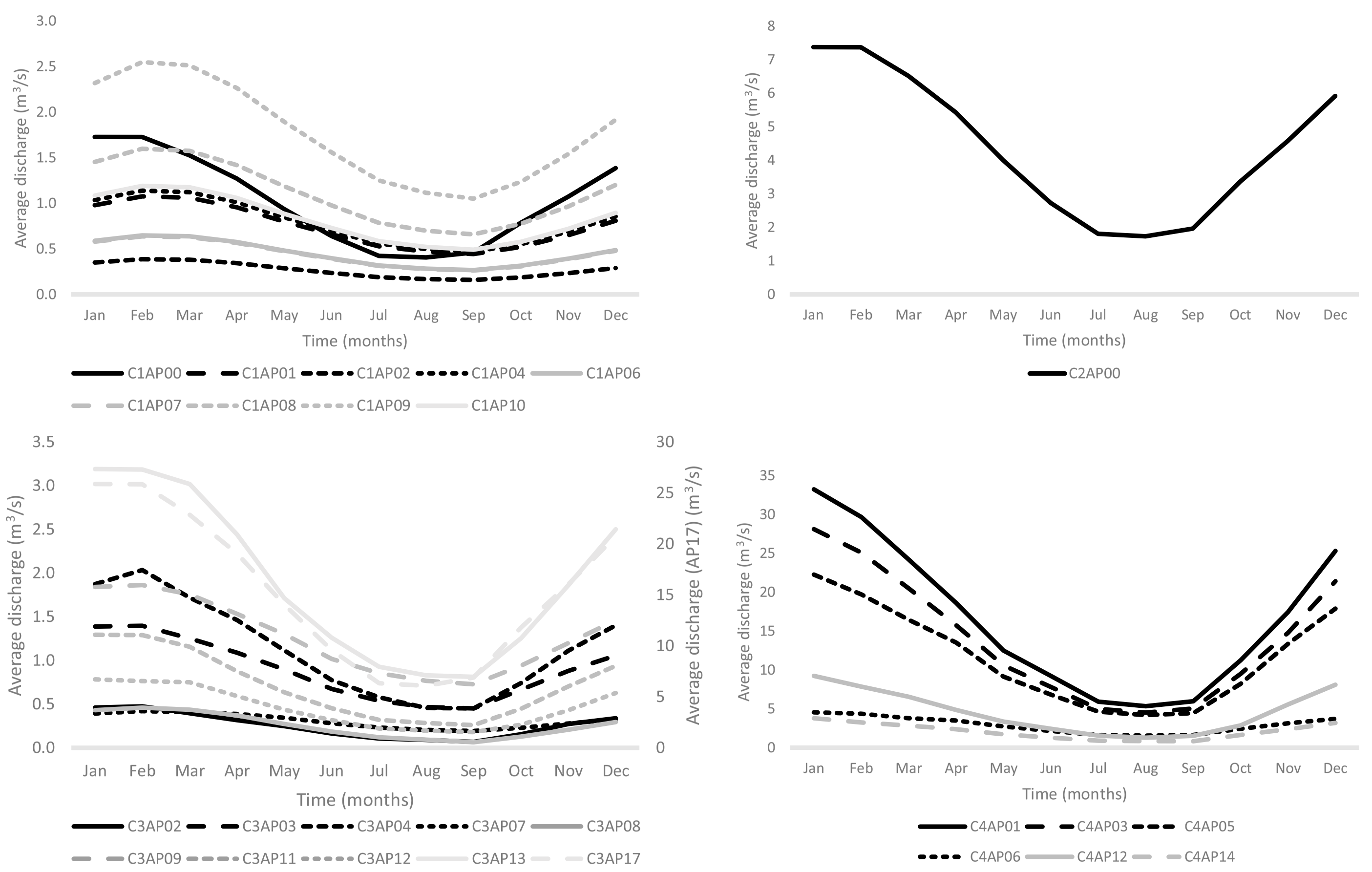

Figure 3.5: Average monthly river flows of each AP area within the study area (1973 to 2012). (Top left) Average monthly river flows of AP areas within the North West Norfolk CAMS area. (Top right) Average monthly river flow of the AP area within the Old Bedford CAMS area. (Bottom left) Average monthly river flows of AP areas within the Cam and Ely Ouse CAMS area. (Bottom right) Average monthly river flows of AP areas within the Upper and Bedford Ouse CAMS area

Table 3.1: Average river flows for each Assessment Point (AP) area (1973 to 2012)

Assessment Point (AP)	Gauge station	Upstream area (km^2)	Q30 flow (m^3/s)	Q50 flow (m^3/s)	Q70 flow (m^3/s)	Q95 flow (m^3/s)
North West Norfolk CAMS (C1)						
- C1AP01	-	103	0.89	0.66	0.49	0.24
- C1AP02	-	37	0.32	0.24	0.18	0.09
- C1AP04	-	109	0.94	0.70	0.52	0.25
- C1AP06	-	62	0.54	0.40	0.29	0.14
- C1AP07	-	61	0.53	0.39	0.29	0.14
- C1AP08	33007	153	1.33	0.99	0.72	0.35
- C1AP09	-	91	2.11	1.57	1.15	0.56
- C1AP10	-	114	0.99	0.74	0.54	0.26
- C1AP00	-	229	1.27	0.83	0.52	0.16
Old Bedford CAMS (C2)						
- C2AP00	-	977	5.43	3.56	2.21	0.68
Cam and Ely Ouse CAMS (C3)						
- C3AP02	33053	114	0.32	0.16	0.08	0.01
- C3AP03	33024	198	1.05	0.69	0.48	0.25
- C3AP04	33021	303	1.31	0.70	0.47	0.26
- C3AP07	33050	61	0.36	0.29	0.22	0.11
- C3AP08	33023	102	0.33	0.15	0.06	0.02
- C3AP09	33014	272	1.47	1.04	0.78	0.44
- C3AP11	33013	206	0.82	0.48	0.30	0.10
- C3AP12	33011	129	0.54	0.32	0.20	0.09
- C3AP13	33019	316	2.31	1.50	0.95	0.50
- C3AP17	33035	3,430	19.06	12.48	7.76	2.38
Upper and Bedford Ouse CAMS (C4)						
- C4AP01	-	3,038	20.54	9.30	5.43	2.90
- C4AP03	33026	2,570	17.37	7.87	4.59	2.45
- C4AP05	33039	1,660	14.59	7.36	4.47	2.37
- C4AP06	33022	541	3.33	2.27	1.69	1.09
- C4AP12	33037	800	5.53	2.27	1.28	0.46
- C4AP14	33015	277	2.59	1.42	0.90	0.55

If gauge station is not present then river flow was calculated using equation 3.1
Source (CEH, 2016)

Generally, the flow duration curves are relatively flat between high and low flow conditions for all AP areas indicating the presence of surface storage (i.e. reservoirs) or groundwater storage (i.e. aquifers) which tend to equalize flows (Searcy, 1959). However, in some AP areas, duration curves are steep below low flow conditions, indicating almost zero flows. Furthermore, average monthly flows indicate that lower flows generally occur during the Summer, when spray irrigation demand is highest, and higher flows during the Winter, when spray irrigation demand is lowest.

3.4 Summary

Overall, Figure 3.5 illustrates the current water availability status of the 24 AP areas defined in this study, excluding the two AP areas which are assessed differently due to their location within the low lying fens (i.e. C1AP00 and C2AP00). At high flows (i.e. Q30) 83 % of the catchment has water available for further licensing with the remainder having restricted water available. However, at moderate flows (i.e. Q50) only 13 % of the catchment has water available for further licensing with 54 % having restricted water available, and 33 % having no water available. At below moderate flows (i.e. Q70) only 4 % of the catchment has water available for further licensing with 13 % having restricted water available, and 83 % having no water available. Finally, at low flows (i.e. Q95) only 4 % of the catchment has water available for further licensing with the remainder having no water available. Therefore, under the current water allocation system there is little opportunity for issuing new abstraction licences within the Great Ouse catchment except at high flows. Furthermore, climate change and demand increases from other sectors is expected to exacerbate the vulnerability of freshwater availability for spray irrigation in this catchment.

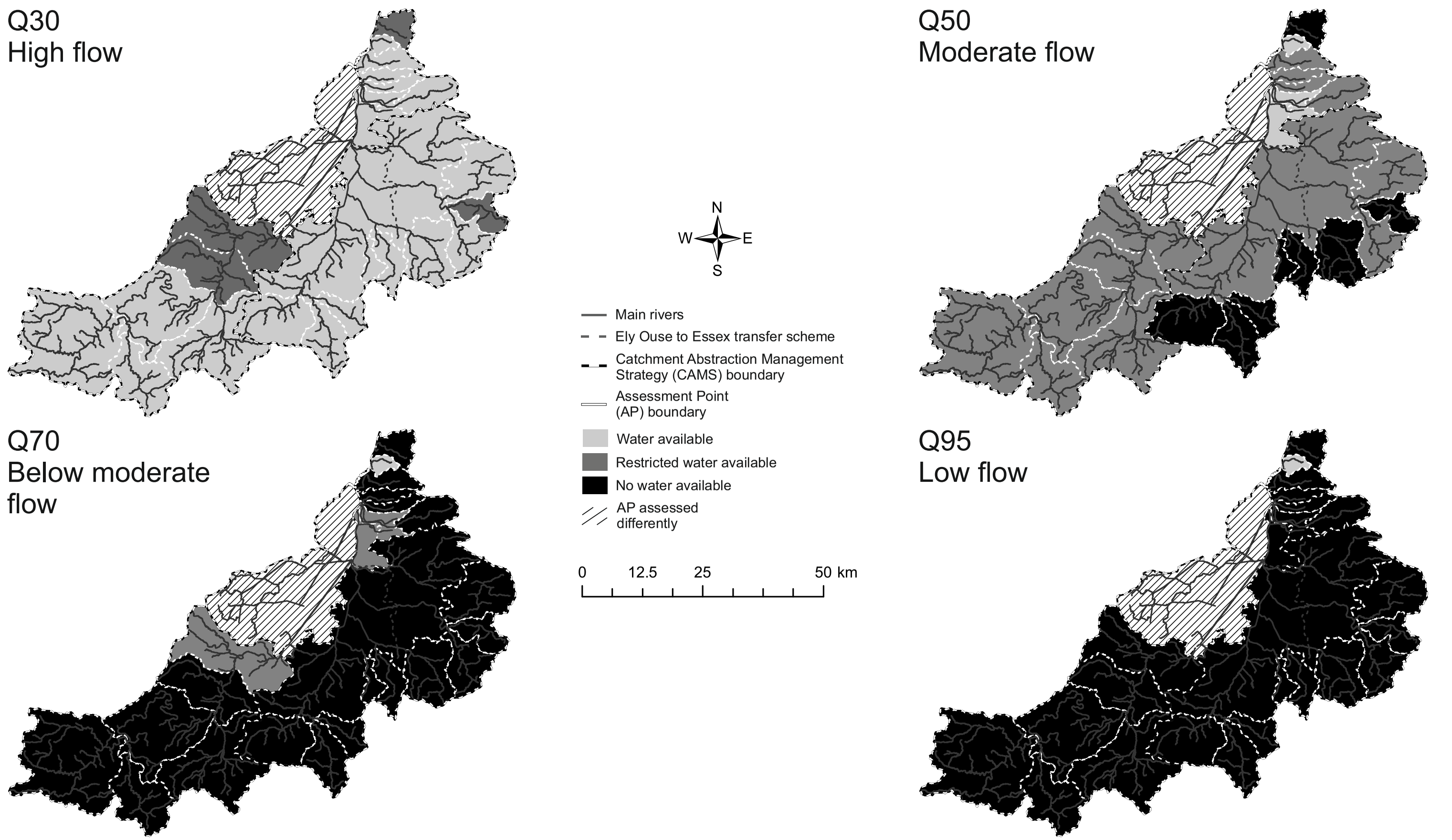

Figure 3.6: Water availability for further licensed abstractions within the study area from high to low flows (2013). (Top left) Water availability at Q30 (i.e. high flow). (Top right) Water availability at Q50 (i.e. moderate flow). (Bottom left) Water availability at Q70 (i.e. below moderate flow). (Bottom right) Water availability at Q95 (i.e. low flow)

Chapter 4

Farmers' behaviours

This chapter presents empirical data which identifies farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England. In this study, the term farmers' refer to spray irrigation licence users' only. After an initial pilot study, a questionnaire was sent to 826 farmers' in the study area, of which 11% responded. The questionnaire, and subsequent analysis, was based on the theoretical framework of the Theory of Planned Behaviour (TPB) (Ajzen, 1985). The results of this study are intended to inform policy decision-makers involved in the design and implementation of the proposed water allocation systems by: 1) understanding how the proposed water allocation systems might be received by farmers' on the ground; and 2) identifying which underlying predictors of intention most influence farmers' decision-making. Therefore, this chapter addresses the first of the three research questions presented in the introductory chapter to this thesis:

Research question 1: *What are farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England? And which underlying predictors of intention most influence their decision-making?*

4.1 Introduction

As discussed in Chapter 1 of this thesis, major water allocation reforms are currently being proposed in England to address the climate and demand change pressures, which the current system is failing to address (DEFRA, 2011). Furthermore, evidence has been presented which highlights how farmer behaviour very much influences how and to what success policy proposals are realised on the ground (Moon and Cocklin, 2011; Home et al., 2014; Feola et al., 2015) (see Chapter 2). Policy decision-makers therefore increasingly require more sophisticated methods of anticipating farmers' motivation to comply with new policy approaches (Austin et al., 1998; Burton, 2004; Emtage et al., 2006; Guillem et al., 2012). The TPB (Ajzen, 1985) was critically reviewed and has been identified as a relatively reliable method of successfully measuring intention and its predictors (see Chapter 2). Furthermore, evidence has been provided which has shown that the addition of past behaviour as a predictor variable can increase the predictive power of the TPB model (Albarracin et al., 2001; Sandberg and Conner, 2008; Rise et al., 2010). In addition, the TPB also provides a means by which the relative importance (weights) of each of the underlying constructs (predictors) of intention can be estimated. Therefore, this chapter presents empirical data, from the selected study area (see Chapter 3), which identifies farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England.

4.2 Materials and Methods

The methodological procedure used in this study can be categorised into four stages: 1) scenario and behaviour selection; 2) questionnaire design; 3) survey procedure; and 4) statistical analysis.

4.2.1 Scenario and behaviour selection

In total there were four scenarios and 18 behaviours selected (see Table 4.1). These included seven strategic (long-term)/water shortage behaviours, four strategic (long-term)/water surplus behaviours, four in-season (short-term)/water shortage behaviours, and three in-season (short-term)/water surplus behaviours. The strategic and in-season scenarios related to farm level water management decisions made once every several growing seasons, and regularly during each season, respectively. The water shortage and surplus scenarios related to decisions when a farmer is unable to meet crop wa-

Table 4.1: Scenarios and behaviours (options) selected

Low Water Usage Options (LWUO)	High Water Usage Options (HWUO)
Strategic (long-term)/water shortage scenario	
- Grow the same crops but over a smaller area	- Increase storage capacity
- Grow less water intensive crops	- Buy more water for the duration of the growing season
- Increase application efficiency	- Apply for a larger abstraction licence
- Change nothing	
Strategic (long-term)/water surplus scenario	
- Sell surplus water for the duration of the growing season	- Grow the same crops but over a larger area
- Change nothing	- Grow more water intensive crops
In-season (short-term)/water shortage scenario	
- Only use your maximum abstraction licence to spread water evenly between all crops	- Buy more water to meet crop water requirements
- Only use your maximum abstraction licence to irrigate your most valuable crops	
- Restrict application (i.e. deficit irrigation)	
In-season (short-term)/water surplus scenario	
- Sell surplus water to maximise profits	- Abstract surplus water for storage
- Just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused	

ter requirements, or has a surplus of water after they meet crop water requirements, respectively. The scenarios and behaviours were selected after consultation with several farmers during multiple UKIA meetings held in and around the selected study area between October 2012 and December 2013. Furthermore, an irrigation specialist with experience in the selected study area reviewed the scenarios and behaviours (K. Weatherhead, personal communication, November 2013) as did the head of water abstraction reform at DEFRA (H. Leveson-Gower, personal communication, December 2013). This selection approach was favoured over holding focus groups as many farmers commented on their time restraints, and the UKIA meetings provided an opportunity to meet several farmers simultaneously.

Under a strategic (long-term)/water shortage scenario farmers require additional water to meet crop water requirements and have the following options available: grow the same crops but over a smaller area; grow less water intensive crops; increase storage capacity; increase application efficiency; buy more water for the duration of the growing season; apply for a larger abstraction licence; or change nothing. Growing the same crops but over a smaller area; growing less water intensive crops; increasing application efficiency; or changing nothing were considered, for the purposes of this study, as Low Water Usage Options (LWUO), as any one of these behaviours ultimately means abstracting the same or less volume of water. Furthermore, farmers who favour these options are expected to experience a reduction in crop quality or yield. In contrast, increasing storage capacity; buying more water for the duration of the growing season; or applying for a larger abstraction licence were considered as High Water Usage Options (HWUO) as any one of these behaviours ultimately means abstracting more water. Farmers who favour these options are expected to reduce the risk of a reduction in crop quality or yield.

Under a strategic (long-term)/water surplus scenario farmers have a surplus of water after meeting crop water requirements and have the following options available: grow the same crops but over a larger area; grow more water intensive crops; sell surplus water for the duration of the growing season; or change nothing. The latter two behaviours were considered as LWUO whilst the first two were considered as HWUO due to the decrease and increase in water used, compared to an average year, respectively. Farmers who favour selling surplus water, a LWUO, are expected to increase their income similar to those farmers who favour the HWUO.

Under an in-season (short-term)/water shortage scenario farmers have fewer options available to meet crop water requirements including: only using their maximum abstraction licence to spread water evenly between all crops; only using their maximum abstraction licence to irrigate their most valuable crops; restricting application (i.e. deficit irrigation); or buying more water to meet crop water requirements. The first three behaviours were considered as LWUO whilst the latter was considered a HWUO for the same reasons presented under a strategic (long-term)/water shortage scenario.

Lastly, under an in-season (short-term)/water surplus scenario farmers also have fewer options available including: selling surplus water to maximise profits; just using their abstraction licence to meet crop water requirements and leaving the remainder of their licence unused; or abstracting surplus water for storage. The first two behaviours were considered as LWUO whilst the latter was considered a HWUO for the same reasons presented under a strategic (long-term)/water surplus scenario.

4.2.2 Questionnaire design

The questionnaire (see Appendix A) was designed into four sections: farm attributes (section A); farmers' behavioural intentions under strategic (long-term) and in-season (short-term) scenarios (sections B and C respectively); and social demographics (section D). In total, there were 108 questions: five associated with section A; 98 associated with sections B and C; and five associated with section D. The design of the questionnaire, as with the scenarios and behaviours selected, was developed after consultation with several farmers during multiple UKIA meetings held in and around the selected study area between October 2012 and December 2013. Furthermore, feedback for the final phrasing of the questions was provided by an irrigation specialist familiar with the study area (K. Weatherhead, personal communication, November 2013) and the head of water abstraction reform at DEFRA (H. Leveson-Gower, personal communication, December 2013).

Section A of the questionnaire attempted to identify farmers' three main irrigated crops (as several farmers reported irrigating more than one crop over equal areas); the irrigated area of each of these crops; the predominant soil type each crop was grown on (as this influenced irrigation water demand); the irrigation technique used for each crop (to assess the efficiency of each farm); and the overall water storage capacity of the farm (to assess farm storage reserves when licensed abstractions were unavailable). Example categories of crops included in the first question, and subsequently used in later analysis, were based on those used by Weatherhead and Rivas Casado (2007) and included: early potatoes; main crop potatoes; sugar beet; orchard fruit; small fruit; vegetables; grass; cereals; and other.

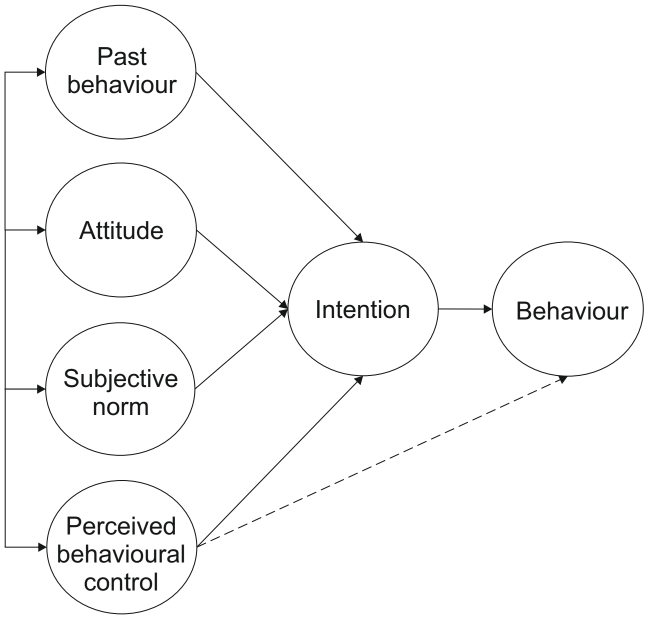

Figure 4.1: The Theory of Planned Behaviour including past behaviour (adapted from Ajzen (1991))

Sections B and C, which were both divided into further water shortage and surplus scenarios, related to the scenarios and behaviours previously discussed. In addition, as the questionnaire was structured based on the theoretical framework of the TPB (Ajzen, 1985) (see Chapter 2), each behaviour consisted of five questions related to overall intention as well as the underlying constructs (or predictors) of intention including: attitude; subjective norm; perceived behavioural control; and past behaviour (see Figure 4.1). A Likert psychometric scale of one to seven (one being negative and seven being positive) was used to record farmers' responses. In regards to subjective norms, farmers were also asked to rank which social group most influenced their decisions. These included: a group interested in water saving and efficiency; a group interested in crop type and quality; and a group consisting of family, friends, and neighbours. Lastly, in regards to past behaviour, an additional question was included asking farmers whether they had actually experienced the scenario.

Section D of the questionnaire attempted to identify farmers' gender; age; level of education (measured by National Qualification Framework level for England, Wales and Northern Ireland); total gross annual farm business income; and whether they had used their abstraction licence within the last ten years.

4.2.3 Survey procedure

The farmers selected for the survey were chosen due to their location within the selected study area (see Chapter 3). The EA provided data regarding the addresses and abstraction point locations for the total population of farmers in the study area (a total of 836) from the National Abstraction Licence Database. A pilot survey was conducted by post, on the 14th January 2014, with a sample of 10 randomly selected farmers. The pilot survey included: the questionnaire; a cover letter; and a consent form. However, this randomly selected sample had to be selected from the total population within the study area, as the EA did not permit additional access to farmers' addresses outside the study area, thus only a small sample were chosen as these farmers were then excluded from the final survey. Farmers selected for the pilot survey had two weeks to complete and return the questionnaire before a reminder was sent. The questionnaire and reminder were posted with first class return envelopes to avoid costs to farmers; however no incentives were offered for completing a questionnaire.

In the initial pilot survey a second perceived behavioural control question, asking farmers to report on the difficulty in performing a behaviour, was included in order to examine the internal control aspect of self-efficacy, such as ability or motivation, rather than simply external control, such as resources (Manstead and Eekelen, 1998):

How difficult or easy would it be to... (e.g. increase application efficiency?)

was used in addition to:

How much do you disagree or agree with the following statements? (e.g. Increasing application efficiency or not is entirely up to you)

The pilot survey response rate was 30 % which was towards the higher end compared to that reported in the survey literature (i.e. 20 % to 30 %) (Yammarino et al., 1991; Pennings et al., 2002). The pilot survey provided valuable feedback, most noticeably highlighting the redundancy of the additional perceived behavioural control question as none of the respondents noted any difference between these two questions with many commenting negatively on the length and repetitiveness of the questionnaire, and in particular those two questions. Therefore, in response to the pilot survey, and to reduce the risk of a low response rate in the final survey, the additional question was removed based on the knowledge that this would not cause problems to the way perceived behavioural control was used as a measure of intention. The final questionnaire was then distributed by post on the 12$^{\text{th}}$ February 2014 to the remaining population of farmers in the study area, a total of 826, offering them one month to respond. No incentives were offered or reminders sent due to available resources.

4.2.4 Statistical analysis

All statistical analyses were performed using SPSS v22. In addition, the EA provided additional licence characteristic data and past abstraction data for those who responded to the questionnaire, rather than the total population, due to EA data restrictions. Licence characteristic data included: licence type (i.e. direct; storage; or direct and storage); licence source (i.e. surface or groundwater); whether licences were time limited or not; and annual and daily licensed volumes. Past abstraction data consisted of monthly abstractions from the start of 2008 to the end of 2012. Furthermore, the statistical analysis for this study was conducted and is presented in two parts. The first part focussed on farm characteristics including: farm attributes; social demographics; licence characteristics; and past abstractions (see Appendix B). The second part focussed on farmers' behavioural intentions (see Appendix C).

Farm characteristics

In regards to farm characteristics, relative frequency tables and histograms were used to highlight the results of the respondents. Furthermore, where comparative data were available, the results were compared to the characteristics of the total surveyed population and farmers in England and Wales in general. In addition, two-tailed tests of association were conducted to explore whether associations existed between: storage capacities and irrigated areas; annual and daily licence limits; annual abstractions and precipitation; and monthly abstractions and precipitation. Although for the first two tests it could be expected that positive associations were more likely, a negative association could not be ruled out, particularly with regards to the role of seasonal restrictions on licences resulting in large daily licence limits for a relatively small annual licence. Conversely for the latter two tests it could be expected that negative associations were more likely, as one would expect abstractions to increase as precipitation decreases. However, additional water available may have meant that farmer's abstract more for storage, whilst less water available may coincide with HoF restrictions. Therefore, the null hypotheses for these tests were that there was no significant association between variables. The appropriate parametric (Pearson's correlation), or non-parametric (Spearman's rank correlation), test of association was used depending on whether the data were normally distributed or not.

The Shapiro-Wilk test was used to test whether quantitative data was normally distributed (Shapiro and Wilk, 1972). The null hypothesis for the Shapiro-Wilk test was that the data are normally distributed. Therefore, if the *p-value* was less than the chosen alpha level, which for this test was .05, then the null hypothesis was rejected suggesting that the data were not from a normal distribution. However, as this test is biased by sample size, normal probability plots were presented for additional verification. Normal probability plots are graphical techniques used to assess whether or not a data set is approximately normally distributed. The data are plotted against a theoretical normal distribution in a way that the data points should form a straight line. Departure from the line indicates the data are not normally distributed (Chambers et al., 1983).

Therefore, with regards to the tests of association, if the *p-value* was less than the chosen alpha level, which for these tests were .05, then the null hypothesis was rejected suggesting that the variables were associated. Furthermore, a Pearson's correlation coefficient (r), or a Spearman's rank correlation coefficient (r_s), of plus or minus 0.7 or greater was considered a strong correlation, plus or minus 0.5 a moderate correlation, and plus or minus 0.3 a weak correlation.

Behavioural intentions

In regards to farmers' behavioural intentions, relative frequency tables were used to summarise the results of the respondents, whilst median and IQR values highlighted the variability of responses for each Likert item. As discussed, each behaviour comprised of five Likert items, relating to each of the TPB constructs, and each Likert item comprised of a seven point Likert item scale ranging from negative to positive. In order to identify respondents preferred behavioural intentions for each scenario, the scores on each Likert item scale were rescaled from minus three to three and multiplied by the number of responses. The total sum of these rescaled Likert items were summed for each behaviour. This provided an overall single value which could be used to rank behaviours from most preferred to least preferred, where a positive or negative value corresponded to a positive or negative overall intention to perform a behaviour.

In addition, sign tests were conducted to test whether behaviours were statistically preferred to the behaviour ranked immediately below. The null hypothesis for the sign test was that the median of the differences between the two behaviours was zero. In addition, the sign test does not make any assumptions about distribution, and was therefore considered appropriate for use with ordinal data. If the *p-value* was less than the chosen alpha level, which for this test was .05, then the null hypothesis was rejected suggesting that there was a difference in medians between the two behaviours. The frequency of positive and negative responses, between the two behaviours, was used to determine whether the difference in medians increased or decreased (Dixon and Mood, 1946). However, rather than perform the sign test on each construct, for each behaviour, only intention was used for simplicity and ease of interpretation and therefore despite the ranking, which takes into consideration all of the constructs, an increase in intention might occur for a lower ranked behaviour.

Studies employing the TPB framework typically use multiple linear regression to examine the relationships between the response and predictor variables (i.e. intention and underlying constructs). Despite this method requiring data measured on a continuous scale (Hankins et al., 2000), these studies usually measure underlying salient beliefs for each construct using multiple Likert items. The Likert items for each construct are then assessed for internal consistency and averaged to form an overall Likert scale for each construct. These Likert scales are often treated as continuous to meet the assumptions required for multiple linear regression (Armitage and Conner, 2001). However, as this study forewent measuring underlying salient beliefs, in order to identify respondents' preferred behaviours from a wider range of behaviours, binary logistic regression was used. This regression technique uses the maximum likelihood method, rather than ordinary least squares, to estimate the probability of a binary response based on one or more categorical predictors (Peng et al., 2002).

This method is to be favoured over ordinal logistic regression, despite the loss of information incurred by dichotomising ordinal scales based on median values (Roozenbeek et al., 2011), due to ease of interpretation and data limitations caused by small sample sizes (i.e. with the data collected in this study complete or quasi-complete separation occurred for each preferred behavioural intention when using ordinal logistic regression thus leading to erroneous results) (Webb et al., 2004). Furthermore, as this study was interested in the respondents' preferred behaviours under each of the four scenarios, binary logistic regressions were only conducted for the highest ranked behaviours. Peng et al. (2002) suggested that in order to evaluate the effectiveness of a binary logistic regression model, it is important to examine: the overall model; statistical tests of individual predictors; goodness-of-fit statistics; and validations of predicted probabilities.

However, prior to conducting the binary logistic regression, tests for multi-collinearity of the dichotomous predictor variables were conducted based on inspection of the correlation matrix and variance inflation factors (VIF). Although no formal cutoff values exist, correlation coefficients greater than 0.8 and VIF values greater than 2.5, when analysing logistic regression models, were considered signs of multi-collinearity following Midi et al. (2010). Moreover, plots of standardised Pearson residuals are presented to highlight any possible outliers exceeding the absolute value of 2.58 which was the cutoff value proposed by Jöreskog and Sörbom (1989). If these occurred, then binary logistic regression was conducted with and without the outliers in order to compare results. Few other assumptions are required for this regression technique other than the response variable (i.e. intention) has to be a dichotomous variable, the categories must be mutually exclusive, and as maximum likelihood coefficients are large sample estimates, a minimum of 50 cases per predictor variable was recommended (Peng et al., 2002). Thus, despite dichotomising the response and predictor variables based on their median values, the inclusion of past behaviour as a predictor variable still resulted in complete or quasi-complete separation of each of the preferred behavioural intentions due to the low response rates obtained for this particular construct, and was therefore not included in the following analyses.

The null hypothesis for the binary logistic regressions was that the regression coefficients (β), or predictor variables, equalled zero. That is, the predictor variables did not improve the predictive ability of the null model (i.e. the constant only model). Overall model evaluation was assessed using the likelihood ratio test. This test uses chi-square (X^2) to compare the difference between the likelihood ratio of the full model (i.e the model including predictors) and the null model based on the -2log likelihood. If the *p-value* was less than the chosen alpha level, which for this test was .05, then the null hypothesis was rejected suggesting that the alternative model (i.e. the model including predictors) was a better model for predicting respondents' behavioural intention.

If the null model was rejected, then the Wald chi-square statistic was used to test the significance of the individual regression coefficients (β) (i.e. the individual predictor variables which are expressed in log odds). If the *p-value* for an individual predictor variable was less than the chosen alpha level, which for this test was .05, then the null hypothesis was rejected suggesting that the predictor variable provides a significant contribution to the model. For ease of interpretation, the exponent of the regression coefficients (Exp(β)), which is the odds ratio, was used to interpret the results. For example, a one unit increase in the predictor variable increases the odds of a farmers' preferred behavioural intention by the value of Exp(β).

In addition, the Hosmer-Lemeshow inferential goodness-of-fit statistic was used to assess the null hypothesis that there was no difference between observed and predicted values. If the *p-value* was greater than the chosen alpha level, which for this test was .05, then the null hypothesis could not be rejected suggesting that the model estimates fit the data at an acceptable level (Hosmer and Lemesbow, 1980). Furthermore, the two descriptive measures of goodness-of-fit which were reported included R^2 indices based on Cox and Snell (1989) and Nagelkerke (1991). However, it is important to note that although these approximate, or pseudo R^2 values, are variations of the R^2 concept used in linear regression, which explains the proportion of variation in the dependent variable explained by the predictor variables, they are not directly comparable (Peng et al., 2002). Lastly, classification tables are presented to validate the predicted probabilities.

4.3 Results and discussion

The section is presented in two parts in relation to the statistical analysis conducted. The first part discusses the respondents farm characteristics which includes: farm attributes; social demographics; licence characteristics; and past abstractions between 2008 to 2012. Farm attributes and social demographics were obtained from the survey (section A and D respectively) whilst licence characteristics and past abstractions, for those who responded to the survey, were obtained from the EA. The second part discusses the respondents' behavioural intentions, for strategic (long-term) and in-season (short-term) scenarios, which were obtained from the survey (sections B and C respectively). Summary statistics with regards to farm characteristics and behavioural intentions are presented in Appendix B and Appendix C respectively. Overall, not including the random sample of farmers who participated in the pilot survey, 11 % of the remaining population of farmers in the study area responded, providing a sample size of 90 farmers.

4.3.1 Farm characteristics

Farm attributes

Table 4.2 provides a summary of the respondents' farm attributes including: the percentage of crops which were irrigated; the percentage of predominant soil types which were irrigated; and the percentage of irrigation application mechanisms used. Main crop potatoes (41 % of respondents) and vegetables (33 %) were the most widely irrigated crops. Sand and loam were the most widely irrigated predominant soil types, 36 % and 35 % respectively. Whilst rainguns were the most widely used irrigation application mechanism used (60 %). In addition, the respondents total irrigated area, based on their three main irrigated crops, was 12,659 ha, with main crop potatoes and vegetables accounting for 46 % and 35 % respectively. Lastly, 49 % of the respondents had a combined storage capacity of 10,134 Ml.

Table 4.2: Respondents' farm attributes (n = 90)

Measure	Respondents (%)
Irrigated crop	
- Early potatoes	5
- Main crop potatoes	41
- Sugar beet	11
- Orchard fruit	1
- Small fruit	1
- Vegetables	33
- Grass	1
- Cereals	7
- Other	2
Predominant soil type	
- Sand	36
- Loam	35
- Peat	16
- Mixed	14
Irrigation application used	
- Raingun	60
- Booms	18
- Sprinkle	2
- Trickle	1
- Mixed	19

Summing errors due to rounding

Figure 4.2 illustrates that the distribution of irrigated areas (top) and storage capacities (bottom) of the respondents were positively skewed. Irrigated areas ranged from 3 ha to 1,558 ha, with a median of 47 ha and an interquartile range (IQR) of 116 ha. Storage capacities ranged from 5 Ml to 2,273 Ml, with a median of 107 Ml and an IQR of 217 Ml. Furthermore, 25 % of respondents irrigated less than 25 ha and 75 % of respondents irrigated less than 141 ha. With regards to those respondents with storage, 25 % had storage capacities of less than 49 Ml whilst 75 % had storage capacities of less than 266 Ml. In addition, for the 49 % of respondents who had storage capacity, there was a strong positive correlation between ranked irrigated area and ranked storage capacity (r_s= .76), which was also statistically significant (p = <.001), thus the null hypothesis could be rejected (see Appendix B).

These results correspond with findings presented by Knox et al. (2010) for the Anglian region who reported an increase in high value crops, between 1990 and 2010, such

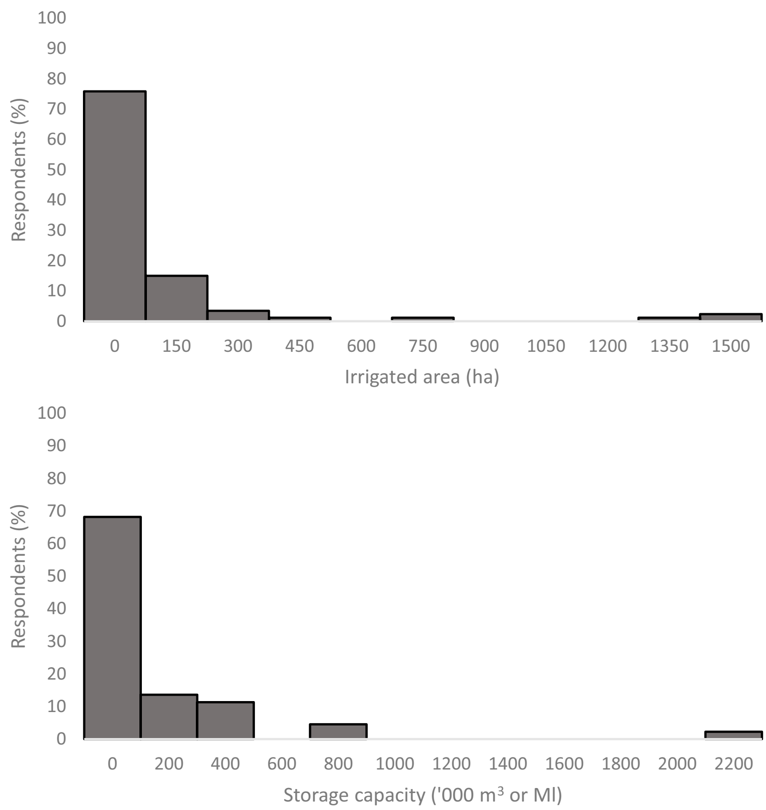

Figure 4.2: Relative frequency histograms of respondents' irrigated areas and storage capacities. (Top) A relative frequency histogram of respondents' irrigated areas. (Bottom) A relative frequency histogram of respondents' storage capacities for those who had storage

as main crop potatoes and vegetables. Furthermore, sand and loam were found to be common soil types present in this region (Hodge et al., 1984). Moreover, approximately 67 % of farmers in England use rainguns as their preferred irrigation application mechanism and 42 % have some level of storage capacity (Weatherhead and Rivas Casado, 2007).

