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An Economic Assessment of the Impacts of Outdoor Water Use Restrictions in South Florida

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AN ECONOMIC ASSESSMENT OF THE IMPACTS OF OUTDOOR WATER USE RESTRICTIONS IN SOUTH FLORIDA

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To: Dean Michael R. Heithaus
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This thesis, written by Lara Kiesau, and entitled An Economic Assessment of the Impacts of Outdoor Water Use Restrictions in South Florida, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this thesis and recommend that it be approved.

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DEDICATION

I dedicate this thesis to my husband John W. Baron and to my parents Petra and Michael Kiesau. Johnny, you were the reason why I came to Miami, to FIU to complete my master's degree. Meeting you was the greatest coincidence I could have ever imagined and coming to Miami to be able to live with you smoothed the path for us to become the funny, loving, strong and thankful couple that we are today. You always support me and offer your help. Without you I would not be where I am today. Furthermore, I am so thankful to my parents who have been supporting me my entire life. Thanks to your help I was able to continue my life and studies so far away from home. You are always there for me, with words and deeds, to make my ideas come true and accomplish the goals I set for myself. Thank you so much! I love you all!

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ABSTRACT OF THE THESIS

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Professor Pallab Mozumder, Major Professor

Population growth and climate change are important factors determining residential water demand. Most residential water consumption can be attributed to outdoor use. To reduce water consumption, outdoor water use restrictions (OWRs) have become a popular policy tool in the last decades. We developed an integrated framework consisting of a Difference-in-Differences (DID) analysis, Value Function approach and Stated Preference Study to perform an economic assessment of the impacts of OWRs in South Florida. The results reveal a usage reduction of up to 133 gallons per person per month due to the strictest OWR, equaling a yearly value of US$26.6-US$54.4 million for South Florida residents. To link with the regional hydrological system, we estimate that a volumetric decrease of 0.9 million acre-feet in Lake Okeechobee could be related to the implementation of this OWR. The findings deliver beneficial information for policy decisions regarding the economic and societal implications of OWRs.

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ABBREVIATIONS AND ACRONYMS

DID	Difference-in-Differences
IWRM	Integrated Water Resources Management
OWR	Outdoor water use restriction
SFWMD	South Florida Water Management District
(UW)DM	(Urban water) demand management
WCA	Water conservation area
WTP	Willingness to pay

1. INTRODUCTION

The scarcity of freshwater is becoming more frequent and more severe worldwide than at any point in human history. South Florida is one of the affected regions with various factors influencing the increasing water stress. Despite the region's tropical climate with a defined rainy season over the summer months, drought events are becoming common, such as the 2006/07 drought (NIDIS National Integrated Drought Information System, 2020). During the 2006-07 drought, it rained 25% less than the average during the winter months, leading to more than 57% of the state experiencing some degree of drought in the subsequent spring (Di Liberto, 2017). Additionally, the temperatures were much higher than usual, making that winter the second hottest since 1895 (Di Liberto, 2017).

Residential water demand is especially high in urbanized areas with high population densities. High water demand can be partially attributed to the rate of water usage in private residences, which amounts to more than 300 gallons of water per day for the average American family (US EPA, 2018). At least 30% of the household consumption occurs outdoors, even a bigger proportion in dry parts of the country, and is used for watering lawns and gardens (US EPA, 2018). Therefore, outdoor water use is responsible for the largest proportion of residential water use in the U.S. (Argo, 2016). As a consequence, conditions such as rising temperatures and decreased or changing precipitation can, in combination with a high and varying consumption, result in increased pressure on freshwater supply (Environmental Protection Agency & Program, 2013) in the Biscayne aquifer. The Biscayne aquifer is the main source of drinking water in South Florida (Miami-Dade County, 2018), and is part of the regional water management system including the Kissimmee Basin, Lake Okeechobee and the Everglades (SFWMD, 2018). About 8.7 million people spread over 16 counties depend on this water system for daily supply (SFWMD, 2019c). Therefore, not only climate change but also growth-related issues, especially in the Miami metropolitan area, need to be considered in water management decisions. One of the pressing issues is the continuing population growth, which is projected to lead to over three million new residents within the next five years (SFWMD, 2019c). In addition, concomitant freshwater demand is estimated to increase by 25% until 2030 compared to 2005 (Environmental Protection Agency & Program, 2013).

To tackle these challenges, the water management districts in Florida including the South Florida Water Management District (SFWMD) follow the principles of Integrated Water Resources Management (IWRM) (Stoa, 2014). Already in 2000, the effective water supply plan indicated that traditional sources would eventually not be enough to satisfy the needs of South Florida's growing population while at the same time treating the natural system sustainably (FDEP, FDEM, FDACS, & SFWMD, 2007). For a long time, the focus laid on supply-side management measures that included dams, reservoirs and distribution systems, and planners modeled for expected future growth with increased capacity (Gordon Foundation, 2004). Water resources were seen as infinite and solely limited by our ability to access and store them, which led to focusing on meeting future projected demands with big, centralized and expensive engineering solutions (Gordon Foundation, 2004). In South Florida, several alternative, "drought resistant" sources were identified and constructed, for instance reclaimed water and brackish water demineralization (FDEP et al., 2007). However, after realizing that supply-side management of water with a continued expansion of infrastructures and development of new water sources have become more and more expensive and unsustainable, both economically and environmentally, there has been a trend towards demand-side management approaches (Karamouz, Moridi, & Nazif, 2010). These management approaches recognize that water is a limited resource that needs to be conserved and used sustainably (Gordon Foundation, 2004). Urban water demand management (UWDM) is focused on measures to increase the efficiency and/or timing of water consumption to maximize the use of the existing capacity (Gordon Foundation, 2004). Despite its initial application as a short-term approach, it has potential to change resource use fundamentally in the long term (Gordon Foundation, 2004).

A common demand-side management tool of UWDM to reduce water consumption and regulate the allocation of water is outdoor water use restrictions (OWRs) (Milman & Polsky, 2016). Even though the U.S. alone has almost 30 state-mandated OWRs, varying by frequency, timing, or duration, previous research has mainly focused on its effectiveness as a policy tool to change people's behavior and conserve water (Kenney, Klein, & Clark, 2004; Loë, Moraru, Kreutzwiser, Schaefer, & Mills, 2001; Milman & Polsky, 2016; Survis & Root, 2012). It has been documented that different OWR programs lead to a reduction of the aggregate water consumption by 14-56%, depending on severity and frequency of the restriction (Grafton & Ward, 2008; Kenney et al., 2004; Renwick & Green, 2000). However, several studies have revealed consumers' willingness to pay (WTP) to avoid OWRs or supply disruptions (Gordon, Chapman, & Blamey, 2001; Hensher, Shore, & Train, 2006; Koss & Sami Khawaja, 2001; Tapsuwan, Brennan, Ingram, & Burton, 2007), which illustrates the potential to allocate water more efficiently than previous restriction programs. Using a variety of models and methods, some studies indicate that OWR programs are economically inefficient. For instance, the economic loss caused by water use restrictions in Sydney, Australia, in 2004-05, aggregated to A$235 million, which equals A$150 per household (Grafton & Ward, 2008). Concerning the welfare impact of OWRs, a direct comparison of study results is limited because different methods have been applied. For example, Mansur & Olmstead (2012) examined daily household consumption data from 11 urban areas in the U.S. and Canada. Using the estimated demand, they were able to determine the shadow price (the estimated price of a good for which no market price exists) for marginal units of restricted water, by implementing a two-day-per-week OWR for households. The average household's shadow price was about three times higher than what they actually paid for their water (Mansur & Olmstead, 2012). Finally, regarding the implications of the price elasticity of water, it was calculated that a drought-related need to decrease demand by 20% with focus on outdoor use would require an increase in marginal water price of about 50% (elasticity of -0.4) (Olmstead & Stavins, 2009). These results show that there may exist substantial gains from adopting price-based approaches to regulate water demand versus using OWRs (Brennan, Tapsuwan, & Ingram, 2007; Buck, Auffhammer, Hamilton, & Sunding, 2016; Grafton & Ward, 2008).

Therefore, the extensive usage of OWRs as a water conservation policy tool in South Florida requires a better understanding of the economic implications to reveal potential costs and benefits for the society. The purpose of the current study is to assess the districtwide OWRs both regarding their effectiveness and economic impacts in the region.

2. LITERATURE REVIEW

2.1 Demand-side Management Policy Tools

Water is technically a renewable resource. However, in human time spans it can be considered a finite or exhaustible resource. Many regions of the world rely on water from aquifers that has accumulated over the course of thousands of years and is now removed at a rate that is much higher than can be refilled by rain. Therefore, water shortages have become increasingly common in many parts of the world, including North America, Europe and Australia. The water utilities need to handle the issue of water supply shortages to ensure a sustainable long-term water supply security. Historically, the focus of water management was on the supply-side management to increase the supply to meet projected water demand challenges (Halich & Stephenson, 2009). However, demographic trends and resource constraints increasingly limit the scope of expanding water supply. Instead, urban water demand management (UWDM) targets an increase of water use efficiency through the application of different measures, such as water pricing and metering, OWRs that promote water conservation, operational and maintenance measures to reduce loss and general consumption, and water saving devices or public participation programs in water conservation (Loë et al., 2001). These approaches can be subdivided into price and non-price measures with the latter requiring a much more active participation from water users (Borisova, Rawls, & Adams, 2013). In general, non-price water demand management tools belong to one of the following categories: public education, technological improvements and water use restrictions (Kenney, Goemans, Klein, Lowrey, & Reidy, 2008). In most cases, water utilities do not solely use price to steer their customers' water consumption (Kenney et al., 2008). Instead, as a result of political pushback, equity concerns, and legal limitations they combine price with non-price policies that aim at the short- or long-term reduction of water consumption (Kenney et al., 2008).

2.1.1 Non-price Tool: Public Education

Public education as a water conservation measure is usually applied in combination with additional measures. Therefore, the pure effect of awareness campaigns is not clearly detectable, but generally expected to reduce water consumption between 2-5% (Baumann, Boland, & Haneman, 1998). However, the impact on water consumption varies widely depending on different education campaign designs, for instance face-to-face campaigns at schools or town halls versus billing inserts and pamphlets. Personal contact and repetitive messages, such as over the radio, presumably have a stronger effect on water conservation than a onetime billing insert. Nonetheless, results can vary significantly: while Renwick & Green (2000) found a water use reduction of 8% caused by a public information campaign (no detail on the nature of the campaign was available), a study from the UK that assessed the effect of an information campaign among 8000 residential customers including direct mailing, radio and newspaper advertisement, found no demand reduction and only 5% of the surveyed population indicated that they had noticed the campaign at all (Howarth & Butler, 2004). The presented findings indicate the existence of great variations among the different designs of this type of approach.

2.1.2 Non-price Tool: Technological Changes

Concerning technological improvements, the National Energy Policy Act requires all new constructions in the U.S., as of 1992, to install the most advanced low-flow toilets, showerheads, faucets, clothes and dishwashers (United States Environmental Protection Agency, 2008). Studies have demonstrated the effect of such regulations, with differing results for retrofit and replacement programs. Both retrofit programs, considered as a temporary measure such as a faucet aerator or a low-flow shower head, and complete replacements with more efficient appliances have shown to lead to water use reductions. Renwick and Archibald (1998) performed an empirical study of household water demand in two Californian cities, revealing that the installation of low-flow toilets reduced consumption by 10% per toilet, low-flow showerheads by 8% per fixture and the adoption of water-efficient irrigation technologies by 11%. A study by Kenney et al. (2008) found similar results with an average reduction of household water consumption of 10% because of participation in an indoor rebate program. Complete replacements with more efficient appliances seem to lead to greater water use reductions than retrofits: Several studies by Mayer et al. (2000; 2003; 2004) analyzed the effects of high-efficiency plumbing fixture retrofits in the U.S. in Seattle, Tampa and the East Bay Municipal Utility District and found indoor savings varying between 37-50% (Mayer, Deoreo, & Lewis, 2000; Mayer, Deoreo, Towler, & Lewis, 2003; Mayer, Deoreo, Towler, Martin, & Lewis, 2004). However, it should be noted that the authors found leakages to account for part of the water conserved, which points to the potential of leakage detection programs to reduce wasting significant amounts of water. Despite the pure conservation success, the cost of the appliance replacement must not be too high compared to the water rates. Otherwise it takes too long to recover the money spent for new appliances through reduced water bills caused by decreased water usage (Barrett, 2004), which removes the incentive to replace the appliance in the first place.

Another study analyzed a program by the Miami-Dade Water and Sewer Department in South Florida which included full retrofit for senior and low-income households, exchange of high-efficiency showerheads and rebates for high-efficiency toilets and clothes washers between 2005 and 2007 (Lee, Tansel, & Balbin, 2011). Overall, within the first and second year of the retrofit water consumption dropped by 6-

14% with toilets and clothes washers leading to higher reductions (Lee et al., 2011). Furthermore, participants who had more than one appliance with higher efficiency reached a greater water use reduction (Lee et al., 2011). Immediately after the retrofit or exchange, participants first increased their water consumption (Lee et al., 2011). This offsetting behavior dissipated after one to two years (Lee et al., 2011).

For outdoor water consumption, technological improvements include smart irrigation devices such as rain sensors or soil moisture sensors. The 2000 Florida Statutes already require every resident "[…] who purchases and installs an automatic lawn sprinkler system after May 1, 1991, shall install a rain sensor device or switch which will override the irrigation cycle of the sprinkler system when adequate rainfall has occurred" (The 2000 Florida Statutes, 2000). However, how closely this regulation is being followed is questionable since enforcement is relatively difficult.

2.1.3 Non-price Tool: Outdoor Water Use Restrictions (OWRs)

Outdoor water use restrictions (OWRs) are among the most popular measures, while they are relatively under-studied (Survis & Root, 2012). Outdoor water use restrictions can either be voluntary or mandatory and most of them do not restrict a certain amount of water per residential customer or household but instead specific times (e.g., not between 10am to 4pm) or uses (e.g., no car washing, no sprinkler using). In other words, certain behaviors are restricted. Since outdoor water use is climate-sensitive and connected to behavioral and cultural factors, it is generally more flexible than indoor water use (Milman & Polsky, 2016). Therefore, OWRs were originally thought to be implemented as a stopgap measure to decrease an immediate or temporary discrepancy between supply and demand, for instance during a drought (Milman & Polsky, 2016). However, OWRs have been implemented as long-term measures in many parts of the world (Milman & Polsky, 2016), aiming to increase the efficiency of irrigation practices. As a consequence of their large abundance, criticism has risen against OWRs, arguing that a scarce resource such as water should be allocated through prices that reveal information about its relative scarcity and value in use to avoid negative economic impacts (Olmstead, 2010). Therefore, the following shall give an overview of the studied impacts of OWRs, summarizing research findings on pure conservation effectiveness, as well as the more recent emphasis on welfare loss and residents' WTP to avoid such restrictions. The combination of these issues will explain the diverging opinions on water restrictions, mainly between politicians and economists.

2.1.3.1 Effectiveness

In general, studies have shown that OWRs can reduce the aggregate water consumption by 4-56%, depending on severity and frequency of the restriction (Loë et al., 2001; Brennan, Tapsuwan, & Ingram, 2007; Grafton & Ward, 2007; Kenney, Klein, & Clark, 2004). A study by Kenney et al. (2004) revealed the significant difference between voluntary and mandatory (one- to three-days-per-week irrigation permitted) restrictions at eight utilities in Colorado in 2002, showing that voluntary restrictions led to water use reductions of 4-12% while the reduction effect of mandatory restrictions varied between 18-56%, depending on strictness. An analysis of the water use from Southwest Florida residents between 1998 and 2010 revealed that tightened OWRs from two- to one-day-per-week watering resulted in a reduction of water consumption of 13% (Boyer, Dukes, Duerr, & Bliznyuk, 2018).

However, there are some limitations that require attention: the design impacts the overall effectiveness in a way that restrictions during certain days or times may not lead to an aggregate water use reduction but only a shift of the consumption (Survis & Root, 2012; Hensher, Shore & Train, 2006), which highlights that compliance does not equal effectiveness (Survis & Root, 2012). Furthermore, OWRs incur additional costs to water supply utilities that, in theory at least, need to monitor and enforce them (Loë et al., 2001).

Examples of non-compliance are delivered by one case study from Southeast Florida that found over-watering during wet periods, caused by neglected temporal changes in weather and lawn water demand (Survis & Root, 2012). Furthermore, a study conducted with household water consumption data in Tampa, Florida assessed the effectiveness of OWRs and found non-compliance having a strong effect, preventing the OWRs from being a successful conservation tool (Ozan & Alsharif, 2013). It was revealed that customers used over 7% more water when the implemented OWR became stricter, from two- to one-day-per-week watering(Ozan & Alsharif, 2013). The study's authors assumed that households were in a dilemma, torn between complying with local conservation regulations and rules imposed by homeowners associations(Ozan & Alsharif, 2013). Potential additional reasons listed included that enforcement was not strict enough and fines not high enough and possibly cultural reasons that put a high importance on the perfection of the lawn (Ozan & Alsharif, 2013). Finally, a remarkable finding of a study from Northern Nevada in 2008 and 2010 was that an official watering schedule with designated days for each household caused wasteful behavior (Castledine, Moeltner, Price, & Stoddard, 2011). Weekly water use was 30-40% higher when customers followed the scheduled days for weekly usage and 50-60% higher for weekly peak consumption compared to periods when customers were allowed to distribute the number of days independently (Castledine et al., 2011). To the author's knowledge, this is the only study assessing this characteristic of OWRs.

The review illustrates that the majority of studies on the effectiveness of OWRs provides evidence of their overall conservation success, with some results highlighting the importance of an appropriate design and potential factors for non-compliance.

2.1.3.2 Willingness to Pay (WTP)

Several studies have surveyed consumers' WTP to avoid different kinds of OWRs or supply disruptions, with diverse results. Many of these studies focus on consumers in Australia who have to deal with the most extensive OWRs: more than 75% of all households are affected by water restrictions (Brennan et al., 2007). A study among residents of Western Australia showed them to have a WTP of additional 22% of the annual water bill to move from one-day to three-day-per-week sprinkler use (Tapsuwan et al., 2007). Compared to that, residents in California were found to be willing to pay up to US$16.92 per month (in 1993 dollars) to avoid a 50% water shortage every 20 years (Koss & Sami Khawaja, 2001). These studies are rather difficult to compare because of the different scenarios assessed, but most results show customers' (in general willing to pay) general WTP to avoid restrictions or shortages. In contrast, one other study conducted in Canberra, Australia, revealed that residents were unwilling to pay to avoid the majority of drought-induced restrictions (Hensher et al., 2006). Interestingly enough, the residents were willing to pay an additional $239 (31.26% of their annual bill) on top of the average water bill to remove the most severe regulation, a daily, year-round restriction (Hensher et al., 2006). However, there were two notable limitations: the study included only three different levels of restriction to choose from and having a defined ending date is both uncommon and unrealistic (Hensher et al., 2006). Since citizens require a clearly defined scenario in order to make informed decisions, these limitations are relevant in most studies. Nevertheless, the majority of studies reveal that people are willing to pay to avoid OWRs which illustrates the potential to allocate water more efficiently.

2.1.3.3 Welfare Impact

Concerning the welfare impacts of OWRs, again direct comparison is limited because different methods have been applied. The welfare costs of OWRs can result from direct implementation costs, their time requirements, the significant investment in public education campaigns and the water utilities' foregone revenues. One production model approach has shown that the net welfare loss for Australian consumers caused by a sprinkler ban amounted to A$347 per household (Brennan et al., 2007). The number was calculated by averaging the time needed for manual watering at 33% of the mean wage rate, and it can climb to as high as A$871 when calculated at 100% wage rate (Brennan et al., 2007). Another study calculated the loss in Marshallian surplus, which is the total welfare consisting of consumer surplus (the difference between what the consumer pays and what he would have been willing to pay) (Murphy, 2019) and producer surplus (the difference between the actual price and the price the producer would be willing to sell it for) (Chappelow, 2019), with the result that raising the volumetric price of water charged to households to achieve the same level of consumption would generate a much bigger Marshallian surplus than the use of mandatory OWRs (Grafton & Ward, 2008). First, the difference between the welfare loss from removing OWRs and implementing a market-clearing price was calculated; next, the benefit from reallocating water from indoor to outdoor was estimated to find a positive Marshallian surplus of A$238 million, which equals A$55 per person (Grafton & Ward, 2008). A study conducted by Mansur & Olmstead (2012) among households in the U.S. and Canada used estimates of marginal prices to reveal price elasticities that strongly varied between customers. Effects of moving to a market-based approach compared to a two-day-per-week OWR was simulated with resulting welfare gains of US$96 per household during the lawn-watering season which was about 29% of the average annual household's expenditures on water (Mansur & Olmstead, 2012). Especially when the heterogeneity of the customers and different values for water uses are considered, estimates of welfare losses increase.

