MARKET MECHANISMS AND EFFICIENT ALLOCATION OF WATER: MODELLING WATER PRICES, OPTION CONTRACTS ON WATER AND ENHANCING FRAMEWORKS

A Dissertation

by

QUINN PATRICK MCCOLLY

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This dissertation meets the standards for scope and quality of
Texas A&M University-Corpus Christi and is hereby approved.

David Yoskowitz, PhD
Chair

Paul Montagna, PhD
Committee Member

Philippe Tissot, PhD
Committee Member

Robert Mace, PhD
Committee Member

David Blanke, PhD
Graduate Faculty Representative

May 2020

ABSTRACT

Issues associated with water scarcity are widespread and growing, making efficient allocation of this precious resource vital. In the face of these growing challenges, the creation of effective tools to enhance our ability to allocate water efficiently will help mitigate the impacts of water shortages and aid in the planning process. This dissertation endeavors to help develop tools for this purpose by harnessing the allocative power of market mechanisms and encourage strong supporting frameworks that aid the implementation of these mechanisms.

Water is critically important for many reasons, chiefly it supports all life on the planet. To examine the possibility of treating water like a commodity, its value needs to be understood in terms that are less abstract, and the common valuation for commodities is price. Therefore, understanding what the monetary value of water is can help inform market participants and architects as to how a market could be priced. Chapter 1 formulates a price for water in the U.S. by examining Australian water market data, applying machine learning to that data to model price, then applying that model in the U.S. to generate a price for water.

Water scarcity is a global issue, and Chapter 2 helps regions where cash water markets are already established by formulating a method to price options on water. Options are a financial tool whose value is based on an underlying asset (in this case water); so, to have a traditional options market it is helpful to have a robust cash market. Australia has a longstanding and active water market, but to date there has not been widespread implementation of options. Part of the problem is that the water market is highly volatile, making it difficult to price options using traditional valuation methods. Chapter 2 explores ways that the model from Chapter 1 can be tuned and combined with volatility calculations to help solve this challenge. By offering a

method to price short-term options where robust cash markets exist, this chapter helps the global community and can offer a road map to future options trading in the U.S.

In addition to short-term options, the development of longer-term options can be beneficial to market participants in the U.S. in general, and Texas in particular. Chapter 3 examines how options are traditionally structured, then modifies those elements so that they may be applied to water options spanning timeframes considerably longer than standard option contracts. Typically, option contracts last 3 months, and these options are designed to cover a span of 5 to 10 years. Initially the motivation for this work was to create a tool that would enable interested parties to deliver environmental flows of water downstream in times of need, but the application of the tool can be more broadly applied and used by any party interested in securing the opportunity to pay for—and take delivery—of water at a later date.

There is another aspect to water markets that needs to be considered when attempting to scale up market operations; existing regulations and frameworks need to be evaluated to understand how well they support highly functioning markets. Chapter 4 looks at current regulations and frameworks in Texas to establish how well they support water markets and notes places where improvements can be made. Some of the suggestions are fairly simple and some of the suggestions are more complex, but the hope is that by looking at what is—and is not—working this chapter will help to move policy makers and potential market participants along a trajectory that can help markets flourish.

DEDICATION

For Grandpa Joe and Abilyn Quinn, the past and the future.

They would have made great pals.

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The graduate school experience is transformative, and the university is not only molding highly trained theoreticians and practitioners but is shaping people to be better citizens. From beginning to end, this endeavor has offered opportunities for growth, and I am not the same person I was when I began. Just as it would not be possible to undertake and complete a project of this size without a high level of support, this metamorphosis was made possible by many people. I would like to extend my deepest appreciation to the following people and institutions that have helped make this journey possible.

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While working in Australia, the Australian government was incredibly helpful, particularly Edwina Carter at the Murray-Darling Basin Authority and the staff members at the Commonwealth Environmental Water Holder's office.

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CHAPTER I:

INTRODUCTION

Purpose and Research Objectives

The purpose of this work is to formulate a defensible price of water, expand the toolkit for efficient allocation of water among a diverse group of buyers and sellers, and evaluate how well current frameworks in Texas are positioned to support the growth of water markets. This dissertation has the following research objectives:

- Determine if a machine learning approach can successfully model the price of Australian water and if that model can be transferred to the U.S. to provide water prices.
- Utilizing the Australian data, determine if the Black-Scholes Merton model (BSM) of options valuation can successfully be used to price Australian water options.
- Establish a method to price long-term water options in Texas.
- Evaluate how well current frameworks in Texas are positioned to support the growth of water markets and made suggestions for possible improvement.

These research questions test the overarching hypothesis: market-based allocation strategies can be successfully expanded to increase their application and improve the efficiency of freshwater distribution. The scholarly merit is multi–faceted, and each chapter of this dissertation will contribute to the development and exploration of solutions for issues surrounding effective and efficient water allocation. Many modelling techniques require large amounts of data, and Australia has the requisite amount of data to develop and evaluate these models. There is a large body of work regarding predictive modelling and water, yet the use of these predictions has not been fully realized in their application to modelling current, and forecasting future, water prices in the Australian marketplace (Michelsen & Young, 1993; O'Donnell & Colby, 2009; Pease & Snyder, 2017; Villinski, 2003). Artificial

Intelligence/Machine Learning (AI/ML) is data intensive, and Australia has a robust cash market for water and so has the requisite amount of data to explore this space. To understand the price of water in Texas, the model built and validated in Australia is transferred to Texas to output a price of water based on local inputs.

Likewise, these predictive tools are useful to inform discussions involving environmental flows of water (Clark et al., 2014; Deo et al., 2017; Murgulet et al., 2017; Shin et al., 2016; Wieland et al., 2010). This work begins to bridge the gap between prediction and action by linking a predictive model to two possible water delivery systems. The first of these is an "on-hand" system, a cash market that can be accessed in times of need. The second delivery system is "on-command," whereby an options market for water is designed that can allow users to buy the option to take delivery of an amount of water, by a stated future date, at a specific price.

In short, this work creates a water price model that informs the discussion of the price of water in Texas, addresses the main problem with pricing short-term water options in Australia, formulates a method to price long-term options in Texas, and evaluates existing frameworks' capacity to support water markets in Texas.

Dissertation Organization and Study Approach

There are four research chapters of this dissertation. Chapter 2 uses AI/ML techniques to model the price of water in Australia using a set of inputs that are also available in the United States. Once the model has been constructed and tested in Australia, it is transferred to the U.S. to aid in pricing water. Chapter 3 also uses ML but predicts Australian water prices 90-days in the future and combines these predictions with volatility calculations for use as inputs in the BSM pricing model for options on Australian water. Chapter 4 takes the experiences from Chapters 2 and 3 and uses them to help build a pricing model for options on water in Texas using the essential elements of a traditional option. Chapter 5 aggregates the lessons learned from the study of successful overseas markets and existing institutions/regulations in Texas to make suggestions regarding improvements to help cash water markets and their derivatives grow.

Water is a scarce resource and human activities are putting increasing pressure on water supplies (Olmstead, 2010). In addition to human uses for water, there are environmental needs for water, too (Montagna et al., 2018; Mott Lacroix et al., 2016; Wheeler et al., 2014). Given growing human demands for water, challenges will continue to face water planners trying to secure water for human and environmental needs. To increase the allocative efficiency of water strategies and policies, an exploration of market-based solutions is warranted.

Efforts to increase the efficient use of water should include the reduction of its waste, yet simply encouraging conservation may not be enough. James Wolfensohn, as World Bank President, noted, "The biggest problem with water is the waste of water through lack of charging" (MacDonald & Tamnhe, 2018). If the water itself is going to be charged for, it must have a monetary value (price) attached to it. To help inform Australian and U.S. market participants this dissertation uses the chapters as building blocks to expand the application of pricing models for water, then expand the types of products that can be traded to distribute water while making suggestions as to how existing frameworks and policies might be improved domestically and abroad.

Chapter II: Pricing Water: Australian Model, U.S. Application

The goal of Chapter 2 is to use AI/ML to model water prices in Australia using inputs that are available in the U.S. After model construction and validation using the long running Australian data, the model is transferred to the U.S. and applied. In the U.S., the model is applied to a watershed (Guadalupe River Basin, Texas) and predicts prices for water given the input values of that region. This work can help potential market participants understand the price of water when it is predicated based on the value of what it can produce as determined by commodity prices, combined with a bio-physical driver (precipitation).

A random forest model is constructed using a combination of market-based variables and bio-physical variables as inputs to produce the price of water as an output. Input variables are selected based on availability and their relationship with water, such as soybeans, cotton, and cattle. In addition, precipitation data is included in the model to capture the interaction between the price of water and its natural supply. This chapter produces a reliable model for Australian water prices, then transfers that model to predict water prices in the Guadalupe River Basin (GRB) Texas, U.S. While limited, the GRB offers options style water contract price information used for initial model validation.

Chapter III: Pricing Options Contracts on Australian Water

Chapter 3 builds on the modelling work in Chapter 2 by using the random forest model to predict Australian water prices 90-days into the future. The primary reason that BSM has not been used to price Australian water markets is that reported prices are extremely volatile (Cui & Schreider, 2009; Williamson et al., 2008). Using the same pricing data as for the Chapter 2 model, volatility is calculated in multiple ways. Combining the modeled future price with the calculated volatility enables BSM to generate options premiums for Australian contracts. This work will help inform architects of an options market in Australia, which in turn will help market participants expand their trading strategies and hedge their risks.

The main goal of Chapter 3 is to revisit previous attempts to price options in Australia by introducing the predictive elements the random forest model offers and an alternative method to calculate volatility. While many efforts have been made to price options in Australia, those efforts have not resulted in a formal marketplace (Cui & Schreider, 2009; Heaney & Hafi, 2005; Page & Hafi, 2007; Williamson et al., 2008). This chapter offers a new approach that may be operationalized in the Australian marketplace or used in conjunction with other experimental methods to successfully bring options to the Australian marketplace.

Chapter IV: Long-Term Options in Texas

Taking the information from the pricing model in Chapter 2 and the lessons from experimenting with option pricing in Chapter 3, this chapter works on pricing long-term options in Texas. Texas is vast, so to narrow the scope of this effort, option contracts are evaluated for use in the GRB. This basin was chosen in part due to the availability of some contract pricing information. The U.S. does not currently have enough supporting data to price water options with traditional methods, so the essential elements of an option will be retained and used with a new pricing method. Structuring an option contract in this location has four main parts: how often the contract would be able to be called (exercised), how much the water is worth, how much the option contract should cost the buyer, and the lifespan of the contract.

To understand how often an option should be callable, this chapter relies on the existing body of work that resulted from Senate Bill 3 (SB3) from the 80th Texas Legislature. SB3 mandated the establishment of a process to find recommended environmental flows of water to coastal environments (Texas Water Development Board, 2019). As part of that process determinations were made that described low/average/high flow years in probabilistic terms which are used here to structure option call frequency. After finding the frequency which an option should be callable, attention is given to price. A pricing approach is rendered using a modified version of the alternative approach by Michelson (Michelsen & Young, 1993). Instead of valuing the water based on the cost of the next available option, the water can be valued in terms of the opportunity cost the seller incurs when an option contract is called.

Chapter V: Evaluating Institutions and Frameworks that Support Efficient Allocation of Water in Texas

For the development of improved water allocation strategies, current frameworks in Texas are examined to establish functionality. This chapter examines existing rules and regulations surrounding water policy and trading, makes comments about possible improvements to the regulations, and highlights existing rules that may allow water options to come to market under current governance.

In Texas, there are some institutions that can (and do) house water banking, trading, and gifting. The Texas Water Bank and the Water Trust could be starting points from which to form an expansive, fruitful framework for efficient allocation of water across the state based on water trade. The Edwards Aquifer Authority and the San Antonio Water System are engaging in banking and a "triggered" type of forbearance—so novel strategies are being developed and employed in the state. There are some water markets in Texas (such as in the Rio Grande Valley) and the development of trade under the Watermaster system may illustrate opportunities for expansion. The fact that water markets have been discussed for decades begs the question: why have robust water markets not developed over the course of this long conversation?

The main goal of this chapter is to offer suggestions centered around changing the existing rules and regulations, as well as discussing what can be done in the existing regime, to better facilitate the use and growth of water markets in Texas.

Conclusion

Water scarcity is expected to continue to be a challenge, both for human needs and environmental needs. This dissertation aims to advance the development of robust water markets by moving the discussion of water markets along the trajectory from theory to practice in the U.S, adding to the water trading product mix in Australia, and suggesting enhancements to frameworks supporting water trading in Texas.

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CHAPTER II:

MODELLING U.S. WATER PRICES

Introduction

Water is a scarce resource, and human activities are putting increasing pressure on water supplies (Olmstead, 2010). In addition to human uses for water, there are environmental needs for water also (Mott Lacroix et al., 2016; Wheeler et al., 2014). Given growing demands for human uses of water, it will become more challenging to plan for water security, for both human uses (agricultural, municipal, industrial) and environmental needs. Environmental needs translate to environmental health which directly affects human wellbeing. To increase the allocative efficiency of water strategies and policies, the exploration and development of market-based solutions in the U.S. is warranted.

In the mid-2010s, South Africa was struggling to meet its water needs during its worst drought in 30 years and had a date ("Day Zero") set for August of 2018 when some municipal taps would run dry (Stoddard, 2018). Rains came and broke the drought, but the event depicts a stark picture of what water scarcity can look like. To push back "Day Zero" farmers had willingly agreed to divert irrigation water to the city to augment supplies (Alexander, 2019). This illustrates the difficult decisions faced during a water crisis, and while sacrificing food production for urban water supplies may be a short-term strategy it can have significant long-term implications. Furthermore, with forward thinking planning, contingencies can be in place to mitigate some of the effects of drought which would help prevent resorting to ad hoc remedies mid-crisis.

When Australia's longest river, the River Murray in the Southern Murray Darling Basin (SMDB), experienced record low flows in the early 2000's the government took a different approach to remedy the problem. To help water flow to its highest and best economic use, the

Australia government began buying back water in 2004 and then implemented a market system finalized by the passage of the 2007 Water Act (Wheeler et al., 2014). Since its inception, the Australian water market has grown significantly and is administered under the Murray-Darling Basin Authority (MDBA). In the SMDB over 2016-17, 301 gigalitres (GL, around 244,000 acre-feet) of water were traded on the entitlement market. Over the same period, 4200 GL (3.4 million acre-feet) were traded on the allocation market on about 17,000 trades (AITHER, 2017). It is important to note that the term “entitlement” is roughly equivalent to a permanent “water right” in the U.S., and “allocation” refers to the annual allotment of water.

Water plays a fundamental role in Earth systems and human existence, and there is no substitute (Vörösmarty et al., 2015). In addition to human uses for water, there are environmental needs and high levels of extraction from rivers has resulted in unhealthy and stressed rivers and their attendant ecosystems (Mott Lacroix et al., 2016; Wheeler et al., 2014). Increases in human diversion from rivers and streams, combined with impoundment via dams, has put increasing pressure on bays and estuaries (Meijer & Van Beek, 2011; Montagna, Hill, & Moulton, 2009; Montagna et al., 2018). Given the challenges surrounding water scarcity and the increasing human demand it is important to forge tools that also allow the environmental demand for water be considered at the same level as the human demand.

Market based solutions will probably not be a panacea for water challenges but could provide a combination of tools used to maximize impact. For example, efforts should include the reduction of water waste because simply encouraging conservation may not be enough. James Wolfensohn, as World Bank President, noted, “The biggest problem with water is the waste of water through lack of charging (MacDonald & Tamnhe, 2018).” To price water in an operational context, so it captures the value of the benefits it provides, involves bringing new data and techniques to the modeling process. Work has been done to model the price of water in the U.S., and water markets exist in countries outside of the U.S., including Australia, South Africa, Chile, Mexico, and more (Endo et al., 2018; Hansen et al., 2014; Khan et al., 2009; Michelsen & Young, 1993; Wichelns, 2010; Williamson et al., 2008).

To understand how water as a commodity may fit in a market context, it will help to understand that price acts as a signal, linking users to resources. Also, an understanding of what characteristics a market needs to function efficiently is important. Price helps market participants by informing them of changes in supply and/or demand of a good or service. As prices increase, this may indicate that the resource is becoming scarcer, or that the demand for water is increasing, or both. The price signal can also encourage conservation of the resource and new technologies to be developed. When a resource has measurable value, and well-defined property rights, there is an incentive to use it more efficiently and direct the allocation of the resource to its highest and best use.

The market must have certain characteristics to operate efficiently, as discussed by Fama (1970) in his seminal work on capital markets. Efficiency would require market prices that reflect all the relevant information, no individual dominates the market, transaction costs are not prohibitive, players are rational, and there is little or no cost to acquire information (Fama, 1970). Considering water in that context, it has been suggested that additional requirements are needed, "Legalization of water reallocation, the separation of water rights and landownership, and the modification of the cancellation rule for non-use (Endo et al., 2018)." While some of these characteristics may exist to some degree in U.S. water markets, there is room for improvement, specifically in Texas with regards to homogeneity of product, permit regulation, and rules regarding the movement of water between basins.

To enhance information available to market participants we test the following hypothesis: can Australian water markets be accurately modelled and, if so, can that model be effectively transferred to other geographies? To test the hypothesis, the price of water is modelled by applying artificial intelligence/machine learning (AI/ML) techniques to a robust data set (the Australian marketplace) using inputs that are also available in other geographic locations. This will allow the validated model to be transferred to other geographies by using values specific to that area to output a price for water in that region. When users have access to reliable water pricing, they may be inclined to expand water markets across the state. Informing discussions related to price discovery will help diverse user groups talk about value in a way that allows for comparisons to be made. These discussions may reveal that different user groups have very different ideas relating to the relationship between value and price. The price modeling undertaken here does not endeavor to ascertain if or how value and price are or should be related, but to provide the information that will help make those conversations fruitful.

Methods

Site Selection and Approach

Previous work has shown that AI/ML methods can closely model water prices in Australian markets (Cui & Schreider, 2009; Khan et al., 2009). In this space it is possible to combine market data with biophysical data to build models that are more holistic. While Kahn et al. (2009) demonstrate the viability of the method, our work expands on their efforts by increasing temporal resolution using daily transactional data and takes the model further via transfer, applying it to a different geography (the U.S.). When price is modelled in this fashion, it represents what a buyer may pay for water in the marketplace. While improvements have been made in the water price modelling space in the Australian market, much of the work has been based on quarterly or monthly input data. This study advances the approach by using data with daily resolution (Khan et al., 2009).

Kahn's work was conducted around the time of Australia's 2007 Water Act, so could not reflect the impacts of the new legislation and pricing mechanisms it precipitated. That work operated under a different paradigm—where prices were pooled as opposed to a more transparent, open marketplace that exists today. In addition, computational power has increased tremendously over the intervening decade, as has the amount of water market data.

Model construction, particularly using AI/ML, is heavily data dependent. The robust Australian water markets have the volume of data required for model development and validation. Australian water trading activity occurs over the entire continent, but more than 90% of trading activity takes place in the SMDB (Figure 2-1). In addition to the availability of water market data, there is a plethora of other data available for the region including crop production, statistics regarding irrigation, crop prices, and climate data. Transferring a model from one geography to another can present challenges. In this case, part of the reason the method is valid because the same crops need the same amount of water to grow, regardless of where they may be located.

Figure 2-1. Murray Darling Basin, Australia
from https://www.mdba.gov.au/sites/default/files/pubs/Murray-Darling_Basin_Boundary.pdf

Australian water markets are the largest in the world, larger than U.S. generally and Texas particularly (Courtenay, 2017). Given this disparity in the amount of data, the Australian market is modelled and transferred to an area in Texas where pricing information is available. The same inputs are used, populated with regional values, and generate a price of water as an output. The Edwards Aquifer runs across the Guadalupe River Basin (GRB, Figure 2-2) and the Edwards Aquifer Authority (EAA) has jurisdiction over much of the San Antonio Segment of the aquifer (Figure 2-3). The EAA offers voluntary programs where irrigation permit holders can option their water for payment (Edwards Aquifer Authority, 2019). In addition, the San Antonio

Water System (SAWS) has a voluntary program whereby participants are paid to participate in a slightly different forbearance program (San Antonio Water System, 2018).

Figure 2-2. The Guadalupe River Basin from thearansasproject.org

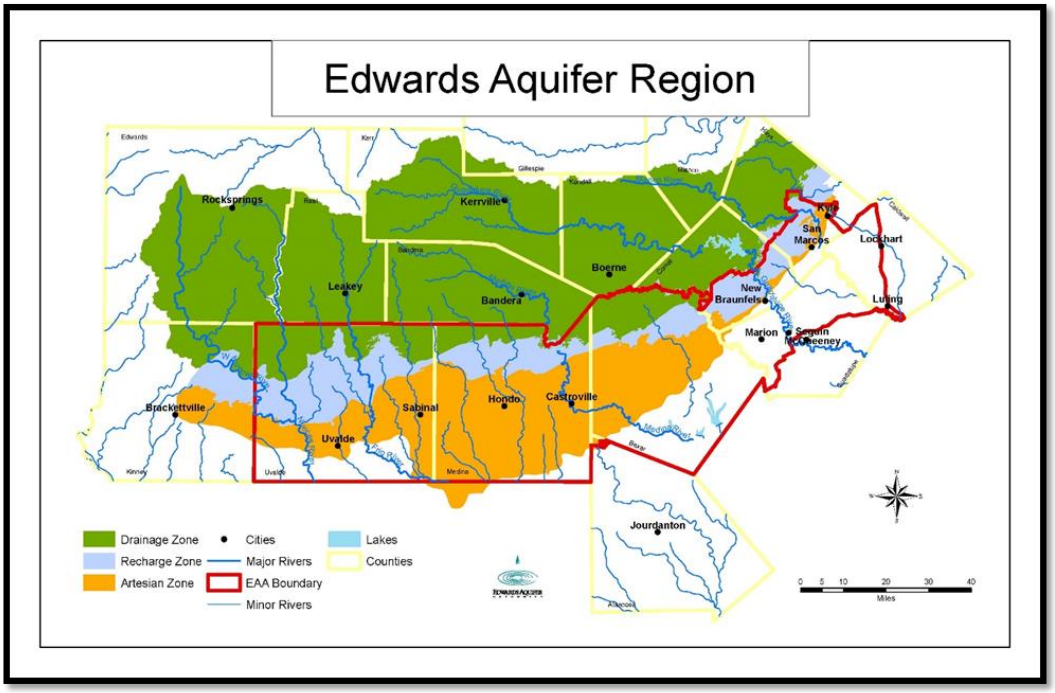

Figure 2-3. Edwards Aquifer Authority jurisdictional boundary (EAA).

The EAA's program is the Voluntary Irrigation Suspension Program Option (VISPO) and provides two types of payments, a standby payment that is paid in years the water is not called (currently $54/AF), and the forbearance payment which is paid in addition to the standby payment in years the water is called (currently $160, previous level was $150). These options are not called at the buyers' discretion, rather water can be called on an annual basis when a well (the J-17 Index Well) is at or below 635 feet on October 1 (Edwards Aquifer Authority, 2019). The program triggered in 2014, and if the program was running would have triggered in 1954, 1955, 1956, 1984, and 1989 (Edwards Aquifer Authority, 2017, 2019).

The SAWS program is the Aquifer Storage and Recovery (ASR) program which is another voluntary forbearance program. Participants are paid $100AF/year in all years regardless if the water is called or not. The ASR trigger would have been activated in all years of the drought of record but has not been triggered since. The triggering event is when the 10-year annual recharge average is at or below 500,000 AF (Edwards Aquifer Authority, 2017, 2019).

To understand how well commodities prices can predict water prices and to transfer the model to predict the price of water in another location, these steps were followed:

1. Gathered and processed the required combination of data: water price, commodities, and precipitation from Australia and the U.S.
2. Built a linear model with Australian data to use as a baseline for testing the performance of AI models.
3. Trained, tested, and evaluated a neural network model with Australian data.
4. Trained, tested, and evaluated a random forest model with Australian data.
5. Chose the optimal model (random forest) and transferred it to the U.S. to predict water prices using U.S. data.

Data

To build a model based on the Australian data, available daily trade data was compiled that includes pricing for the entitlement market (permanent right) and the allocation market (annual allotment). To arrive at a single price for each day, transactions were consolidated by volume weighted average price (VWAP). It is widely known that there are some price reporting issues in the market (ABARES, 2018). Many transactions report a price of zero and these $0 allocation trades usually make up 60-70% of the transactions (Figure 2-4).

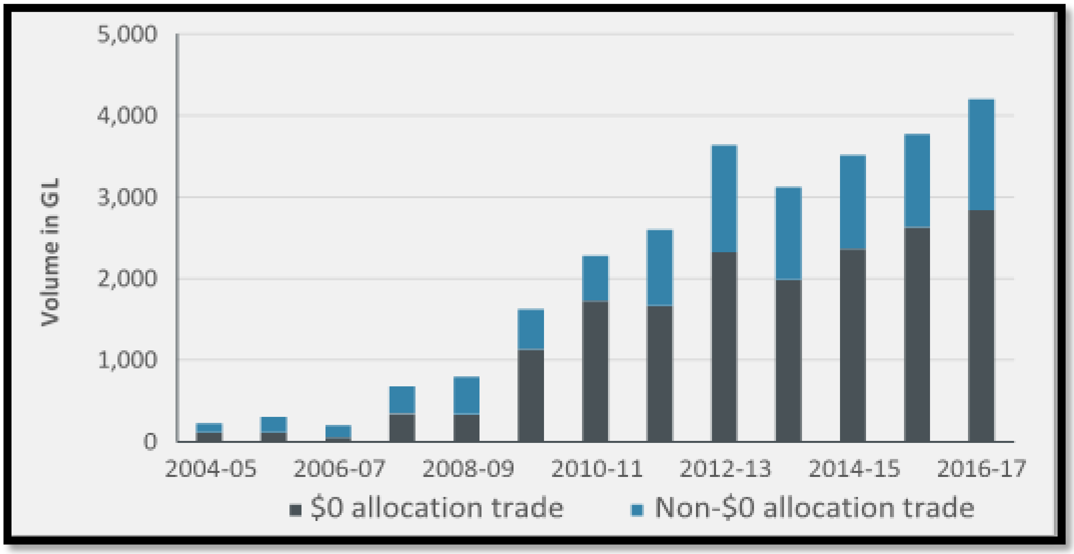

Figure 2-4. Allocation trades reported with and without a zero-value price in terms of volume of water traded (AITHER, 2017).

The Australian government has been looking into this issue and is taking steps to improve the reporting moving forward (Murray-Darling Basin Authority, 2019). Given that the trades reported with a zero price represent something less than a fully open and transparent transaction, those cases were deleted from the data set. Also, there were 5 outlier transactions on the high end of the pricing range. The interquartile range was used to identify outliers and data was removed that had a price over $10,000 (mean prices of the allocation and entitlement trades are around 90 and 155, respectively). In at least one of these cases, the value of the trade likely included the water and the land associated with it due to the preferential tax treatment this receives. as opposed to selling the land in a more conventional real estate transaction (E. Carter, personal communication, October 2018).

To the initial data set, daily closing numbers from the Australian Stock Exchange (ASX) for a variety of commodities were added: barley, sorghum, cotton, and beef. By using water dependent crops in the model, as commodities prices move so will the ability to pay for water and this should be a fair predictor of the price of water. In the case of cotton, the price is tied to the cotton contracts on the Chicago Mercantile Exchange (CME), which is convenient for transferring the model to Texas. The price of cotton was not altered from the CME. The Australian Eastern Young Cattle Indicator was considered as an input, the price of feeder cattle was used instead to aid in transferability. To incorporate a bio-physical element, station level precipitation data from the Australian Bureau of Meteorology (ABM) for the SMDB was included by aggregating those station readings to arrive at one number for precipitation per day. By aggregating the precipitation into one daily number for the river basin, the same method can be used when transferring the model to other basins (Table 2-1).

Table 2-1. Model variables with source and units.

Variable	Entitlement Price	Allocation Price	Feeder Cattle	Sorghum	Cotton	Barley	Precipitation
Source	MDBA daily VWAP	MDBA daily VWAP	MLA	ASX as published	CME daily close	ASX daily close	ABM
Units	AUD/ML	AUD/ML	AUD ¢/kg lwt	AUD/20MT	USD/lb.	AUD/t	mm

In real-time, currency conversions will fluctuate, but during the timeframe of this study the rate was approximately \$1.00 AUD = \$0.75 USD. For all currency conversions this number was used as a constant. The transfer model variables are the same as used for model building (Table 2-1).

Table 2-1. Variables used for model transfer to the U.S.

Variable	Entitlement Price	Allocation Price	Feeder Cattle	Sorghum	Cotton	Barley	Rain
Source	NA	Model output	USDA	USDA/AMS	CME	CME	NOAA
Units	NA	AUD	USD/lb.	USD/bu	USD/lb.	ICE/Bu	mm

Model

A distinction needs to be made between the best model for use in Australia and the model most suited to transfer to Texas. In Australia, there is a robust market for both the temporary allocation of water and the permanent right. The best predictor of either of those prices is the other one, with a Spearman correlation of 0.74. This is helpful for applications in-country but transferring the model may become difficult if the region that the model is being transferred to does not have enough transactional data to use the temporary/permanent pricing relationship as an input. Therefore, sets of models were built for use in Australia which included the entitlement price data as an input, and sets of models intended for transfer omitted this variable as an input.

A linear model was used to establish a baseline to test if increased model complexity equates to increased performance. This was done for models that include the entitlement data (for Australia) and the model for transfer which omitted entitlement data. A third linear model was constructed to predict the natural logarithm of price, then predictions were transformed back to their original range; this prevents the prediction of negative values which are a market impossibility. The general equation for the Australian linear model (Equation 2-1) is:

Equation 2-1

$$\hat{y}_i = \beta_0 + \beta_1 x_{entitlement} + \beta_2 x_{barley} + \beta_3 x_{cotton} + \beta_4 x_{cattle} + \beta_5 x_{sorghum} + \beta_6 x_{rain} + \hat{\varepsilon}_i$$

The equation for the linear model used as a baseline for the transferred model (Equation 2-2) analysis is:

Equation 2-2

$$\hat{y}_i = \beta_0 + \beta_1 x_{barley} + \beta_2 x_{cotton} + \beta_3 x_{cattle} + \beta_4 x_{sorghum} + \beta_5 x_{rain} + \hat{\varepsilon}_i$$

In both linear equations above (2-1 and 2-2), $\hat{y}_i$ is the best fit line for the predicted values of the price of water, β_0 is the intercept, $\beta_1 \ldots \beta_n$ are the coefficients applied to the input variables, and $\hat{\varepsilon}_i$ is the error term. After establishing baseline performance with the linear models, neural network and random forest models were constructed and tested. The random forest was selected for use; it produced better results and offers more insight into the importance of variables in the system. In all cases, the model was constructed using 85% of the data as a training set and validated on the remaining 15% (test set). Modelling has been done to find an optimal ratio for the training/test set split and shown that the ratio should be at least 2/3 to 1/3, though this is often rounded to 70/30 and some advocate for an 80/20 split along Pareto lines (Dobbin & Simon, 2011, Giacomelli, 2013). When seeking the optimal split between training and testing, the number of samples is important and is a factor when a scaling law is constructed (Guyon, 2019). Given the relatively low sample size in the dataset in this case, the decision to split the data 85/15 was made to give the model the largest opportunity to train as possible.

Neural networks are a type of machine learning that have been in use for over 70 years, and while McCulloch & Pitts' paper (1943) is widely cited, a fuller appreciation of the history should include the names Alan Turing and John von Neumann (Mühlenbein, 2006). After a period of dormancy, the ideas were brought back to life in the 1980's (Rumelhart & McClelland, 1987). A network consists of a several interconnected nodes that assign a weight to incoming information. Inbound data is multiplied by the weight associated with connections, the results are combined and multiplied by the activation function then passed to the outbound connection (Hardesty, 2017). When training, all the weights are initially randomized, then the network adjusts weights and biases until similar input data is yielding similar outputs. In this way neural networks can be very accurate with predictions, but the derivation of the weightings and biases says nothing about the relationships in the system, hence are often given the moniker "black box." There are however an increasing number of methods used to extract information from a well calibrated neural network (the "black" box becomes "gray") but such information is not extracted from the model parameters as would be the case for a regression type model. A visual example of how these nodes are interconnected is illustrated by one of the neural networks built during the experimentation (Figure 2-5). The network was built using RStudio (V3.5.2 Eggshell Igloo) for R using the ‘nerualnet’ package by Günter & Fritsch (Günther & Fritsch, 2010).

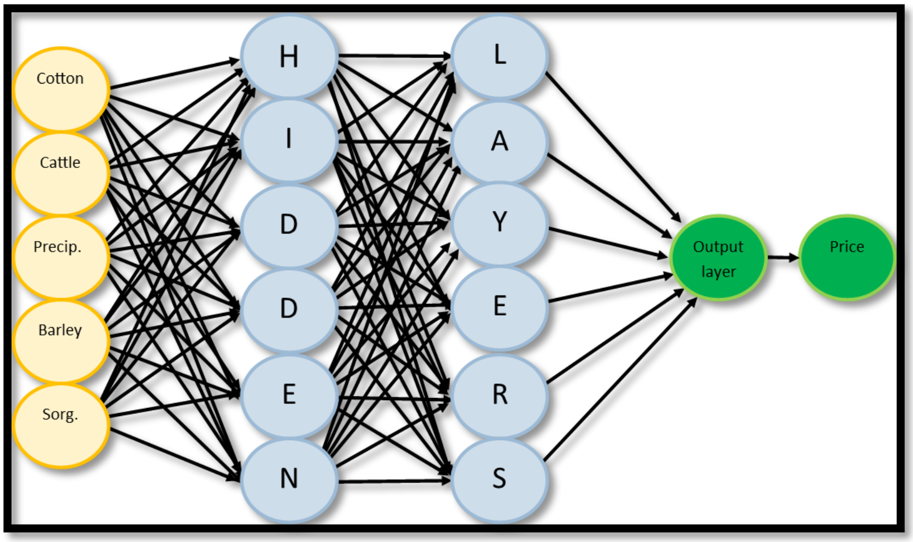

Figure 2-5. Conceptual model of a neural network, inputs get fed from the left, through the hidden layers where weightings are applied to produce a prediction in the output layer on the right.