Social demographics

Table 4.3 provides a summary of the respondents' social demographics including: gender; age; level of eduction acquired (measured by National Qualification Framework level for England, Wales and Northern Ireland); and total gross annual farm business income. The majority of respondents were male (98 %) and aged between 40 and 59 (50

Table 4.3: Respondents' social demographics ($n = 90$)

Measure	Respondents (%)
Gender	
- Male	98
- Female	2
Age	
- 18-39	15
- 40-59	50
- $\geq$ 60	35
[a]Education	
- $\leq$ 2	37
- 3-5	25
- $\geq$ 6	38
[b]Income	
- £0-49,999	5
- £50-99,999	18
- $\geq$ £100,000	77

[a]National Qualification Framework (NQF) levels for England, Wales and Northern Ireland
[b]Total gross annual farm business income

%). In regards to the level of education acquired the respondents were largely divided between those who achieved level two or less and those who achieved level six or more (37 % and 38 % respectively). Furthermore, 77 % of respondents reported a total gross annual farm business income of more than £100,000.

These results correspond with findings from the farm structure survey in 2013 which found that 83 % of farm managers in England were male and 58 % were aged between 45 and 64 (DEFRA, 2013). Furthermore, although reported farm incomes were greater than the average farm income in England (£78,190 in 2010), these are typical within the Anglian region where farms are inherently more profitable (DEFRA, 2014a).

Licence characteristics

Table 4.4 provides a summary of the respondents' licence characteristics including: the percentage of farmers who actively used their licence within the last 10 years;

Table 4.4: Respondents' licence characteristics (n = 90)

Measure	Respondents (%)
Licence use (last 10 years)	
- Yes	98
- No	2
Licence type	
- Direct	51
- Storage	9
- Direct and storage	40
Licence source	
- Surface water	78
- Groundwater	22
Time limited	
- Yes	76
- No	24

Summing errors due to rounding

licence type; licence source; and whether licences were time limited or not. The majority of farmers actively used their licence within the last 10 years (98 %). However, with regards to the percentage of respondents who had storage capacity, a discrepancy occurred between the additional data provided by the EA (31 %) and those who responded to the survey (49 %). It was assumed that the questionnaire data provided a more reliable source of information. Therefore, the additional respondents who had storage were assumed to have updated their licences from direct only to direct and storage, as both data sources reported the same respondents with storage only licences. Whereas the majority of respondents (51 %) owned direct licences, which are generally used during the growing season, only 9 % owned storage only licences, which are generally used during the winter to refill farm storage reservoirs, whilst the remainder (40 %) were able to abstract during the whole year as they owned direct and storage licences. Furthermore, 78 % of respondents owned surface water licences, with the remainder owning groundwater licences, and 76 % owned time limited licences with the remainder owning licences which were not time limited. Jointly the respondents total annual licence limit was 6,645 Ml, whilst their total daily licence limit was 171 Ml.

Figure 4.3 illustrates that the distribution of annual (top) and daily (bottom) licence limits of the respondents were positively skewed, similar to irrigated areas and

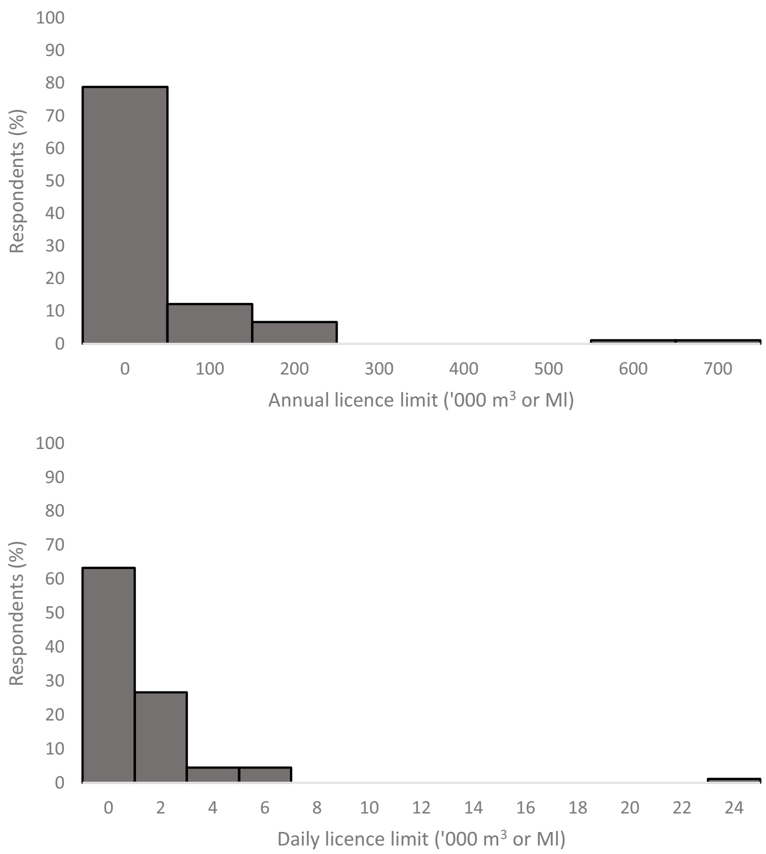

Figure 4.3: Relative frequency histograms of respondents' annual and daily licence limits. (Top) A relative frequency histogram of respondents' annual licence limits. (Bottom) A relative frequency histogram of respondents' daily licence limits

storage capacities. Annual licence limits ranged from 1 Ml to 727 Ml, with a median of 45 Ml and an IQR of 67 Ml. Daily licence limits ranged from <1 Ml to 25 Ml, with a median of 1 Ml and an IQR of 2 Ml. Furthermore, 25 % of respondents annual licence limits were less than 17 Ml and 75 % of respondents annual licence limits were less than 84 Ml. Similarly, 25 % of respondents daily licence limits were less than 1 Ml and 75 % of respondents daily licence limits were less than 2 Ml. In addition, there was a strong positive correlation between ranked annual licence limit and ranked daily licence limit (r_s= .70), which was also statistically significant (p = <.001), thus the null hypothesis could be rejected (see Appendix B).

Past abstractions (2008 to 2012)

On average, the respondents abstracted 36 % of their annual licensed volume between 2008 and 2012 (i.e. 2,395 Ml) (see Appendix B). However, Figure 4.4 (top and middle) illustrate that annual licensed abstractions varied during this period with 51 % being abstracted in 2011 and 24 % in 2012, corresponding with the driest and wettest years since 1973 respectively (see Chapter 3). Furthermore, Figure 4.4 (bottom) illustrates that the respondents' average monthly abstractions, during the same period, varied with the largest volume abstracted in June (435 Ml) and the smallest in October (39 Ml). However, Figure 4.4 (bottom) also indicates two general periods of abstractions in the year. The first corresponds with the growing season (i.e. April to October) when the majority of direct licence users can abstract, accounting for 70 % of average monthly abstractions. The second corresponds with the period outside of the growing season (i.e. November to March) when the majority of storage only licence users can abstract.

In particular, there was a strong, negative, linear correlation between annual abstractions and precipitation (r= -.91), which was also statistically significant (p= $<$.05), thus this null hypothesis could be rejected (see Appendix B). However, there was a weak correlation, with no direction or form, between average monthly abstractions and precipitation (r= .36), which was not statistically significant (p= $>$.05), thus this null hypothesis could not be rejected (see Appendix B). Furthermore, as there were two general periods of abstractions in the year, during the growing season and outside, two further tests of association were conducted respectively. During the growing season, there was a weak correlation, with no direction or form, between average monthly abstractions and precipitation (r= .36), which was not statistically significant (p= $>$.05), thus this null hypothesis could not be rejected (see Appendix B). However, outside of the growing season, there was a strong, positive, linear correlation between average monthly abstractions and precipitation (r= .87), although it was not statistically significant (p= $>$.05), thus this null hypothesis could not be rejected (see Appendix B).

These results indicate that although annual abstractions increased when precipitation decreased, other factors had a strong influence on monthly abstractions other than precipitation. During the growing season, a major contributing factor would likely

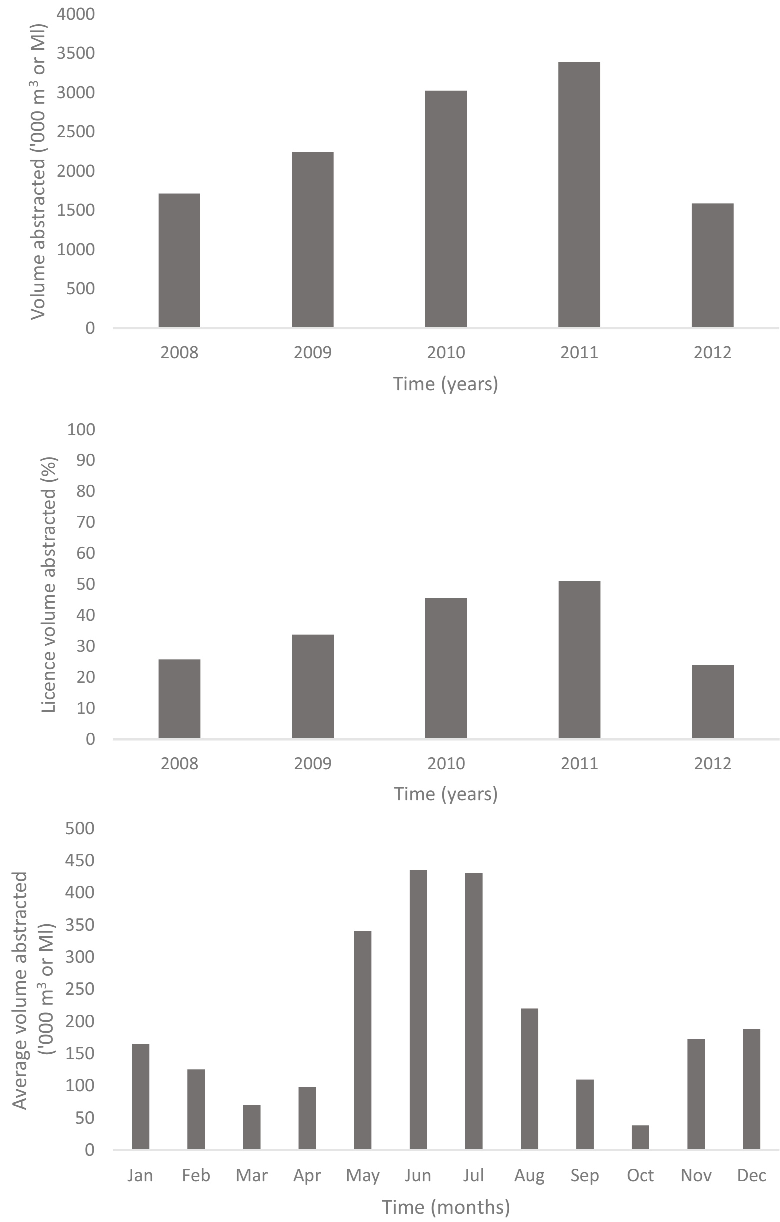

Figure 4.4: Bar charts illustrating respondents' annual, licensed, and average monthly abstractions (2008 to 2012). (Top) A bar chart illustrating respondents' annual abstractions (2008 to 2012). (Middle) A bar chart illustrating the percentage of licence volume abstracted by respondents (2008 to 2012). (Bottom) A bar chart illustrating respondents' average monthly abstractions (2008 to 2012)

include water availability, as less precipitation also means farmers are unable to always abstract water due to HoF restrictions. Outside of the growing season, water availability is less of an issue due to increased precipitation. Thus, a stronger association existed between average monthly abstractions and precipitation, although not significant. Overall, these results indicate that the farm characteristics of the respondents are largely representative of farmers in the Anglian region, and also in England more generally.

4.3.2 Behavioural intentions

The respondents' ranked preferred behavioural intentions for each of the four scenarios are presented in Figure 4.5. LWUO were preferred under all four scenarios: increasing application efficiency under a strategic (long-term)/water shortage scenario; selling surplus water for the duration of the growing season under a strategic (long-term)/water surplus scenario; only using their maximum abstraction licence to irrigate their most valuable crops under an in-season (short-term)/water shortage scenario; and just using their abstraction licence to meet crop water requirements and leaving the remainder of their licence unused under an in-season (short-term)/water surplus scenario. In addition, groups interested in crop type and quality were most influential in respondents decision-making under all scenarios (see Appendix C).

Preferred strategic (long-term)/water shortage behavioural intention

In regards to this scenario, 88 % to 97 % of the respondents answered each Likert item, except for past behaviour, where only 6 % to 8 % answered, due to the fact that only 9 % actually experienced this scenario. Figure 4.5 (top left) indicates that under this scenario the respondents' ranked preferred behavioural intentions, from most preferred to least preferred, were as follows: increase application efficiency (LWUO); increase storage capacity (HWUO); apply for a larger abstraction licence (HWUO); buy more water for the duration of the growing season (HWUO); grow less water intensive crops (LWUO); grow the same crops but over a smaller area (LWUO); and lastly change nothing (LWUO).

Furthermore, a significant median decrease existed between intention to increase application efficiency and intention to increase storage capacity; intention to increase storage capacity and intention to apply for a larger abstraction licence; intention to

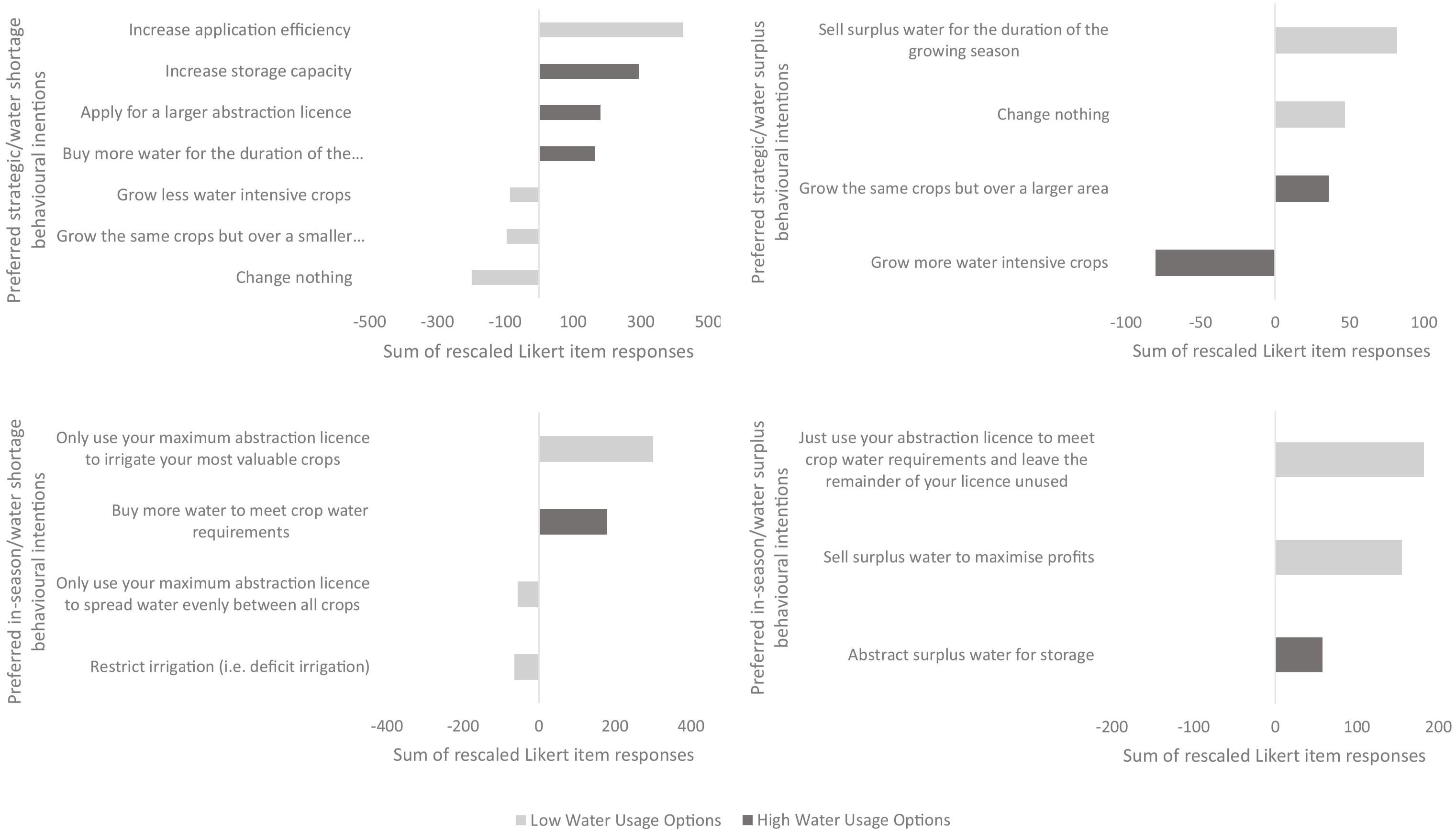

Figure 4.5: Bar charts illustrating respondents' preferred behavioural intentions during strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. (Top left) A bar chart illustrating respondents' preferred strategic (long-term)/water shortage behavioural intentions. (Top right) A bar chart illustrating respondents' preferred strategic (long-term)/water surplus behavioural intentions. (Bottom left) A bar chart illustrating respondents' preferred in-season (short-term)/water shortage behavioural intentions. (Bottom right) A bar chart illustrating respondents' preferred in-season (short-term)/water surplus behavioural intentions

Table 4.5: A binary logistic regression model with regards to respondents' preferred strategic (long-term)/water shortage behavioural intention (n = 79)

[a]Variables	β	SE	Wald (X^2)	df	Sig.	Exp(β)	95 % C.I. for Exp(β) Lower	Upper
Constant	-1.765	.476	13.748	1	.000	.171		
- Attitude	1.146	.545	4.419	1	.036	3.146	1.081	9.159
- SN	1.641	.547	9.009	1	.003	5.160	1.767	15.068
- PBC	.431	.567	.577	1	.448	1.538	.506	4.676

Coefficient (β); Standard error of estimate (SE); Wald chi-square value (Wald (X^2)); Degree of freedom (df); Significance (Sig.); Exponentiated coefficient (Exp(β)); Confidence interval (C.I.)
[a] Subjective norm (SN); Perceived Behavioural Control (PBC)
Model chi-square (X^2) = 22.866 (3 df), p = .000, (-2 log likelihood = 85.623). Hosmer & Lemeshow (X^2) = 1.970 (5 df), p = .853. Cox and Snell R^2 = .251. Nagelkerke R^2 = .337

buy more water for the duration of the growing season and intention to grow less water intensive crops; and intention to grow the same crops but over a smaller area and intention to change nothing. As p= <.05 in each case, the null hypotheses could be rejected for each pair of these behaviours. In addition, a significant median increase existed between intention to grow less water intensive crops and intention to grow the same crops but over a smaller area, p= <.05, thus the null hypothesis between this pair of behaviours could also be rejected (see Appendix C).

A binary logistic regression was performed to examine the effects of attitude, subjective norm, and perceived behavioural control on the likelihood of increasing respondents' intention to increase application efficiency. The logistic regression model was statistically significant, $X^2(3)$ = 22.866, p = <.001, thus the null hypothesis could be rejected (see Table 4.5). Attitude and subjective norm were both significant predictors of intention, p = <.05 and p = <.01 respectively, thus the null hypotheses for these predictor variables could be rejected. However, perceived behavioural control was not a significant predictor of intention, p = >.05, thus the null hypothesis for this predictor could not be rejected. Moreover, a one unit increase in attitude increased the odds of a farmers' intention to increase application efficiency by 3.146 times. A one unit increase in subjective norm increased the odds of a farmers' intention to increase application efficiency by 5.160 times.

Table 4.6: Classification table with regards to respondents' preferred strategic (long-term)/water shortage behavioural intention (n = 79)

		Predicted Intention		% correct
Observed		0	1	
Intention	0	37	7	84.1
	1	12	23	65.7
Overall %				75.9

The cutoff value is .5

Furthermore, no multi-collinearity existed between predictor variables, the number of cases per predictor variables were greater than the recommended value, and no outliers were present, based on the thresholds used in this study (see Appendix C). The Hosmer-Lemeshow goodness-of-fit statistic was insignificant indicating that the model fit the observed data well, $X^2(5) = 1.970$, $p = .853$, thus the null hypothesis could not be rejected. Furthermore, the model explained 34 % (Nagelkerke R^2) of the variance in intention to increase application efficiency and correctly classified 76 % of cases, an improvement over the null model which only classified 56 % of cases correctly (see Table 4.6).

Preferred strategic (long-term)/water surplus behavioural intention

In regards to this scenario, 86 % to 96 % of the respondents answered each Likert item, except for past behaviour, where only 42 % to 50 % answered, due to the fact that only 51 % actually experienced this scenario (noticeably more than the previous strategic (long-term)/water shortage scenario). Figure 4.5 (top right) indicates that under this scenario the respondents' ranked preferred behavioural intentions, from most preferred to least preferred, were as follows: sell surplus water for the duration of the growing season (LWUO); change nothing (LWUO); grow the same crops but over a larger area (HWUO); and lastly grow more water intensive crops (HWUO).

Furthermore, a significant median decrease existed between intention to change nothing and intention to grow the same crops but over a larger area; and intention to grow the same crops but over a larger area and intention to grow more water intensive crops. As $p = <.05$ for both of these cases, the null hypotheses could be rejected for

Table 4.7: A binary logistic regression model with regards to respondents' preferred strategic (long-term)/water surplus behavioural intention (n = 75)

[a]Variables	β	SE	Wald (X^2)	df	Sig.	Exp(β)	95 % C.I. for Exp(β) Lower	Upper
Constant	-1.085	.387	7.850	1	.005	.338		
- Attitude	2.588	1.107	5.463	1	.019	13.309	1.519	116.635
- SN	1.275	.528	5.821	1	.016	3.579	1.270	10.083
- PBC	.535	.643	.693	1	.405	1.708	.484	6.022

Coefficient (β); Standard error of estimate (SE); Wald chi-square value (Wald (X^2)); Degree of freedom (df); Significance (Sig.); Exponentiated coefficient (Exp(β)); Confidence interval (C.I.)
[a] Subjective norm (SN); Perceived Behavioural Control (PBC)
Model chi-square (X^2) = 18.340 (3 df), p = .000, (-2 log likelihood = 85.512).
Hosmer & Lemeshow (X^2) = 2.621 (3 df), p = .454. Cox and Snell R^2 = .217.
Nagelkerke R^2 = .289

each pair of these behaviours (see Appendix C). However, although no significant median difference existed between intention to sell surplus water for the duration of the growing season and intention to change nothing, the prior behaviour was ranked higher.

A binary logistic regression was performed to examine the effects of attitude, subjective norm, and perceived behavioural control on the likelihood of increasing respondents' intention to sell surplus water for the duration of the growing season. The logistic regression model was statistically significant, $X^2(3) = 18.340$, $p = <.001$, thus the null hypothesis could be rejected (see Table 4.7). Attitude and subjective norm were both significant predictors of intention, $p = <.05$ for both predictors, thus the null hypotheses for these predictor variables could be rejected. However, perceived behavioural control was not a significant predictor of intention, $p = >.05$, thus the null hypothesis for this predictor could not be rejected. Moreover, a one unit increase in attitude increased the odds of a farmers' intention to sell surplus water for the duration of the growing season by 13.309 times. A one unit increase in subjective norm increased the odds of a farmers' intention to sell surplus water for the duration of the growing season by 3.579 times.

Furthermore, no multi-collinearity existed between predictor variables, the number of cases per predictor variables were greater than the recommended value, and no outliers were present, based on the thresholds used in this study (see Appendix C). The Hosmer-Lemeshow goodness-of-fit statistic was insignificant indicating that the model

Table 4.8: Classification table with regards to respondents' preferred strategic (long-term)/water surplus behavioural intention ($n = 75$)

		Predicted Intention		% correct
Observed		0	1	
Intention	0	26	13	66.7
	1	10	26	72.2
Overall %				69.3

The cutoff value is .5

fit the observed data well, $X^2(3) = 2.621$, $p = .454$, thus the null hypothesis could not be rejected. Furthermore, the model explained 29 % (Nagelkerke R^2) of the variance in intention to sell surplus water for the duration of the growing season and correctly classified 69 % of cases, an improvement over the null model which only classified 52 % of cases correctly (see Table 4.8).

Preferred in-season (short-term)/water shortage behavioural intention

In regards to this scenario, 87 % to 94 % of the respondents answered each Likert item, except for past behaviour, where only 12 % answered, due to the fact that only 12 % actually experienced this scenario, similar to the previous strategic (long-term)/water shortage scenario. Figure 4.5 (bottom left) indicates that under this scenario the respondents' ranked preferred behavioural intentions, from most preferred to least preferred, were as follows: only use your maximum abstraction licence to irrigate your most valuable crops (LWUO); buy more water to meet crop water requirements (HWUO); only use your maximum abstraction licence to spread water evenly between all crops (LWUO); and lastly restrict irrigation (i.e. deficit irrigation) (LWUO).

Furthermore, a significant median decrease existed between intention to only use your maximum abstraction licence to irrigate your most valuable crops and intention to buy more water to meet crop water requirements; and intention to buy more water to meet crop water requirements and intention to only use your maximum abstraction licence to spread water evenly between all crops. As $p = <.05$ for both of these cases, the null hypotheses could be rejected for each pair of these behaviours (see Appendix C).

Table 4.9: A binary logistic regression model with regards to respondents' preferred in-season (short-term)/water shortage behavioural intention (n = 78)

[a]Variables	β	*SE*	Wald (X^2)	*df*	Sig.	Exp(β)	95 % C.I. for Exp(β) Lower	Upper
Constant	-3.108	.680	20.862	1	.000	.045		
- Attitude	1.588	.750	4.479	1	.034	4.896	1.125	21.312
- SN	2.031	.697	8.479	1	.004	7.619	1.942	29.885
- PBC	1.356	.653	4.314	1	.038	3.882	1.079	13.958

Coefficient (β); Standard error of estimate (*SE*); Wald chi-square value (Wald (X^2)); Degree of freedom (*df*); Significance (Sig.); Exponentiated coefficient (Exp(β)); Confidence interval (C.I.)
[a] Subjective norm (SN); Perceived Behavioural Control (PBC)
Model chi-square (X^2) = 28.167 (3 *df*), p = .000, (-2 log likelihood = 60.639).
Hosmer & Lemeshow (X^2) = 5.055 (4 *df*), p = .282. Cox and Snell R^2 = .303.
Nagelkerke R^2 = .446

A binary logistic regression was performed to examine the effects of attitude, subjective norm, and perceived behavioural control on the likelihood of increasing respondents' intention to only use their maximum abstraction licence to irrigate their most valuable crops. The logistic regression model was statistically significant, $X^2(3) = 28.167$, $p = <.001$, thus the null hypothesis could be rejected (see Table 4.9). Attitude, subjective norm, and perceived behavioural control were all significant predictors of intention, $p = <.05$ for all predictors, thus the null hypotheses for all of the predictor variables could be rejected. Moreover, a one unit increase in attitude increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 4.896 times. A one unit increase in subjective norm increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 7.619 times. Lastly, a one unit increase in perceived behavioural control increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 3.882 times.

However, although no multi-collinearity existed between predictor variables, and the number of cases per predictor variables were greater than the recommended value, there was one noticeable outlier present, based on the thresholds used in this study (see Appendix C). This outlier represented the only respondent who was categorised as one for intention but zero for each of the predictors. Therefore, a second binary logistic regression was performed, after removing the outlier, to compare changes in the model.

Table 4.10: A binary logistic regression model with regards to respondents' preferred in-season (short-term)/water shortage behavioural intention after removing an outlier (n = 77)

[a]Variables	β	SE	Wald (X^2)	df	Sig.	Exp(β)	95 % C.I. for Exp(β) Lower	Upper
Constant	-3.643	.817	19.876	1	.000	.026		
- Attitude	1.708	.774	4.876	1	.027	5.519	1.212	25.139
- SN	2.403	.777	9.556	1	.002	11.056	2.410	50.730
- PBC	1.638	.707	5.366	1	.021	5.146	1.287	20.577

Coefficient (β); Standard error of estimate (SE); Wald chi-square value (Wald (X^2)); Degree of freedom (df); Significance (Sig.); Exponentiated coefficient (Exp(β)); Confidence interval (C.I.)
[a] Subjective norm (SN); Perceived Behavioural Control (PBC)
Model chi-square (X^2) = 32.129 (3 df), p = .000, (-2 log likelihood = 53.853).
Hosmer & Lemeshow (X^2) = 7.215 (4 df), p = .125. Cox and Snell R^2 = .342.
Nagelkerke R^2 = .508

The second binary logistic regression model was statistically significant, $X^2(3) = 32.129$, $p = <.001$, thus the null hypothesis could be rejected (see Table 4.10). Attitude, subjective norm, and perceived behavioural control all continued to be significant predictors of intention, $p = <.05$ for all predictors, thus the null hypotheses for all of the predictor variables could be rejected. Moreover, a one unit increase in attitude increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 5.519 times. A one unit increase in subjective norm increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 11.056 times. Lastly, a one unit increase in perceived behavioural control increased the odds of a farmers' intention to only use their maximum abstraction licence to irrigate their most valuable crops by 5.146 times. Therefore, removing the one noticeable outlier increased the odds ratios of each of the predictor variables.

Furthermore, no multi-collinearity existed between predictor variables, the number of cases per predictor variables were greater than the recommended value, and no outliers were present, based on the thresholds used in this study (see Appendix C). The Hosmer-Lemeshow goodness-of-fit statistic was insignificant indicating that the model fit the observed data well, $X^2(4) = 7.215$, $p = .125$, thus the null hypothesis could not be rejected. Furthermore, the model explained 51 % (Nagelkerke R^2) of the variance in intention to sell surplus water for the duration of the growing season and correctly

Table 4.11: Classification table with regards to respondents' preferred in-season (short-term)/water shortage behavioural intention (n = 77)

		Predicted Intention		% correct
Observed		0	1	
Intention	0	52	6	89.7
	1	5	14	73.7
Overall %				85.7

The cutoff value is .5

classified 86 % of cases, an improvement over the null model which only classified 75 % of cases correctly (see Table 4.11).

Preferred in-season (short-term)/water surplus behavioural intention

In regards to this scenario, 79 % to 91 % of the respondents answered each Likert item, except for past behaviour, where only 42 % to 50 % answered, due to the fact that only 53 % actually experienced this scenario, which is noticeably more than the previous in-season (short-term)/water shortage scenario and similar to the strategic (long-term)/water surplus scenario. Figure 4.5 (bottom right) indicates that under this scenario the respondents' ranked preferred behavioural intentions, from most preferred to least preferred, were as follows: just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused (LWUO); sell surplus water to maximise profits (LWUO); and lastly abstract surplus water for storage (HWUO).

The only significant median decrease existed between intention to sell surplus water to maximise profits and intention to abstract surplus water for storage, as $p = <.05$. Therefore the null hypotheses could be rejected for this pair of behaviours (see Appendix C). However, although no significant median difference existed between intention to just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused and intention to sell surplus water to maximise profits, the prior behaviour was ranked higher, similar to the previous strategic (long-term)/water surplus scenario.

Table 4.12: A binary logistic regression model with regards to respondents' preferred in-season (short-term)/water surplus behavioural intention (n = 72)

[a]Variables	β	*SE*	Wald (X^2)	*df*	Sig.	Exp(β)	95 % C.I. for Exp(β) Lower	Upper
Constant	-21.819	6027.378	.000	1	.997	.000		
- Attitude	$+\infty$	6027.378	.000	1	.997	$+\infty$	-	-
- SN	-.431	.826	.272	1	.602	.650	.129	3.281
- PBC	$+\infty$	6027.378	.000	1	.997	$+\infty$	-	-

Coefficient (β); Standard error of estimate (*SE*); Wald chi-square value (Wald (X^2)); Degree of freedom (*df*); Significance (Sig.); Exponentiated coefficient (Exp(β)); Confidence interval (C.I.)
[a] Subjective norm (SN); Perceived Behavioural Control (PBC)
Model chi-square (X^2) = 40.960 (3 *df*), p = .000, (-2 log likelihood = 37.744).
Hosmer & Lemeshow (X^2) = 2.003 (5 *df*), p = .849. Cox and Snell R^2 = .434.
Nagelkerke R^2 = .653

A binary logistic regression was performed to examine the effects of attitude, subjective norm, and perceived behavioural control on the likelihood of increasing respondents' intention to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused. However, the model failed to converge after 20 iterations suggesting that one or more of the predictor variables were causing complete or quasi-complete separation, due to the sample size being too small. On inspection of the iteration history it was clear that attitude and perceived behavioural control were the responsible variables (see Appendix C). Although the most common approach is to remove the variable or variables causing the issue, others suggest a more desirable approach is to simply do nothing and report the results of the full model, largely due to interaction effects between predictor variables. Either approach should be made in consideration to the original research question attempting to be addressed. Therefore, as this study was interested in understanding the relative importance of each of the underlying constructs, the latter approach was adopted (Allison, 2008).

The binary logistic regression model was statistically significant, $X^2(3) = 40.960$, $p = <.001$, thus the null hypothesis could be rejected (see Table 4.12). However, none of the predictor variables were individually significant, $p = >.05$ for all predictors, thus the null hypothesis could not be rejected for any of the predictor variables. The standard errors and Wald chi-square statistics for attitude and perceived behavioural control are certainly incorrect but those for subjective norm remain valid (Allison, 2008).

Table 4.13: Classification table with regards to respondents' preferred in-season (short-term)/water surplus behavioural intention ($n = 72$)

		Predicted Intention		% correct
Observed		0	1	
Intention	0	55	0	100.0
	1	9	8	47.1
Overall %				87.5

The cutoff value is .5

Furthermore, no multi-collinearity existed between predictor variables, the number of cases per predictor variables were greater than the recommended value, and no outliers were present, based on the thresholds used in this study (see Appendix C). The Hosmer-Lemeshow goodness-of-fit statistic was insignificant indicating that the model fit the observed data well, $X^2(5) = 2.003$, $p = .849$, thus the null hypothesis could not be rejected. Furthermore, the model explained 65 % (Nagelkerke R^2) of the variance in intention to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused and correctly classified 88 % of cases, an improvement over the null model which only classified 76 % of cases correctly (see Table 4.13).

4.4 Summary

Overall, this chapter has analysed empirical data which identified farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems in England. The results of this study are intended to inform policy decision-makers involved in designing the proposed water allocation systems by: 1) understanding how the proposed water allocation systems might be received by farmers' on the ground; and 2) identifying which underlying predictors of intention most influence farmers' decision-making. Therefore, a questionnaire was sent to 826 farmers in the study area of which 11 % responded. Analyses were conducted in regards to respondents' farm characteristics and preferred behavioural intentions based on the theoretical framework of the TPB.

Generally, respondents were representative of farmers in the Anglian region, and in England, as farm characteristics were similar to those presented in other studies (Hodge et al., 1984; Weatherhead and Rivas Casado, 2007; Knox et al., 2010; DEFRA, 2013, 2014a). Under a strategic (long-term)/water shortage scenario farmers' preferred behavioural intention was to increase application efficiency. Under a strategic (long-term)/water surplus scenario farmers' preferred behavioural intentions was to sell surplus water for the duration of the growing season. Under an in-season (short-term)/water shortage scenario farmers' preferred behavioural intention was to only use their maximum abstraction licence to irrigated their most valuable crops. Lastly, under an in-season (short-term)/water surplus scenario farmers' preferred behavioural intention was to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused. Interestingly, all of the preferred behaviours were LWUO as defined in this study.

In addition, the results of the binary logistic regression analyses indicated that attitude and subjective norm were both significant predictors of farmers' intentions under three of the four scenarios (not under an in-season (short-term)/water surplus scenario). Perceived behavioural control was only a significant predictor under an in-season (short-term)/water shortage scenario. Interestingly, subjective norm had a larger influence on farmers' intentions under both strategic (long-term) and in-season (short-term)/water shortage scenarios, whilst attitude had a larger influence on farmers' intention under a strategic (long-term)/water surplus scenario. Past behaviour was not included in the regression analyses due to too few responses for this construct.

