JOINT MITIGATION OF SUPPLY AND FINANCIAL RISK IN REGIONAL WATER SUPPLY MANAGEMENT UNDER UNCERTAINTY

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ABSTRACT

David E. Gorelick: Joint mitigation of supply and financial risk in regional water supply management under uncertainty
(Under the direction of Gregory W. Characklis)

Municipal water utilities are tasked with providing reliable, safe, and affordable drinking water for over 250 million Americans. Accomplishing this can be costly and complicated. In 2017, over $110 billion of public funding alone was spent to maintain United States drinking water infrastructure. Changes in climate, land use, and water demand introduce uncertainty in water availability. Growing variability in supply and demand impacts water supply reliability, increasing volatility of water utility costs and revenues, generating financial risk that disrupts utility operations and raises customer water rates. Water utilities have a range of tools for jointly managing supply and financial risks, including building new supply infrastructure, implementing water use restrictions during droughts, and cooperatively managing infrastructure through inter-utility agreements. To navigate supply and demand uncertainties and provide reliable, affordable water service, it is key for utilities to identify actions and decision-making rules that work effectively under a wide range of future conditions, taking greater advantage of available tools. However, no research in the water supply management and planning field to this point has applied dynamic adaptive management modeling to explore utility hydrologic vulnerability and the financial impacts of regional inter-utility agreements, nor developed adaptive financial modeling to quantify utility budgetary responses to water supply planning decisions. This dissertation employs a novel, integrated supply and financial risk modeling approach to address outstanding questions faced by water utilities, specifically: (1) How vulnerable are utilities to climate and land-use landcover change uncertainty, and how can mitigation action influence their vulnerability? (2) Can inter-utility cooperation help mitigate supply and/or financial risk? (3) How robust are regional inter-utility agreements under uncertainty? (4) How can utilities financially adapt to meet water demands? Results of this work demonstrate: (a) how utility decision-making can mitigate (and sometimes exacerbate) climate and land use change impacts on water availability; (b) the financial benefits and drawbacks of inter-utility regional cooperation, relative to independent utility operation; and (c) the adaptive capacity of water utility budgets to finance water supply infrastructure expansion under uncertainty in demand growth and climate. Addressing these questions highlights the opportunities water utilities have to ensure reliable future water service.

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LIST OF ABBREVIATIONS

AWWA	American Water Works Association
BG	Billion Gallons
CBO	Congressional Budget Office
CIP	Capital Improvement Project
CMIP5	Climate Model Intercomparison Project 5
COT	City of Tampa
CWUP	Consolidated Water Use Permit
DU	Deep Uncertainty
EPA	Environmental Protection Agency
FRAT	Financial Risk Assessment Tool
HRD	Hillsborough River Dam
GCM	General Circulation Model
IPCC	Intergovernmental Panel on Climate Change
kgal	thousand gallons
LHS	Latin Hypercube Sampling
LULC	land use landcover
MG	Million Gallons
MGD	Million Gallons per Day
MOEA	Multi-Objective Evolutionary Algorithm
NC	North Carolina
NRC	National Research Council
NACWA	National Association of Clean Water Agencies
OMS1	Operational Modeling System V1

OROP	Optimized Regional Operations Plan
OWASA	Orange Water and Sewer Authority
TBC	Tampa Bypass Canal
TJCOG	Triangle J Council of Governments
Triangle	North Carolina Research Triangle
R&R	Renewal & Replacement
RCP	Representative Concentration Pathway
RHESSys	Regional Hydro-Ecological Simulation System
ROF	Risk-of-failure
SCH	South-Central Hillsborough County
SOW	state-of-the-world
SWAT	Soil Water Assessment Tool
SWRE	System Wide Reliability Evaluation
SWTP	Surface Water Treatment Plant
TBW	Tampa Bay Water Authority
US	United States
USD	US Dollars
USGS	US Geological Survey
WCU	Well-Characterized Uncertainty
WJLWTP	Western Jordan Lake Water Treatment Plant
WTP	Water Treatment Plant
WUCA	Water Utility Climate Alliance

CHAPTER 1 : INTRODUCTION

Water utilities worldwide share the same mission: to provide a reliable source of high-quality water for customers (AWWA, 2018). Doing so requires utilities to constantly adapt to uncertain future conditions, mitigating risks to water supply through both short-term drought management and long-term infrastructure planning (Gleick, 2003; WUCA, 2016). This is a massive endeavor – in 2017, more than $110 billion USD of public funding alone went toward U.S. water utility infrastructure (CBO, 2018), and the U.S. Environmental Protection Agency estimates nearly $400 billion USD is needed by 2030 to maintain drinking water infrastructure (USEPA, 2011). However, maintaining the high levels of supply capacity needed to meet demand during extreme drought has become much more challenging, as a result of fewer cost-effective expansion options remaining and more restrictive environmental approval processes (NRC, 2012; Perry & Praskievicz, 2017). Consequently, adaptive drought mitigation actions have come into more common use by utilities to counter water supply risks. Conservation (e.g. water use restrictions, drought surcharge pricing, low-flow water fixtures) to reduce water demand (Boyle, 2014; Geller et al., 1983; Kenney et al., 2004; Milman & Polsky, 2016; Olmstead & Stavins, 2009) and transfers of water from adjacent utilities or other users (e.g., agriculture) to temporarily increase supply (Characklis et al., 2006; Gupta & van der Zaag, 2008; Lund & Israel, 1995; NRC, 1992) typically offer lower-cost and less environmentally burdensome options for drought management does infrastructure expansion.

Transfers and temporary conservation carry financial consequences as they are implemented intermittently, dictated by drought. Utility financial stability can be stressed by the sudden occurrence, and the resulting revenue losses or cost increases, of these adaptive drought mitigation measures (Baum & Characklis, 2020; Hughes et al., 2014; Zeff et al., 2020; Zeff & Characklis, 2013). Because water utilities have primarily fixed costs (e.g., debt service on bonds that finance infrastructure), and have prices set to recover revenues which are difficult to change on short notice, any significant variability in costs or revenues can lead to budgetary shortfalls that jeopardize their ability to meet debt obligations (Hughes & Leurig, 2013). Any increase in the risk of missing debt payments or being unable to meet bond covenants – an agreement between a utility and debt holders, requiring the utility to maintain specific financial benchmarks, demonstrating fiscal stability (AWWA, 2011; Raftelis, 2005) – can result in a lower credit rating, increasing a utility's future cost of capital (i.e. interest on debt) and lead to higher costs and increased water rates for customers (Leurig, 2010). This is a critical concern for utility managers, as the financing costs of debt can constitute over 20% of a water utility's operating budget (NACWA, 2015). As water utilities have come to rely increasingly on adaptive drought management measures, jointly managing both financial risk and supply risk has become a growing priority for utilities (Gold et al., 2019; Herman et al., 2015; Paulson et al., 2018). Simultaneous mitigation of supply and financial risk presents a very different set of challenges than have been faced by water utilities in the past, when utilities mostly sought to combat drought by maintaining significant volumes (rarely used) supply capacity, and paid for it via debt service payments that were predictable decades into the future, even as it likely led to higher long-term costs.

Reliably meeting demands under a new paradigm of coupled adaptive water supply and financial management is also made more difficult today by the compounding uncertainties utilities face in both short- and long-term planning (Brown et al., 2015; Harou et al., 2010; Loucks & van Beek, 2017; Lund, 2015). Changes in climate and land use patterns can alter (and already have altered) hydrologic behavior – precipitation patterns, for example (Fig. 1.1) – on which water supply system design is based and from which future water availability is predicted (IPCC, 2014a; World Bank, 2016; WUCA, 2016).

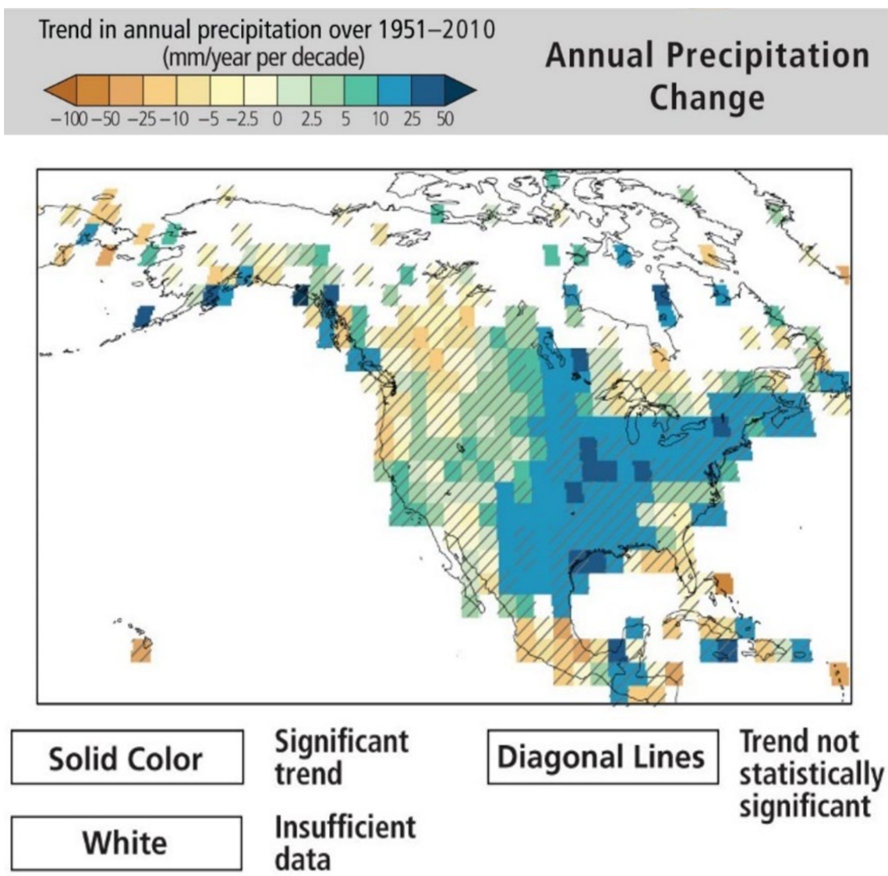

Figure 1.1: Change in annual precipitation between 1951 and 2010 over North America. Adapted from Figure 26-3 of the 2014 Intergovernmental Panel on Climate Change (IPCC) Assessment Report 5 (AR5).

Demand for water is also difficult to predict (Fig. 1.2), due to a mix of factors including weather, climate, population growth, per-capita usage, conservation, and consumer willingness-to-pay (Nawaz et al., 2019). Institutional changes can add complexity to planning, subjecting utilities to unexpected regulatory or governance structures that may imperil their water supply reliability or financial solvency (Beecher, 2013; Ioris, 2012). Inter-utility cooperative agreements that involve sharing supply capacity to reduce long-term costs and increase supply reliability are also increasingly common, further complicating utility supply and financial management (EPA Office of Water, 2017; Silvestre et al., 2018; Tran et al., 2019).

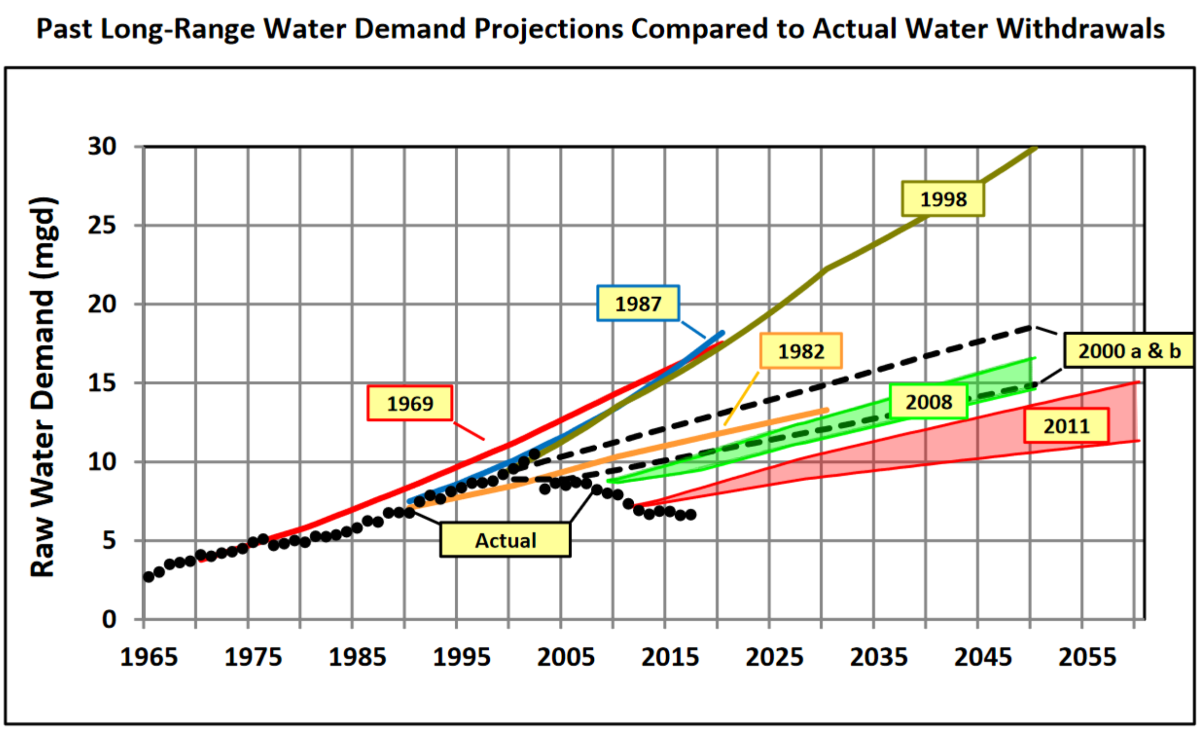

Figure 1.2: Water demand (points) from 1965 to 2018 and long-term demand projections (lines) by the Orange Water and Sewer Authority (OWASA). Dates of projections given in the inset boxes next to projection lines. Figure provided courtesy of OWASA.