Figure 2-5 illustrates a neural network with the input layer, hidden layers, and output layer. To understand how this is constructed, the starting point is the equation for the most basic multi-layer perceptron, comprised of an input with n variables and one output neuron in the output layer, which calculates the function (Equation 2-3):

Equation 2-3

$$o(x) = f\left(w_0 + \sum_{i=1}^{n} w_i x_i\right) = f(w_0 + \mathrm{w}^T x),$$

where w_0 is the intercept, $\mathbf{w} = (w_1,\ldots,w_n)$ is the vector holding all synaptic weights excluding the intercept, and $\mathbf{x} = (x_1,\ldots, xn)$ the vector containing all variables (Günther & Fritsch, 2010). This is the equivalent to a generalized linear model (GLM) with a link function f^{-1}, so calculated weights will equal the regression parameters of the GLM (Günther & Fritsch, 2010).

To expand flexibility of the model, hidden layers are added, expressed as J hidden neurons and calculates (Equation 2-4):

Equation 2-4

$$o(x) = f\left(w_0 + \sum_{j=1}^{J} w_j \cdot f\left(w_{0j} + \sum_{i=1}^{n} w_{ij} x_i\right)\right)$$

$$= f\left(w_0 + \sum_{j=1}^{J} w_j \cdot f\left(w_{0j} + \mathbf{w}_{\boldsymbol{j}}{}^{T} \boldsymbol{x}\right)\right)$$

where w_0 is the intercept of the output layer and w_{0j} are the intercepts of the jth hidden neurons with w_j being the weight associated with the synapse beginning at the jth hidden neuron leading to output neuron $\mathbf{w_j} = (w_1,..,w_{\mathrm{nj}})$ (Günther & Fritsch, 2010). This ($\mathbf{w_j}$) is the vector holding all synaptic weights of the pathways leading to the jth hidden neuron and, again $\mathbf{x}$ is the vector of covariates. This shows that a neural network, at its core, is a typically nonlinear extension from general linear models.

From here output neurons and hidden neurons generate an output $f(g(z_0,z_1,\ldots,z_k)) = f(\mathrm{g}(\mathbf{z}))$ by using all preceding neurons' outputs $z_0,z_1,\ldots,z_k$, where $g : \mathrm{R}^{k+1} \rightarrow \mathrm{R}$ is the integration function and $f : \mathrm{R} \rightarrow \mathrm{R}$ the activation function (Günther & Fritsch, 2010). Neuron $z_0 \equiv 1$ is the intercept's constant 1. The integration function is commonly defined as $g(\mathbf{z})=w_0 z_0+\sum^{\mathrm{k}}_{i=1} w_i z_i = w_0 + \mathbf{w^T z}$. The activation function f is most often a nondecreasing nonlinear and differentiable function, for example a logistic function, and the relation of the function to the response should be considered in selection, just as with GLMs (Günther & Fritsch, 2010).

To fit the network to the data the neural network uses learning algorithms during the training phase of model building. Simply put, the predicted output is compared to the actual output and the weightings adapt based on the comparison. To do this, the network computes an output **o**(**x**) for inputs **x** and current weights. During the training process, output **o** and output **y** will be unequal. An error function is utilized to quantify the difference and provide guidance for the network to learn. To inform this learning, examples of error functions are cross-entropy and the oft-used sum of squared errors (SSE). The cross-entropy equation (Equation 2-5) is:

Equation 2-5

$$E = -\sum_{l=1}^{L}\sum_{h=1}^{H} \left(y_{lh}\log(o_{lh}) + (1 - y_{lh})\log(1 - o_{lh})\right)$$

and the SSE (Equation 6):

Equation 6

$$E = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H} (o_{lh} - y_{lh})^2$$

with these measures, there errors are indexed as output pairs and the weights are adapted progressively following the rules of the learning algorithm (Günther & Fritsch, 2010).

To determine the architecture for the neural network (the number of hidden neurons), the model was optimized using MSE as a predictor of model performance using test set data (May et al., 2011). Models were constructed with the number of hidden neurons in each model being increased from one to ten with 100 ensemble members for each increase in the number of hidden neurons. For each model run training data was randomized (70% of data), 15% of the data was used for testing, and the remaining 15% for validation. From the 100 model runs, mean MSE and standard error were calculated. Model architecture was chosen by examining the minimum MSE for each model; the best model had 3 hidden neurons and was selected for use.

After testing the neural network, the same data was used to build a random forest model. This approach can be imagined as a large group of decision trees, and the order in which the trees are splitting the variables and at what levels can provide more insights about the system and the relative importance of the predictors than the “grey box” nature of the neural network. The random forest was created using RStudio (V3.5.2 Eggshell Igloo) for R using the randomForest package. This package was developed for R by Liaw and Wiener, based on Breiman and Cutler’s previous work developed in Fortran (Breiman, 2001, 2002; A. Liaw & Wiener, 2002). A conceptual illustration of a random forest model is provided in Figure 2-6.

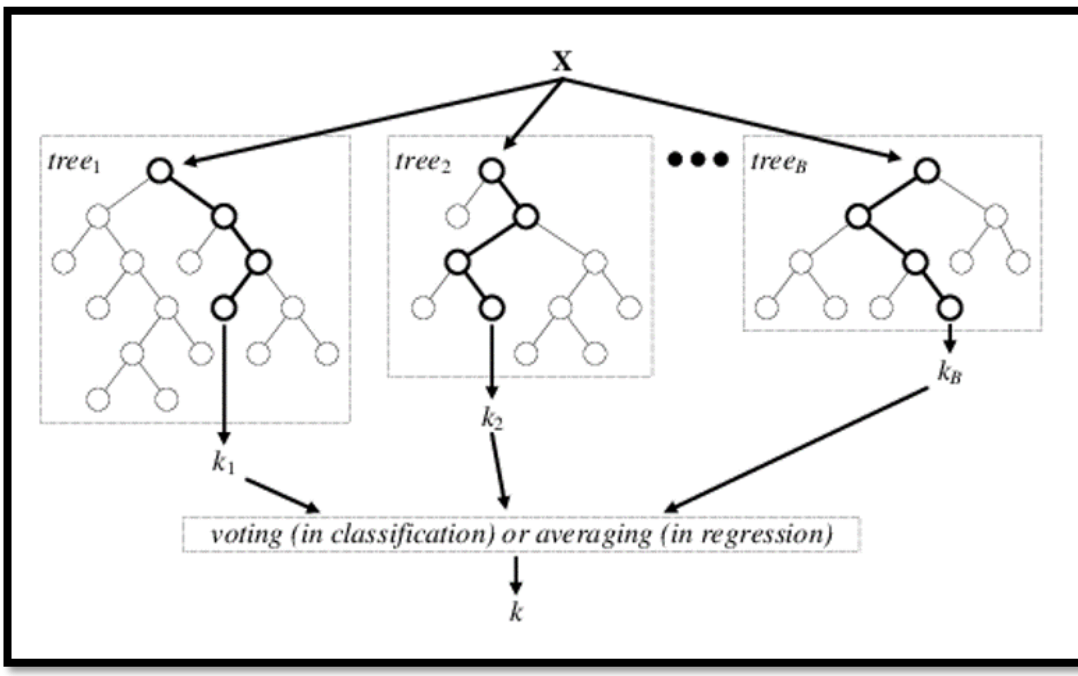

Figure 2-6. Conceptual model of random forest construction and data flow (Vaiciukynas, 2016)

The random forest operates as an ensemble learning method, meaning there are many classifiers and in the end their results are aggregated. Two popular methods for achieving this result are “boosting” and “bagging.” When the results are aggregated it is common for practitioners to use a majority rules approach to the formulation of the final output. In the case of boosting, trees that accurately predict points that were missed by earlier trees get a heavier weighting in the voting. In bagging, trees are not dependent on the previous generation, but majority rules in the voting after trees are constructed using a bootstrap sample of the data (Breiman, 2001; Liaw & Wiener, 2002).

Breiman (2001) pioneered this approach and defines this procedure as, "A random forest is a classifier consisting of a collection of tree-structured classifiers {h(x,Θk),k=1, ...} where the {Θk} are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input **x** (2001)." This paper is not intended to be a study of the method but provides a brief summation of the technique. For a more detailed exploration of this thinking, reading Breiman is recommended.

Breiman makes an interesting observation: that due to the nature of the voting, the wider the margin of winning votes indicates a higher confidence level. This is augmented by the Strong Law of Large Numbers: the more trees that are in the forest the closer the prediction is to convergence. This indicates that when more trees are added it does not result in overfitting, but produces an effect limiting generalization error, this convergence equation is (Equation2-7):

Equation2-7

$$P_{X,Y}(P_{\Theta}(h(\mathbf{X},\Theta)=Y)-\max_{j\neq Y}P_{\Theta}(h(\mathbf{X},\Theta)=j)<0)$$ (Breiman, 2001).

Where Θ is a number of independent random integers between 1 and *K*, **x** is an input vector, and tree structured classifiers are $\{h(\mathbf{x},\Theta_k),k=1,...\}$.

Breiman continues to define a margin function from which relative classifier accuracy can be measured. This relational measure is at the heart of the random forest and is expressed by the theorem for the upper bound generalization error (Equation 2-8):

Equation 2-8

$$PE*\leq\overline{\rho}(1-s^2)/s^2$$

which expresses the relationship between classifiers in terms of the individual strength of the classifiers and the correlation between them, where $PE*$ is the probable error of correlation coefficient, $\overline{\rho}$ is the mean value of correlation and *s* is the strength of classifiers (Breiman, 2001). From here, Breiman defines the c/s2 ratio as = $\overline{\rho}$ / s^2 then defines the two-class margin function as (Equation 2-9):

Equation 2-9

$$mr(\mathbf{X}, Y) = 2P_{\Theta}(h(\mathbf{X}, \Theta) = Y) - 1$$

if the values for Y are taken as +1 and -1 then (Equation 2-10):

Equation 2-10

$$\overline{\rho} = E_{\Theta,\Theta'}[\rho(h(\cdot, \Theta), h(\cdot, \Theta')]$$

Where $\overline{\rho}$ is the correlation between two forest members averaged over the Θ, Θ' distribution (Breiman, 2001).

The model was constructed and validated then transferred to the U.S. to predict a price for water. Equivalent input data was collected and converted volumetrically, and for currency, to the Australian equivalent, then input into the model. After the converted U.S. inputs were fed through the model, the result was expressed in AUD/ML then converted back to USD/AF for ease of communication with an American audience.

<u>Results</u>

A linear model produced the coefficients and predictions $\hat{y}_i$ in AUD for use as a baseline for model comparisons. The equation for the Australian linear model (Equation 2-11) is:

Equation 2-11

$$\hat{y}_i = -34.55 + 0.67x_{entitlement} + 0.05x_{barley} + 0.26x_{cotton} - 0.04x_{cattle} - 0.01x_{sorghum} + 0.01x_{rain} + \widehat{\mathcal{E}}_i$$

$$where\ \mathcal{E} \sim \mathcal{N}(0, 73.49^2)$$

and the results of the Australian linear model baseline prediction indicate the model is capturing the general trend of the market (Figure 2-7). When assessing model performance, the data point values are used, illustrated moving averages have a smoothing effect on the plots of point data and help visualize how well the model is capturing the trend.

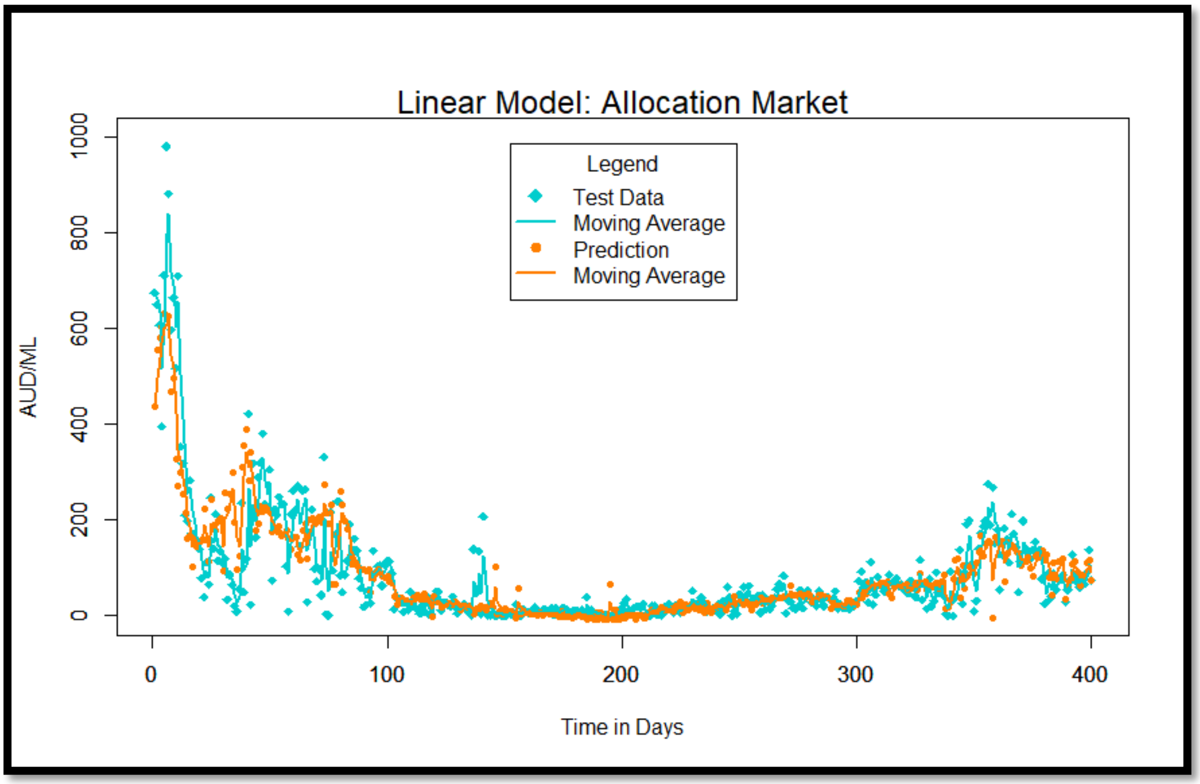

Figure 2-7. Linear model of Australian allocation prices, MSE = 4,722 R^2 = 0.70.

This linear model can be compared to a random forest making predictions with the same data, and results show that the random forest improves on the linear model by decreasing the MSE by 30% and increase the R^2 by 9% (Figure 2-8). This is the last time in the results that model runs were executed with the inclusion of entitlement data as an input.

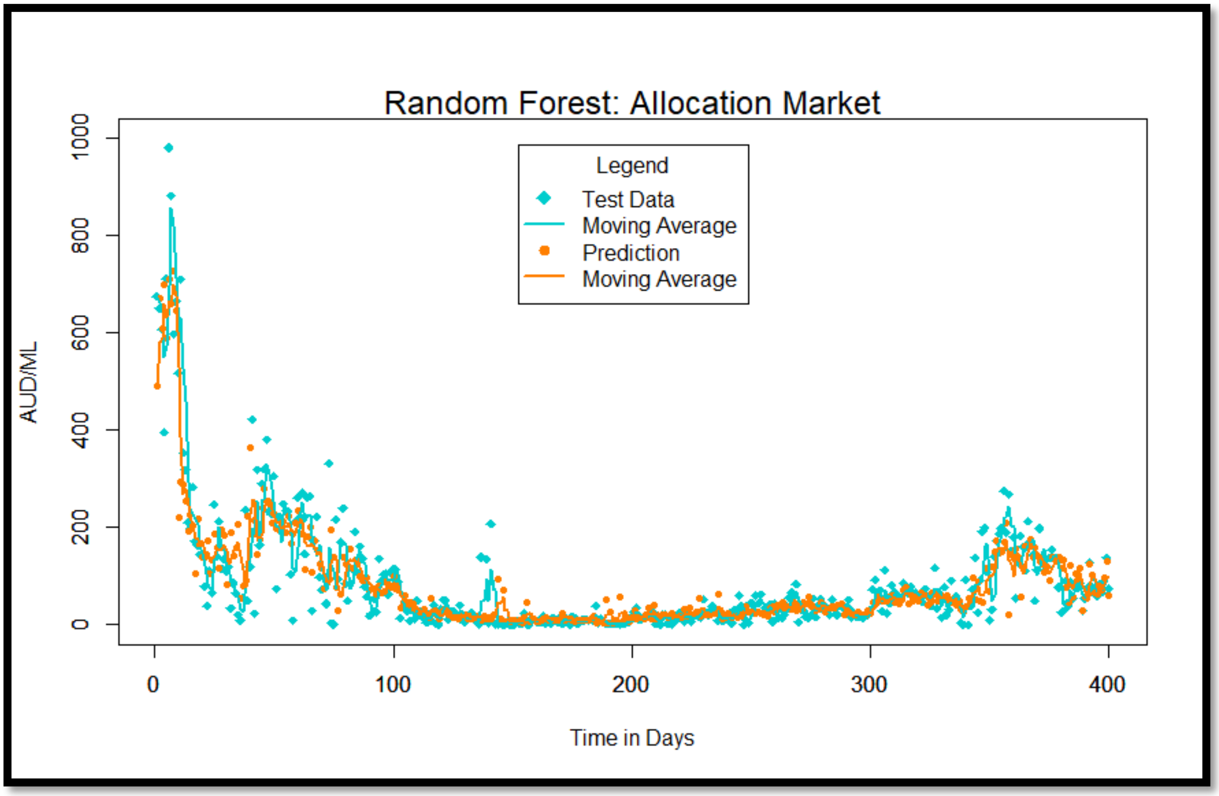

Figure 2-8. Random forest model of Australian allocation prices MSE = 3,276, R^2 = 0.79. Note the improvements in performance where test data variability is high. The random forest improves MSE by 30% and R^2 by 9%.

While MSE is a useful measure when comparing model to model performance, it may not be the best tool to communicate how a model is doing for any given case. To illustrate how well the model is predicting cases, separate models were constructed to predict every data point in the series then a histogram of error was created. This was done for prices and for prices smoothed by the application of 3, 5, and 10-day moving averages to illustrate the effect of smoothing on model accuracy (Figure 2-9).

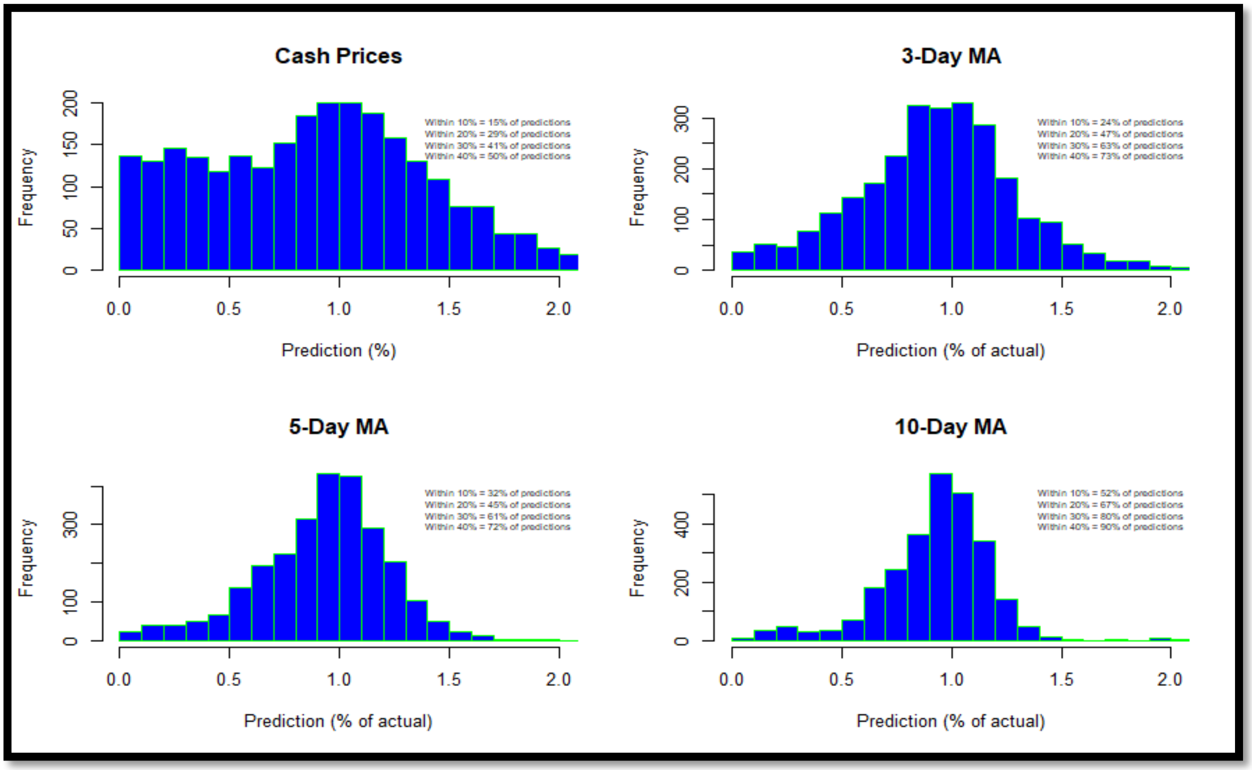

Figure 2-9. Histogram of errors for the allocation market in Australia. As the period of smoothing is lengthened, the model becomes more accurate. The trade-off here is precision for accuracy, users will want to choose if and how to smooth based on their needs.

Moving forward, the models tested are being evaluated with the intention of transferring them to another geography (U.S.) where entitlement pricing is not available for use as an input, thus the variable is dropped here. The equation for the linear model used as a baseline for the transferred model (without entitlement data) analysis is (Equation 2-12):

Equation 2-12

$$\hat{y}_i = 132.56 + 1.32x_{barley} - \ 0.99x_{cotton} - 0.30x_{cattle} - 0.85x_{sorghum} + 0.0006x_{precip} + \hat{\mathcal{E}}_i$$

$$where\ \mathcal{E} \sim \mathcal{N}(0, 115.7^2)$$

Without the highly correlated entitlement data as an input the linear model (Equation 2-12) suffers considerably; MSE more than doubles and R^2 is decreased by more than half (Figure 2-10).

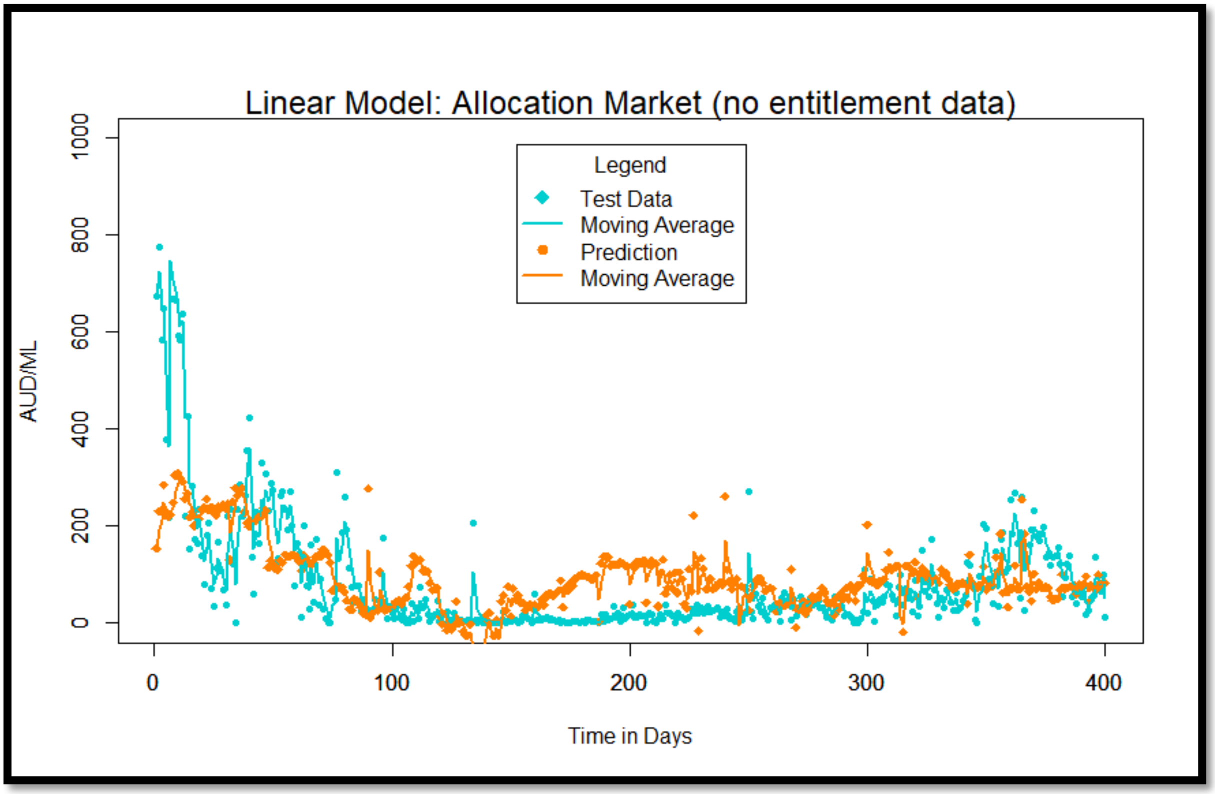

Figure 2-10. Linear model of the allocation market when entitlement data is omitted, MSE = 10,303, R^2 = 0.29. Entitlement prices are highly correlated to allocation prices, without this input driving the linear model the results weaken considerably.

The output of the linear model that omits entitlement data as an input produces sub-zero price predictions. To avoid such predictions, a third linear model was built that predicted the natural logarithm of the price, then predictions were transformed back to the original range to ensure only positive predictions were cast. The linear equation that modeled the natural log (Equation 2-13) of price is:

Equation 2-13

$$\hat{y}_i = 4.36 + .00870x_{barley} - 0.0246x_{cotton} + 0.00021x_{cattle} - 0.00399x_{sorghum} + 0.00001x_{precip} + \hat{\mathcal{E}}_i$$

$$where\ \mathcal{E} \sim \mathcal{N}(0, 1.38^2)$$

and the quality of predictions show further deteriorations in both MSE and R^2 (Figure 2-11).

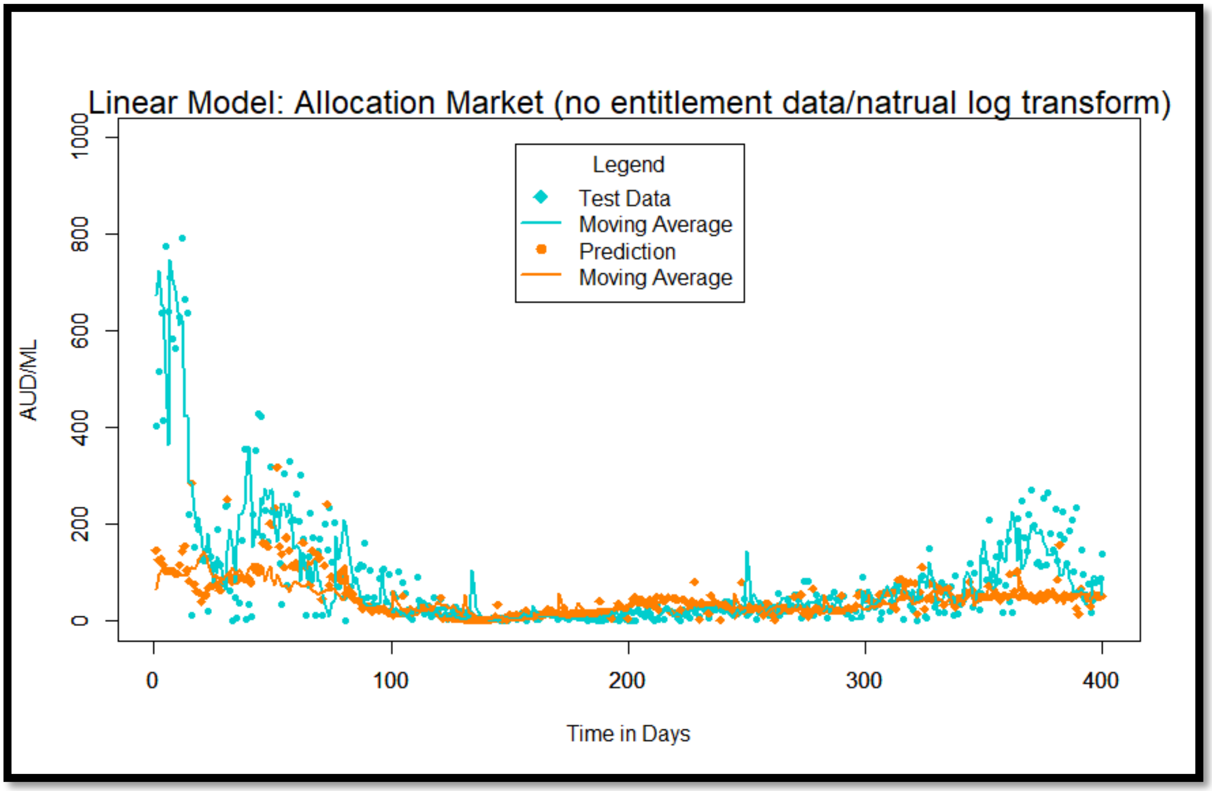

Figure 2-11. Linear model of the allocation market with natural log transformation, MSE = 17,786, R^2 = 0.10. The natural log transformation prevents the linear model from casting sub-zero price predictions but hurts the model's quality.

Now that baseline measures of MSE and R^2 have been established for the linear models without the entitlement data as an input, a neural network and random forest are tested. For the neural network, data was scaled with the min-max method in the interval [0,1], then the output was scaled back. The selected architecture of the neural network was 5 inputs fed into a three-layer network 3x2x1 (sigmoid activation function applied at each layer) with the output of the last neuron predicting the water price. Neural network nodes with weightings were calculated on the training set, and an output schematic generated (Figure 2-12).

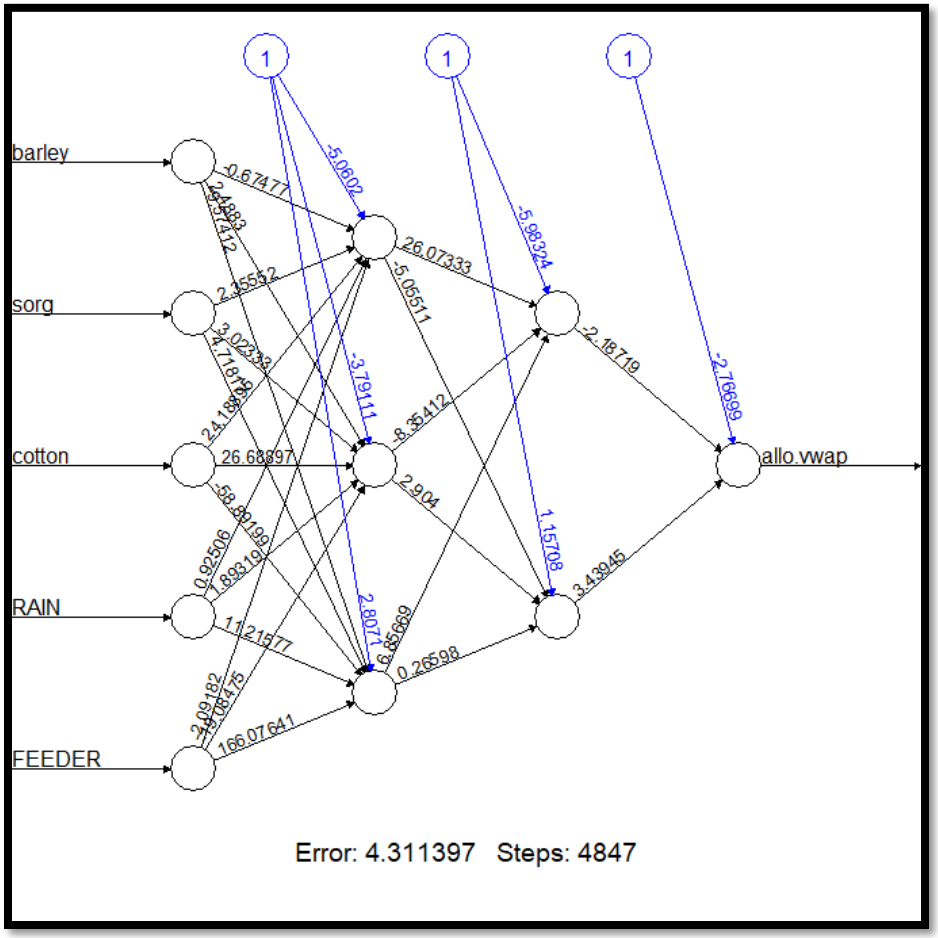

Figure 2-12. Neural network illustrated, input neurons on the left linked to hidden neurons in the middle (3 then 2 then 1), and an output neuron on the right. Linear model (sub-zero predictions allowed) MSE = 10,303, compared to neural network (3,2,1) MSE = 6,229. Black lines show connections and weights, blue lines are added bias terms.

Note that weights and biases are provided for illustrating the process but there is typically no physical information in these model parameters for a neural network. While neural networks can have a high degree of complexity it is advisable to check for overfitting by comparing the error in the test set to the error in the training set. After model construction and training, the neural network makes predictions for the allocation market which are superior to the results of the linear model (Linear model with sub-zero predictions allowed MSE 10,303, compared to neural network 6,229) (Figure 2-13). The neural network captures the trend of the market but is missing sharp price changes as they happen.