Therefore, the results of this study indicate that the proposed water allocation systems, which strongly encourage water licence trading, are not likely to be adopted quickly by farmers in the Anglian region based on their current preferred behavioural intentions, except with regards to selling surplus water during strategic (long-term)/water surplus scenarios. However, if attitude and subjective norm are assumed to be the most influential predictors of farmers' intentions, based on the results of this study, then it would not be surprising to see a gradual increase in the number of farmers trading as more farmer's increasingly understood the operations and the advantages, similar to what occurred in Australia when they first introduced water trading (Bjornlund, 2003).

Finally, this study is intended to inform policy decision-makers involved with the design and implementation of the proposed water allocation systems in England. The results of this study have indicated how the proposals might be received by farmers on the ground under different strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. It also identified the main underlying constructs of the TPB which have the greatest effect in influencing their decision-making.

Chapter 5

A farm typology based on preferred behavioural intentions

This chapter presents a farm typology based on the preferred behavioural intentions of farmers identified in the previous chapter. In particular this chapter offers one of the first typologies designed for policy decision-makers to understand how the proposed water allocation systems in England might be received by particular groups of farmers on the ground. As previously discussed, traditional farm typologies tend to concentrate on particular farm attributes such as farm income, size, or output. However, in respect to policy decision-making a growing number of researchers, and policy decision-makers, are beginning to realise the necessity of identifying farmers' behavioural intentions in aiding the design, implementation, and overall success of policy changes. Therefore, this chapter addresses the second of the three research questions presented in the introductory chapter:

Research question 2: *If farmers share similar behavioural intentions under different scenarios how can traditional farm typologies incorporate these preferred behaviours?*

5.1 Introduction

The importance of understanding farmers' preferred behavioural intentions under different scenarios, and the underlying predictors of intention, for policy decision-making have been discussed (see Chapter 1). Furthermore, the use and development of farm typologies to aid policy decision-makers in effectively designing and implementing policy changes have also been discussed (see Chapter 2). However, an important research gap identified in Chapter 2 highlighted that traditional farm typologies, which focus on physical or economic descriptors, fail to incorporate true farmer behaviour and are therefore of limited value in supporting policy formulations (Guillem et al., 2012). Therefore, this chapter extends the analyses conducted in Chapter 4 by exploring whether farmers who share similar behavioural intention traits also share particular farm characteristics such as: farm attributes; social demographics; licence characteristics; and past abstraction behaviour. This method could provide an alternative tool for policy decision-makers when developing and implementing proposed policy changes by targeting specific farm types based on behavioural intentions which may naturally incorporate elements of more traditional typologies.

5.2 Materials and methods

A conceptual approach was used to categorise farmers into three farm types based on their responses to the behavioural intention scenarios of the questionnaire (sections B and C). The categories used to define the three farm types related to the Low Water Usage Options (LWUO) and High Water Usage Options (HWUO) previously discussed (see section 4.2.1). Individual preferences were determined by rescaling Likert psychometric responses to the Theory of Planned Behaviour (TPB) constructs (Ajzen, 1985), including past behaviour (see Figure 4.1), from -3 to 3 and calculating a median response for each of the 18 behaviours. These median values were then used to calculate an overall median response for all LWUO and all HWUO for each respondent. Data were treated as ordinal and therefore median values were used rather than mean values. Respondents were categorised depending on which median value was greatest. If both median values were tied then this would suggest that the irrigation farmer had no preference overall. Therefore, three farm types existed in this conceptual approach: farmers who preferred HWUO; farmers who preferred LWUO; and farmers who had no preference.

Farm characteristics including: farm attributes; social demographics; licence characteristics; and past abstractions were analysed to compare similarities and differences between the three farm types. Pearson's Chi-square tests (X^2) were conducted to test for statistically significant differences between farm types when examining categorical variables. This test required two main assumptions: independence of observations; and that no cells had an expected frequency of less than one and no more than 20 % had an expected frequency of less than five (Cochran, 1952). Although the first assumption was satisfied by the fact that only one farmer could belong to a single farm type, the second assumption occasionally required amalgamating particular categories, if suitable, to increase expected frequency. Where this occurred, the amalgamated categories are stated along with the test results. The null hypothesis for the Pearson's Chi-square test was that there was no statistically significant difference between farm type and the categorical variable being tested. Therefore, if the *p-value* was less than the chosen alpha level, which for this study was .05, then the null hypothesis was rejected suggesting that there was a significant difference between farm types.

In regards to continuous variables, such as size of irrigated areas, Shapiro-Wilk tests, in addition to normal probability plots, were used to determine whether variables were normally distributed (see Appendix D). Depending on the results of these tests, the appropriate parametric or non-parametric test was then used to explore the null hypothesis that a statistically significant difference existed between the three farm types if the *p-value* was less than the chosen alpha level, which for these tests was .05, (one-way analysis of variance (ANOVA) or Kruskal-Wallis respectively). If such a statistically significant difference existed, then further relevant parametric or non-parametric tests were conducted to test the same null hypothesis but between two farm types (independent t-test or Mann-Whitney U test respectively). However, in regards to Mann-Whitney U tests the difference in median values was reported if the two distributions were similar in shape; otherwise the difference in mean ranks was reported if distributions were not similar.

5.3 Results and discussion

Figure 5.1 illustrates the prevalence of the three farm types: those who preferred LWUO accounting for 23 % of the respondents; those who had no preference accounting for 27 % of the respondents; and those who preferred HWUO accounting for 50 % of the

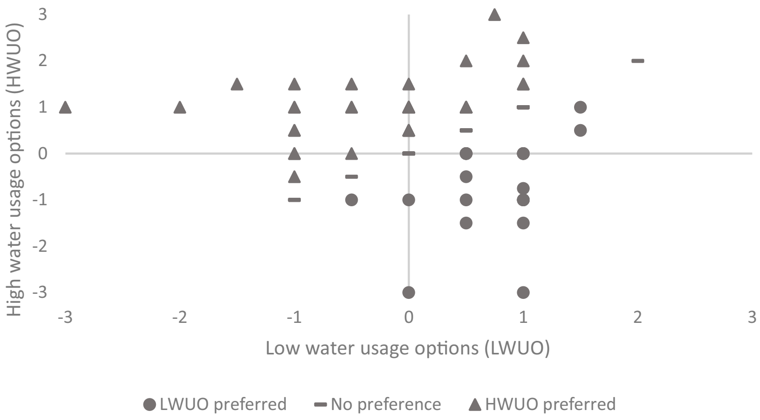

Figure 5.1: A scatter plot indicating three farm types derived from median responses to low water usage options (LWUO) and high water usage options (HWUO), including: respondents who preferred LWUO; respondents who had no preference; and respondents who preferred HWUO ($n = 90$)

respondents. The results indicate that the largest percentage of respondents preferred HWUO whilst the smallest percentage of respondents preferred LWUO. Although it appears farmers from different farm types are clustered close together this is simply a result of the conceptual approach used.

5.3.1 Farm attributes

Table 5.1 provides a comparison of the three farm types' farm attributes. A statistically significant difference existed with regards to irrigation application mechanisms used between those who preferred LWUO and those who had no preference (X^2= 5.033) as p= <.05, and between those who preferred LWUO and those who preferred HWUO (X^2= 9.260) as p= <.05. Thus, the null hypothesis for this farm attribute could be rejected as those who preferred LWUO used significantly more rainguns for irrigating (80 %) compared to those who had no preference or preferred HWUO (58 % and 53 % respectively). In addition, a statistically significant difference existed with regards to storage availability between those who preferred LWUO and those who preferred HWUO (X^2= 7.508) as p= <.05. Thus, the null hypothesis for this farm attribute could also be rejected as those who preferred LWUO consisted of significantly fewer farmers with storage available (24 %) compared with those who preferred HWUO (60 %). However, in regards to irrigated crops and predominant soil types, no statistically

Table 5.1: Farm types' farm attributes (n = 90)

Measure	[a]LWUO preferred (%)	No preference (%)	[b]HWUO preferred (%)
Irrigated crop			
- Main crop potatoes	41	39	42
- Vegetables	24	41	32
- Other (amalgamated)	34	20	26
Pearson chi-square (X^2)(*2 df*)			
- LWUO preferred		3.427	1.290
- No preference			1.137
Predominant soil type			
- Sand	32	45	33
- Loam	32	23	42
- Peat	22	17	12
- Mixed	15	15	13
Pearson chi-square (X^2)(3 *df*)			
- LWUO preferred		1.784	2.611
- No preference			4.705
Irrigation application used			
- Raingun	80	58	53
- Other (amalgamated)	19	42	46
Pearson chi-square (X^2)(1 *df*)			
- LWUO preferred		5.033*	9.260*
- No preference			.407
Storage available			
- Yes	24	50	60
- No	76	50	40
Pearson chi-square (X^2)(1 *df*)			
- LWUO preferred		3.268	7.508*
- No preference			.637

Summing errors due to rounding. (*df*) = Degree of freedom. (*) = $p<.05$
[a] Low water usage options (LWUO)
[b] High water usage options (HWUO)

significant difference existed between the three farm types, as $p= >.05$, thus the null hypotheses for these two farm attributes could not be rejected.

Kruskal-Wallis tests showed that statistically significant differences existed between farm types with regards to irrigated areas (X^2= 6.525) as $p= <.05$, and storage capacities (X^2= 9.280) as $p= <.05$ (see Figure 5.2). In particular, a statistically significant difference existed with regards to irrigated area between those who preferred LWUO and those who preferred HWUO (U= 264) as $p= <.05$. Thus, the null hypothesis for

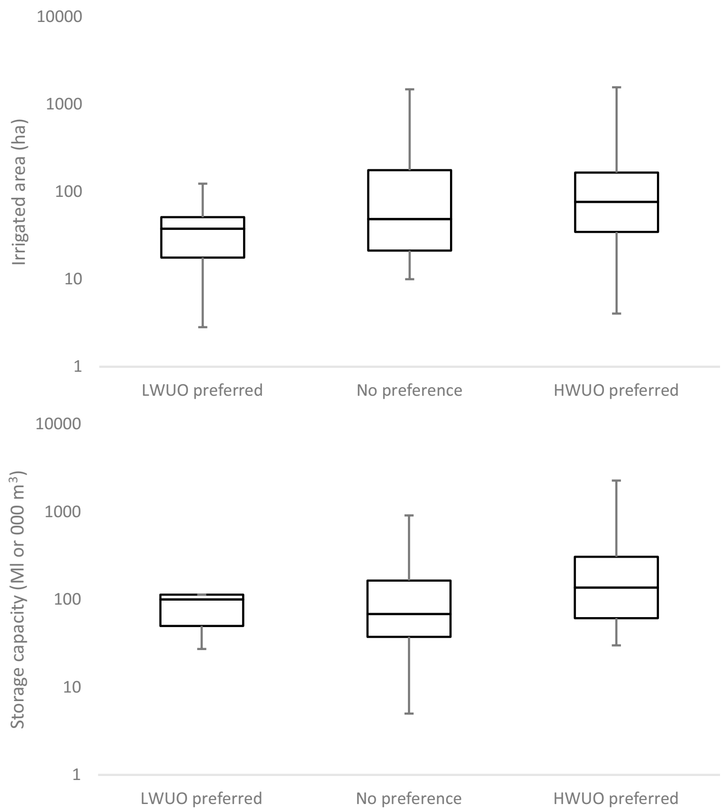

Figure 5.2: Box plots illustrating farm types' irrigated areas and storage capacities. (Top) A box plot illustrating farm types' irrigated areas. (Bottom) A box plot illustrating farm types' storage capacities

this farm attribute could be rejected as those who preferred LWUO irrigated significantly smaller areas (median 38 ha and IQR 33 ha) compared to those who preferred HWUO (median 76 ha and IQR 130 ha). Similarly, a statistically significant difference existed with regards to storage capacity between those who preferred LWUO and those who preferred HWUO ($U=$ 273) as $p= <.05$. Thus, the null hypothesis for this farm attribute could also be rejected as those who preferred LWUO had significantly smaller storage capacities (median 100 Ml and IQR 64 Ml) compared to those who preferred HWUO (median 136 Ml and IQR 245 Ml).

5.3.2 Social demographics

Table 5.2 provides a comparison of the three farm types' social demographics. A statistically significant difference existed with regards to age between those who preferred

Table 5.2: Farm types' social demographics

Measure	[a]LWUO preferred (%)	No preference (%)	[b]HWUO preferred (%)
Gender (n = 86)			
- Male	100	96	98
- Female	0	4	2
Age (n = 88)			
- 18-59	47	63	73
- $\geq$ 60	53	38	27
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		.985	3.993*
- No preference			.868
[c]**Education** (n = 79)			
- $\leq$ 5	87	65	51
- $\geq$ 6	13	35	49
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		2.154	5.785*
- No preference			1.173
[d]**Income** (n = 77)			
- £0-99,999	29	23	22
- $\geq$ £100,000	71	77	78
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		.156	.253
- No preference			.005

Summing errors due to rounding. (*df*) = Degree of freedom. (*) = p<.05
[a] Low water usage options (LWUO)
[b] High water usage options (HWUO)
[c]National Qualification Framework (NQF) levels for England, Wales and Northern Ireland
[d]Total gross annual farm business income

LWUO and those who preferred HWUO (X^2= 3.993) as p= <.05. Thus, the null hypothesis for this social demographic could be rejected as those who preferred LWUO consisted of significantly older farmers (53 % were aged 60 or over) compared with those who preferred HWUO (only 27 % were aged 60 or over). In addition, a statistically significant difference existed with regards to education between those who preferred LWUO and those who preferred HWUO (X^2= 5.785) as p= <.05. Thus, the null hypothesis for this social demographic could also be rejected as those who preferred LWUO consisted of significantly fewer farmers who had achieved a National Qualification Level (NQF) of 6 or higher (only 13 % had a university degree or equivalent) compared with those who preferred HWUO (49 %). However, in regards to gender, the assumptions for conducting Pearson's Chi-square test could not be satisfied as very few female farmers existed. Furthermore, in regards to income, no statistically significant difference existed between the three farm types, as p= >.05, thus the null hypothesis for this social demographic could not be rejected.

5.3.3 Licence characteristics

Table 5.3 provides a comparison of the three farm types' licence characteristics. A statistically significant difference existed with regards to licence type between those who preferred LWUO and those who preferred HWUO (X^2= 7.508) as p= <.05. Thus, the null hypothesis for this licence characteristic could be rejected as those who preferred LWUO consisted of significantly fewer storage, or direct and storage, licence users (76 % owned direct licences only) compared with those who preferred HWUO (only 40 %). In addition, a statistically significant difference existed with regards to time limited licences between those who preferred LWUO and those who preferred HWUO (X^2= 7.698) as p= <.05. Thus, the null hypothesis for this licence characteristic could also be rejected as those who preferred LWUO consisted of significantly fewer farmers who owned time limited licences (52 %) compared with those who preferred HWUO (84 %). However, in regards to licence use during the last 10 years, the assumptions for conducting Pearson's Chi-square test could not be satisfied as very few non-active users existed. Furthermore, in regards to licence source, no statistically significant difference existed between the three farm types, as p= >.05, thus the null hypothesis for this licence characteristic could not be rejected.

Kruskal-Wallis tests showed that statistically significant differences existed between farm types with regards to annual licence limits (X^2= 11.078) as p= <.05, and daily licence limits (X^2= 15.172) as p= <.05 (see Figure 5.3). In particular, a statistically significant difference existed with regards to annual licence limit between those who preferred LWUO and those who had no preference (U= 139) as p= <.05, and between those who preferred LWUO and those who preferred HWUO (U= 240) as p= <.05. Thus, the null hypothesis for this licence characteristic could be rejected as those who preferred LWUO had significantly smaller annual licence limits (median 18 Ml and IQR 26 Ml) compared to those who had no preference (median 49 Ml and IQR 68 Ml), and

Table 5.3: Farm types' licence characteristics (n = 90)

Measure	[a]LWUO preferred (%)	No preference (%)	[b]HWUO preferred (%)
Licence use (last 10 years)			
- Yes	100	92	100
- No	0	8	0
Licence type			
- Direct	76	50	40
- Other (amalgamated)	24	50	60
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		3.268	7.508*
- No preference			.637
Licence source			
- Surface water	81	75	78
- Groundwater	19	25	22
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		.230	.086
- No preference			.068
Time limited			
- Yes	52	79	84
- No	48	21	16
Pearson chi-square (X^2)(*1 df*)			
- LWUO preferred		3.616	7.698*
- No preference			.303

Summing errors due to rounding. (*df*) = Degree of freedom. (*) = p<.05
[a] Low water usage options (LWUO)
[b] High water usage options (HWUO)

compared to those who preferred HWUO (median 55 Ml and IQR 74 ml). Similarly, a statistically significant difference existed with regards to daily licence limit between those who preferred LWUO and those who preferred HWUO (U= 193) as p= <.05, and between those who had no preference and those who preferred HWUO (U= 382) as p= <.05. Thus, the null hypothesis for this licence characteristic could also be rejected as those who preferred LWUO, and those who had no preference, had significantly smaller daily licence limits (median 1 Ml and IQR <1 ml, and median 1 Ml and IQR 2 Ml respectively) compared to those who preferred HWUO (median 2 Ml and IQR 2 ml). Therefore, although those who preferred LWUO had a significantly smaller annual and daily licence limit than those who preferred HWUO, those who had no preference had a significantly larger annual licence limit than those who preferred LWUO but had a significantly smaller daily licence limit than those who preferred HWUO.

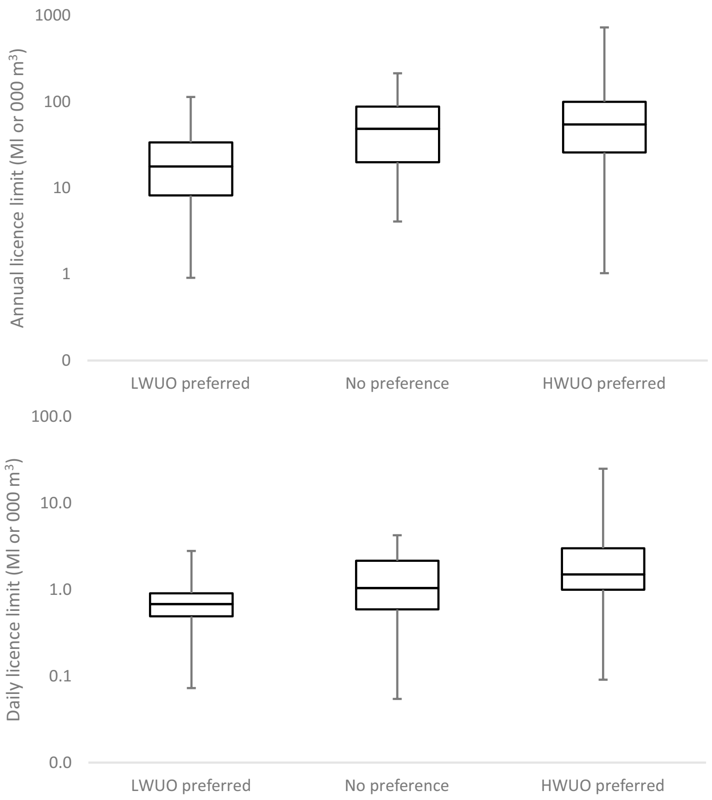

Figure 5.3: Box plots illustrating farm types' annual and daily licence limits. (Top) A box plot illustrating farm types' annual licence limit. (Bottom) A box plot illustrating farm types' daily licence limit

5.3.4 Past abstractions (2008 to 2012)

Kruskal-Wallis tests showed that statistically significant differences existed between farm types with regards to average annual volume abstracted (X^2= 10.294) as p= <.05, and average in-season (i.e. April to October) volume abstracted (X^2= 7.072) as p= <.05 (see Figure 5.4). In particular, a statistically significant difference existed with regards to average annual volume abstracted between those who preferred LWUO and those who had no preference (U= 127) as p= <.05, and between those who preferred LWUO and those who preferred HWUO (U= 269) as p= <.05. Thus, the null hypothesis for this past abstraction characteristic could be rejected as those who preferred LWUO abstracted significantly less on average annually (median 3 Ml and IQR 7 Ml) compared to those who had no preference (median 15 Ml and IQR 31 Ml), and to those who preferred HWUO (median 12 Ml and IQR 20 Ml). Similarly, a statistically significant difference existed with regards to average in-season volume abstracted between

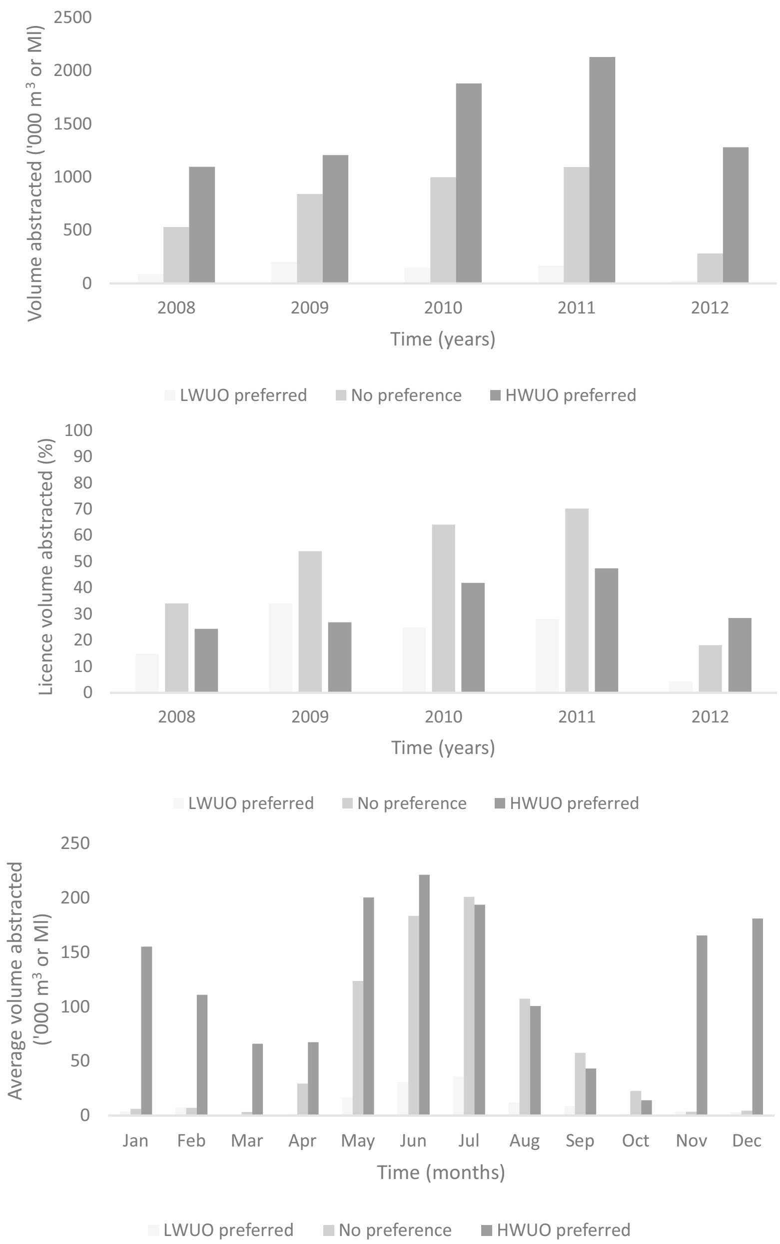

Figure 5.4: Bar charts illustrating farm types and total respondents annual, licensed, and average monthly abstractions (2008 to 2012). (Top) A bar chart illustrating annual abstractions by farm type. (Middle) A bar chart illustrating the percentage of licence volume abstracted by farm type and total respondents. (Bottom) A bar chart illustrating average monthly abstractions by farm type

those who preferred LWUO and those who had no preference (U= 141) as p= <.05. Thus, the null hypothesis for this past abstraction characteristic could also be rejected as those who preferred LWUO abstracted significantly less on average in-season (median <1 Ml and IQR 1 Ml) compared to those who had no preference (median 2 Ml and IQR 5 Ml).

Interestingly, despite those who preferred LWUO and those who had no preference abstracting only 20 % and 5 % out-of-season compared to 53 % for those who preferred HWUO, no statistically significant differences existed between farm types with regards to average out-of-season volume abstracted (X^2= 5.513) as p= >.05. Nonetheless, this higher percentage of water abstracted out-of-season to refill farm storage reservoirs does support earlier findings as those who preferred HWUO consisted of significantly more farmers with storage available, and significantly more farmers who owned storage, and direct and storage, licences compared to those who preferred LWUO.

5.4 Summary

Overall, this study was driven by a growing number of researchers and policy decision-makers realising the necessity of incorporating farmers behavioural intentions into more traditional farm typologies in order to aid the design, implementation, and overall success of policy changes. In particular, this chapter aimed to inform policy decision-makers on how the proposed water policy reform options in England might be received by particular groups, or farm types, on the ground. In doing so, this chapter addressed the second of three research questions set out in the introduction to this thesis, and highlighted again at the start of this chapter. That was, if farmers shared similar behavioural intentions under different scenarios how could traditional farm typologies incorporate these preferred behaviours. This chapter has identified three farm types based on farmers' overall preferred behaviours analysed in the previous chapter: those who preferred LWUO; those who had no preference; and those who preferred HWUO. Furthermore, a series of statistical tests were conducted in order to examine similarities and differences between the three farm types in regards to: farm attributes; social demographics; licence characteristics, and past abstractions.

Table 5.4 provides a summary of the significant differences in farm characteristics identified between the three farm types, in addition to each farm types' preferred behavioural intention under each scenario. Despite farm types being determined based on

Table 5.4: A conceptual farm typology based on respondents' overall preferred behavioural intentions across all four scenarios ($n = 90$)

Measure	[a]LWUO preferred	No preference	[b]HWUO preferred
Farm characteristics (Significant differences)			
- Irrigation application	Mainly rainguns	Mixed	Mixed
- Storage available	Minority		Majority
- Irrigated area	Small		Large
- Storage capacity	Small		Large
- Age (18-59)	Minority		Majority
- [c]Education (≥ 6)	Minority		Majority
- Licence type	Mainly direct		[d]Mainly storage
- Time limited licences	Mixed		Mainly time limited
- Annual licence limit	Small	Large	Large
- Daily licence limit	Small	Small	Large
- Annual abstractions	Small	Large	Large
- In-season abstractions	Small	Large	
Preferred behavioural intentions			
- Strategic (long-term)/ water shortage	Increase application efficiency (LWUO)		
- Strategic (long-term)/ water surplus	Change nothing (LWUO)	Sell surplus water for the duration of the growing season (LWUO)	Grow the same crops but over a larger area (HWUO)
- In-season (short-term)/ water shortage	Only use their maximum abstraction licence to irrigate their most valuable crops (LWUO)		
- In-season (short-term)/ water surplus	Just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused (LWUO)	Sell surplus water to maximise profits (LWUO)	Abstract surplus water for storage (HWUO)

[a] Low water usage options (LWUO)
[b] High water usage options (HWUO)
[c] National Qualification Framework (NQF) levels for England, Wales and Northern Ireland
[d] Includes both storage, and direct and storage licences
See Tables 5.1, 5.2, and 5.3, and Figures 5.2, 5.3, and 5.4 for actual values
See Appendix D for farm types' ranked preferred behavioural intentions

respondents' overall behavioural intentions across all four scenarios, similarities and differences in preferred behavioural intentions existed within each scenario (see Appendix D).

Those who preferred LWUO were generally representative of farmers who irrigated smaller areas, had fewer resources available, and were older and had a lower level of education compared to farmers who preferred HWUO. In particular, fewer resources refer to less available storage and capacity (and therefore fewer storage related licences), smaller annual and daily licence limits, and therefore smaller average annual abstractions compared to those who preferred HWUO. In addition, those who preferred LWUO also relied predominantly on rainguns for irrigation rather than a more mixed approach used by those who had no preference, and those who preferred HWUO.

Conversely, those who preferred HWUO were generally representative of farmers who irrigated larger areas, had greater resources available, and were younger and had a higher level of education compared to farmers who preferred LWUO. In particular, greater resources refer to more available storage and capacity (and therefore more storage related licences), larger annual and daily licence limits, and therefore larger average annual abstractions compared to those who preferred LWUO. In addition, those who preferred HWUO also owned mainly time limited licences compared to a more mixed ratio by those who preferred LWUO. The most likely explanation for this relates to the EA slowly phasing out none-time limited licences, in order for greater control over protecting the environment, as new licences are issued. Therefore, licences issued to younger farmers are perhaps more likely to be time limited compared to older farmers who have retained their none-time limited licences.

Lastly, those who had no preference were unsurprisingly more difficult to define as they shared significant differences with both other farm types, although more in common with those who preferred HWUO. In particular, they relied on a more mixed approach to irrigation, similar to those who preferred HWUO. In addition, they had a greater resource with regards to annual licence limit and therefore had similarly large annual abstractions in comparison to those who preferred HWUO. However, they had a smaller daily licence limit similar to those who preferred LWUO. In addition, those who had no preference abstracted more in-season compared to those who preferred LWUO.

In regards to similarities, all farm types irrigated similar proportions of main crop potatoes and vegetables, on sand and loam which were the predominant soil types.

The majority of farmers were all male, and total gross annual farm business income was over £100,000. Furthermore, the majority had all used their abstraction licences within the last 10 years, and were predominantly all surface water licences.

Interestingly, all farm types shared similar LWUO preferred behavioural intentions under strategic (long-term) and in-season (short-term) water shortage scenarios. That is, under the strategic (long-term)/water shortage scenario they all preferred to increase application efficiency, and under the in-season (short-term)/water shortage scenario they all preferred to only use their maximum abstraction licence to irrigate their most valuable crops. This is not particularly surprising for those who preferred LWUO, or perhaps for those who had no preference. However, with regards to those who preferred HWUO, one explanation could simply be the HWUO available were not regarded as feasible or practical in comparison to the preferred LWUO. For example, increasing storage capacity for many of those who preferred HWUO may not be possible if many already have storage available. Furthermore, many of the farmers would not have experience with trading so buying more water for the duration of the growing season, or buying more water to meet crop water requirements, may have seemed very difficult compared to increasing application efficiency. The same is true with applying for a larger abstraction licence. However, these HWUO were ranked second, third and fourth during a strategic (long-term)/ water shortage, and second during an in-season (short-term)/water shortage by those who preferred HWUO, and by those who had no preference (see Appendix D).

During strategic (long-term) and in-season (short-term) water surplus scenarios each farm type had different preferred behavioural intentions. For example, under a strategic (long-term)/water surplus scenario: those who preferred LWUO preferred to change nothing; those who had no preference preferred to sell surplus water for the duration of the growing season; and those who preferred HWUO preferred to grow the same crops but over a larger area. Similarly, under an in-season (short-term)/water surplus scenario: those who preferred LWUO preferred to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused; those who had no preference preferred to sell surplus water to maximise profits; and those who preferred HWUO preferred to abstract surplus water for storage. As perhaps would be expected, those who preferred LWUO favoured LWUO, whilst those who preferred HWUO favoured HWUO. More interestingly, those who had no preference also favoured LWUO, although rather than doing nothing with the surplus water they preferred to sell. This would suggest that those who had no preference had slightly more in common with those who preferred HWUO in regards to farm characteristics but more in common with those who preferred LWUO in regards to preferred behavioural intentions within each scenario.

This study has shown how farmers' preferred behavioural intentions can be incorporated into more traditional farm typologies, which are typically based on physical or economic descriptors only, and offer valuable support with regards to policy formulation. Therefore, this study has addressed the second research gap identified in Chapter 2, and presented again at the start of this chapter. Furthermore, the typology indicate that the most likely farm types to engage in water licence trading are those who have no preference and those who prefer HWUO. Therefore, the typology could also be used to determine which catchments would likely benefit most from the proposed enhanced water allocation system based on the proportion of farmers who have similar farm characteristics to those who had no preference and those who preferred HWUO.

Chapter 6

Modelling system level patterns of abstraction behaviour

This chapter offers one of the first insights into: 1) how the proposed water allocation systems, both in basic and enhanced catchments, are likely to change water availability for farmers; and 2) the importance of understanding abstraction behaviour in determining the overall success of these systems. The proposed water allocation systems, which are to be implemented by the early 2020s, aim to improve efficiency whilst balancing the needs of licence users and the environment. However, climate change is expected to exacerbate this challenge. Therefore, this chapter presents an empirically based Agent-Based Model (ABM) to understand what system level patterns of abstraction behaviour emerge from individual farmer decisions under different policy (the current and proposed water allocation systems) and climate scenarios (during a selected dry and wet year). Therefore, this chapter addresses the final of the three research questions presented in the introductory chapter:

Research question 3: *What potential system level patterns of abstraction behaviour emerge from individual farm scale decisions under different policy and climate scenarios?*

6.1 Introduction

Major water allocation system reforms have been proposed in England to address the climate and demand change pressures which the current system is failing to address (see Chapter 1). A critical review of the literature highlighted the importance of policy decision-makers, involved in the design and implementation of the proposed water allocation systems, to understand farmers' behaviour at the farm and system level yet very little is understood in either of these areas (see Chapter 2). The Great Ouse catchment was selected as the study area due to the importance of available freshwater resources for agricultural spray irrigation despite it being one of the driest and most water-stressed regions in the UK (see Chapter 3). Chapters 4 and 5 have presented empirical data which identified farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems, and used this data to develop a farm typology based on preferred behavioural intentions rather than traditional farm characteristics. This chapter presents the development and scenario simulation results of an ABM, which utilises the empirical data and typology discussed in the previous chapters, to understand what system level patterns of abstraction behaviour emerge from individual farm decisions under different policy and climate scenarios.

6.2 Materials and methods

The methodological procedure used in this study can be categorised into three stages: 1) model description; 2) policy and climate scenario selection; and 3) statistical analysis.

6.2.1 Model description

The model, developed using NetLogo 5.1.0 (Wilensky, 1999), is described following the standardised Overview, Design concepts, and Details (ODD) protocol designed by Grimm et al. (2006), and updated by (Grimm et al., 2010) (see section 2.3.2).

Purpose

The purpose of this model was to understand the system level patterns of abstraction behaviour which emerge based on farmers' preferred behavioural intentions under different policy and climate scenarios (see section 6.2.2). The aims of the proposed water allocation systems are to improve efficiency whilst balancing the needs of licence users and the environment. Therefore, as this study was only simulating farmers, and the environment was considered to be better protected under the proposed water allocation systems due to the introduction of low flow conditions, four model indicators were used. The four indicators were: monthly licensed volume abstracted; surplus water available; shortage water required; and the percentage of farm Irrigation Water Need (IWN) satisfied (i.e. of main crop potatoes and vegetables) (see Appendix E). Monthly licensed volume abstracted was used to understand the overall system level pattern of farmers abstractions. Surplus water available, and shortage water required, were considered important to highlight the potential for trading, thus improve efficiency, between farmers and other sectors at different times of the year. Finally, the percentage of farm IWN satisfied was used to understand the effectiveness of the different policy scenarios.

Entities, state variables, and scales

There are three types of entities in this model: agents (i.e. farmers); grid cells (i.e. the landscape); and the observer (i.e. the global environment) all of which have their own unique set of state variables (see Table 6.1). Farmers' state variables included two types: those which remain the same during each model setup (i.e. identification and location within the projected landscape of the study area); and those which depend on the farmers' farm type, which is randomly assigned at the start of each model setup. However, the proportion of farmers within each farm type remain the same during each model run and is presented in Section 5.3: 23 % of farmers are those who preferred Low Water Usage Options (LWUO); 27 % are farmers who had no preference; and 50 % are farmers who preferred High Water Usage Options (HWUO). Irrigated areas, storage capacities, and annual licence limits are calculated from distributions, using median, 25th and 75th percentile values, which are unique to each farm type. Therefore, farmers within the same farm type can have different individual values for each of these state variables at the start of each model setup. However, farmers' other state variables are single values depending on their farm type including: the percentage of irrigated area covered by main crop potatoes and vegetables; the percentage of farmers with storage available; the percentage of farmers with storage only licences; and preferred behavioural strategies. In addition, the percentage of crop cover excludes any other crops besides main crop potatoes and vegetables and therefore values differ between

Table 6.1: Entities, state variables, and scales

Variable	Unit	Value (value derived from)
Farmers' state variables		
- Identification	n	1-836
- Location	[a]Coordinates	Figure 3.1
- Farm type	[b]n	Section 5.3
- Irrigated area	m^2	Figure 5.2
- Main crop potato cover	%	Table 5.1
- Vegetable cover	%	Table 5.1
- Storage availability	%	Table 5.1
- Storage only licence	%	Table 5.3
- Storage capacity	m^3	Figure 5.2
- Annual licence limit	m^3	Figure 5.3
- Preferred behavioural strategies		Table 5.4
Landscape state variables		
- [c]AP location	[a]Coordinates	Figure 3.1
- [c]AP name		Figure 3.1
- [c]AP low flow condition (Q95)	m^3	Table 3.1
- [c]AP high flow condition (Q30)	m^3	Table 3.1
Global environment state variables		
- [d]IWN of main crop potatoes	mm	Appendix E
- [d]IWN of vegetables (i.e. carrots)	mm	Appendix E
- [c]AP river discharges (dry year)	m^3	Appendix E
- [c]AP river discharges (wet year)	m^3	Appendix E

[a] British National Grid
[b] Farm types are randomly assigned but proportional to the empirical data in the farm typology
[c] Assessment Point
[d] Irrigation water need

the model and the farm typology. Furthermore, carrots were selected to represent vegetables due to the availability of data with regards to calculating IWN (see Appendix E).