Given the potential uncertainties from many sources, and the wide range of possible mitigation actions that utilities may take to reduce risks, research focus in the field of water supply management and planning has more recently shifted toward identification of robust policies – policies which perform well under uncertainty – to sustain future supply reliability and financial stability (Hoekstra et al., 2018). Dynamic adaptive modeling frameworks have emerged as valuable decision support tools, through which a utility or regional system of multiple utilities can react to changing hydrologic, demand, and institutional conditions by triggering mitigation actions (Kingsborough et al., 2016; Kwakkel et al., 2015; Trindade et al., 2019). However, the broad scope of hydrologic, demand, institutional, and cooperative uncertainties, along with range of potential adaptive capabilities of regional water utility systems, has revealed a number of critical-yet-unaddressed areas of research in water supply and financial risk management and modeling.

This research advances the academic literature of the water resources management field by answering a series of these questions through novel utility-scale modeling, jointly exploring the regional water supply and financial risks facing water utilities and opportunities to mitigate these risks through independent adaptation and regional cooperation. In doing so, this dissertation advances both the methodologies and applications of regional water supply and financial risk management. Those questions are below (along with reference to the chapter of this work in which they are addressed):

How vulnerable are utilities to climate and land-use landcover change uncertainty, and how can mitigation action influence their vulnerability (Chapter 2)? It remains an open question how vulnerable water utilities are with respect to the combined effects of both climate and land-use landcover (LULC) change, as well as the degree to which each represents a major source of uncertainty in future water availability (USGCRP, 2018; World Bank, 2016). Climate and LULC change have been extensively studied separately to assess their hydrologic impacts (Milly et al., 2005; Piao et al., 2010; Schewe et al., 2014), but scrutiny of their joint impacts on water supply has only begun more recently (Forbes et al., 2018; Martin et al., 2017; Morán-Tejeda et al., 2015; Tong et al., 2012). Of past research, few studies of water supply account for water resources management (McDonald et al., 2014) and none consider adaptive management responses by utilities to dynamically mitigate hydrologic risk. Because climate and LULC change are coincident and can occur both gradually and abruptly (especially urban land use change), accounting for dynamic adaptive response by utilities to changes in hydrologic conditions can provide a more realistic picture of a region's vulnerability to hydrologic uncertainty. This chapter is the first study of regional water supply management to explicitly evaluate the impacts of hydrologic change when adaptive utility responses are applied, either for an individual utility or region, representing an advancement in both methodology and application with the water resources management field. This chapter has been published in *Water Resources Research:*

Gorelick, D. E., L. Lin, H. B. Zeff, Y. Kim, J. M. Vose, J. W. Coulston, D. N. Wear, L. E. Band, P. M. Reed, and G. W. Characklis (2020). Accounting for adaptive water supply management when quantifying climate and land cover change vulnerability. *Water Resources Research*, 56, e2019WR025614.

Can inter-utility cooperation help mitigate supply and/or financial risk (Chapter 3)? Uncertainty with respect to future hydrology and demand has the potential to influence utility water supply reliability, but regional context and governance are also important factors. Utilities are searching for cost-effective ways to meet rising demands and ensure supply reliability under uncertainty, and those with limited supply infrastructure expansion options are increasingly considering partnerships with adjacent utilities (Reedy & Mumm, 2012; Sjöstrand et al., 2018). Inter-utility partnerships can be attractive for a number of reasons: reducing costs via economies of scale (Tran et al., 2019); providing access to additional supply options (Reedy & Mumm, 2012); generating a source of revenue from unused capacity, as utilities often maintain surplus supply and treatment capacity (EFC, 2009). Many utilities in the U.S. and internationally already employ inter-utility (or inter-local) agreements as supply management tools through joint ownership and operation of treatment facilities (Apex et al., 2015), intermittent sales of excess supply capacity (Commissioners, 2013; OWASA & Durham, 2009), and many other forms (Kurki et al., 2016; Silvestre et al., 2018). However, outside of limited cost-benefit analyses to compare regional inter-utility agreement alternatives (Sjöstrand et al., 2019), no academic studies have quantified the financial impacts of implementing future agreements within existing regional systems. By studying utility financial outcomes (total debt service paid on infrastructure, added cost per unit of water treated, etc.) under different agreements and demand growth scenarios, this analysis identifies important challenges for regional development. Furthermore, this chapter demonstrates a demand scenario analysis to investigate regional financial risk under inter-utility agreements that contributes to the field through a broadening of existing applications of scenario analysis. This chapter has been published in *Journal – American Water Works Association:*

Gorelick, D. E., Zeff, H. B., Hughes, J., Eskaf, S., & Characklis, G. W. (2019). Exploring Treatment and Capacity-Sharing Agreements Between Water Utilities. *Journal-American Water Works Association*, 111(9), 26-40.

How robust are regional inter-utility agreements under uncertainty (Chapter 4)? While it is necessary to understand both supply and financial outcomes of inter-utility agreements, it is also key to understand how robust the performance of an agreement is under both hydrologic and demand uncertainty. When reducing supply risk, regional cooperation may simultaneously introduce "counterparty risk," as a participating utility can be subject to increased exposure to regional demand and hydrologic uncertainty that impacts other partners to an agreement. Should demands not grow at projected rates after an agreement is reached, or hydrologic patterns change, cooperation among multiple partners (facing different local water supply and demand circumstances) may exacerbate risk rather than mitigating it. Previous studies of inter-utility agreements have not quantified financial risk resulting from their implementation, nor have they compared the robustness of different agreements under uncertainty within a dynamic adaptive management framework where utilities can respond to changing conditions (Arena et al., 2014; Sjöstrand et al., 2019). It is also important to explore the 'stability' of inter-utility agreements – a well-performing regional agreement may not guarantee strong performance for all individual utility partners (Bendz & Boholm, 2019; Dinar & Howitt, 1997; Read et al., 2014). Decision-making from centralized (regional) vs. distributed (local, individual utility) perspectives has been studied in water management (Gold et al., 2019; Herman et al., 2014), but to date no research has focused on how regional and individual utility financial outcomes are simultaneously impacted across differing inter-utility agreements. This analysis demonstrates how robustness conflicts are shared among regional utilities across different agreements, underscoring the benefits inter-utility agreements can offer for managing regional supply and financial risks while simultaneously highlighting conditions that strain cooperation. In doing so, this chapter provides a first-of-its-kind application of regional water supply management policy optimization under uncertainty to evaluate the efficacy of inter-utility agreements. This chapter is currently under review for publication in the journal *Water Resources Research*.

How can utilities financially adapt to meet water demands (Chapter 5)? Consideration of both supply and financial risks means water managers must simultaneously balance investment to ensure reliable water supply with affordability for consumers (Ajami et al., 2018; Baird, 2010; Dickinson et al., 2015; Jeff Hughes et al., 2014; Schwartz et al., 2017). To do so effectively, utilities adapt to changing budgetary conditions (as they do for water supply) to meet key performance benchmarks of financial stability. Such benchmarks include covenants: often required of utilities by creditors seeking assurance that debt issued via bonds will be repaid, covenants represent a key factor in utility budgets (AWWA, 2011; Raftelis, 2005). Violation of covenants risks a downgrade of a utility's credit rating, meaning higher interest rates on bonds for capital projects, raising the cost of debt-financed water supply infrastructure upgrades (Beecher et al., 1993; Hughes et al., 2014; Wirick et al., 1997). However, no academic studies have directly quantified the financial impacts of water supply system adaptation (i.e. supply infrastructure expansion) on utility covenants. Furthermore, no research to date has integrated consideration of covenants into simulation of future utility operations and infrastructure planning, nor used them to trigger adaptive financial responses to preserve budget stability. This research introduces a coupled water supply-financial modeling framework, developed to track utility budgetary decision-making in response to future water demand shifts and infrastructure expansion. No previous studies have developed or tested adaptive financial modeling for water utilities; this chapter thus represents a novel contribution through its methodological advancement of regional water supply management modeling and application in a real-world setting. By quantifying the effects of infrastructure planning decisions and demand growth on covenants and water rates, results of this work reveal the value of integrating dynamic adaptive financial and water supply decision-making for financial risk mitigation for long-term infrastructure planning.

Research done towards completion of this dissertation advances the understanding and modeling of regional water supply resource management and risk mitigation, by addressing shortcomings of the field in accounting for hydrologic and demand uncertainty, as well as critical financial feedbacks and cooperative agreements, in regional supply systems. Takeaways here offer insights to water resource managers on implementation of mitigation strategies to aid their task of providing reliable, affordable water service in the future.

CHAPTER 2 : ACCOUNTING FOR ADAPTIVE WATER SUPPLY MANAGEMENT WHEN QUANTIFYING CLIMATE AND LANDCOVER CHANGE VULNERABILITY[1]

2.1 Introduction

Large population centers are increasingly subject to uncertainty in future water availability, jeopardizing their ability to meet demands (Milly et al., 2005). Climate change will have wide-ranging consequences for freshwater availability (AWWA, 2018; IPCC, 2014a; World Bank, 2016; WUCA, 2016). Shifts in streamflow trends have already been observed over the historic record (Milly et al., 2008), and future projections suggest a greater likelihood of extreme hydrologic events in the form of droughts and flooding (Foley et al., 2005; IPCC, 2014a; Mann & Gleick, 2015). Land use and land cover (LULC) change can also have substantial impact on water availability (Byrd et al., 2015; Martin et al., 2017). Timing and magnitude of runoff can be disrupted through urbanization (Jenerette & Wu, 2001), impacting downstream reservoir storage levels and streamflow. In urban areas, climate and LULC change will jeopardize water supply availability in tandem with increases to population and water demands (McDonald et al., 2011). In order to reliably meet future water demands, it is essential that water utilities are informed on the impacts and interactions of climate and land use changes to water availability.

Climate and LULC changes can furthermore have interactive effects (Pielke, 2005). Many papers have discussed the separate impacts of climate or LULC change on runoff and

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[1] This chapter has been published: Gorelick, D. E., L. Lin, H. B. Zeff, Y. Kim, J. M. Vose, J. W. Coulston, D. N. Wear, L. E. Band, P. M. Reed, and G. W. Characklis (2020). *Water Resources Research*, 56, e2019WR025614. https://doi.org/10.1029/2019WR025614

water availability (N. S. Christensen et al., 2004; Marquès et al., 2013; Piao et al., 2010; Schewe et al., 2014), but until recently few studies had investigated water availability impacts of climate and LULC change in combination or in great detail (Tong et al., 2012; Tu, 2009). Despite more recent work over the past decade, uncertainty remains as to the relative dominance of climate or LULC factors on streamflow changes (Ye et al., 2013).

Furthermore, hydrological response to climate and LULC change will not be regionally uniform. Impacts on water availability vary spatially, owing to the unique characteristics of local eco-hydrologic systems and their responses to environmental change (Forbes et al., 2018). For example, Bhaduri et al. (2000) estimated that an 18% increase in urban land across a watershed in Indiana led to over 80% increase in runoff. Martin et al. (2017) concluded urbanization in a central North Carolina catchment had limited impacts on annual runoff, though future impacts would be heavily dependent on fine-scale type, timing, and location of LULC change within the catchment. Tong et al. (2012) noted that increased urban land cover increases annual runoff and alleviates water shortage during dry years in an Ohio watershed. However, Tu's (2009) analysis of a more urbanized catchment found climate and LULC changes significantly alter the seasonal distribution of streamflow rather than annual runoff. Case-by-case variation in hydrologic response suggests that information on local hydrologic system characteristics becomes essential when considering the mixed effects of climate change and LULC change on water supply (Byrd et al., 2015; Frans et al., 2013; J. Kim et al., 2013; Lopez-Moreno et al., 2014; Martin et al., 2017; Tong et al., 2012; Ye et al., 2013).

While reservoir inflows strongly depend on upstream LULC and climatic conditions, water utility operations and regional population pressures also strongly influence the vulnerability of urban areas to water supply shortages (Zeff et al., 2014). When reservoir levels drop, utilities may implement a variety of mitigation strategies. Both short-term decisions, such as use of conservation or use restrictions (Olmstead et al., 2007; Olmstead & Stavins, 2009b) and transfers of water (Characklis et al., 2006; Gorelick et al., 2018; Palmer & Characklis, 2009), as well as long-term mitigation through infrastructure expansion (Kwakkel et al., 2012; Zeff et al., 2016) can help utilities navigate periods of high water supply risk. Mixing decision-making at different timescales allows planning flexibility for utilities to dynamically adapt to changing conditions (Kwakkel et al., 2015); these adaptive policy pathways have emerged in the academic literature as a state-of-the-art planning paradigm for water utilities (Haasnoot et al., 2013), but have yet to be rigorously applied to questions of climate and LULC hydrologic change.

Along with ensuring reliable water supply for customers, water utilities must also maintain stable, affordable costs. Balancing the tradeoff between service reliability and financial stability requires that utilities track and respond to system conditions other than water availability alone (Zeff & Characklis, 2013). Studies on water availability under climate and LULC change to this point, however, present results that do not strongly capture a broad set of water planning and management objectives. By generally assuming that more (less) water equates to good (bad) outcomes and/or quantifying water availability through simplistic metrics, it is difficult to infer the water supply impacts associated with LULC and climate change without capturing utility-level management responses and their financial implications. For instance, a number of works assess water yield or availability in terms of runoff per capita, ratio of available water to human or environmental demands, or similar indices (Arnell et al., 2011; Arnell & Lloyd-Hughes, 2014; Boithias et al., 2014; Caldwell et al., 2012; Gosling & Arnell, 2016; Rijsberman, 2006; Vorosmarty, 2000). Some studies present water availability changes relative to the historic record of streamflow (Kim et al., 2013). Others have approximated utility action in the form of water supply capacity (reservoir) expansion (Lopez-Moreno et al., 2014). While such techniques are a useful litmus test of climatic and LULC impacts on water supply, they fall short in representing key aspects of reservoir operations and utility decision-making, offering an incomplete picture of resilience to external stressors.