All these case studies are focused on the economic explanation that OWRs cause greater welfare loss compared to increased volumetric prices (Sibly, 2006). These costs arise from the inability of households to equate the marginal cost of water to its marginal benefit in use, which results in households that are willing to pay for their water to satisfy their particular (outdoor) uses but are unable to do so (Sibly, 2006). These findings of significant welfare losses illustrate why economists demand action from politicians who fear the negative outcry that might come with an increase of water prices.

2.1.4 Price tool: Water Rates

Generally, the discussion between price and non-price advocates circles around two main opposing assumptions: price proponents argue that current prices do not reflect the water supply's real economic costs, such as treatment, distribution or costs of current reservoirs (Olmstead & Stavins, 2009). Therefore, if prices were generally higher and increased during droughts, people would react, determined by their preferences, and decrease their water use (Olmstead & Stavins, 2009). In contrast, non-price proponents debate that residential water demand is comparatively price inelastic, meaning that an increase in price would not effectively lead to a water use reduction, and that price cannot be used as a tool to steer a good necessary to satisfy basic human needs (Renwick & Green, 2000).

Following microeconomic theory and empirical research, customers will reduce their consumption when prices increase (Marshall, 1920). The magnitude of the decrease depends on the product's price elasticity, which is the responsiveness of the quantity demanded to a change in price (Marshall, 1920). However, the law of demand assumes consumers to be knowledgeable about prices, which is often violated (Gaudin, 2006). The non-transparency of prices can lead to price elasticities below their actual potential (Gaudin, 2006). Despite that, Olmstead and Stavins (2009) found that water demand is not generally "unresponsive to price".

For instance, a study by Renwick & Green (2000) compared the effectiveness of different demand-side management (DSM) policies, including OWRs and prices, with the help of an econometric model. Over an eight year period in the 1990s (drought 1985-92) residential water demand in California was evaluated to identify how the aggregate quantity demanded was reduced (Renwick & Green, 2000). While water rationing and use restrictions were found to reduce the average household water consumption by 19% and 29%, respectively, a 10% increase in price led to a reduction of 1.6% (Renwick & Green, 2000), which is comparatively low.

Performing a comprehensive meta-analysis, Dalhuisen et al. (2003) assessed 64 regions in the U.S. and Europe concerning their price elasticity and found great variations. While price elasticities in the Eastern U.S. averaged only -0.005, in the Western U.S. they averaged -0.17 (Dalhuisen, Florax, de Groot, & Nijkamp, 2003). The authors link the differences in estimated elasticities to spatial and temporal variations and different research designs, but also to household characteristics (Dalhuisen et al., 2003). An example for the influence of household characteristics on price elasticity could be that low-income households might have the tendency to use only that amount of water which is necessary for their basic needs, while high-income households have more disposable income to spent on recreational water-use activities and price increases do not appear to be significant enough to require a behavioral change. Therefore, mainly middle-income households would reduce their affluent water consumption if prices rise. Compared to the results of Dalhuisen et al., a comprehensive literature survey by Worthington & Hoffman (2008), which includes results from 1980 to 2005 from different regions of the world, found higher price elasticities than Dalhuisen et al. (2003), ranging between -0.25 and -0.75 (Worthington & Hoffman, 2008). To translate these elasticities into understandable values for water conservation targets, using an elasticity of -0.4 as an example, a drought related demand reduction of 20% would require a price increase of about 50% (Reynaud, 2013).

Floridians are supposedly a little more responsive to water rate increases than the average US citizen: a 10% increase in water rate would be expected to lead to a 4 to 8% decrease of water consumption (Whitcomb, 2005). Another influential factor found by an analysis derived from household-level panel data for two California communities showed that outdoor water use appears to be more price elastic than indoor use (Renwick & Archibald, 1998). The finding from Renwick & Archibald's study seems reasonable since outdoor usage is usually recreational use and does not satisfy basic needs. A study by Kenney et al. (2008) looked at the interaction between OWRs and price and revealed that the implementation of restrictions is associated with a 31% decrease of water use, absent of any price for water (Kenney et al., 2008). Naturally, the absence of a price is an unrealistic scenario, but it helps to theorize that with an increasing price, the effect of restrictions decreases due to the price becoming a more significant decision factor (Kenney et al., 2008). Furthermore, the type of price rate structure has an impact on price elasticity, as revealed by Olmstead, Hanemann, &

Stavins (2003). They found a price elasticity of about -0.6 for households facing an increasing block rate structure and -0.19 for those facing uniform marginal prices (Olmstead et al., 2003). Additionally, the amount of information provided on the bill was found to have an impact on price elasticity. A study by Gaudin (2006) focusing on billing information of almost 500 utilities across the US revealed that price-related information increased price elasticity by at least 30%. As a general conclusion it can be noted that water demand is said to be rather “inelastic” at current prices (Olmstead & Stavins, 2009), however, changes in water rates and rate structures, customers’ income and more factors have a crucial influence on this finding. Therefore, to use price as an effective management tool, certain rate structures and overall higher rates could be beneficial.

There are a few supposed advantages to market-based approaches. One is the household’s ability to decide which uses to decrease depending on their individual preferences. Another advantage would be that market-based approaches enable households to respond heterogeneously. Some households would decrease their demand for water-based activities that they do not value enough to justify the price increase, while others would be able to continue participating in those activities if they felt the activity was worth the cost (Olmstead & Stavins, 2009). As previously mentioned, current water prices do not reflect the true price of water, because they are mostly set by the government and have the tendency to not entirely reflect the actual cost of water production and external costs to extract the water and return it as waste (Barrett, 2004). Water metering is a prerequisite to enable water pricing, since it allows charging on a per unit basis, transferring a price-signal to the individual customer and thereby increasing economic efficiency and promoting conservation (Baumann, 1998). Even the sole introduction of metering has shown to lead to a reduction of water consumption, ignoring the effects of different water rate structures (Dalhuisen, de Groot, & Nijkamp, 2001; Dalhuisen & Nijkamp, 2001). A comprehensive survey of more than 10,000 multi-family residences in the U.S. revealed that submetering and a price increase led to a 15.6% reduction in per capita demand, equaling almost 22 gallons per person per day (Mayer et al., 2004). The previous example by Mayer et al. (2004) shows that metering and pricing has an undeniable impact on residential water consumption. In that context, different price rate structures have a steering effect on residential water use. One can differentiate between a flat fee, a uniform rate, a decreasing or increasing block rate structure or a seasonal rate. While a flat fee charges every customer the same fixed price, ignoring the actual individual consumption, a uniform rate means that every 1,000 gallons cost the same. On the contrary, under a decreasing block rate the price of every additional 1,000 gallons of water decreases the more the customer consumes. The exact opposite is the case under an increasing block rate structure, leading to every additional 1,000 gallons used by the customer to cost more than the previous one. All these rate structures refer to the respective billing cycle, which is usually monthly or quarterly. Under a seasonal rate, water prices increase during months of high consumption. For instance, Miami-Dade County Water and Sewer implemented seasonal rates between 1998 and 2004 (Whitcomb, 2005). For six month at a time it was alternated between two different five-block structures (Whitcomb, 2005). The last two price structures mentioned, increasing block rate and seasonal rate, send a price signal to the customers to decrease consumption, which is why they are also called conservation pricing (Inman & Jeffrey, 2006).

In general, to avoid inequity issues between income groups and ensure enough revenue for the utility with simultaneously reduced water consumption, permanent surveys and observations seem to be unavoidable to control the effect a price approach has on water users, resources and utilities. Furthermore, a certain amount which is necessary to cover basic needs should be affordable at a low price (rate structure) while everything that goes beyond this base amount can be charged with a much higher per-unit fee. Alternatively, equity issues could be prevented by a fixed charge that is calculated using property values (as a proxy for a customer's ability to be able to pay for water) or discounted for residents eligible for welfare (Sibly, 2006). Finally, a price increase or conservation pricing can serve as an incentive for the implementation of new water conservation technologies because of a possibility to save money in the long run (Olmstead & Stavins, 2009).

In conclusion, according to Sibly (2006), the pure implementation of OWRs compared to pricing is not an efficient way of water allocation but rather it provides evidence that the charge is inefficient. Only in emergencies OWRs would be the fastest and most effective way to conserve water but not as a long-term measure (Sibly, 2006). Instead, OWRs cause not only utilities but also consumers to experience an economic loss resulting from the foregone economic value/benefits that would be gained from satisfying the water demand through increased water deliveries (Jenkins, Lund, & Howitt, 2003). Therefore, this study performs an economic assessment of the impacts of the OWRs in South Florida.

2.1.5 Additional Considerations

There are a variety of factors influencing not only the effectiveness of DSM tools but also residential water consumption in general that are beyond the control of water utilities. These include for instance local weather, which impacts short-term water usage, especially for outdoor irrigation, and yearly consumption patterns. Therefore, it is not uncommon that weather-related variables are controlled for in regression-based studies evaluating price and nonprice management tools (e.g. Gutzler & Nims, 2005). For instance, the model designed by Kenney et al. (2008) predicted that water consumption would increase by about 2% for every additional 1°Fahrenheit in average daily maximum temperature, while consumption would decrease by about 4% per inch of precipitation. However, beyond that additional uncertainties are prevalent. The exact kind of such weather variables (frequency, total amount, variation) might have an effect and oftentimes researchers have to handle the constraint that water usage data exists only on a monthly level while weather happens daily (Kenney et al., 2008).

Besides weather factors, demographic variables have a significant effect on residential water consumption. Ongoing research revealed that household income, family size, occupants' age and individual preferences concerning water conservation have an impact (Jones & Morris, 1984; Renwick & Green, 2000; (Sheila, Michael, & Robert, 2002). Finally, housing characteristics can have an effect, for instance owning versus renting, the age of the house (and of its appliances), the size of the house and the lot (Renwick & Green, 2000). Unfortunately, limitations of available data impact the ability of researchers to analyze all of these impacts sufficiently.

2.2 Difference-in-Differences Approach

The Difference-in-Differences (DID) approach is a quasi-experimental research design to estimate causal effects and is widely used in empirical economics and policy evaluation (Lechner, 2010). It is used in the current study to estimate the effect of OWRs on residential water use. The DID approach is said to be transparent and suitable to estimate the effects of governmental policy interventions (Angrist & Krueger, 1998). Difference-in-Differences has a long history in economics with early uses dating back to the 1940s (Angrist & Krueger, 1998). Two studies, one by Card & Krueger (1994) assessing the effects of state minimum wage law on employment, and one by Meyer (1990) assessing worker's compensation benefit increases on the length of claims, triggered its wider application.

In most cases, it can be distinguished between four groups which are the treatment group before and after the introduction of the treatment and the control group, likewise before and after the introduction of the treatment (Lechner, 2010). The idea is to compare the difference in outcomes of the affected and unaffected groups, before and after the policy intervention (Bertrand, Duflo, & Mullainathan, 2002) to clearly distinguish the effect attributable to the policy change.

3. METHODOLOGY

The current study seeks to perform an economic assessment of the impacts of OWRs implemented in the SFWMD, where outdoor water use for irrigation and other purposes can account for up to 50% of total residential water use (SFWMD, 2019). After years of drought-related limited periods of OWRs primarily in the 2000s, the SFWMD finally implemented year-round OWRs in 2010. To analyze the effectiveness and economic impacts of OWRs, an integrated framework is developed whose main components are a Difference-in-Differences (DID) approach, a value function model and the application of a discrete choice model. The current study has three primary objectives:

1. To reveal the effectiveness of OWRs in South Florida in terms of reduced water consumption by using the DID approach.
2. To estimate the relationship between the implementation of OWRs and divisions of the hydrological system in South Florida.
3. To compute the revealed preference values for avoiding OWRs, and compare the same with the stated preference values (WTP) estimated in a previous study by Seeteram, Engel, & Mozumder (2018).

The current work is unique because we analyzed residential water use data at different times and at different levels of OWRs as a natural experiment to assess variations in people's actual behavior. The analysis of actual water use behavior should deliver stronger evidence for WTP values than stated preference analysis. Furthermore, the DID approach does not only show a correlation but goes a step further to establish causality by utilizing the interaction term and estimating the treatment effect. The DID approach allows one to estimate the amount of water that residents consumed as a consequence of different OWRs and therefore provides a more precise estimated impact of water use restrictions as a water management policy tool. Finally, the integration of the DID analysis with the physical water management system allows us to connect the human and the natural system, which enables us to estimate a value function of the value addition for the society from OWRs.

3.1 Study Area

The study analyzes the water use data of residents in Southern Florida, United States, ranging from Orlando to the Florida Keys. The region's climate is subtropical to tropical with a pronounced rainy season from May to October (Weather Atlas, 2020). Florida's average daily temperature is 70.7°F, with highest temperatures of 95°F in July and 2,800 hours of sunshine over the course of the year (Weather Atlas, 2020). In January, average lowest temperatures range between 40°F in the northern part (e.g., Pensacola, Tallahassee) and 60°F in the southern part of the state (e.g., West Palm Beach, Miami) (Weather Atlas, 2020). The majority of the annual 55 inches of precipitation occurs in the rainy season, causing an uneven distribution over the course of the year (Weather Atlas, 2020).

Concerning outdoor water use, a few additional aspects are worth mentioning. In Florida, the amount of precipitation usually decreases between March and June, resulting in higher water consumption for outdoor water use (Marella, 1992). Furthermore, because of increasing temperatures from March to May potential evapotranspiration increases, leading to high water demand for grass and outdoor plants which is one reason for increased water consumption from public-supply in these months compared to the rest of the year (Marella, 1992). Finally, irrigation can be required year-round in South Florida because of overall warmer temperatures (Marella, 1992).

The combination of certain climate patterns, which are becoming more unreliable as a result of climate change, with the water use of a continuously growing population (see Table 3.1) are major factors leading to the occurrence of water shortages (FDEP et al., 2007). That is why an efficient and sustainable management of water resources is critical in South Florida.

Table 3.1: Population of 13 Analyzed Counties in South Florida

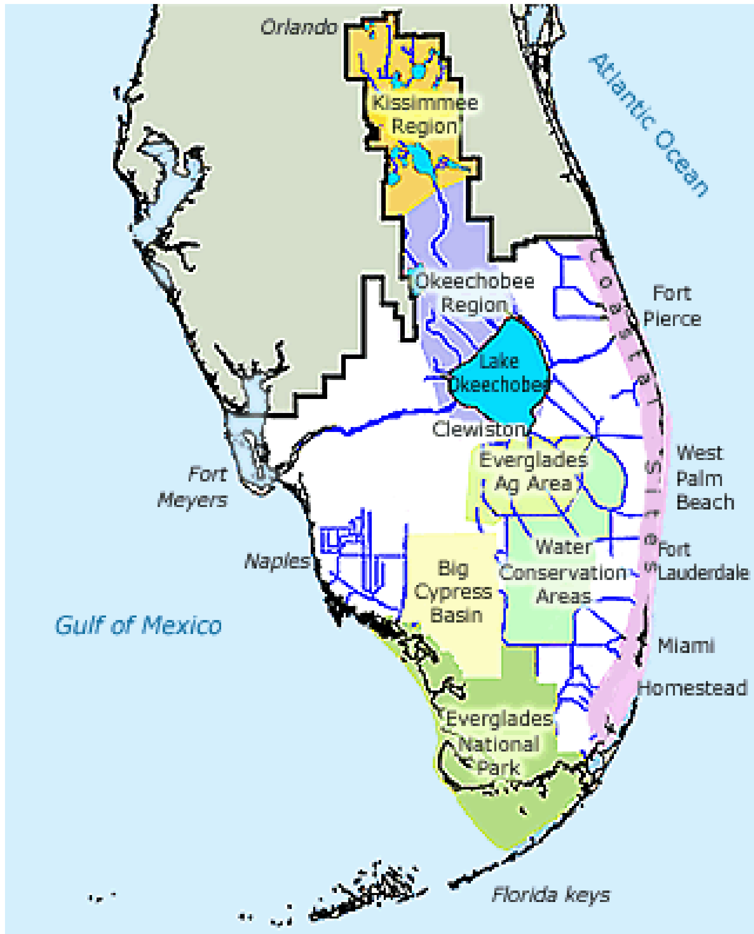
County	**1995**	**2005**	**2015**	**2025**
Broward	1,428,708	1,742,157	1,827,367	2,045,772
Collier	197,055	303,893	343,802	413,739
Glades	8,644	12,168	12,853	13,895
Hendry	31,280	37,861	38,096	41,337
Lee	382,830	545,931	665,845	826,909
Martin	113,550	140,647	150,062	165,756
Miami-Dade	2,076,171	2,395,071	2,653,934	3,062,631
Monroe	79,824	77,608	74,206	75,855
Okeechobee	32,059	38,627	40,052	43,146
Orange	765,731	1,050,333	1,252,396	1,576,726
Osceola	140,490	227,055	308,327	452,354
Palm Beach	988,743	1,273,752	1,378,417	1,559,585
St. Lucie	172,212	238,361	287,749	342,548
Total	**6,417,297**	**8,083,464**	**9,033,106**	**10,620,253**

Source: Office of Economic & Demographic Research (2017)

The state of Florida is divided into five Water Resources Management Districts on the basis of the natural hydrological system. The studied counties are all encompassed, either entirely or partly, in the SFWMD, the agency that manages the regional water resources from Orlando in Central Florida to the Florida Keys in the very South (see Figure 3.1) (Abtew & Huebner, 2002). From the Kissimmee Chain of Lakes and the

Kissimmee River in the North, the water flows South through Lake Okeechobee, the Water Conservation Areas (WCAs) and the Everglades (FDEP et al., 2007). Lake Okeechobee is the main actor in the hydrologic system because its water is essential for the surrounding communities, and for the Everglades Agricultural Area (EAA), the St. Lucie and Caloosahatchee basins (Abtew & Huebner, 2002) and the WCAs. With an area of 1,763 km^2 and an average depth of 2.7 m, it is an important source of water for the canals in Palm Beach, Broward and Miami-Dade and it recharges surface and groundwater supplies (Abtew & Huebner, 2002). Historically, the main objectives of the regulation schedule for Lake Okeechobee have included water supply and flood control, which is why the lake's water levels are a suitable indicator of wet and drought conditions (Abtew & Huebner, 2002). The Upper Kissimmee Chain of Lakes, which includes Lakes Myrtle, Alligator, Mary Jane, Gentry, East Tohopekaliga, Tohopekaliga and Lake Kissimmee, is in turn an essential water source for Lake Okeechobee (Abtew & Huebner, 2002). In the South, the three WCAs follow specific regulation schedules as "part of the water storage and distribution system" (Abtew & Huebner, 2002).