In regards to farmers' preferred behavioural strategies, only in-season (short-term) water shortage and surplus strategies were simulated. The added complexity and large assumptions involved with incorporating the strategic (long-term) water shortage and surplus strategies, particularly with regards to how farmers would increase application efficiency or grow the same crops but over a larger area, were considered to over complicate the model and not provide the most efficient and effective way of addressing the research question. The strategic (long-term) water shortage and surplus strategies were therefore omitted in favour of a simpler but nonetheless more reliable model.

During an in-season (short-term)/water shortage, all three farm types preferred to only use their maximum abstraction licence to irrigate their most valuable crops. In the model, this was defined by which of the two crops represented the largest percentage of irrigated area, as this was considered likely to be the crop which generated the most income. Main crop potatoes represented 63 % and 57 % of irrigated areas for those who preferred LWUO and HWUO respectively, whilst vegetables (i.e. carrots) represented 51 % of irrigated area for those who had no preference. During an in-season (short-term)/water surplus, those who preferred LWUO preferred to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused. Those who had no preference preferred to sell surplus water to maximise profits, whilst those who preferred HWUO preferred to abstract surplus water for storage. However, this final behavioural strategy was designed to automatically occur for all farm types within the model who had storage available. Therefore, those who preferred HWUO performed their second highest ranked behavioural strategy which was to sell surplus water to maximise profits. In addition, although two of the farm types behavioural strategies involved selling surplus water to maximise profits, none of the farm types behavioural strategies involved buying more water to meet crop water requirements, and therefore no trading occurred. Nonetheless, the quantity of surplus water available and shortfall in water required were used as indicators to evaluate the potential for trading, and thus a measure of potential increase in efficiency.

Landscape state variables included: Assessment Point (AP) location, which was a projected shapefile of the study area; AP name; AP low flow conditions (Q95); and AP high flow conditions (Q30). However, low flow conditions were dependent on policy scenario, and were therefore not included when simulating the current water allocation system. Furthermore, HoF data was unavailable for individual farmers and was therefore not included in the model. State variables associated with the global environment, which drive the behaviour and dynamics of the other entities, included IWN of main crop potatoes and vegetables (i.e. carrots), and river discharge of each AP area during both the dry and wet year climate scenarios.

In regards to scales, spatially each grid cell represents 1 km^2 with the extent of the model reflecting the projected landscape of the study area (8,596 km^2) (see Figure 6.1).

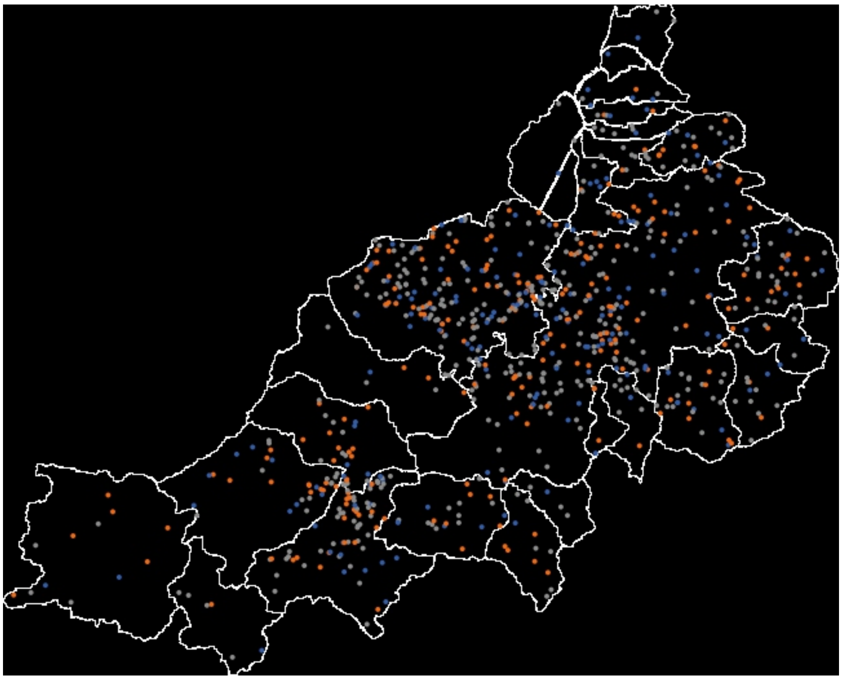

Figure 6.1: Model setup in Netlogo 5.1.0 highlighting each AP location within the Great Ouse catchment and the location of farmers by farm type: those who preferred low water usage options (LWUO) (blue); those who had no preference (orange); and those who preferred high water usage options (HWUO) (grey)

Temporally, each time step represents one month, as this corresponded with available precipitation and temperature data used to derive IWN (see Appendix E). Simulations ran for one year, for both dry and wet years, to indicate in-season (short-term) water shortage and surplus abstraction behaviour during extreme climate scenarios.

Process overview and scheduling

The main order of procedures simulated asynchronously each month in the model are presented in pseudo-code in Figure 6.2. First, the observer runs the monthly parameters including IWN for main crop potatoes and vegetables (i.e. carrots) and river discharge of each AP area. Farmers then calculate how much water they require to satisfy IWN for both crops based on the size of their irrigated area, the percentage of irrigated area each crop represents, and the IWN of both crops. Grid cells, within the projected landscape, then calculate how much water they have available, based on their AP name and the river discharge of that AP area, in addition to low and high

```
to go
   run-monthly-parameters (observer procedure)
   calculate-farm-water-requirements (farmer procedure)
   calculate-ap-water-availability (grid and farmer procedure)
   calculate-farm-water-availability (farmer procedure)
   calculate-farm-water-abstractions (farmer procedure)
   perform-preferred-behavioural-strategies (farmer procedure)
end
```

Figure 6.2: Pseudo code highlighting the main procedures simulated each month in the model

flow conditions derived from river flow data from 1973 to 2012 (see Chapter 3). Within this same procedure, farmers determine how much potential water there is within their AP area as it can vary depending on the water allocation system being simulated, in addition to the climate scenario.

After the previous procedures have been performed, farmers calculate how much water they have available which is determined based on licensed water availability and storage water availability, both of which are dependent on the water allocation system being simulated, in addition to variability of particular variables during initialisation. However, as a farmer may have one or both of these sources of water available during a period when there is no IWN or when there is an IWN the remaining farmer procedures highlighted in the pseudo-code are more simply illustrated in Figure 6.3.

If a farmer has no licensed water available and there is no IWN then they assess whether they need to replenish their storage reservoirs. However, regardless of the result, they have no water available and they are therefore unable to refill their storage reservoirs and as they have not used any of their annual licence limit it remains the same for the procedures next month. Similarly, if a farmer has no licensed water available but there is an IWN then they assess whether they have enough storage water available to satisfy IWN. If they do not have enough to cover IWN then they perform their in-season (short-term)/water shortage behavioural strategy (dependent on farm type) and update their storage water availability for next month accordingly. If, on the other hand, they do have enough to cover IWN they simply update their storage water

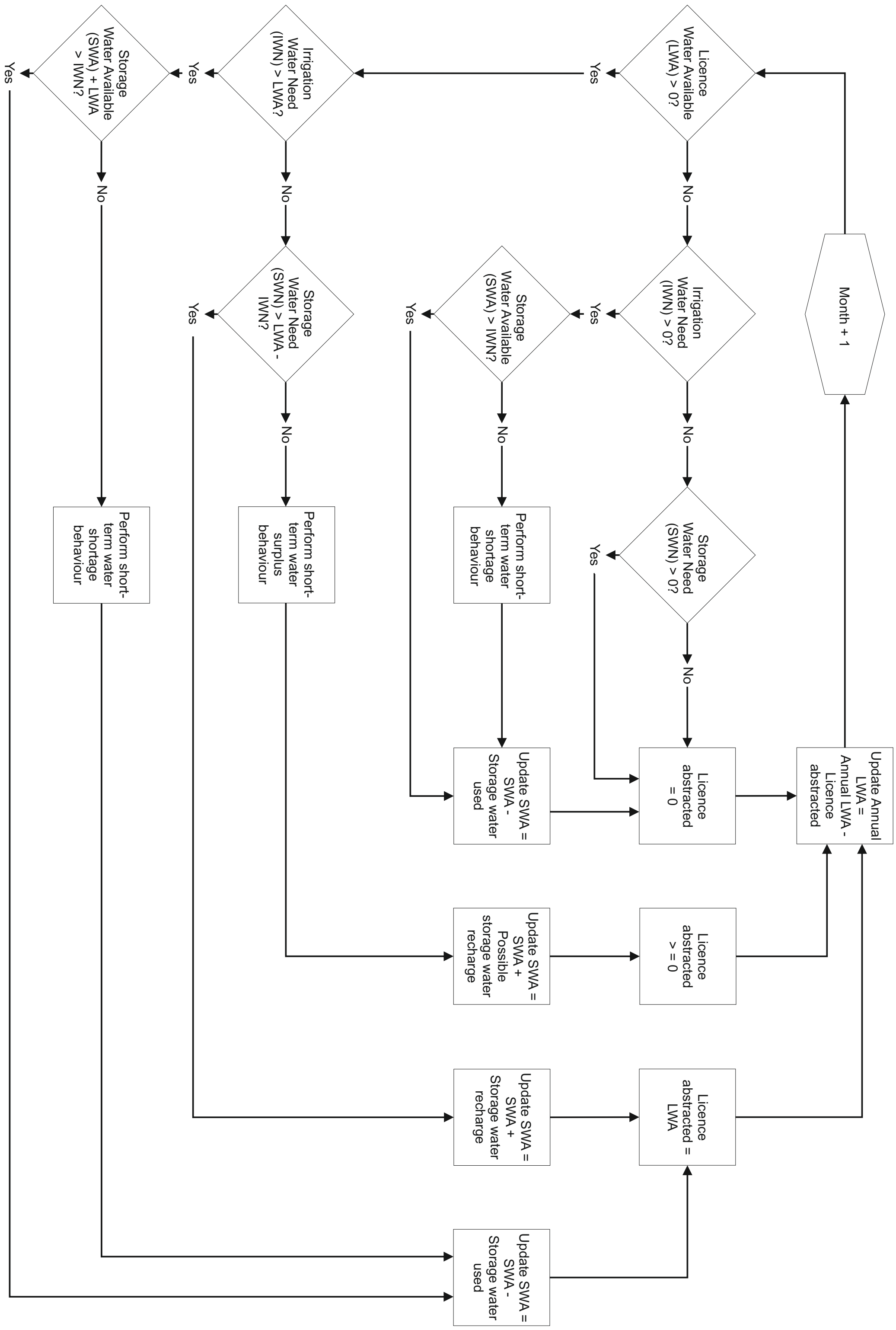

Figure 6.3: Flow diagram illustrating monthly farmer decisions

availability for next month. Either way, no licensed water has been used and therefore their annual licence limit remains the same for next month.

Alternatively, if a farmer has licensed water available and it is greater than total IWN then they assess whether they need to replenish their storage reservoirs with the surplus available. If the surplus available is more than they require to replenish their storage reservoirs then they perform their in-season (short-term)/water surplus behavioural strategy (dependent on farm type) and update their storage water availability and annual licence limit (if they used their licence limit) for next month accordingly. If, on the other hand, the surplus available is less than required to replenish their storage reservoirs then they simply update their storage water availability and annual licence limit (as they used all their licence for that month) for next month accordingly. However, if a farmer has licensed water available and it is less than total IWN then they assess whether they have enough licensed water available plus storage water available to satisfy IWN. If they do not have enough to cover IWN then they perform their in-season (short-term)/water shortage behavioural strategy (dependent on farm type) and update their storage water availability and annual licence limit (as they used all their storage and all their licence for that month) for next month accordingly. If, on the other hand, they do have enough to cover IWN then they simply update their storage water availability and annual licence limit for next month accordingly.

Design concepts

Design concept elements of the ODD protocol have been grouped together to avoid repetition. The general concept underlying this model is the farm typology presented in Chapter 5. In particular the main concept is that individual behavioural strategies and attributes at the farm scale, based on empirical data, will lead to different overall patterns of behaviour at the system level under different water allocation systems (policy scenarios) during dry and wet years (climate scenarios). Furthermore, the indicators which are used to evaluate the different water allocation systems at the system level are model results which emerge from individual farmers performing behavioural strategies at the farm scale. In addition, the main objective of farmers is to satisfy their monthly IWN based on licensed and storage water availability.

In addition, depending on the water allocation system being simulated and the type of licence a farmer possesses, they implicitly assume that they will require some of that licence later in the year and therefore divide their annual licence by the number of months they are permitted to abstract from the environment. This highlights a design in the model which could be improved by incorporating a more sophisticated method for farmers to assume how much water they will require each month. Nonetheless, in the model presented, under the current system those with direct licences can only abstract between April and October (i.e. in-season), those with storage only licences can only abstract between November and March (i.e. out-of-season), whilst those with direct and storage licences can abstract all year. However, this self-imposed limit does not accumulate from one month to the next if unused due to water availability.

Furthermore, all of the global environment state variables, and the landscape state variables on which the farmer is located, are sensed by the individual farmers as these drive their behaviours and dynamics. In regards to the landscape state variables this was considered a reasonable assumption as these simply include location and low and high flow conditions which they would know as part of their licence. However, in regards to global environment state variables, it is more likely that farmers would know the approximate IWN of their crops and river discharge in their AP area, rather than the exact values. Therefore, this highlights another design in the model which could be improved by incorporating a more realistic method for farmers to estimate IWN. Although available water resources within each AP area fluctuate from month to month this only affects farmers under the enhanced water allocation system, where licences increase and decrease proportionally with water availability in the AP area and therefore no direct or indirect interaction between farmers occurs. Finally, stochasticity of particular variables associated with farmers occur during model initialisation including: farm type; irrigated areas; storage capacities; and annual licence limits. However, all of these are based on values presented in the farm typology (see Chapter 5).

Initialisation

At the start of each simulation, each of the 836 farmers are located on their actual geographical location within the projected landscape (i.e. the study area) with a unique

Table 6.2: Summary of scenarios simulated

Scenario	Climate	
	Dry year (1983)	Wet year (1988)
Policy	Current	Current
	Basic	Basic
	Enhanced	Enhanced

identification number. Furthermore, although the proportion of farmers within each farm type are kept the same as the empirical data, their farm types are randomly assigned. This was due to reasons of confidentiality and the EA only providing farmers' locations, except for the 90 respondents which received additional data, and therefore no assumptions could be made regarding which farm type the majority of farmers were more likely to belong to. Farmers' farm type was used to determine their individual state variables as previously discussed.

Input data and submodels

All input data was derived from the previous chapters and the actual model input data, along with the submodels highlighted in Figure 6.2, are presented in Appendix E.

6.2.2 Policy and climate scenarios

Three policy scenarios under two climate scenarios were simulated in this study (see Table 6.2). The three policy scenarios related to: the current water allocation system; the proposed basic water allocation system; and the proposed enhanced water allocation system (see Section 1.1.4). The two climate scenarios related to a dry year and a wet year based on total annual IWN of main crop potatoes and vegetables (i.e. carrots) combined. Appendix E provides a description of how monthly and annual IWN were calculated from 1973 to 2012. Furthermore, 1983 and 1988 were selected as the dry and wet years respectively, as IWN during these years equalled or exceed 20 % and 80 % of annual IWN from 1973 to 2012. This method is commonly adopted for these types of studies (Knox et al., 1997).

6.2.3 Statistical analysis

Statistical analysis in this study was conducted and is presented in two parts: model validation; and policy and climate scenario simulations.

Validation procedure

In order to validate the model, and to explore the sensitivity of the model to variables which vary during initial model setup, 100 simulations were conducted under the current water allocation system scenario, for the period 2008 to 2012, in order to examine whether simulated abstractions for all 836 farmers were similar to measured abstractions of the 90 respondents (see section 5.3.4). Two-tailed tests of association were conducted between the simulated abstractions of the 836 farmers and the measured abstractions of the 90 respondents, for both annual and average monthly abstractions. The null hypotheses for these tests were that there was no significant association between simulated and measured abstractions. As in previous analysis, the Shapiro-Wilk tests, in addition to normal probability plots, were used to determine whether variables were normally distributed (see Appendix E). Depending on the results of these tests, the appropriate parametric (Pearson's correlation) or non-parametric (Spearman's rank correlation) test of association was used.

Therefore, with regards to the tests of association, if the *p-value* was less than the chosen alpha level, which for these tests were .05, then the null hypothesis was rejected suggesting that the variables were associated. Furthermore, a Pearson's correlation coefficient (r), or a Spearman's rank correlation coefficient (r_{s}), of plus or minus 0.7 or greater was considered a strong correlation; plus or minus 0.5 a moderate correlation; and plus or minus 0.3 a weak correlation.

Policy and climate change scenario simulation procedure

As with the model validation, 100 simulations were conducted and the average values for each model indicator were reported (see Appendix E). Shapiro-Wilk tests, in addition to normal probability plots, were used to determine whether variables were normally distributed (see Appendix E). Depending on the results of these tests, the appropriate parametric or non-parametric test was then used to explore the null hypothesis that a statistically significant difference existed between the three policy scenarios, during both the dry and wet year climate scenarios, if the *p-value* was less than the chosen alpha level, which for these tests was .05, (one-way analysis of variance (ANOVA) or Kruskal-Wallis respectively). If such a statistically significant difference existed, then further relevant parametric or non-parametric tests were conducted to test the same null hypothesis but between each pair of farm types (independent t-test or Mann-Whitney U test respectively). However, in regards to Mann-Whitney U tests the difference in median values was reported if the two distributions were similar in shape; otherwise the difference in mean ranks was reported if distributions were not similar.

6.3 Results and discussion

6.3.1 Model validation

Figure 6.4 illustrates there were strong, positive, linear correlations between annual abstractions of the 90 respondents and annual abstractions of the 836 simulated farmers with regards to those who preferred LWUO (r= .92), which was statistically significant ($p= <.05$), thus the null hypothesis could be rejected; and with regards to those who had no preference (r= .95), which was also statistically significant ($p= <.05$), thus the null hypothesis could also be rejected. However, only a moderate, positive, linear correlation existed with regards to those who preferred HWUO (r= .61), which was not statistically significant ($p= >.05$), thus the null hypothesis could not be rejected.

Similarly, Figure 6.4 also illustrates there were strong, positive, linear correlations between average monthly abstractions of the 90 respondents and average monthly abstractions of the 836 simulated farmers with regards to those who preferred LWUO (r= .77), which was statistically significant ($p= <.05$), thus the null hypothesis could be rejected; and with regards to those who had no preference (r= .91), which was also statistically significant ($p= <.05$), thus the null hypothesis could also be rejected. Furthermore, only a moderate, positive, linear correlation existed with regards to those who preferred HWUO (r= .58), however this was statistically significant ($p= <.05$), thus the null hypothesis could be rejected.

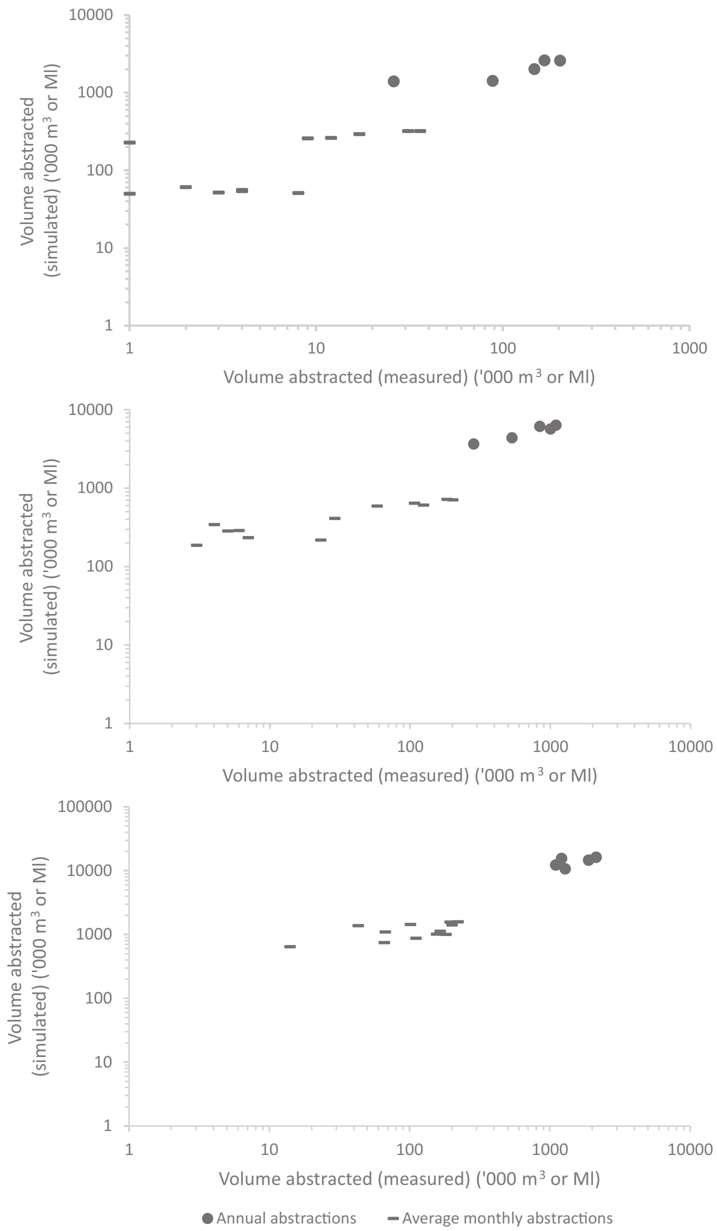

Figure 6.4: Scatter plots indicating the strength of association between simulated annual, and average monthly, abstractions for all 836 farmers and measured annual, and average monthly, abstractions for the 90 respondents, based on the average of 100 simulations. (Top) Pearson's correlation coefficients were $r = .92$, $p = <.05$, and $r = .77$, $p = <.05$, for annual and average monthly abstractions respectively for those who preferred low water usage options (LWUO). (Middle) Pearson's correlation coefficients were $r = .95$, $p = <.05$, and $r = .91$, $p = <.001$, for annual and average monthly abstractions respectively for those who had no preference. (Bottom) Pearson's correlation coefficients were $r = .61$, $p = >.05$, and $r = .58$, $<.05$ for annual and average monthly abstractions respectively for those who preferred high water usage options (HWUO)

Overall, although differences between the measured and simulated abstractions occurred most likely due to over simplification of the model, particularity as HoF for individual licences were not included, the results indicate that the model, based on farmers' preferred behavioural intentions, was relatively reliable at simulating abstractions for each farm type under the current water allocation system between 2008 and 2012. The model could therefore be used to simulate system level patterns of abstraction behaviour under the proposed basic and enhanced water allocation systems during dry and wet years with relative confidence.

6.3.2 Policy and climate change scenario simulations

Kruskal-Wallis tests showed that statistically significant differences existed between policy scenarios with regards to monthly licence volume abstracted during the dry year climate scenario (X^2= 7.002) as $p= <.05$, and during the wet year climate scenario (X^2= 18.029) as $p= <.05$. Furthermore, Kruskal-Wallis tests showed that a statistically significant difference existed between policy scenarios with regards to surplus water available during the wet year climate scenario (X^2= 8.979) as $p= <.05$, but not during the dry year climate scenario (X^2= .295) as $p= >.05$. In addition, Kruskal-Wallis tests showed that no statistically significant differences existed between policy scenarios with regards to shortage water required during the dry year climate scenario (X^2= .065) as $p= >.05$, or during the wet year climate scenario (X^2= .278) as $p= >.05$. Similarly, Kruskal-Wallis tests showed that no statistically significant differences existed between policy scenarios with regards to the percentage of farm IWN satisfied (i.e. main crop potatoes and vegetables combined) during the dry year climate scenario (X^2= .023) as $p= >.05$, or during the wet year climate scenario (X^2= .357) as $p= >.05$ (see Figure 6.5).

In particular, statistically significant differences existed with regards to monthly licence volume abstracted between the current and proposed enhanced water allocation systems during the dry year climate scenario (U= 32) as $p= <.05$, and during the wet year climate scenario (U= 8) as $p= <.05$. Furthermore, statistically significant differences also existed with regards to monthly licence volume abstracted between the proposed basic and proposed enhanced water allocation systems during the dry year

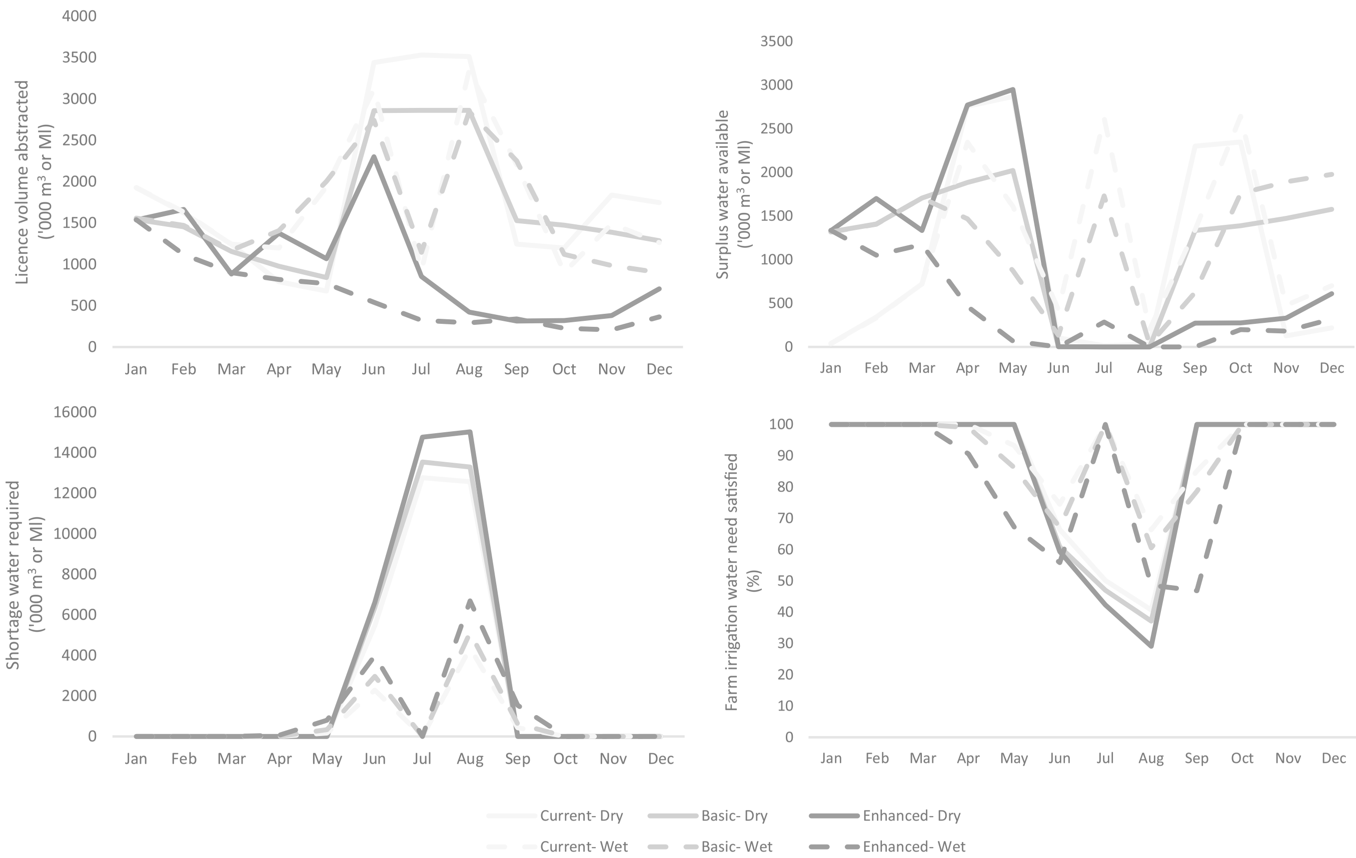

Figure 6.5: Line graphs indicating the potential system level patterns of abstraction behaviour which emerge from individual farm scale decisions under different policy and climate scenarios. (Top left) Line graph indicating the difference in monthly licensed abstractions. (Top right) Line graph indicating the difference in monthly surplus water available. (Bottom left) Line graph indicating the difference in monthly shortage water required. (Bottom right) Line graph indicating the difference in monthly farm irrigation water need (IWN) satisfied (i.e. main crop potatoes and vegetables combined)

climate scenario (U= 34) as p= <.05, and during the wet year climate scenario (U= 10) as p= <.05. Thus, the null hypothesis for this model indicator could be rejected as farmers abstracted significantly less under the proposed enhanced water allocation system, during both the dry (median 868 Ml and IQR 1,106 Ml) and wet (median 452 Ml and IQR 579 Ml) year climate scenarios, compared to the current water allocation system, during both the dry (median 1,684 Ml and IQR 1,854 Ml) and wet (median 1,561 Ml and IQR 928 Ml) year climate scenarios, and also compared to the proposed basic water allocation system, during both the dry (median 1,464 Ml and IQR 1,340 Ml) and wet (median 1,440 Ml and IQR 1,064 Ml) year climate scenarios.

Similarly, statistically significant differences existed during the wet year climate scenario, with regards to surplus water available between the current and proposed enhanced water allocation systems (U= 32) as p= <.05, and between the proposed basic and proposed enhanced water allocation systems (U= 24) as p= <.05. Thus, the null hypothesis for this model indicator could be rejected as farmers during the wet year climate scenario had significantly less surplus water available under the proposed enhanced water allocation system (median 242 Ml and IQR 887 Ml) compared to the current (median 712 Ml and IQR 1,805 Ml) and proposed basic (median 1,437 Ml and IQR 1,064 Ml) water allocation systems.

Overall, the system level patterns of abstraction behaviour which emerged from farmers' preferred behavioural intentions indicate that farmers under the proposed enhanced water allocation system abstracted less on average each month and therefore had less surplus water available compared to the current or proposed basic water allocation systems. This was due to farmers' monthly licensed water availability varying depending on water availability within AP areas (see Appendix E). Nonetheless, despite farmers abstracting less under this system, the percentage of farm IWN satisfied did not significantly vary under any of the policy scenarios. Therefore, the results of the simulations based on farmers' preferred behavioural intentions, would indicate that the proposed enhanced water allocation system, at least at the system level, offered the greatest protection for the environment as low flow conditions were enforced, and fewer abstractions occurred overall without significantly effecting the percentage of farm IWN satisfied.

However, perhaps unsurprisingly, the results also indicate that surplus water was generally available outside of the growing season whilst a shortage of water was exhibited during the growing season. This would suggest that regardless of policy scenario, few trades are likely to occur between farmers. However, this is partly a model limitation as the growing season started at the same time for all farmers, thus increases and decreases in IWN occurred at the same time, whilst in reality it may be staggered. Nonetheless, even if the growing season was staggered, few trades are likely to occur but the results do highlight the potential for water licence trading with other sectors.

6.4 Summary

Overall, this study has provided a first insight into how the proposed water allocation reforms, both in basic and enhanced catchments, are likely to change water availability for farmers. Furthermore, it has indicated the importance of understanding abstraction behaviour in determining the overall success of these reforms. In doing so, this chapter addressed the third of three research questions set out in the introduction to this thesis, and highlighted again at the start of this chapter. That was, what potential system level patterns of abstraction behaviour emerge from individual farm scale decisions under different policy and climate scenarios.

The development of an ABM was presented and validated by comparing simulated abstractions for the period 2008 to 2012 with measured abstractions for the same period based on farmers' preferred behavioural intentions. The policy and climate scenario simulations indicated that the proposed enhanced water allocation system offered the greatest protection to the environment at the system level, as a result of less water abstracted and low flow conditions being introduced, whilst not significantly reducing the percentage of farm IWN satisfied. Furthermore, despite model limitations, the simulation results indicate few trades are likely to occur between farmers, even if preferred behavioural intentions were to change, as surplus water was generally only available outside of the growing season, whilst a shortage of water was indicated during the growing season. Nonetheless, the proposed enhanced water allocation system appears to offer the greatest potential of increasing efficiency with regards to balancing the needs of licence users, at least farmers, with the environment.

Chapter 7

Discussion and conclusions

As discussed in the introduction to this thesis, water resource management in England is currently in a long-term transition from large-scale, high-cost, centralised infrastructure projects to low-cost, community-scale, decentralised systems. A major aspect of this transition is the introduction of water markets where water licence trading can occur to improve efficiency. Water licence trading has been in operation in several countries for several decades and has been available in England since 2003 (DEFRA, 2011). However, due to several reasons, mainly regarding institutional barriers which deter farmers from trading, very few trades have actually occurred in England. Similar institutional barriers were found to exist in other countries (Thobani, 1998; Zhang, 2007). However, the current water allocation system in England is considered by the regulatory authorities as inadequate to provide users with the ability to adapt to climate change whilst providing adequate protection for the environment (EA, 2008; DEFRA, 2011).

In response, DEFRA proposed the basic and enhanced water allocation systems to address the inadequacies of the current system and encourage water licence trading (see Chapter 1). However, it was argued that the success of the proposed water allocation systems, particularly with regards to water licence trading, very much depended on the preferred behavioural intentions of the users on the ground (Feola et al., 2015). This factor formed the rationale for this research as very little was understood with regards to how the proposed water allocation systems in England would be received by licence users, in particular by farmers, who were the main focus of this study (see Chapter 3).

Therefore, this thesis has presented three studies which have attempted to understand farmers' behavioural intentions under different climate and proposed water allocation system scenarios, in order to assess whether the proposals will achieve their intended aim. These studies included: an empirical investigation within the Great Ouse catchment in eastern England to understand farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems; the development of a conceptual typology based on farmers preferred behavioural intentions rather than more traditional attributes such as income or farm size; and the development, and policy and climate scenario simulation results, of an ABM used to understand the system level patterns of abstraction behaviour which emerge from individual farm level decisions. This chapter discusses some of the main limitations of the methods used and attempts to place the results within the context of the wider literature.

7.1 Understanding farmer behaviour

There is an increasing body of literature which supports the rationale that any individuals or group of individuals, who are directly affected by changes in policy, particularly with regards to water and land management, should be a key consideration in the design and implementation of that policy change (Austin et al., 1998; Burton, 2004; Emtage et al., 2006; Guillem et al., 2012). Moreover, several studies have shown that farmers' behaviour very much influences how and to what success policy proposals are realised on the ground (Bjornlund, 2003; Moon and Cocklin, 2011; Home et al., 2014; Feola et al., 2015). However, several challenges remain in understanding individuals' intentions and associated behaviours, and methods to incorporate these into practical policy applications.

The main challenges in understanding individual behaviours' are associated with the complexity and limitations of the theoretical behavioural models used. In particular, to what extent can current behavioural models accurately measure an individual's intention, and to what extent is that intention a true measure of an individual's behaviour. The more reliable the behavioural model, the more likely policy decision-makers are to incorporate them into the design and implementation stages of policy changes. Although each model offers particular advantages and disadvantages, this research was based on one of the most widely used and influential models for predicting human social behaviour, the TPB (Ajzen, 1985). However, as previously discussed one of the main criticisms of this model, in addition to normal survey limitation biases such as respondents answering how they think they should rather than honestly or whether only those responded who were interested in the subject, concerns efficacy (i.e. the predictive ability of the model) (Sniehotta et al., 2014).

Meta-analytical reviews found that the TPB explained between 40-49 % of the variance in intention (Sheeran et al., 1999; Armitage and Conner, 2001; Hagger et al., 2002; Trafimow et al., 2002; Schulze and Wittmann, 2003; McEachan et al., 2011). The adapted TPB model used in this study explained between 29-65 % of the variance in intention based on Nagelkerke's R^2. However, as binary logistic regression was used rather than multiple linear regression, there are no direct analogues to the coefficient of determination (i.e. R^2) used in ordinary least squares, and therefore the aforementioned pseudo R^2 value was used (Bewick et al., 2005). As a result, these different methodological approaches should be considered when comparing the results of this study with those reported in meta-analytical reviews. Although, the results of this study suggest a comparatively high percentage of variance explained, incorporating associated salient beliefs for each construct would likely improve the results. Therefore, a more robust methodology may consider using farmer focus groups to determine salient beliefs. This would have likely provided a more robust set of behaviours and potentially explained a higher percentage of variance in intention (Ajzen, 2011).

Attitude and subjective norm were found to be the main predictors of farmers' intention for three of the four scenarios: strategic (long-term) water shortage and water surplus scenarios; and the in-season (short-term) water shortage scenario. For the latter scenario, perceived behavioural control was also found to be a significant predictor of farmers' intention. Interestingly, previous studies also found attitude to be a significant predictor of farmers' behaviour, and not perceived behavioural control, suggesting that farmers tend to have complete volitional control with regards to long-term decision-making at the farm scale (Wauters et al., 2010; Poppenborg and Koellner, 2013).