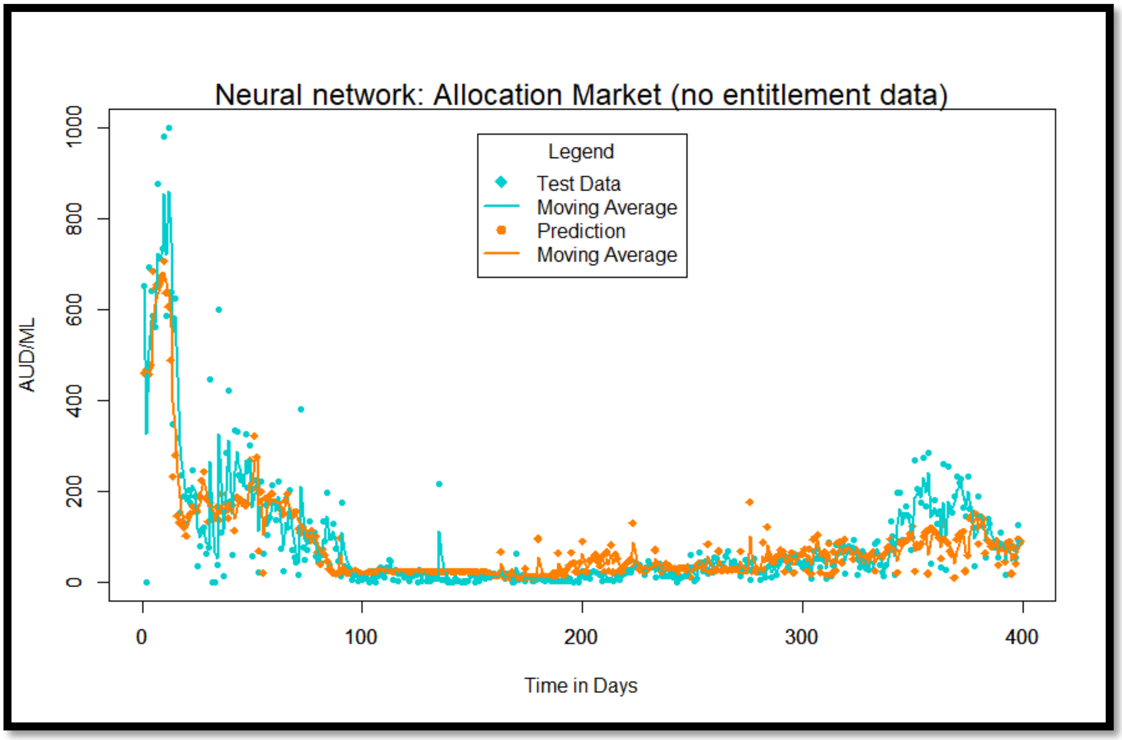

Figure 2-13. Neural network predictions for the allocation market, MSE = 6,229 R^2 = 0.70. Neural networks generally require large amounts of data to train effectively, the size of the dataset in this application may be the limiting factor in the model's ability to predict sharp price deviations.

Lastly, a random forest was constructed, trained and tested. To illustrate the conceptual random forest model provided above (Figure 2-6), a branch from one tree was clipped (Figure 2-14).

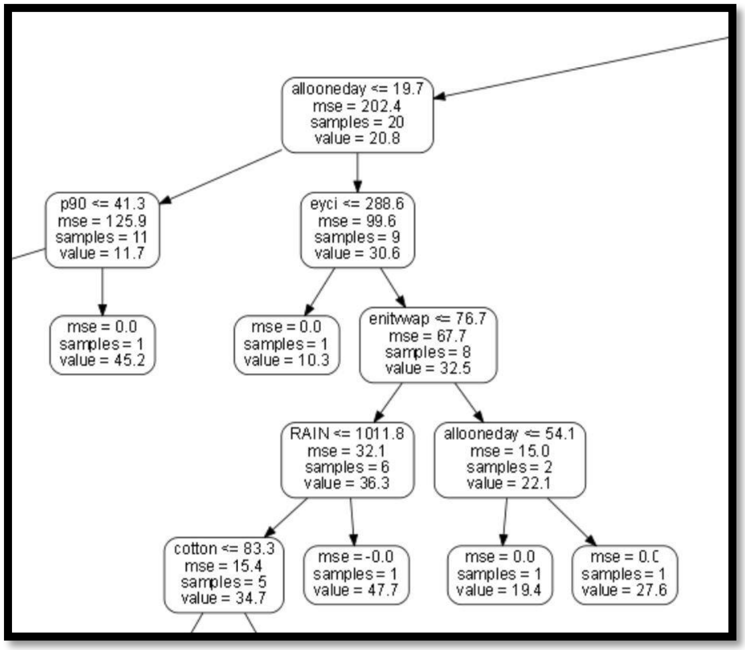

Figure 2-14. Small snip from random forest model to illustrate function.

The size of the trees makes including an entire tree in an illustration impossible, but to better communicate scale, around ¼ of a tree is depicted (Figure 2-15).

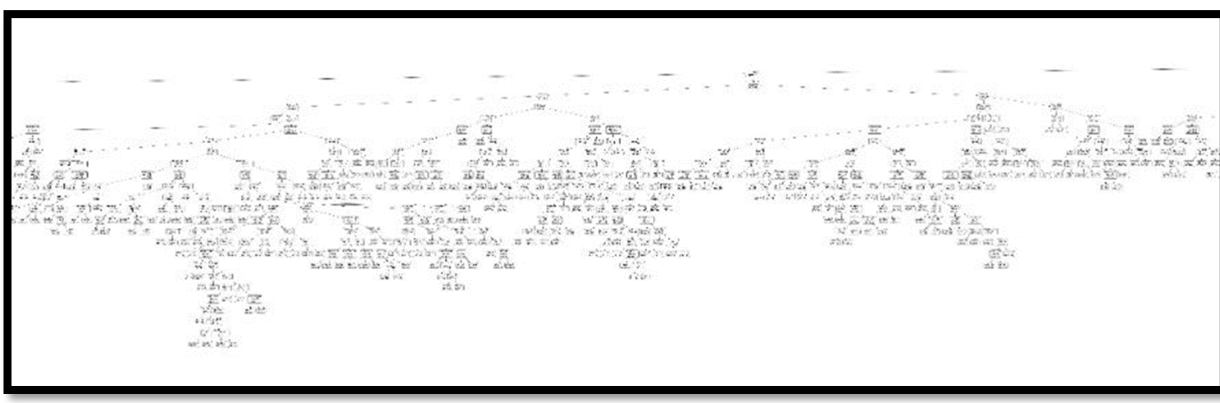

Figure 2-15. Approximately one quarter of a tree taken from the random forest for illustration. In model runs, models with up to 10,000 trees were tested, and 1,000 tree forests were ultimately used for all model runs.

A consideration when using random forest modelling is how many trees to include in a forest. Computational power is less limiting than ever, making it possible to simply add trees to the forest until the error of the prediction stops improving (Figure 2-16). Improvement stops around 300 trees for this study, but a forest with 10,000 trees was grown and there was no further reduction in error.

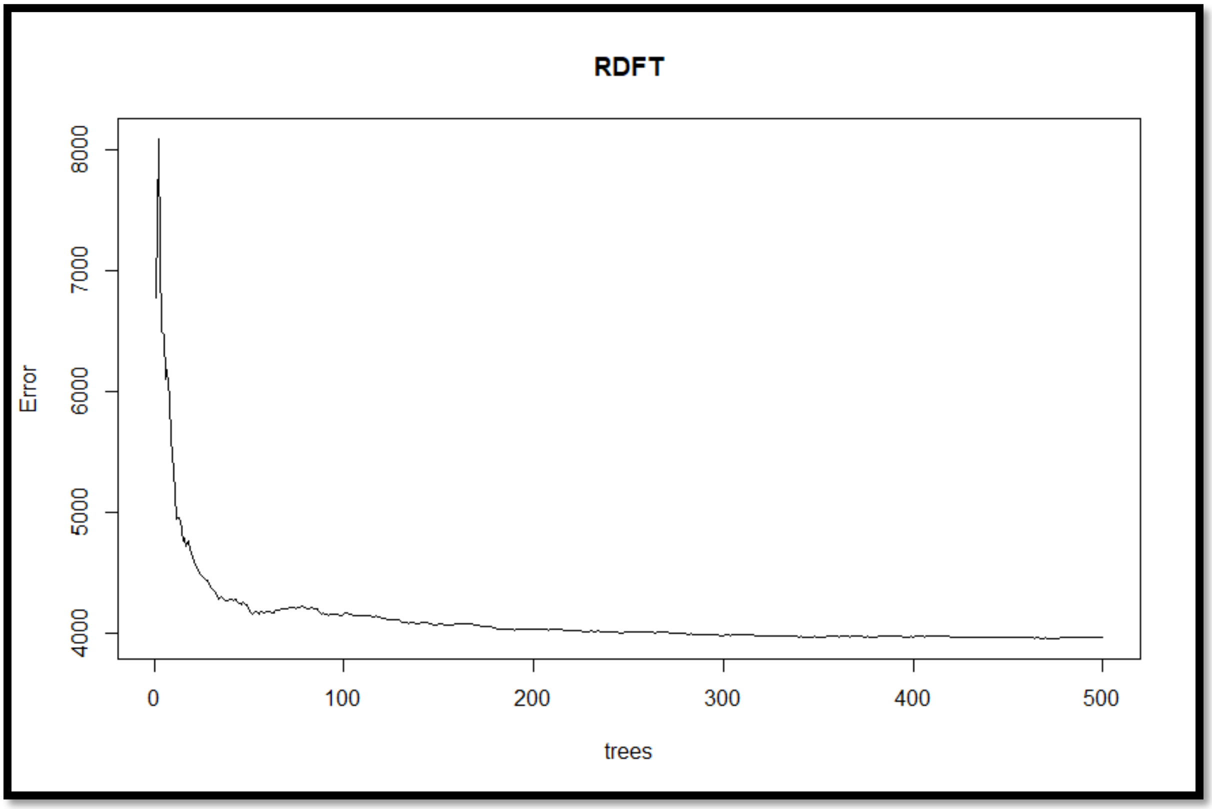

Figure 2-16. Random forest (RDFT) showing the error decrease as the number of trees increases until leveling off around 300. A forest with 10,000 trees was grown and between 500 trees and 10,000 there was no further reduction in error.

To ensure that the error was reduced as much as possible the forest was grown with 1,000 trees to build the model and the predictions are the best in terms of both MSE and R^2 of all tested models (Figure 2-17). Looking at where the neural network was off trend (particularly around the 100 and 200 day mark) compared to the random forest indicates that while both models are generally on trend there are market conditions that the random forest is better able to predict (Figure 2-13 and Figure 2-17).

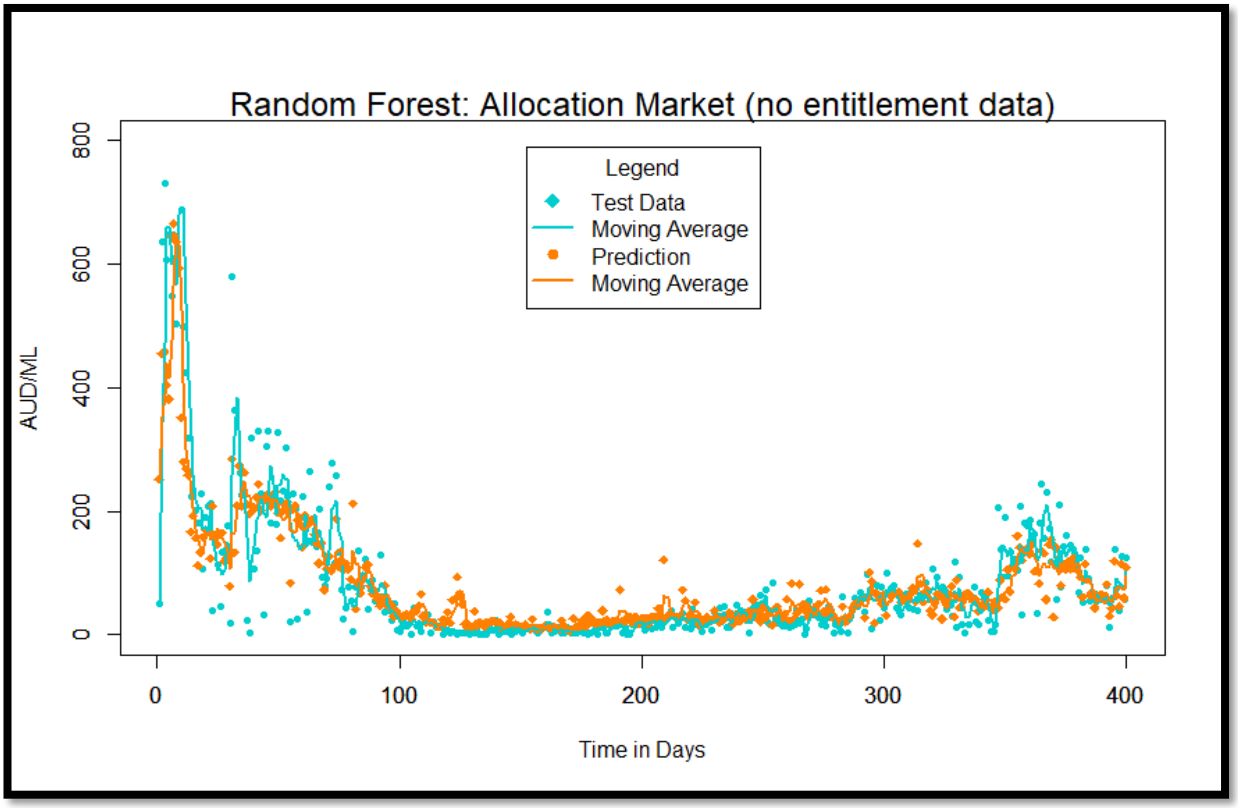

Figure 2-17. Random forest model of Australian allocation prices, without entitlement prices, MSE = 4097 R^2 = 0.74. A model run was executed that omitted the precipitation data and produced similar results, MSE = 4182 R^2 = 0.74

In summary, the performance metrics indicate that the random forest model was the best, followed by the neural network and the linear model (Table 2-2). While in this case the random forest was superior, neural networks will sometimes outperform them. Given the variability inherent in data, no one algorithm will outperform any other algorithm all the time (Wolpert & Macready, 1997). In this application the limiting factor to neural network performance was probably the amount of data available. As a longer price history becomes available it will be worthwhile to revisit this comparison, though both models will likely see improved performance with access to more data.

Table 2-2. Summary of performance data for predictive models as tested on Australian data and illustrated above.

Model LM (linear model) RF (random forest)	R^2	MSE
LM allocation market (Figure 2-7)	0.70	4,722
RF allocation market (Figure 2-8)	0.79	3,276
LM allocation market-no entitlement data (Figure 2-10)	0.29	10,303
LM allocation market-no entitlement/log transform (Figure 2-11)	0.10	17,786
NN allocation market-no entitlement data (Figure 2-13)	0.65	5,496
RF allocation market-no entitlement data (Figure 2-17)	0.74	4,097
RF allocation market-no entitlement/rain data	0.74	4,182

The random forest was chosen to model U.S. water prices based on its performance as measured by MSE and R^2 (Table 2-2). The model was then transferred to the U.S. and used to generate water prices. In the first case a general prediction was made based on commodity prices. Precipitation data was omitted from this model to avoid having to incorporate nationwide precipitation data. While there is no water market to compare the result to measure accuracy the results provide a place to start a conversation around water prices and enable the visualization of how water prices may move with their correlated commodities (Figure 2-18).

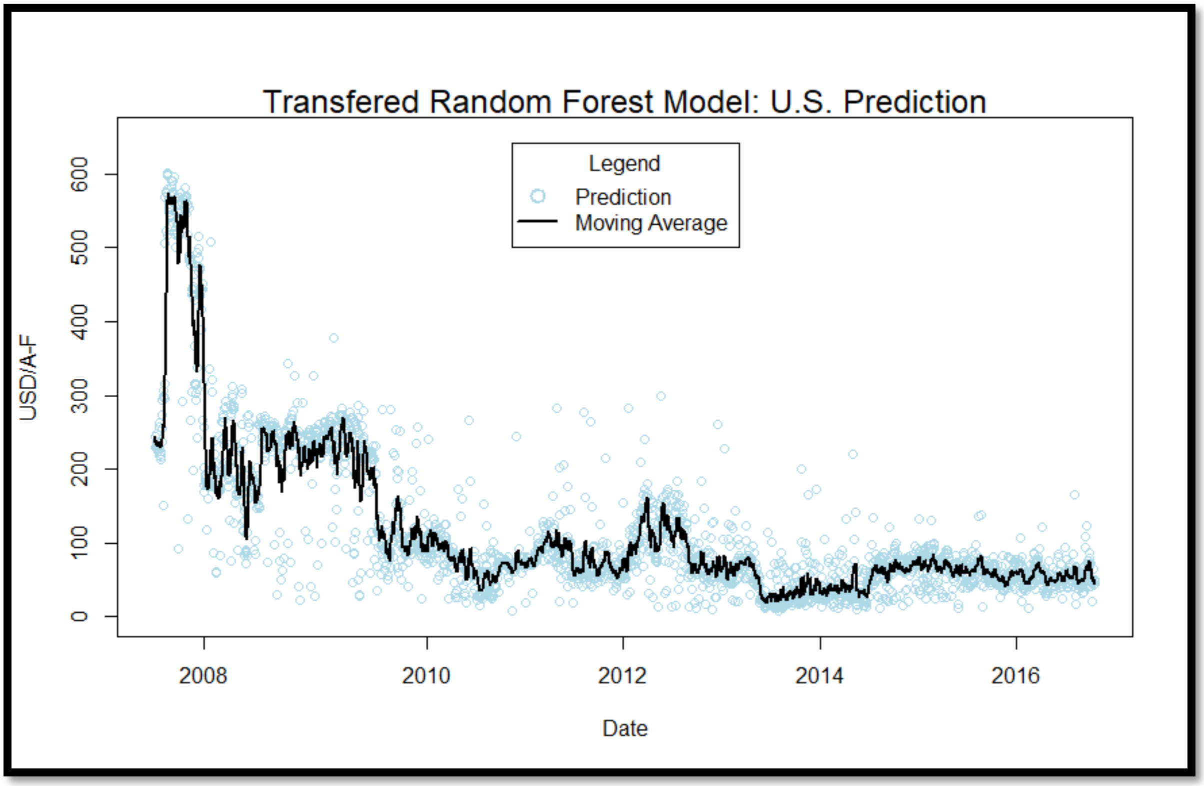

Figure 2-18. Water price prediction; U.S. commodities data as inputs.

The MDB is one large basin (~1million/km^2), so to begin to look at model outputs generated with identical inputs the model was applied to one basin, with the same commodity inputs and the same basin wide, station level precipitation data aggregated to one daily number just as was used in model construction and training (Australian Bureau of Statistics, 2010). Outputs generated with precipitation data in the GRB for 2010 and 2011 produce basin level predictions for a calendar year (Figure 2-19 and 2-20).

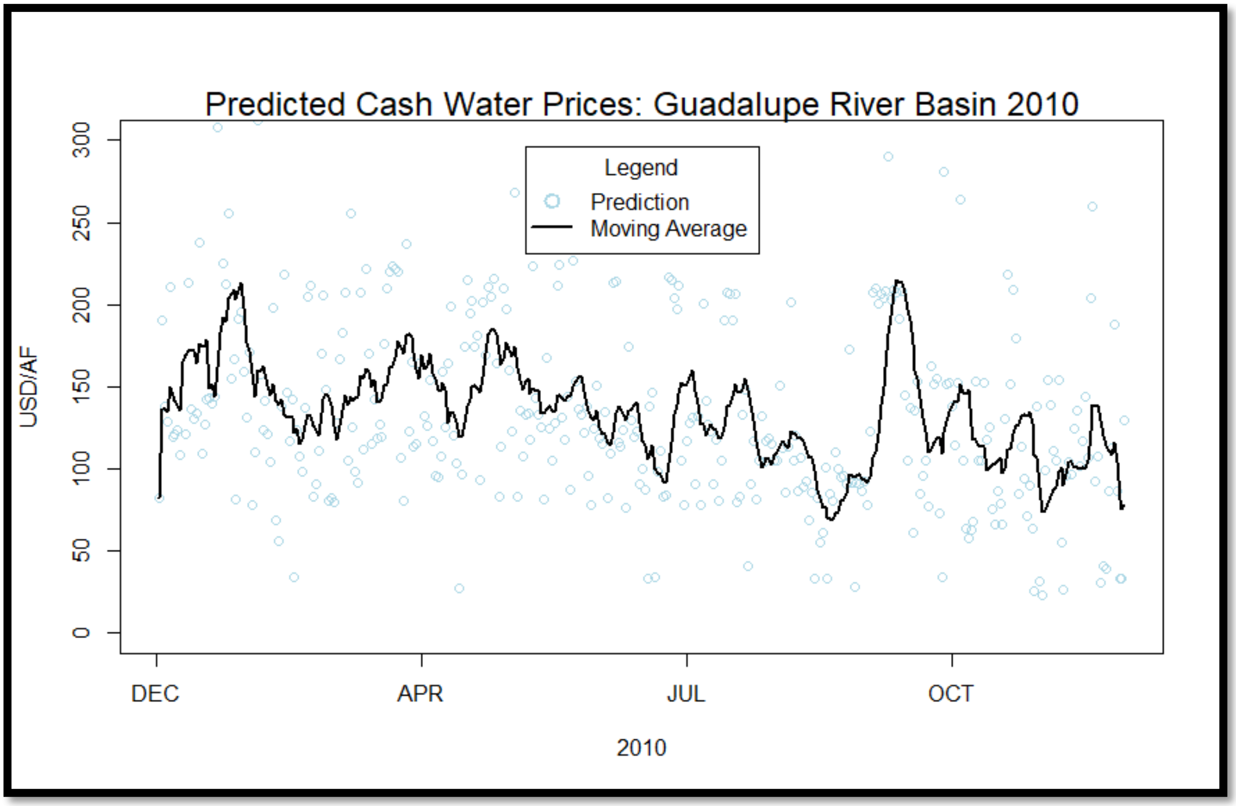

Figure 2-19. Random forest model prediction of cash prices for water in the Guadalupe River Basin for 2010, MSE and R^2 values cannot be calculated without corresponding market data.

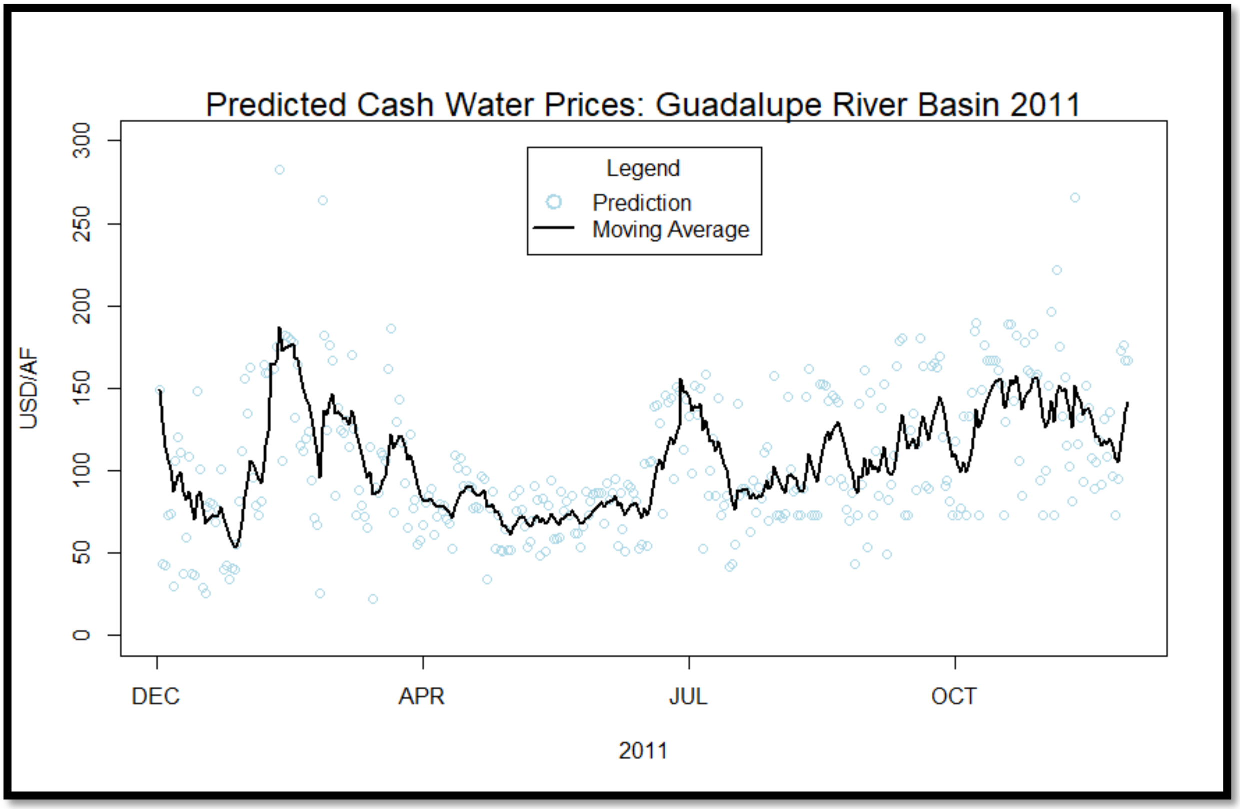

Figure 2-20. Random forest model prediction of cash prices for water in the Guadalupe River Basin for 2011 based on the value of the commodity inputs and the precipitation.

The two payment for water programs currently operating in the GRB (VISPO and ASR) are discussed above. The ASR program pays enrolled water rights holders $100AF year, in both called years and standby years and the VISPO pays participants $54/AF in standby years and $160 in years the water is called (though that is augmented by the $54/AF participation payment). Plotting the payment for water in called years begins to show that the model is casting predictions that are in the realm of current market activity, with predictions spanning the range of ASR/VISPO payments and an average predicted value of $106 in 2011 (Figure 2-21).

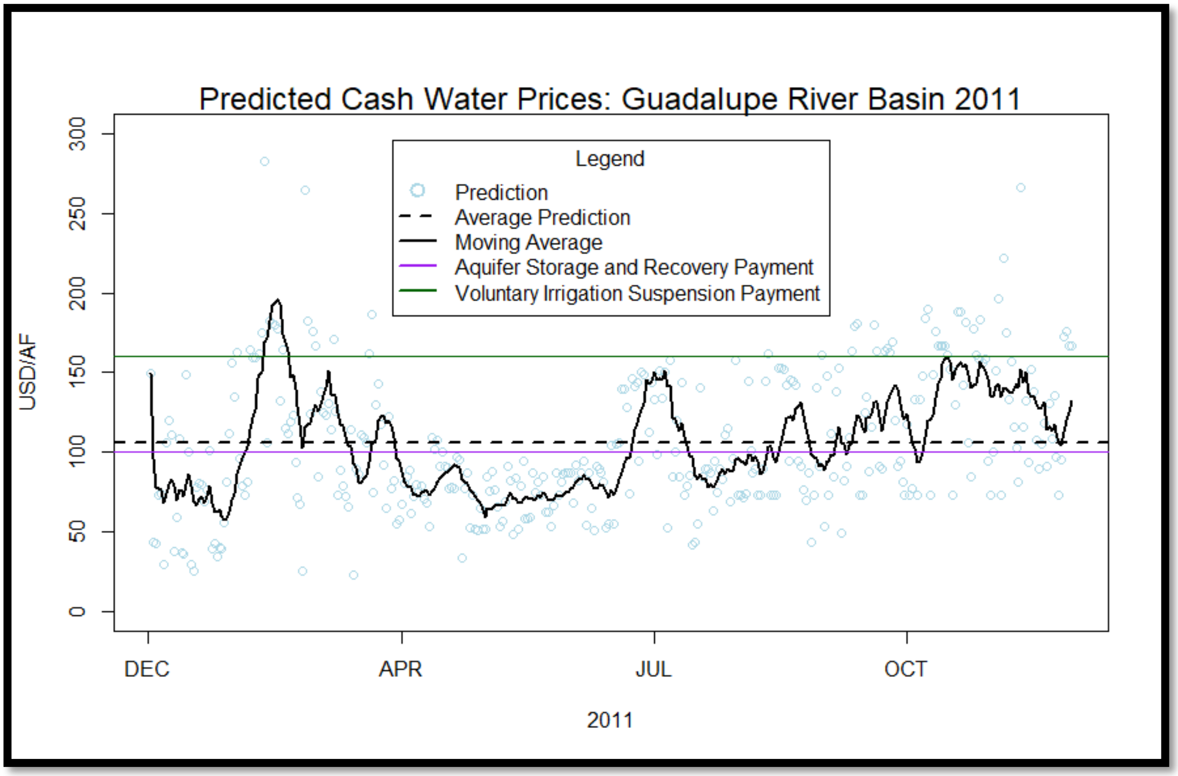

Figure 2-21. Model predictions as compared to payments being made for water. Aquifer Storage and Recovery (ASR) payments are $100/AF in all years and Voluntary Irrigation Suspension Program Option (VISPO) payments are $54/AF payment in all years and an additional $160/AF in years the water is called.

A more detailed examination will have to incorporate the payments received in non-called years as well as the VISPO program payment in called years to get a more accurate understanding of how program participants are being compensated for their water in the GRB.

<u>Discussion</u>

Australian Markets

This work continues the work that began with Khan et al. (2009) and fits alongside current efforts to model water prices being done by public and private entities. It is difficult to compare these results as being equivalent constructs with Khan et al.'s given the structural changes in the marketplace. Khan et al.'s work took place before the Water Act of 2007 so was modelling prices during the time of pooled pricing as opposed to the bid ask system post-2007.

Also, their work included allocation percentages as a main input driver, and this work does not. Considering those differences, the results generated here produce performance in line with the work that was done in the pooled pricing environment. This work also extends model use by transferring a validated model to a different location to generate price information.

In Australia, water price modelling is being done in the public sector by groups such as the Australian Bureau of Agricultural and Resource Economics and Sciences, and in the private sector by consulting firms such as Aither (ABARES, 2018; AITHER, 2017). Generally, those models are constructed using indexed commodities numbers and often produce quarterly price outputs. The research here enhances those efforts by increasing resolution to model prices daily and do so with a model that can be transferred.

Australian water markets are often volatile, which drives high variance in market data; therefore, variance in predictions can be high, too. This has been thoroughly discussed by Williamson (2008) who presents an excellent summation. The modeling results indicate it is possible to predict Australian water prices for any given day reliably. In the case of the allocation (temporary) market (Figures 4 and 5), non-linear modelling techniques offer better performance than linear approaches. This is partly due to the generally non-linear relationship between model inputs and outputs. Different agricultural products have different seasonal requirements and life cycles and behave in a nonlinear fashion in reaction to climatic variability. Even if seasonal variation among inputs could be calculated with enough certainty to remove via de-trending, there would still be the issue of the variability of natural precipitation affecting the system as well as the unpredictable effect of human behavior in the marketplace—and thus price. This is particularly highlighted by the contrasting performance of the linear model with, and without, the entitlement pricing data. The entitlement pricing is highly correlated to the allocation price in a linear fashion, so when it is present the model does well. When that variable is removed the linear model suffers a loss in performance, losing half of the R^2 value and doubling the MSE (from 0.70 to 0.29 and from 4,722 to 10,303).

It is important to remember that the trading regimes are impacted by a human component that can be both emotional and irrational and can contribute to the non-linearity of the system. Non-linearity of a system makes the modelling problem ideally suited for AI/ML approaches when sufficient data covering most potential cases is available. Neural networks were tested, but performance was lower than that generated by the random forest models (Figure 2-13, Table 2-2). The random forest approach offers the additional benefit of being more informative about the system generally by providing information ranking the inputs by importance. Data is a limiting factor in this case. Neural networks do best when they have very large data sets to learn from, and market data that is distilled to a daily number is constrained to the number of trading days in the time period. While in this case the random forest outperformed the neural network (Table 2-2), if there were more cases in the dataset the neural network might have outperformed the random forest. Generally, if time and resources allow, best practices may be to run both. This would allow for an evaluation of which model affords the superior prediction, while also capturing the secondary information about the system that the random forest provides. As more input variables are added to the model and performance will continue to be tested, but even in the present iteration the model can predict Australian water prices with useful performance for market modeling and potentially operation.

Model Transfer

To transfer the allocation model to the U.S., the original Australian model was modified by omitting the entitlement input. This had to be done because there is not enough data regarding entitlement prices in the U.S. to run the model with it as an input. As markets develop that may change, but the data requirements of the model were too great to use it in this case. When predicting allocation markets the entitlement variable was the most important predictor, and vice versa in terms of the prediction of entitlement market's relationship with allocation pricing. Results from the omission of that key variable saw only a marginal decrease in model performance (Figures 5 and 8). MSE values of the two models (with entitlement data and without) are 3246 and 3826 respectively and the R^2 dropped from 0.76 to 0.71. While both numbers indicate a decrease in performance, the drop is not precipitous enough to affect practical model application.

Model runs were also executed without precipitation as an input; there may be geographies that want to use a water pricing model but lack historical data on the bio-physical input (precipitation). Also, to form a general model over large geographic areas, the model was trained without the use of precipitation data. Model runs with and without precipitation as a predictor showed no loss of model performance. Commodities prices are derived from market makers that are using weather predictions in there trading strategies, so the commodities prices themselves indirectly include the effect of the precipitation data, which may explain why the precipitation itself did not drive the model. Moving forward other determinants of supply (e.g. dam levels) may be included as inputs to see if there are additional supply side factors that may be impacting daily water price numbers to a greater extent than precipitation.

Finding suitable data in the U.S. to validate the model is challenging. In the West, where the country is most arid, much of the water provided to users is subsidized by the government, which hinders the type of price discovery available in a market (Fahlund et al., 2014). Water traded on a market (regardless of the state) often has very high price variability between buyers based on who they represent (e.g. mining interests typically pay more than agricultural interests) which again make an understanding of price data difficult (Brown, 2006; Yoskowitz, 1999). This paper adds to the understanding of pricing water by, though model transfer, framing the price of water in terms of the correlated prices of the commodities it produces.

The scope of the prediction was then narrowed to the basin level, and the model was transferred to the Guadalupe River Basin, Texas, USA. Model runs for 2010 and 2011 (Figures 11 and 12) in the GRB show that price predictions are consistent with the forbearance payments being paid in a quasi-market setting. In 2010 the mean price predicted is $137.60 and in 2011 the mean predicted price was $114.16. In the GRB this is compared to the VISPO payments of $160/AF and the ASR payment of $100/AF in all years as discussed above. The goal was not to have the model predict the forbearance payment number, and neither the VISPO nor the ASR payment is arrived at in a market setting or mathematically calculated outside of what is an acceptable business cost to the EAA/SAWS and its members (to our knowledge). With pricing information of cash water trades in the U.S. being so scarce, the GRB was chosen to gauge if the transferred model outputs prices that are reasonable when compared to quasi-market activity. This comparison has considerable limitations given the nature of the VISPO/ASR pricing methods and model uncertainty; yet the model is making predictions that are realistic if judged in terms of the range of ASR ($100/AF) to VISPO ($160/AF) payments.

Conclusion

The results indicate that it is possible to model and predict water prices in the Australian marketplace, then transfer that model to other geographies to approximate water prices. The conclusions that can be drawn fall into three categories: for Australia, for model transfer, and for the applicability of the method in general. In Australia, spot water markets are highly developed, allocating large volumes of water on an annual basis. Market participants can benefit from applications of a price modelling tool to help them understand the factors driving the system and to make sound decisions. AI based modelling techniques showed notable improvements over linear modelling techniques. Given that the market is highly developed, a next step in the application of AI/ML techniques may be to help expand the financial product mix available to the water trading community by helping to launch more complex offerings, such as futures and options.