This work seeks to move beyond previous analyses of water availability by evaluating hydrologic (i.e. climate and LULC) change at two stages, (1) as water availability output from eco-hydrologic modeling (reservoir inflows) and (2) as indicators of management system performance at a water utility scale. Our framework can therefore address two main questions not convincingly analyzed by previous work: (1) what are the regional impacts of hydrologic change with and without management system consideration; (2) how can management decision-making influence the impacts of hydrologic change? This methodology is applied to a case study within the larger Research Triangle region of central North Carolina, a rapidly growing and urbanizing region where substantial hydrologic and water resource management modeling of current and future conditions has already begun (Gorelick et al., 2018; Herman et al., 2016; Kim et al., 2017; Kirsch et al., 2013; Zeff et al., 2016) but to this point is yet to be consolidated into a coupled modeling framework. In doing so, we show both the relative influences of climate change and LULC change on water management, and that representation of water availability without consideration of utility decision-making can obscure important controls on provision of water for human use. While this work is not meant as a comprehensive study over all regions with respect to eco-hydrological, climatic, and land use aspects specific to the Research Triangle, we present a generalizable methodology for water supply vulnerability assessment, reproducible across the US where comparable data is available.

2.2 Methods

This study applies a multi-step methodology (Fig. 2.1) to evaluate water supply vulnerability due to climate and LULC change. Projected changes in temperature and precipitation from general circulation models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) integrated with local climate records are used to project future climate, while LULC change is projected from 2011 baseline conditions across urban and forested landscapes, including expected changes in forest ecological composition and structure (Fig. 2.1a). Projections are used to drive regional eco-hydrologic modeling, simulating future water availability for regional reservoirs (Fig. 2.1b). Four future hydrologic scenarios are tested: (1) baseline, where current climate and land use patterns are static across the modeling period; (2) climate change, following an intermediate emissions scenario (Intergovernmental Panel on Climate Change's [IPCC] Representative Concentration Pathway [RCP] 6.0 Scenario); (3) high resolution LULC changes, projected based on biophysical and socio-economic factors; (4) simultaneous climate and LULC change.

To comprehensively evaluate management and planning outcomes, an exploratory stochastic scenario analysis was used to better account for variability within eco-hydrologic modeling projections (Fig. 2.1c). The expanded stochastic analysis is applied to simulation of water utility decision-making for three Research Triangle utilities (Cary, Durham, Orange Water and Sewer Authority [OWASA]), where performance in evaluated based on three operational performance indicators under each hydrologic scenario (Fig. 2.1d) from 2015 to 2060. Water availability is evaluated before (as reservoir inflows) and after (in terms of utility service reliability, conservation implementation frequency, and infrastructure investment indicators) consideration of utility decision-making to better understand the interactions between hydrologic change and management actions.

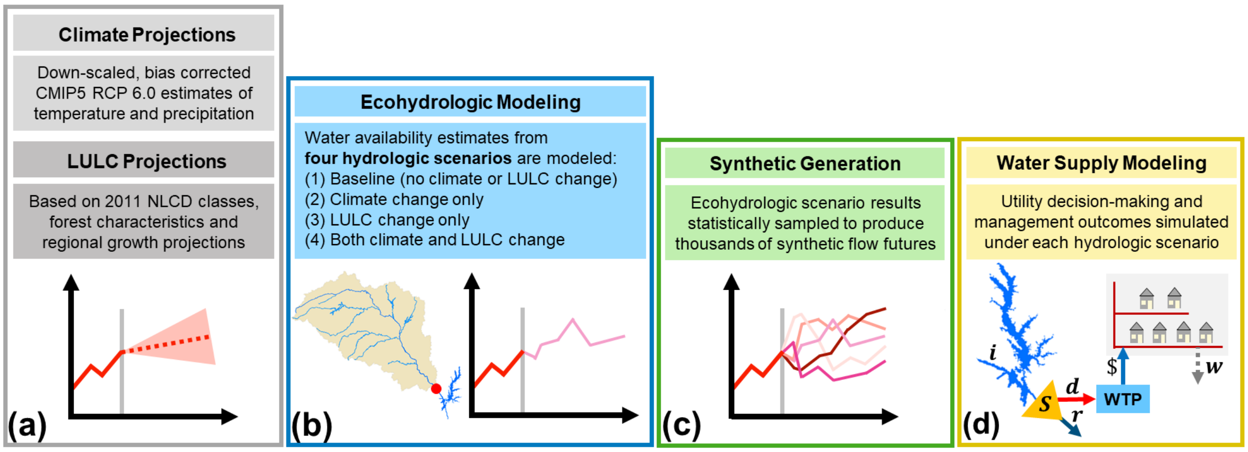

Figure 2.1: Study modeling framework for assessing water availability under hydrologic change in the Research Triangle. Climate and LULC change projections (a) drive eco-hydrologic modeling to simulate water availability under four hydrologic scenarios (b). Water availability estimates are sampled to produce synthetic realizations of future reservoir inflows (c), which drive water supply management modeling for the region to determine utility performance outcomes (d).

2.2.1 Regional characteristics

Our exploratory scenario analysis is tested within the greater Research Triangle region of North Carolina (henceforth Triangle) and its surrounding water supply drainage catchments (Fig. 2.2). Home to over 2 million residents, the Triangle is bracing for rapid population and economic growth over the next half-century (TJCOG, 2014) and the accompanying land use changes. Significant increases to urban area are projected for the Triangle, consistent with expectations for the Southeast US at large (Carter et al., 2018; Wear, 2013), that will alter streamflow patterns as forest cover is reduced. The Triangle falls within the Southeast climate region (Carter et al., 2018) with hot and humid weather in summertime and high temperature variation in winter.

Average annual precipitation across the historical record is 1124 millimeters per year (mm/yr), while in the more recent 1990-1999 decade average annual precipitation in the Triangle was 1,167 mm/yr with a standard deviation of 142 mm/yr. Annual runoff is on average only about 26% of the annual precipitation partially due to high evapotranspiration from forested land that still dominates the region. Future hydrologic conditions in the region, resulting from climate change, are also highly uncertain. Though predictive skill of precipitation in climate models for the Southeast US remains low (Seager et al., 2009), the area has experienced increased frequency of extreme flooding and drought events that is expected to worsen (Aalst et al., 2014).

Split across two major drainage basins – the Neuse River and Cape Fear River Basins – a number of smaller basins (or catchments) are delineated in this study based on drainage into regional water supply reservoirs (Fig. 2.2, beige). The majority of urbanized area and water demand fall within the service areas of three water utilities in the Triangle – Durham, Cary, and OWASA, with combined 2010 average demands of almost 50 million gallons/day (TJCOG, 2014) – whose water supply is dependent on outflow from watersheds within the larger Neuse and Cape Fear River Basins (Fig. 2.2). The Flat River (USGS 02085500) and Little River (USGS 0208521324) basins drain, respectively, into Durham's Lake Michie and Little River reservoirs within the Neuse River basin. Cane Creek (USGS 02096846) and Morgan Creek (USGS 02097464) basins drain into OWASA's Cane Creek and University Lake reservoirs. The Haw River (USGS 02096960) and New Hope River (USGS 02097314) basins drain to Jordan Lake, which is managed by the United States Army Corps of Engineers and serves as the primary water supply source for Cary. Urbanized drainage areas of Triangle cities also contribute runoff to Jordan Lake (Fig. 2.2, pink).

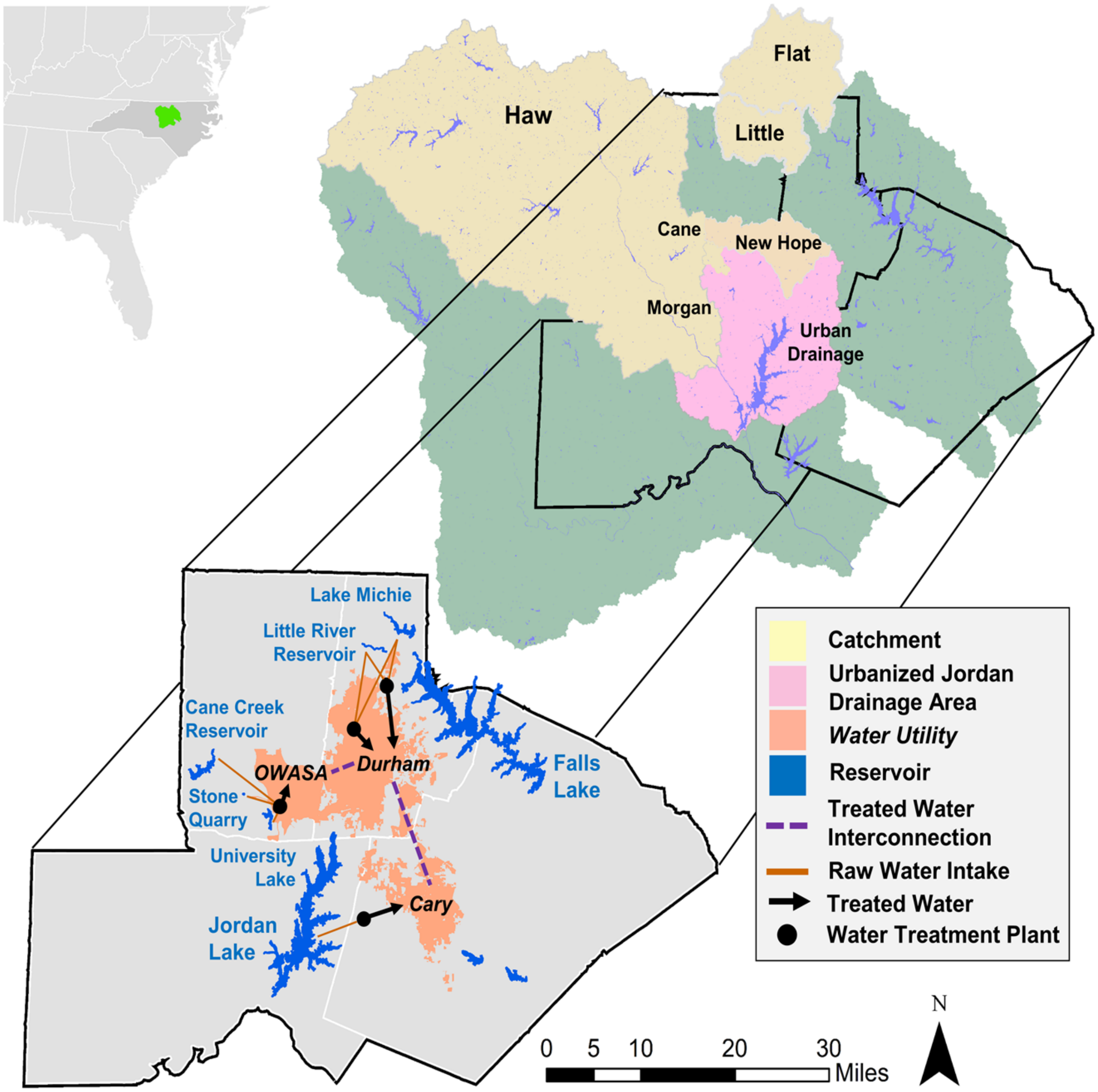

Figure 2.2: Research Triangle region of the Southeast US. Six watersheds (beige) contribute inflows to regional reservoirs (blue) along with additional, ungaged runoff from urban basins (pink). Study reservoirs provide water supply to three urban utilities (orange), which may also transfer treated water through existing interconnections (purple, dashed).

Subbasins of the Triangle have distinct land use characteristics that can result in varied hydrological patterns between them (Table 2.1). Forest and pasture land dominate Durham's Flat River and Little River catchments. The Haw River basin, primarily located west of the heavily populated cities of the Research Triangle, as well as Cane Creek and Morgan Creek basins, are largely undeveloped, covered by forested area, pasture and some row crops. Land around Jordan Lake (Fig. 2.2; pink) and New Hope Creek catchments is dominated by older urban and rapidly urbanizing areas but otherwise surrounded by forest and residual agricultural land. The Triangle is in a topographical transitional zone between the coastal plain and the Piedmont plateau, having an average slope of 5.6% with geologic settings of fractured crystalline bedrock and rolling hills to the west and a lower-lying Triassic basic dominated by deep sedimentary rock to the east running through Durham. Though a rapidly urbanizing and growing region, forest currently dominates the greater Triangle, primarily consisting of Carya tomentosa (hickory), Quercus alba (white oak), Q. rubra (red oak), Q. prinus (chestnut oak), Liriodendron tulipifera (tulip tree) and Liquidambar styraciflua (sweetgum). About 19% of forested area is evergreen forest with pine plantations (loblolly pine).

Table 2.1: Regional and watershed-level landcover characteristics (2010) for the Research Triangle. Primary landcover is forest, followed by roughly equal proportions of pasture and urban land.