Figure 3.1: Hydrological Divisions of the South Florida Water Management District

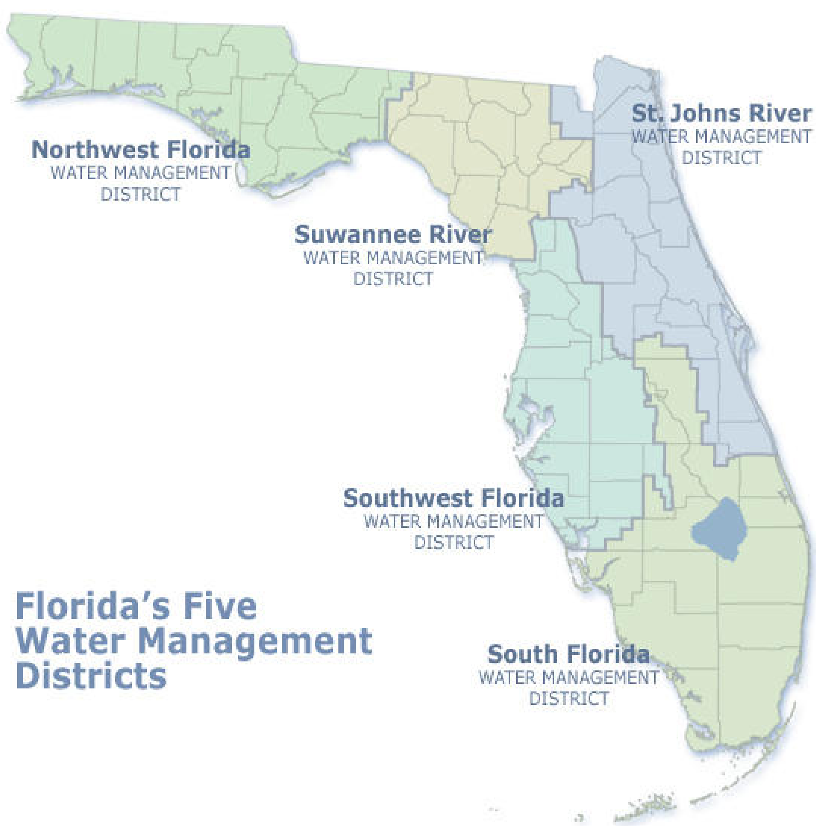


Source: (SFWMD, 2019b)

3.2 Data Description

A group of 16 counties belongs to the SFWMD. Ten of these counties are located entirely within the SFWMD, which are Broward, Collier, Glades, Hendry, Lee, Martin, Miami-Dade, Monroe, Palm Beach and St. Lucie. The other six counties are split between the SFWMD and one of the neighboring water management districts which are St. John's River Water Management District in the Northeast and Southwest Florida Water Management District in the Northwest. For the purpose of the current study, data from 13 counties could be analyzed concerning the OWRs' effect on the residential water use. We could include water use data of the ten counties that are entirely within the SFWMD as well as the parts of Okeechobee, Orange and Osceola that also fall within the borders of the SFWMD. As a result of incomplete water use data of the three remaining counties, Charlotte, Highlands and Polk, they were excluded from the DID analysis. However, they could be included in the value function approach.

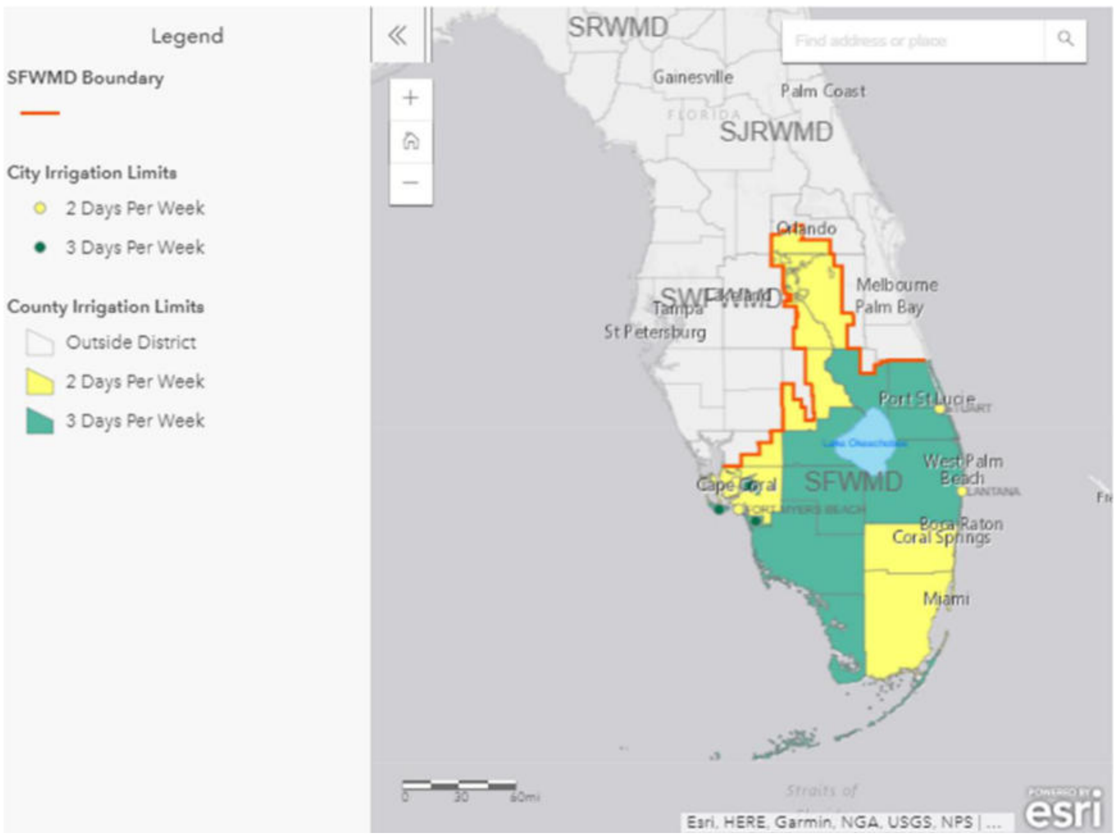
Figure 3.2: Florida's Five Water Management Districts



Adapted from SFWMD (2018)

The type of water use data we used falls under the category of public supply, which is defined as “Water withdrawn by public and private water suppliers and delivered to groups of users […] such as domestic, commercial, industrial, thermoelectric power, public water use, and other water use.” (Marella, 1992). A clear separation of the portion served to residential users was not possible because of the type of the data. Therefore, a few factors need to be considered for the interpretation of results: the exact number of people served was provided, of which residential users account for the largest portion (Marella, 1992); the number of non-permanent residents (tourists) using water is not documented; all customers in the SFWMD have to follow OWRs but exact outdoor consumption is not measured.

Figure 3.3: Overview of the Outdoor Water Use Restrictions in the South Florida Water Management District



Source: SFWMD (2019)

The areas of the 16 counties that are located within the SFWMD's boundaries follow one of two irrigation restrictions today (see Figure 3.3): one of the two OWRs allows two-days-per-week of outdoor water use (yellow) while the other OWR allows three-days-per-week outdoor water use (green). The fragmentation of the SFWMD is the result of a compromise between politicians, water managers, utilities and the landscaping industry (Reid, 2012). Unlike the rest of Florida, the SFWMD targeted a districtwide three-days-per-week OWR taking into consideration arguments from the landscaping industry and water utilities (Reid, 2012). However, local governments were given the freedom to choose a stricter two-days-per-week OWR (Reid, 2012), for instance to decrease confusion in those split counties in the North of the district.

Furthermore, some bigger cities have a different rule than their surrounding counties, which could not be considered in the present analysis. Because of the spatial level of the analysis, which is the county level, only the overall county's OWRs could be considered. The districtwide, year-round landscape irrigation rule has been in effect since 2010. Before 2010, counties or parts of counties would follow varying types of OWRs predominantly in times of dry periods or drought events (see Figure 3.4). The different types of OWRs can be categorized into three groups that will be referred to from now on as *OWRP_1*, *OWRP_2* and *OWRP_3* (for **O**utdoor **W**ater use **R**estriction **P**hase 1, 2 or 3). Outdoor Water use Restriction Phase 1 (*OWRP_1*) is the least strict with three-days-per-week outdoor water use permitted and officially referred to as Phase 1 restriction (FDEP et al., 2007). This restriction is followed by Outdoor Water use Restriction Phase 2 (*OWRP_2*) which allows two-days-per-week outdoor watering and is called Phase 2 restriction (FDEP et al., 2007). The strictest restriction is called Outdoor Water use Restriction Phase 3 (*OWRP_3*) which restricts outdoor water use to only one-day-per-week and is referred to as Phase 3 restriction (FDEP et al., 2007). In times of drought, *OWRP_1* (Phase 1) aimed for a 15% overall water use reduction, *OWRP_2* (Phase 2) targeted a 30% water use reduction and *OWRP_3* (Phase 3) was set to reduce overall consumption by 45% (FDEP et al., 2007).

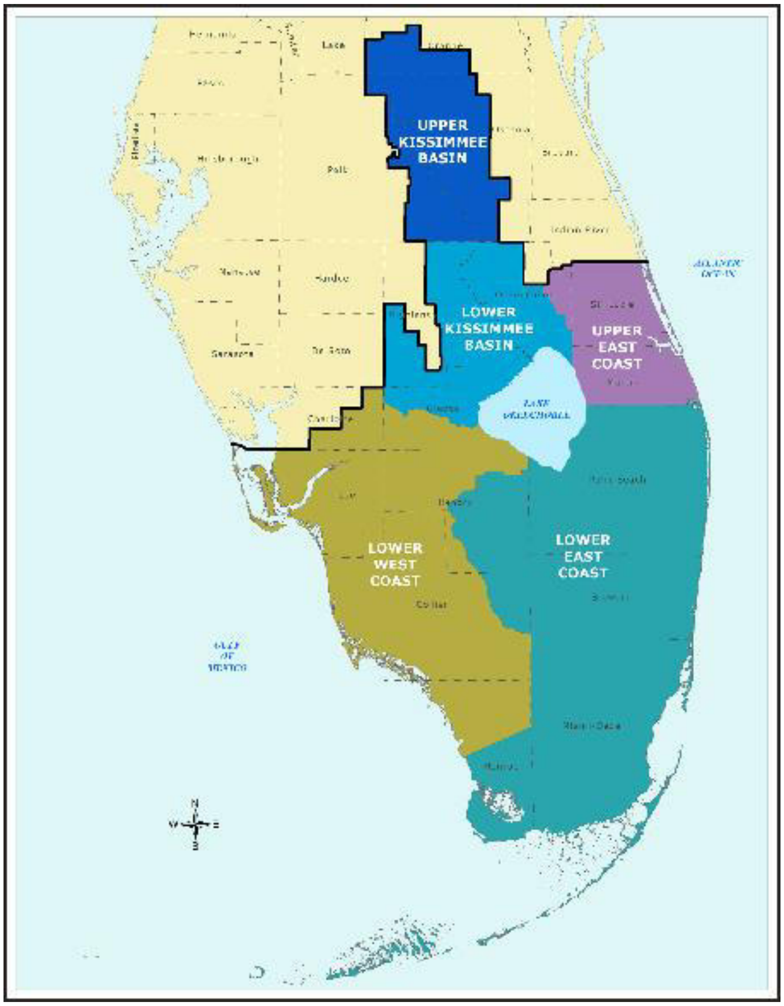
Within our period of analysis, starting in 1985, the first time that OWRs were implemented was caused by a districtwide drought that lasted from June 1989 to May 1990 (Trimble, Marban, Sculley, & Beach, 1990). As a consequence, the OWRs started as a demand-side water management tool in November 1989 and were in effect until May of the following year (Trimble et al., 1990). Exact information on the strictness of the OWRs was inaccessible which is why the intermediate, most commonly implemented *OWRP_2* was assumed for the analysis (see Figure 3.4). To the author's knowledge, after the drought ended in 1990 there were no restrictions in effect for almost ten years. The only regulation that residents have been following continuously up until now, is that no outdoor watering is allowed between 10 a.m. and 4 p.m. caused by peak evapotranspiration during these hours (Bates, 2009). The next dry period occurred around the year 2000, which was the driest year on record up to that time with November 1999 to May 2001 as the driest dry-wet-dry season (FDEP et al., 2007). As a consequence, Lake Okeechobee's water level dropped to the lowest stages ever recorded until then (FDEP et al., 2007), which was the reason why the SFWMD implemented *OWRP_2* and *OWRP_3* with the latter applying to surface water use in certain areas only (SFWMD, 2002). As mentioned before, due to the spatial level of analysis, only the general *OWRP_2* implemented at the county level that lasted from December 2000/January 2001 to September 2001 was considered (SFWMD, 2002). When it was detectable and implemented at the county level, *OWRP_1* was also considered (SFWMD, 2002).

Figure 3.4: Overview of Different Phases and Timing of the Outdoor Water Use Restrictions in 13 South Florida Counties

County	1989/ 1990	1985- 2000	2000/ 2001	2003/ 2004	2005/ 2006	2006/ 2007	2007	2007	2008	2008/ 2009	Since 2010
Broward			Jan-Sep 01 Phase II			Nov 06 – Apr 07 Phase II	May & June 07 Phase III	July – Dec 07 Phase II	Jan – Apr 08 Phase III		
Collier			Dec-Sep 01 Phase II	Jan 03 – Phase I	Oct 06 Phase I	Nov 06 Phase II	- Phase II	Dec 07 Phase II	Jan – Apr 08 Phase III		Phase
Glades			Dec-Sep 01 Phase II			Nov 06 – Phase III	Mar 07 Phase III	Apr – Dec 07 Phase II	Jan – Apr 08 Phase III		I
Hendry			Dec-Sep 01 Phase II			Nov 06 – Phase III	Mar 07 Phase III	Apr – Dec 07 Phase II	Jan – Apr 08 Phase III		
Lee	Nov 89 -	Restricted	Dec-Sep 01 Phase II	Jan 03 – Phase I	Oct 06 Phase I	Nov 06 Phase II	- Phase II	Dec 07 Phase II	Jan – Apr 08 Phase III	May 08 –	
Martin	May 90	10am-	Dec-Sep 01 Phase I			Nov 06 –Mar 07 Phase II	Apr 07 Phase I	May – Dec 07 Phase II	Jan – Apr 08 Phase III	Dec 09	
Miami-Dade	Phase II	4pm	Jan-Sep 01 Phase II			Nov 06 Phase II	- Phase II	Dec 07 Phase II	Jan – Apr 08 Phase III	Phase II	
Monroe			Dec-Sep 01 Phase II					Apr – Dec 07 Phase II	Jan – Apr 08 Phase III		
Okeechobee			Jan-Sep 01 Phase II				Apr - June 07 Phase I	July – Dec 07 Phase II	Jan – Apr 08 Phase III		Phase
Orange			April-Sep 01 Phase II		App.	Jan 04	-	Dec 09			II
Osceola			Jan-Sep 01 Phase II				Phase II				
Palm Beach			Jan-Sep 01 Phase II			Nov 06 – Apr 07 Phase II	May & June 07 Phase III	July – Dec 07 Phase II	Jan – Apr 08 Phase III		
St. Lucie			Dec, Jan-Sep 01 Phase I, Phase II			Nov 06 –Mar 07 Phase II	Apr 07 Phase I	May – Dec 07 Phase II	Jan – Apr 08 Phase III		

Concerning the exact order of counties implementing different phases of OWRs from 2003 onwards, the available information is difficult to access which is why we have made several careful assumptions to address these challenges. Starting in 2003, Lee and Collier counties were the only regions that implemented *OWRP_1* for a prolonged period of time independently of a drought (Bates, 2009). The next drought event took place in 2006-07 when South Florida broke a new drought record and experienced one of the driest periods in recorded climate history (SFWMD, 2009). From here on it starts to become a little bit challenging to keep track of which county had what kind of restriction in place when. The majority of counties in the SFWMD implemented *OWRP_2* as a response to the dry conditions (Bates, 2009). Exceptions were Glades and Hendry that followed *OWRP_3*, while Monroe and Okeechobee did not have any restrictions yet (FDEP et al., 2007). Orange and Osceola, partly located in St. John's Water Management District, presumably followed *OWRP_2* already a little before the other counties due to the endeavor to decrease the confusion among those counties' residents (Bates, 2009). Another reason for the seemingly random variations between counties is their allocation into different regional groups that serve the purpose of water supply planning (see Figure 3.5). Therefore, implementing drought restrictions within the boundaries of these regions resulted in OWRs that were not applicable to the entire county, which is why the exact division and implementation of OWRs could not always be considered in the analysis.

Figure 3.5: The Water Supply Planning Regions of the South Florida Water Management District



Source: SFWMD (2018)

At least from July to December 2007, all 13 counties had *OWRP_2* in place, turning into *OWRP_3* from January to April 2008 for all counties except Orange and Osceola that continued following St. John's *OWRP_2* (SFWMD, 2009). Subsequently, the restrictions were not entirely removed. Instead, *OWRP_2* remained implemented throughout the entire decision-making process about districtwide OWRs from June 2008 to December 2009 (Bates, 2009). In 2010, the year-round landscape irrigation rule came into effect, requiring a minimum of *OWRP_1* in all counties, with some counties voluntarily implementing the stricter version, *OWRP_2*.

3.2.1 Variable Description and Preparation

For the DID approach we could analyze almost 4,000 observations. Water use data were taken from the Scientific Investigation Report, 2015 from Marella (2019). The *Per capita water use* was used as the dependent variable, ranging between 1,234.5 and 11,700.7 gallons (see Table 3.2) with a mean value of 5395.99 gallons. The wide range of the values could not be verified by us, but it might be explicable with unobservable factors that can lead to high or low outliers. High outliers could result from uncounted tourists using water that falls under the category of public water use. Higher observed uses per resident are possible when these guests, as additional temporary water users, are not counted. A similar situation applies to other increased uses resulting from non-residential customers such as commercial or industrial consumers, who use greater volumes of water and their proportion can vary between counties. Low outliers (less water consumption per resident) on the other hand could result from residents using private wells for outdoor use and thereby reducing their overall water use.

Table 3.2: Overview of the Continuous Variables

Variable	Observations	Mean	St. Deviation	Min	Max
Per capita water use (dependent variable in DID)	4,000	5,400	1,590	1,240	11,700
Bachelor's degree or higher	4,000	19.2	7.4	6.2	34
Median household income	4,000	36,700	8,940	16,400	61,200
Lake Okeechobee water level (in feet)	4,870	14.1	1.98	8.94	18.3
Lake Kissimmee water level (in feet)	4,870	50.5	1.1	48	53
WCA water level (in feet)	4,870	13	0.64	11.2	15.5
Precipitation (in inch)	4,870	4.5	3.8	0	29.4
Evaporation (in inch)	4,870	0.25	0.07	0.1	0.49

Table 3.3: Description of the Dummy and Categorial Variables

Dummy and categorial variables	Variable description
OWRP_1	Phase 1 restriction with three-days-per-week outdoor watering allowed; 0=inactive, 1=active
OWRP_2	Phase 2 restriction with two-days-per-week outdoor watering allowed; 0=inactive, 1=active
OWRP_3	Phase 3 restriction with one-day-per-week outdoor watering allowed; 0=inactive, 1=active
Treatment2007	0=before 2007, 1=including and after 2007
Interaction1	Interaction: OWRP_1 x Treatment2007; 0=inactive, 1=active
Interaction2	Interaction: OWRP_2 x Treatment2007; 0=inactive, 1=active
Interaction3	Interaction: OWRP_3 x Treatment2007; 0=inactive, 1=active
Number of restricted days (dependent variable in value function)	0=no OWR, 4=OWRP_1, 5=OWRP_2, 6=OWRP_3

For some counties, data on population served were incomplete, which is why in some cases the county's actual population was used (Broward 2011, all of Monroe), provided by the Office of Economic & Demographic Research (2017). If the actual population appeared to be too high compared to existing values, the gaps were filled using linear interpolation. The respective years' *Per capita water use* was calculated, using this value. This method was applied to Collier (2011) and Orange (1998).

The water use data for Monroe county were included in the Miami-Dade usage because the water is provided by Miami-Dade Water and Sewer. The exported amount of water is documented clearly and used for this study. However, the actual number of residents served was not provided and so the county's total population had to be used as a proxy.

Regarding the weather data, which originally included the total monthly *Precipitation* in inches and the average monthly *Temperature* in degree Fahrenheit, data from one weather station in each county were used. The data were provided by the Florida Climate Center (2019) and by NOAA (2019). Predominantly in the earlier years, only daily data were available from which the monthly average for *Temperature* or sum for *Precipitation* was calculated. Where data on entire months were missing, values were calculated based on averages from existing months. For incomplete *Temperature* data, the average of the existing data was taken and for incomplete *Precipitation* data the sum of the existing days was extrapolated.

The variable for educational attainment is called *Bachelor's degree or higher* and the data were provided by the Unites States Census Bureau (2019). Finally, the data on *Median household income* were downloaded from the online platform "American Fact Finder" provided by the United States Census Bureau (2019). In both cases, there were no exact data available for every individual month and year for each county, so the missing values were calculated with linear interpolation.