The exploration of training and validating a model with robust data, then transferring that model to a target geography, is promising. Based on the limited availability of validation opportunities, the conclusion is that the results are encouraging, but not definitive. It is important to frame the utility of the output in terms of who will be using the predictions, and for what. With the launch of the California water pricing index (NQH2O) it certainly appears that there will be opportunities to test the model in burgeoning markets (WFM Staff, 2019). Using the pricing information in the GRB was a good starting point. However, considering how the GRB pricing is established the utility of the prices for validation is limited. Looking ahead, the model can be tested where there is a higher degree of market driven price activity: the Rio Grande Valley. The RGV operates under a different paradigm than much of the state of Texas, so it was not used in this work where the motivation was to illustrate water pricing methods for the state in general. The RGV also has hydrology that naturally lends itself to the utilization of a natural conveyance of water with the location of the dam upstream. There are other international markets—such as in South Africa—where the model can also be transferred in future work.

Computational power has grown and continues to grow at incredible rates. In addition, the amount and availability of data is greater than it has ever been. Taking these two facts into consideration, the possibilities for AI/ML as applied to problem solving are staggering. This paper helps to illustrate how these techniques can use data creatively to find novel ways to model possible answers to our questions. Using market data to learn about our interface with the environment is a new direction. Moving forward work will be done to look at other places where market data can be correlated to environmental effects and there may be applications where predictive modelling with this data can offer insights into the downstream effects of our economic activity without having to put technicians or sensors in the field.

The model may become more adaptive if a better correlated variable is found to use in place of rain, other variables will be evaluated for the purpose such as soil moisture content and dam levels. Also, increasing the number of input variables may increase model accuracy and improve the opportunities for model transfer. Even if additional inputs cannot be found, Breiman makes an interesting suggestion regarding datasets with a small number of inputs. He suggests randomly combining the inputs to create "new" inputs to include in forest building to improve the forest (Breiman, 2001). As model transfer develops, increasing the amount of available inputs in the training set will allow for variable selection to increase, thus increasing the applicability of the analog. To help the Australian marketplace develop, the model has been predicting future prices of water, and from that it may be possible to price an option for the Australian marketplace. In the U.S. the pricing data can help inform discussions of market development, as well as help formulate fair market prices. In addition, though a robust cash market will need to be in place, an objective is to price options on water in the U.S.—both traditional short-term options as well as longer term 5-10-year option styled products.

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CHAPTER III:

PRICING OPTIONS CONTRACTS ON AUSTRALIAN WATER

Introduction

Spot markets for Australian water are longstanding and highly active, having matured over the past decades. These markets are the primary mechanism for delivering water in the Southern Murray Darling Basin (SMDB), where over 90% of the country's water is traded (Australian Bureau of Agricultural and Resource Economics [ABARES], 2018). As the cash market has grown, efforts have been made to price derivatives in the marketplace with limited success. To date, derivatives have not been marketed on a formal exchange. Having a viable method to price options would help bring this product to market and aid participants by giving them increased flexibility in their future planning to secure the water they may need to help insure against catastrophic price activity.

Cash prices are often referred to as spot prices, as they are the cost to buy something "on the spot." An option is a financial instrument that gives the buyer the right (option) to buy an amount of a commodity at a specific price until a specified date in the future, called the expiration date (Williamson et al., 2008). Another common term in options trading is "strike price." The strike price is the price an option holder will pay for the underlying asset if they choose to exercise the contract. There are several reasons options are useful, particularly for cost management and supply management. The benefits of having options on Australian water have been widely discussed (Cui & Schreider, 2009; Plummer & Schreider, 2015; Williamson et al., 2008). These contracts help water buyers plan for future needs by securing the right to make future purchases. If, for example, a farmer knows that she will have financial difficulty if the price of water rises to a certain level, she could mitigate that possibility by buying options to secure the right to make water purchase at a more desirable price should the need arise.

Pricing water options is challenging, particularly due to high levels of volatility in the Australian cash water market. When discussing volatility in markets there are two types: historical and implied. The main conceptual difference is that historical volatility looks backward in time, and implied volatility attempts to look forward. Historical volatility can be calculated by looking at price activity in terms of deviation from the mean. Implied volatility can only be calculated if the option price is known, then it is possible calculate implied volatility. Implied volatility is a measure of what traders expect will happen to price from the present to the date the option expires. In the absence of an options market that would provide contract price data, this work focuses on historical volatility. Bear in mind that after option strike prices have been set, the price at which an option is trading will change to reflect market sentiment and be expressed as implied volatility. This allows for dynamic pricing of the asset to align with market participants' expectations of price activity. Volatility has inspired much work that attempts to account for it in pricing models. Building on this concept, option pricing models have been constructed that allow for seasonal price jumps to occur or that omit the most volatile data (Cui & Schreider, 2009; Williamson et al., 2008). This paper offers a new method for valuation that combines a volatility calculation with the output of a predictive model to inform the Black-Scholes (or Black-Scholes-Merton (BSM)) mathematical model to produce option prices. BSM is the original, and by far the most popular, continuous-time mathematical model used in finance (Capinski & Kopp, 2012). It has been observed that the traditional BSM method for pricing options is incompatible with the price behavior of water markets (Cui & Schreider, 2009; Plummer & Schreider, 2015; Williamson et al., 2008). Villinski's work in the Rio Grande Valley

(RGV), Texas, indicated that volatility of the asset does not behave in a manner consistent enough to apply the BSM model to derive options' valuations (Villinski, 2003). However, it should be noted that Villinski also mentioned other compatibility issues with water markets and BSM, particularly transaction costs and the low trading volumes in the cash market she studied in the area. When looking at the price history in the RGV, there is significant price discrimination between different types of buyers which is impacting volatility calculations (Yoskowitz, 1999). A necessary assumption in the BSM model is that prices are continuous and follow geometric Brownian motion (Black & Scholes, 1973). In short, the arguments generally agree that the price behavior of water fails to meet necessary BSM assumptions, particularly that volatility of the underlying asset is known and constant.

While water may fail to meet the assumption regarding Brownian motion, almost all underlying instruments that options contracts are based on also fail to meet this criterion, at least sometimes. For example, while common stocks in the U.S. may not be as volatile as spot water prices in Australia, they can certainly fail to meet the same standard. Price jumps (or gaps) routinely occur based on earnings, news, or both, and these gaps are a break from the Brownian price assumption. Some of the most dramatic price jumps in the U.S. stock market were in 1929 and 1987 when the market crashed (Cui & Schreider, 2009). In 2020 markets saw historic swings resulting from the pandemic involving COVID-19. Given that options are routinely traded on common stocks and priced with BSM, BSM pricing may yet work for water markets as well.

In the U.S., work has been done to price options on water. One method involves pricing an option based on the cost of the next best alternative supply. If there is a positive present value, then the option has net economic benefit, which is when the buyer of an asset purchases it for a price less than what they were willing to pay (Michelsen & Young, 1993). While this may be useful for framing the price of water, the technique does not produce a value for the option's premium (the amount the buyer of the option pays the seller to purchase the contract, apart from the value of the underlying asset). As mentioned above, experiments with BSM pricing have been conducted in water markets, but in thinly traded markets (markets where there is not much activity) these efforts were not fruitful (Villinski, 2003). More recently an exchange traded fund (ETF) has been introduced as a water pricing index for some California markets (WFM Staff, 2019). This index is not currently traded on the exchange, but the plan is to use it to price derivatives as Veles Water introduces options and futures in the next few months (as of September 30, 2019 [L. Coogan, personal communication, September 30, 2019]).

In Australia, efforts were made to build options by applying the ideas from Michelson (2008). Some of this work revolved around reconciling the differences in the risk associated with trading permanent rights and temporary allocations and using options to augment environmental flows (Heaney & Hafi, 2005). In Australia, permanent rights are similar to water rights in the U.S. and represent a holder's entitlement to a share of water annually. Temporary allocations represent the actual amount of water delivered to permanent rights holders in a given year. The same "cost of next alternative" method was also applied in Australia to create a dry year option that would move water to urban areas in times of drought (Page & Hafi, 2007). There is interest in developing Australian options, but currently they are only trading futures (called "forwards") in one-off transactions (T. Wilks, personal communication, October 2018). Current price reporting systems do not have the ability to record these trades accurately, so these one-off transactions contribute to misleading price reporting in cash markets. A crude technique to identify forward transactions is to look at the price history and identify clustered trades that appear to be outliers, which may be forwards. It is indiscernible if those trades were made in the past, or the prices represent what price the water will trade hands at in future (T. Wilks, personal communication, October 2018).

A literature review has not revealed any existing work that uses a combination of the predictive capabilities of Artificial Intelligence (AI)/Machine Learning (ML) with historical volatility calculations to price an option using BSM. AI/ML has been used in the water price modelling space, but only in terms of spot markets and generally with quarterly resolution (Khan et al., 2009). Options have been experimented with, but these attempts did not include the AI component to help frame strike prices (Williamson et al., 2008).

This work tests the hypothesis: BSM can price options on Australian water if volatility can be lowered and random forest model outputs can predict future Australian water price activity accurately enough to be used to frame options' strike prices. Therefore, the hypothesis is tested: Volatility levels in the Australian water market can be consistently calculated at < 300%.

If volatility can be accounted for in a defensible fashion, and a reliable strike price framed, it should be possible to bring options to Australian water markets using BSM. In this case, these strike prices can be used to mitigate some market concerns regarding the use of smoothed volatility in the BSM equation. If the model does well, an accurate price prediction should help alleviate market participants' concerns that risk may be understated as a result of dampening volatility calculations. Therefore, this paper will calculate volatility, frame a strike price, and output option values. If options can successfully be priced for the Australian marketplace, market participants may benefit from the additional trading strategies that would emerge for planning needs.

Methods

Site Selection and General Approach

To revisit the possibility that BSM can be used to price options on water in Australia the following multi-step approach was taken:

1. Alter the random forest from Chapter 2 to model prices 90 days into the future, performing additional data processing as necessary.

2. Calculate historic volatilities for the Australian cash water market and evaluate alternate calculation methods.

3. Using strike prices provided by the predictive model (1), combined with volatility calculations from (2) generate BSM pricing chains.

4. Evaluate and discuss the results.

The study site is the SMDB in southeastern Australia (Figure 3-1), where over 90% of water trading occurs in the country and where modelling and derivatives pricing efforts are currently underway.

Figure 3-1. Murray Darling Basin, Australia
from https://www.mdba.gov.au/sites/default/files/pubs/Murray-Darling_Basin_Boundry.pdf

Predictive Model

This chapter uses the modelling efforts from Chapter 2, and a detailed explanation of the methodology used in the random forest models can be found in Chapter 2, or for a general understanding see Breiman (2001). Taking the modelling method from the previous chapter the random forest model, a decision tree, was tuned to predict cash water prices 90 days in the future–the typical lifespan of an option—by using commodities data and precipitation as inputs.

The data was comprised of prices for water, sorghum, cotton, beef, barley, and precipitation (identical to Chapter 2) from the SMDB with one significant adjustment.

Market data naturally occurs as a time series, so when zero value trades were removed from the data set, the resulting dataset showed gaps in that time series. For example, if the price of water 90 days from today is a zero-value trade there is not a data point to predict, rather the 90th instance would be a day near, but not at, today plus 90. To achieve the goal of making a 90-day prediction to price options, those dates with no match were removed from the set (around 500 of the 2500 cases). Experiments were conducted to impute the missing data—both via multi-variate and k-nearest neighbor methods—but the model performed sufficiently by simply removing the zero priced trades. The model was trained and tested on actual reported trade data as opposed to data that was arrived at synthetically via imputation.

The 90-day time horizon was chosen to mirror how many options currently trade. These 90-day periods equate to four option periods per calendar year and naturally coincide with farmers' seasonal needs. First, predictions were made for all years combined using 85% of data for training and 15% for validation. Then, quarters were tested that were representative of typical quarters in the market as measured by volatility; in each case, the model was trained on all data except the target quarter and the quarter leading up to it, then tested on the target quarter. This ensured that the model was not privy to the test data while it was being trained. Two quarters (180 days) were omitted so that the predictive model could use the first 90 days to make a prediction for the next 90-day period. The predictions were then used to calculate 10-day moving averages (MAs) for use as strike prices in the BSM calculations.

Predictions for the 90th day from the date the prediction was made were tested, as were 3, 10, 20 and 30-day MAs. Ultimately, a 10-day MA was chosen to represent the price prediction for initial option pricing. Trades in the test data are reported with both the final day number and the 10-day MA as well. The goal of the test is not to see if the model can make precise predictions 90 days into the future, but to see if the model can generate predictions accurate enough to inform initial pricing of options effectively most of the time. When options are created for stocks the strike price often begins at fair market value; for a stock this is simply the price of the stock on the day the option was created. When combined with the known volatility of the stock the option can be priced, but with water the volatility is too great to rely on this approach. The use of an MA has a smoothing effect which decreases the impact of outliers and questionable data points in both the predictions and test sets. There is a tradeoff between accuracy and precision and 10 days is a good fulcrum for offering a fair idea of price by diluting the impact of transactions with high variability and capturing the tone of the market near the expiration date of the option. If trade reporting improves and volumes increase, the data will improve, and it may be possible to shorten the number of periods in the MA in the future. However, some market makers and participants may want to increase the number of periods in the MA, but there will be a point of diminishing returns. Too much smoothing can suppress volatility to levels that are deemed unrealistic to market participants who are assuming the market risk by selling options.

Volatility

Volatility is the most important variable when pricing options. Volatility is a measure of how much prices generally move from the mean in daily trading, is the common measure of an asset's risk, and is a key component to options pricing. The higher the volatility the more expensive an option will generally be. There are two types of volatility commonly used in options parlance: historical and implied. Conceptually the main difference between the two is that historical volatility is calculated by looking backwards in time, at prices that have already been recorded. Implied volatility is what traders are more interested in because it attempts to account for the volatility that may occur between now and the time an option expires. This creates a bit of a paradox when it comes to initial pricing. To find implied volatility, BSM is solved for volatility by entering the option price with the other variables into the pricing equation. However, to know the option price you either need to have a market to refer to or know the volatility to solve the equation. This is where the historical volatility becomes useful, as it can be used to solve BSM. This backward-looking volatility often expresses volatility at levels very different than what traders anticipate (expressed in implied volatility).

Characteristics of volatility's impact on option premiums are non-linear and the effects of volatility are affected by the spread between the spot price and the strike price. However, sub-600% volatility levels begin to produce the pricing normally associated with BSM curves, and levels under 300% begin to create more attractive pricing. Volatility above 1000% tends to produce option prices that begin to approach spot price, which is the maximum (Figure 3-2). For reference, in early 2020 stocks whose options display high implied volatility include Tesla, Agile Therapeutics, and Intelsat and implied volatility was around 170%, 250% and 290% respectively. Crude oil contracts set to expire in 10 days were trading with implied volatility ranging from 20-45%, gold contracts with 50 days remaining were hovering around 10%, and corn generally is between 10-20%.

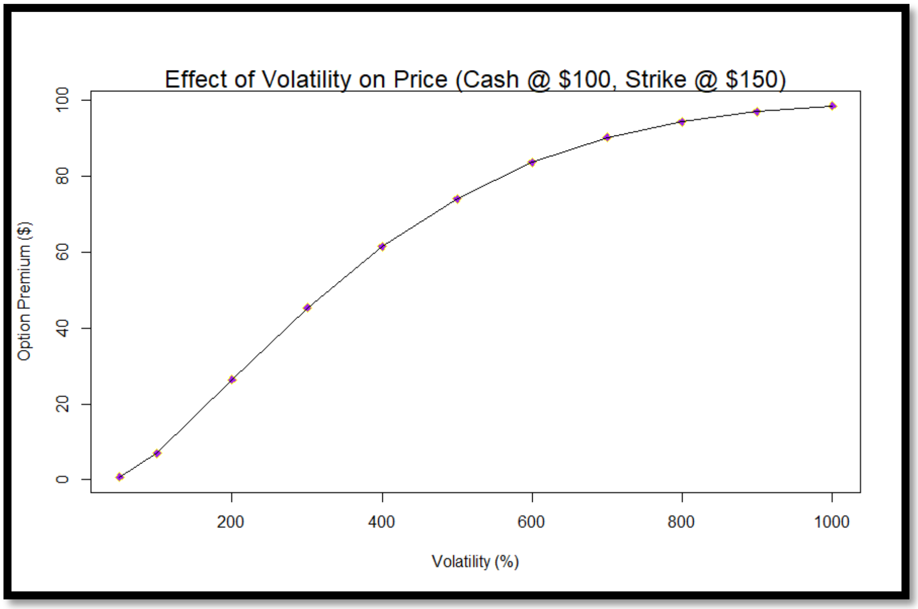

Figure 3-2. Volatility's relationship with price when spot price is $7.49 and strike price is $37. The non-linearity of the relationship implies that small decreases in volatility, particularly at the tails, have little impact on premium as calculated by BSM.

Originally, the model put forward in BSM calculates volatility using the standard deviation of daily log returns applied to historical prices (Black & Scholes, 1973). The first standard practice to calculate volatility was equal weighting of historic averages; volatility for the next *n* days was forecast by an equally weighted average of returns squared over the previous *n* days (Alexander, 2008). Since that time, other measures of volatility have been developed. Parkinson's was the first advanced technique and used daily highs and lows, but it assumes continuous trading (Bennett & Gil, 2012; Yu, 2002). Garman-Klass incorporates opening and closing prices, and the Yang-Zhang approach can handle drifts and jumps but assumes continuous pricing (Bennett & Gil, 2012). In the case of the robust, but still developing, Australian market there are significant limitations regarding the timeliness and accuracy of price reporting. For example, a trade consummated at the open of any given trading day might not get reported until the afternoon, or even possibly on another day. These limitations impose challenges to using standard volatility calculations, but as reporting becomes more reliable these methods may become relevant.

Confining ourselves to more basic volatility calculations still leaves some decisions to be made. Volatility can be calculated using a variety of methods: only matching periods in history, with the output from the predictive model (future volatility), over that last 12 months, or any number of other ways (e.g. 10-day, 21-day, etc.). To understand which calculation would best inform options pricing annual volatility and quarterly volatility within each year were both computed.

For these calculations, volatility was calculated over each quarter of the data set using Equation 3-1, which is a widely accepted measure of volatility (Alexander, 2008; Padhi & Shaikh, 2014).

Equation 3-1

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\left(R_i - R_{avg}\right)^2}{n-1}}$$

In Equation 3-1, σ is the measure of volatility, calculated as the sum of the square of all the differences between the daily price (R_i) and the average price (R_{avg}) divided by the number of periods minus 1. It is important to remember that the formula yields a daily measure of volatility, so to communicate volatility over a time period, the daily number must be multiplied by the square of the number of periods being examined. To calculate annualized volatility, this means multiplying the result of the above equation by the square root of 252 (the number of trading days in a year).

Volatility is calculated from Equation 3-1 using a time period identical to the option (90 days) looking back from the day the option would have been conceived and annualized. Given the high degree of variability inherent in reported water prices, volatility was originally calculated four different ways: looking back at 90 days of prices, the 3-day MA of those prices,

prices without outliers (1.5x the interquartile range (IQR)), and finally, using the 3-day MA of prices excluding outliers. After executing these calculations, the decision was made to also calculate the volatility of the 10-day moving average of prices as well.

Black-Scholes-Merton

With a strike price generated by the predictive model (Equation 2-7 through 2-10) and using calculated volatilities (Equation 3-1) option pricing can be derived using BSM. The Black-Scholes-Merton partial differential equation is:

Equation 3-2

$$\frac{\partial V}{\partial t} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS\frac{\partial V}{\partial S} - rV = 0$$

where V = price of option, S = asset price, t = time, r = risk free interest rate, and σ = volatility (Black & Scholes, 1973). In a practical setting the risk-free interest rate will fluctuate based on prevailing market conditions, but for the purposes of illustration all calculations of BSM here set $r = 0$.

<u>Results</u>

Volatility Calculations

The influence of volatility in the BSM calculation is of paramount importance. Initially, quarterly and annual volatility numbers were calculated using Australian water prices to understand what level of volatility is in the marketplace, these numbers were then averaged to understand how volatility has behaved over time (Figure 3-3). Volatility for many common stocks is in the 5-30% range, but there are exceptions. For example, in January 2020 the stock with the highest volatility was Advanced Micro Devices (AMD). Looking at option prices for AMD, implied volatility levels range up to ~450%. Even if volatility calculations for water are higher than the normal 5-30% range, but are in the realm of AMD, options may be marketable. In commodities markets, a volatility of 100% is not uncommon—particularly in crude oil.

Average volatility for Australian water across quarters is 142%, the lowest quarterly average is Q1 (101%), and the highest quarterly average is Q3 (194%). The last number is greatly influenced by the volatility that occurred in the first two years the market began trading. In its infancy, the market may have been susceptible to greater price fluctuations as participants learned valuation and trading techniques. If those years are removed from the average for all years, the number shrinks from 195% to 157% and will be treated as its own case, as the first two years represent the market in its infancy. As an aside, prices from the first two years were included when training the predictive model as it maximized the range of prices the model was able to learn from, enhancing the model's ability to predict prices over the extended range of prices these years include.

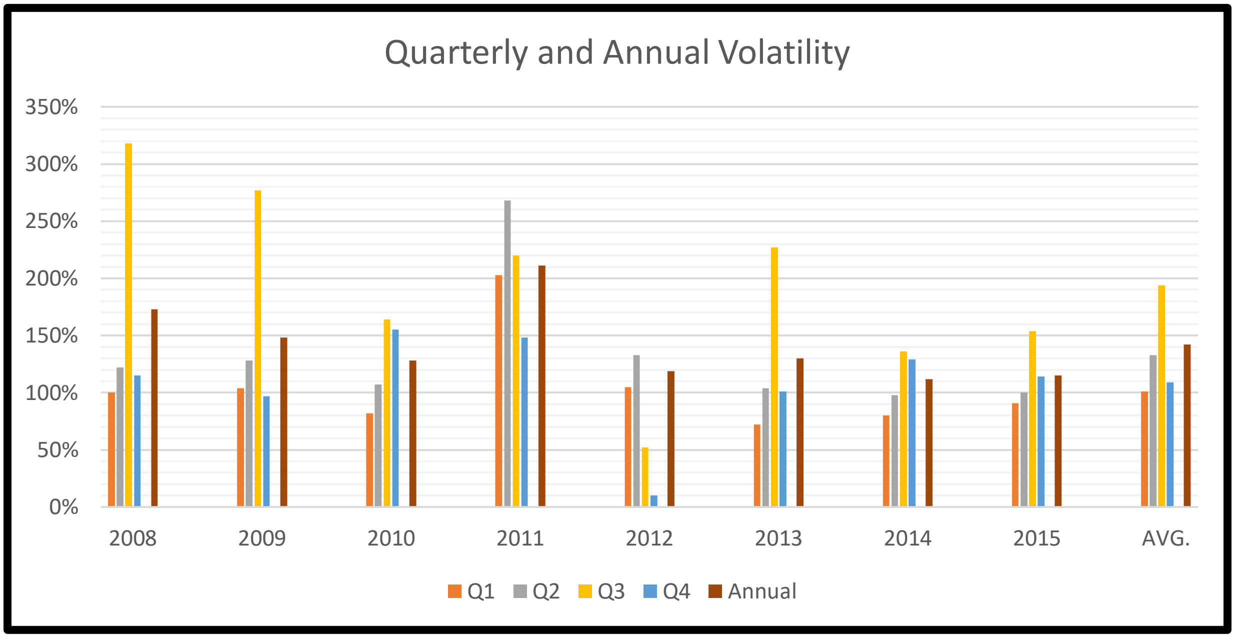

Figure 3-3. Daily volatility: Australian water prices calculated quarterly and annually for 2008-15, average quarterly volatility can be seen on the right. Average volatility across quarters is 142%, the lowest quarterly average is 101%, and the highest quarterly average is 194%.

After calculating daily volatility on a quarterly basis and finding the average over all quarters (Figure 3-3, averages on right), those average volatility numbers were evaluated in conjunction with the predictive model and BSM. Price data is required for the predictive model to generate output, so quarters were selected from the dataset where the volatility was similar to the averages to be tested to represent periods of average volatility, low volatility and high volatility (Table 3-1).

Table 3-1. Historical volatility levels with quarters matched for model runs.

Volatility Level	Calculated Volatility (Figure 3-3, AVG.)	Volatility for Test
Average	142%	136% (3Q 2014)
Low	101%	100% (2Q 2015)
High (all years)	194%	203% (1Q 2011)
High (without 2008-09)	157%	155% (3Q 2010)

Volatility was calculated five ways for the periods used as proxies for historical levels: using daily prices, the 3-day MA of daily prices, daily prices with outliers omitted, the 3-day MA of prices without outliers, and the 10-day MA of prices. The objective is to see if a method produces sub-300% volatilities. The main consideration when removing outliers is that when outliers are not prevalent, volatility is not reduced by the omission of them. By the admission of the Australian government and market participants price data is imperfect so the goal was to find a way to reduce volatility to account for the inaccuracies. When outliers are present, and removed, it causes the 3-day MA to have lower volatilities (Table 3-2). The longer the period of the MA the greater reduction in volatility.

Table 3-2. Annualized volatility percentages calculated for the historical periods selected to emulate market conditions during periods of average, low and high volatility. The longer the period of the moving average the greater the impact on the volatility calculation. Omitting outliers influences calculated volatility when outliers are present, reduces volatility only marginally in normal market conditions.

Volatility Calculated From:	Average Volatility	Low Volatility	High Volatility	High Volatility (w/o first 2 years)
Daily Prices	1582%	1391%	2400%	1620%
3-day MA of prices	455%	474%	495%	692%
Prices w/o outliers	1582%	1356%	991%	1620%
3-day MA of prices w/o outliers	455%	451%	317%	692%
10-day MA of prices	121%	165%	131%	174%

The higher the volatility of the period the greater the MA smoothing had on the data, yet in all cases using the shorter period MA results in high levels of volatility in comparison to volatilities of options commonly traded in various markets. Changing the length of the period used in the smoothing affects the results of the volatility calculation. Application of smoothing techniques reduces volatility to usable levels but does not always preserve the relationship between periods. It is possible to consistently produce sub-300% volatility levels if the 10-day MA is applied to cash prices before the volatility calculation is executed.

Strike Prices

Knowing that today's price of water is not going to work as a starting point for options strike prices, due to the volatility, the predictive model was employed to provide initial strike prices for options. To understand how well the AI/ML predictive model is working, a linear model was constructed, for comparison, to predict prices 90 days into the future and produced an R^2 value of 0.46 and an MSE of 7479. The random forest cast a prediction using the same data and produced an $R^2 = 0.71$ and MSE = 2888 (Figure 3-4). Plots of predictive results are presented in terms of the model casting predictions on the test set which is a subset of the original data the model has never seen. The test set is comprised of data points randomly selected from the original dataset that are in order chronologically, but not necessarily concurrently.

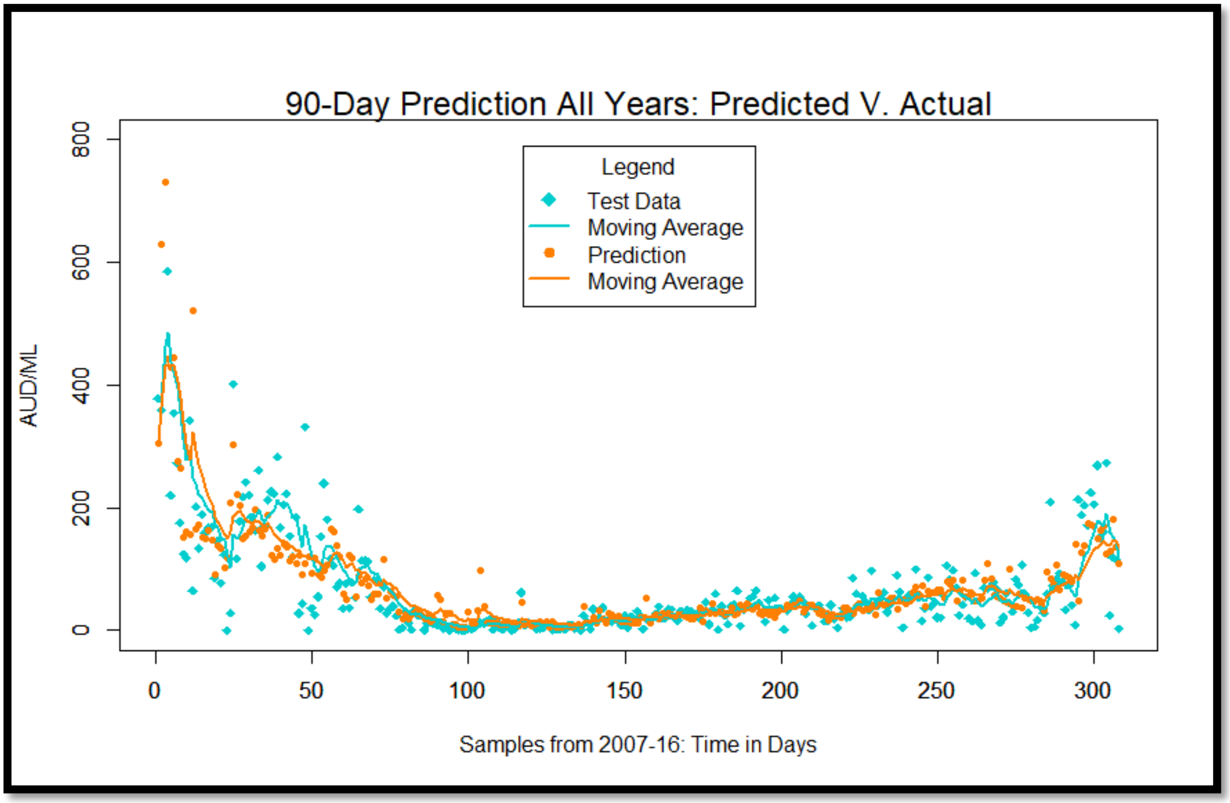

Figure 3-4. Random forest prediction 90 days ahead, 15% of data as test set: $R^2 = 0.71$ and MSE = 2888 as compared to the linear model which produced an $R^2 = 0.46$, MSE = 7479 indicating that the random forest is tracking future pricing and does so better than the linear approach.

While the MSE allows a comparison of model performance against another model and gives an understanding of the magnitude of error of the model generally, it may not be the best tool to communicate how the model is performing for any given prediction. To better illustrate this, and to test the hypothesis, a separate model was created to predict every day in the series. After these predictions were made both the predicted prices and the test data prices were smoothed with the same 10-day MA, then a histogram of model performance was generated by dividing the real price by the predicted to depict model accuracy in terms of frequency (Figure 3-5). Drilling down into the histogram of error data, the model is predicting within 34% of the target 68% of the time and is within 50% of the target 86% of the time.

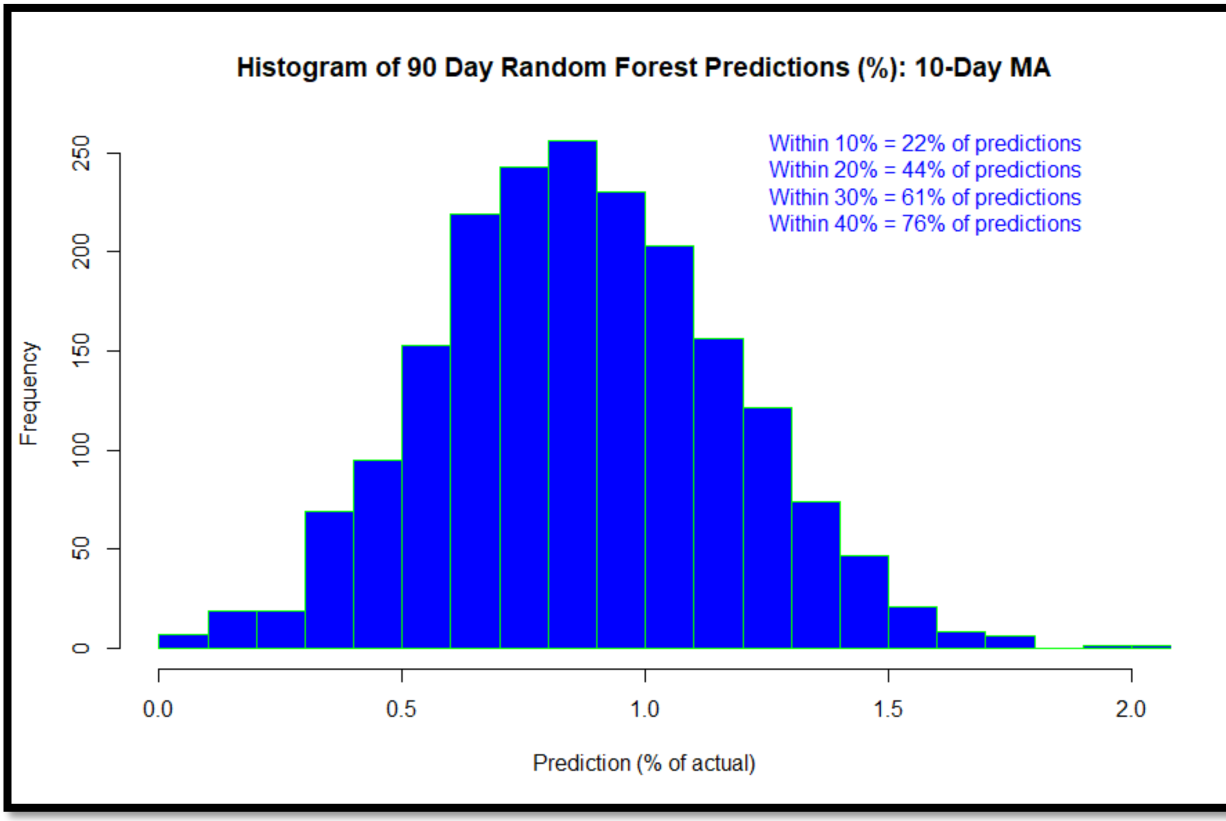

Figure 3-5. Histogram of accuracy of random forest predictions for water prices 90 days into the future with 10-day MAs. Separate models were constructed for every day in the series to express accuracy and frequency in a way that market participants can use.

If market participants favor the 3-day MA a histogram of error was also created for every day in that scenario and less smoothing results in a decrease in general accuracy and wider dispersion of error (Figure 3-6).