Watershed	Catchment drainage area (sq. km)	% Forest	% Pasture/ Agriculture	% Low-intensity urban	% High-intensity urban
Cane Creek	19.7	78.7	17.2	4.0	0.0
Morgan Creek	21.4	75.4	19.4	4.6	0.0
Flat River	385.1	64.4	28.3	6.2	0.7
Little River	202.7	66.8	27.3	5.4	0.1
New Hope Creek	198.9	56.4	5.4	30.5	7.4
Haw River	3359.6	51.5	27.8	15.4	3.5
Regional Average		**59.5**	**19.8**	**15.1**	**3.2**

2.2.2 Climate and land use projections

2.2.2.1 CMIP5 Projections

To project climate change across the Triangle, we evaluated both historical regional climate patterns and CMIP5 climate projections (Table 2.2). Historical climate records were collected by the National Weather Service (NWS) Cooperative Observation Program (COOP) from stations across North Carolina, providing daily maximum and minimum temperature and daily precipitation from 1940 to 2010. Generally, monthly temperatures decreased slightly during the period of 1940-1975 but show warming from 1980 to present time. Monthly precipitation, by contrast, did not vary significantly year-to-year in the Triangle but displayed a consistent seasonal pattern of high precipitation in winter (Jan-Mar) and summer (Jul-Sept) and low precipitation in spring (Apr-Jun) and fall (Oct-Dec).

The CMIP5 GCM products of monthly average daily temperature and monthly precipitation were provided in a statistically downscaled form at 1/8-degree (~12 km) spatial resolution. Downscaling and bias correction were previously done using the bias correction and spatial disaggregation (BCSD) and daily bias-correction and constructed analogs (BCCA) techniques (Brekke et al., 2013). CMIP5 projections under RCP 6.0 were used, consistent with LULC change projections by previous studies of central North Carolina (Martin et al., 2017; Wear, 2013). Six GCMs (Table 2.2) were selected for evaluation and eco-hydrologic model application – downscaled products from these GCMs are each available at monthly timescale, from 1950 to 2099 at 1/8-degree resolution. Downscaled, daily results were available for the region, however the available daily data, particularly precipitation, are highly inconsistent with the historical records in terms of seasonality and auto-correlation structures. To prevent these inconsistencies from translating into streamflow prediction and alter hydrologic dynamics in the eco-hydrologic models, monthly GCM results combined with historical records were instead used to project future climate that has consistent auto-correlation structure and seasonality of weather.

Table 2.2: Selected CMIP5 GCMs. Downscaled products of each were used to forecast climate change in the Triangle to 2060.

GCM		Primary reference
Commonwealth Scientific and Industrial Research Organization, Atmospheric Research, Australia	CSIRO	Gordon et al., 2002
NASA/Goddard Institute for Space Studies, USA	GISS	Russell et al., 2000
Met Office Hadley Center	HADG	Gordon et al., 2000
National Center for Atmospheric Research, USA	CCSM	Collins et al., 2006
Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change, Japan	MIROC	Hasumi & Emori, 2007
U.S. Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory, USA	GFDL	Delworth et al., 2006

This set of six GCMs was chosen to provide a diverse assessment of climate futures, spanning the wide range of GCM precipitation and temperature projections for the Triangle. Each GCM has unique seasonal change trajectories for temperature and precipitation (Fig. 2.3). Both GFDL and GISS show large increases in precipitation during spring to fall with moderate increase in winter; GFDL suggests high increases in temperature for all seasons; GISS suggests a relatively muted increase in temperature for all seasons; CCSM shows moderate increase in precipitation in winter and spring; CSIRO projects small precipitation increases in winter and moderated increase in spring and fall; HADG and MIROC project minimal change in summer precipitation. In terms of reservoir recharge, GFDL, GISS, and CCSM show precipitation increase in winter, which benefits reservoir recharge whereas CSIRO, HADG, and MIROC show little precipitation increase in winter.

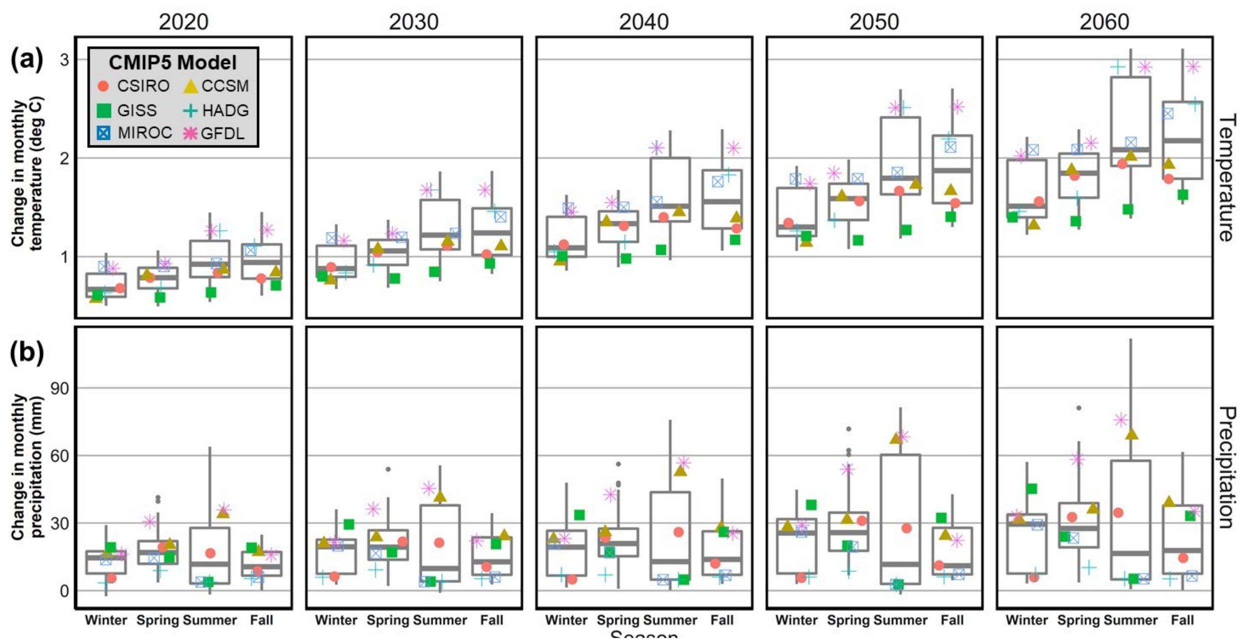

Figure 2.3: Triangle projections of temperature (a) and precipitation (b) under climate change relative to recent conditions (2000-2010), aggregated seasonally and decadally. Specific results for each of six CMIP5 GCMs overlaid on boxplots.

Downscaled CMIP5 outputs were averaged and aggregated by COOP station using Thiessen polygons to compare against historical data. Across the historical period (1950-1975), downscaled CMIP5 temperatures did not show decreasing trends reflected by COOP records. Seasonal CMIP5 and COOP precipitation patterns showed agreement, but CMIP5 winter precipitations were not as high as observed. Additionally, CMIP5 daily/weekly precipitation patterns were quite different from the observed record in terms of autocorrelation and distribution of events. As a result, we did not directly use CMIP5 daily outputs for our study because historical trends were not adequately preserved and instead combined COOP observed data with CMIP5 projected trends following a change-factors approach for climate projection (as in Martin et al., 2017). In order to preserve autocorrelation in monthly and daily meteorological COOP data, monthly time series from 1978-2010 (period of warming) were first de-trended then projected (recycling each 30 years) following CMIP5 monthly trends. Monthly delta factors for temperature and precipitation were then applied to the 30-year daily data. This method preserved interannual variability at monthly and daily time scales.

2.2.2.2 Landcover modeling and projections

Output from a statistical spatial model described by Martin et al. (2017) and Wear (2013) of plausible change across land cover classes at 30-meter spatial resolution was used to project future LULC and forest change in the Triangle (Fig. 2.4). We note that these methods provide information on current, and project future, forest ecosystem conditions required for our eco-hydrological modeling approach to integrate feedbacks between climate, land cover, ecosystem water use, with surface and subsurface water stores and fluxes. The methods are designed to balance consistency with climate projections based on emissions/economic scenarios, with local development conditions, trends and planning at municipal levels. The methods follow Martin et al. (2017), but also incorporate planning projections of development suitability in the Triangle synthesized by the Triangle J Council of Governments (TJCOG) to further condition land use transition probabilities. Methods are described in detail in Martin et al. (2017), though a brief summary is provided here.

Estimating baseline and future land use at a 30 meter (m) resolution required a multimodel approach that included data from the US Forest Service's Forest Inventory and Analysis (FIA) and the 2011 National Land Cover Database (NLCD). The FIA consists of a network of permanent forest plots, including urban forest, that are inventoried on a regular basis for stand overstory and understory species, tree size class, crown conditions and other information. The NLCD classifies vegetation heights <5 m as shrub/scrub land cover (LC), even if the land use is young forest. To account for this, forest land use was translated from LC using a model derived from FIA observations, a time series of NLCD land cover, and current NLCD percent tree canopy cover. All pixels assigned as forest land use were assigned attributes such as forest type from a plot in the FIA database with similar characteristics (e.g., climate, topography, soils) using an ensemble approach. All other land use types were assigned using the 2011 NLCD.

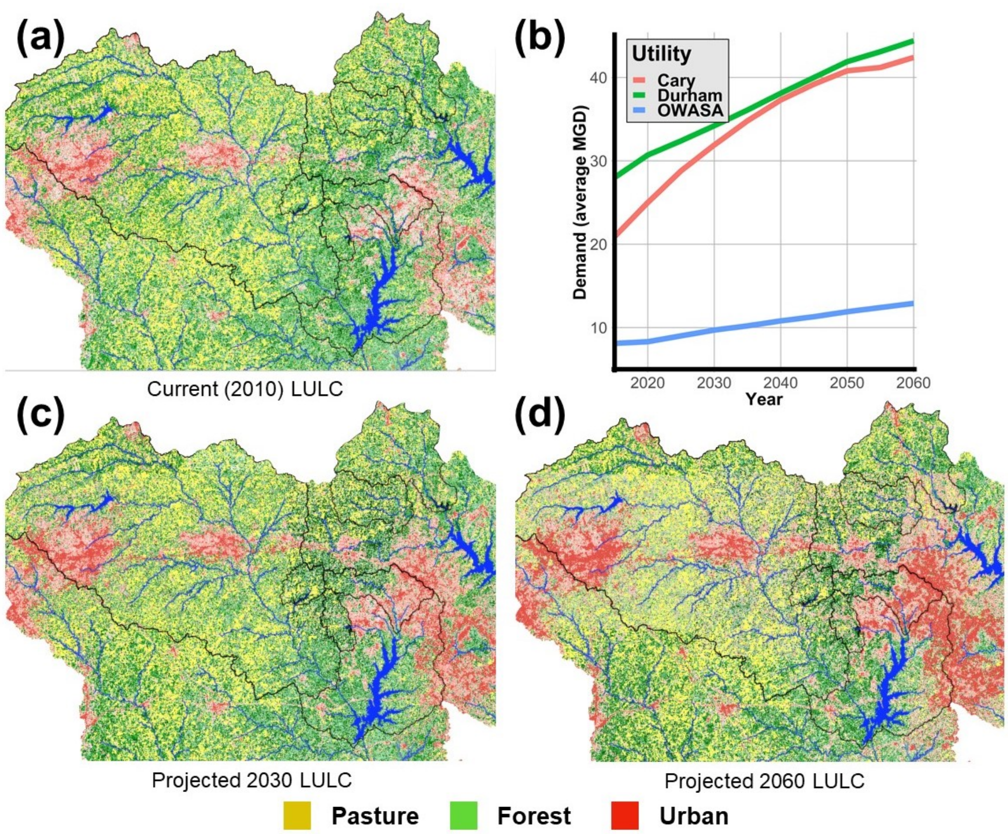

Figure 2.4: Land use for current (a) and projected (c,d) decades across the Triangle and corresponding regional water demand growth projections (b). A reduction of dense forested area in future decades is observed due to continued urban growth.

County-level land use change is projected as a function of regional county-level population growth and socioeconomic projections (household income, agricultural land values) consistent with economic assumptions in the climate model emissions scenarios as described by Wear (2013). Future forest conditions are projected using the US Forest Service Assessment System (US-FAS) (Martin et al. 2017) that provides future forest conditions for every FIA plot based on projected climate, forest age, forest type, and likelihood of harvest. County-level LU projections were refined to a 30-m scale using a spatial allocation model that determined the probability of each pixel converting to a different land use or remaining the same. Changes in forest conditions (e.g., growth, forest type, etc.) are derived from the US-FAS projections that are allocated to each plot using plot-level spatial imputations.

Rapid urban development is anticipated to occur in and around the cities of Chapel Hill, Cary, Durham, and Raleigh that constitute the traditional Research Triangle region (Fig. 2.4, righthand areas on a,c,d). The expected types of development include intensifying existing urban area (i.e., from low urban density to high urban density), increased sprawl of existing metropolitan areas, and new urbanizing rural areas in the forested hillslopes of the Triangle. Areas outside the traditional Triangle urban areas, such as the Haw River basin feeding Jordan Lake, however, are projected to remain relatively rural. There is minimal future urban development expected in the Haw Basin; outside two population centers of Greensboro (Fig. 2.4, red areas in map area to the left) and Burlington (Fig. 2.4, center red areas of a,c,d), the basin is expected to maintain its levels of pastureland and forest. Urbanization is expected to occur to greater extents beginning in 2030 based on development projections from each regional municipality, depending on the trajectory of development envisioned (and planned for by regional governments) in currently rural watershed areas. This information was used to condition transition probabilities of land use and the effects of land use transition based on proximal land use, projected at decadal time steps in LULC modeling. However, as an approximation of variability in the effect of urbanization, the specific type of urbanization (ex: the prevalence of highly vs. moderately impervious surfaces in future development) was varied between land-use parameterizations of eco-hydrologic models (as described in following sections).