For the value function approach, we could analyze 4,900 observations because of the inclusion of some additional years of data from Charlotte, Highlands and Polk counties. The independent variable was called *Number of restricted days* per week and varied between 0 and 6, which implies that there were periods without restrictions (0 days restricted equals 7 days outdoor watering allowed in a week) and periods with the strictest *OWRP_3* with 6 days restricted (1 day per week watering allowed). *Lake Okeechobee*, *Lake Kissimmee* and *WCAs* variables imply the monthly average water levels of those three water bodies. Data were obtained from DBHydro, an online database that stores hydrological data provided by the SFWMD (2019a). Water stages ranged between 8.9 and 18.3 feet for *Lake Okeechobee*, 48 and 53 feet for *Lake Kissimmee* and 11.2 and 15.5 feet for *WCA*s (see Table 3.2). Finally, *Evaporation,* which represents average monthly evaporation, was also obtained from DBHydro (SFWMD, 2019a) and varied between 0.1 and 0.49 inches.

For the statistical analysis of the data, Stata 15 was used (StataCorp, 2017). Before running the actual regression analysis, we tested the data for different types of correlations, including cross-sectional dependence, heteroskedasticity and autocorrelation. To test for cross-sectional dependence, we used the Breusch-Pagan LM test in a fixed-effects linear model. The test rejected the null hypothesis of no existing cross-sectional dependence, which means that our data show signs of cross-sectional dependence. To test for heteroskedasticity, we used the LR test, which rejected the null hypothesis of homoskedasticity. This result means that heteroskedasticity is present in our dataset. Finally, we tested the data for autocorrelation using the Wooldridge test.

The null hypothesis of no first-order autocorrelation was rejected which means that autocorrelation is present.

3.3 Difference-in-Differences Approach

The idea of the DID approach is to compare the difference in outcomes of the affected and unaffected groups, before and after a policy intervention to remove the effect of the time trend and the pre-existing difference between the groups and isolate the pure treatment effect (see Figure 3.6).

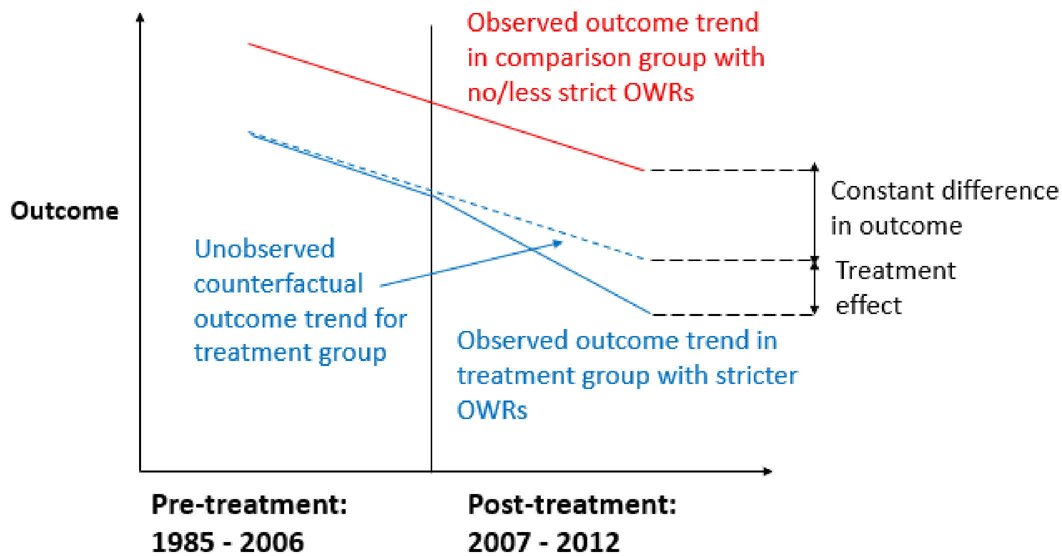


Figure 3.6: Visualization of the Difference-in-Differences Approach

Adapted from: Columbia University (2019)

The DID estimate is measured by calculating the difference between the change in the two outcomes before and after the treatment in the two different groups (treatment and control), which is equal to the estimated regression coefficient on the interaction of the dummy variable for a treatment group with the dummy variable for the after-treatment period (Goodman-Bacon, 2019):

$$y_{it} = \beta_0 + \beta_i TREAT_i + \beta_t POST_t + \beta_{it} TREAT_i \times POST_t + u_{it} \qquad (1)$$

With i and t signifying each group and period of time, $\beta_i TREAT_i$ stands for the treatment group, $\beta_t POST_t$ stands for the post-treatment time period and $\beta_{it} TREAT_i \times POST_i$ is the interaction term of the two, revealing the effect of the treatment in the group that was treated. In this way, an estimate of the “effect” of the treatment in the pre-treatment period (when there is none) can be used to remove the effect of confounding factors that might cause confusion when post-treatment outcomes of treated and non-treated groups are compared (Lechner, 2010). Most real-life applications deviate from this basic setup as a result of treatments starting at different times (Goodman-Bacon, 2019).

In the setup of the current study there is not one single group treated with OWRs and another group without any OWRs (see Figure 3.6). Instead, all counties implemented different phases of OWRs at different times. To set up a clear distinction between before and after the treatment, all periods when counties had OWRs in place before November 2006 were removed from the data. Then, starting from the end of 2006/beginning of 2007, all counties had OWRs implemented continuously. Therefore, instead of comparing a treatment group with a control group we compare groups of counties with the same kind of OWR implemented. For instance, the group of counties with *OWRP_3*, used as the treatment group, is compared to the other counties without *OWRP_3* as the control group. The advantage of the explained approach is its simplicity and its potential to avoid endogeneity problems that usually occur when comparing heterogeneous agents, which are counties in our case (Bertrand, Duflo, & Mullainathan, 2002).

For the DID approach, a linear fixed-effects model is combined with the basic DID regression model. The bare linear fixed-effects model looks like the following (Allison, 2009):

$$y_{it} = \mu_t + \beta x_{it} + \gamma z_i + \alpha_i + \varepsilon_{it} \tag{2}$$

Since panel data are used, there is a set of individuals ($i = 1, \ldots, n$), which are the 13 counties, each of whom has monthly data for 27 years ($t = 1, \ldots, T$). In the above equation, y_{it} is the dependent variable, which is *Per capita water use.* There are several predictor variables, some of which vary over time. These are represented by the vector x_{it} (Allison, 2009). A second set of predictor variables are those that do not vary over time, represented by z_i. The variable μ_t is an intercept that can vary between each period, while β and γ are vectors of coefficients. Furthermore, there are two error terms α_i and ε_{it} , which behave differently from one another. While ε_{it} varies for each county in every point in time, α_i does only vary for each county but stays constant over time (Allison, 2009). Therefore, α_i represents the combined effect of all unobserved variables constant over time, which is called individual heterogeneity (Brüderl & Ludwig, 2015) on y, while ε_{it} represents variation at each point in time, that is purely random (Allison, 2009). The two terms can only be identified with panel data because person-specific characteristics can only be assumed from repeated observations (Brüderl & Ludwig, 2015).

The advantage of fixed-effects regression models is that repeated observations on individuals are used to control for unobserved and invariant characteristics that relate not only to the outcomes but also to the explanatory variables (Angrist & Krueger, 1998). Therefore, fixed-effects can be useful when causal inference is aimed for to provide unbiased estimates of causal effects if unobserved confounders might be present (Gangl, 2010). To check for robustness, we ran three fixed-effects linear regression models for each OWR, the first time controlling for variation between counties, the second time expanded to control for variation between months through the inclusion of monthly dummy variables, and the third time expanded to control for variation between years through the inclusion of yearly dummy variables. To address the first-order autocorrelation we decided to run an alternative fixed-effects linear model that considered this kind of disturbance.

A third model was combined with the DID, called Generalized Estimation Equation (GEE), which is similar to a Generalized Linear Mixed Model (GLMM) because it can include subject-specific random effects (Hong & Ottoboni, 2017). Unlike GLMM, GEE does not require parametric assumptions (Hong & Ottoboni, 2017). Instead, the within-subject covariance structure is estimated through averaging over all subjects (Hong & Ottoboni, 2017). To describe the relationship between covariates and response, GEE chooses iteratively the best β (Hong & Ottoboni, 2017). The GEE can estimate population average effects and their standard errors (Hong & Ottoboni, 2017). To run the model in Stata, a covariance needs to be specified. If no covariance is specified, the default setting corresponds to the equal-correlation model (Stata Press, 2017). However, β will be estimated consistently even if the chosen covariance structure does not match (Hong & Ottoboni, 2017), though, wrong standard errors will be received, which can be corrected by choosing the option of robust standard errors. The Huber/White/sandwich estimator of variance is used to generate valid standard errors even though the within group correlations deviate from the original hypothesis in the specified correlation structure (Stata Press, 2017). The generalized linear model form looks as follows (Stata Press, 2017 following Zeger & Liang (1986)):

$$g\{E(y_{it})\} = x_{it}\beta, \qquad y \sim F \; with \; parameters \; \theta_{it} \tag{3}$$

Where $i = 1,..., m$ and $t = 1,..., n_i$, with n_i observations for each group's identifier i. The substitution of different definitions for $g(\,)$, which is the link function, and F, the distributional family, results in various models (Stata Press, 2017). One example can be if y_{it} is normally distributed (Gaussian) and $g(\,)$ is the so called identity function, which would have the following form (Stata Press, 2017 following Zeger & Liang (1986)):

$$E(y_{it}) = x_{it}\beta, \qquad y \sim N(\,) \tag{4}$$

This procedure yields a linear regression, a random-effects regression or other such models, depending on what is assumed to be the correlation structure (Zeger & Liang, 1986). Both of these models were used to analyze the effects of *OWRP_2* and *OWRP_3* on *Per capita water use*.

Furthermore, we fit a panel-data linear model with feasible generalized least squares for *OWRP_3* as the main independent variable in the DID model. The basic equation from which the model is developed can be written as (Stata Press, 2017):

$$y_{it} = x_{it}\beta + \epsilon_{it} \tag{5}$$

Where $i = 1,...,m$ is the number of panels (counties) and $t = 1,...,T_i$ is the number of observations for panel i (Stata Press, 2017). Basically, y can be written as an n by *1* vector of outcomes, x as an n by k matrix of predictors with β being a k by *1* parameter vector and ϵ as an n by *1* vector of unobserved error terms (Miller, 2017). Depending on the assumptions on the structure of the matrices, various models can be specified (Miller, 2017).

3.4 Value Function Approach

The conceptual framework behind the value function approach aims to establish a connection between a dollar value in the social system and a hydrological flow in the natural/physical system. In the case of South Florida, the dollar value is the monetary value of the estimated amount of water that is conserved by the residential water consumers due to the OWRs. In other words, this dollar value is the saved money for the customers who have a reduced water bill because they used less water due to the restrictions. So, the first step connects a monetary value of the saved water with the estimated saved amount of water caused by OWRs (see Figure 3.7). We derived the volumetric amount of conserved water from the regression results of the DID approach using the predicted amount, specific for *OWRP_3*. To obtain the respective monetary value, we used available data from a South Florida water utilities rate study from 2018 that revealed an inflation rate of 5.7% per year (Beecher, 2016). This inflation rate is much higher than the overall rate of inflation. For a simplified comparison, we calculated the water rates in 2020 dollars. The utility with the highest and the lowest rates in each county were used to calculate the respective cost for the amount of water not used. Most utilities have an increasing block rate structure, which means that with increasing consumption the price per 1,000 gallons of water increases. In the calculation process, we considered the general average water consumption in every county and calculated the price of the saved water in the respective tier in which the reduction occurred. In the second step, the value function regression model enabled us to relate the OWRs to several water use related variables in the regional hydrological system. More specifically, the hydrological value function allowed to develop a relation between *Lake*

Okeechobee water level and the *Number of restricted days*. The third step connects the value of the conserved water from step one to the hydrological variable, namely *Lake Okeechobee* water level, which is the main objective of this approach. Through the intermediate step we could monetize a specific water flow in the hydrological system based on how it relates to the implementation of OWRs, resulting in saved costs for consumers.

Figure 3.7: Conceptual Framework

1. **Value of water (saved money for customers) = F (Reduced use of water due to OWRs)**
    - Relationship between the water amount (static volume) saved due to restrictions and the value of that water ($)

    (The amount of OWR-related water savings, as estimated through DID approach, is given its monetary value on the basis of counties' utility rates.)

2. **Outdoor water use restrictions (OWRs) = F (hydrological flow (volume) at Lake Okeechobee, Lake Kissimmee and the WCAs)**
    - Relationship between restrictions (OWRs) and water flow (volume) in the hydrological system (Lake Okeechobee)

    (Established through the estimation of the value function.)

3. **Value of water (saved money due to reduced use of water) = F (OWRs (hydrological flow))**
    - Connecting $ value with the hydrological flow (volume)

    (Computed monetary value of saved water (from step 1.) is connected to water volume in hydrological system received from value function (from step 2.).)

Especially for low counts like in our case (values of *Number of restricted days* between 0 and 6), OLS regression is not the proper choice either. The traditional negative binomial distribution is usually symbolized as NB2 (Cameron & Trivedi, 1986) and derived from a so-called Poisson-gamma mixture distribution (Hilbe, 2011).

The negative binomial regression, which is a type of generalized linear model, can be explained by the following parametrization, given by Hilbe (2011):

$$p(y) = P(Y = y) = \frac{\Gamma\left(y + \frac{1}{\alpha}\right)}{\Gamma(y + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{1}{1 + \alpha\,\mu}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\,\mu}{1 + \alpha\,\mu}\right)^{y}, \tag{6}$$

where $\mu > 0$ is the mean of Y and $\alpha > 0$ is the heterogeneity parameter. The parametrization is derived as a Poisson-gamma mixture (Zwilling, 2013). The traditional NB2 model is

$$\ln \mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \tag{7}$$

While the predictor variables x_1, x_2, …, x_p are given, the population regression coefficients β_0, β_1, β_2, …, β_p need to be estimated (Zwilling, 2013). When a random sample with n observations is given, the dependent variable y_1 and the predictor variables $x_{1i}, x_{2i}, \dots, x_{pi}$ can be observed for subject i (Zwilling, 2013). We can use vector and matrix notation, letting $\beta = \left(\beta_0\ \beta_1\ \beta_2\ \dots\ \beta_p\right)^T$, and then enter the predictor data into the design matrix X as follows:

$$X = \begin{pmatrix} 1 & x_{11} & x_{12} & \dots & x_{1p} \\ 1 & x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix} \tag{8}$$

The i^{th} row of X is designated as x_i and (7) is exponentiated, so that the distribution (6) can be written as

$$p(y_i) = \frac{\Gamma(y_i + {}^1/_\alpha)}{\Gamma(y_i + 1)\Gamma({}^1/_\alpha)} \left(\frac{1}{1 + \alpha\, e^{x_i \cdot \beta}}\right)^{1/\alpha} \left(\frac{\alpha\, e^{x_i \cdot \beta}}{1 + \alpha\, e^{x_i \cdot \beta}}\right)^{y_i}, i = 1, 2, \dots, n. \tag{9}$$

Then, α and β are estimated using maximum likelihood estimation with the following function (Zwilling, 2013):

$$L(\alpha, \beta) = \prod_{i=1}^{n} p(y_i) = \prod_{i=1}^{n} \frac{\Gamma(y_i + {}^1/_\alpha)}{\Gamma(y_i + 1)\Gamma({}^1/_\alpha)} \left(\frac{1}{1 + \alpha\, e^{x_i \cdot \beta}}\right)^{1/\alpha} \left(\frac{\alpha\, e^{x_i \cdot \beta}}{1 + \alpha\, e^{x_i \cdot \beta}}\right)^{y_i}, \tag{10}$$

while the log-likelihood function looks like (Zwilling, 2013):

$$\begin{aligned} \ln L(\alpha, \beta) = \sum_{i=1}^{n} (y_i ln\alpha + y_i(x_i \cdot \beta) - \left(y_i + \frac{1}{\alpha}\right) \ln\left(1 + \alpha e^{x_i \cdot \beta}\right) \\ + ln\Gamma\left(y_i + \frac{1}{\alpha}\right) - ln\Gamma(y_i + 1) - ln\Gamma\left(\frac{1}{\alpha}\right)) \end{aligned} \tag{11}$$

The maximum likelihood estimates are the values of α and β that maximize $lnL(\alpha, \beta)$ (Zwilling, 2013). Furthermore, the estimated variance-covariance matrix of the estimators is $\Sigma = -H^{-1}$, with H being the Hessian matrix of second derivatives of the log-likelihood function (Zwilling, 2013). The variance-covariance matrix can be used to find the usual Wald confidence intervals and *p*-values of the coefficient estimates (Zwilling, 2013).

The interpretation of coefficients resulting from count models, in our case a negative binomial regression model, can be challenging since they are shown in logged form (Meyer, 2020). Conveniently, the regression coefficients can also be reported in so-called incidence rate-ratios. Therefore, we ran the same regression again with having the incidence rate-ratios displayed. Finally, we also applied a GLS model with population average that we described in the previous section on the DID approach.

3.5 Comparison with Stated Preference Study

The stated preference discrete choice model, which was designed and implemented by Seeteram (2014) as part of her Master thesis research (Seeteram, 2014; Seeteram, Engel, & Mozumder, 2018), provides the WTP of South Florida residents to avoid OWRs. The study outline was extended, based on an earlier study by Milon et al. (1999), that examined the valuation of ecosystem services provided by the Everglades. Through an online survey, households in South Florida were provided with important background information about different scenarios, which outlined management and restoration alternatives with varying attributes for Lake Okeechobee, the Everglades National Park and WCAs accompanied by certain OWRs. A set of 20 different choice cards with hydrological variables was designed, combining different degrees of protection or conservation with OWRs and a monetary fee based on which the respondents had to make their choices. The respondents indicated their preferred management plan and agreed on the corresponding cost for its implementation (Seeteram et al., 2018). The study revealed that respondents in the general public stated a marginal WTP value of US$25.70-32.40 (US$10.58-13.35 in 2004 dollar) per one unit

OWR (equivalent to one day) per year to avoid both indoor and outdoor water use restrictions on the household level (Seeteram, 2014). Furthermore, pro-environmentalists stated a marginal WTP of US$44.00 (US$18.14 in 2004 dollar) per one unit OWR per year to avoid such restrictions (Seeteram et al., 2018). The average WTP was US$58.00-87.00 (US$23.90-35.85 in 2004 dollar) per year (Seeteram, 2014). Based on that, it was estimated that the South Florida population is willing to pay between US$59.2-66.3 million (US$24.4-27.3 million in 2004 dollar) per year (n=2,044,741 households) to avoid OWRs (Seeteram, 2014). The findings from the stated preference study by Seeteram (2014), specifically the estimated WTP values for a relaxation of OWRs, are compared to the revealed preference value of OWRs obtained from the current study to find potential differences between stated and revealed preferences among South Florida residents.

4. RESULTS

4.1 Difference-in-Differences Approach

The results from the different DID regression models show varying effects of the three different levels of OWRs. Table 4.1 gives an overview of the results of the fixed-effects regression that considered autocorrelation for all three types of OWRs, while Tables 4.2, 4.3 and 4.4 show the regular fixed-effects regression results for each OWR individually. These models controlled for variations on three levels, county, monthly and yearly which we used as a robustness check.

The *Interaction* of *OWRP_1* was not found significantly correlated to the dependent variable, *Per capita water use* in our analysis. The fixed-effects linear regression model that considered autocorrelation revealed a negative and insignificant effect of *OWRP_1* (-175.86) and a positive and insignificant effect of the *Interaction* (79.29) (see Table 4.1).