Although this study has provided a first insight into how farmers' may respond to the proposed water allocation systems in England, there is clearly a considerable percentage of variance in intention which was left unexplained and therefore other factors, not measured, could influence farmers' behavioural intentions. As previously mentioned, a more robust methodology which measures salient beliefs may highlight some of these other factors. Furthermore, the intention-behaviour gap remains which is likely to exacerbate the longer the time interval between measuring intentions and farmers actually performing the behaviours (Orbell and Sheeran, 1998; Sniehotta et al., 2005). As the proposed water allocation systems are only being introduced in the early 2020s, farmers' intentions may change again, and therefore, this study should only be used as a preliminary understanding at this current time. Nonetheless, when water trading was first introduced in southeastern Australia in 1989 very few farmers participated in water licence trading for the first ten years. However, an increasing number of farmers participated in temporary licence trades as more farmers increasingly understood the operations and the advantages of a secure, reliable, fast, and cheap water transfer (Bjornlund, 2003).

7.2 Validity and utility of a behavioural farm typology

Although farm typologies clearly offer policy decision-makers a useful tool for categorising farms, and making more informed policy decisions, the main criticism of farm typologies, which this study attempted to address, is that they fail to fully capture true farmer behaviour and are therefore of limited value in supporting policy formulation (Guillem et al., 2012). Although the conceptual approach used in this study identified three farm types, which featured significant differences in farm characteristics, alternative data-driven approaches such as cluster analysis (Barnes et al., 2011), or stratification of farmers based on particular farm characteristics, might have identified different farm types, and thus different preferred behavioural intentions. However, the conceptual approach used was considered more appropriate when using ordinal Likert-item measures of behaviour.

Nonetheless, although the validity of the typology is difficult to assess unless used in practice, it certainly offers utility for policy decision-makers who can use the information with regards to implementing the proposed water allocation systems in England. In particular, identifying which farmers are more or less likely to engage with particular aspects of the proposals, such as water licence trading, may be used in deciding which catchments should be categorised as basic or enhanced.

Within the wider sphere of policy decision-making, behavioural typologies clearly offer greater value in supporting policy formulation compared to more traditional typologies. However, limitations also exist with regards to the added complexity involved in developing a behavioural typology (i.e. measuring individual behavioural intentions), and the effects of the intention-behaviour gap. In this sense, behavioural farm typologies may be more valuable for policy formulation (Guillem et al., 2012) rather than continual monitoring of policy interventions, and policy decision-makers should not rely solely on behavioural intentions but also on more traditional farm characteristics (Schmitzberger et al., 2005; Emtage et al., 2006, 2007; Gorton et al., 2008; Pike, 2008; Barnes et al., 2011; Poppenborg and Koellner, 2013).

7.3 Utility of the Agent-Based Model (ABM)

This research has highlighted the importance of understanding farmers' preferred behavioural intentions with regards to the proposed water allocation systems in England. Furthermore, understanding the system level patterns of abstraction behaviour which could emerge from individual decision-making at the farm scale provides valuable information for policy decision-makers. However, although the ABM developed highlighted the potential effects of the proposed water allocation systems, several limitations of the model exist.

One of the main limitations of this model was its ability to only model in-season (short-term) water shortage and surplus preferred behavioural strategies, during a selected dry and wet year climate scenario, rather than model behaviours over a longer time period. With the latter approach, strategic (long-term) water shortage and surplus preferred behaviours could have been implemented, despite the added complexity of the model, to highlight the long-term effects of proposed policy changes. If the model had incorporated strategic behavioural strategies, then all farm types, during strategic (long-term)/water shortage scenarios, would have simply increased their application efficiency which would ultimately reduce abstractions at the system level during the growing season, regardless of policy or climate scenario. However, during strategic (long-term)/water surplus scenarios, more water would be abstracted during the growing season as a result of those who preferred high water usage options (HWUO) growing the same crops but over a larger area. Furthermore, as the strategies for those who preferred low water usage options (LWUO), and those who had no preference, were to change nothing and sell surplus water for the duration of the growing season respectively, very little in regards to overall system level patterns of abstraction would have changed, as no trading occurred as buying was not a preferred behavioural strategy of any of the farmers. However, this highlights another limitation of the model.

The purpose of the model was to understand the potential system level patterns of abstraction behaviour which were likely to emerge based on farmers' preferred behavioural intentions. However, as none of the farmers' preferred behavioural intentions involved buying more water, either strategically or in-season, no trading occurred in the model. Therefore, only the potential for trading at the system level was simulated based on surplus water available and shortage water indicated. Furthermore, although previous studies, such as that in southeastern Australia, have found that an increasing number of farmers participated in temporary water licence trading (i.e. weekly, monthly, or seasonal), very few participated in permanent water licence trading due to: differential tax treatment; policy uncertainty; institutional barriers such as administrative complexity and costs; and farmers' perception that water rights are an inherent part of their property (Bjornlund, 2003). Nonetheless, the results of the simulations highlighted that even if trading was available, very few trades would likely occur, even if farmers growing seasons would be staggered, as very little overlap would exist with regards to when surplus water was available and shortage water was required. Therefore, despite these limitations, the results of the model would suggest that farmers, who do not already have storage available, are best investing in storage to make use of the surplus water available out-of-season.

Another limitation of the model concerns the lack of planning and learning to change adaptive strategies. A more sophisticated model would perhaps incorporate the ability of farmers to better plan their irrigation water needs (IWN) during the year. In the current model, this is simply divided by the number of months their licence was available. However, in reality farmers know, approximately, from previous years when demand is likely to be greatest and when it is likely to be less. Furthermore, if farmers continually experienced particular water shortage or surplus scenarios they may very well change their behavioural strategies, which would certainly alter the system level patterns of abstraction behaviour. Therefore, a model which simulates abstraction behaviour over consecutive years could incorporate planning and learning from previous seasons. Data regarding how farmers actually plan their abstractions each year could be obtained during focus groups used to measure salient beliefs.

Overall, the model presented, as with any, was a simplified representation of reality. Nonetheless, despite the limitations discussed, the scenario simulation results indicated that the proposed enhanced water allocation system was likely to achieve its intended aim of increasing efficiency whilst balancing the needs of licence users and the environment, more than the current or proposed basic water allocation system. Furthermore, incorporating other licence users would likely open up greater opportunities for water licence trading. However, although the proposed enhanced water allocation system was designed to facilitate trading more easily than the proposed basic system, the method used to derive water shares under the enhanced system may result in fewer trades as licences adjust to reflect users needs, and therefore less surplus water would be available compared to the proposed basic system.

Previous studies have also used ABM to simulate different policy or climate scenarios related to individual behavioural strategies and changes in land use or resources (Schlüter and Pahl-Wostl, 2007; Galán et al., 2009; Acosta et al., 2014). However, one of the main limitations that each of these studies concluded with regards to ABM concerns the fact that as the models are developed based on behavioural strategies of particular groups of individuals, often within a particular geographic location, then generalising the model for a wider population or different geographic location may be difficult. Therefore, although the simulation results presented in this study are designed based on farmers currently operating within the Great Ouse catchment, the framework of the model, after adapting it to another area, could be generalised to other catchments.

7.4 Overview of conclusions

Farmer water abstraction behaviour in response to different policy and climate scenarios was investigated, in an area of eastern England, to assess whether the proposed water allocation systems in England would achieve their intended aim (i.e. to increase efficiency whilst balancing the needs of licences users and the environment). Three studies were conducted to understand farmers' preferred behavioural intentions, explore the utility of a farm typology developed based on farmers' behavioural intentions, and to examine the potential system level patterns of abstraction behaviour which emerge, under different policy and climate scenarios, based on farmers' preferred behavioural intentions. The main conclusions of this research are:

1. The TPB provides a relatively reliable method of successfully measuring farmers' intentions and underlying predictors. The TPB explained between 29-65 % of the variance in intention which was similar to the range found by meta-analytical reviews (i.e. 40-49 %). Furthermore, attitude and subjective norm were found to be the main significant predictors of farmers' intentions, at least in three of the four water shortage and surplus scenarios including: the strategic (long-term) water shortage and surplus scenarios; and the in-season (short-term)/water shortage scenario. In addition, with regards to the latter scenario, perceived behavioural control was also found to be a significant predictor of intention. Therefore, these results indicate that farmers, at least in regards to these behaviours, believe they have greater volitional control with regards to decision-making in the long-term compared to the short-term.

2. Behavioural farm typologies offer greater value in supporting policy formulations compared to traditional farm typologies. Developing a typology based on individual behavioural intentions provides greater utility to policy decision-makers, compared to more traditional typologies, as physical or economic attributes alone may fail to fully capture an individuals' intention. Depending on the policy formulation, this is likely to be of great interest, and very valuable to those involved in the policy formulation. However, the additional insights come at a cost with regards to added complexity in developing the typology (i.e. having to measure individual intentions), and inherent limitations with any behavioural approach such as the intention-behaviour gap (i.e. the utility of a behavioural typology becomes less the longer the period between policy formulation and intervention).

3. Significant differences in farm characteristics existed between the farm types derived in this study. Those who preferred Low Water Usage Options (LWUO) were generally representative of farmers who irrigated smaller areas, used predominantly rainguns as their irrigation application mechanism, had less storage available, and were older and had a lower level of education compared to farmers who preferred High Water Usage Option (HWUO). In addition, those who preferred LWUO predominantly used rainguns as their main irrigation application mechanism whilst those who preferred HWUO, and those who had no preference, used a mix of different application mechanisms. Furthermore, those who preferred LWUO generally had a mix of both time limited and none-time limited licences whilst those who preferred HWUO predominantly had time limited licences. Interestingly, those who had no preference were generally representative of farmers who had larger annual licence limits and past annual abstractions (similar to those who preferred HWUO) compared to farmers who preferred LWUO. However, those who had no preference also had smaller daily licence limits (similar to those who preferred LWUO) compared to those who preferred HWUO. In addition, those who had no preference abstracted more in-season compared to those who preferred LWUO.

4. All farm types' preferred Low Water Usage Option (LWUO) under strategic (long-term) and in-season (short-term) water shortage scenarios. Despite farmers' overall preferred behaviour in regards to all 18 behaviours assessed, each farm type preferred LWUO during water shortage scenarios. Under a strategic (long-term) scenario this was to increase application efficiency. Under an in-season (short-term) scenario this was to only use their maximum abstraction licence to irrigate their most valuable crops. Although this is not surprising for those who preferred LWUO, or perhaps even for those who had no preference. The feasibility or perhaps lack of experience under the current water allocation system could have contributed to the preferred behaviour of those who preferred HWUO. However, during water surplus scenarios, those who preferred LWUO and those who had no preference preferred LWUO, and those who preferred HWUO preferred HWUO.

5. ABM offer a valuable tool for policy decision-makers involved with policy formulation. In the context of this study, the ABM developed and used to understand what system level patterns of abstraction behaviour emerge based on individual farm level decision-making, indicated the proposed enhanced water allocation system provided the greatest ability to balance the needs of licence users whilst protecting the environment. However, this ABM did not incorporate licence users from other sectors in the catchment and therefore generalising ABM results to wider populations or other geographic locations may be difficult. Therefore, although ABM can provide an insight into system level patterns of policy interventions, they are perhaps limited in their utility to the area or population of interest.

6. The success of the proposed water allocation systems, with regards to encouraging water licence trading is dependent on both institutional changes and changes in users' intentions. The importance of institutions being designed to encourage and facilitate water licence trading was discussed in the introduction to this thesis (see Chapter 1). However, as evident in several countries, including the UK, one of the main reasons farmers do not trade was due to high transaction costs and where transaction costs were low reasons included: management, legal, administrative, and fiscal barriers (Zhang, 2007). Therefore, although policy decision-makers can utilise the results of this study to identify which farmers are more or less likely to engage with water licence trading, without changing current institutional barriers, the proposed water allocation systems are not likely to succeed.

7. Although water licence trading is likely to increase efficiency at the system level this should be coupled with a long-term strategy to increase storage capacity and application efficiency at the farm level. The results of the policy and climate scenario simulations suggest that very few trades are likely to occur between farmers. However, this is also due to several limitations within the model, but nonetheless very little overlap appears to occur between surplus water being available and shortage water being required. Where overlap does occur, trading would likely provide a viable method of improving efficiency. However, for the majority of farmers, policies focussing on increasing storage capacity and improving application efficiency are more likely to increase efficiency at the system level.

7.5 Further research

This research provides a first investigation into understanding farmers' preferred behavioural intentions with regards to the proposed water allocation systems in England. In particular, the three studies presented attempted to address the three research gaps identified in Chapter 2. These included: understanding farmers' preferred behavioural intentions under different scenarios of water shortage and surplus with regards to the proposed water allocation systems; the potential utility of developing a farm typology based on farmers' preferred behavioural intentions with regards to the proposed water allocation systems; and lastly understanding the potential system level patterns of abstraction behaviour which emerge from individual farm level decision-making, under different policy and climate scenario, with regards to the proposed water allocation systems. However, although the methods and results of this research have direct policy application they have also highlighted several limitations and areas for further research.

In regards to measuring individual behaviour using the TPB, this research has identified several limitations with the approach used in this study. Further research is required to improve the variance in intention explained by predictor variables by either measuring farmers' salient beliefs, within the theoretical framework of the TPB (Ajzen, 2011), or adopting an alternative behavioural approach such as the temporal self-regulation theory (Hall and Fong, 2007), which emphasises temporal dynamics and lends itself more readily to experimental tests (Sniehotta et al., 2014). In addition, focus groups may provide a more valuable approach in understanding individual behaviours (Wauters et al., 2010). However, measuring salient beliefs was considered in the design of the study but a more direct approach was adopted in order to assess a greater number of behaviours. Therefore, further research may consider focussing on fewer behaviours but in more detail.

In addition, further research is required to understand the full validity and utility of behavioural farm typologies used for policy formulation, intervention, and monitoring (Barnes et al., 2011). This research only highlighted the potential utility of the typology for policy formulation based on farmers' preferred behavioural intentions. However, if behavioural typologies are to become more widely used, then further studies are required to assess their practical applications, and the extent of the usefulness in policy decision-making (i.e. do individuals perform the behaviours they intended).

Further research is also required to simulate water trading at the system level under the different policy and climate scenarios. Although this study highlighted the potential for water trading by measuring surplus water available and shortage water required, a more sophisticated model could incorporate an economic element to individual farmers' strategies. Zhang et al. (2014) concluded a similar observation, arguing that further research with regards to water trading between farmers is required, and should preferably use a dataset with sufficient observations on water transactions in order to test the assumptions we draw regarding factors which drive developing water markets. In addition, more work is required to understand how the proposed water allocation systems in England would operate when other licence users are included from other sectors, such as public water supply companies and electricity supply industries.

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Appendix A

Questionnaire

Section A: This section is about your general irrigation practice			
What are the three main crops you usually irrigate (e.g. early potatoes, main crop potatoes, sugar beet, orchard fruit, small fruit, vegetables, grass, cereals)?			
How large an irrigated area do these main crops usually cover (ha or acres)?	ha acres	ha acres	ha acres
What is the predominant soil type these crops usually grow on?	Sand ☐ Loam ☐ Peat ☐	Sand ☐ Loam ☐ Peat ☐	Sand ☐ Loam ☐ Peat ☐
What type of irrigation application infrastructure do you usually use?	Rainguns ☐ Booms ☐ Sprinklers ☐ Trickle ☐	Rainguns ☐ Booms ☐ Sprinklers ☐ Trickle ☐	Rainguns ☐ Booms ☐ Sprinklers ☐ Trickle ☐
If applicable, what is the approximate size of your water storage capacity? (Please indicate unit of measurement such as mega litres, cubic metres, millions of gallons, acre-inches)			

Section B: This section is about strategic decision making

Part 1: Water Shortage

If (HYPOTHETICALLY) you repeatedly, during the last 10 years, didn't have enough water to meet crop water requirements...

...What would you, as key decision maker in your farm business, intend to do next season?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Grow the same crops but over a smaller area	☐	☐	☐	☐	☐	☐	☐
Grow less water intensive crops	☐	☐	☐	☐	☐	☐	☐
Increase storage capacity	☐	☐	☐	☐	☐	☐	☐
Increase application efficiency	☐	☐	☐	☐	☐	☐	☐
Buy more water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
Apply for a larger abstraction licence	☐	☐	☐	☐	☐	☐	☐
Change nothing	☐	☐	☐	☐	☐	☐	☐

...How advantageous or disadvantageous would each of the following actions be for your farm business?	Extremely disadvantageous	Very disadvantageous	Disadvantageous	Not sure	Advantageous	Very advantageous	Extremely advantageous
Growing the same crops but over a smaller area would be...	☐	☐	☐	☐	☐	☐	☐
Growing less water intensive crops would be...	☐	☐	☐	☐	☐	☐	☐
Increasing storage capacity would be...	☐	☐	☐	☐	☐	☐	☐
Increasing application efficiency would be...	☐	☐	☐	☐	☐	☐	☐
Buying more water for the duration of the growing season would be...	☐	☐	☐	☐	☐	☐	☐
Applying for a larger abstraction licence would be...	☐	☐	☐	☐	☐	☐	☐
Changing nothing would be...	☐	☐	☐	☐	☐	☐	☐

...Which of the following social groups would most influence your strategic decision making?	Please rank numerically, 1 being most influential
Groups interested in water saving and efficiency (e.g. Water abstraction group(s), National Farmers Union (NFU), Environmental Agency (EA), Defra, UK Irrigation Association (UKIA))	
Groups interested in crop type and quality (e.g. main buyer(s), agronomist, business advisor(s))	
Family, friends and neighbours	

...The social group you ranked as 1 would think that you *(definitely shouldn't* to *definitely should)*...	Definitely shouldn't	Very much shouldn't	Shouldn't	Not sure	Should	Very much should	Definitely should
...Grow the same crops but over a smaller area	☐	☐	☐	☐	☐	☐	☐
...Grow less water intensive crops	☐	☐	☐	☐	☐	☐	☐
...Increase storage capacity	☐	☐	☐	☐	☐	☐	☐
...Increase application efficiency	☐	☐	☐	☐	☐	☐	☐
...Buy more water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
...Apply for a larger abstraction licence	☐	☐	☐	☐	☐	☐	☐
...Change nothing	☐	☐	☐	☐	☐	☐	☐

...How much do you disagree or agree with the following statements?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Growing the same crops but over a smaller area or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Growing less water intensive crops or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Increasing storage capacity or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Increasing application efficiency or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Buying more water for the duration of the growing season or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Applying for a larger abstraction licence or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Changing nothing or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Have you repeatedly, during the last 10 years, not had enough water to meet crop water requirements? If NO please skip to PART 2	Yes ☐			No ☐			
If YES (IN REALITY) you repeatedly didn't have enough water to meet crop water requirements, what did you do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Grew the same crops but over a smaller area	☐	☐	☐	☐	☐	☐	☐
Grew less water intensive crops	☐	☐	☐	☐	☐	☐	☐
Increased storage capacity	☐	☐	☐	☐	☐	☐	☐
Increased application efficiency	☐	☐	☐	☐	☐	☐	☐
Bought more water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
Applied for a larger abstraction licence	☐	☐	☐	☐	☐	☐	☐
Changed nothing	☐	☐	☐	☐	☐	☐	☐
Part 2: Water Surplus							
If (HYPOTHETICALLY) you repeatedly, during the last 10 years, had a surplus of water after you met crop water requirements...							
...What would you, as key decision maker in your farm business, intend to do next season?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Grow the same crops but over a larger area	☐	☐	☐	☐	☐	☐	☐
Grow more water intensive crops	☐	☐	☐	☐	☐	☐	☐
Sell surplus water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
Change nothing	☐	☐	☐	☐	☐	☐	☐
...How advantageous or disadvantageous would each of the following actions be for your farm business?	Extremely disadvantageous	Very disadvantageous	Disadvantageous	Not sure	Advantageous	Very advantageous	Extremely advantageous
Growing the same crops but over a larger area would be...	☐	☐	☐	☐	☐	☐	☐
Growing more water intensive crops would be...	☐	☐	☐	☐	☐	☐	☐
Selling surplus water for the duration of the growing season would be...	☐	☐	☐	☐	☐	☐	☐
Changing nothing would be...	☐	☐	☐	☐	☐	☐	☐

...Which of the following social groups would most influence your strategic decision making?	Please rank numerically, 1 being most influential						
Groups interested in water saving and efficiency (e.g. Water abstraction group(s), National Farmers Union (NFU), Environmental Agency (EA), Defra, UK Irrigation Association (UKIA))							
Groups interested in crop type and quality (e.g. main buyer(s), agronomist, business advisor(s))							
Family, friends and neighbours							
...The social group you ranked as 1 would think that you *(definitely shouldn't* to *definitely should)*…	Definitely shouldn't	Very much shouldn't	Shouldn't	Not sure	Should	Very much should	Definitely should
...Grow the same crops but over a larger area	☐	☐	☐	☐	☐	☐	☐
...Grow more water intensive crops	☐	☐	☐	☐	☐	☐	☐
...Sell surplus water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
...Change nothing	☐	☐	☐	☐	☐	☐	☐
...How much do you disagree or agree with the following statements?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Growing the same crops but over a larger area or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Growing more water intensive crops or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Selling surplus water for the duration of the growing season or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Changing nothing or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Have you repeatedly, during the last 10 years, had a surplus of water after you met crop water requirements? If NO please skip to SECTION C	Yes ☐			No ☐			
If YES (IN REALITY) you repeatedly had a surplus of water after you met crop water requirements, what did you do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Grew the same crops but over a larger area	☐	☐	☐	☐	☐	☐	☐
Grew more water intensive crops	☐	☐	☐	☐	☐	☐	☐
Sold surplus water for the duration of the growing season	☐	☐	☐	☐	☐	☐	☐
Changed nothing	☐	☐	☐	☐	☐	☐	☐

Section C: This section is about decision making during the growing season							
Part 1: Water Shortage							
If (HYPOTHETICALLY) you repeatedly didn't have enough water to meet crop water requirements during a growing season...							
...What would you, as key decision maker in your farm business, intend to do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Only use your maximum abstraction licence to spread water evenly between all crops	☐	☐	☐	☐	☐	☐	☐
Only use your maximum abstraction licence to irrigate your most valuable crops	☐	☐	☐	☐	☐	☐	☐
Restrict application (i.e. deficit irrigation)	☐	☐	☐	☐	☐	☐	☐
Buy more water to meet crop water requirements	☐	☐	☐	☐	☐	☐	☐
...How advantageous or disadvantageous would each of the following actions be for your farm business?	Extremely disadvantageous	Very disadvantageous	Disadvantageous	Not sure	Advantageous	Very advantageous	Extremely advantageous
Only using your maximum abstraction licence to spread water evenly between all crops would be...	☐	☐	☐	☐	☐	☐	☐
Only using your maximum abstraction licence to irrigate your most valuable crops would be...	☐	☐	☐	☐	☐	☐	☐
Restricting application (i.e. deficit irrigation) would be...	☐	☐	☐	☐	☐	☐	☐
Buying more water to meet crop water requirements would be...	☐	☐	☐	☐	☐	☐	☐
...Which of the following social groups would most influence your decision making during the growing season?	Please rank numerically, 1 being most influential						
Groups interested in water saving and efficiency (e.g. Water abstraction group(s), National Farmers Union (NFU), Environmental Agency (EA), Defra, UK Irrigation Association (UKIA))							
Groups interested in crop type and quality (e.g. main buyer(s), agronomist, business advisor(s))							
Family, friends and neighbours							
...The social group you ranked as 1 would think that you *(definitely shouldn't* to *definitely should)*...	Definitely shouldn't	Very much shouldn't	Shouldn't	Not sure	Should	Very much should	Definitely should
...Only use your maximum abstraction licence to spread water evenly between all crops	☐	☐	☐	☐	☐	☐	☐
...Only use your maximum abstraction licence to irrigate your most valuable crops	☐	☐	☐	☐	☐	☐	☐
...Restrict application (i.e. deficit irrigation)	☐	☐	☐	☐	☐	☐	☐
...Buy more water to meet crop water requirements	☐	☐	☐	☐	☐	☐	☐

...How much do you disagree or agree with the following statements?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Only using your maximum abstraction licence to spread water evenly between all crops or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Only using your maximum abstraction licence to irrigate your most valuable crops or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Restricting application (i.e. deficit irrigation) or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Buying more water to meet crop water requirements or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Have you repeatedly not had enough water to meet crop water requirements during a growing season? If NO please skip to PART 2	Yes ☐				No ☐		
If YES (IN REALITY) you repeatedly didn't have enough water to meet crop water requirements during a growing season, what did you do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Only used your maximum abstraction licence to spread water evenly between all crops	☐	☐	☐	☐	☐	☐	☐
Only used your maximum abstraction licence to irrigate your most valuable crops	☐	☐	☐	☐	☐	☐	☐
Restricted application (i.e. deficit irrigation)	☐	☐	☐	☐	☐	☐	☐
Bought more water to meet crop water requirements	☐	☐	☐	☐	☐	☐	☐
Part 2: Water Surplus							
If (HYPOTHETICALLY) you repeatedly had a surplus of water after you met crop water requirements during the growing season...							
...What would you, as key decision maker in your farm business, intend to do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Sell surplus water to maximise profits	☐	☐	☐	☐	☐	☐	☐
Just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused	☐	☐	☐	☐	☐	☐	☐
Abstract surplus water for storage	☐	☐	☐	☐	☐	☐	☐
...How advantageous or disadvantageous would each of the following actions be for your farm business?	Extremely disadvantageous	Very disadvantageous	Disadvantageous	Not sure	Advantageous	Very advantageous	Extremely advantageous
Selling surplus water to maximise profits would be...	☐	☐	☐	☐	☐	☐	☐
Just using your abstraction licence to meet crop water requirements and leaving the remainder of your licence unused would be...	☐	☐	☐	☐	☐	☐	☐
Abstracting surplus water for storage would be...	☐	☐	☐	☐	☐	☐	☐

...Which of the following social groups would most influence your decision making during the growing season?	Please rank numerically, 1 being most influential						
Groups interested in water saving and efficiency (e.g. Water abstraction group(s), National Farmers Union (NFU), Environmental Agency (EA), Defra, UK Irrigation Association (UKIA))							
Groups interested in crop type and quality (e.g. main buyer(s), agronomist, business advisor(s))							
Family, friends and neighbours							
...The social group you ranked as 1 would think that you *(definitely shouldn't* to *definitely should)...*	Definitely shouldn't	Very much shouldn't	Shouldn't	Not sure	Should	Very much should	Definitely should
...Sell surplus water to maximise profits	☐	☐	☐	☐	☐	☐	☐
...Just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused	☐	☐	☐	☐	☐	☐	☐
...Abstract surplus water for storage	☐	☐	☐	☐	☐	☐	☐
...How much do you disagree or agree with the following statements?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Selling surplus water to maximise profits or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Just using your abstraction licence to meet crop water requirements and leaving the remainder of your licence unused or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Abstracting surplus water for storage or not is entirely up to you	☐	☐	☐	☐	☐	☐	☐
Have you repeatedly had a surplus of water after you met crop water requirements during a growing season? If NO please skip to SECTION D	Yes ☐			No ☐			
If (IN REALITY) you repeatedly had a surplus of water after you met crop water requirements during the growing season, what did you do?	Strongly disagree	Very much disagree	Disagree	Not sure	Agree	Very much agree	Strongly agree
Sold surplus water to maximise profits	☐	☐	☐	☐	☐	☐	☐
Just used your abstraction licence to meet crop water requirements and left the remainder of your licence unused	☐	☐	☐	☐	☐	☐	☐
Abstracted surplus water for storage	☐	☐	☐	☐	☐	☐	☐

Section D: Demographic Questions

What is your gender?

Male	Female
☐	☐

What is your age?

18-29	30-39	40-49	50-59	60-69	70 +
☐	☐	☐	☐	☐	☐

What is your highest level of education completed?

NQF Level	*Example Qualification*	
Entry Level:	Entry level certificate/ Foundation diploma/ BTEC Level 1	☐
Level 1-2:	O-Levels (A*-G)/ Higher Dip	☐
Level 3-5:	A-Levels (A*-E)/ Advance Dip/ Foundation Deg/ HND/ Dip FE	☐
Level 6:	Bachelors (Honours) Degree/ Graduate Dip/ Professional CE	☐
Level 7:	Masters Degree/ PGDip/ PGCert/ Postgraduate CE	☐
Level 8:	Doctoral Degree (Doctorates and Higher Doctorates)	☐

On average, what is your total gross annual farm business income?

£0-4,999	£5-9,999	£10-£14,999	£15-£19,999	£20-£29,999
☐	☐	☐	☐	☐
£30-£39,999	£40-£49,999	£50-74,999	£75-£99,999	£100,000+
☐	☐	☐	☐	☐

Have you used your licence at all in the last 10 years?

Yes	No
☐	☐

Appendix B

Summary statistics of farm characteristics

Table B.1: Farm attributes (section A of survey)

Crop category	Irrigated (%)	Area (ha)	Soil type (%) Sa	Lo	Pe	M	Irrigation method (%) R	B	S	T	M
Main crop 1 (n=90)											
- Early pot.	10	503	56	33	11	0	67	11	0	0	22
- Main crop pot.	72	4,819	28	40	20	12	65	11	2	0	23
- Sugar beet	2	110	50	0	50	0	100	0	0	0	0
- Orchard fruit	1	3	0	100	0	0	0	0	0	100	0
- Small fruit	0	0	0	0	0	0	0	0	0	0	0
- Vegetables	13	1,243	50	25	8	17	50	17	8	0	25
- Grass	0	0	0	0	0	0	0	0	0	0	0
- Cereals	0	0	0	0	0	0	0	0	0	0	0
- Other	1	20	0	0	0	0	0	0	0	0	100
- Missing	0	-	-	-	-	-	-	-	-	-	-
Total	100	6,699	34	37	18	11	62	11	2	1	23
Main crop 2 (n=54)											
- Early pot.	0	0	0	0	0	0	0	0	0	0	0
- Main crop pot.	10	930	11	33	33	22	44	11	0	0	44
- Sugar beet	12	191	20	50	10	20	70	30	0	0	0
- Orchard fruit	0	0	0	0	0	0	0	0	0	0	0
- Small fruit	1	1	0	100	0	0	0	0	0	100	0
- Vegetables	32	1,634	57	18	14	11	62	24	0	0	14
- Grass	0	0	0	0	0	0	0	0	0	0	0
- Cereals	3	200	0	67	0	33	67	0	0	0	33
- Other	1	4	100	0	0	0	100	0	0	0	0
- Missing	40	-	-	-	-	-	-	-	-	-	-
Total	100	2,959	38	31	15	15	60	21	0	2	17
Main crop 3 (n=39)											
- Early pot.	0	0	0	0	0	0	0	0	0	0	0
- Main crop pot.	1	16	100	0	0	0	100	0	0	0	0
- Sugar beet	9	504	43	14	0	43	63	13	0	0	25
- Orchard fruit	0	0	0	0	0	0	0	0	0	0	0
- Small fruit	0	0	0	0	0	0	0	0	0	0	0
- Vegetables	21	1,540	37	37	16	11	42	37	5	0	16
- Grass	1	12	0	100	0	0	100	0	0	0	0
- Cereals	10	925	22	44	11	22	67	33	0	0	0
- Other	1	4	100	0	0	0	100	0	0	0	0
- Missing	57	-	-	-	-	-	-	-	-	-	-
Total	100	3,001	37	34	11	18	56	28	3	0	13
Total (amalgamation of main crops 1, 2 and 3 excluding missing data)											
- Early pot.	5	503	56	33	11	0	67	11	0	0	22
- Main crop pot.	41	5,765	27	39	21	13	63	11	1	0	25
- Sugar beet	11	805	32	32	11	26	70	20	0	0	10
- Orchard fruit	1	3	0	100	0	0	0	0	0	100	0
- Small fruit	1	1	0	100	0	0	0	0	0	100	0
- Vegetables	33	4,417	49	25	14	12	53	27	3	0	17
- Grass	1	12	0	100	0	0	100	0	0	0	0
- Cereals	7	1,125	17	50	8	25	67	25	0	0	8
- Other	2	28	100	0	0	0	67	0	0	0	33
Total	100	12,659	36	35	16	14	60	18	2	1	19

Summing errors due to rounding. Potatoes (pot.); Sand (Sa); Loam (Lo); Peat (Pe); Mixed (M); Raingun (R); Boom (B); Sprinkler (S); Trickle (T)

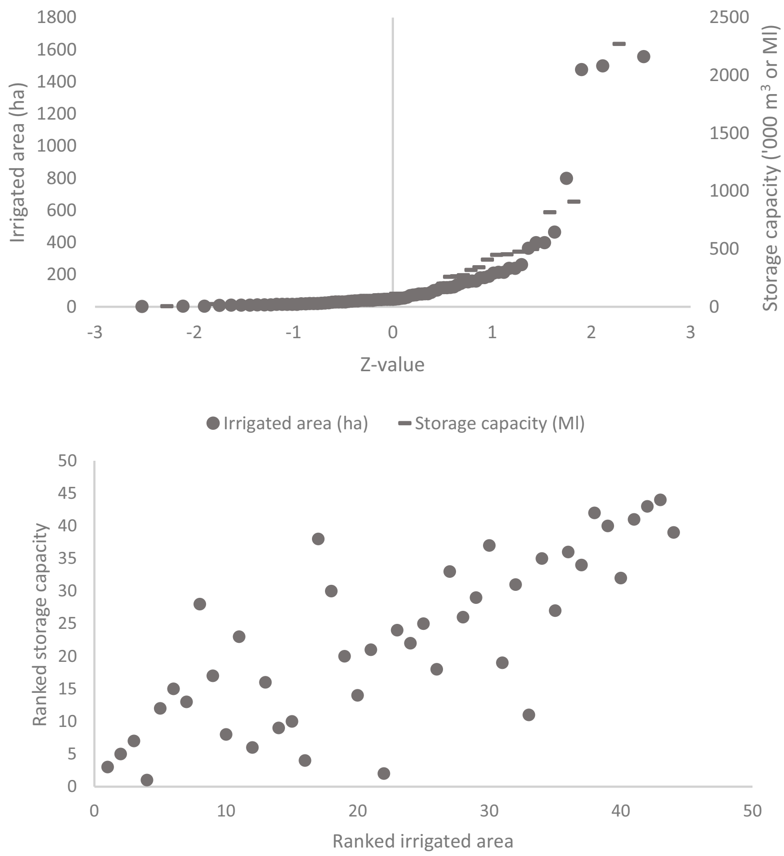

Figure B.1: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to irrigated area and storage capacity. (Top) A normal probability plot illustrating that neither variables were normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between ranked irrigated area and ranked storage capacity (Spearman's rank correlation coefficient r_s= .76, $p= <.001$)

Table B.2: Social demographics (section D of survey) (n = 90)

Measure	Respondents (%)
Gender	
- Male	93
- Female	2
- Missing	4
Age	
- 18-29	7
- 30-39	8
- 40-49	21
- 50-59	28
- 60-69	23
- $\geq$ 70	11
- Missing	2
[a]Education (NQF level)	
- <1	3
- 1-2	29
- 3-5	22
- 6	28
- 7	6
- 8	0
- Missing	12
[b]Income (£)	
- 0-4,999	0
- 5-9,999	0
- 10-14,999	0
- 15-19,999	1
- 20-29,999	3
- 30-39,999	0
- 40-49,999	0
- 50-74,999	8
- 75-99,999	8
- $\geq$ 100,000	66
- Missing	14
Licence use (last 10 years)	
- Yes	96
- No	2
- Missing	2

[a]National Qualification Framework (NQF) levels for England, Wales and Northern Ireland
[b]Total gross annual farm business income

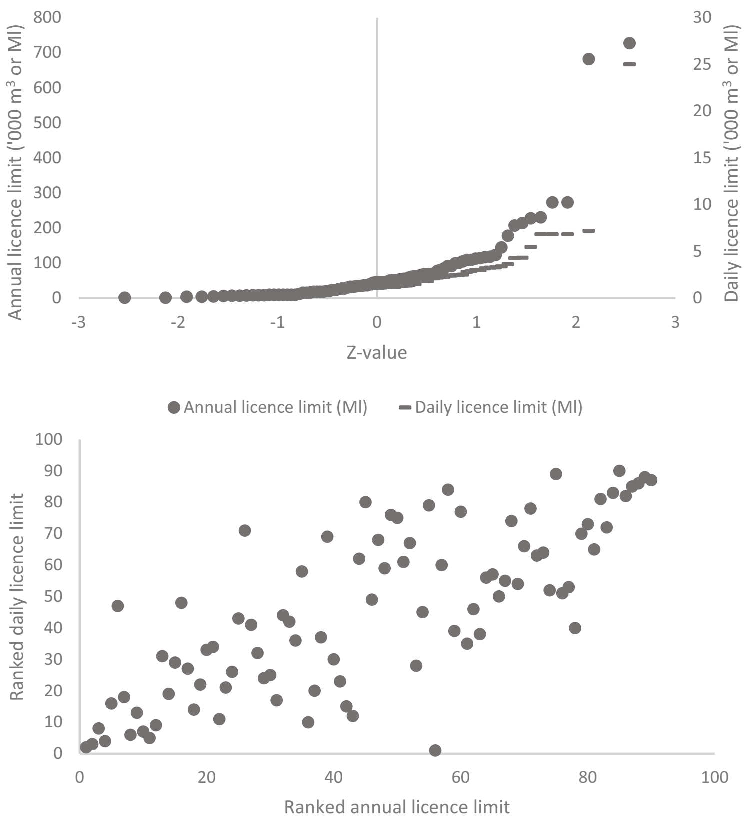

Figure B.2: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to annual and daily licence limits. (Top) A normal probability plot illustrating that neither variables were normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between ranked annual licence limit and ranked daily licence limit (Spearman's rank correlation coefficient r_s= .70, p= <.001)