2.2.3 Eco-hydrologic modeling

2.2.3.1 Model selection

The impact of each modeled hydrologic scenario on regional water availability was determined using both the Regional Hydro-Ecologic Simulation Systems (RHESSys) model (Tague & Band, 2004a) and the Soil and Water Assessment Tool model (SWAT; Neitsch et al., 2011). Both models have been widely used for LULC change and climate change studies, with SWAT frequently applied for larger basins (Bucak et al., 2017; Du et al., 2013; J. Kim et al., 2013; Yuri Kim et al., 2017; Schilling et al., 2009; Yin et al., 2017) and RHESSys in small and medium size catchments where greater detail in the spatial pattern of land cover, vegetation, and infrastructure is required (Bart et al., 2016; Hwang et al., 2018; Martin et al., 2017; Shin et al., 2019; Zia et al., 2016). Additionally, RHESSys has been widely applied in simulation of spatially-distributed surface and subsurface runoff, evapotranspiration, carbon and nitrogen cycling, and soil moisture under various land use and climate change scenarios (e.g., Band et al., 1996; Bart et al., 2016; Garcia et al., 2016; Hanan et al., 2017; Hwang et al., 2009, 2018; Lin, 2013; Lin et al., 2015; Martin et al., 2017; Miles & Band, 2015; Tague & Band, 2004b).

Both RHESSys and SWAT were applied in this study to suit the level of development and potential land use management in the Triangle water supply catchments and broader Haw

River basin. SWAT modeling of hydrologic processes is implemented in hydrologic response units (HRUs) that independently contribute to catchment runoff irrespective of position in the landscape as it is spatially lumped at the sub-basin level and does not provide distributed routing (Meng et al., 2018), making SWAT suitable for modeling large basins with spatially well-segregated landscapes (e.g. forested land clearly separated from urban centers and agricultural lands) such as the Haw River basin. RHESSys does not use generalized HRUs (as in SWAT), but parameterizes each patch (typically grid cells, but can be multi-resolution or non-grid meshes) based on local canopy, soil, land use and topographic conditions. SWAT HRUs are formed by intersecting soil and land use type with slope classes, though only one slope class was used here as terrain of Triangle basins is relatively flat.

By contrast, RHESSys is a fully distributed model that simulates surface/subsurface processes and routes water and solutes through each grid cell. This allows representation of routing among interspersed land covers within the terrestrial flow fields, and spatially explicit management options such as stream buffer requirements. RHESSys couples elements of the ecosystem models BIOME-BGC (Running & Hunt, 1993) and CENTURY (Parton et al., 1987), with a distributed watershed model for surface and subsurface lateral flowpaths, with surface and subsurface water flux modified from Wigmosta et al. (1994). Additionally, sub-grid LULC configurations can also be implemented in the RHESSys model, enabling RHESSys to handle mixed and heterogeneous LULC at a fine spatial resolution (e.g. multiple canopy layers, pervious and impervious surfaces, suitable for urban regions). Projected LULC change can be directly incorporated into grid and sub-grid levels within RHESSys, interacting with soil properties, flow paths, and ecosystems.

RHESSys uses a landscape hierarchical structure over nested patch, hillslope and watershed scales, and operates at high resolution, facilitating the direct representation of detailed urban to rural development on hydrologic and ecosystem processes. Eco-hydrologic process components at the patch, hillslope and catchment scales simulate feedbacks and interaction between climate, atmospheric CO2, forest composition and structure, and development form to generate runoff, streamflow, groundwater flow, and evapotranspiration dynamics. As forest conditions are highly variable in space and will vary in time, with forest as the dominant land use, the eco-hydrologic components are considered necessary to estimate future response to climate change. These features are particularly important when projecting urban expansion and management in Durham, Chapel Hill, Cary, and their local catchments containing urban, mixed land uses (Fig. 2.4) that are expanding into forested land. As a result, RHESSys was used for more detailed eco-hydrologic modeling in all catchments for this work, other than the Haw River basin.

More detail on RHESSys and SWAT model development for this study can be found in subsections 2.2.3.2 and 2.2.3.3 and in sub-sections S1 and S2 of Chapter 7, section 2.A. Previous comparisons of SWAT and RHESSys streamflow simulations in the Flat River (one of Durham’s water supply watersheds) over the gauge record (since 1926), showed comparable results, and comparison of projected SWAT and RHESSys streamflow from 2020 – 2060 showed good agreement with the exception of a very wet period around 2040 (Y. Kim et al., 2008).

2.2.3.2 Model calibration and bias correction

Both RHESSys and SWAT models were calibrated and validated at the USGS gaged catchments that are the major tributaries to the reservoirs. Eco-hydrologic models were calibrated using a standard Monte Carlo method and data from 2000-2003 water years, in which 2001 is a dry year and 2002 is a wet year. Calibration was then validated with data from 2007-2009 water years. Peak NSE for gauged water supply watersheds range from .71 to .89 for monthly flow for the calibration period, and 0.58 to 0.88 for monthly flow for the validation period. More details for model calibration statistics are given in Table S2.1. Parameters from best-performing models, with weekly Nash-Sutcliffe Efficiency (NSE) coefficient and weekly log NSE values in the top 10% of calibrations, were used to generate water availability estimates. Due to rapid growth in the Triangle over the historic period, only relatively recent observations were used to calibrate and validate the eco-hydrologic models, carefully selecting calibration and validation periods containing hydrologic dynamics (i.e., both wet and dry years) important for this work.

To capture the lengthy historical record of reservoir inflows, long-period simulations of calibrated RHESSys and SWAT models were additionally performed. Modeled reservoir inflows were compared to empirical estimates of historical reservoir inflows at USGS gage sites in the region from 1930-2011 for bias correction (HydroLogics, 2011; Kirsch et al., 2013). These empirical estimates of unimpaired reservoir inflows were previously adjusted to remove effects of reservoir operations and consumptive withdrawals (i.e., municipal, industrial, agricultural demands) as well as gage location (if a gage is not located immediately upstream of a reservoir, additional inflow is added to account for runoff into the reservoir below the gage) (HydroLogics, 2011). Additional bias correction using these products was done to be consistent with Triangle utilities who make use of this reservoir inflow product for planning purposes and therefore ensure consistent inflow prediction from eco-hydrologic models for input to water supply management modeling; more detail on bias correction and validation is available in Chapter 7.

2.2.3.3 Eco-hydrologic model simulation

To account for uncertainty in eco-hydrologic and LULC modeling, multiple model parameterizations were undertaken to provide multiple realizations of water availability under each hydrologic scenario tested. As described previously, we used six different CMIP5 RCP 6.0 GCMs to project future climate change. For LULC change, we used six (separate) projected sets of 30-m resolution LULC change, three following a higher rate of urban development, three following a slower trajectory (see section 2.A in Chapter 7 for detail). Each of the projected sets contain six LULC states representing decadal change in each of the six decades from 2010-2019 to 2060-2069, as well as three levels of urban canopy projection for the developed areas. Based on model fit during the calibration-validation process, we selected four parameter sets at each gaged catchment that produced the best model predictions on streamflow in calibration-validation period and long historical period for eco-hydrological simulation (Chapter 7, Table S2.1). In all, 24 combinations of model parameter sets, LULC realizations, GCMs and urban canopy levels were selected for simulation (Chapter 7, Table S2.2). Each of the 24 combinations was chosen to capture possible extreme scenarios (i.e., worst scenario approach) such as a dry climate with intense urban development. Multiple inflow timeseries were generated from these selected combinations for each scenario and represent the uncertainty in this multi-step process.

2.2.4 Water availability scenarios

Incorporating climate and LULC trends of specific modeled hydrologic scenarios, RHESSys and SWAT simulations of the Triangle provide bias-corrected estimates of future water availability to 2060 under a range of parameterizations. This study focuses on the outcomes of four distinct future scenarios (Fig. 2.1b): (1) baseline; (2) climate change; (3) land use and landcover change; (4) simultaneous climate and land use-landcover change. Climate trends projections of CMIP5 outputs of temperature and precipitation are applied to observed records for modeled scenarios 2 and 4 to simulate climate change over the Triangle region. For scenarios 1 and 3, where climatic conditions are unchanged from present time, no perturbations were made to observed climate records. Simultaneously, scenarios 3 and 4 assume LULC change across watersheds of the Triangle; scenarios 1 and 2, by contrast, assume future Triangle landcover use patterns remain similar to current conditions. Water availability from each modeled scenario was determined by forcing RHESSys and SWAT eco-hydrologic models, described above, with climate station data projections either with (scenarios 2 and 4) or without (scenarios 1 and 3) a climate change signal, as described in the previous sub-section, along with one of two assumptions about future LULC change (static landscape into the future, scenarios 1 and 2, versus urban growth and forest reductions, scenarios 3 and 4).

It should be noted that the scenario analysis described in this section (2.2.4) is separate from the simulations described as being produced by eco-hydrologic modeling in section 2.2.3. The projections of climate and land use previously developed to drive eco-hydrologic modeling ("multiple model parameterizations" referred to in section 2.2.3.3) are not the same as the hydrologic scenarios defined here. Each scenario, as detailed in the remainder of section 2.2 and results, consists of multiple eco-hydrologic model simulations, each simulation a different parameterization of the eco-hydrologic model under a different CMIP5 and/or LULC trend.

2.2.5 Synthetic hydrology development

Each eco-hydrologic projection of water availability, just as the historic record itself, represents a single realization of stochastic environmental processes. Constrained by computational intensity of eco-hydrologic modeling, evaluation of management decision-making and outcomes under only a handful of eco-hydrologic model simulations cannot effectively locate robust management strategies. However, use of stochastic, or "synthetic" generation of hydrology has been widely applied in the field of water resources management to resolve issues of limited data availability and for evaluation of management strategies (Borgomeo et al., 2015; Hao & Singh, 2016; Herman et al., 2016; Kirsch et al., 2013; Nowak et al., 2010; Quinn et al., 2017). Synthetic generation is especially valuable for questions of system performance, where evaluation under the historical record alone can produce an inaccurate representation of outcomes, even under stationary hydrologic conditions, and over-estimations in the robustness or viability of tested management actions (Loucks & van Beek, 2017; Vogel & Stedinger, 1988).

To capture a more comprehensive range of hydrologic variability, eco-hydrologic model simulations of water availability (reservoir inflows) were statistically sampled to generate thousands of stochastic reservoir inflow timeseries (realizations). Generating synthetic hydrology allows for a more robust identification of effective management strategies, subjecting water supply management decision-making (described in the following section) to a wider array of extreme high and low flow conditions than is possible from eco-hydrologic modeling products alone (Fig. 2.5).

Simulated eco-hydrologic model outputs, each driven using a different GCM and/or LULC parameterization, were statistically re-sampled to generate 1,000 future timeseries of streamflow and lake evaporation for the region over the study period for each scenario. This process ensures that differences in temperature and precipitation projections from selected GCMs, as well as discrepancies in LULC projections, are represented in synthetic hydrology developed for water supply scenario analysis. Eco-hydrologic model parameterizations/simulations were sampled equally within each scenario – if 20 eco-hydrologic simulations were done for the a given scenario, each simulation was re-sampled to create 50 synthetic realizations of regional hydrology based on its specific results, for 1,000 total realizations – which implies that any modeled climate or land use change effect was given equal probability of occurrence.

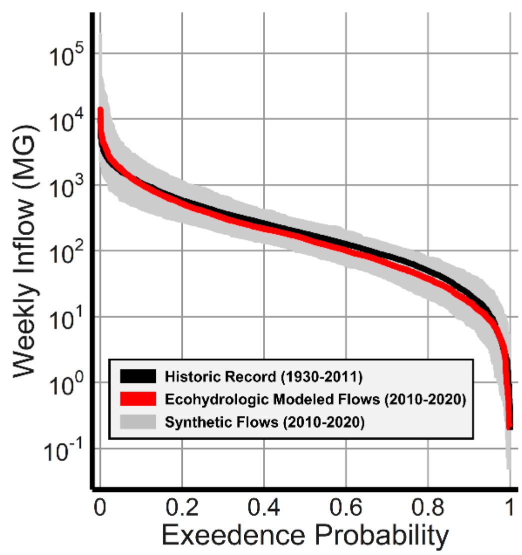

Figure 2.5: Example comparison of historic Durham reservoir inflows from the Little River (black) to eco-hydrologically-modeled (red) and synthetic, stochastic (grey) products. Modeled results from 2010-2020 based on stationary (historic) hydrologic conditions.

Another reason to employ synthetic generation is to evaluate impacts of hydrologic non-stationarity (Herman et al., 2016), such as changes due to climate or LULC change. This work built upon an existing streamflow generator for stationary hydrology (Giuliani et al., 2017; Quinn et al., 2017), sampling from decadally-shifting eco-hydrologic modeling outputs to generate transient reservoir inflow and lake net evaporation records, correlated across multiple Triangle sites, at a monthly time step through Cholesky decomposition (Kirsch et al., 2013), and dis-aggregated using a k-nearest neighbor method (Nowak et al., 2010) to a weekly time step for water supply modeling. Due to the non-stationary nature of eco-hydrologic outputs under climate and land-use change, sampling was done decadally to capture shifting statistical properties of eco-hydrologically simulated records and 10-year synthetic realizations were combined to produce complete stochastic timeseries futures. More detailed description of generator construction and validation can be found in Supplement S3 in Chapter 7. For each hydrologic scenario described in the previous section, one-thousand synthetic futures of inflow and net evaporation from 2010 to 2060, the planning period for regional water utilities, were generated for each regional reservoir.

2.2.6 Water supply management modeling

2.2.6.1 Modeling framework

A comprehensive analysis of water availability and the impact of future hydrologic change on urban water supply is incomplete without consideration of water utility controls on water management. Given eco-hydrologic modeling output of reservoir inflows to three major Triangle utilities – Cary (Jordan Lake), Durham (Little River Reservoir and Lake Michie), and OWASA (Cane Creek Reservoir, University Lake, and Stone Quarry) – this work simulates weekly utility decision-making from 2015 to 2060 (consistent with previous work by Zeff et al. [2016] in the Triangle) under each climate and LULC scenario in order to assess the impact of change on utility performance indicators (outcomes). Monte Carlo model simulations for each evaluation of the water supply model simulate weekly decision-making under 1,000 separate synthetic hydrologic futures (synthetic development described in previous section and Chapter 7).