Table 4.1: Fixed-effects Linear Regression Results Considering Autocorrelation for All Three Outdoor Water Use Restrictions[1]

VARIABLES	MODEL 1 (OWRP_1)	MODEL 2 (OWRP_2)	MODEL 3 (OWRP_3)
R-SQ	0.2424	0.2433	0.2451
CONS	3573.93***	3444.26***	3550.58***
OWRS	-175.86	-476.20***	-969.86***
TREATMENT2007	-1,102.71***	-1,234.87***	-1,177.06***
INTERACTION	79.29	463.03***	917.83***
MEDIAN HOUSEHOLD INCOME	0.03**	0.03***	0.03***
BACHELOR'S DEGREE OR HIGHER	57.54**	61.65***	55.43**

[1] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

The regular fixed-effects regression model on the other hand revealed a positive correlation of *OWRP_1* with *Per capita water use*, significant at the 10% level (Model 1: 501.47; Model 2: 478.17; Model 3: 483.52). The *Interaction_1* was found to be negatively and insignificantly correlated to *Per capita water use* (Model 1: -197.29; Model 2: -181.44) (see Table 4.2). The coefficients of *Treatment2007, Median household income* and *Bachelor or higher* are all significant at the 1% level and very similar in Models 1 and 2 of the regular fixed-effect linear regression (see Table 4.2). *Treatment2007* has a coefficient between -980 and -985, *Median household income* has a coefficient of 0.017 and *Bachelor's degree or higher* has a coefficient of -42. In Model 2, monthly dummy variables are included with *September* removed as the reference month since that month had the lowest usage on average. One can see that all coefficients of the other months are significantly and positively correlated with *Per capita water use* (between 205.57 for February and 869.64 for May). Model 3 deviates from the other two Models in that the *constant* is negative (-1,277.744), *Treatment2007* is negative (-484.89), *Interactoion_1* is positive (60.299) and the coefficients of *Median household income* (0.16) and *Bachelor or higher* (-72.47) are much greater (see Table 4.2). The monthly dummy variables have very similar coefficients. For the included yearly dummy variables, *Year_12* was removed beforehand for being the year with the lowest average *Per capita water use* and served therefore as the reference year. Furthermore, the regression dropped *Year_06* due to collinearity. From *Year_85* until *Year_05* the coefficient is significant and positive implying that per capita water use was steadily decreasing for those two decades (from Year_85: 3,687.95; to Year_05: 884.83).

Table 4.2: Fixed-effects Linear Regression Output for Outdoor Water Use Restriction Phase 1 Under Different Control[2]

VARIABLES	MODEL 1	MODEL 2	MODEL 3
CONTROLLED FOR	County variance	County and monthly variance	County, monthly and yearly variance
R-SQ	0.0004	0.0028	0.3004
CONS	5,773.51***	5,345.49***	-1,277.744***
OWRP_1	501.47*	478.17*	483.52*

TREATMENT2007	-985.29***	-980.59***	-484.89***
INTERACTION_1	-197.29	-181.44	60.299
MEDIAN HOUSEHOLD INCOME	0.017***	0.017***	0.16***
BACHELOR OR HIGHER	-42.25***	-42.37***	-72.47***
JANUARY		514.36***	517.01***
FEBRUARY		205.57***	208.52***
MARCH		823.29***	825.94***
APRIL		680.36***	680.73***
MAY		869.64***	870.77***
JUNE		270.53***	269.06***
JULY		310.94***	310.94***
AUGUST		323.09***	323.09***
SEPTEMBER		removed	removed
OCTOBER		381.04***	386.32***
NOVEMBER		472.76***	488.59***
DECEMBER		555.77***	571.12***
YEAR_85			3,687.95***
YEAR_86			3,674.36***
YEAR_87			3,453.83***
YEAR_88			3,354.899***
YEAR_89			3,193.94***
YEAR_90			2,881.48***
YEAR_91			2,562.63***
YEAR_92			2,515.79***
YEAR_93			2,360.95***
YEAR_94			2,123.45***
YEAR_95			1,754.63***
YEAR_96			1,923.83***
YEAR_97			1,684.3***
YEAR_98			1,725.61***
YEAR_99			1,739.91***
YEAR_00			1,365.698***
YEAR_01			1,147.16***
YEAR_02			1,233.13***
YEAR_03			1,070.74***
YEAR_04			1,076.86***
YEAR_05			884.83***
YEAR_06			Omitted
YEAR_07			-330.63***
YEAR_08			-95.9
YEAR_09			335.01***
YEAR_10			118.74
YEAR_11			23.42
YEAR_12			removed

[2] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

Three different regression models were applied to test the DID approach with *OWRP_2* as the main treatment variable. Model 2 in Table 4.1 shows the results of a fixed-effects linear model considering autocorrelation. The coefficients are all significant with values of about -476 for *OWRP_2*, -1,235 for *Treatment2007*, 463 for the *Interaction_2*, 0.03 for *Median household income* and about 62 for *Bachelor's degree or higher*. Compared to this, Table 4.3 shows the results of the fixed-effects linear regression with increasing control. In Model 1, two of the main variables, *OWRP_2* and *Interaction_2* with values of -168 and -132, respectively, were not significantly correlated to *Per capita water use* (see Table 4.3).

Table 4.3: Fixed-effects Linear Regression Results for Outdoor Water Use Restriction Phase 2 Under Different Control[3]

VARIABLES	MODEL 1	MODEL 2	MODEL 3
CONTROLLED	County variance	County and monthly variance	County, monthly and yearly variance
R-SQ	0.0000	0.0052	0.2969
CONS	5,730.93***	5,305.12***	-1,347.43
OWRP_2	-167.72	-191.25*	-22.42
TREATMENT2007	-719.25***	-735.91***	1.97
INTERACTION_2	-131.81	-78.79	-356.89***
MEDIAN HOUSEHOLD INCOME	0.017***	0.016***	0.017***
BACHELOR OR HIGHER	-38.23***	-38.37***	-74.92***
JANUARY		502.06***	499.44***
FEBRUARY		193.56***	190.95***
MARCH		811.82***	809.54***
APRIL		671.64***	669.36***
MAY		869.18***	870.61***
JUNE		269.88***	268.91***
JULY		310.94***	310.94***
AUGUST		323.09***	323.09***
SEPTEMBER		removed	Removed
OCTOBER		380.25***	384.96***
NOVEMBER		475.95***	487.83***
DECEMBER		566.03***	574.98***
YEAR_85			3,734.74***
YEAR_86			3,718.07***
YEAR_87			3,494.46***
YEAR_88			3,392.45***
YEAR_89			3,229.67***
YEAR_90			2,908.31***
YEAR_91			2,592.62***
YEAR_92			2,543.58***
YEAR_93			2,386.54***
YEAR_94			2,146.85***

YEAR_95	1,775.83***
YEAR_96	1,942.84***
YEAR_97	1,701.10***
YEAR_98	1,740.22***
YEAR_99	1,755.42***
YEAR_00	1,411.83***
YEAR_01	1,155.54***
YEAR_02	1,246.55***
YEAR_03	1,083.80***
YEAR_04	1,082.91***
YEAR_05	890.14***
YEAR_06	Omitted
YEAR_07	-470.03***
YEAR_08	-315.23***
YEAR_09	230.34**
YEAR_10	118.93
YEAR_11	23.32
YEAR_12	removed

[3] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

Treatment2007, *Median household income* and *Bachelor's degree or higher* were all significant with values of -719, 0.017 and -38, respectively. Results of Model 2 including monthly variance are mostly comparable concerning the levels of significance and actual values. The coefficient of *OWRP_2* increased to -191 and shows a 10% level significance while the coefficient of *Interaction_2* decreased to -79 (see Table 4.3). Regarding the monthly dummy variables, *September* was again set as the reference category removed due to having the lowest *Per capita water use* on average. All remaining months are significantly and positively correlated to *Per capita water use* (between 193.56 in February and 869.18 in May). Model 3, considering county, monthly and yearly variation, greatly deviates from the other two models. The constant is not significant anymore and negative (-1,347.43), the coefficient of *OWRP_2* is much smaller (-22.42), the coefficient of *Treatment2007* is slightly positive and insignificant (1.97) and the coefficient of *Interaction_2* is significantly correlated to *Per capita water use* (-356.89) (see Table 4.3). What remained very similar are *Median household income* (0.017) and the coefficients of the monthly variables. With regard to the yearly dummy variables, *Year_12* was removed beforehand due to having the smallest average

Per capita water use (used as reference category), *Year_06* was dropped due to collinearity and from *Year_85* to *Year_05* all of the coefficients are positive and significant (from Year_85: 3,734.74; to Year_05: 890.14).

Finally, a population-averaged linear model with robust standard errors was applied (see Table 4.4). Overall, these results are very similar to Model 1 of the fixed-effects linear models with *OWRP_2* (-171.513) and *Interaction_2* (-128.996) being negatively but not significantly correlated to *Per capita water use*. *Median household income* (0.016) and *Bachelor's degree or higher* (-34.539) do not have a significant correlation with *Per capita water use* like in the fixed-effects models, leaving only *Treatment2007* being significantly and negatively correlated to *Per capita water use* (-723.12).

Table 4.4: Regression Results for Outdoor Water Use Restriction Phase 2 (2 Days per Week Watering Allowed), Dependent Variable Per Capita Water Use[5]

VARIABLES	MODEL (POPULATION-AVERAGED WITH ROBUST STANDARD ERRORS)
CONS	5735.708***
OWRP_2	-171.513
TREATMENT2007	-723.12***
INTERACTION_2	-128.996
MEDIAN HOUSEHOLD INCOME	0.016
BACHELOR'S DEGREE OR HIGHER	-34.539

[5] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

For the DID approach using *OWRP_3* as the main treatment variable, we applied four different regression models: Model 3 of Table 4.1 shows results of a fixed-effects linear regression considering autocorrelation, Model 1 to 3 in Table 4.5 show results of a fixed-effects linear regression model that includes an increasing number of control variables for county, county plus monthly and county plus monthly plus yearly variation. Finally, Table 4.6 displays the results of a feasible generalized least squares (Model 1) and a population-averaged model (Model 2).

The fixed-effects linear regression considering autocorrelation (Table 4.1, Model 3) shows significant results for all included variables. *OWRP_3* has a coefficient of almost -970, *Treatment2007* of -1,177, the respective *Interaction* of almost 918, *Median household income* of 0.03 and *Bachelor's degree or higher* of about 55 (see Table 4.1). Compared to this, the results from the regular fixed-effects linear regression models show great differences for all variables. In Table 4.5, Model 1, showing results after controlling for county variation, and Model 2, showing results for county plus monthly variation, are very similar.

Table 4.5: Fixed-effects Linear Regression Results for Outdoor Water Use Restriction Phase 3 Under Different Control[6]

VARIABLES	**MODEL 1**	**MODEL 2**	**MODEL 3**
CONTROLLED	County variance	County and monthly variance	County, monthly and yearly variance
R-SQ	0.0006	0.0022	0.2692
CONS	5,790.27***	5,360.33***	-1,282.24***
OWRP_3	-2,230.99***	-2,307.697***	-1,590.89***
TREATMENT2007	-889.24***	-881.296***	-171.93
INTERACTION_3	2,207.04***	2,174.71***	1,467.51***
MEDIAN HOUSEHOLD INCOME	0.017***	0.017***	0.17***
BACHELOR OR HIGHER	-43.09***	-44.10***	-85.87***
JANUARY		519.71***	521.84***
FEBRUARY		211.21***	213.34***
MARCH		828.63***	830.76***
APRIL		687.64***	689.82***
MAY		871.898***	874.38***
JUNE		272.68***	272.65***
JULY		310.94***	310.94***
AUGUST		323.09***	323.09***
SEPTEMBER		Removed	removed
OCTOBER		379.73***	385.17***
NOVEMBER		485.01***	496.34***
DECEMBER		572.33***	583.21***
YEAR_85			3,715.45***
YEAR_86			3,695.95***
YEAR_87			3,469.51***
YEAR_88			3,364.67***
YEAR_89			3,198.72***
YEAR_90			2,882.434***
YEAR_91			2,559.35***
YEAR_92			2,509.21***

YEAR_93	2,351.06***
YEAR_94	2,110.27***
YEAR_95	1,738.15***
YEAR_96	1,904.05***
YEAR_97	1,661.21***
YEAR_98	1,699.22***
YEAR_99	1,713.32***
YEAR_00	1,369.73***
YEAR_01	1,116.86***
YEAR_02	1,206.82***
YEAR_03	1,044.67***
YEAR_04	1,039.64***
YEAR_05	849.32***
YEAR_06	Omitted
YEAR_07	-674.27***
YEAR_08	-427.47***
YEAR_09	-11.48
YEAR_10	118.61
YEAR_11	22.52***
YEAR_12	removed

[6] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

In Model 1, *OWRP_3* has a coefficient of about -2,231, *Treatment2007* of about -889 and *Interaction_3* of 2,207, compared to Model 2 with a coefficient of *OWRP_3* of -2,308, *Treatment2007* of -881 and *Interaction_3* of 2,175 (see Table 4.5). In both models, the coefficient of *Median household income* is 0.017 and the coefficient of *Bachelor's degree or higher* is about -44. The included monthly dummy variables show, just like in the previous two cases, all positive and significant coefficients after *September* was removed as the reference month (between 211.21 for February and 871.898 for May). Again, Model 3 controlling for county, monthly and yearly variance, deviates from the other two models. The *constant* is not positive but has a significant coefficient of -1,282, *OWRP_3* has a significant coefficient of almost -1,591, *Treatment2007* is not significant with about -172, and the *Interaction* is significant with almost 1,468. *Median household income* received the same value (0.17) while the coefficient of *Bachelor's degree or higher* decreased to about -86. The coefficients for the monthly variables are very similar, while the yearly variables are significantly and positively correlated from *Year_85* to *Year_05* with *Year_12* removed as the reference category and *Year_06* dropped for collinearity (from Year_85: 3,715.45; to Year_05: 849.32).

Table 4.6: Regression Results for Outdoor Water Use Restriction Phase 3 (1 Day per Week Watering Allowed), Dependent Variable Per Capita Water Use[7]

VARIABLES	**MODEL 1 (FEASIBLE GENERALIZED LEAST SQUARES, ITERATED)**	**MODEL 2 (POPULATION-AVERAGED)**
CONS	3935.099***	5795.216***
OWRP_3	-1498.603**	-2226.074***
TREATMENT2007	-1260.147***	-893.567***
INTERACTION_3	1555.516**	2206.097***
MEDIAN HOUSEHOLD INCOME	-0.009**	0.016***
BACHELOR'S DEGREE OR HIGHER	109.458***	-39.396***

[7] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

The remaining two models in Table 4.6 show results of a feasible generalized least squares model and of a population-averaged model. In Model 1, all variables are significant with the coefficient of *OWRP_3* having a value of about -1,489, *Treatment2007* of about 1,260, *Interaction_3* of about 1,556, *Median household income* of -0.009 and *Bachelor's degree or higher* of around 109. Model 2 on the other hand resulted in coefficient values very similar to the fixed-effects linear regression Model 1 and 2 in Table 4.5, all being significant.

Based on Model 2 of the regular fixed-effect linear regression models (see Table 4.2, 4.3 and 4.5) and on the results of the fixed-effects linear regression considering autocorrelation (see Table 4.1), we predicted the marginal effects for all three OWRs. This is basically the predicted average *Per capita water use* per month considering the effect of different variables (see Figure 4.7). Despite different regression outputs, one can see that the results of most of the variables are no more than a few hundred gallons apart from each other. A closer look at the results of the model that considers autocorrelation, one can see an average *Per capita water use* of just around 5,700 gallons when neither *Treatment2007* nor *OWR* is active (see ***0 0)***. When *Treatment2007* is active, referring to all counties in the period between 2007 to 2012, the predicted average *Per capita use* is between 4,500 and 4,600 gallons per month (see ***0 1***). Under active *OWRs*, the average predicted *Per capita water use* decreases with increasing stringency of the restriction, with about 5,522 gallons under *OWRP_1*, about 5,255 gallons under *OWRP_2* and about 4,739 gallons under *OWRP_3* (see ***1 0***).

Table 4.7: Marginal Effects Based on Fixed-effects Linear Regression Results[8]

INDEPENDENT VARIABLE	MODEL 1 (OWRP_1)	MODEL 2 (OWRP_2)	MODEL 3 (OWRP_3)
CONSIDERING AUTOCORRELATION			
OWR			
0	5,439.91***	5,442.48***	5,432.89***
1	5,282.62***	5,074.71***	4,677.97***
TREATMENT2007			
0	5,684.64***	5,653.38***	5,694.94***
1	4,588.02***	4,494.63***	4,530.74***
OWR##TREATMENT2007			
0 0	5,698.14***	5,731.66***	5,708.53***
0 1	4,595.43***	4,496.79***	4,531.47***
1 0	5,522.28***	5,255.45***	4,738.67***
1 1	4,498.86***	4,483.61***	4,479.44***
CONTROLLED FOR COUNTY AND MONTHLY VARIANCE			
OWR			
0	5,372.65***	5,438.94***	5,400.03***
1	5,808.34***	5,229.24***	3,601.595***
TREATMENT2007			
0	5,639.1***	5,579.83***	5,574.08***
1	4,644.48***	4,830.97***	4,723.25***
OWR##TREATMENT2007			
0 0	5,602.28***	5,611.27***	5,606.41***
0 1	4,621.69***	4,875.36***	4,725.11***
1 0	6,080.46***	5,420.02***	3,298.71***
1 1	4,918.43***	4,605.32***	4,592.12***

[8] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

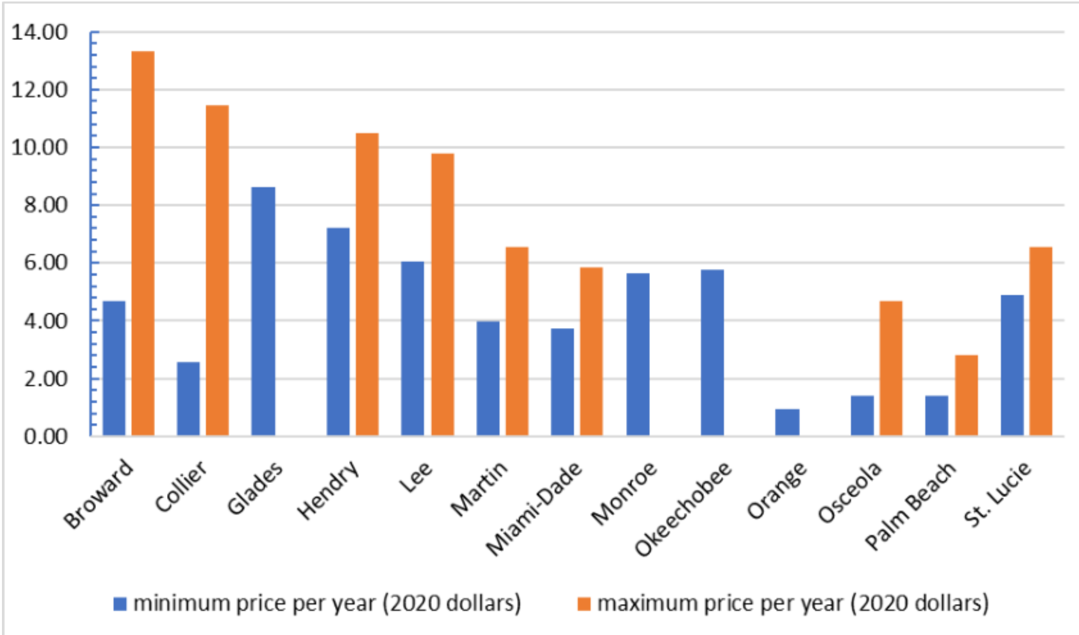
Finally, the exact treatment effect of each restriction is estimated when *Treatment2007* and *OWR*s are in effect simultaneously, showing that the predicted average *Per capita water use* for *OWRP_1* would be almost 4,500 gallons, for *OWRP_2* about 4,484 gallons and for *OWRP_3* almost 4,480 gallons (see ***1 1*** in Table 4.7).

Looking at the margins based on the regular fixed-effects regression model, one can see an average *Per capita water use* of just above 5,600 gallons when neither *Treatment2007* nor *OWR* is active (see ***0 0)*** which is about 100 gallons less than predicted with the other model. When *Treatment2007* is active, referring to all counties in the period between 2007 to 2012, the predicted average *Per capita use* varies between almost 4,622 gallons for the *OWRP_1* model and 4,875 gallons per month for the *OWRP_2* model (see ***0 1***). Under active *OWRs*, the average predicted *Per capita water use* decreases steeply with increasing stringency of the restrictions, with about 6,080 gallons under *OWRP_1*, about 5,420 gallons under *OWRP_2* and almost 3,300 gallons under *OWRP_3* (see ***1 0***). Finally, the exact treatment effect of each restriction is calculated when *Treatment2007* and *OWR*s are in effect simultaneously, showing that the predicted average *Per capita water use* for *OWRP_1* would be about 4,918 gallons, for *OWRP_2* about 4,605 gallons and for *OWRP_3* almost 4,592 gallons (see ***1 1***). These values are all below the individual values of both *Treatment2007* and the respective OWR (see Table 4.7).