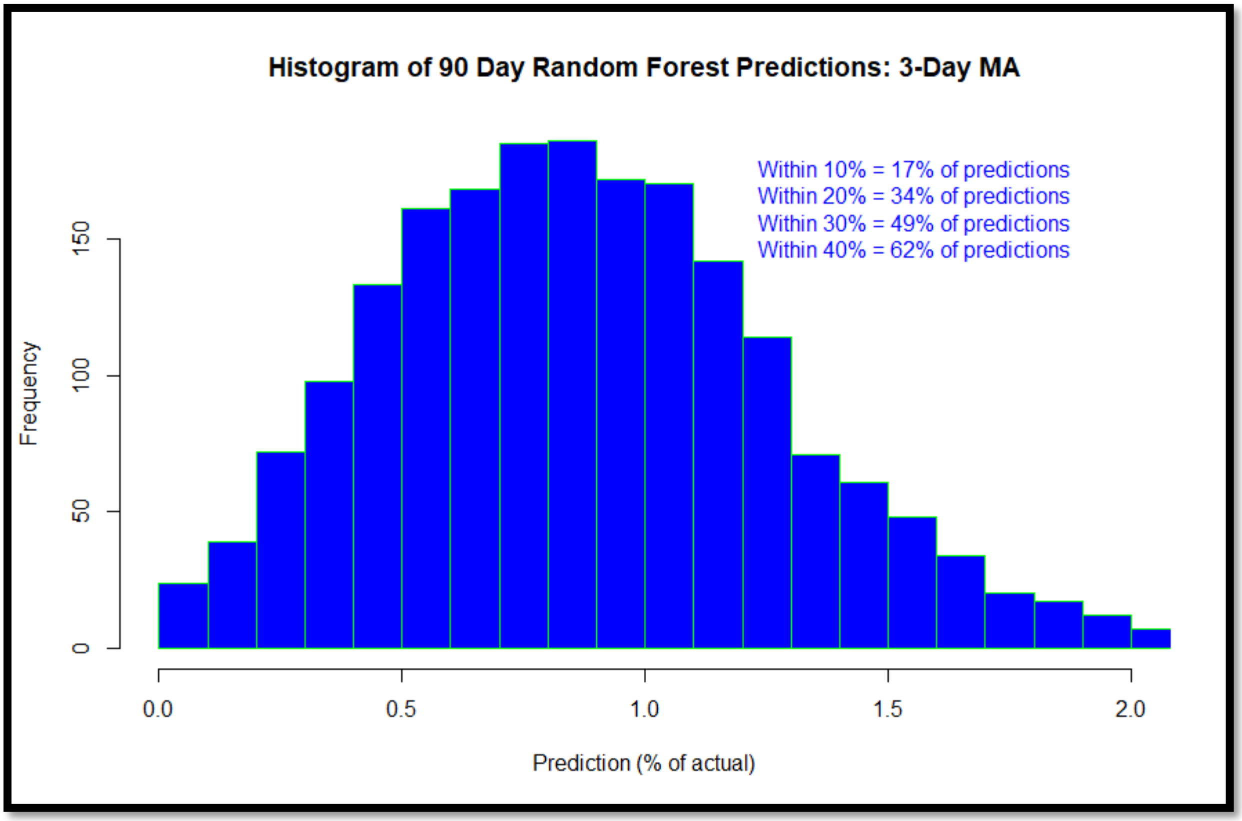

Figure 3-6. Histogram of error for every day in the series calculated with a 3-day MA of prices. Combined with Figure 3-5, this implies that the shorter the time of the MA the less accurate the prediction becomes.

To test the effect of longer-term predictions on model accuracy, models were also constructed to predict shorter timeframes. As the time shortens between the day the prediction is made and the day the prediction is for, we would expect the model to produce more accurate predictions. In this case the model does move toward convergence as we shorten the time horizon as illustrated by the histogram of error for predictions made 5 days into the future (Figure 3-7).

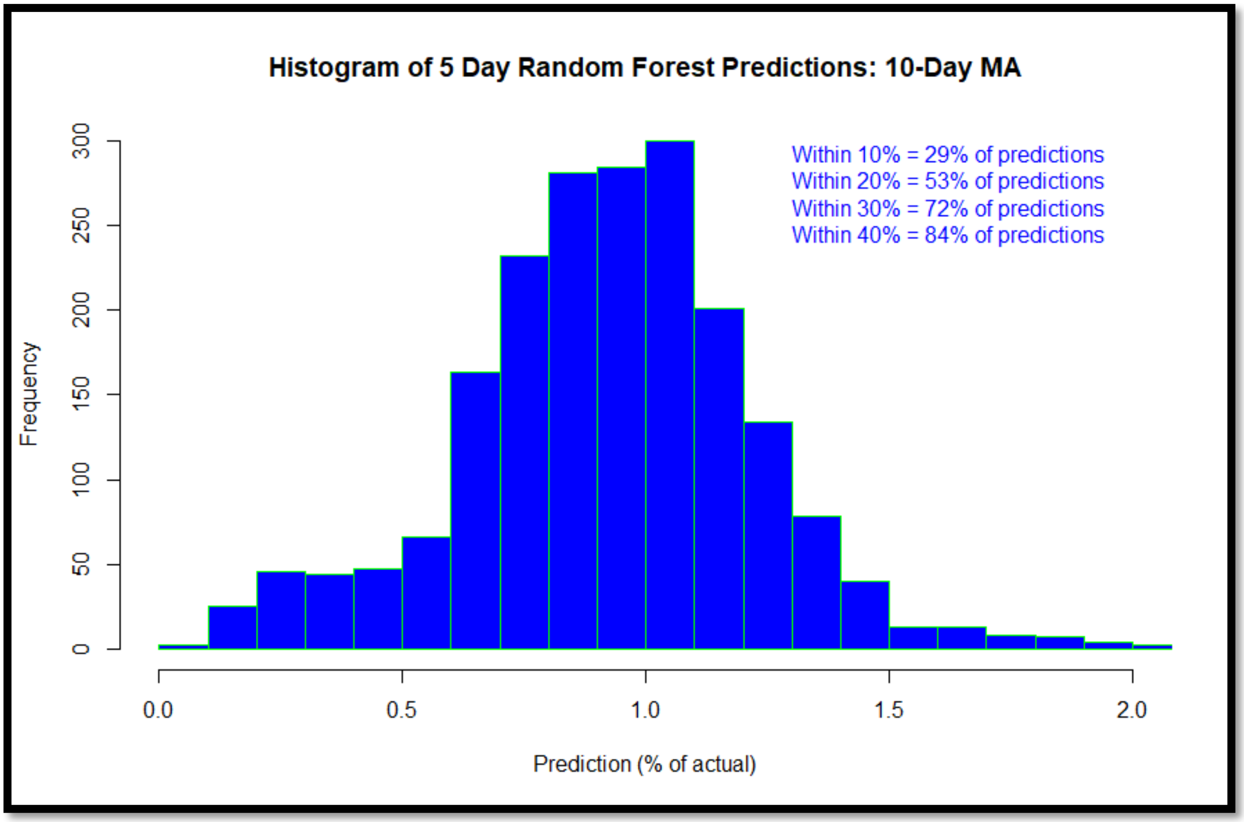

Figure 3-7. The random forest model predicts prices 5 days ahead illustrating that the likelihood of more accurate predictions increases as the time span of the prediction decreases.

Next, model predictions were made and compared to the MAs of actual prices for the periods representing the volatility scenarios above (average, low, high, high without the first two years). First the period mirroring the average historical volatility was tested (Figure 3-8). This period has a volatility of 155%, near the average historical volatility of 157%.

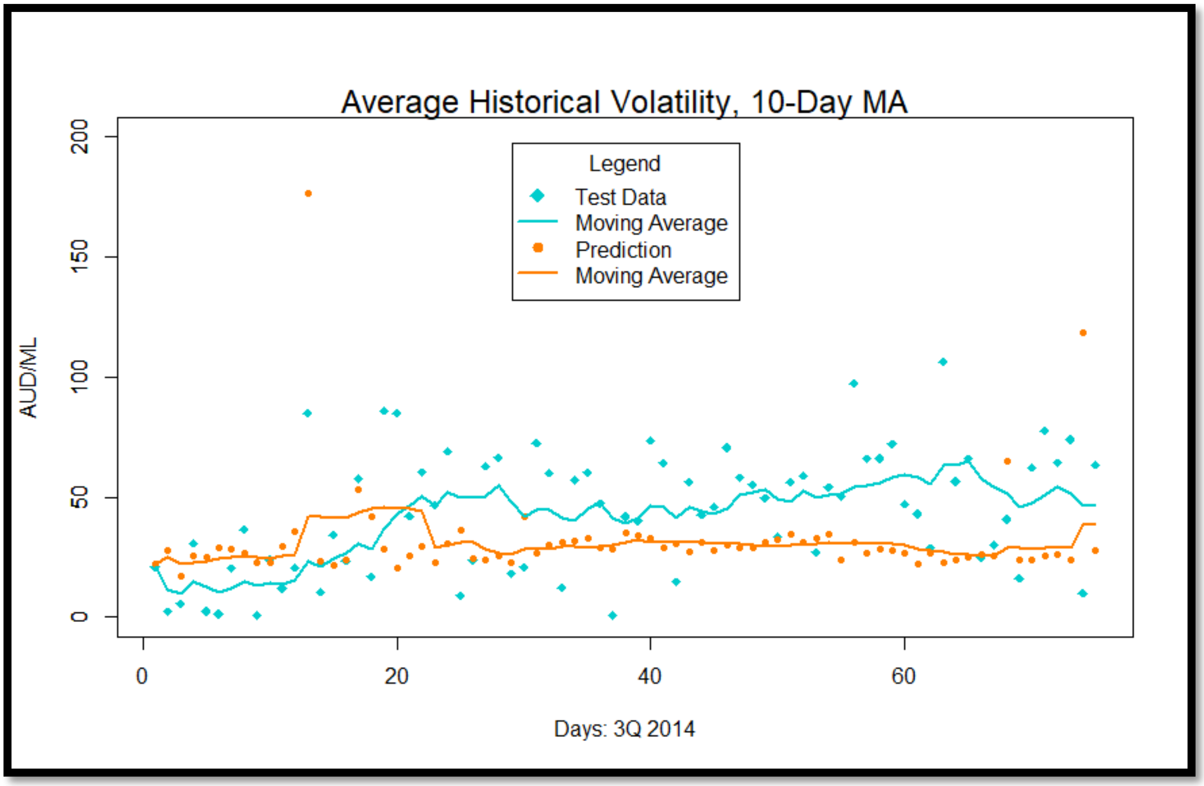

Figure 3-8. Random forest predictions for the period of average historical volatility; the last day's prediction represents the expiration date of an option at the end of 3Q with MSE = 1143, using MAs diffuses the impact of variability in either the pricing data or by the predictive model.

For predictions made for an *average volatility* scenario (3Q 2014), the value of the prediction of the MA on day 90 is $46.32 and the MA of the actual price of water for the same $38.59. Price movement illustrates how using MAs smooths predictions. In this case the model cast a high prediction on the second to last day. This would be problematic if that prediction came on the last day of the period and MAs were not being used as the model produced a strike price over $100 (Figure 3-8). Next, a model projection for a “low” volatility period was executed and did worse than the year with average volatility above in terms of MSE (Figure 3-9 & 3-4).

The expectation might be that the model should do better during low volatilities, however while MSE describes how well the model did over the course of the period—the calculation of MSE is driven by valuations, making period to period comparisons of MSE impractical.

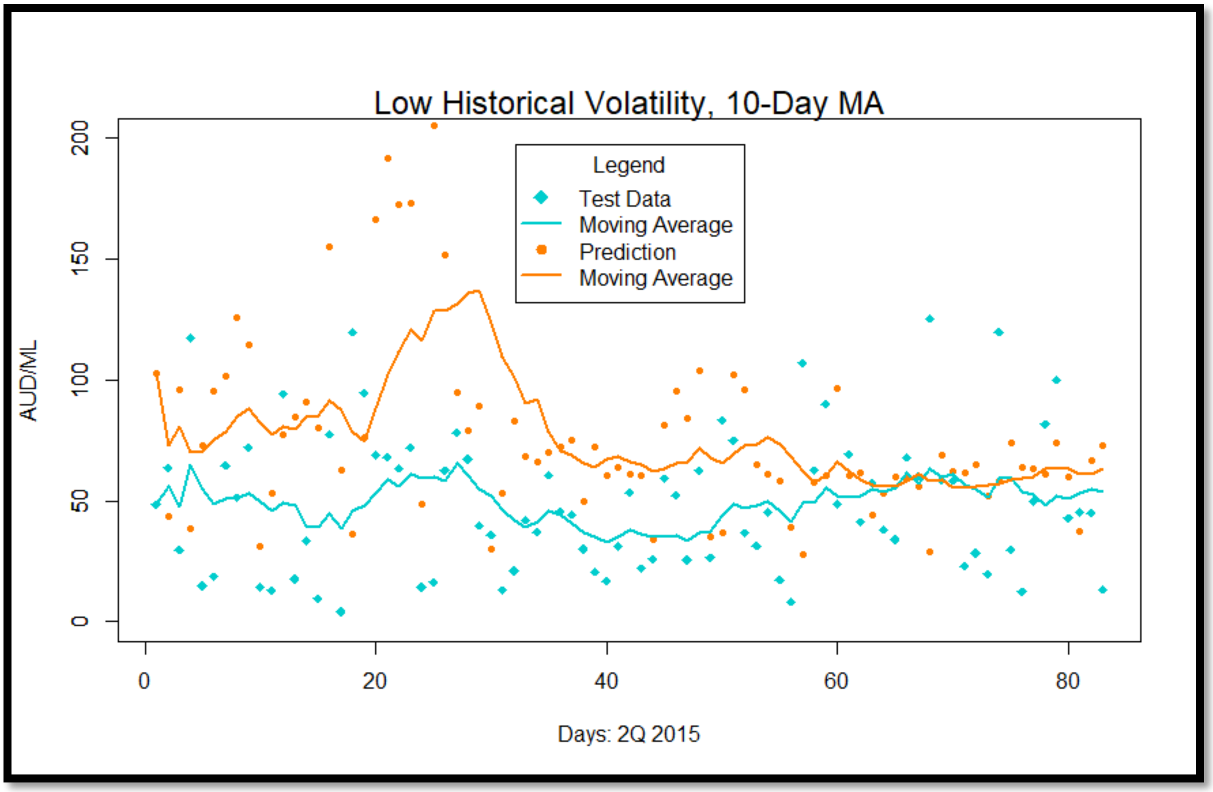

Figure 3-9. During a low volatility period the model output a MA strike price of \$63.13, with the actual coming in at \$53.99, MSE = 2784.

Another method to understand model performance is to look at how similar the prediction is to the observed prices. In the case of average volatility, the prediction and the actual differed by ~20%, during low volatility the differential was ~14.5%, though this is too small a sample to draw broad conclusions; for a clearer overall picture see the histogram of error (Figure 3-5).

Finally, two high volatility scenarios were modeled; the first model included all years (Figure 3-10, σ = 194%) and the second model excludes the first two years (2008-09) of the market data (Figure 3-11, σ = 157%). The high volatility scenario that includes all years highlights a serious limitation of random forest models. The last five trades in that period are: $0.95, $1.68, $5.58, $5.57, and $0.64. During training, the model had very limited opportunities to learn from these low pricing environments. Therefore, when attempting to predict prices the model suffers and shows bias the random forest cannot perform linear extrapolation.

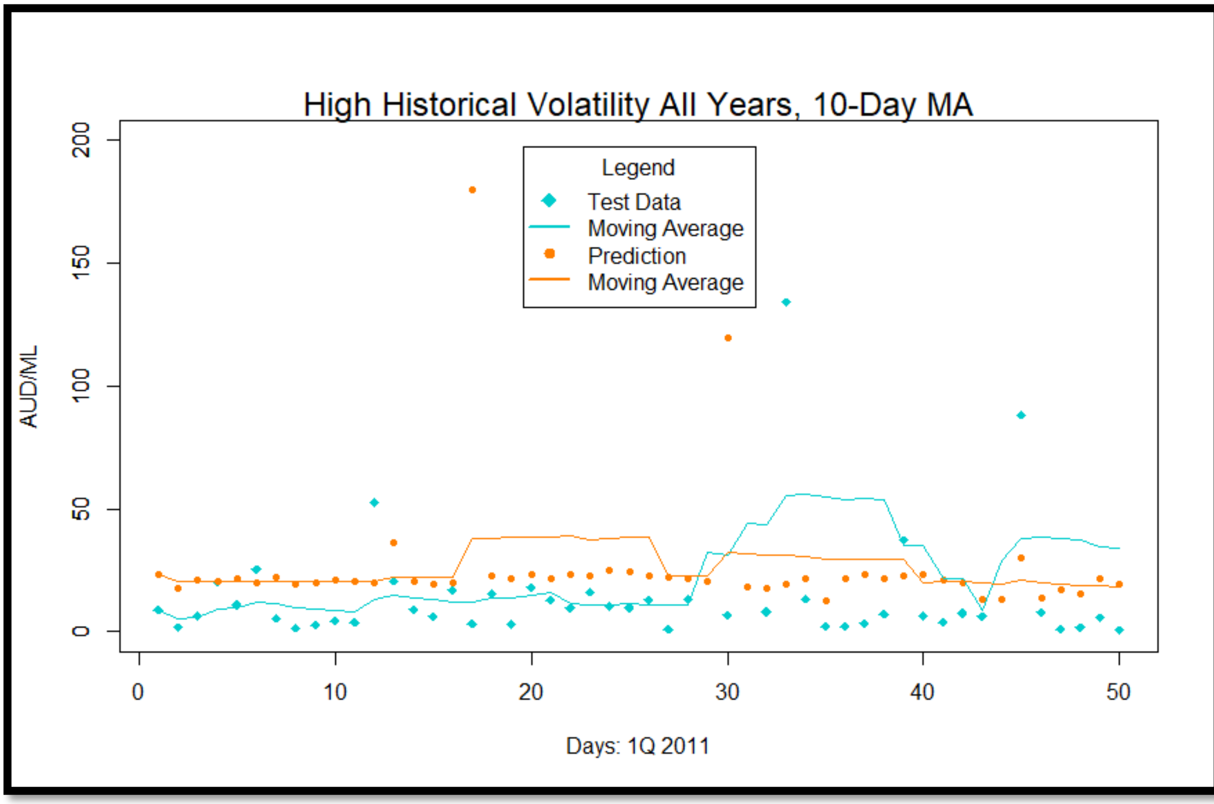

Figure 3-10. Predictions for a period of high volatility (1Q 2011), MA predicted value $33.86, actual value $18.51, MSE = 3300. While the model is on trend, it is consistently pricing the periods too high. This illustrates a limitation of the random forest method; with few periods at these low prices to train on, the model has trouble casting predictions in this range.

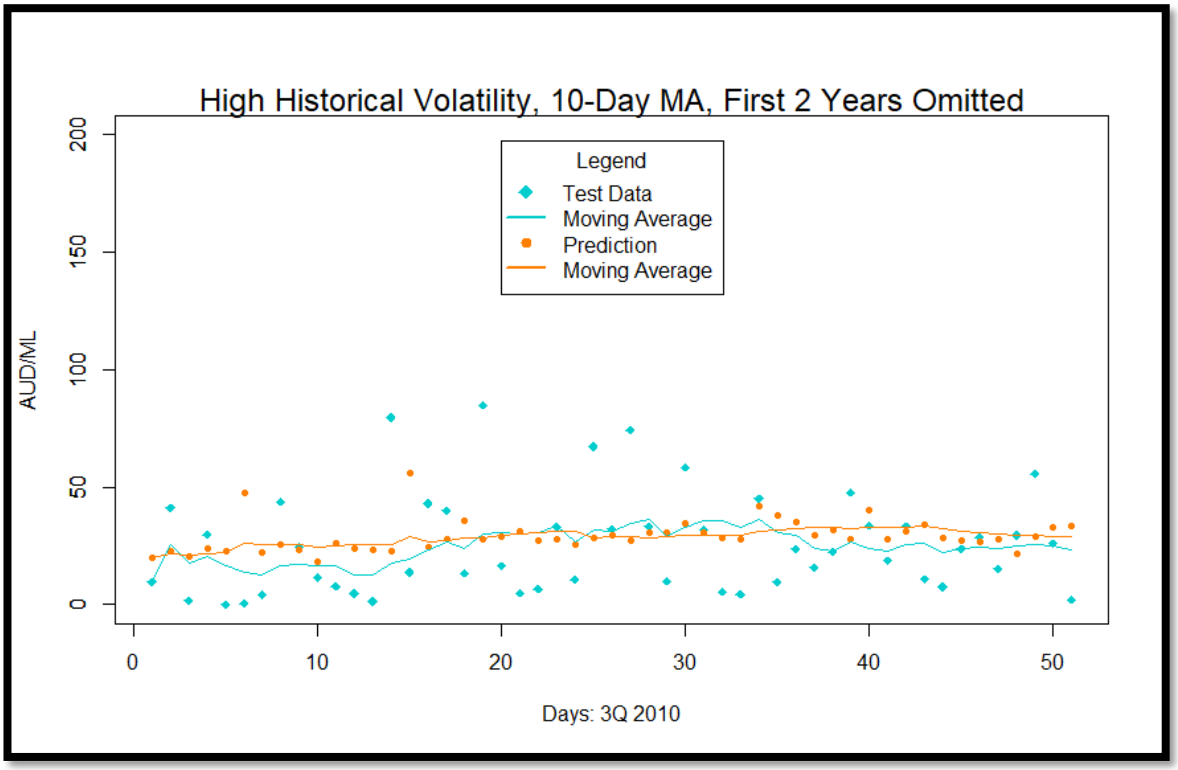

Figure 3-11. Example of model predictions during a time on the low end of the high volatility scenario, MSE = 529. While the model appears to be on trend when looking at the MAs, it is being helped by the test data on the high side. Without those trades raising the average, the model would show more bias.

As with MSE, volatility is a function of deviation from the mean, and both high volatility periods modeled would have had extremely low volatilities if not for the few data points affecting the calculation (Figure 3-10 & Figure 3-11). In terms of the hypothesis, the 10-day MA performed better than the testing parameter of 34% accuracy 50% of the time by being within 30% of target 60% of the time.

Black-Scholes-Merton Pricing

The goal was to evaluate if BSM can be used to price options on Australian water, predicated on the success of the volatility dampening and the accuracy of the predictive model. Using volatility calculated from smoothed cash prices and a strike price determined by the predictive model, BSM priced options in a range that may be attractive to market participants. For input values the 3-day MA of the cash price was used for asset value and the 10-day MA of predicted value 90 days into the future was used as the strike price (MA Cash, MA Pred 90 in Table 3-3).

Table 3-3. Input variable information for use in BSM for all periods. Cash is today's actual price, MA Cash is the 3-day MA of cash prices, Cash 90 is the price in 90 days, MA Cash 90 is the MA of prices in 90 days and MA Pred 90 is the MA of predicted price 90 days ahead. For the price equation MA Cash is used as today's value, MA Pred 90 is used as the strike price.

Volatility Period	Cash	MA Cash	Cash 90	MA Cash 90	MA Pred 90
Average	$20.92	$36.28	$63.47	$38.59	$46.32
Low	$48.40	$46.32	$13.38	$63.13	$53.99
High	$8.73	$10.51	$0.64	$18.51	$33.89
High (w/o first 2 years)	$9.58	$7.49	$2.11	$29.22	$23.21

In all modeled scenarios, which captured a range of historical volatilities, BSM prices were lowered post-smoothing to levels that may attract market participants (Figure 3-12 to Figure 3-15).

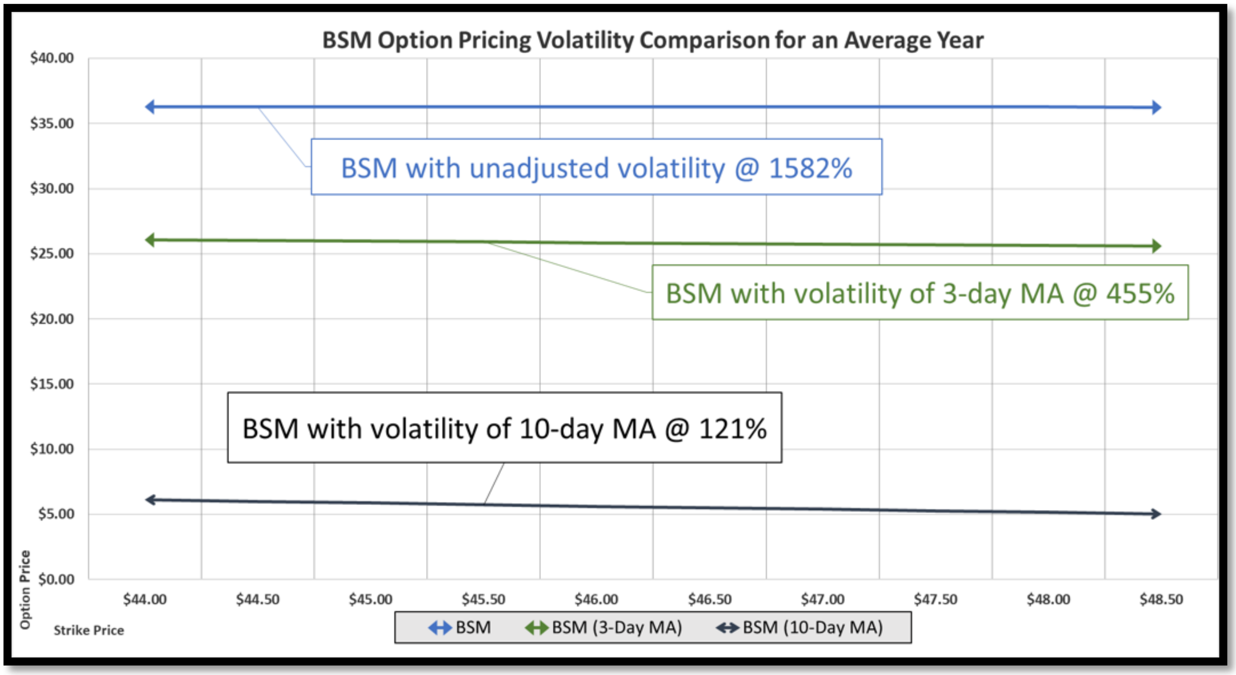

Figure 3-12. Black-Scholes-Merton at modeled strike price calculated for an average year with different volatilities; lower volatilities result in lower prices. Extending the MA from 3 to 10 days lowers the volatility to 121%, slightly lower than the unannualized historical average of 136%. In this case, today's value = $36.28, predicted 90-day strike = $46.50, actual 90-day value = $38.59,

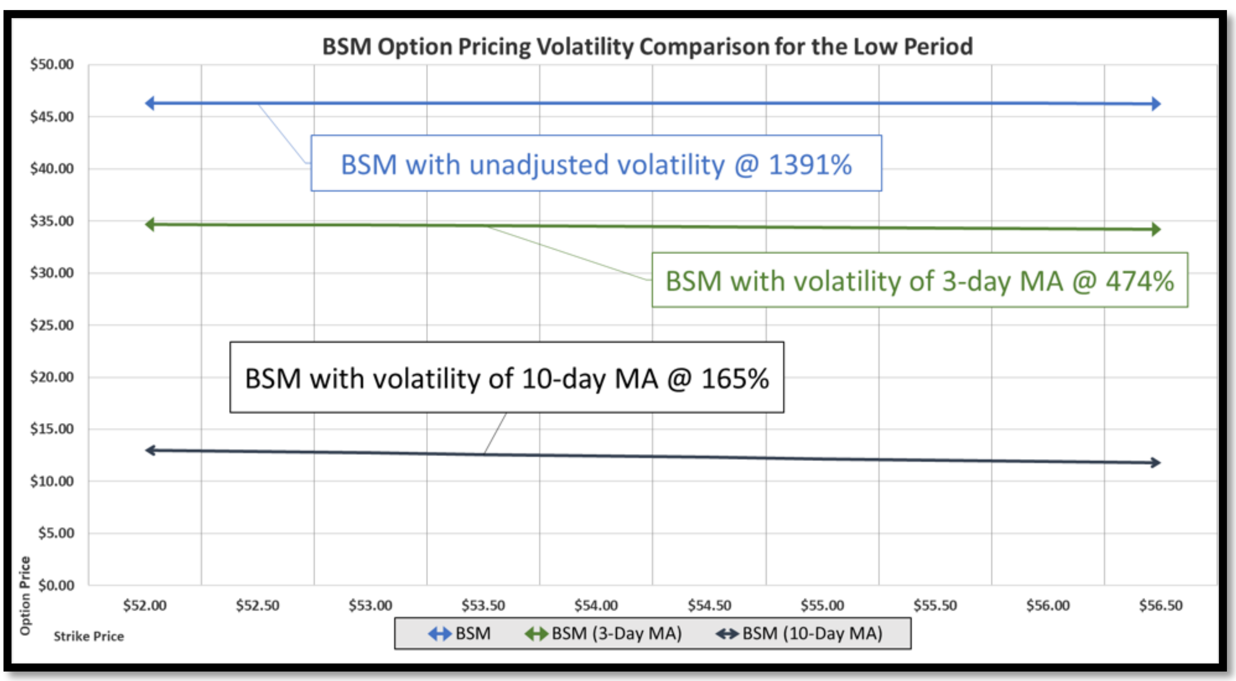

Figure 3-13. Black-Scholes-Merton pricing for a low volatility year, with volatilities of 1391%, 474%, and 165% calculated.

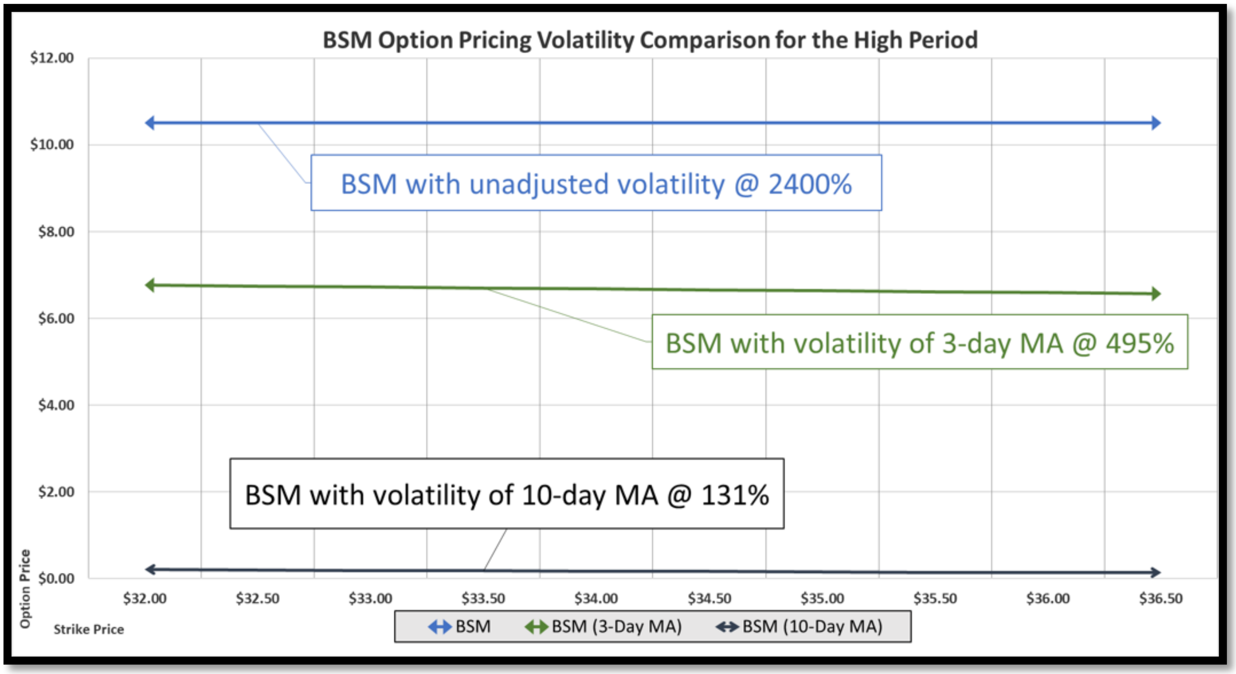

Figure 3-14. Options prices for the high volatility scenario at 2400%, 495%, and 131%. While the predictive model missed the mark this quarter ($33.89 predicted vs. 18.51 actual) it indicates that the more the model is wrong out of the money, the cheaper the option becomes, thus limits the downside risk of the inaccurate prediction.

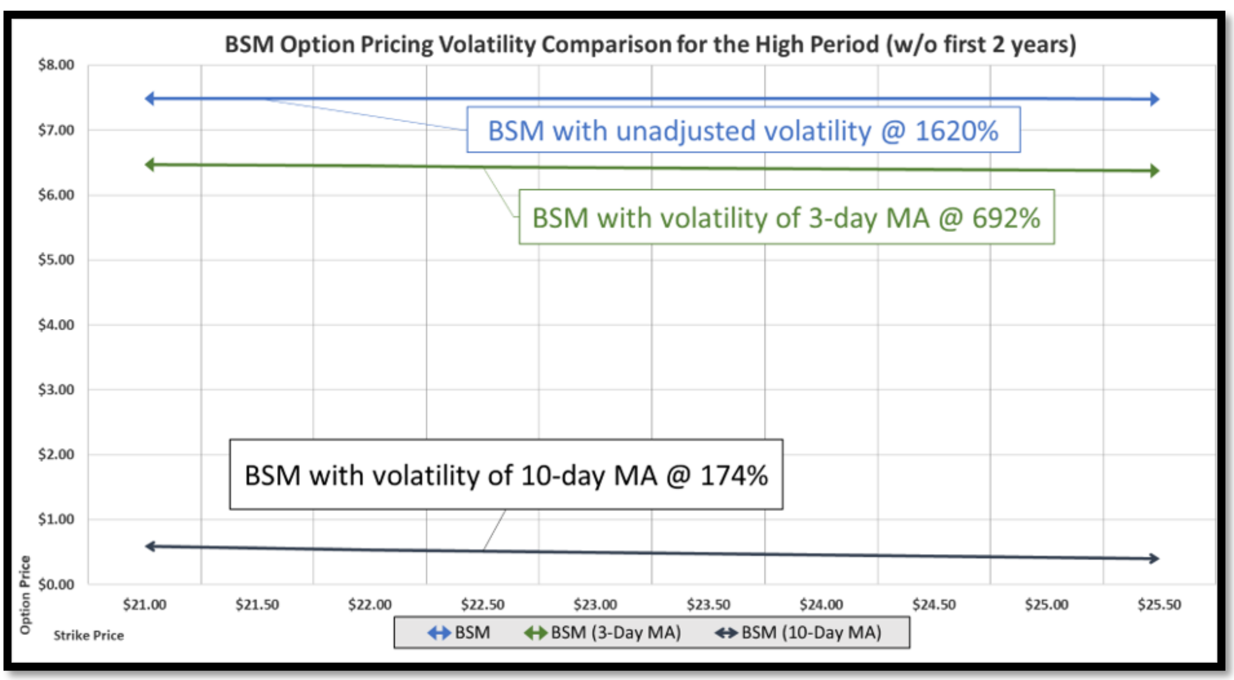

Figure 3-15. Option pricing for the low end of the high volatility scenario, volatility at 1620%, 692%, and 174%.