Current and future regional water demand for each utility are based on projections of population and per-capita water use by TJCOG (2014), while week-to-week modeled demands are determined based on a joint probability density function with reservoir inflows, randomly sampled to perturb weekly demands based on relatively wet or dry hydrologic conditions (Gorelick et al., 2018). Each regional utility's projection of demand growth was developed based on a wide number of factors including population and economic growth expectations, changes to service boundaries, adjustments in per-capita water use across different water use sectors, effects of pricing and price elasticity of demand on water use, among other factors (TJCOG, 2014). Broadly speaking, population growth is expected to occur for all Triangle municipalities while per-capita demands fall with an increase in demand-side efficiency (such as more prevalent low-flow fixtures in households). These two effects result in an overall water demand increase for the region as population growth more than offsets per-capita demand reductions.

Utility decisions to build infrastructure or utilize short-term mitigation strategies are triggered by each utility's perceived risk-of-failure (ROF), quantifying the probability of utility water supply falling below 20% of capacity over the following year, a failure threshold set based on conversations with Triangle utility officials. Risk-of-failure triggers, set as decision variables for each model evaluation, control when infrastructure is constructed, when water transfers occur, and when use restrictions are enacted. The set of ROF triggers and other parameters governing utility decision-making over a model evaluation can be referred to as the development pathway followed by the Triangle utilities. Balancing the use of infrastructure investment and short-term mitigation (conservation, water transfers) within a portfolio of water supply management actions influences tradeoffs across both short- and long-term performance indicators. Short-term mitigation during drought periods can push large structural investments into the future, influencing long-term planning pathways, but represent unexpected variable costs. Infrastructure built in response to infrequent drought events can be a very expensive strategy to address low-frequency supply risk, impacting the magnitude and timing of short-term action as well. Used in tandem as part of dynamic adaptive policy pathways, mixing decisions at different timescales can provide benefits in terms of planning flexibility but carry tradeoffs in terms of system performance.

The initial (historic) state of the water supply management model reflects current regional development conditions in the Triangle, adapted from a regional water management model designed for Triangle water utilities which was validated against historical conditions (HydroLogics, 2011). Further validation of reservoir operations under historic conditions has been done as part of past research in the Triangle (Kirsch et al., 2013); for additional detail on Triangle water supply modeling, implementation of ROF and decision variable specification, see Gorelick et al. (2018) and Zeff et al. (2016).

2.2.6.2 Utility performance metrics

Each evaluation of the regional water supply model simulates utility decisions across one-thousand independent hydrologic realizations under a single set of decision triggers – ROF triggers for water transfers, infrastructure, restriction use, etc. – and calculates performance indicators (outcomes) based on aggregations of utility performance across all 1,000 realizations (timeseries from 2015-2060), described in Equations 1-3 below. Performance indicators of water supply reliability, use restriction frequency, and infrastructure investment are formulated following a risk-averse, “mini-max” approach that determines utility robustness to uncertainty by identifying worst-case outcomes regionally and across time (McPhail et al., 2018); water managers tend to be risk-averse (Mozenter et al., 2018), and mini-max performance objective formulation mirrors such risk preferences. The form and justification of each performance indicator are below.

Reliability of the Triangle f_{Rel} for one model evaluation is represented by the worst-performing utility u, within the set of all regional water utilities U, in terms of annual failure F across each realization r (with $N_r = 1{,}000$ realizations) and simulation year y in the set of years Y (2015-2060, $N_y = 46$ years). A year of any simulation within a model evaluation within which at least one week has total reservoir storage for the utility in question below 20% of capacity is considered to be in failure, and the value of F for that year takes the value 1. Any year without weekly failures takes the value $F = 0$. Utilities have a clear objective to provide reliable water service; minimization of the reliability indicator value represents regional improvement in utility performance (Eq. 1). Any disruption of water service or supply failure carries serious financial penalties for a utility, not to mention the public health and safety concerns with regard to pipe seepage that worsen as system failure persists.

$$\text{Min}\, f_{Rel} = \max_{U}\left[\frac{\max_{Y}\left(\sum_r F_{r,u,y}\right)}{N_r}\right] \qquad (1)$$

Similarly, water utilities hope to minimize restriction use frequency f_{Rest} (Eq. 2); constant imposition of conservation upon customers can be unpopular. Restriction use R is summed across all years and realizations – any year with restrictions gives the value $R = 1$, with $R = 0$ for other years – and the worst-performing utility in terms of conservation frequency represents the regional indicator value. The competing nature of reliability and conservation frequency utility indicators implies a tradeoff in performance, which has been observed by past work in the Triangle (Gorelick et al., 2018; Zeff et al., 2014); with reduced incidence of use restriction, reliability declines (failure rate increases), and vice versa.

$$\text{Min}\, f_{Rest} = \max_{U}\left[\frac{\sum_r \sum_y R_{r,u,y}}{N_r N_y}\right] \quad (2)$$

Conservation programs by a water utility can reduce water use during drought but result in reduced revenues (financial risk), introducing revenue volatility and jeopardize a water utility's financial stability (Jeffrey Hughes & Leurig, 2013). Utilities consistently facing financial hardship also run the risk of credit downgrades; future infrastructure maintenance or expansion then become more expensive as interest rates on bonds increase, in turn leading to increased rates for customers. Similarly, utilities are interested in minimizing the infrastructure investment costs necessary to sustainably meet long-term demand, avoiding the rate increases accompanying a large debt burden. An indicator of regional infrastructure investment f_{Cost} is calculated to measure average realization present-value infrastructure costs across a model evaluation (Eq. 3).

Debt service payments $DS_{r,u,y}$ on infrastructure bonds made in each year y of each realization r for each utility u are discounted in time at a discount rate d of 5% (implying that deferred infrastructure investment, and reduced present-value cost, is preferable in terms of system performance) and summed across time. Calculation of the cost indicator for a model evaluation of discounted debt service payments is done by averaging total discounted debt service of each realization, which is summed across each entire realization rather than each year (whereas the previous two performance metrics rely on annual measures).

$$\text{Min}\, f_{Cost} = \max_{U}\left[\frac{\sum_r \sum_y \frac{DS_{r,u,y}}{(1+d)^{y-1}}}{N_r}\right] \quad (3)$$

Though subtle aspects of our utility performance metrics are region-specific (i.e. the reservoir storage level that designates a storage "failure"), objectives of minimizing water supply failures, mandatory use restriction implementation, and financial risk are all critical and generalizable goals of every water utility.

2.6.3 Infrastructure development pathways

In line with Triangle utility goals of maintaining high reliability and low restriction use frequency two well-behaved solutions – two contrasting water supply model parameter sets, chosen from a Pareto-approximate set of solutions for the Triangle utilities originally optimized by Zeff et al. (2016) – were selected that maintain reliability greater than 96% (failure one year in twenty-five on aggregate) and restriction frequency less than 20% (one-in-five years on average) under baseline (scenario 1) conditions.

The two solutions, or "development pathways," were based on operational designs outlined in planning studies by regional utilities (TJCOG 2014). A development pathway can be thought of as one infrastructure development sequence which, combined with short-term drought mitigation options available to each utility, represents a single parameterization of the water utility decision-making model (one "state of the world"). While a single pathway is constituted of available infrastructure options in a given evaluation of the water supply model, sequencing of infrastructure options in each realization is dynamic. Utilities may trigger infrastructure construction when ROF rises above a pre-defined trigger level; because ROF is recalculated weekly as conditions change, infrastructure investment is adaptive to hydrologic change through its dependence on ROF for implementation.

The development pathways prioritize short-term drought mitigation and infrastructure investment decision-making differently; their contrasting behavior – based on differences in risk tolerance (ROF) triggers – emphasizes the potential short- and long-term management controls on water supply management performance outcomes regionally and for individual utilities. Each of the two pathways was evaluated under all four hydrologic scenarios. Measuring performance with respect to supply reliability, conservation frequency, and infrastructure investment indicators under simulations of high baseline (no climate or LULC change) performance can demonstrate the broad physical and financial influence of hydrologic change on regional water resource management systems, including the ability of hydrologic change to exacerbate tradeoffs across performance indicators relative to baseline conditions.

2.3 Results

The following text and figures describe regional water availability under each of four modeled hydrologic scenarios – (1) future hydrology consistent with present-day climate and land use conditions; (2) climate change in line with IPCC RCP 6.0 projections; (3) LULC change, largely continued urbanization of the region (and forest ecosystem change); (4) combined effects of climate and LULC change – through measures of inflow to Triangle reservoirs as well as utility performance indicators of supply reliability, conservation (use restriction) frequency, and infrastructure cost. Figure 2.6 highlights the differences in streamflow to regional reservoirs under each hydrologic scenario and across time. Figure 2.7 visualizes performance indicators for each Triangle utility and the overall region under all hydrologic scenarios, exploring indicator performance tradeoffs and impacts of infrastructure development across two select development pathways. Figure 2.8 details an example of time-evolving risk and infrastructure decision-making for one regional utility.

2.3.1 Raw water availability

A common water availability metric of use is streamflow, or reservoir inflow. Fig. 2.6 shows 52-week (1-year) moving sum Triangle reservoir inflows for each utility of the study, both before and after 2030. This temporal division at 2030 is useful for this region as more significant development of the contributing water supply watersheds is projected to begin at or after this date, with prior development concentrating in areas that do not drain into the water supply reservoirs considered in this analysis. Inflows to each utility are quantified for drought events of low probability – return periods of 5 years or longer – and differentiated by hydrologic scenario.

The intention of Fig. 2.6 is to visualize how water availability is quantified as a direct output from eco-hydrologic modeling, before any consideration of management.

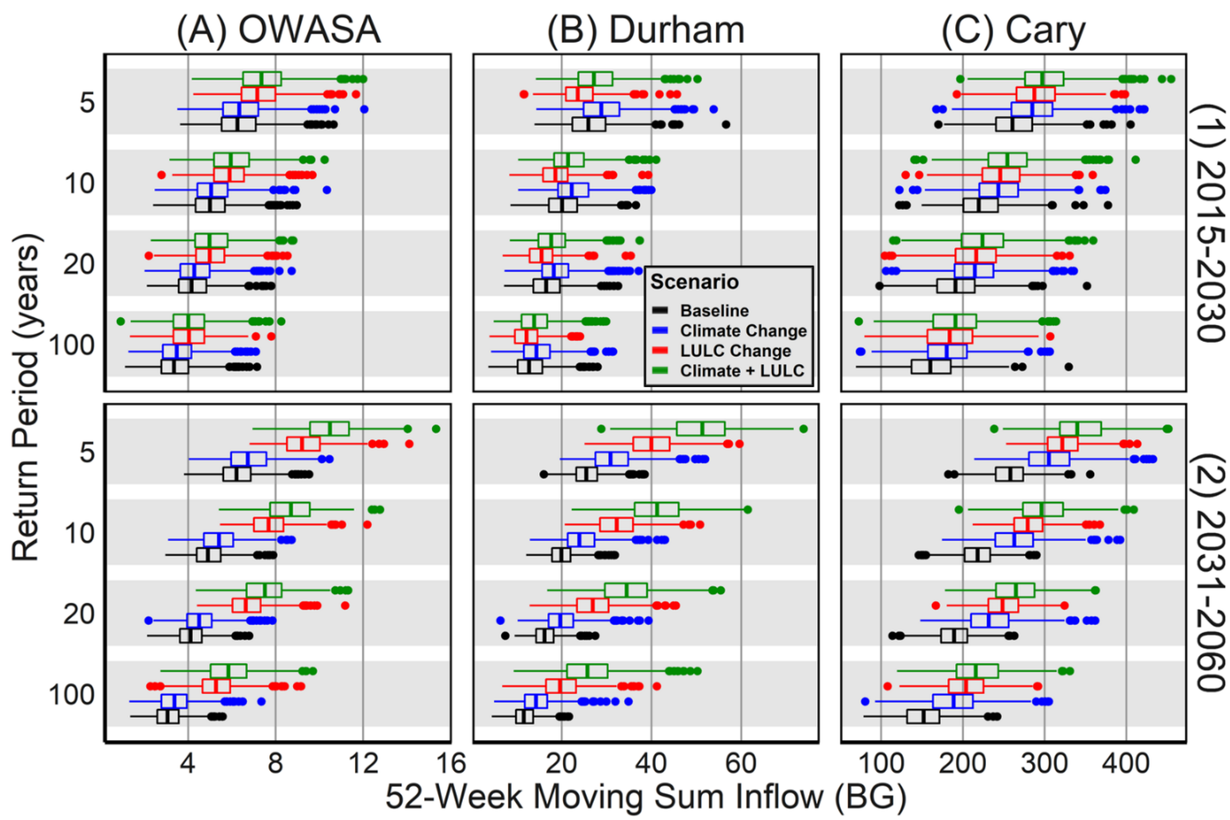

Figure 2.6: 52-week (1-year) moving sum of reservoir inflows for low-flow return periods, given for Triangle utilities (panel columns) before and after 2030 (panel rows) under each hydrologic scenario (colors). Box plot ranges show the distribution of flows for each return period across 1,000 synthetic hydrologic realizations. Both climate (blue) and LULC change (red) increase reservoir inflows and act additively in combination (green). Inflows after 2030 (bottom row of panels) are greater under hydrologic change than before 2030 (top row).