Table 4.7 reveals that, looking at the model controlling for county and monthly variance, about 133 gallons of water per person per month are saved under *OWRP_3* (4,725.11 – 4,592.12) compared to the average of other OWRs. The savings due to *OWRP_3* compared to before the treatment period would be around 1,014 gallons per person per month (5,606.41 – 4,592.12). We used both these numbers to calculate a monthly monetary value for these amounts of water saved in each county. To accomplish this, the most and the least expensive water rate structure in each county were used to calculate the average dollar value of the saved water in 2020 dollar. The respective tier of water billing rate was considered, which means that we took into consideration the average amount of water that was consumed per person in each county despite the reduction of *OWRP_3*. For instance, if the price of the saved 133 gallons was calculated in the 3,000 to 5,000 gallons tier with a higher price per 1,000 gallons than it would have been in the 1,000 to 2,000 gallons tier. This is important to obtain a realistic picture of the amount of Dollars saved (for the consumers) or forgone (for the utilities). Those two values were then divided by two to obtain the average billing rate. This procedure was followed for both amounts and all counties to find specific values and extrapolated to receive the total monetary value of the saved amount of water for the whole year. Figure 4.1 and 4.2 illustrate the variation of water rates among the 13 different counties considered here. Over the course of a year almost 1,600 gallons of water per person could be saved due to the *OWRP_3*, compared to the average usage within the *Treatment2007* period, whereas it would be almost 12,170 gallons per person compared to the pre-treatment average usage.

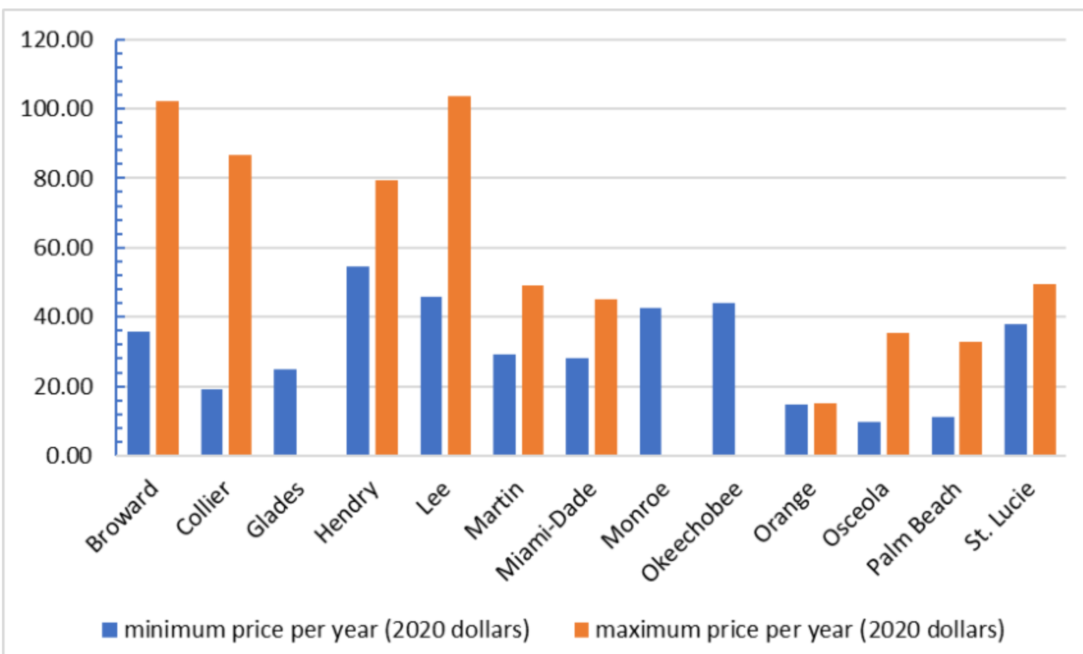
The water rates vary significantly between counties, leading to the different monetary values for the 1,600 gallons of water saved (see Figure 4.1). Residents in Orange could save the smallest amount of money (US$1) while some residents in Broward could save most money with over US$13. The average value is US$4.90. Figure 4.2 illustrates the monetary value of 12,170 gallons saved in one year. The saved costs range between US$9.80 in Osceola and US$103.60 in Lee with an average value of US$44.60.

Figure 4.1: Monetary Value of Water Saved due to Outdoor Water Use Restriction Phase 3[9]



[9] 1,596 gallons per person per year, difference to consumption when less stringent restrictions are implemented

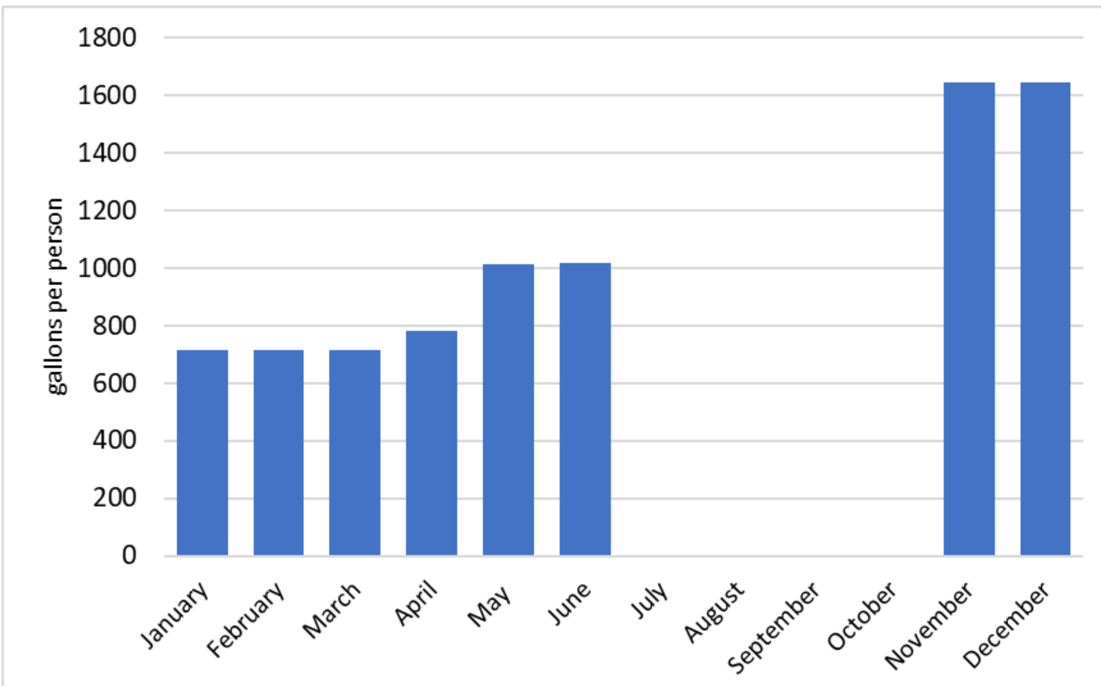
Figure 4.2: Monetary Value of Water Saved due to Outdoor Water Use Restriction Phase 3[10]



[10] 12,168 gallons per person per year, difference to no restriction at all

Furthermore, based on the regular fixed-effects linear regression model considering county and monthly variations we predicted the specific amount of water that could be saved in each month of implemented *OWRP_3* compared to the overall average usage (before and after treatment 2007). In Figure 4.3 one can see a significant variation between the beginning and the end of the year.

Figure 4.3: Predicted Average Amount of Water Saved due to Outdoor Water Use Restriction Phase 3 in Different Months[11]



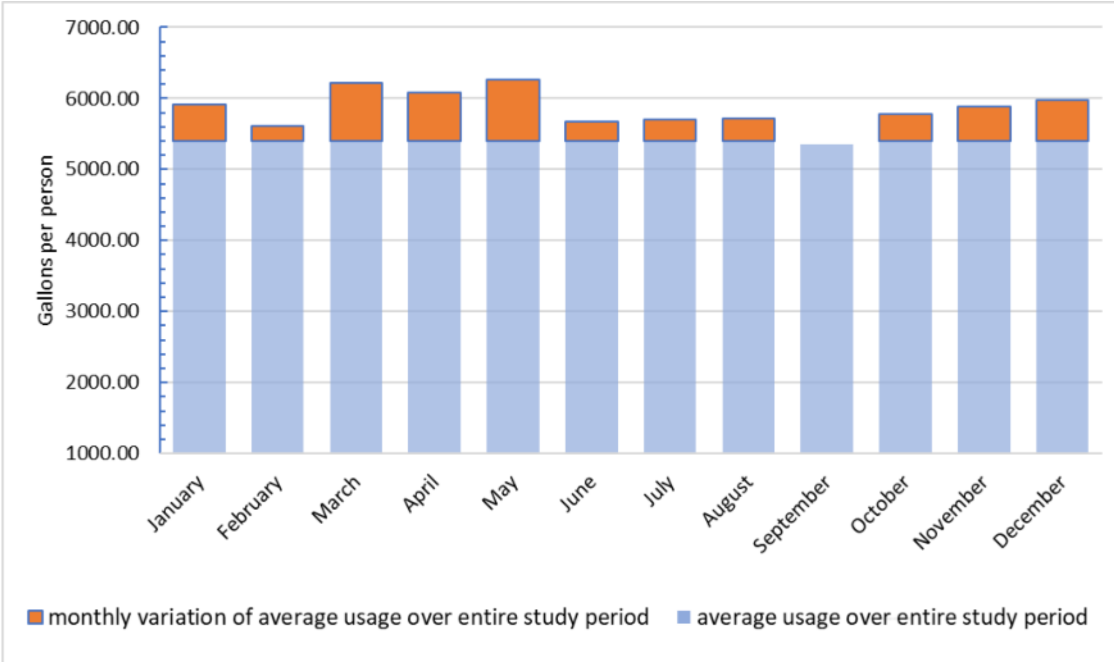
[11] no values for July-October since Phase 3 restriction was never implemented in these months

For the four months between July to October, there were no such specific visible savings since *OWRP_3* was never in effect during these months in any given year. We could estimate the values for January to April based on the data from eleven counties (except Orange and Osceola county) and both May and June, and November and December based on data from two counties only (Broward and Osceola for May-June, Glades and Hendry for November-December). The results show that the comparatively smallest amount of water (about 700 gallons of water per person per month) was saved when the majority of counties had to follow *OWRP_3* in 2008 due to a districtwide drought event, followed by the two months when only Broward and Palm Beach followed this rule in 2007 with a reduction of about 1,000 gallons (see Figure 4.3). The greatest savings were reached with over 1,600 gallons of water per person when *OWRP_3* was implemented in Collier and Hendry even earlier at the end of 2006.

In a next step we used the average monthly amount of water saved in all counties (133 gallons) and the respective monetary values to extrapolate it to the entire SFWMD level. In 2008, the entire district's population was a little over 7.1 million people. All of them together would have saved almost 11.4 billion gallons in an entire year due to *OWRP_3*. The monetary value of this would equal more than US$42.2 million today. These values were used in the analysis of the value function approach.

Finally, Figure 4.4 shows how *Per capita water use* varied across months between 1985 to 2012. Across all 13 counties and 27 years, water use was comparatively at its lowest in September, with an average amount of 5,360 gallons per person. The month with the greatest average water consumption was May with an average additional consumed amount of almost 900, bringing the overall average usage up to 6,360 gallons per person. One can see a slow and steady increase of water use from October to December. The water use remains almost stagnant from December through January. February shows a significant drop in average water use. The average consumption is substantially increased from March to May. And lastly, June through August show another noticeable decrease in consumption (see Figure 4.4).

Figure 4.4: Comparison of Differences in General Water Use over Months



4.2 Value Function Approach

The regression models used for the value function show that certain hydrological factors were significantly correlated to the dependent variable *Number of restricted days*, while results for others were less obvious. Four different models were used to analyze the relation between hydrological variables and the *Number of restricted days*: Model 1 is a fixed-effects negative binomial regression, Model 2 is a negative binomial regression, reported as incidence-rate ratios, Model 3 is a population-averaged negative binomial regression with robust standard errors and Model 4 is a population-averaged negative binomial with robust standard errors and independent correlation (correlation between time points is independent) (see Tables 4.8 and 4.9). These models show all variables except *WCA* water level to be significantly correlated to the dependent variable *Number of restricted days*. *Temperature* was excluded from the analysis due to collinearity with *Precipitation.*

Table 4.8: Regression Results for the Hydrological Model of OWRs, Dependent Variable Number of Restricted Days[12] (1)

VARIABLES	MODEL 1 (FIXED-EFFECTS NEGATIVE BINOMIAL)	MODEL 2 (NEGATIVE BINOMIAL, REPORTED AS INCIDENCE-RATE RATIOS)
CON	-16.001***	-1.12e-07***
PRECIPITATION	-0.017**	0.983**
LAKE OKEECHOBEE	-0.545***	0.5798***
LAKE KISSIMMEE	0.412***	1.51***
EVAPORATION	2.015***	7.449***
WCA	0.053	1.054

[12] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

The coefficients' signs are similar in all models and in Model 3 and Model 4 the magnitude of the coefficients is also very similar. One can see that the *Number of restricted days* increases with low *Precipitation* and low *Lake Okeechobee* water level (coefficients -0.015/-0.017 for *Precipitation* and -0.55/-0.43/-0.45 for *Lake Okeechobee*). The coefficients of *Lake Kissimmee* water level*, Evaporation* and *WCA* water level increase with increasing *Number of restricted days* (0.41/0.36/0.37 for *Lake Kissimmee*; 2/1.8 for *Evaporation* and 0.053/0.024/0.027 for *WCA*). To better understand these results, we had the fixed-effects negative binomial model reported as incidence-rate ratios (see Table 4.8, Model 2). The incidence-rate ratios reveal that for a 1% increase in *Precipitation,* we can expect a decrease in *Number of restricted days* by a factor of 0.98. For a 1% increase in the *Lake Okeechobee* water level, the *Number of restricted days* decreases by a factor of 0.58. By contrast, for a 1% increase in the *Lake Kissimmee* water level, the *Number of restricted days* increases by a factor of 1.51. Finally, for a 1% increase in *Evaporation* and the *WCA* water level, we can expect an increase in the *Number of restricted days* by a factor of 7.5 and 1.1, respectively.

Table 4.9: Regression Results for the Hydrological Model of OWRs, Dependent Variable Number of Restricted Days[13] (2)

VARIABLES	MODEL 3 (POPULATION-AVERAGED AS NEGATIVE BINOMIAL AND WITH ROBUST STANDARD ERRORS)	MODEL 4 (POPULATION-AVERAGED AS NEGATIVE BINOMIAL AND WITH ROBUST STANDARD ERRORS AND INDEPENDENT CORRELATION)
CON	-12.608***	13.3295***
PRECIPITATION	-0.015**	-0.017*
LAKE OKEECHOBEE	-0.432***	-0.448***
LAKE KISSIMMEE	0.359***	0.374***
EVAPORATION	1.787***	1.816***
WCA	0.024	0.027

[13] * indicates significance at 0.10; ** indicates significance at 0.05; *** indicates significance at 0.01

Based on the relation between *Lake Okeechobee* water level and *Number of restricted days* established in these regression models, we can apply the framework developed in Figure 3.7. The first step is to connect a monetary value with the amount of water that is saved due to *OWRP_3*, which is possible with the DID regression model outputs. Based on those results, we can predict how much water would be saved in a year for each county and then extrapolate it to almost 11.4 billion gallons (133 gal x 12 months x 7.1 million people) for the entire population of the SFWMD. A monetary value for the saved amount of water could be calculated for each county and extrapolated, revealing a total of more than US$42.2 million (US$21.7 million in 2008 dollar) for the entire SFWMD. Then we can use the relation established between the OWRs and the hydrological system. In this model, the dependent variable is not *Per capita water use* but *Number of restricted days.* As explained before, the incidence-rate ratios reveal that for a 1% increase of the *Lake Okeechobee* water level the *Number of restricted days* in a week can be expected to decrease by a factor of 0.58, which means that if the lakes' water level falls by 1% we can expect that we will have almost half an additional day of water use restriction. Furthermore, we calculated the exact reductions of the *Lake Okeechobee* water level that correspond to an increasing *Number of restricted days* (see

Figure 4.5), then illustrated the relation in percent (see Figure 4.6) and finally transformed it into a volume that is related to different OWRs (see Figure 4.7).

Figure 4.5: Water Level of Lake Okeechobee in Relation to Number of Restricted Days

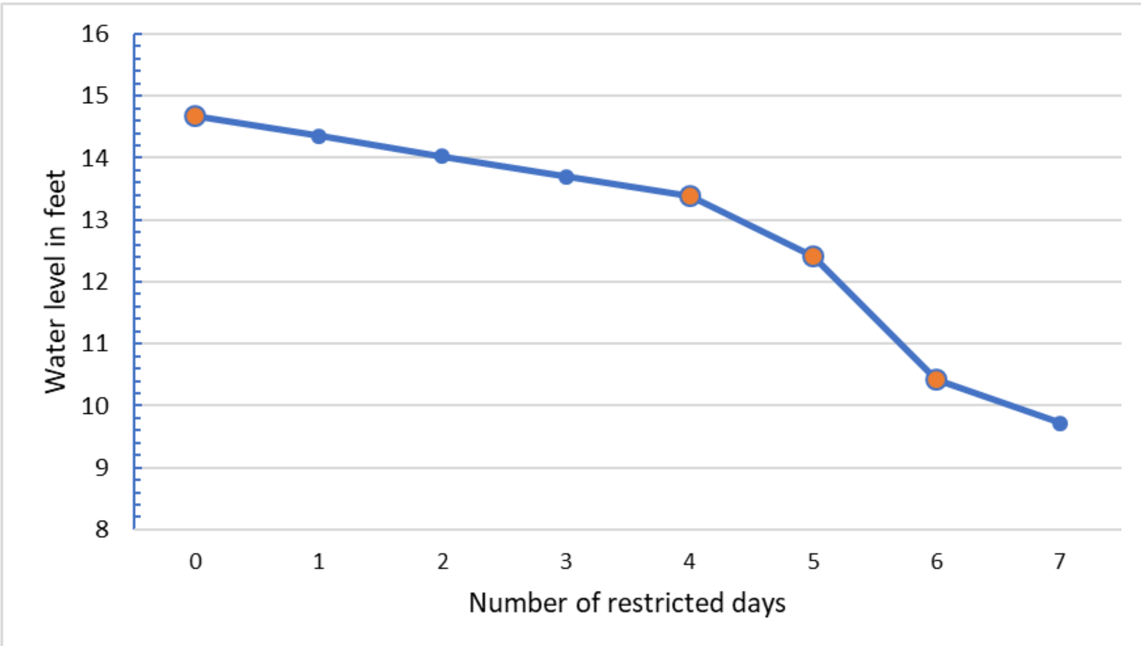
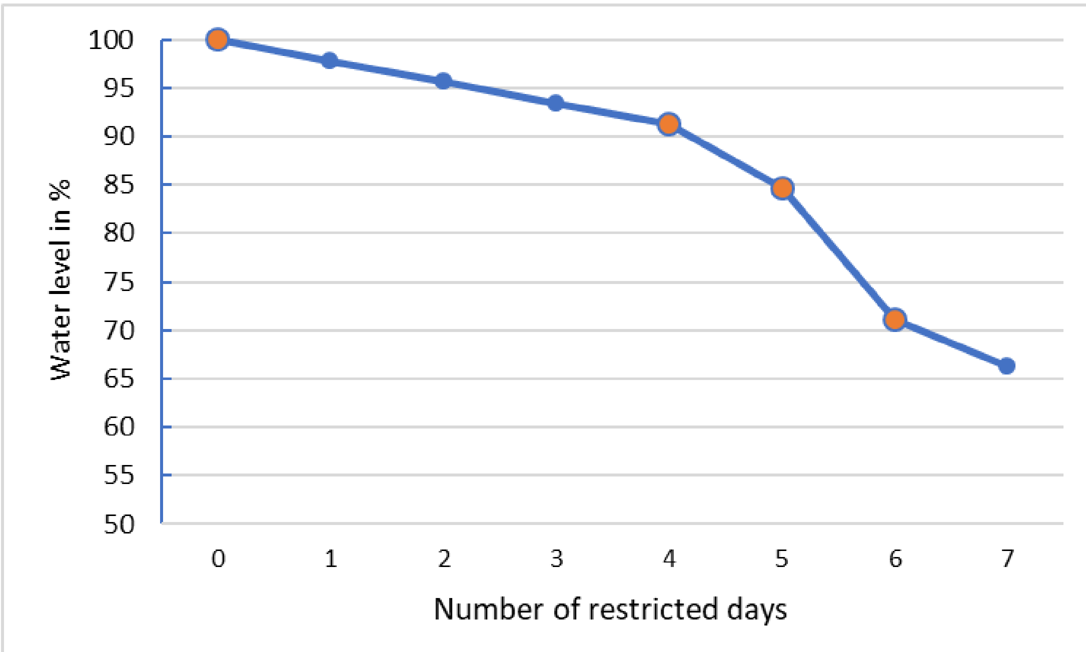


Figure 4.5 shows that the predicted average water level of *Lake Okeechobee* is 14.7 feet when there are no restrictions implemented. The orange points indicate the values based on actual data. Since there is no such OWR restricting outdoor water usage to six, five or four days or less than once a week, the blue values were interpolated. Decreasing water level in *Lake Okeechobee* is related to an increasing *Number of restricted days*, reaching an average 13.4 feet at 4 restricted days which is equivalent to *OWRP_1*, 12.4 feet at 5 restricted days which is equivalent to *OWRP_2* and a low of 10.4 feet at 6 restricted days which is equivalent to *OWRP_3*.