Table B.3: Past abstractions between 2008 and 2012 ('000 m^3 or Ml)

Month	2008	2009	2010	2011	2012	Average	S.D.
Jan	107	96	232	324	67	165	108.89
Feb	46	33	208	285	57	126	113.81
Mar	35	4	13	149	151	70	73.36
Apr	26	35	50	216	162	98	85.87
May	152	274	348	661	269	341	192.10
Jun	289	646	561	509	172	435	197.82
Jul	428	334	883	388	120	431	279.61
Aug	176	271	172	289	193	220	55.21
Sep	61	237	35	104	112	110	77.71
Oct	4	72	6	78	32	39	35.27
Nov	201	79	237	148	199	173	61.17
Dec	191	169	284	242	58	189	85.64
Annual	1,715	2,249	3,028	3,393	1,591	2,395	794.71

Summing errors due to rounding

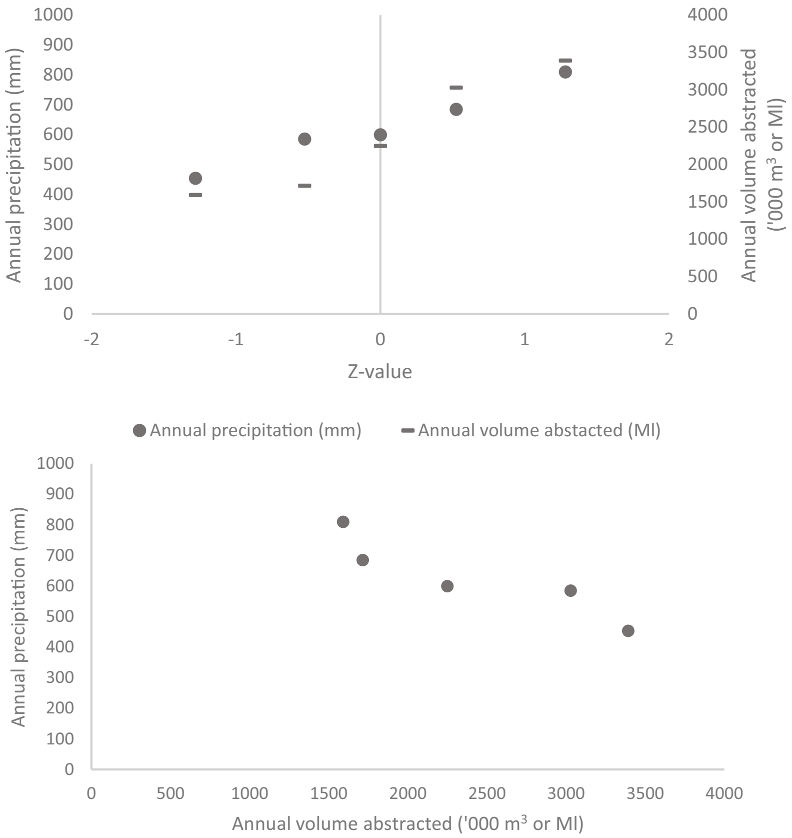

Figure B.3: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to annual abstractions and precipitation. (Top) A normal probability plot illustrating that both variables were normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between annual abstractions and annual precipitation (Pearson's correlation coefficient $r=$ -.91, $p= <.05$)

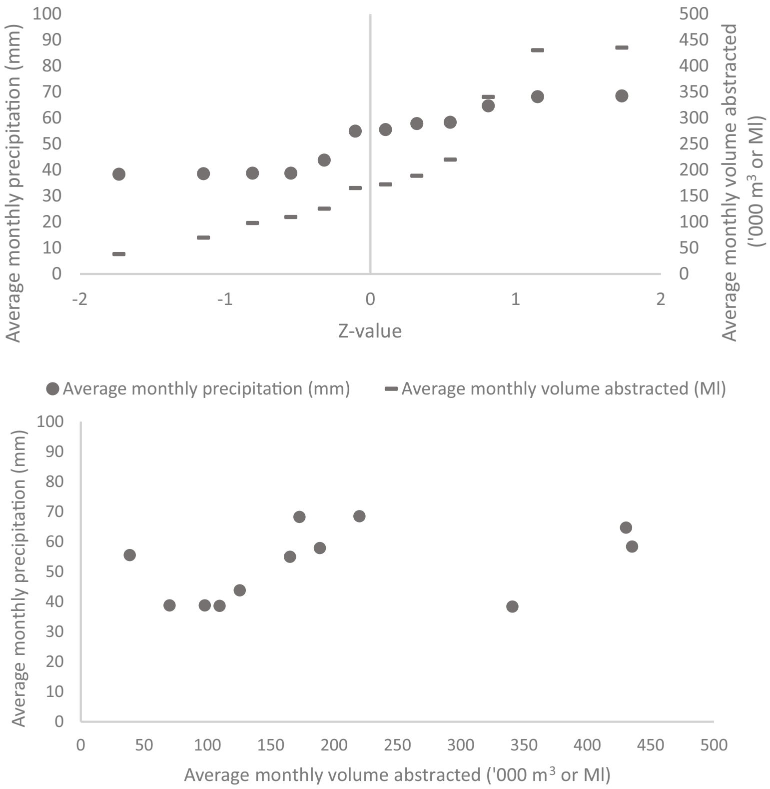

Figure B.4: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to average monthly abstractions and precipitation. (Top) A normal probability plot illustrating that both variables were approximately normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between average monthly abstractions and average monthly precipitation (Pearson's correlation coefficient $r= .36$, $p= >.05$)

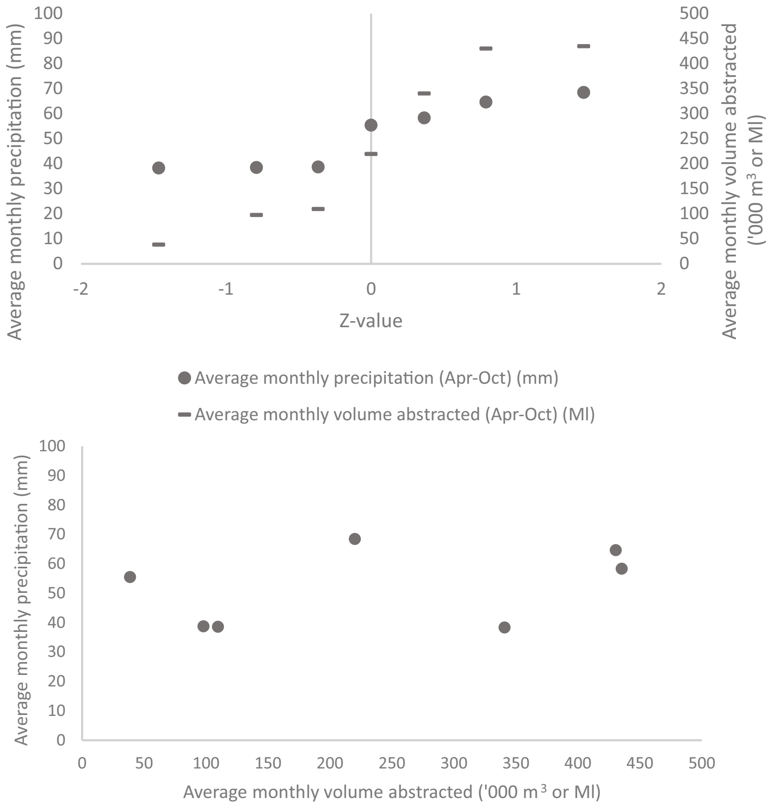

Figure B.5: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to average monthly abstractions and precipitation in-season (Apr-Oct). (Top) A normal probability plot illustrating that both variables were approximately normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between average monthly abstractions and average monthly precipitation in-season (Apr-Oct) (Pearson's correlation coefficient $r = .36$, $p = >.05$)

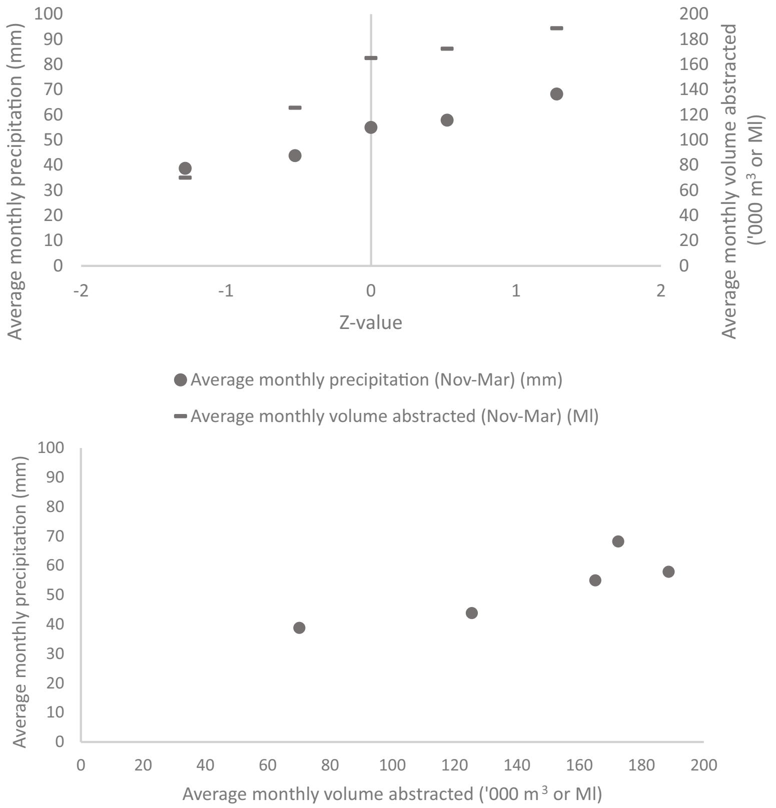

Figure B.6: A normal probability plot illustrating distribution, and a scatter plot indicating strength of association, with regards to average monthly abstractions and precipitation out-of-season (Nov-Mar). (Top) A normal probability plot illustrating that both variables were approximately normally distributed which supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for both variables. (Bottom) A scatter plot indicating the strength of association between average monthly abstractions and average monthly precipitation out-of-season (Nov-Mar) (Pearson's correlation coefficient $r = .87$, $p = >.05$)

Appendix C

Summary statistics of behavioural intentions

Table C.1: Strategic (long-term)/water shortage behavioural intentions (section B of survey)

Behaviour	[b]Likert item responses (%) (n=90)								Median	IQR
-[a]Construct	1	2	3	4	5	6	7	Missing		
Grow the same crops but over a smaller area										
- I	16	7	16	14	32	6	7	3	4	2
- A	17	28	41	4	6	0	0	4	3	1
- SN	7	10	18	23	28	7	0	8	4	2
- PBC	7	9	12	3	32	10	22	4	5	3
- PB	0	1	3	1	1	0	0	93	3	2
Grow less water intensive crops										
- I	17	9	22	12	26	9	0	6	3	3
- A	11	17	38	16	13	0	0	6	3	2
- SN	9	10	21	16	30	4	0	10	4	2
- PBC	8	2	20	2	24	16	22	6	5	3
- PB	0	1	2	1	2	0	0	93	4	2
Increase storage capacity										
- I	8	4	9	10	23	13	23	9	5	3
- A	4	2	6	6	32	19	19	12	5	1
- SN	2	1	2	13	37	12	20	12	5	1
- PBC	10	4	23	2	22	14	16	8	5	3
- PB	1	0	2	1	1	0	1	93	4	3
Increase application efficiency										
- I	1	2	2	10	36	24	18	7	5	1
- A	1	0	0	2	46	29	17	6	5	1
- SN	1	0	0	8	38	24	20	9	5	1
- PBC	11	1	20	4	26	17	14	7	5	3
- PB	0	0	1	1	2	0	1	94	5	2
Buy more water for the duration of the growing season										
- I	10	4	13	22	31	7	7	6	4	2
- A	2	7	10	22	27	19	7	7	5	2
- SN	2	0	4	32	32	12	4	12	5	1
- PBC	6	6	19	4	32	13	13	7	5	3
- PB	0	0	2	1	2	2	0	92	5	3
Apply for a larger abstraction licence										
- I	7	8	14	13	36	3	11	8	5	2
- A	2	3	7	21	30	14	13	9	5	2
- SN	4	1	11	23	26	14	9	11	5	2
- PBC	9	8	20	4	19	12	20	8	5	3
- PB	0	1	0	1	2	1	0	94	5	3
Change nothing										
- I	33	8	22	13	9	2	7	6	3	3
- A	17	11	36	21	7	1	1	7	3	2
- SN	17	10	30	23	8	1	0	11	3	2
- PBC	12	0	12	3	30	13	22	7	5	3
- PB	1	1	3	1	0	0	1	92	3	2

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)

[b](I), (PBC), and (PB) = strongly disagree (1) to strongly agree (7); (A) = extremely disadvantageous (1) to extremely advantageous (7); and (SN) = definitely shouldn't (1) to definitely should (7) (4 = not sure for all constructs)

Table C.2: Preferred strategic (long-term)/water shortage behavioural intentions

Behaviour	[b]Rescaled Likert item responses								$\sum Totals$	[c]Sign test
-[a]Construct	-3	-2	-1	(n=)	1	2	3	Total		(-,+,=)
Increase application efficiency									425	
- I	-3	-4	-2	(84)	32	44	48	115		29,15,37*
- A	-3	0	0	(85)	41	52	45	135		
- SN	-3	0	0	(82)	34	44	54	129		
- PBC	-30	-2	-18	(84)	23	30	39	42		
- PB	0	0	-1	(5)	2	0	3	4		
Increase storage capacity									294	
- I	-21	-8	-8	(82)	21	24	63	71		33,15,32*
- A	-12	-4	-5	(79)	29	34	51	93		
- SN	-6	-2	-2	(79)	33	22	54	99		
- PBC	-27	-8	-21	(83)	20	26	42	32		
- PB	-3	0	-2	(6)	1	0	3	-1		
Apply for a larger abstraction licence									182	
- I	-18	-14	-13	(83)	32	6	30	23		26,19,38
- A	-6	-6	-6	(82)	27	26	36	71		
- SN	-12	-2	-10	(80)	23	26	24	49		
- PBC	-24	-14	-18	(83)	17	22	54	37		
- PB	0	-2	0	(5)	2	2	0	2		
Buy more water for the duration of the growing season									164	
- I	-27	-8	-12	(85)	28	12	18	11		42,21,21*
- A	-6	-12	-9	(84)	24	34	18	49		
- SN	-6	0	-4	(79)	29	22	12	53		
- PBC	-15	-10	-17	(84)	29	24	36	47		
- PB	0	0	-2	(7)	2	4	0	4		
Grow less water intensive crops									-85	
- I	-45	-16	-20	(85)	23	16	0	-42		15,32,38*
- A	-30	-30	-34	(85)	12	0	0	-82		
- SN	-24	-18	-19	(81)	27	8	0	-26		
- PBC	-21	-4	-18	(85)	22	28	60	67		
- PB	0	-2	-2	(6)	2	0	0	-2		
Grow the same crops but over a smaller area									-95	
- I	-42	-12	-14	(87)	29	10	18	-11		52,17,14*
- A	-45	-50	-37	(86)	5	0	0	-127		
- SN	-18	-18	-16	(83)	25	12	0	-15		
- PBC	-18	-16	-11	(86)	29	18	60	62		
- PB	0	-2	-3	(6)	1	0	0	-4		
Change nothing									-199	
- I	-90	-14	-20	(85)	8	4	18	-94		
- A	-45	-20	-32	(84)	6	2	3	-86		
- SN	-45	-18	-27	(80)	7	2	0	-81		
- PBC	-33	0	-11	(84)	27	24	60	67		
- PB	-3	-2	-3	(7)	0	0	3	-5		

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b]Likert item scores rescaled from -3 to 3 and multiplied by number of responses
[c]Positive difference (+); negative difference (-); and ties (=). (*) = $p<.05$.

Table C.3: Tests for multi-collinearity, and recommended number of cases, in relation to respondents' preferred strategic (long-term)/water shortage behavioural intention. Tests for multi-collinearity of the predictor variables (i.e. attitude, subjective norm (SN), and perceived behavioural control (PBC)) in relation to the binary response variable (i.e. intention) where 0 = strongly disagree to agree and 1 = very much agree to strongly agree with the intention to increase application efficiency (n = 79)

Measure	Attitude	SN	PBC	VIF	Frequency	
					0	1
- Intention	.388	.467	.135			
- Attitude		.416	.044	1.210	42	37
- SN			.134	1.230	41	38
- PBC				1.019	53	26

Variance Inflation Factor (VIF)

Table C.4: Strategic (long-term)/water surplus behavioural intentions (section B of survey)

Behaviour -[a]Construct	[b]Likert item responses (%) (n=90) 1	2	3	4	5	6	7	Missing	Median	IQR
Grow the same crops but over a larger area										
- I	3	2	41	17	21	3	3	9	3	2
- A	4	7	24	19	32	6	3	4	4	2
- SN	3	4	19	28	24	6	1	14	4	2
- PBC	4	2	17	2	39	6	23	7	5	4
- PB	7	2	21	2	9	1	1	57	3	2
Grow more water intensive crops										
- I	4	4	52	14	12	3	0	9	3	1
- A	4	6	32	26	23	4	0	4	4	2
- SN	7	3	31	27	17	2	0	13	4	1
- PBC	4	2	22	2	34	7	21	7	5	3
- PB	9	1	24	1	6	2	0	57	3	0
Sell surplus water for the duration of the growing season										
- I	7	7	21	14	34	4	6	7	4	2
- A	7	2	6	20	48	8	6	4	5	1
- SN	3	2	9	32	31	7	2	13	4	1
- PBC	11	2	21	8	28	8	16	7	5	3
- PB	8	1	17	4	7	4	1	58	3	2
Change nothing										
- I	8	3	18	19	30	8	8	7	4	2
- A	7	4	26	34	18	1	6	4	4	2
- SN	6	7	23	30	16	4	0	14	4	1
- PBC	9	2	20	9	26	4	24	6	5	4
- PB	4	1	12	4	17	1	10	50	5	2

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b](I), (PBC), and (PB) = strongly disagree (1) to strongly agree (7); (A) = extremely disadvantageous (1) to extremely advantageous (7); and (SN) = definitely shouldn't (1) to definitely should (7) (4 = not sure for all constructs)

Table C.5: Preferred strategic (long-term)/water surplus behavioural intentions

Behaviour -[a]Construct	[b]Rescaled Likert item responses -3	-2	-1	(n=)	1	2	3	Total	$\sum Totals$	[c]Sign test (-,+,=)
Sell surplus water for the duration of the growing season									82	
- I	-18	-12	-19	(84)	31	8	15	5		29,29,21
- A	-18	-4	-5	(86)	43	14	15	45		
- SN	-9	-4	-8	(78)	28	12	6	25		
- PBC	-30	-4	-19	(84)	25	14	42	28		
- PB	-21	-2	-15	(38)	6	8	3	-21		
Change nothing									47	
- I	-21	-6	-16	(84)	27	14	21	19		41,21,17*
- A	-18	-8	-23	(86)	16	2	15	-16		
- SN	-15	-12	-21	(77)	14	8	0	-26		
- PBC	-24	-4	-18	(85)	23	8	66	51		
- PB	-12	-2	-11	(45)	15	2	27	19		
Grow the same crops but over a larger area									36	
- I	-9	-4	-37	(82)	19	6	9	-16		25, 6,51*
- A	-12	-12	-22	(86)	29	10	9	2		
- SN	-9	-8	-17	(77)	22	10	3	1		
- PBC	-12	-4	-15	(84)	35	10	63	77		
- PB	-18	-4	-19	(39)	8	2	3	-28		
Grow more water intensive crops									-80	
- I	-12	-8	-47	(82)	11	6	0	-50		
- A	-12	-10	-29	(86)	21	8	0	-22		
- SN	-18	-6	-28	(78)	15	4	0	-33		
- PBC	-12	-4	-20	(84)	31	12	57	64		
- PB	-24	-2	-22	(39)	5	4	0	-39		

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b]Likert item scores rescaled from -3 to 3 and multiplied by number of responses
[c]Positive difference (+); negative difference (-); and ties (=). (*) = p<.05.

Table C.6: Tests for multi-collinearity, and recommended number of cases, in relation to respondents' preferred strategic (long-term)/water surplus behavioural intention. Tests for multi-collinearity of the predictor variables (i.e. attitude, subjective norm (SN), and perceived behavioural control (PBC)) in relation to the binary response variable (i.e. intention) where 0 = strongly disagree to not sure and 1 = agree to strongly agree with the intention to sell surplus water for the duration of the growing season (n = 75)

Measure	Attitude	SN	PBC	VIF	Frequency 0	1
- Intention	.356	.332	.181			
- Attitude		.141	.136	1.033	64	11
- SN			.196	1.054	40	35
- PBC				1.053	58	17

Variance Inflation Factor (VIF)

Table C.7: In-season (short-term)/water shortage behavioural intentions (section C of survey)

Behaviour	[b]Likert item responses (%) (n=90)								Median	IQR
-[a]Construct	1	2	3	4	5	6	7	Missing		
Only use your maximum abstraction licence to spread water evenly between all crops										
- I	16	6	32	7	16	9	10	6	3	2
- A	7	17	42	10	11	4	2	7	3	2
- SN	10	2	20	22	24	6	4	11	4	2
- PBC	10	6	17	3	27	13	17	8	5	3
- PB	2	1	3	1	3	1	0	88	3	3
Only use your maximum abstraction licence to irrigate your most valuable crops										
- I	7	0	6	1	33	23	24	6	6	2
- A	3	4	19	11	40	8	8	7	5	2
- SN	3	1	4	12	31	24	12	11	5	1
- PBC	9	4	14	6	29	13	17	8	5	3
- PB	0	1	1	2	4	1	2	88	5	2
Restrict irrigation (i.e. deficit irrigation)										
- I	7	3	22	18	33	4	2	10	4	2
- A	10	18	40	16	7	0	2	8	3	2
- SN	8	4	20	28	17	8	3	12	4	2
- PBC	9	8	17	4	29	11	13	9	5	3
- PB	1	1	2	2	6	0	0	88	4	2
Buy more water to meet crop water requirements										
- I	9	3	8	14	33	14	7	11	5	1
- A	4	2	11	17	36	12	8	10	5	1
- SN	3	0	4	26	36	9	9	13	5	1
- PBC	9	6	13	10	31	7	13	11	5	2
- PB	2	0	1	1	6	0	2	88	5	2

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b](I), (PBC), and (PB) = strongly disagree (1) to strongly agree (7); (A) = extremely disadvantageous (1) to extremely advantageous (7); and (SN) = definitely shouldn't (1) to definitely should (7) (4 = not sure for all constructs)

Table C.8: Preferred in-season (short-term)/water shortage behavioural intentions

Behaviour	[b]Rescaled Likert item responses								$\sum Totals$	[c]Sign test
-[a]Construct	-3	-2	-1	(n=)	1	2	3	Total		(-,+,=)
Only use your maximum abstraction licence to irrigate your most valuable crops									301	
- I	-18	0	-5	(85)	30	42	66	115		42,13,25*
- A	-9	-8	-17	(84)	36	14	21	37		
- SN	-9	-2	-4	(80)	28	44	33	90		
- PBC	-24	-8	-13	(83)	26	24	45	50		
- PB	0	-2	-1	(11)	4	2	6	9		
Buy more water to meet crop water requirements									179	
- I	-24	-6	-7	(80)	30	26	18	37		43,19,18*
- A	-12	-4	-10	(81)	32	22	21	49		
- SN	-9	0	-4	(78)	32	16	24	59		
- PBC	-24	-10	-12	(80)	28	12	36	30		
- PB	-6	0	-1	(11)	5	0	6	4		
Only use your maximum abstraction licence to spread water evenly between all crops									-56	
- I	-42	-10	-29	(85)	14	16	27	-24		21,29,31
- A	-18	-30	-38	(84)	10	8	6	-62		
- SN	-27	-4	-18	(80)	22	10	12	-5		
- PBC	-27	-10	-15	(83)	24	24	45	41		
- PB	-6	-2	-3	(11)	3	2	0	-6		
Restrict irrigation (i.e. deficit irrigation)									-65	
- I	-18	-6	-20	(81)	30	8	6	0		
- A	-27	-32	-36	(83)	6	0	6	-83		
- SN	-21	-8	-18	(79)	15	14	9	-9		
- PBC	-24	-14	-15	(82)	26	20	36	29		
- PB	-3	-2	-2	(11)	5	0	0	-2		

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b]Likert item scores rescaled from -3 to 3 and multiplied by number of responses
[c]Positive difference (+); negative difference (-); and ties (=). (*) = p<.05.

Table C.9: Tests for multi-collinearity, and recommended number of cases, in relation to respondents' preferred in-season (short-term)/water shortage behavioural intention. Tests for multi-collinearity of the predictor variables (i.e. attitude, subjective norm (SN), and perceived behavioural control (PBC)) in relation to the binary response variable (i.e. intention) where 0 = strongly disagree to very much agree and 1 = strongly agree with the intention to only use your maximum abstraction licence to irrigate your most valuable crops (n = 78)

Measure	Attitude	SN	PBC	VIF	Frequency	
					0	1
- Intention	.446	.483	.313			
- Attitude		.410	.181	1.219	65	13
- SN			.180	1.219	47	31
- PBC				1.048	51	27

Variance Inflation Factor (VIF)

Table C.10: Tests for multi-collinearity, and recommended number of cases, in relation to respondents' preferred in-season (short-term)/water shortage behavioural intention after removing an outlier. Tests for multi-collinearity of the predictor variables (i.e. attitude, subjective norm (SN), and perceived behavioural control (PBC)) in relation to the binary response variable (i.e. intention) where 0 = strongly disagree to very much agree and 1 = strongly agree with the intention to only use your maximum abstraction licence to irrigate your most valuable crops (n = 77)

Measure	Attitude	SN	PBC	VIF	Frequency	
					0	1
- Intention	.466	.513	.337			
- Attitude		.408	.177	1.216	64	13
- SN			.174	1.215	46	31
- PBC				1.046	50	27

Variance Inflation Factor (VIF)

Table C.11: In-season (short-term)/water surplus behavioural intentions (section C of survey)

Behaviour	[b]Likert item responses (%) (n=90)								Median	IQR
-[a]Construct	1	2	3	4	5	6	7	Missing		
Sell surplus water to maximise profits										
- I	8	0	14	27	14	16	9	12	4	3
- A	3	0	3	16	40	18	9	11	5	2
- SN	6	1	10	27	26	7	7	18	4	1
- PBC	9	1	18	4	32	7	18	11	5	3
- PB	9	1	19	2	9	1	1	58	3	2
Just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused										
- I	3	2	16	12	37	11	10	9	5	1
- A	2	2	23	28	28	1	3	12	4	2
- SN	2	4	13	22	30	1	9	18	4	1
- PBC	10	6	13	8	28	6	19	11	5	3
- PB	0	1	1	3	30	3	11	50	5	1
Abstract surplus water for storage										
- I	6	6	23	18	18	6	6	19	4	2
- A	6	2	10	18	36	8	4	17	5	1
- SN	6	1	10	26	26	3	8	21	4	1
- PBC	10	1	17	11	24	4	18	14	5	3
- PB	7	2	19	4	10	1	1	56	3	2

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)

[b](I), (PBC), and (PB) = strongly disagree (1) to strongly agree (7); (A) = extremely disadvantageous (1) to extremely advantageous (7); and (SN) = definitely shouldn't (1) to definitely should (7) (4 = not sure for all constructs)

Table C.12: Preferred in-season (short-term)/water surplus behavioural intentions

Behaviour -[a]Construct	[b]Rescaled Likert item responses -3	-2	-1	(n=)	1	2	3	Total	$\sum Totals$	[c]Sign test (-,+,=)
Just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused									182	
- I	-9	-4	-14	(82)	33	20	27	53		37,29,11
- A	-6	-4	-21	(79)	25	2	9	5		
- SN	-6	-8	-12	(74)	27	2	24	27		
- PBC	-27	-10	-12	(80)	25	10	51	37		
- PB	0	-2	-1	(45)	27	6	30	60		
Sell surplus water to maximise profits									155	
- I	-21	0	-13	(79)	13	28	24	31		33,16,23*
- A	-9	0	-3	(80)	36	32	24	80		
- SN	-15	-2	-9	(74)	23	12	18	27		
- PBC	-24	-2	-16	(80)	29	12	48	47		
- PB	-24	-2	-17	(38)	8	2	3	-30		
Abstract surplus water for storage									58	
- I	-15	-10	-21	(73)	16	10	15	-5		
- A	-15	-4	-9	(75)	32	14	12	30		
- SN	-15	-2	-9	(71)	23	6	21	24		
- PBC	-27	-2	-15	(77)	22	8	48	34		
- PB	-18	-4	-17	(40)	9	2	3	-25		

[a]Theory of Planned Behaviour constructs: Intention (I); Attitude (A); Subjective Norm (SN); Perceived Behavioural Control (PBC); and Past Behaviour (PB)
[b]Likert item scores rescaled from -3 to 3 and multiplied by number of responses
[c]Positive difference (+); negative difference (-); and ties (=). (*) = $p<.05$.

Table C.13: Tests for multi-collinearity, and recommended number of cases, in relation to respondents' preferred in-season (short-term)/water surplus behavioural intention. Tests for multi-collinearity of the predictor variables (i.e. attitude, subjective norm (SN), and perceived behavioural control (PBC)) in relation to the binary response variable (i.e. intention) where 0 = strongly disagree to agree and 1 = very much agree to strongly agree with the intention to just use your abstraction licence to meet crop water requirements and leave the remainder of your licence unused (n = 72)

Measure	Attitude	SN	PBC	VIF	Frequency 0	1
- Intention	.467	.129	.483			
- Attitude		.158	.003	1.026	46	26
- SN			.097	1.035	38	34
- PBC				1.010	50	22

Variance Inflation Factor (VIF)

Table C.14: Iteration history with regards to respondents' preferred in-season (short-term)/water surplus behavioural intention ($n = 72$)

Iteration	-2log	Coefficients			
	likelihood	Constant	Attitude	SN	PBC
1	50.304	-2.205	1.641	.032	1.773
2	42.001	-3.492	2.771	-.102	2.849
3	39.176	-4.677	3.912	-.297	3.941
4	38.243	-5.779	5.006	-.406	5.013
5	37.925	-6.809	6.035	-.429	6.038
6	37.811	-7.816	7.041	-.430	7.044
7	37.769	-8.818	8.043	-.431	8.046
8	37.753	-9.818	9.044	-.431	9.047
9	37.747	-10.819	10.044	-.431	10.047
10	37.745	-11.819	11.044	-.431	11.047
11	37.745	-12.819	12.044	-.431	12.047
12	37.744	-13.819	13.044	-.431	13.047
13	37.744	-14.819	14.044	-.431	14.047
14	37.744	-15.819	15.044	-.431	15.047
15	37.744	-16.819	16.044	-.431	16.047
16	37.744	-17.819	17.044	-.431	17.047
17	37.744	-18.819	18.044	-.431	18.047
18	37.744	-19.819	19.044	-.431	19.047
19	37.744	-20.819	20.044	-.431	20.047
20	37.744	-21.819	21.044	-.431	21.047

Estimation terminated at iteration 20 because maximum iterations had been reached. Final solution was not found

Table C.15: Influential social group (section B and C of survey)

Scenario	[b]Ranking (%) (n=90)			
-[a]Social group	1	2	3	Missing
Strategic (long-term)/water shortage				
- A	27	49	18	7
- B	58	30	3	9
- C	10	12	66	12
Strategic (long-term)/water surplus				
- A	27	53	13	7
- B	60	29	4	7
- C	10	10	69	11
In-season (short-term)/water shortage				
- A	29	48	13	10
- B	52	31	6	11
- C	11	10	64	14
In-season (short-term)/water surplus				
- A	23	47	14	16
- B	53	23	7	17
- C	9	13	58	20

[a]Groups interested in water saving and efficiency (A); Groups interested in crop type and quality (B); and family, friends and neighbours (C)
[b]Most influential (1) to least influential (3)

Table C.16: Actual experience of scenario (section B and C of survey)

Scenario	Experienced (%) (n=90)		
	Yes	No	Missing
Strategic (long-term)/water shortage			
	9	90	1
Strategic (long-term)/water surplus			
	51	47	2
In-season (short-term)/water shortage			
	12	80	8
In-season (short-term)/water surplus			
	53	36	11

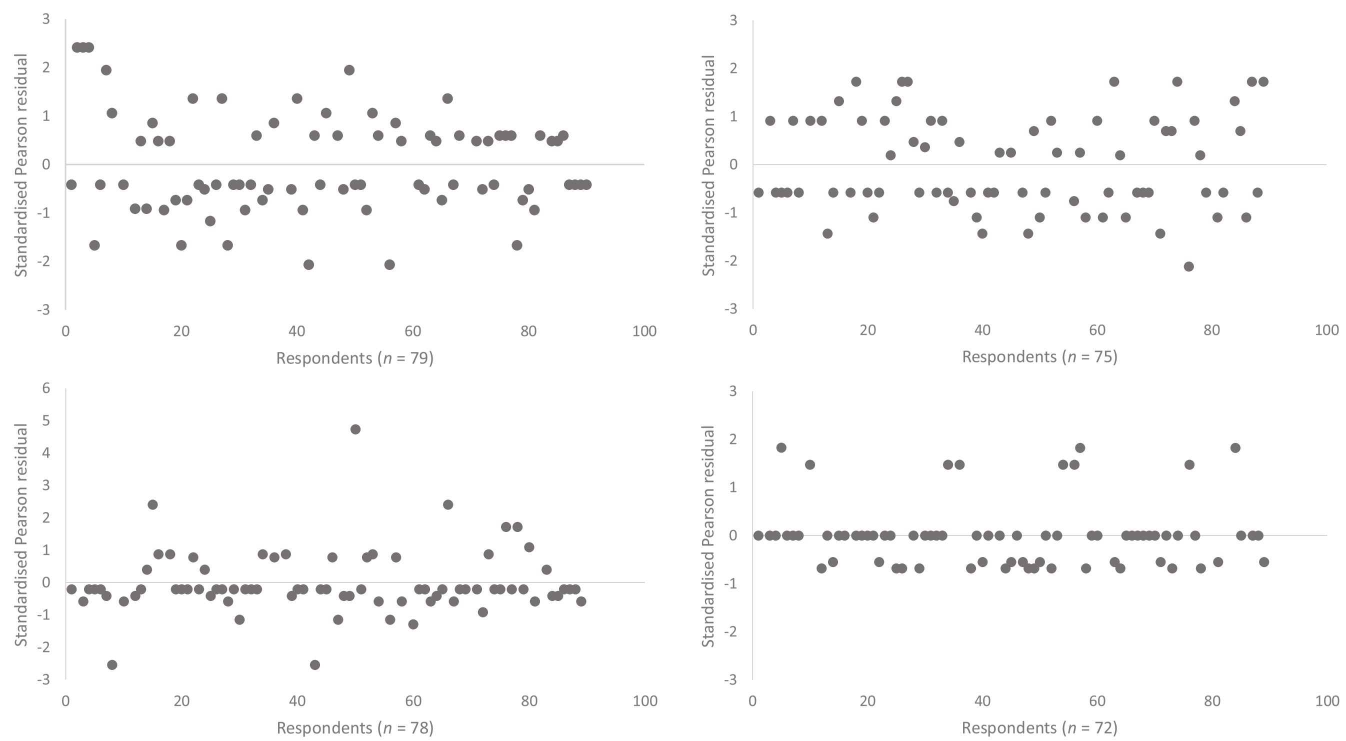

Figure C.1: Scatter plots illustrating standardised Pearson residuals with regards to respondents' preferred behavioural intentions during strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. (Top left) A scatter plot illustrating standardised Pearson residuals with regards to respondents' preferred strategic (long-term)/water shortage behavioural intention. (Top right) A scatter plot illustrating standardised Pearson residuals with regards to respondents' preferred strategic (long-term)/water surplus behavioural intention. (Bottom left) A scatter plot illustrating standardised Pearson residuals with regards to respondents' preferred in-season (short-term)/water shortage behavioural intention. (Bottom right) A scatter plot illustrating standardised Pearson residuals with regards to respondents' preferred in-season (short-term)/water surplus behavioural intention