2.3.1.1 Hydrologic change influence on reservoir inflows

Climate (Fig. 2.6, blue) and LULC change (Fig. 2.6, red) result in an increase to water availability during drought across all utilities before and after 2030 with the exception of pre-2030 Durham. The effects of climate and LULC hydrologic change were additive, with largest increases to water availability seen when both effects were modeled in tandem (Fig. 2.6, green). One exception to inflow increases can be seen for Durham under LULC alone before 2030 (Fig. 2.6(B)(1)); flows under LULC change in this case were similar to flows under baseline conditions (Fig. 2.6, black) or slightly reduced on average for low-flow return periods. Durham water supply catchments are more rural, without significant development envisioned before 2030. Variability of inflows, demonstrated by the width of boxplots in Fig. 2.6, tended to increase under hydrologic change relative to baseline conditions. Climate change generally displayed wider variability in inflows than LULC change. The combination of climate and LULC change effects caused the widest ranges in reservoir inflow availability (Fig. 2.6, green). With respect to reservoir inflows, results here indicate that both climate and LULC change could reduce the probability of low-flow, drought events across the Triangle.

2.3.1.2 Differences of inflow across space and time

The impacts of climate and LULC change on drought flow severity varied between utility and between early (pre-2030) and late (2031-2060) time periods. The impacts of hydrologic change manifest more heavily after 2030 (Fig. 2.6(2)) than before (Fig. 2.6(1)). The largest absolute increases to inflows relative to baseline conditions due to either climate or LULC change were seen in Cary (Fig. 2.6I), while largest percentage increases were seen in Durham (Fig. 2.6(B)). Before 2030, climate change increases Durham inflows while LULC change maintains or reduces flows relative to baseline conditions (Fig. 2.6(B)(1)). LULC change increased OWASA inflows to a much larger degree than climate change across both time periods (Fig. 2.6(A)).

2.3.2 Utility operational impacts of hydrologic changes

Measuring utility performance under hydrologic change through reservoir water availability alone does not capture additional factors, such as demand growth or financial risk, controlling management outcomes. Figure 2.7 summarizes utility performance according to indicators of reliability (measured as storage failure frequency; Fig. 2.7, left axis of each panel), restriction use frequency (center axis of each panel), and infrastructure investment (right axis) for each utility (and the total region) under two contrasting development pathways. Each panel of Fig. 2.7 is a separate parallel axis plot; each panel contains multiple lines across all three performance indicators. One line represents an evaluation of the water supply model and its performance for each indicator. To compare the performance of an evaluation against another, observe their relative locations on the plot – if one line crosses a vertical indicator axis at a lower point than another line, the former model evaluation has performed better than the latter based on that indicator (an ideal evaluation of the model would result in a horizontal line across the bottom of the plot).

Eight separate model evaluations (2 development pathways by 4 hydrologic scenarios) are shown in Fig. 2.7; each evaluation's indicator outcomes are given for every utility (Fig. 2.7, rows) and for the region as a whole. Differences between indicator values of separate model evaluations (lines) are absolute changes in indicator value. Reliability indicator values on Fig. 2.7 range from 0% (an ideal level of no failures) to 4% (1-in-25 years experiences storage failure); restriction frequency ranges from 0% (ideal, no restriction use) to 5% (1-in-20 years implemented conservation); infrastructure investment range in Fig. 2.7 ranges from $0 (ideal, no infrastructure spending triggered) to $500 million (discounted total over the 2015-2060 year period). In comparison to Fig. 2.6, Fig. 2.7 is intended to demonstrate by contrast the complex nature of utility vulnerability to hydrologic change when considering performance based on management objectives, rather than reservoir inflow and water availability alone.

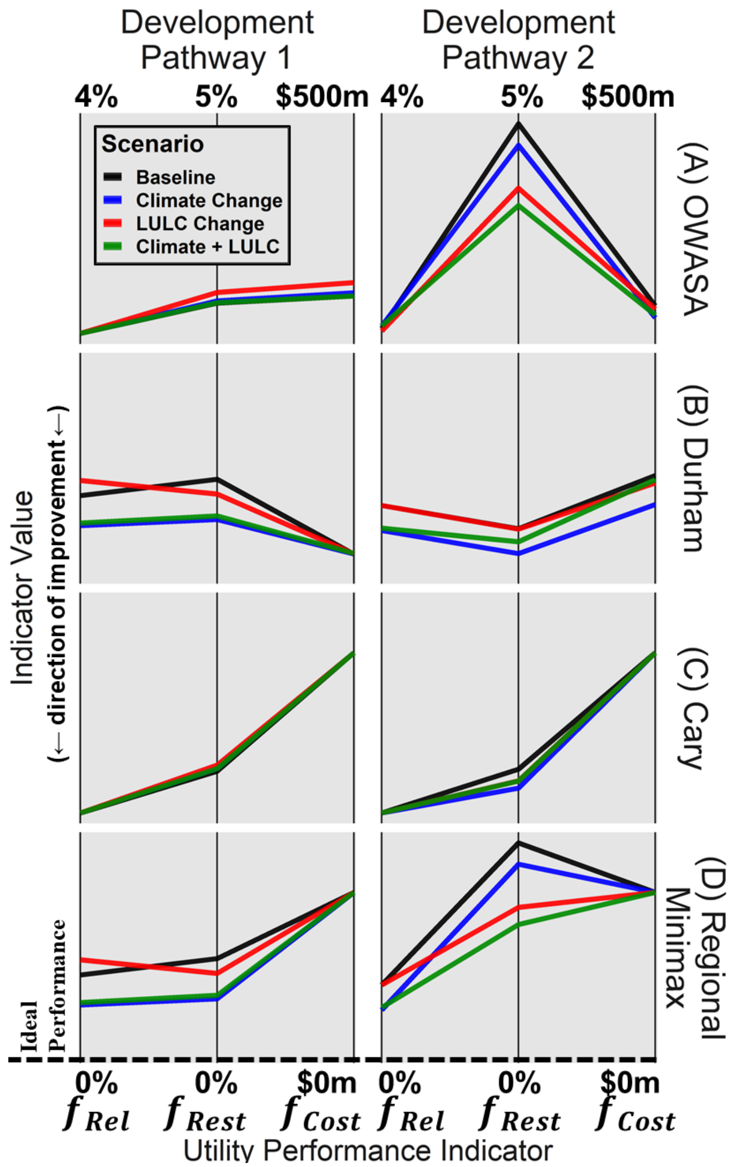

Figure 2.7: Panels of parallel axis plots showing modeled outcomes based on three regional utility performance indicators. Model evaluations under tested hydrologic scenarios (colors) are given for each regional utility and the overall region (rows) for two contrasting development pathways (columns). Each line represents one model evaluation's performance across each indicator.

2.3.2.1 Comparing reservoir inflow and utility performance indicators

While reservoir inflows increase regionally as a result of climate and/or LULC change, the effect of hydrologic change on utility performance indicators was not as direct. In some cases, trends of increased reservoir inflows seen in Fig. 2.6 under each hydrologic scenario were reflected in management indicators – OWASA restriction frequency under development pathway 2 (Fig. 2.7(A)(2), center axis) is an example of this. In other cases, inflow increases did not result in improved management outcomes; Durham reliability under development pathway 1 degraded under LULC change relative to baseline conditions (Fig. 2.7(B)(1), left axis, red). In other cases, hydrologic change had marginal influence on management objectives – Cary experienced little change in indicator value due to hydrologic change, and infrastructure investment indicators across all utilities were relatively inelastic to hydrologic change. Climate change was generally more influential than LULC change in improving indicator values relative to baseline (Fig. 2.7(D)(1)) despite often contributing less reservoir inflow (Fig. 2.6), though the opposite was true in some cases (Fig. 2.7(A)(2)).

2.3.2.2 Differences between utility outcomes

Indicator performance varied widely between utilities. OWASA and Cary, already with very reliable performance levels under baseline conditions, did not see substantial improvement in reliability due to hydrologic change (Fig. 2.7(A and C), left axes). Durham, on the other hand, consistently saw reliability improvement as a result of climate change, but not LULC change (Fig. 2.7(B)). Infrastructure investment indicator values for Cary were unaffected by hydrologic change; Cary expands water treatment capacity based on demand growth targets that occur soon after 2015, which hydrologic change does not impact. Durham saw varied impact of hydrologic change on infrastructure investment, which was also dependent on the development pathway (more detail in next sub-section). Climate change and combined climate and LULC change impacts infrastructure investment improvement for OWASA more-so than LULC change, as they were for restriction use frequency in Durham.

2.3.2.3 Differences between development pathway outcomes

How utility performance indicators responded to hydrologic change was also dependent on the development pathway followed. Under pathway 1 (Fig. 2.7, left panels), infrastructure development opportunities are more extensive for OWASA but restricted for Durham – the opposite is true for those utilities in pathway 2 (Fig. 2.7, right panels). Pathway 1 prioritizes the option for Durham and OWASA to jointly develop water withdrawal and treatment infrastructure on Jordan Lake, followed by additional, independent options such as implementation of reclaimed water reuse for Durham or University Lake expansion for OWASA. Under pathway 2, Jordan Lake development is still prioritized, though OWASA is now allotted a larger treatment (and financing) allocation in the Jordan Lake development than allocated in pathway 1, and the opposite is true for Durham. In both pathways, Cary has the singular option to expand its Jordan Lake water treatment plant. Both prioritization order and permitting period, the number of years from 2015 that must elapse before a project can be built, factored into the relative availability and implementation of infrastructure in either pathways 1 or 2. A full list of potential infrastructure development options and their implementation constraints for Triangle utilities is provided in Table 1 of Zeff et al. (2016).

Risk tolerance levels (ROF trigger levels for infrastructure development and restriction use) also differed between pathways. OWASA's short-term risk tolerance in pathway 1 is much greater (ROF trigger for restriction use is higher) than in pathway 2, leading to a more substantial influence of hydrologic changes on the restriction use indicator in pathway 2 (with a low ROF trigger level, restriction use is more frequent and sensitive to mild or moderate droughts). Under pathway 1, LULC change also results in a degradation in Durham reliability relative to baseline conditions, while pathway 2 showed no reduction in reliability due to LULC change (Fig. 2.7(B), red, left axis). Because the development pathways shown here represent two different sets of decision-making "rules" for utilities, our results demonstrate that utility actions can influence management outcomes and provide considerably control over hydrologic change impacts on water resource systems.

When more infrastructure development options were available, more variability in the infrastructure investment indicator also occurred. In pathway 1, hydrologic change did not impact infrastructure investment indicator levels for Durham, while they are affected in pathway 2 (Fig. 2.7(B)(2)), especially by climate change. LULC change increased infrastructure investment relative to baseline for OWASA under pathway 1 (Fig. 2.7(A)(1), red), but led to a slight reduction in investment under pathway 2.

2.3.3 Durham hydrologic change impacts

To explore the mechanisms driving utility performance outcomes under hydrologic change, we present detailed results for Durham under both tested development pathways in Fig. 2.8. The four panels of Fig. 2.8(a) show weekly storage failure frequency histograms for Durham reservoirs across 1,000 hydrologic realizations tested under each hydrologic scenario. These results are given for both development pathways (panel columns) before and after 2030 (panel rows). The two panels of Fig. 2.8(b) give timeseries examples of two realizations of weekly

Durham reservoir storage from 2015-2060 under either climate (left panel) or LULC (right panel) change and following both development pathways (line type). While Figures 2.6 and 2.7 visualize simulation-scale vulnerability at a regional level, Fig. 2.8 provides realization-level details to reveal the interplay between individual realizations of hydrologic change and their impact on water availability when infrastructure and management are considered.

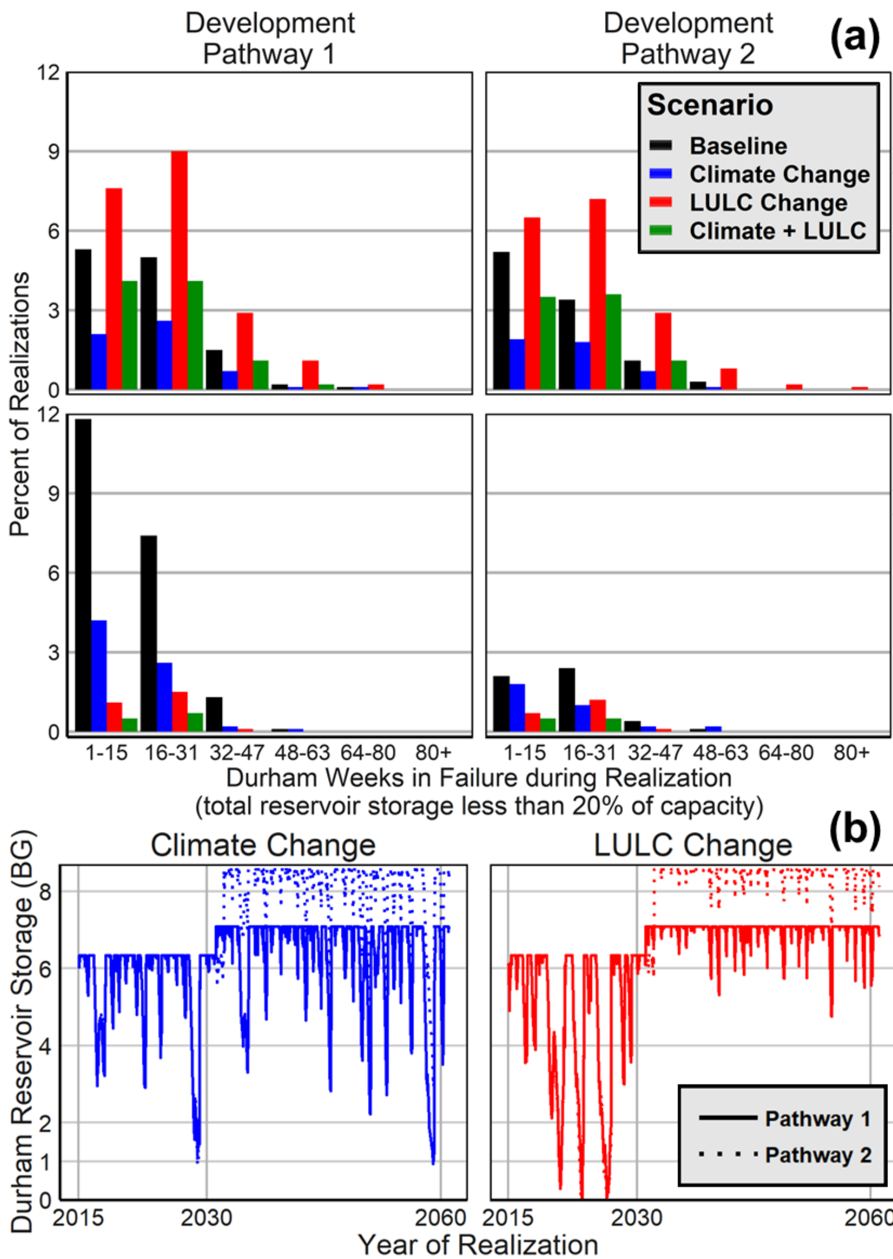

Figure 2.8: (a) Histograms of Durham weekly storage failure frequency across 1,000 synthetic hydrologic realizations, differentiated by hydrologic scenario (color), development pathway (column), and time period (row). Each panel shows the percent of all realizations that see a given range of storage failure. (b) Timeseries examples of Durham reservoir storage for a single realization under climate (left panel) and LULC (right panel) change for each of the two development pathways modeled (line type). Discontinuity around 2032-2033 due to infrastructure development.