Figure 4.6 shows, similar to Figure 4.5, the relationship between the water level change of *Lake Okeechobee* and the *Number of restricted days*, but now in percentage of water level. Setting the average water level when there are no restrictions as 100%

(14.7 feet), we calculated that an *OWRP_1* is associated with a 9% drop of *Lake Okeechobee* water level. A 15% decrease is related to *OWRP_2* and a much greater 29% decrease is related to the implementation of *OWRP_3*.

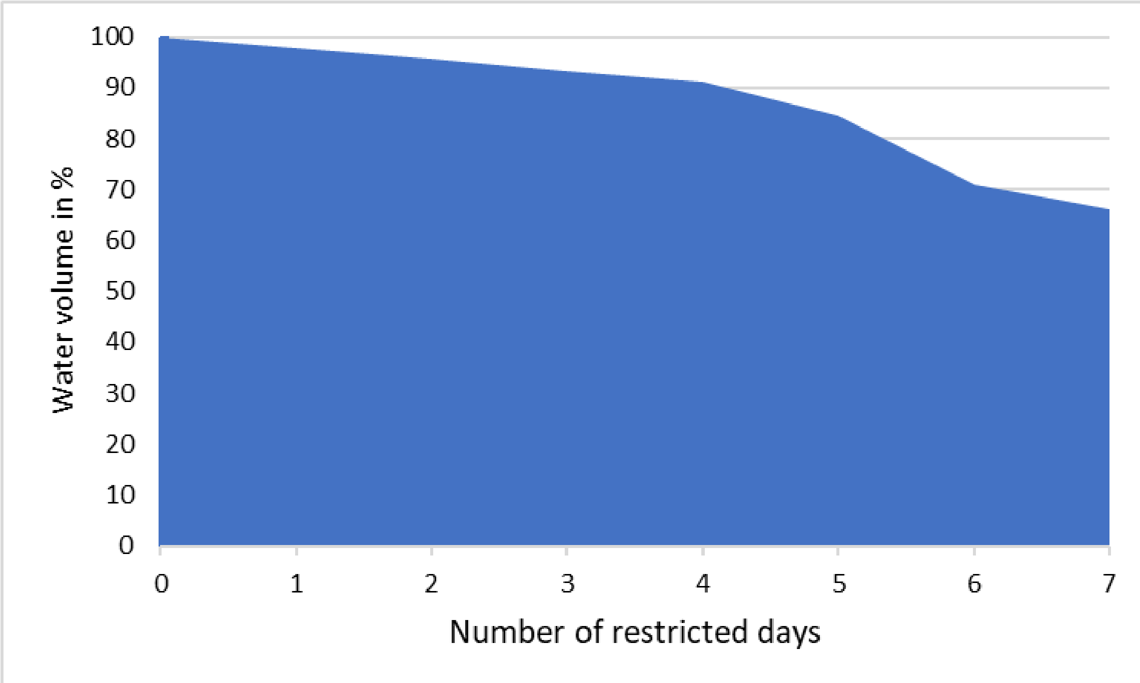
Figure 4.6: Percentage Change of Lake Okeechobee's Water Level in Relation to Number of Restricted Days[14]



[14] 14.7 feet set as 100%

Using the average lake surface area of *Lake Okeechobee* of 467,000 acres, we convert the water levels in feet into corresponding lake volumes in acre-feet (U.S. Army Corps of Engineers, 2008). Our model predicts that no restrictions occur around a volume of 6.9 million acre-feet in Lake Okeechobee (see Figure 4.7). Based on our results, we can expect *OWRP_1* coincides with a volume of around 6.2 million acre-feet, *OWRP_2* coincides with a volume of about 5.8 million acre-feet and *OWRP_3* coincides with a volume of around 4.9 million acre-feet, a very significant decrease of 29%.

Figure 4.7: Percentage Change in Volume of Lake Okeechobee in Relation to Number of Restricted Days

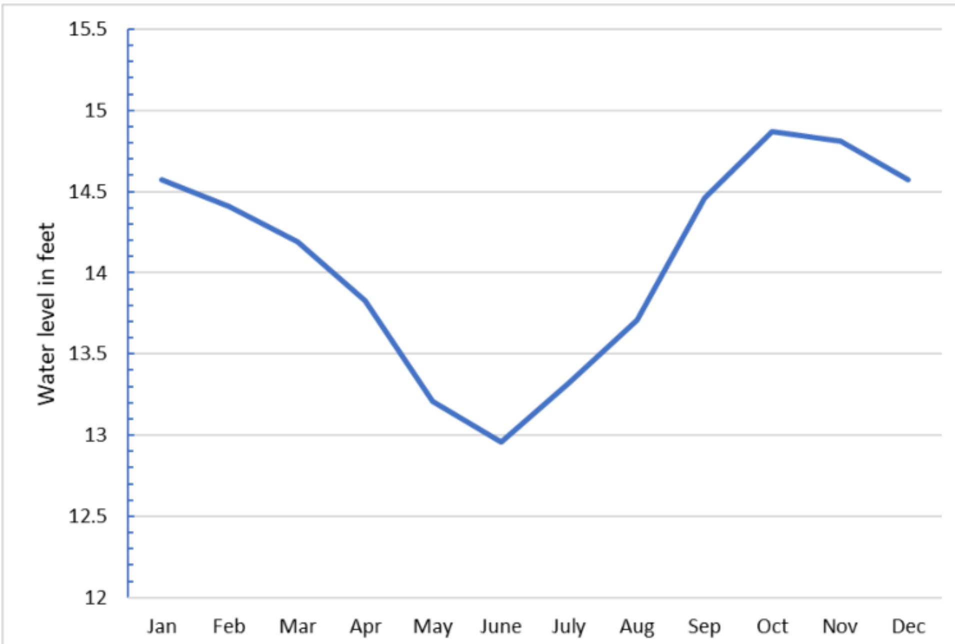


The last step is to connect the monetary value from the water saved due to *OWRP_3* with the water in the hydrological system. We calculated the monetary value of the water saved due to *OWRP_3*, which implies that the volume of water that decreased in the hydrological system, more specifically in Lake Okeechobee, can be assigned to a monetary value. Therefore, a decrease of Lake Okeechobee of almost 0.9 million acre-feet can be assigned a monetary value of more than US$42.2 million (US$21.7 million in 2008 dollar). Here we took the difference between the average volume related to *OWRP_2* and the average volume related to *OWRP_3* (5.8 – 4.9million acre-feet) in Lake Okeechobee.

Furthermore, it was also possible to calculate the average water levels of *Lake Okeechobee* over the course of the year between 1985 to 2012. One can see a variation between wet season, from May to October, and dry season from November to April.

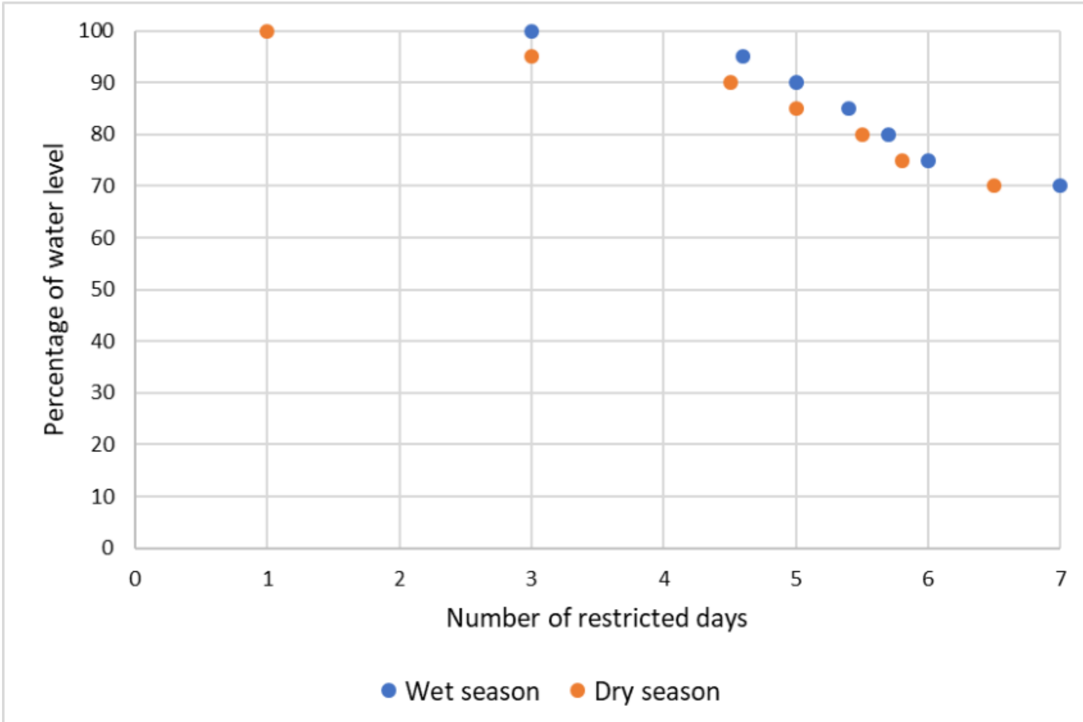
Higher lake levels of above 14 feet are normal from September to March and lower lake levels from April to August (see Figure 4.8). Based on this seasonal variation in *Lake Okeechobee* water level, the probability of having OWRs in place also varies.

Figure 4.8: Average Monthly Water Level of Lake Okeechobee 1985-2012



Finally, Figure 4.9 shows the difference between the *Lake Okeechobee* water levels in the dry and wet season. In the wet season, signified by the blue dots, the maximum average water level (which is around 13 feet) coincided with three days of restriction. In general, actual water restrictions are related to smaller decreases in *Lake Okeechobee* water levels, for instance a 10% reduction of water level leads to *OWRP_2*. Compared to that, the 100% *Lake Okeechobee* average water level of the dry season, indicated by the orange dots, is related to one day of restriction and a 20% reduction in water level is associated with *OWRP_2* (see Figure 4.9).

Figure 4.9: Relation of Lake Okeechobee's Seasonal Lake Levels to Number of Restricted Days



4.3 Comparison with Stated Preference Results

The study by Seteeram et al. (2018) reported that the stated WTP values of survey respondents ranges between US$25.70-32.40 (US$10.58-13.35 in 2004 dollars) per unit OWR to avoid restrictions, while the average WTP is US$58.00-87.00 (US$23.90-35.85 in 2004 dollars) per year (Seeteram, 2014). Based on these numbers, it was estimated that the South Florida population was willing to pay between US$59.2-66.3 million (US$24.4-27.3 million in 2004 dollars) (n=2,044,741 households) to avoid OWRs (Seeteram, 2014). The monetary value that we received from the DID regression was between US$25.8-54.4 million (in 2020 dollars), based on the lowest and highest water utility rate in each county. Therefore, the stated WTP is about US$5-40.5 million higher than the monetary value we calculated for the saved water. It is important to understand that the WTP results from Seeteram et al. (2018) are related to the marginal

WTP, for one unit decrease of restriction. This means going from *OWRP_3* to *OWRP_2*, one additional day of irrigation is allowed. In the current study, the monetary value relates to a similar unit since we calculated the reduced amount of water due to *OWRP_3*, and its monetary value, compared to the average usage from 2007 to 2012, a time period when all counties had *OWRP_1* or *OWRP_2* implemented.

5. DISCUSSION AND CONCLUSION

5.1 Discussion

5.1.1 Difference-in-Differences Approach

Overall, we were not able to establish a causal relation in the DID analysis between *OWRP_1* and a decrease of *Per capita water use*. Neither the pure *OWRP_1* nor the treatment effect expressed by the *Interaction_1* were significantly correlated (at the 0.01 levels) to *Per capita water use* in any of the applied models. This might result from *OWRP_1* being the least strict OWR mechanism. In the phase after 2007, there was no month or county without any implemented restrictions. Therefore, *OWRP_1* allowed the comparatively highest water consumption for outdoor use. As a consequence, it is not surprising that no reducing effect of this type of restriction could be found.

In contrast, it was possible to establish a causal relation in the DID analysis between *OWRP_2* and *Per capita water use,* however only in the fixed-effects linear regression model that considered autocorrelation. The other models delivered insignificant results for both *OWRP_2* and *Interaction_2*. The results of the fixed-effects linear regression model considering autocorrelation revealed that *OWRP_2* is correlated to a decrease of *Per capita water use* of about 476 gallons per month, while the *Interaction_2* is positively correlated. To understand this, it is necessary to consider *Treatment2007*, which is also negatively correlated to *Per capita water use*, revealing a reduced water consumption of 1,235 gallons per month in the period after 2007 compared to the average usage before 2007. What is most interesting in the context of the DID approach though is the effect of the *Interaction_2*, which can be better understood when looking at the margins. They reveal the actual amount of water used under different treatments. The predicted marginal effects calculated after the fixed-effects linear regression considering autocorrelation show an average water consumption under the influence of *Interaction_2* of almost 4,484 gallons per person per month. Compared to the average usage in the post-treatment period, which is almost 4,497 gallons, a small amount of 13 gallons are saved. Looking at the predicted margins calculated after the fixed-effects linear regression controlling for county and monthly correlation, the savings appear to be much bigger. With an average usage of about 4,605 gallons per person per month under *Interaction_2* and an average consumption of about 4,875 gallons in the post-treatment period, a reduction of 270 gallons per person per month could be calculated. Although these results are not congruent, it is possible to draw a few conclusions. Due to the partly insignificant results received, it is not possible to state with entire certainty that a specific reducing effect of this restriction on *Per capita water use* is proven. The margins have predicted a reducing effect of 13 and 270 gallons, respectively, depending on the model used. Since 13 gallons have been predicted by the fixed-effects linear regression model with autocorrelation and it has delivered significant results beforehand, one could argue that at least 13 gallons have been saved due to *OWRP_2* compared to *OWRP_1*. This is a relatively small reduction resulting from one additional day of OWR. On the other hand, with *OWRP_1* as the baseline after 2007 one could argue, that the overall *Per capita water use* was already reduced so much due to only three-days watering allowed that an additional restricted day did not have a major impact on the average water consumption. On a large scale, permitted watering on two or three days a week may not have had such an influential effect on how and when residents used water outside since most of them may only water twice per week with restrictions present.

The DID approach applied with *OWRP_3* as the major independent variable unanimously established a causal relation between the most stringent type of restriction and *Per capita water use,* revealing a significant and decreasing effect in the regular fixed-effects linear regression model and in the model considering autocorrelation. More importantly, the *Interaction_3* is found to be significant. The predicted margins illustrate that the restriction in the period from 2007 to 2012 led to an average reduction of *Per capita water use* of 51 (considering autocorrelation) or 133 (considering county and monthly variation) gallons per person per month, depending on the model. *OWRP_3* was only ever implemented for a comparatively short time, a few months, and these periods were drought periods with residents following OWRs nonstop and increased efforts to raise awareness. The results indicate a success of these efforts with residents adjusting their behavior.

Overall, a causal effect of the implemented OWRs could only be clearly shown for *OWRP_3*. However, this does not mean that there is none for *OWRP_2* and *OWRP_1*. Instead, limitations of the data could have caused non-significance of the coefficients to weaken the results. Besides that, potential reasons for non-compliance or constrained compliance exist as explained in the literature review, such as consumers not being aware of the more stringent restriction, residents being in a dilemma between following OWRs or homeowner association rules or customers changing the water use in a strategic way that only shifts the amount used for watering from one day to the other. The actual reasons for certain types of water consumption behavior will remain unclear in the current study based on aggregate data.

The other two explanatory variables in the DID models, *Median household income* and *Bachelor's degree or higher* showed interesting and mostly matching results. *Median household income* revealed to be highly significantly and positively correlated to *Per capita water use* (0.017) in the majority of models. This indicates that households with a higher income tend to use more water than those with a lower income. This is not surprising and corresponds to findings from previous studies (Fielding, Russell, Spinks, & Mankad, 2012; Gregory & Di Leo, 2003; Harlan, Yabiku, Larsen, & Brazel, 2009). As explained in the literature review, a higher income allows customers to maintain a certain affluent lifestyle with more water-consuming fixtures like additional bathrooms and bathtubs in the house, bigger yards and pools. Compared to this, the second variable, *Bachelor's degree or higher* was significantly correlated with *Per capita water use* but sometimes negatively and sometimes positively, depending on the model. The value of the coefficient ranged between -38 (in the fixed-effects linear regression model controlling for county and monthly variation with *OWRP_2* as the main predictor variable) and -44 (for the models with *OWRP_1* and *OWRP_3*). In the fixed-effects linear regression controlling for autocorrelation, the value of this coefficient was positive and between 55 to 62, making the effect of this variable inconsistent. In previous studies, both increasing and decreasing correlations between water use and education have been observed. On the one hand it can be argued that an increased level of education can advance knowledge and thus increase awareness of issues such as water scarcity and its impacts, translating it into reduced water consumption (Dean, Lindsay, Fielding, & Smith, 2016). On the other hand, higher personal water consumption can be related to showing off ones socioeconomic status when better education, leading to higher income, is associated with affluence, which can again manifest in a bigger house and garden with additional indoor and outdoor water appliances (Dean et al., 2016). Another influential factor might be political identity, related to increased or decreased awareness of environmental issues. The inconsistent finding on the effect of education reveals the complexity of such factors and indicates, that single variables and their interactions can be more difficult to understand than assumed.

The variations between the predicted amounts of water saved in each given month due to *OWRP_3* compared to no restriction at all can reveal something about the time when this restriction was implemented. When looking at the timeline of OWRs we can see that Glades and Hendry were the first counties where *OWRP_3* was implemented, which was at the beginning of a two-year drought phase from November 2006 until March 2007. These two counties revealed the greatest water use reduction with an average decrease of 1,600 gallons per person per month among all counties that had this restriction implemented at any point in time compared to the overall average usage. Broward and Palm Beach county followed in May/June 2007 with a smaller reduction effect of about 1,000 gallons per person per month. By that time, people in these two counties already followed *OWRP_2* since the previous November, potentially causing less responsiveness for the more stringent restriction. Finally, when all counties except Orange and Osceola had *OWRP_3* implemented from January to April 2008, the resulting reductions were comparatively smaller (700 gallons per person per month) compared to the overall average usage. After more than one year of drought with respective restrictions and concomitant messaging, responsiveness might have come to a lower level. Residents might have been desensitized by previous episodes of water conservation and messaging. Besides the author's personal observations, Whitcomb (2005) stated that there is some evidence that residents may not be entirely following OWRs. Similar to other water conservation regulations, such as required rain sensors on automatic irrigation systems, weak enforcement can result in policy instruments that are lacking in their effectiveness (Whitcomb, 2005). A similar finding was explained in a study by Ozan & Alsharif (2013a), that investigated the effect of OWRs in Tampa, Florida. They found that water usage even increased with more stringent OWRs. Users with more citations due to violations increased their consumption the most. Reasons given by the authors included a possible discrepancy between local water use policies including OWRs and homeowner association regulations. Furthermore, the simultaneity of drought and *OWRP_3* might have contradicted the homeowners' constraint to keep their lawn green (Ozan & Alsharif, 2013). In this context, landscaping advocates argue that the actual water demand of turfgrass is not considered in the setup of OWRs, with *OWRP_3* resulting in most grasses being underwatered. Therefore, it would not make a big difference to ban irrigation entirely at that point (Ozan & Alsharif, 2013).