Appendix D

Summary statistics of farm types

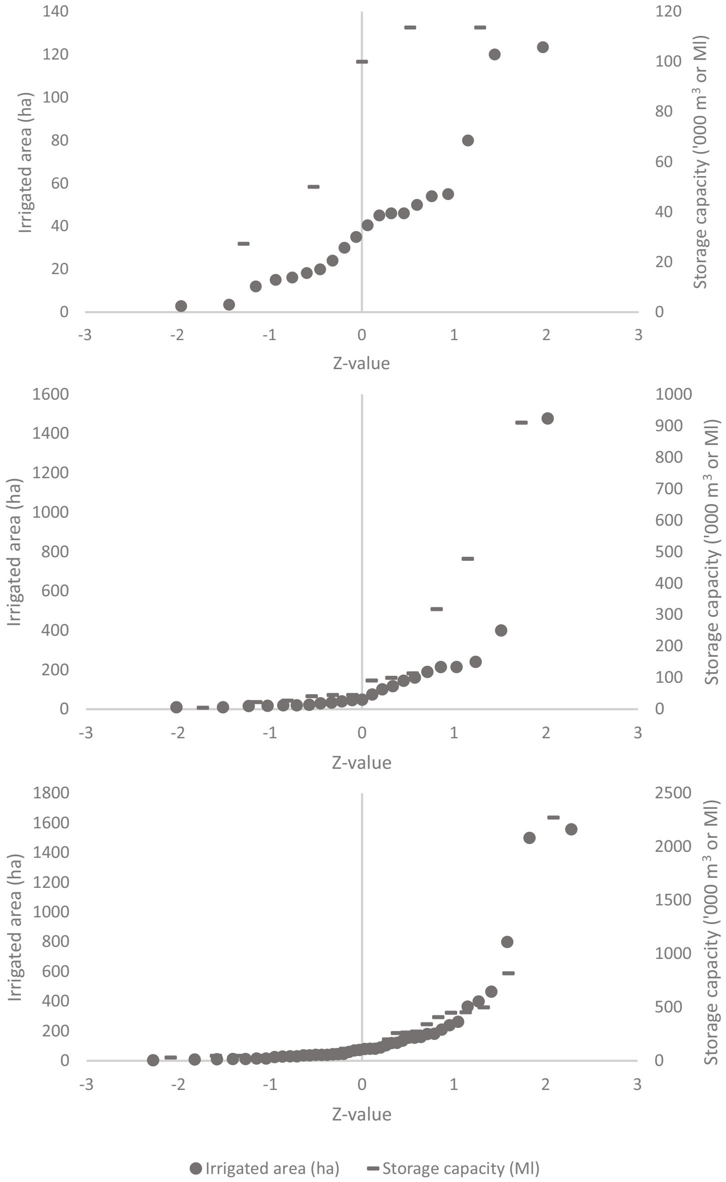

Figure D.1: Normal probability plots illustrating distribution with regards to irrigated area and storage capacity for each farm type. (Top) A normal probability plot illustrating that neither variables were normally distributed for those who preferred LWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Middle) A normal probability plot illustrating that neither variables were normally distributed for those who had no preference which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Bottom) A normal probability plot illustrating that neither variables were normally distributed for those who preferred HWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables

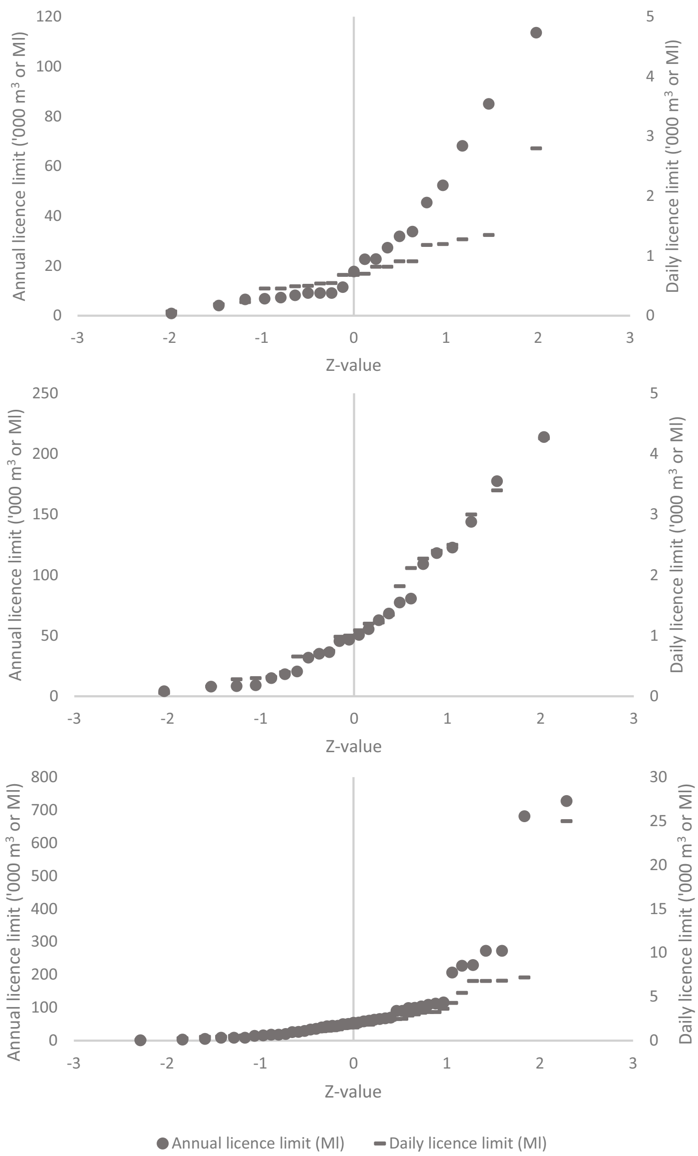

Figure D.2: Normal probability plots illustrating distribution with regards to annual and daily licence limits for each farm type. (Top) A normal probability plot illustrating that neither variables were normally distributed for those who preferred LWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Middle) A normal probability plot illustrating that neither variables were normally distributed for those who had no preference which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables. (Bottom) A normal probability plot illustrating that neither variables were normally distributed for those who preferred HWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for both variables

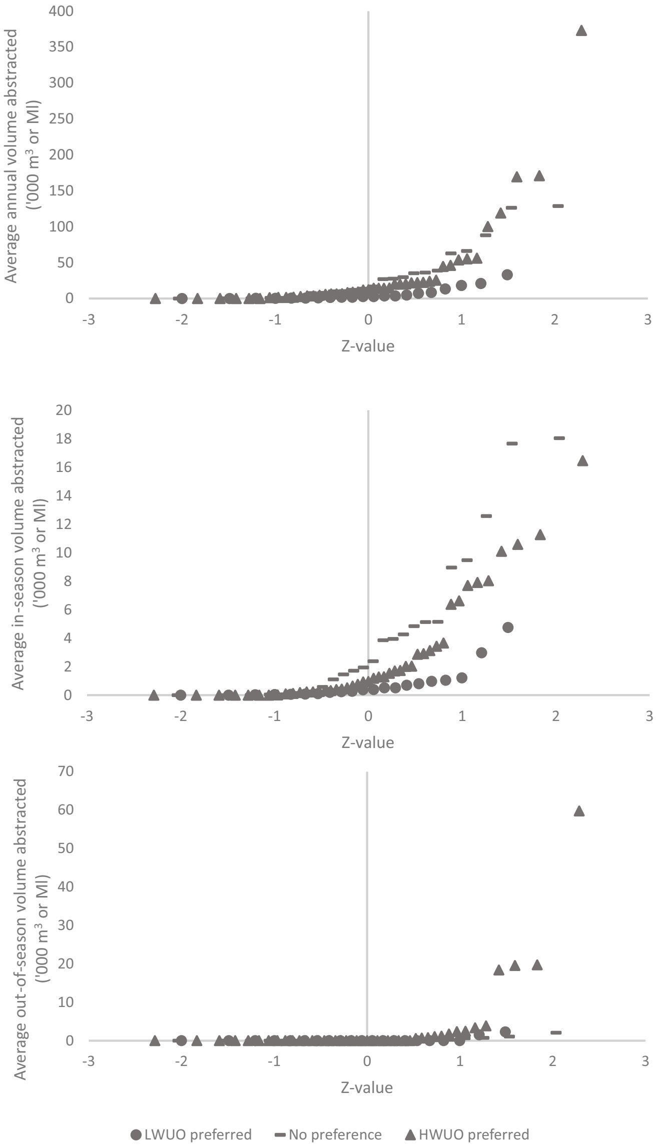

Figure D.3: Normal probability plots illustrating distribution with regards to annual, in-season, and out-of-season abstractions for each farm type. (Top) A normal probability plot illustrating that none of the variables were normally distributed for those who preferred LWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for all variables. (Middle) A normal probability plot illustrating that none of the variables were normally distributed for those who had no preference which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for all variables. (Bottom) A normal probability plot illustrating that none of the variables were normally distributed for those who preferred HWUO which supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for all variables

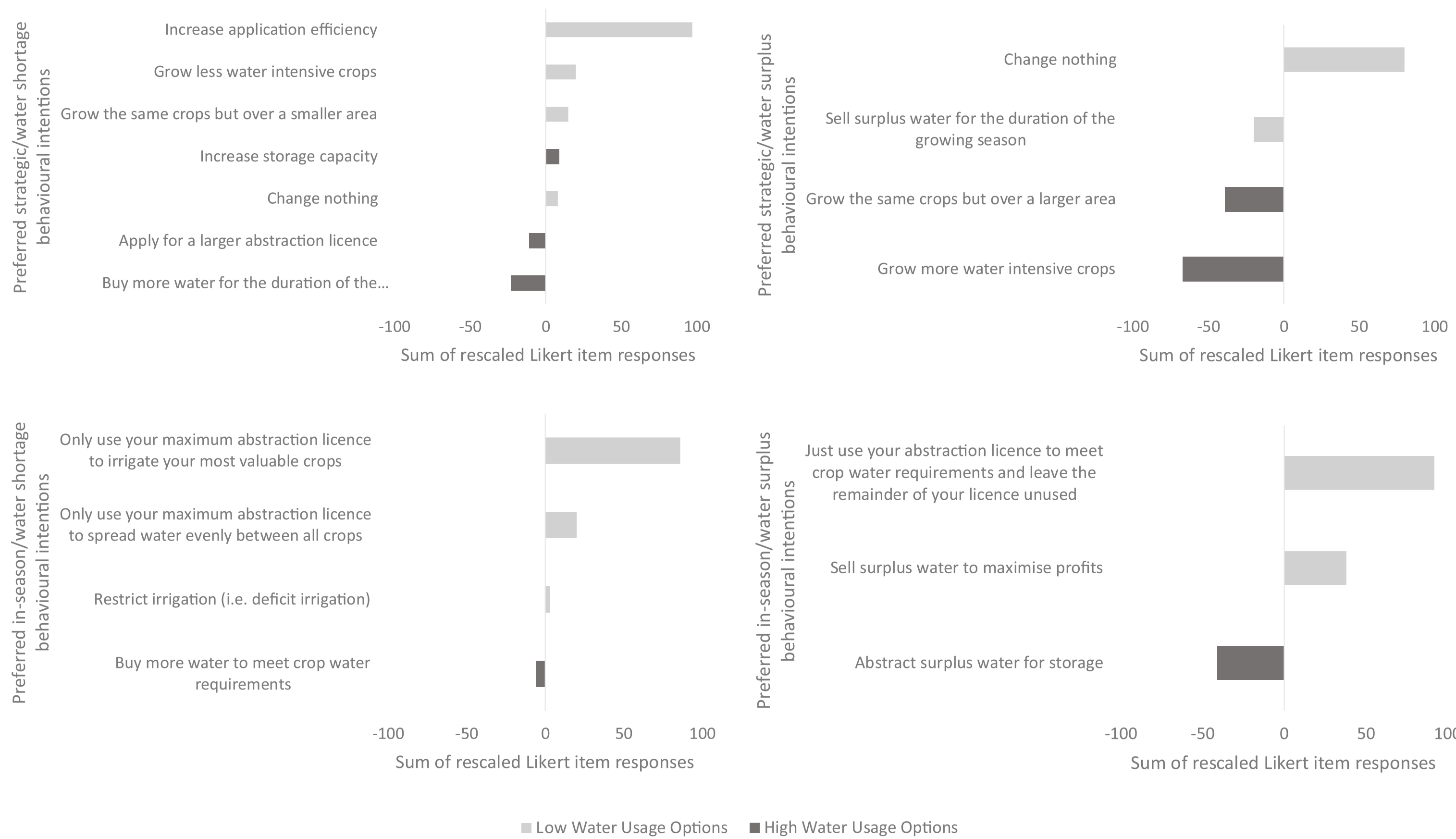

Figure D.4: Bar charts illustrating the preferred behavioural intentions of those who preferred LWUO during strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. (Top left) A bar chart illustrating the preferred strategic (long-term)/water shortage behavioural intentions of those who preferred LWUO. (Top right) A bar chart illustrating the preferred strategic (long-term)/water surplus behavioural intentions of those who preferred LWUO. (Bottom left) A bar chart illustrating the preferred in-season (short-term)/water shortage behavioural intentions of those who preferred LWUO. (Bottom right) A bar chart illustrating the preferred in-season (short-term)/water surplus behavioural intentions of those who preferred LWUO

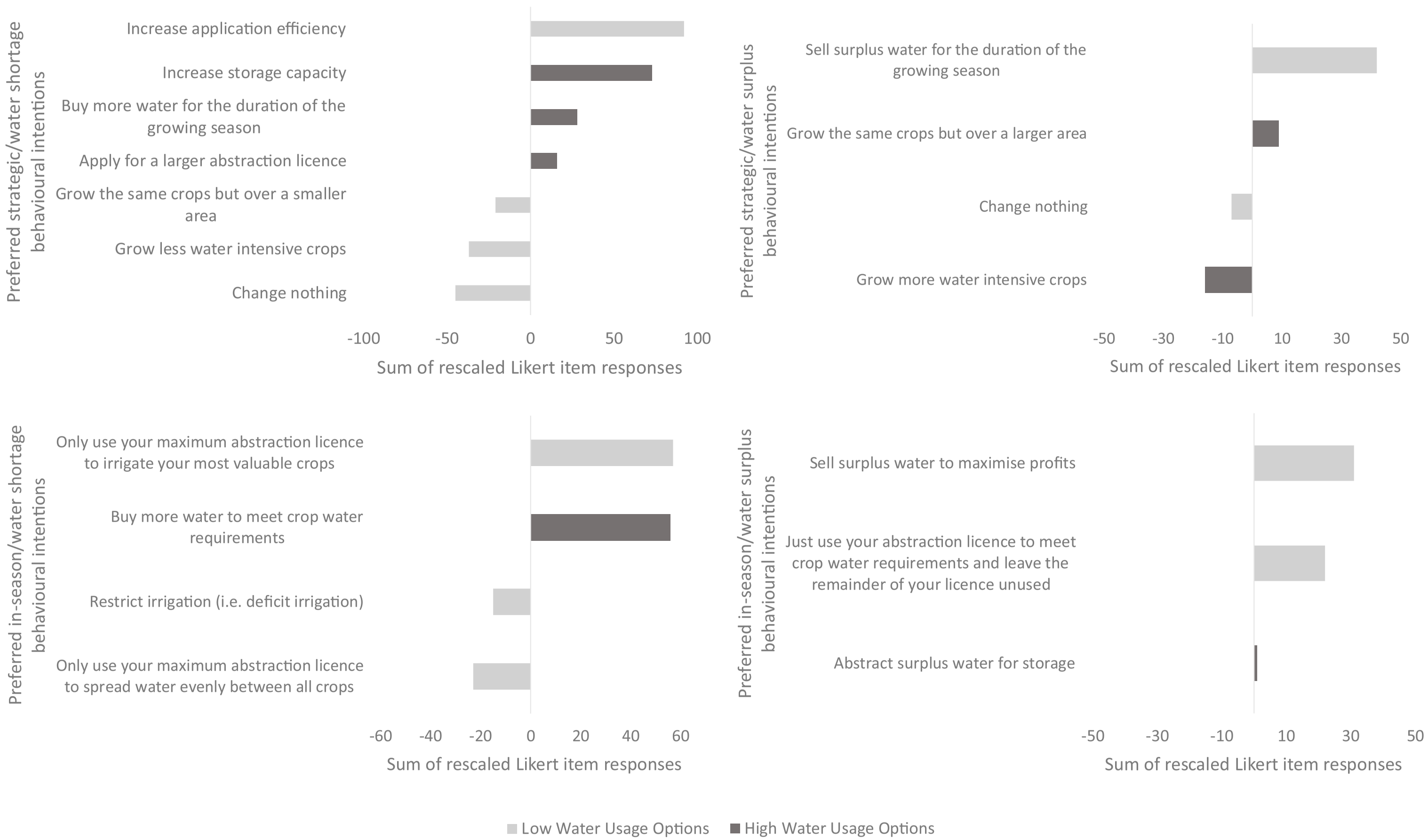

Figure D.5: Bar charts illustrating the preferred behavioural intentions of those who had no preference during strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. (Top left) A bar chart illustrating the preferred strategic (long-term)/water shortage behavioural intentions of those who had no preference. (Top right) A bar chart illustrating the preferred strategic (long-term)/water surplus behavioural intentions of those who had no preference. (Bottom left) A bar chart illustrating the preferred in-season (short-term)/water shortage behavioural intentions of those who had no preference. (Bottom right) A bar chart illustrating the preferred in-season (short-term)/water surplus behavioural intentions of those who had no preference

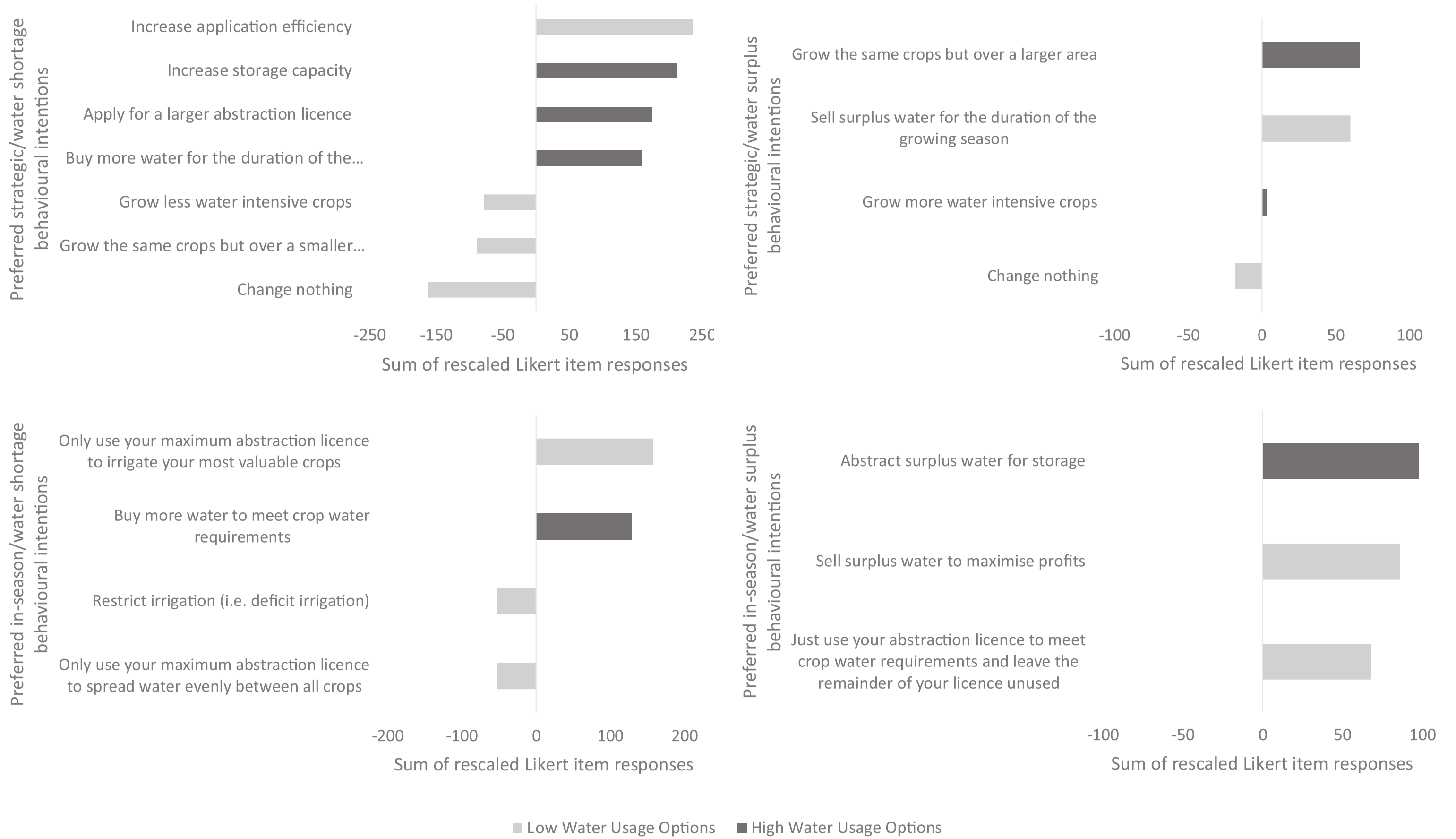

Figure D.6: Bar charts illustrating the preferred behavioural intentions of those who preferred HWUO during strategic (long-term) and in-season (short-term) water shortage and surplus scenarios. (Top left) A bar chart illustrating the preferred strategic (long-term)/water shortage behavioural intentions of those who preferred HWUO. (Top right) A bar chart illustrating the preferred strategic (long-term)/water surplus behavioural intentions of those who preferred HWUO. (Bottom left) A bar chart illustrating the preferred in-season (short-term)/water shortage behavioural intentions of those who preferred HWUO. (Bottom right) A bar chart illustrating the preferred in-season (short-term)/water surplus behavioural intentions of those who preferred HWUO

Appendix E

Model description

E.1 Irrigation Water Need (IWN)

E.1.1 Calculating irrigation water need (IWN)

In addition to soil, air, and sunlight crops need water to grow. Where precipitation is not enough to meet crop water needs alone irrigation is required and in this form is usually referred to as supplemental irrigation. IWN in this study was calculated using the method proposed by Brouwer and Heibloem (1986) as:

$$IWN = ET_c - Pe \tag{E.1}$$

where ET_c equals crop evapotranspiration (i.e. crop water need); and Pe equals effective precipitation (i.e. precipitation which is retained within the root zone).

E.1.2 Calculating crop evapotranspiration (ET_c)

Crop evapotranspiration (ET_c), under optimal conditions, can be affected by: climate (i.e. radiation; air temperature; humidity; and wind speed); crop type (i.e. as different crops, and even varieties of the same crop, have different daily and seasonal crop water demands); and the growth stage of the crop (i.e. as a fully grown crop will require more water than the same crop which has just been planted) (Brouwer and Heibloem, 1986). ET_c in this study was calculated using the method proposed by Allen et al. (1998) as:

$$ET_c = ET_o K_c \tag{E.2}$$

where ET_o equals reference evapotranspiration; and K_c equals a crop coefficient.

E.1.3 Calculating reference evapotranspiration (ET_o)

There are multiple methods for calculating reference evapotranspiration (ET_o) which can broadly be categorised into: water-budget; mass-transfer; combination; radiation; and temperature-based methods (Xu and Singh, 2002). The Food and Agricultural Organisation of the United Nations (FAO) recommend the use of the Penman-Monteith method, a combination-based method, as it has shown to provide relatively accurate results in a variety of locations and climates using a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1}, and an albedo of 0.23 (Allen et al., 1998). However, despite the accuracy of this method the main criticism concerns the large data requirements, which for many areas are not recorded, and include: radiation; air temperature; air humidity; and wind speed data.

As an alternative method, when data is limited, the FAO propose the use of the 1985 Hargreaves method, a temperature-based method, which has shown reasonable results with global validity and only requires minimum and maximum air temperature (Allen et al., 1998). In addition, the 1985 Hargreaves method has commonly been used for providing ET_o predictions for weekly or longer periods for use in irrigation scheduling at the farm and regional level (Hargreaves and Allen, 2003). Eight years of measured lysimeter evapotranspiration of a cool season grass (*Alta fescue*), with a crop height of between 0.08 and 0.15 m, at Davis, California, was used as the reference crop (Hargreaves and Samani, 1985). ET_o in this study was calculated using the method proposed by Hargreaves and Samani (1985) as:

$$ET_o = CR_a(\frac{Tmax + Tmin}{2} + 17.8)(Tmax - Tmin)^E \tag{E.3}$$

where C and E are parameters of the equation with suggested values of 0.0023 and 0.50 respectively although several studies have indicated that local calibration of these parameters is necessary in order to improve precision (Luo et al., 2014); R_a equals extraterrestrial radiation; and $Tmax$ and $Tmin$ equal maximum and minimum temperature (^{0}C) respectively.

E.1.4 Calculating extraterrestrial radiation (R_a)

The solar radiation received at the top of the earth's atmosphere on a horizontal surface is called the extraterrestrial (solar) radiation (R_a). If the sun is directly overhead, the angle of incidence is zero and R_a equals 0.0820 MJ m^{-2} min^{-1}. Therefore, as seasons change the position of the sun and length of day also change thus R_a is a function of latitude, date, and time (Allen et al., 1998). R_a in this study was calculated using the method proposed by Allen et al. (1998) as:

$$R_a = \frac{24(60)}{\pi} G_{sc} d_r (\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)) \tag{E.4}$$

$$d_r = 1 + 0.033 \cos(\frac{2\pi}{365} J) \tag{E.5}$$

$$\omega_s = \arccos(-\tan(j) \tan(d)) \tag{E.6}$$

$$j = \frac{\pi}{180}(degree + \frac{minute}{60}) \tag{E.7}$$

$$d = 0.409 \sin(\frac{2\pi}{365} J - 1.39) \tag{E.8}$$

where G_{sc} equals the solar constant 0.0820 MJ m^{-2} min^{-1}; d_{r} equals the inverse relative distance between the earth and sun (see equation E.5); J equals the day of the year (between 1 and 365 or 366 in a leap year); ω_{s} equals the sunset hour angle (see equation E.6); j equals latitude in radians (see equation E.7); and d equals solar decimation (see equation E.8). Furthermore, to convert R_{a} into equivalent mm day^{-1} it can be multiplied by 0.408 (a conversion factor equal to the inverse of the latent heat of vaporisation).

Therefore, monthly and annual ET_{o} values were calculated for the study area from 1973 to 2012 using: regional average minimum and maximum temperature data obtained from the UK Met Office (MetOffice, 2016); the central point of the study area to determine latitude (i.e. $52^{0}21$' N); and the 15^{th} day of each month to determine day of the year. Furthermore, Figure E.1 (top) illustrates the minimum, average, and maximum ET_{o} values from 1962 to 1996 presented by Hess (1996) for the months April to September at Silsoe College, Bedfordshire (located within the study area) which were used to calibrate the model. Initial results of the uncalibrated model using the suggested values of 0.0023 and 0.50 for parameters C and E, and temperature data for the same period, resulted in an overestimation of ET_{o} values. Therefore the parameters were reduced systematically until ET_{o} values were similar to those presented by Hess (1996) using values 0.0020 and 0.30 for parameters C and E respectively. In addition, Figure E.1 (bottom) illustrates a strong, positive, linear correlation between the average ET_{o} values presented by Hess (1996) and those calibrated for this study for the period 1962 to 1996 (r= .99) which was also statistically significant (p= <.001).

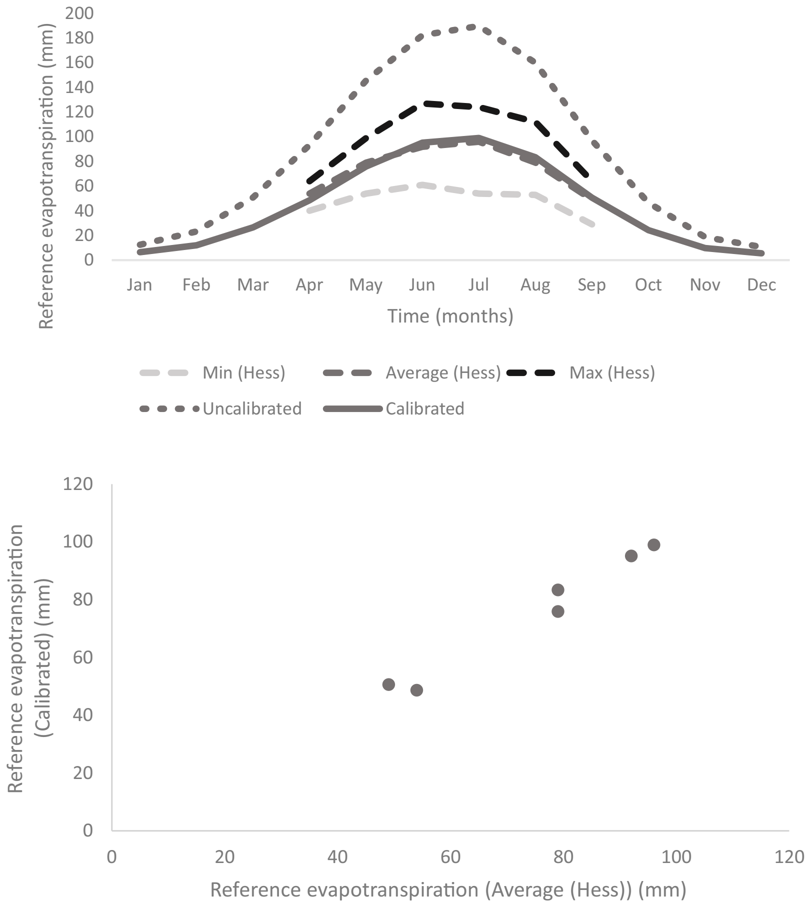

Figure E.1: A line graph and scatter plot indicating the strength of association between monthly reference evapotranspiration calibrated in this study and those presented by Hess (1996) (1962 to 1996). (Top) A line graph indicating calibrated and uncalibrated monthly reference evapotranspiration (ET_o) in relation to those presented by Hess (1996) (1962 to 1996). (Bottom) A scatter plot indicating the strength of association between average ET_o presented by Hess (1996) and calibrated ET_o for this study (1962 to 1996) (Pearson's correlation coefficient $r= .99$, $p= <.001$)

E.1.5 Calculating crop coefficients (K_c)

The relationship between ET_c and ET_o is given by the crop coefficient (K_c). To determine K_c values it is necessary to know: the total growing period for each crop; the various growth stages of each crop; and the K_c values for each crop for each of the growing stages (Brouwer and Heibloem, 1986). Two crops were selected which represented the two most irrigated crop categories in the study area: main crop potatoes (*Solanum tuberosum*) which accounted for 41 % of irrigated crops and vegetables (carrots) (*Daucus carota*) which represented 33 % of irrigated crops. Carrots were selected to represent vegetables similar to the study presented by Knox et al. (1997) which examined IWN at Silsoe College, Bedforshire. The total growing period, in days, for

Table E.1: Input data for deriving crop coefficient (K_c) values

Measure	Main crop potatoes	Vegetables (i.e. carrots)
Planting date	1st Apr.	1st May
Harvest date	15th Sep.	20th Sep.
Total growing days	168	143
- Initial stage	40	31
- Crop development stage	61	76
- Mid-season stage	31	18
- Late-season stage	36	18
K_c values		
- Initial stage	0.45	0.45
- Crop development stage	0.75	0.75
- Mid-season stage	1.10	1.00
- Late-season stage	0.85	1.00

each crop is from planting, or transplanting, to harvest. Once the total growing period is known the total number of days is divided into four growing stages: the initial stage (i.e. from planting, or transplanting until the crop covers approximately 10 to 20 % of the ground); the crop development stage (i.e. from the initial stage until full ground cover); the mid-season stage (i.e. from the crop development stage until the crop reaches maturity); and the late-season stage (i.e. from mid-season until harvest). Although K_c values provided by Brouwer and Heibloem (1986) were used in this study local data regarding: planting and harvest dates; length of crop growth stages and K_c values at full cover (i.e. mid-season stage) were derived from Knox et al. (1997) and are presented in Table E.1.

However, the number of days for each crop growing stage does not always equate to the number of days in each month. Therefore, when this occurred K_c in this study was calculated using the method proposed by Brouwer and Heibloem (1986) as:

$$K_c = (\frac{n^{stage1}}{n^{month}} * {K_c}^{stage1}) + (\frac{n^{stage2}}{n^{month}} * {K_c}^{stage2}) \qquad \text{(E.9)}$$

where n^{month} equals the number of days in a given month; n^{stage1} and n^{stage2} equal the number of growing days in the given month associated with each growing stage; and ${K_c}^{\mathrm{stage1}}$ and ${K_c}^{\mathrm{stage2}}$ equal the corresponding K_c values for relevant growing stages.

E.1.6 Calculating effective precipitation (Pe)

Only precipitation water which is retained within the root zone can be utilised by crops (i.e. commonly referred to as effective precipitation (Pe)) whilst the remainder is lost through: evaporation; deep percolation; or surface run-off. The main factors which determine the amount of precipitation which is retained in the root zone include: climate; soil texture; soil structure; and depth of the root zone. Although more complex methods can be used to calculate Pe the method used in this study was that proposed by Brouwer and Heibloem (1986) as:

$$Pe = 0.8P - 25 \quad \text{if} \quad P > 75 \tag{E.10}$$

$$Pe = 0.6P - 10 \quad \text{if} \quad P < 75 \tag{E.11}$$

where P equals precipitation (mm month^{-1}).

Therefore, monthly and annual IWN were calculated for main crop potatoes and vegetables (i.e. carrots) from 1973 to 2012. Furthermore, 1983 and 1988 were selected as the dry and wet years used as the climate scenarios for this study based on total annual IWN (i.e. combined IWN of the two crops) which was equalled or exceeded 20 % and 80 % of years respectively which is a method commonly adopted for these types of studies (Knox et al., 1997) (see Figure E.2).

Moreover, Table E.2 presents IWN for each crop, and the total, during both the dry and wet years. Interestingly, although total IWN for both crops is greatest during the dry year (i.e. 138 Ml and 119 Ml respectively) compared to the wet year (i.e. 64 Ml and 48 Ml respectively) irrigation is still required for a longer period of time during the wet year for both crops. In particular, main crop potatoes required supplemental irrigation from June to August during the dry year but from April to September, excluding July, during the wet year. Vegetables (i.e. carrots) also required supplemental irrigation from June to August during the dry year but from June to September, excluding July, during the wet year.

In addition, Knox et al. (1997) reported IWN of 235 mm and 164 mm for main crop potatoes and vegetables (i.e. carrots) respectively, during a design dry year based on data obtained between 1973 and 1992, on medium available water capacity soil whilst the method presented in this study calculated IWN of 251 mm and 195 mm, on average, using temperature and precipitation data for the same period. However, the estimates presented by Knox et al. (1997) were based on an irrigation water requirement model using: different climate data; a two layer soil water balance model to estimate soil water storage; and the Penman-Monteith method to calculate ET_{o}. Therefore, the dry and wet years used as the two climate scenarios for this study represent reasonable IWN estimates.