To contextualize this result, the volatility and associated premium is compared to a variety of currently traded assets (Table 3-4),

Table 3-4. Option Price Comparison for a period of average volatility for Australian water, Applied Micro Devices (AMD), Crude Oil and Virgin Galactic (SPCE) with expiration dates near 90 days in the future.

Asset	Cash	Strike	Volatility	Option Price
Water (Average Vol.)	$36.28	$46.50	121%	$5.00
AMD	$54.75	$55.00	49.95%	$5.43
Crude Oil	$51.79	$53.00	32.68%	$2.20
SPCE	$27.18	$35.00	97%	$4.50

While it is impossible to perform a test that will reveal if market participants will trade at these option price levels, looking at pricing for other assets is appears that the prices BSM is generating are reasonable.

Discussion

This study has shown that random forest modelling yields better results than linear modelling techniques for future price prediction. The question becomes, is the accuracy of the random forest model good enough to use to frame options strike prices for water when predicting prices 90 days into the future? The performance of the model suggests that from a probabilistic standpoint the model can work (Figure 3-4, Table 3-5). Three of the four predictions in the various volatility scenarios fall within 20% of the actual reported trades. Given this is a very small sample, the histogram of error for smoothed prediction was created and corroborates the general accuracy of the model (Figure 3-5). Model predictions are within 34% of the target 68%

of the time and this may be enough to garner the trust of market participants, as markets are dynamic and self-correcting, and prices adjust through time, but they need a place to start. Secondly, if strike prices for options in a water market can effectively be framed by a reliable predictive model it will alleviate some of the risk concerns surrounding volatility or artificially dampened volatility which will help bring options to market.

There are drawbacks and limitations to the model's use. Since the training set teaches the random forest how to make predictions, in years when input data is not familiar, the model has trouble making predictions. In situations where new input data is totally unfamiliar to the model it will predict its high or low known output; it cannot extrapolate linear trends. This is shown in the period of his historic volatility when water prices over the quarter were unusually low (Figure 3-10). The model was unable to cast predictions to match these low valuations, resulting in predictions that were too high. This problem is endemic in random forest modelling and was noted in the original work on the technique (Breiman, 2001). In a similar fashion, in situations where the market begins to set new highs, the accompanying commodities prices will ostensibly be setting new highs as well, thus creating the same problem for the model. To mitigate this effect a metric may need to be developed by which the model can signal that its input values have large enough variation from the training values to render predictions unreliable, to be used caveat emptor.

The data continues to present problems for regulators, as well as modelers, and the Australian government is looking at ways to improve this. A final report addressing the issue is due out in November 2020 (Murray-Darling Basin Authority, 2019). Efforts were made to remove data that was arguably unrealistic from the data set using accepted inter-quartile range (IQR) practices. While this rids the data set of unreliable points above the IQR, it has a limited capacity to remove odd data points on the low side. Market values do not go below zero, and there are cases when the IQR calculation only allowed for removal of points lower than zero. This may result in the inclusion of irregular data on the low end of the price spectrum. However, the only way to remove those points would require the creation of an arbitrary rule of exclusion which can be difficult to defend. Therefore, those points were left in the dataset and the values used for calculations were smoothed with MAs. Over time, the number and frequency of these points should diminish as reporting improves.

As mentioned, a key element of an options market is that it is dynamic and can self-correct over time. It is possible to price an option chain without the predictive model by simply pricing them with as many strike prices as buyers are interested in. The idea behind the model is that it can offer market participants a glimpse of where prices might be headed to better inform them as they make risk assessments and purchasing decisions. As options are rolled out, a two-step process to valuation may be useful. In the first step output from the predictive model is combined with volatility calculations and cash prices to initially price options chains. After that initial pricing, options pricing could be continuously updated using a combination of updated predictive model prices (as time decreases toward expiration) which could possibly include shorter term time series analysis as a component of those valuations

The volatility levels in the Australian water market are high enough that they are likely the reason why a formal options market has not come to fruition. Everyone knows that prices are not accurate, so the question becomes how wrong are they. This has been widely explored and discussed and many have pointed to volatility as the problem variable (Cui & Schreider, 2009; Heaney & Hafi, 2005; Williamson et al., 2008). However, this has not precluded options from being traded. In much the same way that water was traded before the formal organization of the

SMDB water market, one-off options transactions are taking place as "forwards" (T. Wilks, personal communication, October 2018). These one-off transactions are possible, in part, due to the willingness of the buyer and seller to agree on the value of the volatility present.

When using historical data for volatility calculations on Australian water, the first two years of trading have great impact on historical averages. Though scenarios were modelled with and without the first two years of market data, those years were included in training for all the other model training applications. The reason is that the more data the model has to train on the better it should be, and by seeing these market fluctuations that increase the range of the training data the model has improved capabilities to predict these price points should valuations begin to trade in the same range in the future. To understand how well the model predicted prices for each quarter, predictions are compared to the actual reported numbers (Table 3-5).

Table 3-5. Comparison of the 10-day MA of model predictions and actual prices for the periods matching historical volatility levels in the Australian water market.

Period	MA Actual	MA Prediction	% Difference
Low Volatility	$63.13	$53.99	14.5%
Average Volatility	$38.59	$46.32	20%
High Volatility (all years)	$18.51	$33.56	181%
High Volatility (excluding first two year)	$29.22	$23.21	20.6%

Overall, the model was able to stay within 21% of the actual price when making predictions except for the high volatility situation using all years. While this may be party driven by the volatility of the period, there are model limitations at play here as well as random forest models cannot extrapolate and generally do poorly when they are modelling data that extends the range of prediction. As expected, the lower the volatility, the better the model generally performed except when high variability was driven by outlier data points that could be justifiably removed.

Using the calculated volatility (annualized) generally forces BSM to value options at levels approaching or identical to cash prices, which might not be particularly attractive to potential market participants because the option is less attractive if you can simply buy the actual commodity for the same amount of money. If you buy the option, you still must pay for the asset should you chose to exercise the contract. To develop a viable option valuation, alternative methods for calculating volatility may need to be considered to give a fledgling market the opportunity to grow. This is partly what Michelson & Young are referring to when they argue that water fails to meet the necessary assumptions regarding price activity (1993). However, many options are priced on instruments (e.g. U.S. stocks) that—at least occasionally—fail to meet the same assumptions. So, many instruments fail to meet needed assumptions regarding price and geometric Brownian motion (which frames the assumption regarding the normal movement of stock prices), but water prices in Australia fail in a spectacular fashion. In addition, the high variance of reported prices and intra-season price jumps also make options valuations problematic (Plummer & Schreider, 2015). Similarly, studies have shown that options on wheat indicates that agricultural commodities have less than ideal volatilities as well and undergo large price jumps. Yet, the derivatives markets for these commodities still flourish, though they often rely on different pricing approaches (Koekebakker & Lien, 2004).

Given the inherent imperfections in the available data (particularly uniform, accurate pricing and timeliness), a different approach may be warranted to revisit the applicability of BSM for pricing of water market options. To reduce the impact of price inconsistencies on the volatility calculation, the volume weighted average price can be smoothed. Though experiments were conducted that removed the outliers and looked at a 3-day MA of the resulting prices, a simpler approach is to use the 10-day MA. Not only does this produce volatility lower than the 3-day it does so more consistently by not relying on outlier removal to partly achieve the goal. This smoothing decreases the impact of bad data points that resulted from reporting issues. However, this technique will preserve the seasonal nature of the volatility fluctuations and should provide a more usable number to inform initial pricing of an options market for water. Again, if we agree that the prices are wrong, dampening volatility though smoothing is how we can account for that; but how much of an adjustment is made will be a point of discussion by market participants. This smoothing has been done in other financial application, such as using a weighted MA over long timeframes where the more current periods are more heavily weighted than earlier periods (Yu, 2002).

The method for calculating volatility can be varied if the market participants agree on that method and are comfortable with the results it yields. This paper has outlined methods for calculating volatility in an options market for water. While ultimately the decision to use a particular calculation will have to be agreed upon by consensus, using the 10-day MA of prices may be a reasonable starting point. This eliminates some erroneous prices that are too high and smooths the unreasonably low prices that an IQR filter would not remove. It would help improve the shape of the BSM pricing curve if volatility was lower, but any method that artificially lowers it will materially affect the contract and the level of risk communicated, which can only be partially offset by the predictive model. It is also important to remember that once the market begins trading, implied volatility becomes more important than historical which is another avenue by which the market can self-correct.

Arguments have been made that BSM is not well suited to the task of pricing options on water, but this paper suggests that BSM may yet be useful (Cui & Schreider, 2009; Villinski, 2003; Williamson et al., 2008). However, if market participants cannot agree on modifying the calculations for volatility or adjusting the contract size, the usefulness of BSM outputs is in serious jeopardy. If that is the case, there are still approaches that may solve the pricing conundrum. Work has been done to price options in the agricultural markets that involves reliance on jump diffusion and mean reversion and they may be enhanced by incorporating the outputs of a predictive model (Cui & Schreider, 2009; Dharmawan, 2017; Koekebakker & Lien, 2004).

To illustrate the effect of volatility on option pricing, BSM option premiums are illustrated using three methods for calculating volatility: cash prices of water, 3-day MA of cash prices, and a 10-day MA of cash prices. In short, the higher the volatility the higher an options premium should be, and as an option is priced more out-of-the money its premium should generally decrease. For example, consider stock XYZ trading at $100 and you want to buy a call option (giving you the right to buy it). The higher above a $100 strike price, the cheaper the option should be. It should be much cheaper to buy the right to buy XYZ at a strike price of $200 than $110, as the probability of the option being exercised has an inverse relationship with the distance between the strike price and the cash price. Volatility for many common stocks is in the 5-30% range and for commodities, a volatility of 100% is not uncommon.

BSM often outputs an option premium price for Australian water that is equivalent to the spot price of the asset, which is the maximum value, when cash prices are used to calculate volatility. The Australian government has commented on the issues surrounding accurate reporting of cash water prices and promises to make improvements. If this reporting is improved, the volatility currently expressed in the water market may self-correct if the more accurate reporting shows prices are behaving in a less chaotic fashion. To lessen the effect of the price reporting issues in the Australian water market, the three-day MA of the cash price is used as the current asset price. Using a MA of cash prices is not usually done, but in most markets, prices are reliable so there is no need to consider it. There is considerable evidence that the professional and academic communities agree that using moving averages is a legitimate method to capture and understand trends and to formulate trading strategies (Federal Reserve Bank of Dallas, 2020; Federal Reserve Bank of St. Louis, 2015; Gunasekarage & Power, 2001; Hatchett et al., 2010).

With reliability issues in the data, using the average helps smooth out the impact of erroneous data. If a questionable cash price data point happened to fall on the day a prediction was being made, and the resulting prediction was poor, the conclusion could be drawn that the model was doing poorly when it may have been the fault of the data point. Also, there exists the possibility that any one prediction may be unusually poor, the three or ten-day MA of the price or the prediction is a safer number to use as it smooths these out.

The goal is not to make precise predictions for any given day, but to inform options pricing models with a generally accurate range of where the asset value may be in the future. In the low volatility scenario, for example, looking at the difference between the cash price and the three-day average cash price is a good example of why using MAs makes sense, as even though the Cash 90 price is $13.38 the MA Cash 90 price is $63.13, so is a better indicator of where values are in the marketplace (Table 3-3). The reason it might be considered better is that it has more of the surrounding price activity incorporated into the calculation. Using the MA of the 90-day prediction ($53.99 round to $54) as a midpoint strike price, options chains can be constructed with different volatilities. There is a near linear relationship between volatility and premium as volatility moves from 474% to 165% (35%) options price moves from $35.00 to $12.50 (35%), but this is not the rule.

In this case of high volatility, the model missed the mark in terms of predicting the price for reasons discussed above (Figure 3-10), but the plot of the premium price is still useful to illustrate what a poor prediction can cause (Figure 3-14). Even though the predictive model was off target in this case, the BSM 10-day MA contracts were priced more cheaply because of this. So, if a participant bought $34 calls, they would have lost less than $1.00/contract.

Conclusion

As with the previous work of Williamson et. al. (2008) or Cui & Schreider (2009) the efforts here have challenges but also show potential. As market price reporting improves, the techniques outlined here will benefit, as will Williamson's (2008). The model may be accurate enough to avoid having to make special dispensation for seasonal jumps, but another possibility is that this work could be used in conjunction with Cui & Schreider (2009) to better handle those jumps. In short, the method here offers an alternative way to use BSM in pricing Australian water options. Part of the success of a fledgling option market using our approach will be driven by how well the model is received, how willing buyers and sellers are to rethink volatility calculations, and how receptive those market participants are to adjusting contract size.

Modeled strike prices provide a probabilistic view of future market movement, and volatility can be lowered by smoothing prices with a moving average; these variables can be fed into BSM to generate options prices. The more accurate the model, the more confidence market participants will have in the model, which should affect their willingness to assume risk in the market. However, even if the option value seems too high to be palatable to buyers (i.e.

approaching, or at, spot prices) there is one element of the contract that is entirely within the control of participants: the contract size.

In the U.S., one stock option contract represents 1 share of stock. In the world of commodities and currency, contract sizes vary. For example, one Canadian dollar futures contract is equal to C$100,000, on the Chicago Board of Trade a soybean contract is 5,000 bushels and in Australia they trade in the metric ton (Intercontinental Exchange, 2020). How much water should one water option represent? If volatility is calculated using prices, BSM outputs often approach or match cash prices. In this case, maybe the option contract should represent 10 megaliters (ML, often called “Meg”). Given that Australian water is traded by the ML, this would mean that at inception the buyer of a call paid 10% of the total trade as a premium if they exercise the option (where spot = strike). Manipulating contract size may offer a way to bring these contracts to market, if the market participants are all comfortable with those contract specifications.

This actual contract size is debatable, the point here is that unless volatility can be agreed to be calculated in a fashion that systematically lowers its impact on the BSM price model, changing the size of the contract may be the best place to make BSM option valuations work in a practical setting. Unlike the thinly traded market that was studied first by Yoskowitz (1999) and then by Villinski (2003) in the Rio Grande Valley, Texas, the Australian market has the requisite data to continue to experiment with BSM. The results produced here indicate that if BSM is going to be used effectively participants may have to alter contract size or volatility calculations, otherwise the BSM outputs will be of least practical utility in times of high volatility when users need them the most. When options are priced market participants are pricing risk and given high levels of variability (and thus volatility) in the marketplace we have outlined a way to mitigate some of this risk. By informing strike prices and market participants with the results of a predictive model, confidence should increase in initial option prices which can balance some of the damped volatility levels resulting from smoothing. If this balance can be struck, and perhaps combined with novel contract sizing, BSM may be successfully applied to burgeoning Australian water options markets.

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CHAPTER IV:

PRICING OPTIONS ON WATER IN TEXAS

Introduction

Purpose

Noted geographer John Wesley Powell used the 100th Meridian as the dividing line between the wet and arid regions of the country. This line runs through central Texas; roughly half of the state is positioned where it is wet, the other half where it is arid (Powell, 1879). More recently, it has been shown that the dividing line has shifted to the east and now runs at the 98th Meridian, which means the state is getting drier (Seager et al., 2018). Climate change is altering patterns in precipitation which makes future planning – especially around water - challenging given this increased variability (Chang et al., 2016). Population is also projected to increase in Texas and will put upward pressure on water demands (Dore, 2005). It has been estimated that if plans are not made to secure more water and there is a drought of record in the year 2070, municipalities will have half of the water they need to serve their citizens much less the needs for environmental water (Texas Water Development Board, 2017).

Planning to meet water needs has two temporal components: what is needed today and what will be needed in the future. This work is focused on the latter and seeks to illustrate how future needs can be addressed using the concepts of financial derivatives to build an option market for water. An *option* allows a buyer to purchase a contract for a cash payment (premium) that entitles them to make a future purchase of a specified amount of something at a specified price within an agreed upon timeline. For example, consider a tee shirt manufacturer who buys cotton for production and the company is profitable when they buy cotton for $0.75 per pound or less. Today, the price of cotton is $0.70 per pound and the tee shirt manufacturer is concerned about rising prices. The manufacturer could simply buy cotton today, but this presents three main problems: the manufacturer has to store it, the manufacturer may not get shirt orders to require the cotton, and the price of cotton could go down putting the tee shirt maker at a disadvantage. Here is where the option is useful, as when the company buys options, they are securing the right to an amount of cotton at a price by a specific date. This privilege does cost the manufacturer some money (called the premium) but allows the tee shirt maker to mitigate their risk if prices climb. Options increase flexibility in planning for future needs as they allow the buyer to adapt to changing conditions affecting both supply and demand and allow the buyer to mitigate some of the risk associated with future uncertainty (Colby et al., 2014; Hearne & Donoso, 2014). While most options in the U.S. are built with three-month lifespans—particularly those widely traded on established exchanges such as the Chicago Board of Options Exchange—water contracts in this work will be considered using longer horizons (5-10 years).

The initial motivation for this work stemmed from trying to find a tool to help interested parties obtain water for the environment. Environmental flows of water into bays and estuaries provide critical ecological functions to the system, and those flows have been greatly diminished by human extraction and impoundment upstream (Meijer & Van Beek, 2011; Montagna et al., 2009; Montagna, Chaloupka, et al., 2018). In naturally occurring low flow years, human needs persist. During these times, it would be beneficial if environmental managers had access to water that could be left in stream to flow to the coast. Affecting salinity across the bay or estuary may be too great a task, but if environmental water was sent downstream in times of drought, a refuge may be created at the head of the bay in low flow years. This would give estuarine dependent fauna a refuge from the low flow conditions and shorten recovery times.

Securing permanent water rights for environmental water has proven to be difficult in Texas (see the Texas Environmental Flows Initiative), and spot market transactions are difficult to execute in markets that do not have well established institutional support (Yoskowitz, 1999). Derivatives are considered as being a viable solution to deliver the kind of situational adaptivity required to meet demands for reliable water. The applicability and utility of these arrangements goes beyond environmental uses. Municipalities, industry, farmers, and anyone who has exposure to the risks associated with the uncertain reliability of water supplies can benefit from the use of these types of contracts.

Option Pricing Efforts to Date

Efforts have been made to price water options in foreign and domestic markets (Cui & Schreider, 2009; Villinski, 2003; Williamson et al., 2008). While much of this work has been done using traditionally accepted pricing mechanisms, novel work has been conducted to price options based on the cost of the next least expensive alternative, with the difference representing price (Michelsen & Young, 1993). While the previous work does help understand the price of water as an option, it does not calculate a price for the premium. In other words, the method offers no way to calculate the cash price to be paid to the seller for the assumed risk of the option being exercised (known as being "called"). There have been other pricing efforts similar to Michelsen & Young's in that efforts are made to price the asset based on scarcity. This scarcity pricing can be tied to the cost of the alternative (a la Michelsen), based on changes in operating costs, or more dynamic pricing that sets a schedule based on readings of a chosen scarcity metric like dam levels (FE Staff, 2011).

One issue with pricing water options in Texas, and many other locations, is the limited availability of cash market pricing on which to base options values, particularly if the method uses traditional pricing mechanisms. The most popular pricing model for options is the Black-Scholes-Merton (BSM) model which is the foundation for derivatives theory (Glantz & Kissell, 2014). To address this type of data challenge, previous work has been conducted in California to build options based on 72 years of simulated price data extrapolated from an actual 18-month price history (Williams, 2007). Facing drought in the 1990's, California took steps to enhance allocative strategies with the establishment of a Water Bank and water supply options (Jercich, 1997). This fledgling market was in the process of issuing options, but market activity was curtailed when rains came and ended the drought.

The Rio Grande Valley (RGV) has the most active spot (cash) market in Texas, yet it is not perfect: as research has shown, there existed significant price discrimination among buyer groups with irrigators tending to pay far less than industrial interests (Yoskowitz, 1999). It was in the RGV that Villinski tried to use traditional pricing mechanisms yet found markets to be too thin to yield reliable outputs (Villinski, 2003). The RGV does offer a natural water delivery system via the Rio Grande river and a Watermaster system conducive to trade, so this region may still have the potential to be a good candidate for trading options in the future. The Watermaster system is not used throughout the state (there are four: Brazos, Concho, Rio Grande, and South Texas. See Figure 4-1), and the ability to facilitate trading in the different Watermaster areas varies. Institutional characteristics for trading surface water efficiently across Texas is not consistent and lacking in many cases (White et al., 2017).

Figure 4-1: Texas Watermaster Areas, tceq.texas.gov

There are examples of options used for environmental water in Texas. The Edwards Aquifer Habitat Conservation Plan offers two options styled programs available to irrigation permit holders. The Voluntary Irrigation Suspension Program Option (VISPO) pays enrolled rights holders on an annual basis for participating in the program and makes an additional payment in years that they need to use the water. This water is not called at the discretion of the buyer but happens automatically if a triggering event takes place. The trigger is the water level of the J-17 Index Well located at the base of the water tower near the national cemetery at Fort Sam Houston in San Antonio. If the water level is at or below 635 feet on the first of October of each year, the participants suspend use of their water for the following year (Edwards Aquifer

Authority, 2019). There is also the Aquifer Storage and Recovery program (ASR), whereby when recharge averages are under 500,000 AF the water is called into forbearance and pumped into the ground at the San Antonio Water System's Twin Oaks facility. The main difference between VISPO and ASR is that VISPO leaves water in the system and ASR pumps it underground (J. Hernandez, personal communication, June 2019). The Edwards Aquifer is located in the southern half of central Texas and is comprised of a Contributing Zone, a Recharge Zone, and an Artesian Zone (Figure 4-2).

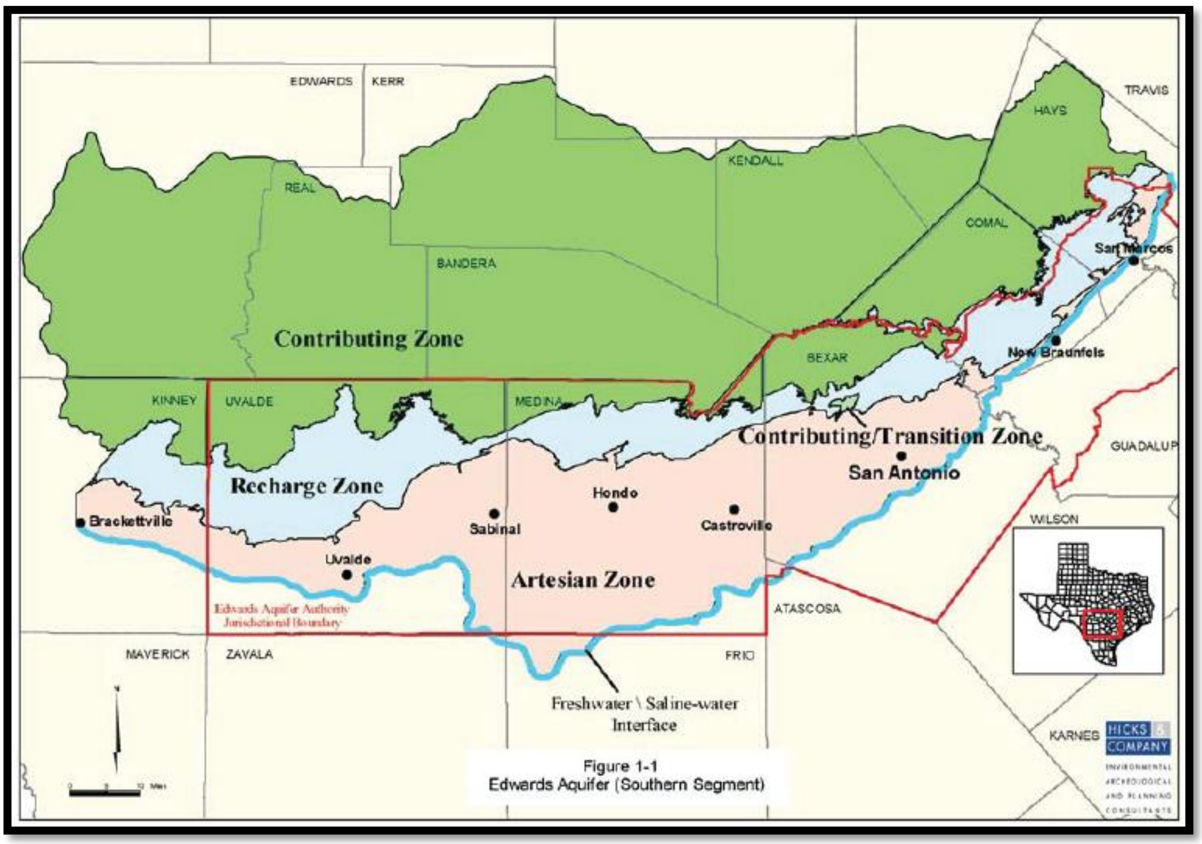

Figure 4-2: Edwards Aquifer contributing zone, recharge zone, and artesian zone. From the Edwards Aquifer Recovery Implementation Program.

The Edwards Aquifer is managed by the Edwards Aquifer Authority (EAA) which was created in 1993 by the Texas Legislature in response to legal battles of spring flow levels and endangered species (Edwards Aquifer Authority, 2019). There are many aspects of the creation, implementation, and growth of the EAA, but regarding the VISPO and ASR there is one feature about their administration of water rights that is particularly important. When the EAA administered water rights, it provided 2 AF for every acre of irrigated land. One of these AF can be traded away at the farmers discretion, even if this involves changing the use of the water. In this way, irrigators can enter into the forbearance program without having to file a "change of use" application with the Texas Commission on Environmental Quality (TCEQ) which they would in the case of surface water, who administers water rights in the state (J. Hernandez, personal communication, June 2019).

This "change of use" component is important to burgeoning water markets (spot or option). If a sale, lease, or other transfer of a water right from one entity to another involves a change in the use of the water allocated by that permit, then an application must be filed with TCEQ (Dowell, 2013). Even if these change of use applications are approved for the years of an option where water is called, it is at best an administrative barrier to trade. At worst, this requirement could effectively deter market participants from conducting business as the risks associated with buying and selling contracts that have no guarantee of being approved by TCEQ may present too many challenges. There are other challenges presented by existing frameworks discussed in Chapter 5. It is important to note that the ASR and VISPO are designed to option water from irrigators accessing groundwater. In the case of the Edwards Aquifer there is some crossover as the groundwater does feed the Comal and San Marcos springs thus becoming surface water. While this work is concerned with developing water markets for surface water, the pricing of water by the EAA is used for comparison due to the limited availability of transactional data surrounding surface water outside of the RGV.

Objective

Texas, and other states, could benefit from additional tools being brought to bear for water markets. The objective of this work is to develop an effective water option contract process by developing a method for structuring and pricing them.

Methods

Study Site and Approach

The approach to building a long-term water option in Texas is a synthesis of other attempts to build water options combined with elements commonly found in derivatives. This methodology can be applied anywhere water is traded, and in this case was applied in Texas. Modeling and validation work in the previous chapters used the Guadalupe River Basin (GRB), which has some existing options-style programs that offers data for comparison.

There are two components that comprise an options contract: the elements that make it a contract and the elements that define it as an option. To be considered a contract the agreement must have mutual assent, offer and acceptance, adequate consideration, capacity and legality (Staff & Gilkis, 2007). This information is provided as a broad understanding of what the contract involves and should not be viewed as legal advice.

To make a contract an option, it needs to be an arrangement where the holder (who bought the contract for consideration) can buy or sell an amount of an underlying asset during a specified time at a specified price (Windcli et al., 2001). In the case of a water option the buyer of an option would be buying the right to take delivery of a specific amount of water from the seller at the buyer's discretion anytime between the time of purchase of the option and an expiration date, with payment for the water due when exercised. Much of the important information regarding an option contract offered for sale is found in its listing (Figure 4-3).

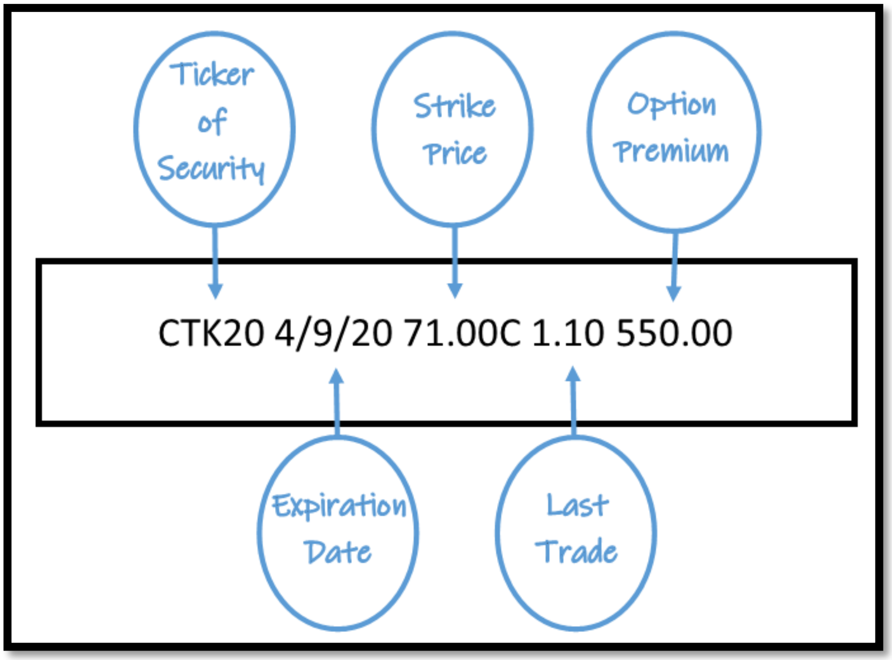

Figure 4-3: Example of an option description with labels: the ticker symbol is the asset the option is based on, for CTK20 the CT is cotton the K represents the month code (May) and 20 is the year The expiration date is the date by which the option must be exercised or it expires worthless, the strike price is the price at which the asset can be optioned with the C next to it indicating it is a call. The last trade is the last transaction price as expressed in terms of option points (here 1 option point equals $500), which translates to $550.00 in option premium the buyer pays the seller for the contract.

The ticker is an abbreviation that refers to the security the option is for (Figure 4-3). There is no mention of contract size as by definition cotton contracts represent 50,000 pounds (approximately 100 bales). In the U.S. one stock option is generally worth 1 shares of common stock. The expiration date indicates the date when the option contract is no longer valid. The strike price is the price per share at which the option may be exercised, and the option price is how much the option contract costs initially. "Call" indicates the option gives the holder the right to buy the underlying asset, a "put" is the option to sell. To understand why a farmer might buy a put, an example might be helpful. Farmer X plants 100 acres of some crop that requires 20 inches of rain to grow; that is 166 AF. The Farmer is allocated 100 AF as per his surface water permit, so he is relying on 66 AF to come from precipitation. Shortly after planting, he becomes very skeptical about the chances of getting the supplemental rain he needs and is afraid the crop might fail. The fact that precipitation is low should make his 100 AF allotment of surface water valuable. Instead of simply selling the water, if he buys a put contract, he will have the opportunity to sell his water if he chooses before expiration, thereby mitigating his losses if the crop fails. While puts may be offered in water markets eventually, this work focuses on pricing calls (the option to buy water) as they are more broadly applicable and easier to grasp conceptually.

This chapter takes the common elements of an option contract and adjusts their application so that they may be applied to water; call options are constructed by using standard elements in an options contract and combining them with an approach to pricing using opportunity cost.

Water Option Specifications

Contract Size

The amount of water that an option contract represents can be anything the buyer and seller agree on, but for ease of standardization a common volume is useful. If one contract equals one AF, many contracts would have to be executed to transact meaningful quantities of water, if contracts are set at 100 AF it would be onerous to create one-off contracts for sizes under that. For utility, one contract might represent 10 AF to accommodate the sub-100 AF market, another standard contract could be set to 100 AF, and a 1000 AF contract would facilitate the execution of larger transactions. Again, these volumes can be set to anything, but there are benefits of standardization in the marketplace. By standardizing contracts market efficiency is increased, legal fees are lowered, product knowledge is simplified, and competition is encouraged by making it easy to compare terms (Patterson, 2013).

Prices: Option and Water

Price will be a critical component driving success or failure of water option contracts. The sale of the permanent water right is not being considered here, only the use of the water allocated to that right in a given year. These would be considered cash transactions if they occur at the time the trade is consummated. They can also be referred to as short-term leases. If an individual sells their water in a given year, they are effectively leasing out the water right (Brown, 2006). This distinction is important, as when aggregating data for cash transactions some of these transactions may have been recorded as short-term leases.

An option for surface water has two components: the payment for the option and the payment for the water itself. This is similar to the composition of commonly traded options for stocks and commodities; there is a premium (the payment for the option) and the cost to pay for the underlying asset when called (at the strike price). The payment for the water would be constructed first, then the payment for the option would be produced as a function of that price. This method may be useful to price water diverted from any use, but in this case the water being priced would have been used for irrigation as outlined in a permit.

As spot markets develop, it may be possible to use the modelling techniques and volatility calculations from Chapters 2 and 3 to price U.S. water options. However, those techniques depend on markets with continuous trading that are operating efficiently. Until there are more robust spot markets in the U.S. these methods may not work reliably. Existing water transactions can provide the range of current and historical prices, but this range is so great, and the geographic variability so high, that historical pricing information will be of limited utility to formulate an option pricing tool that can be broadly applied. While the pricing information may help inform a localized market, the following discussion of price history will illustrate the breadth of range and variation.

In the U.S. there are often price differences between geographies and price disparities between user groups. The general trend is that agricultural to urban trades are priced higher than those between agricultural interests (Brewer et al., 2008). Similarly, in the RGV, mining/oil and gas interests paid more for their water than the agricultural interests charged each other (Yoskowitz, 1999). These price differences can be significant and persist over long timeframes (Table 4-1).