Summarizing, DID with *OWRP_3* was the only model that showed entirely significant results in this analysis, while *OWRP_2* revealed a significant treatment effect only in one of the models, however, a stronger effect than resulting from *OWRP_3*.

The observed change in water use over months varies between an average of 5,360 gallons per person in September and 6,232 gallons per person in May over the entire study period of 27 years and across all 13 counties. This variation is partly appearing arbitrary and therefore difficult to interpret in a concise way. Broadly speaking, one could argue that comparatively lower water consumption from June through October could match with the rainy season in South Florida, when the weather is usually shaped by greater amounts of precipitation. In the dry season between November to March, water usage is slightly higher, potentially due to reduced amounts of precipitation. For April and May, based on the climate graphs, the temperatures are usually already increasing while the rain has not increased yet, requiring residents to balance the resulting need for water. Another reason might be that more tourists and part-time residents visit during the dry season, which is more likely given the more comfortable season in South Florida with lower temperatures and reduced likelihood of experiencing thunderstorms and hurricanes. Furthermore, it is winter in the Northern hemisphere where many tourists come from, leading to increased numbers of visitors that may be recognizable in the counties' water use.

Finally, the coefficients of the yearly dummy variables simply indicate that average *Per capita water use* decreased over the course of the years compared to the last analyzed year 2012 which had the lowest average *Per capita water use*. This can potentially be related to general improvements in the water saving technologies of appliances and increased awareness.

5.1.2 Value Function Approach

The hydrological variables used in the value function approach are in all four regression models significantly correlated to the *Number of restricted days*. *Number of restricted days* decreased with an increasing *Precipitation*. Since drier weather conditions partly result from less precipitation, it seems logical that the *Number of restricted days* increases the drier it becomes. The difficulty of including climate variables such as temperature and precipitation is based in the potential multitude of different aspects of such variables, such as daily maximum or average temperature, number of rain events, average amount of rain or sum, which can all have varying impacts on the results of an analysis. *Lake Okeechobee* water level is also negatively correlated to *Number of restricted days* which means that when the lake's water level decreased, additional days of water restrictions were put ina place. Again, a decreasing water level could be related to drought or drier conditions, triggering more stringent water restrictions to be implemented. However, one must keep in mind that *Lake Okeechobee* is not only impacted by the local weather but has also been managed under a complex management plan, letting water in from the Kissimmee Chain of Lakes and out to the adjacent canals or WCAs to follow the various objectives, such as flood control, navigation, water supply for agricultural irrigation, the Everglades National Park and regional groundwater control (U.S. Army Corps of Engineers, 2008). Therefore, a direct causal relation between a decreasing water level (due to evaporation or water allocation) in a drier climate and increasing restrictions is challenging. *Lake Kissimmee* water level is positively correlated to *Number of restricted days,* which means that the water level in the lake raised when OWRs became more stringent. At first sight, this does not appear to be logical. It could potentially be explained, at least partly, with its importance as nesting and foraging habitat for the Everglades snail kite that is focused on in restoration plans in regards to Lake Kissimmee (Community Development Department, 2015). Connected to targeted higher water levels that are closer to historical stages, it is particularly mentioned that Lake Kissimmee is meant to serve as a refuge for the snail kite during drought conditions in Lake Okeechobee (Community Development Department, 2015; FWC, 1994). However, how strong the impact of this management target is can only be assumed and for how long this management purpose has already been followed could not exactly be determined. *Evaporation* is positively correlated to *Number of restricted days,* as well, signifying that increased evaporation (due to drier and/or hotter weather) was related to increasingly stringent OWRs, which appears logical. Finally, *WCAs* water level is also positively but not significantly correlated to *Number of restricted days.* Among other purposes, WCAs are, right after Lake Okeechobee, the second most important source of water for irrigation during the dry season and water is taken from them to increase canal and groundwater stages (Abtew & Ciuca, 2016). Based on this information, a decreasing relation should have been observed.

Looking at the change of *Lake Okeechobee* water level and its relation to the *Number of restricted days,* one can see that 14.7 feet, which was the overall average water level of the analyzed period, equates to a volume of 6.9 million acre-feet (14.7 feet x 467,000 acre, from U.S. Army Corps of Engineers (2008)). Filled with this amount of water, the probability of OWRs is very low. A drop of 9% to 6.2 million acre-feet, is the average volume corresponding to *OWRP_1*, while *OWRP_2* could be related to an average volume of 5.8 million acre-feet. These volumes correspond to water levels of 13.4 and 12.4 feet (U.S. Army Corps of Engineers, 2008), respectively, which are within the boundaries that the lake's water level is managed. Due to the nonstop implementation of *OWRP_1* and *OWRP_2* since 2007, these values appear relatively high for being related to the implementation of OWRs. In contrast, *OWRP_3* occurs at an average volume of 4.9 million acre-feet, which equates to a reduction of Lake Okeechobee volume of 29%. In other words, almost a third of the lake's average water volume, corresponding to an amount of 2 million acre-feet, has either left the lake, been used or evaporated, when *OWRP_3* is implemented.

The last step of the framework is the connection of the water volume in the hydrological system with the monetary value related to the water saved due to *OWRP_3* in the human/social system. Therefore, we can assign a revealed preference value for 0.9 million acre-feet, which is the reduced lake volume going from *OWRP_2* to *OWRP_3*, to a sum of between US$25.8-54.4 million.

Before we continue to connect this revealed WTP value with the stated WTP, it is worth noting that the *Lake Okeechobee* water level varies over the time of the year, as mentioned before not only due to climate variables but also due to management decisions. Therefore, the results show that the lake's water levels have been much lower in the wet season to enable the storage of water when heavy rain events happen. However, at the same time the probability for OWRs is theoretically much higher than it is in the dry season. Already a 10% decrease of the *Lake Okeechobee* water level in the dry season is related to *OWRP_2*, whereas the same restriction corresponds to an almost 20% reduction of the average water level in the wet season. These findings appear counterintuitive, but they are mostly the result of water management decisions.

5.1.3 Comparison with Stated Preference Study

The discrete choice analysis by Seeteram et al. (2018) found respondents' stated willingness to pay for a relaxation of OWRs. The current study used a DID and a value function approach to find revealed preferences. The connection of these two studies allows for a great opportunity to compare stated and revealed preference information for outdoor water use from South Florida residents. In the current study, the monetary value of the saved/restricted water due to *OWRP_3* compared to less stringent restrictions turned out to be between US$25.8-54.4 million for all South Florida residents for an entire year. The stated WTP of respondents for using additional amounts of water, in other words relaxing OWRs, was calculated to be US$59.2-66.3 million (US$24.4-27.3 million in 2004 dollars) for all South Florida households for a year (Seeteram, 2014). This value relates to a one-unit step, for instance going from *OWRP_3* to *OWRP_2*. Therefore, it becomes clear that in this specific case the South Floridians' stated WTP is about between US$5-40.5 million higher than the estimated value of the water saved in 2008. This finding indicates that residents would be willing to pay more money for using additional amounts of water. The monetary value that South Florida residents ascribe to the water they saved seems to be higher than the rates they must pay for that water. With regard to water conservation, the results indicate that higher water rates would be necessary to achieve a reduction of water consumption via a price signal alone. If lower water rates are favored, OWRs can help to reduce the consumption. Besides that, while the stated WTP in Seeteram et al. (2018) was set to be equal for every one-unit decrease of OWRs, it is probable that varying amounts of water are saved due to different OWRs. Therefore, to go from *OWRP_2* to *OWRP_1* (potentially a greater difference in water use than between *OWRP_3* and *OWRP_2*) may have a greater monetary value and therefore cost the people more money.

5.2 Limitations

Within the scope of this graduate thesis research, data from 13 and 16 counties, respectively, over the course of 27 years were analyzed. The data were provided by employees of the SFWMD. Due to the type of water use data and the geographical and time scale used to analyze the data, certain limitations exist concerning the validity of the analysis. As briefly explained in the methods section, the study analysis is based on public-supply water use data, which does not reveal clear information about the exact amount of water used by a certain number of exclusively residential customers. The number of people (permanently living in South Florida) served was known and regarding OWRs, all kinds of customers need to follow these restrictions. However, the usage of non-residential users that consume water on a bigger scale than individual households is included in the data which warps the results on *Per capita water use*. Furthermore, the number of tourists visiting South Florida every year cannot be considered due to lacking information on the variation between counties, months and years. Therefore, the values derived for *Per capita water use* are probably in general slightly too high in this study.

Additionally, data were used on the county level, which is a rather broad scale to analyze water use data. Other studies used single household data provided by individual water utilities. The advantage of our approach is that we were able to cover a greater area than an analysis on the household level that is likely to cover only a smaller number of customers. Nonetheless, the disadvantage of the county level analysis is that in some cases millions of people's water use behavior is analyzed without being able to monitor the individual user's or neighborhood's actions and motives. Similarly, weather data were applied to entire counties, using precipitation and temperature from one single weather station in the entire county. Especially in South Florida, where very local weather events are common, such data can only be a proxy for areas farther away from the measuring stations. This limitation applies also to educational attainment and household income, which is always relating to the entire county, not able to show the variability between residents within a county.

Concerning the focus of this analysis, the spatial and temporal variation could not always be considered entirely. On the spatial scale, the analysis took place on the county level, while restrictions were sometimes implemented on a regional scale (e.g. Lower East Coast, Upper West Coast etc.) or even on a local scale (e.g. cities or certain neighborhoods). On the temporal scale, while this analysis used months as the smallest unit, OWRs were rarely implemented on the first of a given month and did sometimes not last longer than two weeks. We tried to consider this variation as good as possible but unavoidably, some of the details could not be modeled in the analysis. Therefore, the observed effects of certain OWRs could not be estimated as accurately as I would have hoped.

Another aspect that could not be considered was the usage of private irrigation wells or reclaimed wastewater instead of potable water provided by the water utilities (Marella, 1992). This water can be used for most outside uses such as irrigation. Previous studies on the density and frequency of such wells have shown that they were already within the thousands in the 1970s and 80s (Marella, 1992). Nonetheless, private irrigation wells are neither permitted nor inventoried on a county level basis, and so information about them is very limited while they are assumed to exist in substantial numbers (Marella, 1992). Therefore, the existence of private irrigation wells might be one reason for confounding the *Per capita water use* reduction of residential consumption, which cannot be isolated without additional data that do not yet exist. Furthermore, following an informational report from the SFWMD from 2014, several utilities have wastewater treatment facilities and deliver the recycled water to residential irrigation purposes, for instance in Collier county with over 18 million gallons per day sent to 20,000 residences and 23 golf courses or Palm Beach county with 14 million gallons per day sent to 6,000 residences, ten golf courses and two parks (SFWMD, 2014). Therefore, increasing use of reused wastewater might be another invisible reason for reduced water consumption from utilities over the years.

Additionally, other water management tools might have had impacts too. Local retrofit programs and information campaigns have been implemented in South Florida within the last decades and efforts to encourage the adoption of Florida-friendly landscaping principles have increased as well, while their effectiveness was only partly monitored. Some information exists only at the utility level and is therefore not readily available (SFWMD, 2008). To reach out to all utilities within the borders of the SFWMD to collect all information regarding conservation measures between 1985 to 2012 was beyond the scope of this thesis. Therefore, their impacts might have had a masking effect that was impossible to distinguish from the effects of the analyzed OWRs. Finally, changing water rate structures, including not only increases but also switching from one rate structure to another might have had an undetected impact, because, in the scope of this thesis, it was impossible to find almost 30 years of water rate information for all 93 utilities (those serving >2,000 people) within the SFWMD (SFWMD, 2017).

5.3 Concluding Remarks

In summary, the demand-side management policy tools are much cheaper than supply-side measures and they help reduce pressure on the existing water supply. Therefore, they are a more sustainable approach which is positive for the environment. Overall, OWRs are a successful management approach in most cases, considering the specific circumstances and the appropriate design of the restriction. However, it became clear that it is important for local water supply managers to also take into account the effort and resources required for the implementation of different measures. For instance, OWRs call for information dissemination and at least a minimum of enforcement which both have financial and political costs. Additionally, they need the users' participation and willingness to change behavior which is more difficult to exactly predict than many other measures. Furthermore, the more specific the more effective any DSM tool can be. That is why knowledge of certain characteristics about the target community is crucial, such as neighborhood characteristics. On top of that, the expectations of the policy should be stated clearly to be able to assess its success and reach its full conservation potential. In this regard it is important to point out the possible advantages of implementing an additional, consumption-steering price tool in combination with OWRs. The advantage of prices is that the necessary infrastructure already exists, and no extra staff or time is needed to monitor compliance while the consumers' welfare is likely to increase.

The main goal of this thesis was to perform an economic analysis of the OWRs in South Florida to enable us to draw conclusions about the impacts of this type of demand-side management tool. Our approach consisted of three parts that built on each other to provide a comprehensive assessment of the effects of this policy tool. Our results have revealed varying conservation effects of the different OWRs which was not surprising. While we could not establish a relation between the least stringent *OWRP_1* and *Per capita water use*, this relationship was possible to establish between *OWRP_2*/*OWRP_3* and *Per capita water use*. Both restrictions were found to have a decreasing effect on residential water consumption. Noteworthy is the finding that the most stringent *OWRP_3* did not lead to a similarly strong decrease of water consumption like *OWRP_2*. Interference with other unobserved factors seem to have a strong effect on residential water use as well.

The established connection between the water resource in the human and in the natural system was insightful in the sense that it increased the understanding of how variables on both sides cause reactions on each other. The theoretically established relation between the water in Lake Okeechobee and OWRs in residential neighborhoods could be developed and, despite a multitude of additional influential factors, simplifies how these two variables are linked.

Regarding the monetary value of the water saved, the study could reveal a disparity between the residents' stated WTP to reduce the extent of restrictions and the water's actual monetary value. South Florida residents stated that they would be willing to pay a much greater amount of money for relaxing the OWRs than the actual monetary value of the water. This highlights the potential to change the current DSM tools in a way that increases the customers' welfare through access to increased amounts of water, potentially connected to an increased water rate for greater amounts of consumption.

Certain additional water access could be purchasable while the main target, to reduce the overall consumption of water, would still be encouraged via the existing OWRs.

Finally, this analysis showed that the effect of a specific water management tool is difficult to isolate, especially when the available data are only accessible on a broader scale and additional information on other implemented measures or influencing factors is lacking. Therefore, future research should focus on the interaction of multiple DSM measures at the same time. Their potentially synergistical or additive effect is of increased interest to water managers to achieve the sustainable water management goals and objectives.

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APPENDIX

Comparison of studies on OWR concerning effectiveness, welfare outcome, WTP, Model/Method & Geography
(This list is not intended to be exhaustive)

Study	**OWR Design**	**Effectiveness**	**Welfare impact**	**WTP**	**Model/Method**	**Geography**
(Shaw & Maidment, 1988)	Voluntary and mandatory lawn irrigation, plant irrigation every few days	No effect for voluntary, 31% (every 10 days) to 39 %(never) reduction for mandatory				Texas, USA
(Shaw et el., 1992)	Voluntary & mandatory	Average 25% and 36% reduction, respectively			Statistical model	Southern CA, USA
(Kenney, Klein & Clark, 2004)	Voluntary vs mandatory	4-12% reduction vs 18-56% reduction, respectively, compared to “expected use” (before restrictions)			Regression analysis, predictive regression model	Colorado, USA
(Halich & Stephenson, 2009)	Mandatory & voluntary with different levels of information	Reductions ranging from 0-7% for voluntary and 4-22% for mandatory (with increasing information & enforcement for mandatory)				USA
(Ozan & Alsharif, 2013)	From twice- to once-a-week OWR	Increase 7.14%			GIS mapping & statistical data analysis	Tampa, Florida

Study	OWR Design	Effectiveness	Welfare impact	WTP	Model/Method	Geography
(Mini et al., 2014)	Voluntary restrictions; Mandatory, limited to 2 days per week plus increased water rates	No savings for voluntary; highest savings 19-23% reduction for mandatory			Linear mixed-effects regression model	Los Angeles, CA, USA
(Renwick & Green, 2000)		10% increase in price will reduce aggregate water demand by 1.6%; water rationing/use restrictions will reduce average household demand by 19%/29%			Econometric model with price, climate & water demand equations	California, USA
(Loë et al., 2001)		Almost 30% of all savings, 10-20% outdoor water use reduction			Questionnaire	
(Kenney et al., 2008)		12% reduction			Demand model as function of observable and unobservable variables, fixed effects regression	Coloradon, USA
(Survis & Root, 2012)		Overwatering occurred			Conservation effectiveness ratio (CER)	Southeast Florida, USA

Study	OWR Design	Effectiveness	Welfare impact	WTP	Model/Method	Geography
(Pérez-Urdinales & Baerenklau, 2020)		14-32% reduction			Household production theory & stochastic frontier analysis	California, USA
(Brennan et al., 2007)		36% reduction under mild restrictions, 42% during complete sprinkler ban	Net welfare cost under complete sprinkler ban between $347 per household when time costs are low to $871 when time measured at full wage rate		Production model	Australia
(Grafton & Ward, 2008)		14% decline in aggregate water consumption	Positive Marshallian surplus of price vs. rationing $238 mil., $55 per person, $150 per household		Estimation of demand, calculation of choke price & Marshallian surplus	Sydney, Australia
(Roibas, Garcia-Valiñas, & Fernandez-Llera, 2018)			Varying from €1.68 for 2.5% reduction to €31.83 for 15% reduction		Simulation analysis	Sevilla, Spain

Study	OWR Design	Effectiveness	Welfare impact	WTP	Model/Method	Geography
(Woo, 1994)			Per capita compensation variation (CV=amount of additional money needed to reach initial utility after price change) estimate $221-$1607 per month		Model with utility function, virtual price, double log, linear demand function	Hong Kong
(Griffin & Mjelde, 2000)				$25.34-$34.39 to avoid an occurrence of water restrictions; average $9.76/month (1/4 of water bill) to improve future supply security levels (in 1997 US-Dollars)	Contingent valuation method	USA
(Gordon et al., 2001)				Additional $150/year for more voluntary management instead of mandatory restrictions	Choice modeling approach	Canberra, Australia
(Koss & Sami Khawaja, 2001)				$11.67-16.92/month (1993 US-Dollars) to avoid restrictions of varying severity	Contingent valuation method	California, USA

Study	OWR Design	Effectiveness	Welfare impact	WTP	Model/Method	Geography
(Jenkins et al., 2003)			US$ 1.6 billion per year from water scarcity		Loss function	California, USA
(de los Angeles Garcia Valiñas, 2006)			Average losses 19.52€ (in 2001 € per m^3)	If restrictions >6 hours/day virtual price three times higher than real price	Concept of consumer surplus, virtual prices, generalized method of moments	Sevilla, Spain
(Hensher, Shore & Train, 2006)				Lack WTP to avoid most types of restrictions; but up to $239 (31.26%) extra on water bill to move from complete sprinkler restrictions every day all year round to no restrictions	Stated choice experiment	Canberra, Australia
(Tapsuwan et al., 2007)				Moving from one to three-day sprinkler use, 22% extra on annual water bill	Choice experiments	Perth, Western Australia
(Cooper, Burton, & Crase, 2011)			$113-292, depending on individual income, owning a lawn and local water situation		Multiple-bounded discrete choice contingent valuation study	New South Wales & Victoria, Australia

Study	OWR Design	Effectiveness	Welfare impact	WTP	Model/Method	Geography
(Mansur & Olmstead, 2012)			Gain of $96 per household during lawn watering season, 29% of average annual household expenditures on water	To move from no watering to two days per week WTP of $5.36 per thousand gallons, instead of $1.79	Usage of demand estimates, calculation of shadow price, price elasticity	11 North American cities
(Buck et al., 2016)			For 10/20/30% reduction for single family $1,458/2,153/3,426 losses per acre-foot	$64-633 for 10-30% reduction per acre-foot	Econometric model including demand estimation	California, USA