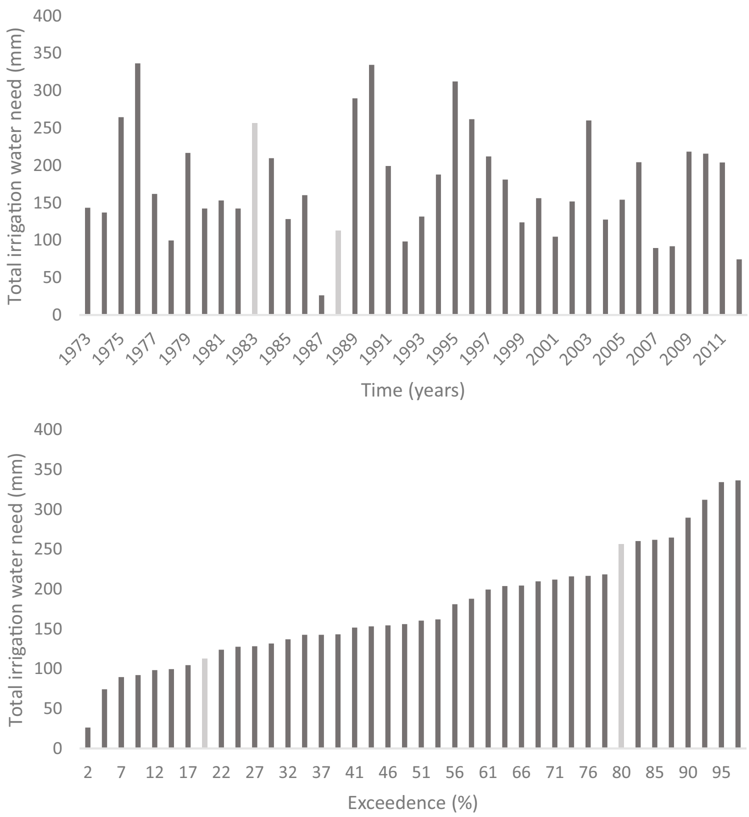

Figure E.2: Bar charts illustrating total annual irrigation water need (IWN) of main crop potatoes and vegetables (i.e. carrots) for the study area from 1973 to 2012 highlighting dry and wet years (i.e. 1983 and 1988 respectively). (Top) A bar chart illustrating total annual irrigation water need (IWN) of main crop potatoes and vegetables (i.e. carrots) for the study area from 1973 to 2012 highlighting dry and wet years (i.e. 1983 and 1988 respectively). (Bottom) A bar chart illustrating the percentage of years which exceeded particular levels of total annual IWN of main crop potatoes and vegetables (i.e. carrots) for the study area, for the period 1973 to 2012, highlighting dry and wet years (i.e. 1983 and 1988 respectively)

Table E.2: Irrigation water needs (IWN) during dry and wet years (i.e. 1983 and 1988 respectively)

Month	Pot_{-dry} (mm)	Veg_{-dry} (mm)	$Total_{-dry}$ (mm)	Pot_{-wet} (mm)	Veg_{-wet} (mm)	$Total_{-wet}$ (mm)
- Jan	0	0	0	0	0	0
- Feb	0	0	0	0	0	0
- Mar	0	0	0	0	0	0
- Apr	0	0	0	3	0	3
- May	0	0	0	9	0	9
- Jun	33	33	66	18	18	37
- Jul	60	43	103	0	0	0
- Aug	45	42	87	28	25	53
- Sep	0	0	0	7	4	11
- Oct	0	0	0	0	0	0
- Nov	0	0	0	0	0	0
- Dec	0	0	0	0	0	0
- Annual	138	119	256	64	48	113

E.2 Input data

Table E.3: Model input data with regards to farm type parameters

Variable	[a]LWUO preferred	No preference	[b]HWUO preferred
Farm type	1	2	3
Number of farmers	192	226	418
Median irrigated area (m^2)	380,000	490,000	760,000
- 75th percentile (m^2)	510,000	1,760,000	1,650,000
- 25th percentile (m^2)	180,000	210,000	350,000
Main crop potato cover (%)	.63	.49	.57
Vegetable cover (%)	.37	.51	.43
Storage availability (%)	.24	.5	.6
Storage only licence (%)	.0	.16	.22
Median storage capacity (m^3)	100,000	68,000	136,000
- 75th percentile (m^3)	114,000	165,000	307,000
- 25th percentile (m^3)	50,000	38,000	61,000
Median annual licence limit (m^3)	17,727	48,595	54,500
- 75th percentile (m^3)	33,773	87,730	100,000
- 25th percentile (m^3)	8,190	19,884	25,846

[a] Low water usage options (LWUO)
[b] High water usage options (HWUO)

Table E.4: Model input data with regards to Assessment Point (AP) names, and low (Q95) and high (Q30) flow conditions (m^3/s)

Assessment Point (AP) name	Low flow condition (Q95) (m^3/s)	High flow condition (Q30) (m^3/s)
C1AP01	0.24	0.89
C1AP02	0.09	0.32
C1AP04	0.25	0.94
C1AP06	0.14	0.54
C1AP07	0.14	0.53
C1AP08	0.35	1.33
C1AP09	0.56	2.11
C1AP10	0.26	0.99
C1AP00	0.16	1.27
C2AP00	0.68	5.43
C3AP02	0.01	0.32
C3AP03	0.25	1.05
C3AP04	0.26	1.31
C3AP07	0.11	0.36
C3AP08	0.02	0.33
C3AP09	0.44	1.47
C3AP11	0.10	0.82
C3AP12	0.09	0.54
C3AP13	0.50	2.31
C3AP17	2.38	19.06
C4AP01	2.90	20.54
C4AP03	2.45	17.37
C4AP05	2.37	14.59
C4AP06	1.09	3.33
C4AP12	0.46	5.53
C4AP14	0.55	2.59

Table E.5: Model input data during a dry year (1983) with regards to Irrigation Water Needs (IWN) of main crop potatoes and vegetables (i.e. carrots) (mm), and river discharge for each Assessment Point (AP) area (m^3/s)

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$IWN_{potatoes}$	0	0	0	0	0	33	60	45	0	0	0	0
$IWN_{vegetables}$	0	0	0	0	0	33	43	42	0	0	0	0
$C1AP01_{discharge}$	1.14	1.25	1.10	1.20	1.36	1.14	0.75	0.52	0.55	0.54	0.48	0.54
$C1AP02_{discharge}$	0.41	0.45	0.39	0.43	0.49	0.41	0.27	0.19	0.20	0.19	0.17	0.19
$C1AP04_{discharge}$	1.21	1.32	1.16	1.27	1.44	1.21	0.79	0.55	0.59	0.57	0.51	0.57
$C1AP06_{discharge}$	0.69	0.75	0.66	0.72	0.82	0.69	0.45	0.31	0.33	0.32	0.29	0.33
$C1AP07_{discharge}$	0.67	0.74	0.65	0.71	0.80	0.68	0.44	0.31	0.33	0.32	0.29	0.32
$C1AP08_{discharge}$	1.69	1.86	1.63	1.78	2.02	1.70	1.11	0.77	0.82	0.80	0.72	0.81
$C1AP09_{discharge}$	2.70	2.96	2.60	2.85	3.22	2.71	1.77	1.24	1.31	1.27	1.14	1.28
$C1AP10_{discharge}$	1.26	1.38	1.22	1.33	1.50	1.27	0.83	0.58	0.61	0.60	0.53	0.60
$C1AP00_{discharge}$	1.86	2.17	1.40	2.40	2.32	1.40	0.55	0.33	0.46	0.49	0.58	0.91
$C2AP00_{discharge}$	7.92	9.27	5.98	10.26	9.91	5.97	2.35	1.39	1.96	2.07	2.49	3.87
$C3AP02_{discharge}$	0.41	0.71	0.36	0.92	0.62	0.40	0.20	0.13	0.10	0.08	0.07	0.09
$C3AP03_{discharge}$	1.52	1.77	1.29	2.23	1.68	1.30	0.81	0.70	0.58	0.58	0.64	0.77
$C3AP04_{discharge}$	1.95	2.22	1.61	3.11	2.38	1.88	0.99	0.64	0.58	0.54	0.62	0.91
$C3AP07_{discharge}$	0.54	0.60	0.49	0.64	0.69	0.58	0.41	0.33	0.30	0.27	0.30	0.34
$C3AP08_{discharge}$	0.60	0.75	0.48	0.93	0.86	0.67	0.36	0.21	0.13	0.11	0.11	0.20
$C3AP09_{discharge}$	1.81	2.43	1.67	2.83	3.48	1.88	1.29	1.04	0.97	0.92	0.96	1.16
$C3AP11_{discharge}$	1.00	1.49	0.80	1.97	1.82	0.80	0.46	0.33	0.32	0.31	0.34	0.45
$C3AP12_{discharge}$	0.72	0.91	0.60	1.14	1.07	0.54	0.36	0.25	0.23	0.24	0.27	0.38
$C3AP13_{discharge}$	3.06	3.56	2.50	3.50	3.13	1.69	0.88	0.52	0.61	0.68	0.91	1.60
$C3AP17_{discharge}$	27.82	32.56	21.01	36.02	34.79	20.95	8.24	4.90	6.87	7.26	8.75	13.60
$C4AP01_{discharge}$	20.89	22.49	15.50	38.69	40.52	18.89	6.82	3.90	5.64	5.18	5.31	13.78
$C4AP03_{discharge}$	17.67	19.03	13.12	32.73	34.27	15.98	5.77	3.30	4.77	4.38	4.49	11.66
$C4AP05_{discharge}$	14.92	15.21	11.91	24.42	27.80	11.49	4.60	2.99	3.72	3.81	4.17	9.66
$C4AP06_{discharge}$	3.96	4.18	3.44	6.52	5.27	4.15	2.10	1.70	1.99	1.90	2.05	2.76
$C4AP12_{discharge}$	7.65	6.59	5.76	11.99	14.38	5.07	1.98	1.12	1.34	1.45	1.60	4.63
$C4AP14_{discharge}$	3.02	2.96	2.48	4.74	4.42	2.17	1.11	0.81	0.90	1.06	1.15	2.41

Table E.6: Model input data during a wet year (1988) with regards to Irrigation Water Needs (IWN) of main crop potatoes and vegetables (i.e. carrots) (mm), and river discharge for each Assessment Point (AP) area (m^3/s)

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$IWN_{potatoes}$	0	0	0	3	9	18	0	28	7	0	0	0
$IWN_{vegetables}$	0	0	0	0	0	18	0	25	4	0	0	0
$C1AP01_{discharge}$	1.73	1.88	1.85	1.49	1.20	0.86	0.77	0.57	0.57	0.55	0.52	0.62
$C1AP02_{discharge}$	0.62	0.67	0.66	0.54	0.43	0.31	0.28	0.21	0.20	0.20	0.19	0.22
$C1AP04_{discharge}$	1.83	1.99	1.95	1.58	1.27	0.91	0.81	0.61	0.60	0.58	0.55	0.66
$C1AP06_{discharge}$	1.04	1.13	1.11	0.90	0.72	0.52	0.46	0.34	0.34	0.33	0.31	0.37
$C1AP07_{discharge}$	1.02	1.11	1.09	0.88	0.71	0.51	0.45	0.34	0.34	0.33	0.31	0.37
$C1AP08_{discharge}$	2.57	2.79	2.74	2.22	1.78	1.28	1.14	0.85	0.85	0.82	0.77	0.92
$C1AP09_{discharge}$	4.09	4.45	4.37	3.54	2.84	2.05	1.82	1.36	1.35	1.31	1.23	1.47
$C1AP10_{discharge}$	1.91	2.08	2.04	1.65	1.33	0.96	0.85	0.63	0.63	0.61	0.58	0.69
$C1AP00_{discharge}$	3.80	2.89	2.79	1.76	1.08	0.78	0.90	0.50	0.56	0.63	0.63	1.06
$C2AP00_{discharge}$	16.20	12.33	11.91	7.52	4.62	3.31	3.83	2.13	2.37	2.71	2.70	4.53
$C3AP02_{discharge}$	0.46	0.47	0.39	0.32	0.25	0.16	0.11	0.09	0.07	0.16	0.27	0.34
$C3AP03_{discharge}$	3.59	2.40	2.30	1.54	1.22	1.01	0.99	0.68	0.64	0.74	0.69	0.78
$C3AP04_{discharge}$	4.64	3.51	2.75	1.90	1.45	1.06	0.89	0.60	0.66	0.65	0.62	0.98
$C3AP07_{discharge}$	0.78	0.66	0.69	0.55	0.45	0.38	0.37	0.27	0.31	0.28	0.28	0.31
$C3AP08_{discharge}$	1.37	0.91	1.05	0.64	0.46	0.33	0.24	0.15	0.10	0.10	0.10	0.17
$C3AP09_{discharge}$	4.50	2.91	3.32	2.33	1.85	1.45	1.39	1.03	0.99	1.10	1.02	1.16
$C3AP11_{discharge}$	3.19	1.83	2.19	1.27	0.88	0.61	0.57	0.37	0.35	0.64	0.44	0.66
$C3AP12_{discharge}$	1.98	1.15	1.51	0.90	0.66	0.46	0.44	0.29	0.26	0.36	0.34	0.42
$C3AP13_{discharge}$	5.48	5.08	5.51	3.40	2.25	1.48	1.69	1.02	1.04	2.11	1.65	2.44
$C3AP17_{discharge}$	56.86	43.30	41.81	26.42	16.21	11.63	13.43	7.49	8.33	9.50	9.48	15.91
$C4AP01_{discharge}$	60.76	42.31	33.21	15.67	11.18	6.33	11.38	4.67	7.30	7.91	6.92	14.73
$C4AP03_{discharge}$	51.40	35.79	28.09	13.26	9.46	5.35	9.63	3.95	6.17	6.69	5.85	12.46
$C4AP05_{discharge}$	42.08	26.26	21.06	9.13	6.69	4.44	7.93	3.53	5.31	5.82	4.72	9.77
$C4AP06_{discharge}$	9.28	6.15	5.61	3.97	3.62	2.60	2.91	1.93	2.28	2.64	2.34	2.76
$C4AP12_{discharge}$	15.92	9.28	6.75	1.84	1.17	0.84	1.88	0.69	0.92	0.91	1.13	2.03
$C4AP14_{discharge}$	7.04	3.88	3.09	1.51	1.33	1.06	1.54	0.77	1.11	1.54	1.21	1.70

E.3 Submodels

Submodels presented below relate to those briefly described in Figure 6.2.

E.3.1 run-monthly-parameters

The first submodel is an observer procedure which sets the global environment state variables including: IWN of main crop potatoes; IWN of vegetables (i.e. carrots); and AP river discharges. However, these variables vary depending on the climate scenario being simulated (i.e. a dry or wet year). Nonetheless, the input data are converted to m^3 per month, and therefore the global environment state variables were set as:

$$IWN_{pot}(m^3) = IWN_{pot}(mm)/1000 \quad \text{(E.12)}$$

$$IWN_{veg}(m^3) = IWN_{veg}(mm)/1000 \quad \text{(E.13)}$$

$$AP_{discharge}(m^3) = AP_{discharge}(m^3/s) * 60 * 60 * 24 * 30 \quad \text{(E.14)}$$

where IWN_{pot} and IWN_{veg} equal IWN of main crop potatoes and vegetables (i.e. carrots) respectively; and $AP_{\text{discahrge}}$ equals the river discharge of an AP area.

E.3.2 calculate-farm-water-requirements

The second submodel is a farmer procedure which sets IWN of main crop potatoes, vegetables (i.e. carrots), and the total IWN of the two combined for each farmer (i.e. farm water requirements). These were calculated as:

$$FarmIWN_{pot}(m^3) = IWN_{pot}(m^3) * (IA(m^2) * CC_{pot}(\%)) \quad \text{(E.15)}$$

$$FarmIWN_{veg}(m^3) = IWN_{veg}(m^3) * (IA(m^2) * CC_{veg}(\%)) \quad \text{(E.16)}$$

$$FarmIWN_{total}(m^3) = FarmIWN_{pot}(m^3) + FarmIWN_{veg}(m^3) \quad \text{(E.17)}$$

where $FarmIWN_{\text{pot}}$ and $FarmIWN_{\text{veg}}$ equal farm IWN of main crop potatoes and vegetables (i.e. carrots) respectively; IA equals irrigated area of the farm; CC_{pot} and CC_{veg} equal the percentage crop cover of main crop potatoes and vegetables respectively; and $FarmIWN_{\text{total}}$ equals the total IWN of the farm.

E.3.3 calculate-ap-water-availability

The third submodel involves both grid and farmer procedures. First, water availability, and low (Q95) and high (Q30) flow conditions converted to m^3, were set for each AP area (i.e. landscape state variables) as:

$$AP_{water-available}(m^3) = AP_{discharge}(m^3) \tag{E.18}$$

$$AP_{low-flow}(m^3) = AP_{low-flow}(m^3/s) * 60 * 60 * 24 * 30 \tag{E.19}$$

$$AP_{high-flow}(m^3) = AP_{high-flow}(m^3/s) * 60 * 60 * 24 * 30 \tag{E.20}$$

where $AP_{\text{water}-\text{available}}$ equals water availability in an AP area; $AP_{\text{low}-\text{flow}}$ and $AP_{\text{high}-\text{flow}}$ equal the low and high flow conditions of an AP area respectively.

Secondly, each farmer then calculates how much water is available in the AP in which they are located. Under the current water allocation system, water availability was set as equation E.18, as no low flow conditions are enforced by the regulatory authority, and therefore all water was available. In reality, some licences have HoF conditions attached to them but as this data was unavailable, HoF were not included in the model. However, under the proposed water allocation systems, low flow conditions are enforced and therefore water availability was set as:

$$AP_{water-available}(m^3) = AP_{water-available}(m^3) - AP_{low-flow}(m^3) \tag{E.21}$$

E.3.4 calculate-farm-water-availability

The fourth submodel is a farmer procedure which calculates farmers' monthly licensed water available, and storage water available (i.e. their two sources of water). However, monthly licensed water available depends on the policy scenario being simulated as seasonal restrictions on licences are only enforced under the current system. Therefore, monthly licensed water available for each licence type was set as:

$$Licence_{direct}(m^3) = Licence_{annual}(m^3)/7 \tag{E.22}$$

$$Licence_{storage}(m^3) = Licence_{annual}(m^3)/5 \tag{E.23}$$

$$Licence_{directandstorage}(m^3) = Licence_{annual}(m^3)/12 \tag{E.24}$$

where $Licence_{\text{direct}}$ equals monthly licensed water available for farmers with direct licences (i.e. 7 months of the year during in-season); $Licence_{\text{annual}}$ equals farmers annual licence limit derived during model initialisation; $Licence_{\text{storage}}$ equals monthly licensed water available for farmers with storage only licences (i.e. 5 months of the year during out-of-season); and $Licence_{\text{directandstorage}}$ equals monthly licensed water available for farmers with direct and storage licences (i.e. 12 months of the year).

Therefore, under the current water allocation system, if water was available within an AP area, farmers' monthly licensed water availability was set depending on their licence type. If water was unavailable in the AP area, then no farmers' would have monthly licensed water available. However, under the basic and enhanced water allocation systems, seasonal restrictions on licences are removed, and therefore, in the model, all licences became direct and storage, as farmers could abstract for 12 months of the year, as long as water was available within the AP area. Furthermore, under the enhanced water allocation system, monthly licensed water availability was based on a share of available water within an AP area. Therefore, during the first month of the year a percentage was calculated for each farmer as:

$$Licence_{share}(\%) = Licence_{directandstorage}(m^3)/AP_{water-available-proposed}(m^3) \tag{E.25}$$

where $Licence_{\text{share}}$*(%)* equals the percentage used in subsequent months to derive monthly licensed water availability. Therefore, in subsequent months, monthly licensed water availability was set as:

$$Licence_{share}(m^3) = Licence_{share}(\%) * AP_{water-available-proposed}(m^3) \tag{E.26}$$

where $Licence_{\text{share}}$ equals monthly water available for farmers under the proposed enhanced water allocation system.

Overall, licensed water available depended on the policy scenario being simulated but was set as one of the above for each farmer and is referred to simply as $\text{Licence}_{\text{available}}$ for the remainder of the submodels. Furthermore, storage water available was set as:

$$Storage_{available}(m^3) = Storage_{annual}(m^3) \tag{E.27}$$

where $Storage_{\text{available}}$ equals farmers' storage water available; and $Storage_{\text{annual}}$ equals farmers storage capacity derived during model initialisation.

E.3.5 calculate-farm-water-abstractions

The fifth submodel is a more complex farmer procedure which calculates farmers' monthly licensed abstractions, and storage water balance (i.e. how much they abstract to refill and how much they abstract to satisfy IWN) (see Figure 6.3). Furthermore, the procedures involved have been discussed in Section 6.2.1 and are not repeated here. Nonetheless, this section provides the main calculations involved. If a farmer had monthly licensed water available, and it was greater than their IWN, then licence abstracted for IWN was set as:

$$Licence_{abstractedforIWN}(m^3) = FarmIWN_{total}(m^3) \tag{E.28}$$

however, if a farmer had monthly licensed water available, and it was less than their IWN, then licence abstracted for IWN was set as:

$$Licence_{abstractedforIWN}(m^3) = Licence_{available}(m^3) \tag{E.29}$$

where $Licence_{\text{abstractedforIWN}}$ equals the volume of monthly licensed water available abstracted to satisfy IWN.

After licensed water available has been abstracted for farm IWN, farmers calculate whether they have surplus water available for storage. This is set as:

$$Licence_{availableforstorage}(m^3) = Licence_{available}(m^3) - Licence_{abstractedforIWN}(m^3) \tag{E.30}$$

where $Licence_{\text{availableforstorage}}$ equals the remainder of the monthly licensed volume available which was not used to satisfy IWN. Farmers also calculate whether they require to use their storage to satisfy farm IWN, if their monthly licensed volume available was not enough. If a farmer has storage water available, and it was greater than the shortage required to satisfy farm IWN, then:

$$Storage_{abstractedforIWN}(m^3) = FarmIWN_{total}(m^3) - Licence_{abstractedforIWN}(m^3) \tag{E.31}$$

however, if a farmer has storage water available, and it was less than the shortage required to satisfy farm IWN, then:

$$Storage_{abstractedforIWN}(m^3) = Storage_{available}(m^3) \tag{E.32}$$

where $Storage_{\text{abstractedforIWN}}$ equals the volume of storage water available abstracted to satisfy IWN.

Farmers then record how much of their storage water they have remaining, and the how much they require to replenish to full capacity. These are set as:

$$Storage_{limitnextmonth}(m^3) = Storage_{limitnextmonth}(m^3) - Storage_{abstractedforIWN}(m^3) \tag{E.33}$$

and;

$$Storage_{deficitnextmonth}(m^3) = Storage_{annual}(m^3) - Storage_{limitnextmonth}(m^3) \tag{E.34}$$

where $Storage_{\text{limitnextmonth}}$ equals how much storage water a farmer has remaining; and $Storage_{\text{deficitnextmonth}}$ equals how much water a farmer requires to replenish their farm storage reservoir. Therefore, if a storage water deficit exists, and licence available for storage was less than the deficit, then:

$$Licence_{abstractedforstorage}(m^3) = Licence_{availableforstorage}(m^3) \tag{E.35}$$

or where licence available for storage was greater than the deficit, then:

$$Licence_{abstractedforstorage}(m^3) = Storage_{deficitnextmonth}(m^3) \tag{E.36}$$

where $Licence_{\text{abstractedforstorage}}$ equals the volume of monthly licensed water available which was abstracted to replenish a farm storage reservoir. In addition, if licensed water is abstracted for storage then the storage limit next month is updated accordingly:

$$Storage_{limitnextmonth}(m^3) = Storage_{limitnextmonth}(m^3) + Licence_{abstractedforstorage}(m^3) \tag{E.37}$$

Furthermore, farmers' also record how much of their annual and monthly licensed water they have available for the following month. These are set as:

$$\begin{aligned} Licence_{annuallimitnextmonth}(m^3) = Licence_{annuallimitnextmonth}(m^3) - \\ Licence_{abstractedforIWN}(m^3) - Licence_{abstractedforstorage}(m^3) \end{aligned} \tag{E.38}$$

and if licence annual limit next month is greater than their licence monthly limit next month, then:

$$Licence_{monthlylimitnextmonth}(m^3) = Licence_{annuallimitnextmonth}(m^3) \tag{E.39}$$

however, if it less, then:

$$Licence_{monthlylimitnextmonth}(m^3) = Licence_{monthlylimitnextmonth}(m^3) \tag{E.40}$$

where $Licence_{\text{annuallimitnextmonth}}$ equals annual licensed volume remaining which was set to annual licence limit during model initialisation; and $Licence_{\text{annuallimitnextmonth}}$ equals the monthly licensed volume remaining depending on the volume of their annual licence remaining. Lastly, farmers calculate the total volume of licensed water they abstracted:

$$Licence_{abstractedtotal}(m^3) = Licence_{abstractedforIWN}(m^3) + Licence_{abstractedforstorage}(m^3) \tag{E.41}$$

E.3.6 perform-preferred-behavioural-strategies

This final submodel is another farmer procedure where farmers' perform, if required, their in-season (short-term) water shortage and surplus behaviours as discussed in Section 6.2.1. These are dependent on farm type and whether behaviours are triggered in the model. However, first, farmers calculate how much water they have in total to satisfy their farm IWN:

$$FarmIWN_{totalavailable}(m^3) = Licence_{abstractedforIWN}(m^3) + Storage_{abstractedforIWN}(m^3) \tag{E.42}$$

where $FarmIWN_{\text{totalavailable}}$ equals the total water that the farmer has at their disposal. This is then divided equally between the two crops, if they require it:

$$PotIWN_{totalavailable}(m^3) = (100/FarmIWN_{total}(m^3)) * FarmIWN_{pot}(m^3) \tag{E.43}$$

$$PotIWN_{available}(m^3) = (PotIWN_{totalavailable}(m^3)/100) * FarmIWN_{totalavailable}(m^3) \tag{E.44}$$

$$VegIWN_{totalavailable}(m^3) = (100/FarmIWN_{total}(m^3)) * FarmIWN_{veg}(m^3) \tag{E.45}$$

$$VegIWN_{available}(m^3) = (VegIWN_{totalavailable}(m^3)/100) * FarmIWN_{totalavailable}(m^3) \tag{E.46}$$

where $PotIWN_{\text{totalavailable}}$ and $VegIWN_{\text{totalavailable}}$ are temporary variables which equal the volume of farm IWN available which is required by each crop; $PotIWN_{\text{available}}$ and $VegIWN_{\text{available}}$ equal the actual volume of water which is available for each crop.

Farmers then determine whether they have a shortage or surplus of water. If the total volume of water a farmer has at their disposal is less than their farm IWN, then they have a shortage:

$$Shortage(m^3) = FarmIWN_{total}(m^3) - FarmIWN_{totalavailable}(m^3) \tag{E.47}$$

If, however, the total volume of licensed water abstracted was less than their total licensed water available, then they have a surplus:

$$Surplus(m^3) = Licence_{available}(m^3) - Licence_{abstractedtotal}(m^3) \tag{E.48}$$

As all farmers preferred to only use their maximum abstraction licence to irrigate their most valuable crops, then they all perform the same strategy. In this model, their most valuable crop was considered the crop which covered the largest percentage of their irrigated area. Therefore, if a shortage existed, and main crop potatoes were the predominant crop, and their IWN was greater than the farm IWN available, then:

$$PotIWN_{applied}(m^3) = FarmIWN_{totalavailable}(m^3 \tag{E.49}$$

and;

$$VegIWN_{applied}(m^3) = 0 \tag{E.50}$$

where $PotIWN_{\text{applied}}$ equals the total volume of water available to satisfy IWN of main crop potatoes; and $VegIWN_{\text{applied}}$ equals the total volume of water available to satisfy IWN of vegetables (i.e. carrots). However, if main crop potatoes IWN was less than the farm IWN available, then:

$$PotIWN_{applied}(m^3) = FarmIWN_{pot}(m^3) \tag{E.51}$$

and;

$$VegIWN_{applied}(m^3) = FarmIWN_{totalavailable}(m^3 - PotIWN_{applied}(m^3) \tag{E.52}$$

Conversely, when vegetables (i.e. carrots) were the predominant crop, the same calculations were performed, and not repeated here, except the role of main crop potatoes and vegetables (i.e. carrots) were switched. Furthermore, if a water shortage did not occur then farmers divided their total water available equally between the two crops based on the percentage of their crop cover as previously discussed.

If a water surplus existed, then those who preferred LWUO preferred to just use their abstraction licence to meet crop water requirements and leave the remainder of their licence unused. Those who had no preference preferred to sell surplus water to maximise profits. Whilst those who preferred HWUO preferred to abstract surplus water for storage. However, as the latter strategy was performed automatically by all farm types, if farmers had storage available, those who preferred HWUO reverted to their second preference, to sell surplus water to maximise profits. Therefore, although nothing was to be reported for those who preferred LWUO, the quantity of water available for sale was recorded for those who had no preference and those who preferred HWUO:

$$Surplus_{availableforsale}(m^3) = Surplus(m^3) \tag{E.53}$$

E.4 Results

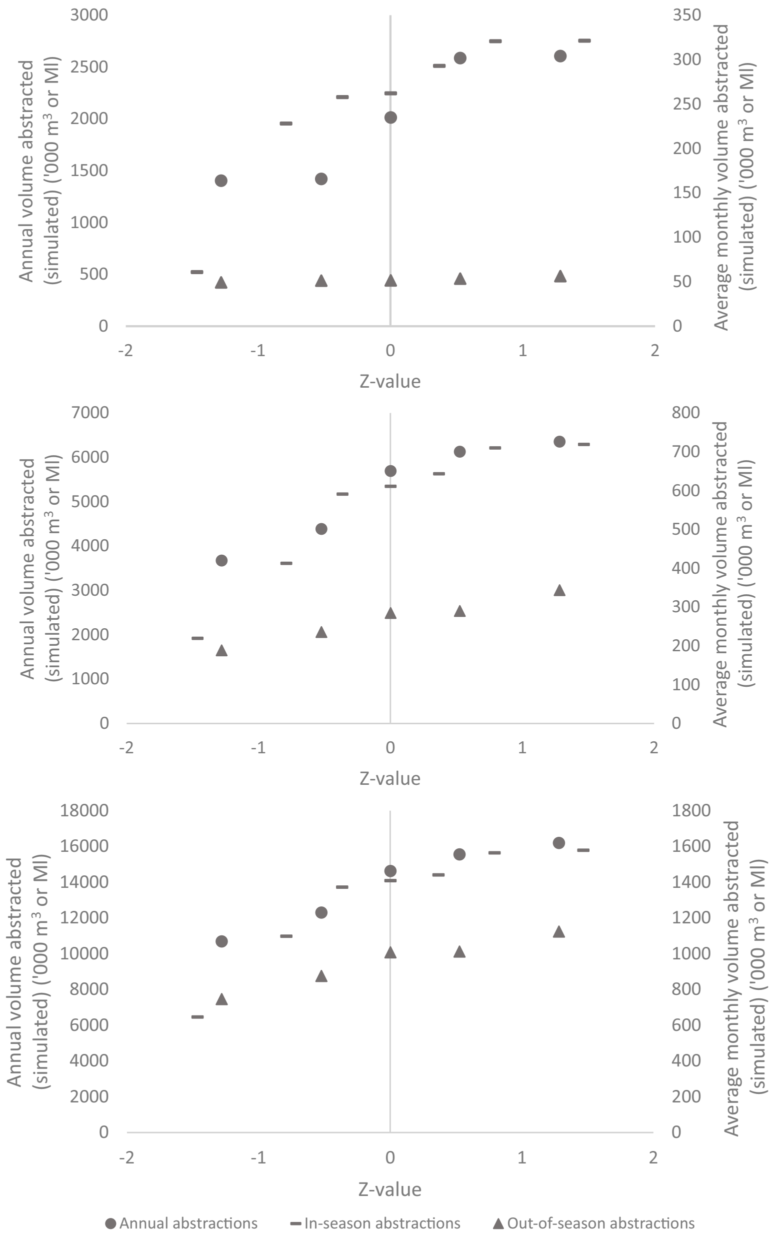

Figure E.3: Normal probability plots illustrating distribution with regards to annual, in-season, and out-of-season abstractions for each simulated farm type. (Top) A normal probability plot illustrating that annual, and out-of-season, abstractions were normally distributed, whilst in-season abstractions were not for those who preferred LWUO. This supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for both annual and out-of-season abstractions, whilst $p = <.05$ for in-season abstractions. (Middle) A normal probability plot illustrating that all of the variables were normally distributed for those who had no preference. This supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for all of variables. (Bottom) A normal probability plot illustrating that all of the variables were normally distributed for those who preferred HWUO. This supports the results of the Shapiro-Wilk tests of normality as $p = >.05$ for all of variables

Table E.7: System level patterns of abstraction behaviour based on the preferred behavioural intentions of each farm type under current (CS), basic (BS), and enhanced (ES) water allocation systems during the dry year (1983) and wet year (1988) climate scenarios

Scenario	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Licence volume abstracted (Ml)													
- CS-Dry	1,925	1,622	1,242	789	677	3,441	3,531	3,512	1,244	1,197	1,838	1,746	22,765
- CS-Wet	1,929	1,632	1,244	1,198	1,936	3,118	923	3,345	2,204	902	1,490	1,264	21,185
- BS-Dry	1,543	1,454	1,157	978	840	2,858	2,862	2,862	1,529	1,473	1,389	1,285	20,231
- BS-Wet	1,560	1,471	1,171	1,408	2,004	2,744	1,146	2,845	2,252	1,120	985	900	19,605
- ES-Dry	1,537	1,663	884	1,377	1,068	2,301	852	421	315	319	381	704	11,821
- ES-Wet	1,540	1,117	901	818	768	540	323	294	339	226	208	364	7,438
Surplus water available (Ml)													
- CS-Dry	40	342	722	2,756	2,869	104	14	34	2,301	2,348	126	219	11,876
- CS-Wet	36	334	721	2,346	1,608	426	2,621	199	1,341	2,642	476	702	13,453
- BS-Dry	1,319	1,408	1,705	1,884	2,022	4	0	0	1,333	1,389	1,473	1,577	14,114
- BS-Wet	1,317	1,406	1,706	1,468	873	133	1,731	31	625	1,757	1,892	1,977	14,917
- ES-Dry	1,331	1,701	1,335	2,770	2,949	2	0	0	272	276	330	609	11,576
- ES-Wet	1,336	1,050	1,172	465	67	0	285	0	0	198	182	320	5,074
Shortage water required (Ml)													
- CS-Dry	0	0	0	0	0	5,471	12,771	15,572	0	0	0	0	30,814
- CS-Wet	0	0	0	0	163	2,288	0	4,356	425	0	0	0	7,232
- BS-Dry	0	0	0	0	0	6,357	13,543	13,297	0	0	0	0	33,196
- BS-Wet	0	0	0	7	334	2,962	0	5,125	615	0	0	0	9,044
- ES-Dry	0	0	0	0	0	6,620	14,765	15,032	0	0	0	0	36,417
- ES-Wet	0	0	0	68	797	3,988	0	6,692	1,534	0	0	0	13,078
Farm irrigation water need satisfied (%)													
- CS-Dry	-	-	-	-	-	66	50	41	-	-	-	-	52
- CS-Wet	-	-	-	100	93	74	-	66	85	-	-	-	84
- BS-Dry	-	-	-	-	-	61	47	37	-	-	-	-	48
- BS-Wet	-	-	-	99	86	67	-	61	79	-	-	-	78
- ES-Dry	-	-	-	-	-	59	42	29	-	-	-	-	44
- ES-Wet	-	-	-	91	67	56	-	49	47	-	-	-	62

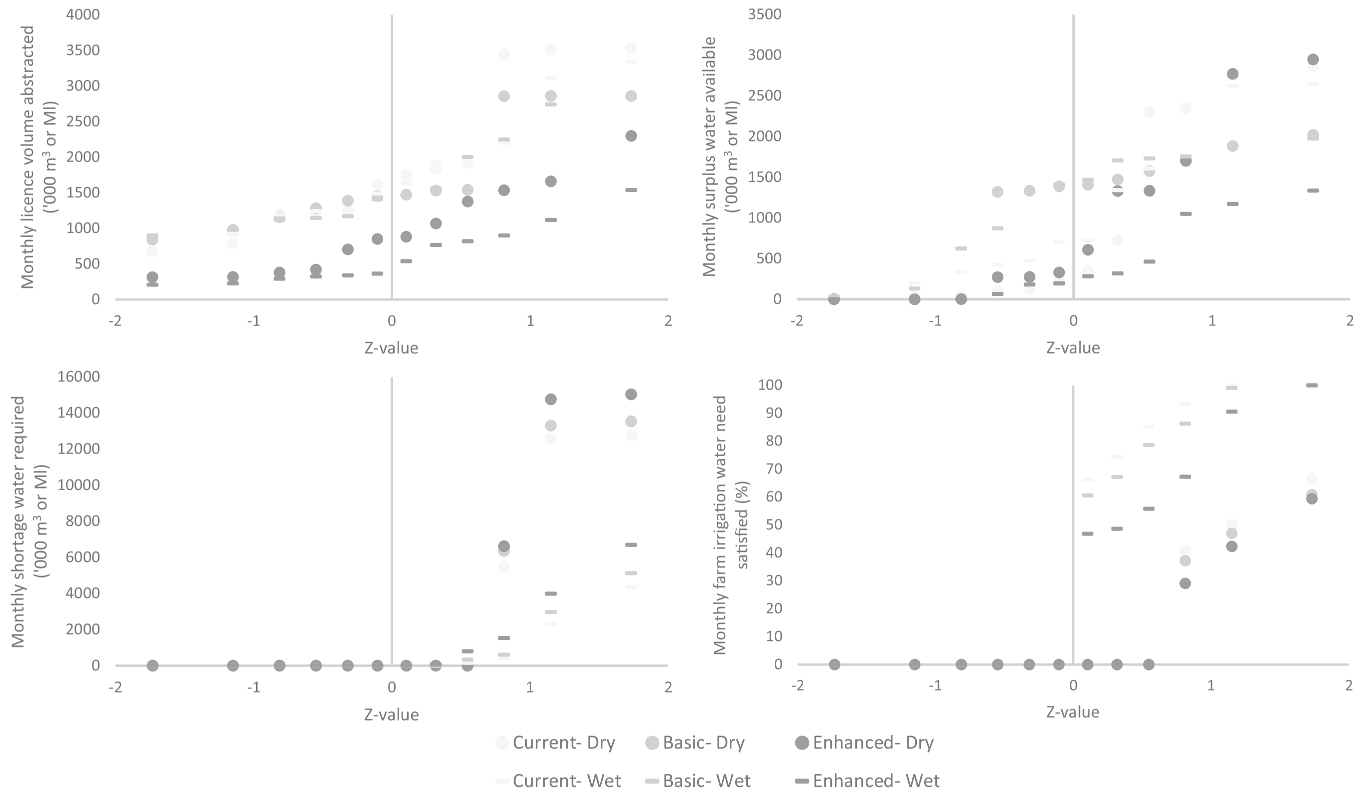

Figure E.4: Normal probability plots illustrating distribution with regards to monthly licence volume abstracted, surplus water available, shortage water required, and farm irrigation water need satisfied under each policy scenario for both dry and wet year climate scenarios. (Top left) A normal probability plot illustrating that licence volume abstracted was not normally distributed under any of the policy or climate scenarios. This supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ under the current and proposed basic water allocation systems during the dry year climate scenario, whilst $p = >.05$, but only marginally, under the remaining policy and climate scenarios. (Top right) A normal probability plot illustrating that surplus water available was not normally distributed under any of the policy or climate scenarios. This supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ under all policy scenarios during the dry year climate scenario and under the proposed enhanced water allocation system during the wet year climate scenario, whilst $p = >.05$, but only marginally, under the remaining policy scenarios. (Bottom left) A normal probability plot illustrating that shortage water required was not normally distributed under any of the policy or climate scenarios. This supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for all policy and climate scenarios. (Bottom right) A normal probability plot illustrating that farm irrigation water need satisfied was not normally distributed under any of the policy or climate scenarios. This supports the results of the Shapiro-Wilk tests of normality as $p = <.05$ for all policy and climate scenarios