Table 4-1. Price differences between agricultural and urban interests from 1987 to 2005, compiled from the *Water Strategist* for Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Texas, Utah, Wyoming, and Washington, n price per acre foot (Brewer et al., 2008).

	Ag-to-Urban Lease	Ag-to-Ag Lease	Ag-to-Urban Sales	Ag-to-Ag Sales
Mean price	$114	$29	$4,366	$1,747
Median price	$40	$10	$2,643	$1,235
# of observations	189	178	1,013	169

Prices not only differ when user groups are compared, but across different geographies as well. For example, in Southern California's Imperial Irrigation District in 2001, farmers were paying $13.50 per AF while a developer near the South Rim of the Grand Canyon National Park was willing to pay $20,000 an AF for water from the Colorado river (Brewer et al., 2008). With these regional and user anomalies it will be very difficult to create an option contract that can accommodate all situations. The method for valuation may be transferable, but the resulting prices may deter transactions in some locations and market participants can expect price differences across geographies.

However, the reason for the price disparities may illuminate how to construct an option. These price disparities exist as an expression of the sellers' understanding that water can be transferred to a higher value use, and their desire to be compensated for it (Table 4-1). Potential sellers probably will not be willing to lose money from a transaction with a lower-value user, but they might be willing to trade if they are paid what they would have made had they kept it with the knowledge that the resulting use equates to equal or lesser economic value. For example, a farmer would have used that water as an input for crop production and, given the right conditions, would have earned a profit from producing and selling the crop. If farmers can be compensated for at least the amount of profit foregone this might open the opportunity for water to flow to a higher valued ecological use.

The approach used here to price options in Texas will be to find the monetary value of what the user is sacrificing (the opportunity cost) by leasing out their water for environmental or other purposes. This valuation method has been explored in the Pacific Northwest as a means to boost streamflow to sustain native fish by having farmers decrease their level of irrigation (Jaeger & Mikesell, 2002). To find pricing tools, water sales and leases were examined as well as estimates derived from land sales, economic models, and contingent contracts, with the contracts operating on a triggered basis similar to the VISPO program (Jaeger & Mikesell, 2002). Other environmental water pricing methods have been explored when the federal government was evaluating how to acquire water, these include: bilateral bargaining, standing offers, and auctions (Simon, 1998). The opportunity cost method may also afford the seller some benefits in addition to their water payment. For example, the seller may rest their field in years the water is called, take time off, or perform farm maintenance. Furthermore, the farmer could decide to switch crops and convert to dry land farming for the year, essentially allowing them to work the land twice that year. They would be paid for the water they did not use and be paid for the dry land crop they raised in place of the irrigated crop.

Calculating the Monetary Value of the Water in an Option

An irrigator's water is priced at the intersection of what they are willing-to-accept and what a buyer is willing-to-pay. To help find a reasonable pricing mechanism based on opportunity cost, the U.S. Department of Agriculture publishes cost and return statistics for crops in various geographies (U.S. Department of Agriculture, 2019).

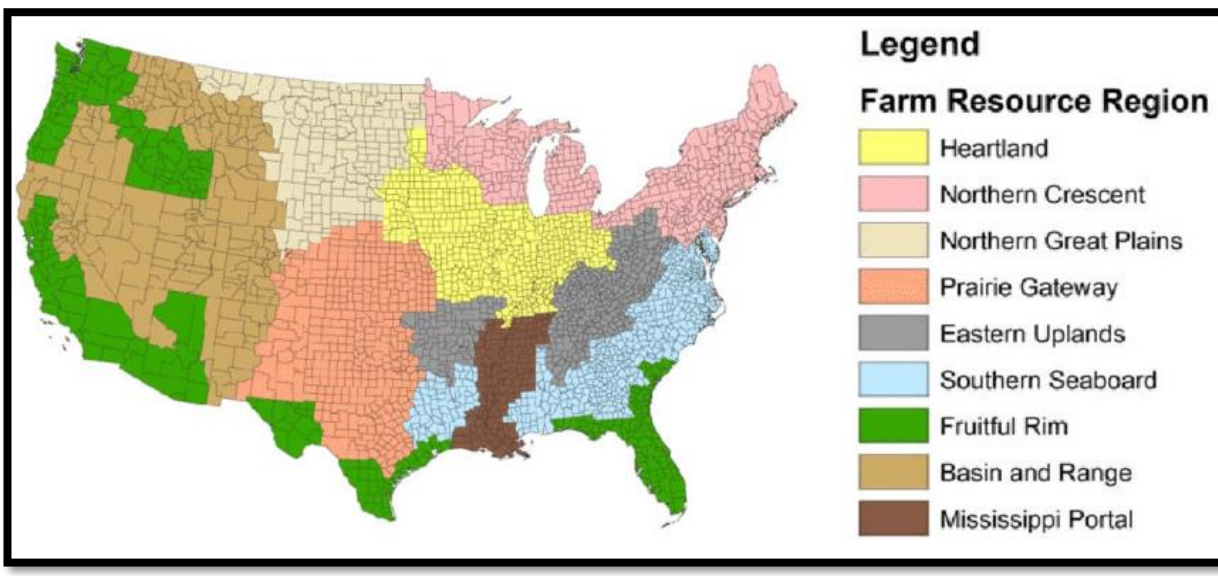

Figure 4-4: Farm Resource Regions defined by USDA in 2000 to compartmentalize farming specialization by region (West et al., 2011).

When considering these statistics, it is important to note the differences for the same crop between regions. This is largely driven by variations in yield. For example, the differences in cotton costs and returns for 2018 between the coastal Fruitful Rim (FR) and the Prairie Gateway (PG) are considerable (Table 4-2).

Table 4-2 Cost and return data for the 2018 cotton crop in the Prairie Gateway and Fruitful Rim regions, excluding government payments; all numbers are U.S. dollars per acre *(*USDA ERS - Commodity Costs and Returns, *2019.).*

2018 Cost/Return (in dollars)	FR	PG
Gross value of production		
Primary product cotton lint	732.60	313.17
Secondary product cottonseed	131.67	48.51
Total, gross value of production	**864.27**	**361.68**
Operating costs		
Seed	81.7	47.61
Fertilizer [a]	78.27	20.47
Chemicals	94	34.83
Custom services	31.18	8.99
Fuel, lube, and electricity	80.33	42.98
Repairs	67.49	43.44
Ginning	150.19	56.14
Purchased irrigation water	35.97	0.02
Interest on operating inputs	6.47	2.66
Total, operating costs	**625.6**	**257.14**
Allocated overhead		
Hired labor	40.66	13.8
Opportunity cost of unpaid labor	33.03	49.46
Capital recovery of machinery and equipment	207.02	130.33
Opportunity cost of land	157.14	40.89
Taxes and insurance	15.3	10.21
General farm overhead	33.72	11.24
Total, allocated overhead	**486.87**	**255.93**
Costs listed		
Total, costs listed	**1112.47**	**513.07**
Net		
Value of production (less total costs listed)	**-248.2**	**-151.39**
Value of production (less operating costs)	**238.67**	**104.54**
Supporting Information		
Yield (pounds per planted acre)	740	429
Price (dollars per pound)	0.99	0.73
Cottonseed Yield (pounds per planted acre)	1197	693
Cottonseed Price (dollars per pound)	0.11	0.07
Enterprise size (planted acres)	370	931
Dryland (percent of acres)	46%	72%
Irrigated (percent of acres)	54%	28%

Price differences between regions highlight the benefit of having an option contract that allows for locally adjusted price information to be used when water options contracts are structured (Table 4-2). For both Fruitful Rim and the Prairie Gateway cotton, and across the spectrum of crops generally, there is a consistent theme in the net category; net value of production less total listed costs is generally a loss, and net value less operating costs generally shows a profit (U.S. Department of Agriculture, 2019). Neither of these scenarios accounts for government payments, so government payments aside, the payment to the irrigator for water will probably need to be between the net of operating costs and total cost numbers to account for some overhead that will remain a liability even in years the land is not farmed.

To illustrate what may incentivize the irrigator to engage in an options contract, the water for 1 acre of cotton from the Fruitful Rim and the Prairie Gateway will be priced. First, the value of production and operating costs will be taken at face value, though these numbers could be adjusted during negotiations with sellers to account for local farm gate pricing or other variables such as silage costs. Given that the farmer will not incur operating costs, those costs are deducted from the value of production to arrive at a net number (Table 4-4). Allocated overhead is then considered and is where adjustments may have to be made to the net (Table 4-3).

Table 4-3. Components of allocated overhead in farm operations, if they will be included in adjusting water payments, and the reason.

Allocated Overhead	Included in Payment? (Y/N)	Reason
Cost for hired labor	N	Not needed that year
Opportunity cost of unpaid labor	N	Farmer can look for work
Capital recovery of machinery	N	Book as depreciating asset
Opportunity cost of land	N	Farmer can lease or use it
Taxes and insurance	Y	Remain a fixed liability
General overhead	Y	Remain a fixed liability

Cost for hired labor can be removed, as there is no need to hire help to produce the crop that the water would have been used for. Opportunity cost of unpaid labor can also be removed, as in any year the water is called the farmer has an opportunity to look for other work. Capital recovery of machinery can be removed as the farmer can book this as a depreciating asset for tax purposes. Opportunity cost of land can be omitted, as the farmer is free to lease or farm it with a dry land crop in a called year. Taxes and insurance still need to be paid as does the general overhead so are added to the net to calculate a total water payment (Table 4-4).

Table 4-4. Fruitful Rim and Prairie Gateway adjustments to prices to buy cotton farmer's water in 2018 dollars.

Fruitful Rim Cotton	Dollars		Prairie Gateway Cotton	Dollars
Gross value of production	864.27		Gross value of production	361.68
Total operating costs	625.60		Total operating costs	257.14
Net	**238.67**		**Net**	**104.54**
Allocation cost adjustments			**Allocation cost adjustments**	
Taxes and insurance	15.30		Taxes and insurance	10.21
General Farm overhead	33.72		General Farm overhead	11.24
Total water payment	**$287.69**		**Total water payment**	**$125.99**

This is a blueprint of how the opportunity cost pricing mechanism can work and is only intended to illustrate a starting point for negotiations. When establishing payment, a calculation involving the amount of precipitation the sellers' location receives during the growing season will need to be factored in to understand how much irrigation water is going onto an acre of land. In addition to the listed operating and allocated costs there may be other considerations important to sellers that come to light as further research is conducted. Given the differing financial realities in various locations, having an instrument that can suit these unique situations may encourage participation in an options market. However, variability in pricing may drive buyers to locations where they are getting advantageous rates—particularly if the water is intended for environmental use downstream. If there was an efficient market in place, these price discrepancies may encourage farmer to farmer transactions at higher costs than the traditionally deeply discounted prices they have charged each other as compared to what they often charge municipalities or industry (Table 4-1).

There is also a significant consideration in the data regarding the cost of irrigation (Table 4-2). Cost to irrigate the Fruitful Rim is almost $36.00 (per acre) while the cost is $0.02 (per acre) for the Prairie Gateway. This is important because the option contact must specify how much water it represents, and an irrigator can only option water he can deliver. Therefore, the pricing must be clearly communicated in terms of how much water goes with the contract. To determine what crop price a farmer receives for water may entail looking at their farming activity and basing the price on the highest percentage of land cover, on farmers' most valuable crop, or on a prorated basis based on land use. These are some of the possibilities to begin the conversation and are meant as starting points to engage potential sellers in dialog. If this degree of specificity becomes onerous, examining the region from a macro view may offer a solution by classifying the payment structure based on the dominant crop. For example, if more than a set percentage of farms in an area are growing a specific crop, price for water in that region generally could be based on overall land use numbers.

The amount of surface supplied irrigation water that a farmer uses to grow a crop will vary based on the amount of precipitation that they annually receive, and the water demand of that crop. This added complexity will have to be worked out for the differing geographies of the state, and a basin by basin approach may be the best method to accommodate this variability.

To begin trading options contracts it might be easiest to find areas in Texas where farmers generally rely on an AF of irrigation. This would mean that to lease a farmer's water by paying him his lost revenue for 100 acres of crop, the buyer would receive a 100 AF of water. This "one for one" arrangement would facilitate transactions by making the terms clear and easy to understand. While this will not work for all situations (consider if groundwater is a portion of a farmer's irrigation strategy) nor for all geographies, it will be a good place to begin executing transactions to prove the method.

In addition to paying for the water in leased years, the buyer will also have to pay a premium to the seller for entering the transaction. Historically, the value of an option premium has been calculated using BSM (Black & Scholes, 1973; Villinski, 2003; Williamson et al., 2008). The value of an option premium using this method includes components that are not available for the methodology outlined here, but there is a useful lesson in BSM for pricing the option premium in the fashion outlined above. The maximum value that BSM will produce for an option premium is the cash value of the underlying asset, and that premium allows the buyer to exercise the option one time. In the absence of an existing method to price the value of the premium on these long-term water options in Texas, using the maximum value might be a reasonable place to start.

If the contracts are structured to pay the farmer the cash value of a year's worth of yield from their crop, then the premium can be set to that same value; one year of lost revenue based on current yield and pricing. As with all market-based instruments, these numbers will have to be negotiated between buyer and seller, but if an agreement can be reached it may be possible to standardize this payment method to accrue the benefits. A point of negotiation will probably revolve around if one year of opportunity cost will adequately motivate a farmer to enter a contract whereby, she will lease out the water for 1 or 2 years. Participants may want a year of premium for each call year allowed by the contract, but again, negotiations will discover the appropriate payment for all interested parties. Premiums paid can be negotiated; but in the absence of historical methodology for pricing these new contracts, the use of BSM can help guide initial price discussions.

Expiration and Call Features

Options for many U.S. securities have a 3-month lifespan, expiring on a quarterly basis. While a similar time horizon was discussed in Chapter 3 for Australian water options, this chapter focuses on a longer-term contract. As mentioned above, this work was initially conceived to craft a mitigating solution to the longer-term implications of low flow years affecting environmental flows, and for an option to be relevant in this space it needs to have a lifespan that can accommodate inter-annual variability of water flow rate. Therefore, options are constructed with 5- and 10-year expirations to give buyers a high degree of long-term risk management.

With a traditional American option, the buyer of the option can exercise it once at, or before, expiration. To make long-term water options as useful as possible, this call feature will be expanded. In addition to greater flexibility, expansion of the call feature will help lower the number of transactions that buyers need to achieve their risk management goals. For water options, call features have been constructed to align with the probable needs of the buyers based on statistical frequency of low flow years.

Senate Bill 3 (SB 3, 80th Texas Legislature) was designed to determine environmental flow standards for the major bay systems and major river basins in Texas (Texas Water Development Board, 2019). From there, the SB 3 Science Advisory Committee for Environmental Flows (SAC) offered guidance to use Hydrology-Based Environmental Flow Regime (HEFR) to help basin advisory groups develop flow recommendations (Albright, 2009). HEFR methodology is described in detail in the SAC guide where they offer a two-step process that outputs a flow matrix of values for wet, average, and dry conditions. Using an approach that characterizes the frequency curve by bounding the "average" conditions at the 25th and 75th percentile to mark the "dry" and "wet" conditions has been used in the past (Richter et al., 1996, 1998). This is not the only accepted method in use. The standard precipitation index approach has been modified to establish probabilities for wet and dry conditions at 31% each, and normal conditions at 38% (McKee et al., 1993; Svoboda et al., 2002). Hydrological systems are dynamic and complex and involve base flows and pulse events which both affect ecological functions so the best method to discuss frequency will be partly determined by the use intended (Ramírez-Hernández et al., 2015). In the environmental flows recommendations reports, recommendations are made that characterize the frequency curve of available water in terms of quartiles (Figure 4-5, bottom left).

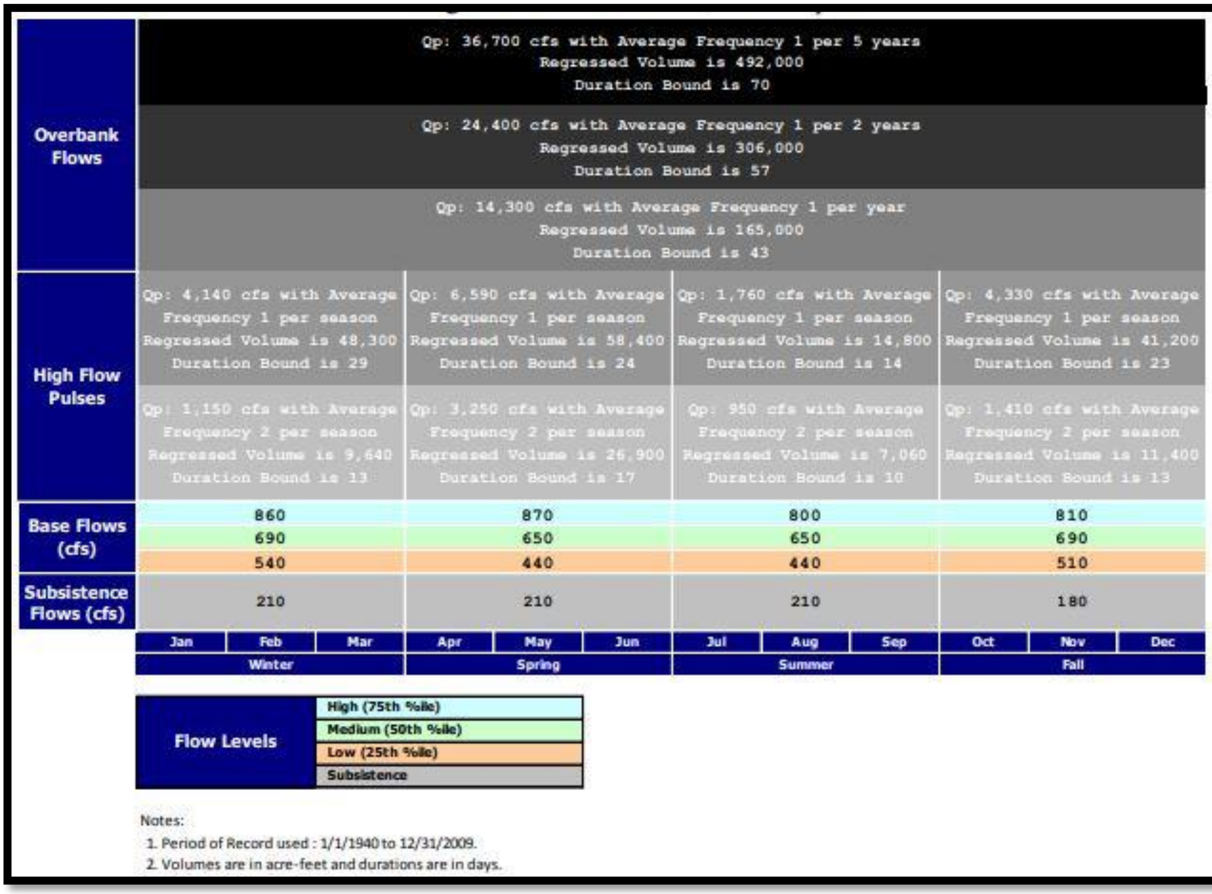

Figure 4-5. Environmental Flow Regime Recommendation for the Guadalupe River at Gonzales (Basin and Bay Expert Science Team, 2011).

For the purpose of structuring the call feature of a water option, we use these value classifications. The conditions are usually associated—in terms of frequency—with the 25th percentile, median, and the 75th percentile of the frequency curve, thus HEFR outputs are designed to identify low flow conditions at the values on the curve associated with the 25th percentile of occurrence, or at a point specified by the user (Opdyke et al., 2014)(Figure 4-6).

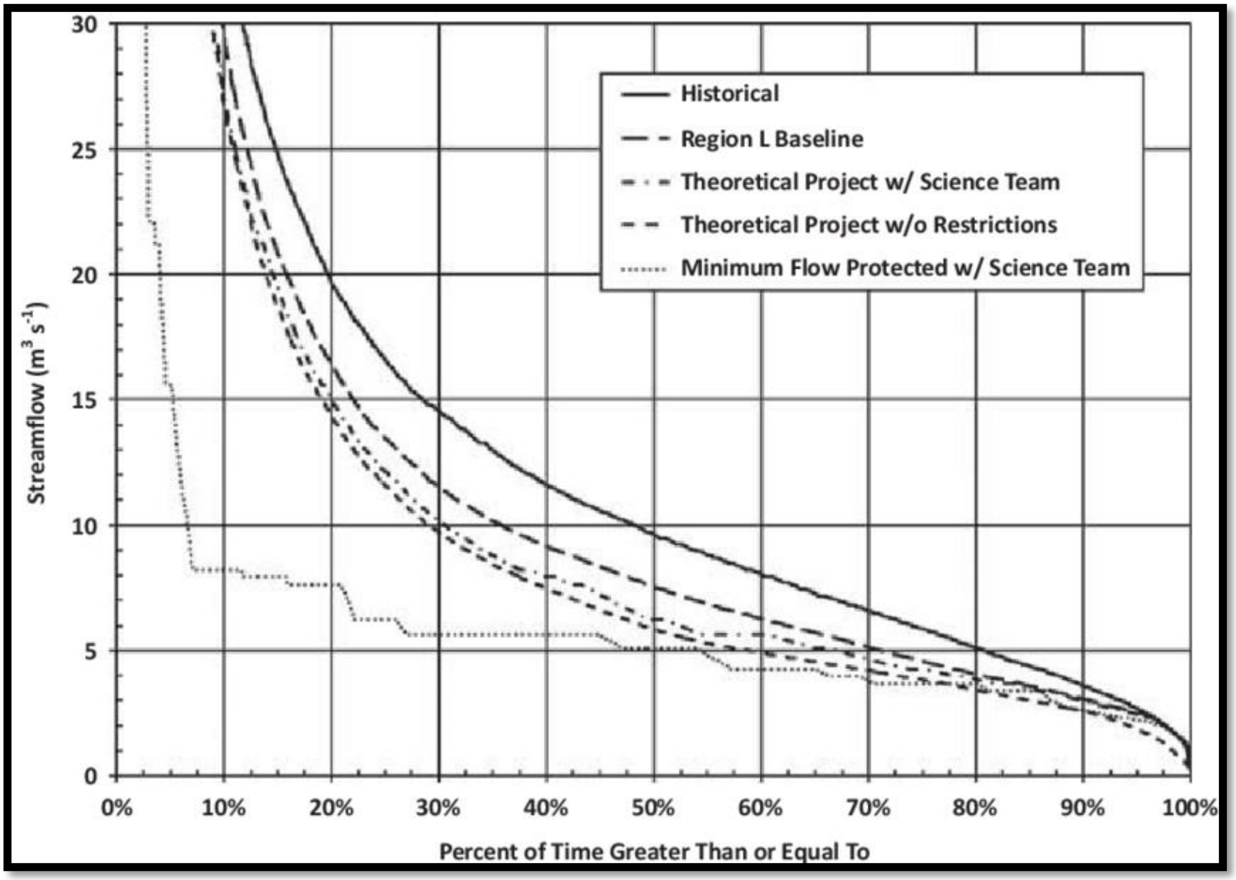

Figure 4-6: Flow frequency curve for the San Antonio River at Goliad (Opdyke et al., 2014)

If buyers of water options are concerned with risk mitigation in low flow years, then aligning the call feature with the statistical percentages presented by the HEFR output should meet their needs, so an option should be callable around 25% of the time. To mesh with this percentage, options could be structured to have lifespans of 4 or 8 years, making the call feature ¼ or 2/8 years. Other lifespans can be used but would have call features not exactly aligned with the 25th percentile. It would be very complicated to try and call ½ a year's worth of water. Therefore, to arrive near the 25% mark, on a 10-year option it would be callable in 2 out of 10 years, with a 3rd year purchase possible with the payment of additional premium. In the case of the 5-year option, it could be callable 1 year with a similarly structured possibility of a second year added.

Consider the following example, an irrigator sells a water option to an environmental manager for a price as outlined above. This gives the environmental manager the opportunity to buy two years of water from the irrigator in the next 10 years. The contract holder (the environmental manager) decides she needs water 4 years into the contract, so she pays the irrigator for the water at the time she calls it. The option holder then decides she needs water in year 6 but is concerned that she may need water in the next 3 years. He calls the second option for water in year 6, and to secure the right for one additional year, she pays the irrigator ½ of the initial premium that was paid to originally secure the contract, allowing one more year of water to be called before the end of the 10 years. In the case of a 5-year option the same mechanism could be used to allow the contract to be callable 1 year in 5 with a second year added in a similar fashion. While these riders do add complexity to the structure, they provide for a larger risk window to be covered with each option and do so while ensuring the seller is compensated in a clearly defined way. While there will likely be negotiations around the specifics, options contracts for water will share some essential elements (Table 4-5).

Table 4-5. Essential Elements of a water options contract.

Element	Description
Expiration	The lifespan of the contract. Options contracts contain a date that specifies the date by which the contact can be exercised before it expires and is no longer valid. The key difference between water options and other options is that the lifespan is expected to be much longer (5/10-years instead of a few months).
Call Feature	This describes how and when the buyer may exercise the contract. Options on other assets can generally be called once. Given the longer-term nature of water options, a starting point for negotiations would be to have 5-year options callable once and 10-year options callable twice; this approximates the 25% frequency of low flow years produced by the HEFR methodology.
Strike Price	This specifies how much the buyer will pay the seller for the asset in the event the option is exercised. The opportunity cost method would make this payment equal to the income forgone by the seller incurred by not using water in the called year. Again, a point of negotiation will be if this price is determined when the contract is signed or is based on market value in the called year.
Premium	This is the option price—how much the buyer pays the seller for entering the contract. The maximum value BSM can output is equal to the cash value of the asset and this could be used in discussions around premium. An important discussion point will be how this is structured in the 5-year option as opposed to the 10-year.

Discussion

Water Options in Texas

Based on the success of the cash markets in the RGV and the success of the options styled VISPO/ASR arrangements, it certainly seems plausible that there is enough demand for water trading products to take them to the next level. The methods set out here illustrate an example of how a cotton farmer might be compensated. However, the goal was to find a method that can work knowing that some of the particulars will have to be negotiated. When possible, the effort was made to use a specific example for illustration, but the ideas here can also be starting points for conversations. On the other hand, efforts were also made to avoid being too general, as the more highly tailored each individual deal becomes the more it moves away from standardization in the marketplace. When possible, standardization of as many contacts as possible helps market participants in many ways as mentioned above.

Irrigators have shown willingness to engage in long term contractual commitments involving their water. The VISPO program discussed above has offered 5 and 10-year enrollment options and has had success with both. There are times when only the 5-year option is available for enrollment, but that has been a function of the budget and not of participant interest (J. Hernandez, personal communication, June 2019). Both the ASR and the VISPO have been successful in offering water purchase programs that are based on a triggered style of water option. The more traditional option outlined here enhances these trading products in two primary ways. In terms of the buyer, the contract is exercised at buyers' discretion, giving them greater control over when the contract is called as opposed to when call features are triggered by an event. From the sellers' standpoint, these contracts have a clear path to pricing that attempts to adequately compensate them for the revenue they will lose by participating through fair determination of strike price, plus and added incentive to participate in the arrangement via the premium payment.

There may be sellers apart from irrigators who are willing to use a pricing structure based on payments to irrigators to option some their water. For example, river authorities may be willing to option some of their water if their current needs are met particularly when, with an option, they would still retain long-term ownership of those rights. Additionally, industrial interests hold permits representing large amounts of water. The Dow Chemical Company holds many permits, but water right number 5334 with a priority date of 1940 entitles them to 4 million acre-feet. When the company is experiencing a slow business cycle, production may be down, so some of that water may not be in use which could create an opportunity to engage them as a seller of water options.

In negotiating with irrigators, it is important to remember that farming has a unique and deep-rooted cultural identity and these contracts are not meant to usurp the importance of farmers or diminish their contributions to society. In addition, while not within the scope of this work, it is imperative to consider the economic implications to farming communities when taking arable land out of production. There could be significant ripple effects resulting from the execution of water options contracts that need to be considered. In future work, attention will be given to what percentage of farming activity may be suspended in a region before the impact of those economic ripples is unacceptably high. The experience of the Owens Valley dealing with the city of Los Angeles at the dawn of the 20th century provides an extreme example of what effect these ripples can have. Whether or not the gains Los Angeles made by purchasing the water from Owens Valley justify the cost to the latter is debatable. Regardless, the effects on the Owens Valley were tremendous, ultimately killing the farming industry and communities by dehydration (Reisner, 1985).

The opportunity cost pricing method may successfully establish guidance for options contracts when the alternative use for the water has less measurable value than the foregone crop but may not effectively compete with high value buyers willing to bid for water. For example, if the opportunity cost method is applied to a corn crop and calculates a payment to the farmer of $125/ac. a manufacturing interest may be willing to pay a much higher price for the same water. Knowing that these buyers exist may hinder sellers' willingness to enter long term contracts where their payments are determined by the profits from their land use instead of a negotiation between what the buyer is willing-to-pay and what the farmer is willing-to-accept.

The combination of the opportunity cost pricing method with the enhanced call feature (as buyers' discretion in lieu of triggering) and the long-term lifespan of the contracts eliminates some of the issues raised in pricing in the Pacific Northwest and when procuring water for the U.S. government (Jaeger & Mikesell, 2002; Simon, 1998). Long term contracts reduce transaction costs as compared to bilateral bargaining and avoid the possibility of collusion that accompanies auctions for water markets; a key will be establish and maintain credible commitments by the parties involved in the transactions (Simon, 1998).

When Should Options be Exercised?

Existing forbearance programs have aspects that resemble options, but one notable difference is that the option is "triggered" by water levels as opposed to simply being exercised ("called") at the option holders' discretion. The options described in this work are intended to be callable at the buyer's discretion. Along the longitudes that Texas covers there is incredible variation in the amount of precipitation, and there are several very diverse groups that use large volumes of water in the state (Texas Water Development Board, 2020; Montagna, Hu, et al., 2018). Therefore, it is impossible to craft a call metric that will be useful to all user groups across geographies, but a brief description may offer guidance as to how these metrics might be constructed for the environmental manager and an authority that manages supplies at a reservoir.

Environmental managers concerned with environmental flows of water to bays and estuaries could use existing HEFR outputs to establish their own triggering mechanisms. If a manager is not satisfied with HEFR they could possibly use salinity as an indicator of flow levels. Work has explored both salinity values as well as the amount of salinity variation and one, or a combination, of these measurements could inform decisions (Montagna et al., 2009;

Montagna et al., 2002; Montagna, Chaloupka, et al., 2018). What also might be helpful for the manager is to understand the reference condition, or the optimum condition, of their chosen metric so they can understand when the system may be under duress. With changes in precipitation across the state come changes in flow regime, so it is important to remember that each system will have its own salinity values and variations that indicate normal functioning.

Municipalities could look to their reservoir levels and make some determinations about what levels would cause them to act to secure additional water. These decisions can be made proactively, as having the reservoir is akin to having a bank. If water options are procured upstream and then called, the reservoir has the potential to use that water to pull out of drought conditions, use the water, or even sell the water downstream. These options can offer great flexibility to organizations that can bank their own water.

The RGV offers a good example of where an active spot market for water in Texas and makes it a strong candidate for implementation of an options market (Villinski, 2003; Yoskowitz, 1999). However, the Watermaster system in place in the RGV gives that market some unique characteristics not found throughout the state, such as the surface rights being correlative. Correlative rights are allocated differently than rights under a seniority system. Instead of curtailing water delivery to junior rights holders when supplies are low, all users' allocations are reduced proportionally when shortages occur (Texas Water Development Board, 2020). The implication is that if options contracts are successfully marketed in the RGV that are based on these characteristics, it does not assure that similarly structured contracts will be of use elsewhere in Texas. The RGV also has hydrology that naturally lends itself to the utilization of a natural conveyance of water with the location of the dam upstream so also possesses advantages in terms of water delivery. Institutional frameworks in each basin system that provide the space for effective markets to develop will be critical (see chapter 5). It may be possible to design options for use under a Watermaster using more traditional pricing methods and use the method outlined here for other parts of the state, but there is no reason that the methods designed here could not be applied to areas with a Watermaster.

Conclusion

The flexibility that options contracts offer make them a promising solution to the issues of scarcity facing Texas. These contracts can be an attractive tool to the myriad water users throughout the state. To bring these contracts to market, more work will have to be done to make sure that buyer and seller needs are met in the product. A logical next step would be to engage those user groups to better understand how interested they are at different price points and what elements would have to be present in the contracts to buy or sell them. There are regulatory hurdles that will have to be addressed to allow for the development of water markets and their attendant derivatives in Texas. For a discussion of the hurdles that may be impeding the development of these markets see Chapter 5. Even with the roadblocks to progress, these contracts offer the possibility of enough benefits that further investigation and development of them is warranted and if transactions are kept between participants in the same basin, they may be deployable under current governance. The model outlined here offers a method to price water options in Texas, but this model will likely need to be adapted to accommodate unforeseen issues. This is a starting point for negotiations that can advance the growth of water options along a trajectory leading to opportunities for implementation state-wide and possibly beyond.

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CHAPTER V

FRAMEWORKS AND INSTITUTIONS

Introduction

Purpose

To further develop market-based water allocation strategies, it will be helpful to understand current frameworks in Texas to assess their functionality. In Texas, there are some institutions that can (and do) house water banking, trading, and gifting. The Texas Water Bank and the Water Trust could be starting points from which to form an expansive, fruitful framework for using water markets for efficient allocation of water across the state (Texas Water Bank & Trust | Texas Water Development Board, 2020). The Edwards Aquifer and the San Antonio Water System are engaging in banking (as Aquifer Storage and Recovery) and 'triggered' type of forbearance—so novel strategies are being developed and employed in the state (Edwards Aquifer Authority, 2019). There are some water markets in Texas, particularly in the Rio Grande Valley (RGV) under the Watermaster system, and these markets may have opportunities for broader application (Villinski, 2003; Yoskowitz, 1999). In addition, there may be space where user partnerships are not fully developed and could be expanded with mutually beneficial results. For example, a strategic reserve formed by municipalities, private enterprise, irrigators and environmental advocates could help all involved.

This evaluation of the tools available to allocate water is necessitated by the reality that demand for water is outpacing supply, and in 2020 Texas is estimated to have a water shortfall of 4.8 million acre-feet (5,920 Gl) during a repeat of the drought of record and is expected to grow in ensuing decades (Texas Water Development Board, 2017). This shortfall can be partially mitigated by improving our existing allocation policies and by enhancing delivery tools that fit with these policies. Market mechanisms can help price water, as well as facilitate the allocation of water to its highest and best use.

Research Questions

This survey chapter examines historical development of water policy and regulations in Texas and makes observations and suggestions regarding two questions: What is Texas doing well to support water markets and what changes could be made to support and enhance the development of water markets in the state.

Background and Relevance

In some ways, the story of humankind is the story of its relationship with water and the rise and fall of communities has ebbed and flowed with their ability to reliably secure freshwater. Water plays a fundamental role in Earth systems and human existence, and there is no substitute (Vörösmarty et al., 2015). While approaches may differ, the need to manage the resource is universal. Global management approaches are divided by sovereign countries, which have their own unique geographies. This makes generalization about best practices difficult and raises issues about how resources will be managed when their spatial orientation crosses human imposed boundaries (McGraw, 2018; Norman et al., 2013; Sánchez-Munguía, 2011).

Even within a country, management and regulation of water can vary widely. In the U.S., for example, this division of jurisdiction can result in differing policies at both the intrastate and interstate level. In Texas the rules that govern water rights differ by location: although much of the state is governed by the prior appropriation doctrine, the area under the RGV Watermaster uses a system of correlative rights (Texas Water Development Board, 2020). There are cases where states sit on the same resource, as is the case with the Ogallala Aquifer. The view from the

Texas/New Mexico line offers a stark contrast—verdant green on the Texas side and desert on the New Mexico side. This divide is caused by differences in the states' regulation of groundwater; in New Mexico regulations restrict groundwater pumping while in Texas these regulations do not exist (McGraw, 2018). This again raises the challenge of multi-jurisdictional management of a shared resource. In the U.S., at least one geographic generalization was made by explorer John Wesley Powell, who divided the country into two regions: the Arid Region of the west, and the Humid Region of the east (Powell, 1879). Powell notes anomalies in this generalization—e.g. the Pacific Northwest—but the main point is that land east of the 100th meridian could support agriculture without irrigation, and land west of that meridian could not, based on an annual requirement of 20 inches (Powell, 1879). However, we know that this general rule is not applicable today with the application of irrigation. In some ways, then, the history of water management in the U.S. is the history of water in the west.

Volumes have been written that detail the history of water management in the West generally and in Texas particularly. For the former, Reisner's *Cadillac Desert* (1985) has been described as the definitive account, and the latter is well chronicled by McGraw in *A Thirsty Land* (McGraw, 2018; Reisner, 1985). The work in this chapter seeks to understand the effects of more recent legislation and Texas water law as they relate to the ability of markets to function effectively in the state through an economic lens.

History of Water and Regulation in Texas

Development of Water Management Policies

Two states, California and Colorado, established variations on the same principle to establish their system of water rights. Initially, as the Mormons settled the west in the mid-19th century, the need for effective water management arose with the influx of people and the scarcity of the resource (Krakauer, 2003). The Mormons generally favored a system that shared the resource with the aim of promoting beneficial use (InTeGrate, 2017). However, over time "Prior Appropriation Doctrine" superseded the beneficial use principles. Prior appropriation, more simply, is the "first come, first served" approach to management. This doctrine allows an interested party to secure water rights for use (i.e., agriculture, mining) when they do not have river access from their land. This method also laid the foundation for the development of senior rights and junior rights, where the junior rights holders may not receive a share of water in drier years. Prior appropriation also included a use clause where in a given year if a right was unused in accordance with its parameters the holder lost it (InTeGrate, 2017).

Water Management in Texas

Texas resembles the California Doctrine as the model for water management in the state, which is a combination of the Prior Appropriation Doctrine and the Riparian Doctrine (Templer, 2010). This is not to say that Texas used California as the model, but that the systems are similar and the vernacular is known as the "California Doctrine" (Jarvis, 2008; Templer, 2010). The Riparian Doctrine relates to treatment of owner of land adjacent to a body of water or river and states that the owner has the right to make reasonable use of the water in so far as that use does not adversely affect the ability of users downstream from also making reasonable use of the resource, too (Jarvis, 2008). It is against this backdrop, of organically developed doctrine, that the Texas Water Code has evolved and was in place until the 1960's.

A major re-evaluation of Texas water rights came on the heels of the drought of record in the 1950's and resulted in the creation of the Texas Water Development Board (TWDB) in 1957 and the enactment of the Adjudication Act in 1967 (Jarvis, 2008). The intent of the Adjudication

Act was to eliminate (or improve) the somewhat chaotic water rights system, in part by quantifying and taking an inventory of all water rights and limiting the riparian rights. The result was the elimination of the previously used dual system and a move toward a single statutory system of rights (Jarvis, 2008). The TWDB was formed by both legislative act and constitutional amendment and was initially authorized to issue $200 million in State of Texas General Obligation Water Development Bonds for the conservation and development of Texas' water resources (Jasinski, 2010). The TWDB aims to provide leadership, financial assistance, and planning for the conservation and smart use of water while the Texas Commission on Environmental Quality (TCEQ) objective is to protect the state's public health and natural resources. The code has strengths and weaknesses and an evaluation of the code and the frameworks it provides for water marketing are examined.

Legislative Developments Since the 1950's

While many developments have affected Texas water administration and law since the drought of record, creation of the TWDB and the Adjudication Act, the turn of the millennium saw the formation and passage of four major water bills that have shaped current water regulations (White et al., 2017). The beginning of this legislation came in 1997 with the passage of SB 1, which mandated the TWDB craft a state water plan every five years and created extensive regional water planning groups. The bill also streamlined the financial aspect of state water planning by consolidating the specialized funds administered by the TWDB into one location, the Texas Water Development Fund II. There was an associated, but separate, funding bill. HB 1802 was intended to establish fees and make appropriations to fund water projects, but it died in committee. From there, the Texas the Water Infrastructure Fund was created by SB 2 in 2001 and sought to fund and streamline what the authorities created by SB 1, which would provide water to every Texan through 2050 at a cost of roughly $17 billion financed by the state (Legislative Reference Library of Texas, 2019). The funding sources originally associated with the bill were fees and taxes; these were strongly opposed and were removed from the bill before its passage.

In 2007 environmental flow standards were addressed for all the major bay systems and river basins in the state with the passage of SB 3. This bill was crafted to create a process that was scientific, consensus-based and stakeholder driven and offered an accelerated mechanism to formulate environmental flow standards that TCEQ could use to set standards in each basin (Texas Water Development Board, 2019).

Evaluating Frameworks in Texas Water Markets

Efficient Capital Markets

The extent to which a market performs can be measured by how efficiently it functions. Therefore, to understand how well a market is constructed, it is necessary to understand what qualities make if efficient. Markets are not perfect, but the idea of a perfect market can be useful to measure how well institutional frameworks foster market growth. In the late 1960's Eugene Fama worked on his ideas regarding efficient capital markets and described an efficient market as one where prices reflect all available information (Fama, 1970). Fama also worked on the General Equilibrium Theory building on the approaches of Tobin and Markowitz, all of which operate under the assumption that the market is perfectly competitive (Fama & MacBeth, 1973; Markowitz, 1959; Tobin, 1958).

The perfectly competitive market has the following characteristics:

- There are many buyers and sellers in the market, none can influence the market price directly.

- There are no barriers to enter/exit the market.
- Products in the market are homogeneous.
- Perfect knowledge of the marketplace exits, and there are few transactions costs.
- Factors of production are perfectly mobile and transport costs are insignificant.
- No externalities arise from production or consumption (Hashimzade et al., 2017).

Again, these characteristics do not exist in practice, but are the assumptions under which theoretical experiments can be conducted and are a helpful guide to assess markets that do exist. Using the perfectly competitive market, water policies in Texas will be evaluated based on how well they adhere to these assumptions.

Many Buyers and Sellers

The number of existing buyers and sellers is difficult to quantify, but an estimate of the number of potential market participants is possible and appears to have enough interest to support markets (Texas Commission on Environmental Quality, 2019). While SB 1 conveyed a sense that water supplies could meet growing demand though the redistribution of available supply, that vision has not been realized. This redistribution would be voluntary, but to date transactional water transfers has not grown significantly. However, the number of interested parties is not the limiting factor, but the surrounding policies, regulations, and laws are preventing potential market participants from creating an active market (White et al., 2017).

The number of buyers can include anyone who wants to procure water for beneficial use. This includes municipalities, industry, irrigators, environmental groups, and more. The number of sellers can fluctuate based on the number of active water permits. The TCEQ reports over 9,000 water rights as active in their database, and these rights holders are all potential sellers (Texas Commission on Environmental Quality, 2019). In addition, river authorities may act as both buyers and sellers depending on the conditions. While there is not currently a high number of buyers and sellers in discrete water markets, the potential to have enough exists. This indicates that improvements can be made to the system that will increase the number of participants, thus increasing the overall efficiency of the market.

Barriers to Entry

The depth and complexity of regulations surrounding the administration of water rights in Texas can act as its own barrier. To buy a water right or lease water from another individual there are administrative procedures that must be followed. Particularly in the case of buying a water right, most individuals would be advised to hire an attorney specializing in water law. Comparing this to buying a stock or a commodity where a brokerage account is simply opened and funded to transact business, the administrative procedures regarding water transactions present barriers to entering the market.

To see how some of the administrative burdens have been eased, lessons can be learned by the changes made under the Watermaster system in the RGV. The adjudication of water rights established the correlative treatment of rights for irrigators and gave the Watermaster some administration powers that can be carried out in situ. Instead of going for permitting review, change of use issues are administered by the Watermaster and involve a conversion factor applied when the use is changed (Schoolmaster, 1991). This facilitates trade by allowing the administrative procedures to be done regionally which increases efficiency, particularly in the case of a transaction involving the change of water use. Water transactions elsewhere in the state that do not involve a change of use are straightforward; a simple change of ownership is filed with the TCEQ. Most surface rights transactions do involve a change of use, which requires a substantial approval process involving the TCEQ and involves considerable review of the change (Texas Water Development Board, 2019)

Products are Homogeneous

Homogeneity of product is important, if not essential, to the creation and operation of an efficient marketplace. The commodities traded on a mercantile exchange are an example of homogeneous products. Cotton, orange juice, and light sweet crude are examples of products that can be bought from any market participant, that when delivered, will be identical. Though all water rights have been adjudicated in Texas, most of the state allocates water to these rights using the prior appropriation doctrine, which expressly makes each permit unique. The seniority system of rights (first in time, first in right) approach means that the reliability of the permit is tied to its date, and each right has a date that gives it this uniqueness or heterogeneity. It will be difficult to have a centralized auction market when the items for sale are materially different. So, while the water might be homogenous the right is not.

One solution, although not simple to enact, would be to revamp the prior appropriation doctrine used to allocate water rights across the state, making these permits all the same, as was done in the RGV. This would mean that in a dry year all permit holders would see a reduction in allocation on an equal percentage basis. Not only has this strategy worked in the RGV, but in foreign markets as well. When Australia was moving to a market-based system for allocating water in the Murray-Darling Basin, one of the first steps they took was to fully adjudicate water rights and move away from the seniority system (E. Carter, personal communication, August 2018). This is a significant change to current water rights administration and may be met with significant resistance—particularly by those who hold the most senior rights. However, if this change provides clear benefits to the people of Texas it may be justified, as the surface waters of Texas technically belong to the people.

The interbasin transfer rule has also affected homogeneity. The passage of SB 1 in 1997 included the junior rights provision, which made the seniority of any right transferred across basins be the most junior of all rights in the source basin. For example, if you have a right dated 1940, and transfer it to another individual in another basin the new date of the right is effectively today. This adds complexity to the sale of water and can have a large impact on the ability to move water between basins. For the water right permit holder in a basin that has water in abundance and would like to market water to a neighboring basin, this presents a current barrier.

Perfect Knowledge Exists; Costs Are Low

There will never be perfect knowledge in a marketplace, but asymmetries of information lead to inefficient markets. Transactional data regarding water trades is simply not easily available on a statewide basis. One needs only to visit the website of the RGV, the Texas Water Bank, or the Texas Water Trust to see how little information is provided (http://www.twdb.texas.gov/waterplanning/waterbank/index.asp).

As mentioned in the barriers to entry section, if the services of a lawyer need to be retained to research the possibility of a transaction, costs can be significant. With some existing structure in place, the Texas Water Bank may be modified to accommodate a wide range of transactions at a basin level. To encourage a market to grow in Texas it may be possible to have the TWDB (or some other entity, i.e. TCEQ) offer an incentive to market sellers to list water for sale at the Water Bank. Maybe a very slight reduction (or discount) of another fee currently being charged to river authorities could act as an inducement to get them to list their water for sale on a publicly available site.

Transport Costs Are Insignificant and No Externalities Arise

Regardless of the location of a water market, transport costs will generally be significant, and externalities will arise. One way to mitigate transport costs is to place markets in locations that have a river or canal system in place that can act as a conveyance for market traded water delivery. In Australia over 90% of trading occurs in the Murray-Darling Basin, where the positioning of the rivers and engineered conveyance systems provides a delivery system for traded water (Figure 5-1).

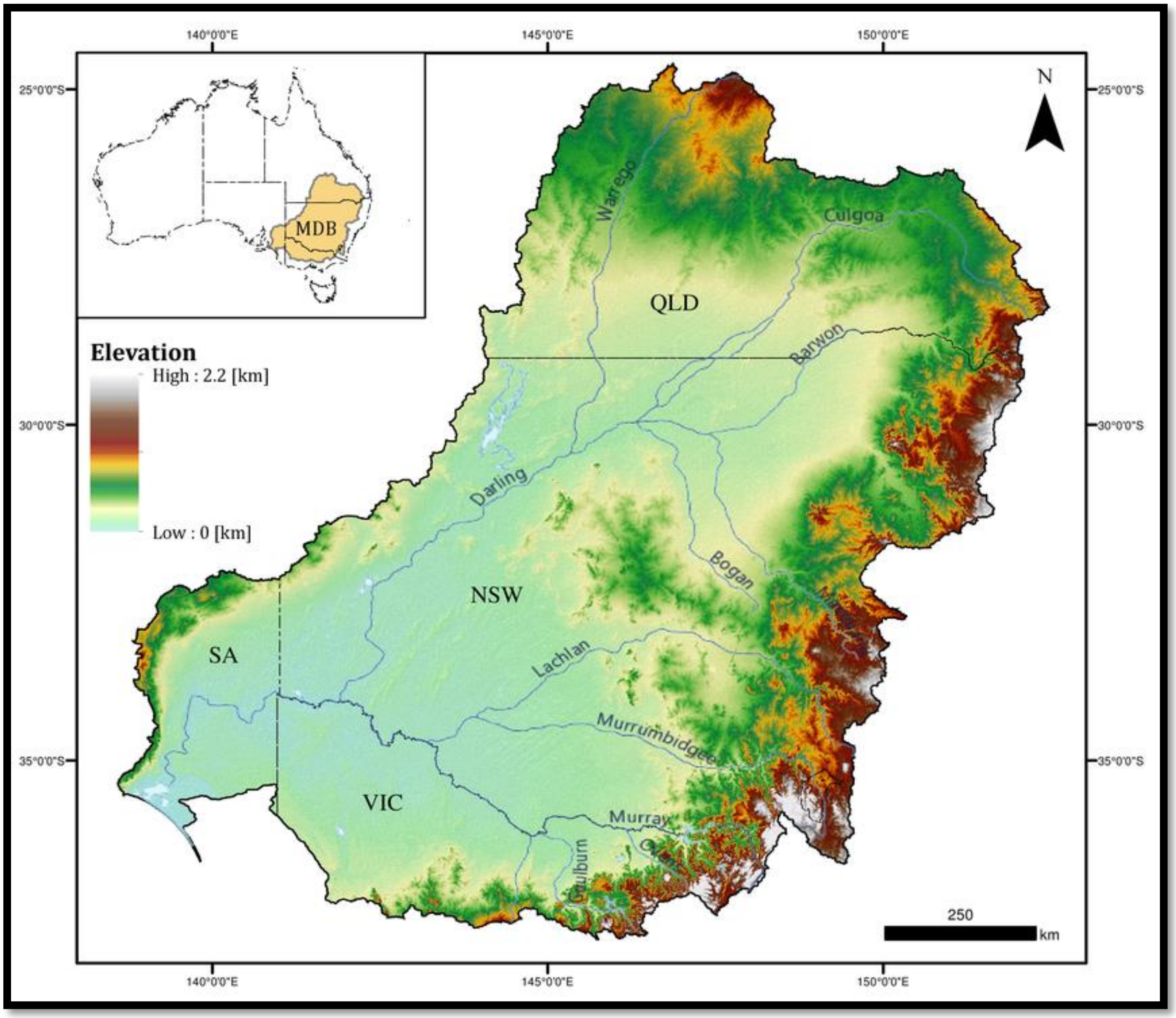

Figure 5-1. Water markets in the Murray-Darling Basin in south east Australia use the interconnected rivers to transport water traded in the marketplace (Heimhuber et al., 2016).

Markets could be designed to price water at the point of diversion which would price water without considering transport, or markets could be designed that operate along a natural watercourse to use the natural flow to facilitate delivery. Meaningful volumes of water take up a large amount of space and to transport these volumes in a different fashion is expensive. For example, the Mary Rhodes Pipeline project was completed in 1998. The pipeline is 101 miles long, has two pump stations, and cost $116 million (City of Corpus Christi, 2019). Phase II of the Mary Rhodes Pipeline pumps water 42 miles using two pump stations and a sedimentation basin from the Colorado to Phase I and cost $154 million (City of Corpus Christi, 2019). Moving water via pipeline can work but is expensive; beneficiaries of the water must weigh the long-term benefits with the short-term construction costs.

Discussion

Markets can be a tool to aid efficient allocation of scarce resources but need to be created in ways that foster their effective functioning. Water markets in Texas could benefit from some improvements. There are challenges to these improvements, but they can be addressed. Many of the shortcomings of the status quo stem from larger issues relating to the complexity of regulatory oversight and administrative procedures. In addition to recommending a streamlining of the administrative process, there are two issues that can be addressed on their own.

The prior appropriation doctrine may not be compatible with efficient markets. The prior appropriation doctrine is not new, nor is it endemic to Texas, being the law in other western states. It may be possible to structure a market so that there are micro-markets under the larger umbrella; this could mean having a separate market for water rights based on seniority grouped into time frames: 1900-1920, 1921-1940, etc. However, even this grouping will mean that there will be years when some rights within a group are watered and some are not. It may be possible to move toward correlative rights and label the time frames simply group 1, 2, etc. so that rights can be equal within a grouping but some of the senior aspects can be retained. This suggestion may not be the ideal solution, but the point is that it might be possible to move to homogeneous products incrementally to avoid the shock and backlash that proposing abolishing the prior appropriation doctrine might cause.

For a market to operate efficiently the simplest approach may be to do what was done in Australia and the RGV, revisit how water is allocated by rights so that when there is a shortage, all allocated water is reduced by the same percentage basis across permit holders. This suggestion may be too radical to implement in one move, but the softer approaches in the previous paragraph are ideas that may move the evolution of water rights administration along a positive trajectory while still being palatable to the users. Senior water rights have value, and those that hold them may be reluctant to move to a system that could effectively lower the value of their right. However, these rights are granted by the state who is administering them for the benefit of the people of Texas and if there are better ways to serve the people then the status quo is providing they should be explored.

Another element of the regulatory environment that could help encourage water markets would be the repeal of the junior water rights provision found in SB 1. SB 1 was passed in 1997 and as far back as at least 1999 arguments have been made to eliminate this provision (Resource Economics, 1999). The elimination of this provision could make it easier for water transactions to occur across basins, which would spur the growth of markets. While it is speculation to suggest that eliminating the junior rights provision will help markets, its continuation certainly curtails the growth of markets (Neeley, 2014). This repeal may have other benefits, such as possibly reducing the amount of current and future groundwater extraction. The junior provision has been credited by some as leading to the proliferation of groundwater districts since its inception (Mace, 2016)

There is legislation currently in place that can greatly impact TCEQ's ability to reevaluate environmental flow issues. The SB 3 process mandates that when new water permit applications are submitted TCEQ take into consideration the potential impacts on the environment when rendering a decision. This mandate does not give TCEQ the power to retroactively evaluate permits in place, and with most of the available water being already permitted this means that the new regulations will not have much impact with regards to environmental planning. However, if a permit undergoes any type of change (e.g. change of use, change of ownership) this could be viewed as an action that creates a new permit. Being “new” this re-permitted water may need to be reviewed for environmental impacts as per SB 3. This could be a way to give the SB 3 requirements broader application to permits already in place. However, this may not have the effect of increasing interest or participation in a market. If this application of the SB 3 is tested, and works, people may simply be more reluctant to effect transactions that will put them at risk of going through this process. However, this may be a way for TCEQ to follow the spirit of SB 3 by considering environmental needs when issuing permits that are comprised of a change to an existing permit, which may be particularly useful in systems where water is oversubscribed.

Lastly, there is a section in the Texas Water Code (Section 297.18. Interbasin Transfers, Texas Water Code, 11.085) that provides for interbasin transfers that are exempt from most of the requirements that normally apply to these transactions, including the junior rights provision. In the code, under subsection (k) item 3 states that one of the types of transactions exempt from the normal regulations is “a proposed transfer from a basin to its adjoining coastal basin.” If this provision were utilized to a greater extent, inter-basin transfers could take place all along the Texas coast and remain exempt from the normal permitting process. We searched the legislative notes to ascertain the spirit of this provision but no notes surrounding this point were on file. Communicating with one of the participants during the discussion around SB 1 it was relayed that the coastal exemption to interbasin transfers, “was included because of the significant number of interbasin transfers already occurring in the coastal areas and the need for such transfers to continue being done easily in the future; all coastal regions supported the exemption not just the Houston-area" (C.J. Parham Treadway, personal communication, March 2020). If demand for transfers is great enough to encourage large volumes of water to be traded under this exemption, the scope of this exemption may have to be tested in court if these transactions draw the attention of regulators.

There are many ways to improve frameworks supporting the development and growth of water markets in Texas, ranging from the simple—and fairly easy—to more aggressive actions requiring legislative interventions. To understand the potential impacts of suggested changes, these changes can be considered in terms of how they might move supporting frameworks toward higher levels of market efficiency (Table 5-1).

Table 5-1. Suggestion actions, and potential impacts, to enchance frameworks supporting water and water rights trading in Texas.

ACTION	IMPACT
Eliminate junior rights provision	Ease restrictions on inter-basin transfers, facilitate surface water trade, possibly relieve pressure on groundwater supplies.
Move toward correlative rights (RGV)	Makes permits more homogeneous, reduce transaction costs, ease spread of information.
Maintain central record of transactions and publicly posted bid/ask market	Increase information flow, increase transparency, decrease transaction costs, encourage buyers and sellers to participate, lower administrative barriers to entry.
Use coastal basin exemption	Facilitate trading without requiring legislative intervention.

Elimination of the junior rights provision would require a legislative change. Despite this, recommendations to pursue this course of action are widespread (Vaca et al., 2019, White et al., 2017). Looking at the number of interbasin transfers, before the passage of SB 1 (1980-96) there were 28 interbasin transfers, after passage there were 3 transfers (1997-2006) and 1 after 2006;

these numbers indicate that the junior rights provision has hampered these transactions (Vaca et al., 2019). Even if this provision is repealed, it will still mean that TCEQ must weigh the gain to the receiving basin against the loss of the exporting basin when making permit approval determinations, as found in *San Antonio v. Texas Water Commission* (Neeley, 2014). If there is a loss to the exporting basin, there may be ways to satisfy the TCEQ's concern about an inequality by offering a payment to the exporting basin (funded by a portion of the transaction value) to mitigate the loss incurred (White et al., 2017). Even within a basin transporting water upstream may have environmental and economic consequences, but these impacts may also be mitigated. Water planners are also calling for the repeal of the junior rights provision as evidenced by Regions C, H, and N all making that recommendation in their (as of 2014) latest water plan, and region I requesting a new exemption be added that exempts transactions which leave 125% of water required to meet needs in the exporting basin (Neeley, 2014). With the desire to repeal this provision coming from many different groups, there may be enough public support to motivate the political will to address this issue. In Australia the restrictions surrounding these types of transfers were greatly reduced as one of the first steps in the water reforms that led to the successful creation of markets (Hanemann & Young, 2020).

To move toward a system that administers rights on a correlative basis instead of based on prior appropriation will be difficult. In Texas, suggestions are being made that can move policy along this trajectory without totally upending the system. Recently, the idea of expanding the Watermaster system has been discussed by introducing a "Watermaster Lite" that could begin to facilitate transactions with decreased administrative intervention (Vaca et al., 2019). While this particular suggestion does have complications, it serves to illustrate that it may be possible to begin to move allocation policy in a direction that can support water markets better than the status quo. Simply put, if permits can be made more homogeneous it will be easier to trade them.

The maintenance of a central data repository might need legislative action, at least to fund it. Either building a new platform to house and furnish transaction data or expanding the existing capabilities of the Texas Water Bank would require an initial investment and some level of staffing. The benefits of making this investment could be considerable, with gains likely in both market transparency and efficiency. Having a publicly accessible data source would also decrease asymmetries of information which would help equalize the information available to market participants.

Exploiting the coastal basin exemption would not require legislative intervention and builds a common practice that has been established and accepted as mentioned above. To move significant amounts of water will require a viable system of transmission to get the water from seller to buyer and if this involves a pipeline it would be an expensive proposition. Despite this expense, the prospect of moving water from East Texas across coastal basins unfettered by some of the onerous administrative oversight might draw investors.

Conclusion

This work continues the conversation regarding Texas water markets. There is a broad selection of work in the space, and this paper has contrived to find a few areas where the current frameworks can be changed or used differently to encourage the development of these markets (Mace, 2016; White et al., 2017; Yoskowitz, 1999). Taking the approach that Yoskowitz used to apply the ideal market concept in the RGV and applying it to the state has shed light on what improvements might be made (1999). Moving toward efficient markets will probably require some changes at the institutional level, and that possibility will depend on the political will to enact them. To improve the information available to architects of developing water markets it may be fruitful to return to the Rio Grande Valley to look for policies that may be transferred or expanded to other parts of the state.

Yoskowitz studied markets in the RGV two decades ago, and the region was, and is, trading water (1999). To build water markets in the most effective way possible, an updated study of activity in the RGV may offer suggestions regarding what has, and has not, worked. While the reality of water markets across Texas is still only a possibility, the potential increases in the allocative efficiency of this precious resource justify continued work toward this goal. Many of the suggestions made here have been made by others, but as Occam's razor dictates, the simplest solution is often best and should be used before more complex approaches are pursued (Vaca et al., 2019.; White et al., 2017).

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CHAPTER VI:

CONCLUSION

Summary of Research Findings and Suggestions for Future Research

This work found that:

- Yes, a machine learning approach can successfully model the price of Australian water, and if that model can be transferred to the U.S. to provide water prices.
- The Black-Scholes Merton model of options valuation can successfully be used to price Australian water options.
- The opportunity cost method can price long-term water options in Texas.
- Current frameworks in Texas allow for some water trading but might better support the growth of water markets by adopting some changes.

These results indicate that, yes, market-based allocation strategies can be successfully expanded to increase their application and improve the efficiency of freshwater distribution.

Australia and the U.S.

Building and transferring the predictive model from Australia to the U.S. has illustrated that a predictive model can be transferred between two systems that share common variables, though the broader implication has wider applicability. Chapter 1 uses market data to predict a phenomenon that would often be thought of as driven by biophysical forces. Once the validity of the model and its transferability is understood, we can begin to think about other ways to creatively use data to help us solve problems. Many datasets that may have been considered unrelated to each other may have relationships to the same output making them useful to use in combination. When framing our research questions, these relationships may be revealed if we broaden our approach to consider where these intersections may exist. As computational power and data collection continue to grow, these previously hidden intersections should become easier to exploit—provided we are looking for them.

The next logical step is to evaluate more variables and consider adding them as inputs to improve the model. If the model considers more detail and smaller scale, it may increase the capacity to capture nuanced price movements. For example, land use coverage may be included to sharpen water valuation in any given region. To enhance the bio-physical inputs, experiments using satellite soil moisture content readings and/or reservoir capacities might increase the model's ability to incorporate the importance of the natural supply of water. Soil moisture content may also help more accurately capture precipitation moving through the system by tracking lag times between precipitation events and the arrival of that water downstream. Reservoir water levels would help measure the pressure that existing supply may exert on market prices. This data can be added to the model and transferred to other geographies in a similar fashion to the pricing model built in Chapter 2, provided data for those inputs is available in both locations. As water markets grow, the data will improve, so the model will improve, too. In addition to improvements in data quantity, increases in the quantity of data may encourage future modelling efforts to revisit applications of neural networks, as the amount of data may have limited performance in the cases presented here.

Looking at ways to increase model applicability in a wider range of U.S. settings would increase practical application. For example, building a model on an Australian region dominated by almond farming might yield better application of the model to domestic landscapes dominated by almond farms than simply using results produced by the general model. Also, now that exchange-traded fund (ETF) style products are beginning to come to the market, particularly the Veles ETF product derived from the California water markets, it will be possible to take this pricing method and use it to make informed trading decisions, particularly if arbitrage opportunities appear to exist when considering the price of the ETF and the model output. Likewise, this pricing model could be used to develop trading tools for use in Australia, particularly if lagged variables are experimented with that can allow for a glimpse into what input variable activity might do to water price activity in the next few trading periods. For example, if certain geographies have a lag time of 4 days, and there is a rain event on Thursday, trades may be executed on Friday in anticipation of the impact of the lagged variable arriving on Sunday ahead of Monday's trading.

Short-term Options in Australia

Results indicate the possibility to trade options on water in Australia is viable using BSM. Two of the biggest challenges are the flaws in the data and the calculation of volatility. In terms of the data, the zero value trades create a problem, as do the prices reported at dubious levels. The Australian government is taking steps to correct these issues so should be resolved over time. I would note here that some of these issues are related to limitations of reporting systems and do not necessarily stem from deceptive practices.

The challenge with volatility calculations is significant; historic volatility is a measure of price deviation from the mean. If there is bad data in the set, it changes both the mean value, and the further that the bad data is from the mean, the more it will increase the result of the volatility calculation. As above, as the data gets cleaner, this volatility calculation will be more aligned with reality. However, it may simply be that volatility for Australian spot markets is incredibly high.

If BSM is to be used, volatility must be included in the formula, but there is no specific method BSM specifically requires for calculating it. This means that volatility can be adjusted or calculated by any means that all market participants can agree is fair. Another possibility is that volatility's impact on price can be mitigated by altering the size of the obligation represented by one option contract. Preliminary investigations are pointing toward a contract size whereby one option contract is equal to the right to buy 10 ML of water, but specifics can be worked out with future research and by gauging market participant sentiment.

Long-term Options in Texas

By using established frequency curve information combined with an approach that prices options based on the opportunity cost to the seller this chapter provides a method to begin to price options on water in Texas. The logical next step seems to be outreach and engagement with possible market participants. Success when brokering these transactions will largely depend on finding terms that are agreeable to both sides. A method for structure and price was presented in this work, but the exact dollar amounts will have to be negotiated. To be of the most use, contracts will benefit from some standardization to increase efficiency, increase the ease of communicating terms, and decrease legal costs.

It will be interesting to see how market participants utilize the marketplace and if transactions are executed that were not necessarily in the scope of the initial motivation for contract construction. For example, irrigator to irrigator options contracts could be put into place that would only be called when two different crops are at price points spread in such a fashion that the diversion of the water to a higher value crop would yield a profit even after the option premium and price to call is calculated into the costs. This could be particularly true across farm regions where differences between cost/return number is great. Upstream farmers may find it profitable to simply sell their water to downstream farmers if the price disparity is great, as the upland farmer's margins may not be significantly impacted by this strategy.

Institutional Frameworks

For markets to operate efficiently, they need to have some fundamental traits, one of which is homogeneity of product. If water rights remain tethered to a seniority system, it will be hard, if not impossible, to look at them equally; this is an impediment to market development. In addition, the restrictions on Inter-Basin Transfers (particularly the seniority clause) will hamper efforts to grow markets unless they are lifted. The coastal exemption may be a place where transactions can take place between basins and avoid some of the transfer permitting process.

It is important to remember that the surface waters of Texas are owned by the people, and an argument can be made that if the people would best be served by the existence of water markets, it might be time to revisit the seniority system that is in place. If the IBT rules can be relaxed, there may be an opportunity for large-scale water trading across watersheds. If abandoned oil and gas pipelines can be found along desirable water routes, it may be possible to clean them and co-opt them for use in a system of water transfer that can begin to move large volumes of water great distances without having to invest the capital to install the infrastructure.

Closing Thoughts

Problems of scarcity and decisions surrounding allocation of resources have been humankind's constant companions. We have made industrial and technological strides that allow us to reshape the Earth itself to enable the extraction of more resources than ever. It is becoming increasingly apparent that this extraction has significant negative effects downstream. These effects are becoming so great as to impair the systems that are critical to the functioning of our habitat, and we ignore them at our peril.

The simplest first step to halting or reversing this process is to use less, thus conserving more, and sharing more with the environment. Whether or not we can do this, it seems reasonable that when we make decisions to extract and use resources, we do it in the most efficient way possible. Water is precious and has no substitute, and the surface waters of Texas are held in trust by the State for the benefit of its citizens. It is important that policy makers are in place who are willing to make decisions that are aligned with the public good and adapt new solutions to the problems we face.

BIOGRAPHIC STATEMENT

Quinn McColly grew up on the shores of Lake Michigan and developed a love for the natural world at a young age, running through the Indiana forests and playing at the Indiana Dunes National Lakeshore. As an adult, he has enjoyed opportunities to work on the floor of the Chicago Stock Exchange and as a financial advisor. The birth of his daughter Abilyn inspired him to change direction.

After having Abby, he decided to spend the rest of his life working to make the world a better place for her generation and generations to follow. To move toward this goal, he knew that he needed more education, and found an opportunity at the Harte Research Institute at Texas A&M Corpus Christi to move along this trajectory. It was incredibly fortunate for him to find an advisor who was working at the juncture of economics and environmental issues who saw how Quinn might fit into this space.

This was the perfect situation to merge his previous experience in the financial world with the concepts of environmental management and socioeconomics to help find solutions to some of the challenges we face. In particular, Quinn has enjoyed synthesizing his understanding of market function with modelling techniques and news ways to think about how we are using data. He has always tried to make sure his professional life is challenging but enjoyable and is happy to be working on things that pique his curiosity.

When he is not working, he enjoys spending time working in the yard, messing up woodworking projects, sailing his sunfish on the Laguna Madre, and doing whatever makes Heather and Abby happy.