2.3.3.1 Storage failure frequency under baseline conditions

Durham storage failure frequency in each realization, used to calculate the reliability performance indicator as shown in Equation 1, is distributed unevenly in time and differs between development pathways for each hydrologic scenario. Under baseline conditions (Fig. 8(a), black), failure frequency is relatively consistent across development pathways before 2030 (Fig. 2.8(a)(A), black). After 2030, baseline failures are much more common under development pathway 1 than pathway 2 (Fig. 2.8(a)(B), black). This difference in frequency is primarily caused by infrastructure development availability – Durham has limited ability to expand infrastructure to meet growing demands in pathway 1, leading to increased storage failure relative to pathway 2.

2.3.3.2 Failure frequency under hydrologic change

The same behavior of failure frequency exhibited under baseline conditions is also observed under the climate change scenario to a lesser degree (Fig. 2.8(a), blue). Failure frequency for Durham under the LULC change scenario is greater than baseline conditions before 2030 (Fig. 2.8(a)(A), red compared to black), and failures with combined LULC and climate change are greater than those under just climate change before 2030 (Fig. 2.8(a)(A), green compared to blue). This behavior as a result of LULC change is linked to trends in reservoir inflows to Durham before 2030 (Fig. 2.6(a)(B)(1), red). Drought event flows under LULC change were found to be approximately equal to, or slightly lower than, baseline flows on average, while also exhibiting extreme values beyond those observed under baseline conditions for some return periods. The change to extreme flow event frequency, as well as small changes in average drought flows, had heavy influence on failure rates for Durham under LULC change before 2030. After 2030, however, hydrologic scenarios with LULC change (Fig. 2.8(a)(B), red and green histograms) show failure rates lower than those observed under baseline or climate change conditions for both development pathways.

2.3.3.3 Influence of short-term drought mitigation

Both short and long-term utility decision-making, as well as hydrologic change, had influence over Durham's susceptibility to storage failure. Based on regional infrastructure planning, Durham has limited ability to expand storage or treatment capacity infrastructure until at least 2030 in either development pathway. As a result, differences in failure frequency between pathways before 2030 (Fig. 2.8(a)(A)) are primarily due to hydrologic change and short-term drought mitigation actions (i.e. use restrictions) only. Short-term mitigation is carried out when risk-of-failure levels for Durham reach a fixed trigger level, which is higher (less risk averse) for development pathway 1 than for pathway 2 (higher risk aversion). Because of differences in utility decision-making related to drought mitigation, failure frequency for Durham before 2030 is reduced under pathway 2 (Fig. 2.8(a)(A)(2)) more than under pathway 1 (Fig. 2.8(a)(A)(1)) for all hydrologic scenarios. Mitigation is also more effective at reducing failure rate in baseline (black) and LULC change (red) scenarios before 2030 in Durham, as neither scenario sees increases to reservoir inflows in this time period relative to scenarios under climate change.

2.3.3.4 Relative influences of infrastructure investment and hydrologic change

After 2027, infrastructure development is available for Durham (Fig. 2.8(b)), greatly reducing the frequency of storage failure after 2030 in most cases (Fig. 2.8(a)(B)). However, under development pathway 1, baseline and climate change scenarios see either a continuation or increase of failure frequency after 2030 relative to before 2030 (Fig. 2.8(a)(1), blue and black). At the same time, both hydrologic scenarios including LULC change (Fig. 2.8(a)(1), red and green) see substantial reductions in failure frequency after 2030 in pathway 1. These different outcomes are a result of two concurrent causes: (1) urbanization in the Durham reservoir catchments that ramps up after 2030, and (2) expansion of water supply infrastructure. Under baseline and climate change only scenarios, no LULC change resulting from urbanization occurs to further increase water availability to reservoirs after 2030. With LULC change effects, the remaining two hydrologic scenarios utilize excess urban (and exburban) runoff to reduce storage failure frequency from 2030-2060.

The level to which infrastructure is expanded can be as consequential as hydrologic change. Under baseline and climate change conditions, development pathway 1 is less effective than pathway 2 at reducing storage failure frequency (Fig. 2.8(a)(B), black and blue). Without additional reservoir inflow from LULC change, the major differences in failure frequency are due to the differing degrees of infrastructure expansion. An example of this behavior is given for one realization of Durham reservoir storage under the climate change scenario for both development pathways (Fig. 2.8(b), left panel). Development pathway 2 (Fig. 2.8(b), dotted line) sees Durham opt to expand reservoir capacity after 2030 to a greater degree than pathway 1 (Fig. 2.8(b), solid line). Because climate change does not increase reservoir inflows as substantially as LULC change, demand growth outpaces long-run water availability increases due to climate change. The additional reservoir capacity available in pathway 2 insulates Durham from storage failures that pathway 1 experiences (Fig. 2.8(b), left panel – difference between solid and dotted lines of 2058 drought event). The same drop in failure frequency due to additional storage capacity in pathway 2 is also observed for baseline hydrologic conditions.

2.3.3.5 LULC urbanization timing effects on failure frequency

Timing of urbanization in Durham catchments has a different impact on failure frequency. Between development pathways 1 and 2, Durham failure frequency is effectively unchanged after 2030 if LULC change occurs (Fig. 2.8(a)(B), red and green) despite differences in infrastructure investment noted in the previous paragraph. Urbanization begins to drive reservoir inflow increases after 2030 when additional development occurs in Durham catchments, a later shift than seen in Cary or OWASA. This additional inflow provides Durham enough water (relative to baseline conditions) to offset future demand growth. However, the abrupt change to LULC combined with a reliance on risk-of-failure (calculated based on a moving window of past hydrologic conditions) to trigger infrastructure development means that Durham is slow to adapt to this hydrologic regime shift. As a result, no matter to what degree water supply infrastructure is expanded after 2030, LULC change drives late-term reduction in failure frequency (Fig. 2.8(b), right panel). While baseline and climate change scenarios depend on more infrastructure investment to reduce supply failure, LULC change improves supply reliability irrespective of the level of infrastructure expansion.

2.4 Discussion

To understand the effects hydrologic change may have on the Triangle regional system, as well as how management decision-making can influence outcomes under hydrologic change, a number of factors must be considered: (1) hydroclimatic factors driving changes to regional water availability; (2) the impact of hydroclimatic changes on reservoir inflows and utility performance; (3) influence of utility decisions on performance indicators and their interactions with hydrologic change.

2.4.1 Eco-hydrologic drivers of water availability

Changes to streamflow as a result of climate or LULC change manifest differently across seasons. For ease of comprehension, we detail the causes of inflow changes for the growing season (May – October) and the dormant season when most reservoir recharge occurs (November – April). In the Triangle, where reservoirs are sized anticipating that they will refill annually, utility managers expect reservoirs to be full or near full at the end of April. The following six months, the growing season, experience the bulk of outdoor water use and increased evapotranspiration not present in colder months, and reservoir volumes are generally reduced.

Under climate change, an increase in precipitation during the dormant season relative to baseline (hydrologically stationary) conditions results in increased reservoir recharge. During the growing season increase in flows is not as evident, possibly due to increased summer and fall temperatures that extend the growth period for vegetation, increasing evapotranspiration (ET) in early spring and late fall. Under LULC change, runoff increases over urbanizing areas in the Triangle (area surrounding Jordan Lake, including Durham catchments) but does so to a smaller degree over the larger Haw River Basin that is projected to remain heavily forested (Fig. 2.6I, difference before and after 2030). Where forest land cover is converted to urban developed area, leaf area index is reduced and runoff significantly increases due to a drop in ET. The magnitude of this effect is dependent upon the type of urban development; whether development is dense (sprawling) or more (less) intensive, which varied between LULC projections, can influence the effect of urbanization on reservoir inflow. In this work, LULC change through urbanization increases runoff through a decrease in ET and increased impervious surface, while climate change increases runoff through increased precipitation in the Triangle.

Climate change generally resulted in wider variability in reservoir inflows than did LULC change. This may partially be due to development in the Triangle being, and expected to continue being, dominated by relatively low density forms of urbanization with significant remaining forest and open development (low impervious area). This development increases groundwater recharge, increasing base flows, while limiting increases in stormflow compared to dense development. The areas projected to have increasing dense development are largely outside the contributing watershed areas for the Triangle. Therefore, the impacts of urbanization in the Triangle are somewhat mitigated compared to climate change based on the form of development largely anticipated. Of course, results are sensitive to the projected land use changes based on rates and types of development.

Though climate change may be a strong driver of change to streamflows, climate effects and LULC effects are not necessarily additive in terms of their joint effects on water availability (i.e. Figure 2.6 distributions). In our study region, runoff generation is primarily controlled by precipitation, water consumption by forest (i.e., evapotranspiration), and the type of urban development that occurs. Most of the denser new development in the Triangle is outside of the drainage areas to the regional reservoirs, and small amounts of LULC change in Triangle catchments are dominated by the simulated effects of climate change and in places can offset climate change effects. However, should deforestation (i.e., LULC change) become more prevalent, as is expected after 2030, LULC change can have strong effects on return flows, yielding streamflow signals that are different than those from climate change as evapotranspiration patterns change. Climate change widens the variation of return flows, but LULC change increases flow while also decreasing its variation. When both effects occur in tandem our results indicate an increase in overall flow with wider variation, but not in a linear additive sense. This nonlinear behavior can be strongly influenced by specific types of LULC development that, in cases, offset some effects of climate change. As an example, increased growing season length and temperature due to climate change can increase annual ET, but be offset by impervious surface runoff and increased soil and groundwater recharge in open areas, supporting higher baseflows.

It should be noted that while modeling baselines for eco-hydrologic studies are typically given as 30-year periods, our baseline was limited to 2000-2010. Land use has changed dramatically over the most recent 30-year period, with population doubling and the development of two regional water supply reservoirs. Therefore, baseline streamflow conditions over a longer period would introduce strong non-stationarity. The 2000-2010 decade included a range of very wet to very dry conditions (with the wettest and driest years in decades) but was not (at the decadal level) unusually wet or dry. There has been a progressive warming in the region over the past three decades, consistent with most other global regions. It was not our purpose to establish 2000-2010 as a long-term historic mean, as climate, land use, and streamflow regimes have been changing. We note that a thirty year mean temperature and level of urbanization would be biased low compared to current conditions. Given our use of a delta method for downscaling, it is crucial that we capture as complete a picture of historical variability as possible. At the same time, our hybrid approach using eco-hydrologic models in combination with synthetic streamflow generation is also valuable as a means of capturing the internal variability of the hydrologic system.

Land use in the Triangle has been rapidly changing with the expansion of low to medium density urban areas, and some densification of city centers. Water quality of reservoirs receiving urban runoff is of high interest, and the extent of stormwater controls is under intense debate. We did not explicitly incorporate stormwater management facilities in the simulations of urban areas, but most of this implementation was in the form of detention storage during this period, and was not designed for flow volume reduction at weekly to monthly time steps. Our eco-hydrologic modeling was evaluated with weekly to monthly flow levels, consistent with the water resources model resolution. Finer temporal scale evaluation (e.g. hourly, daily) would be limited by both available precipitation records for some of our water supply watersheds, and are less relevant for water supply evaluation. However, further incorporation of flood potential and water quality trends based on hydroclimate and land use development would require finer temporal and spatial model resolution. An additional reason for using RHESSys for urban area flow modeling is the ability to scale the simulations to much finer resolutions to resolve individual stormwater control features and the increasing set of green infrastructure and urban canopy in the area (e.g. Miles and Band, 2015) which requires detailed ecohydrological process representation. This links the analysis of full watershed runoff and reservoir recharge to methods to evaluate scenario risk management approaches to both water quantity and quality mitigation, which is the subject of follow-on research.

2.4.2 Hydrologic impacts on utility performance

Generally, when more water was available to reservoirs through hydrologic change, reliability improves and restriction usage falls. However, indicator performance varied widely between utilities. Drawing water from the largest reservoir in the Triangle, Jordan Lake, Cary indicator performance was relatively unaffected by hydrologic change or shifts in reservoir inflows (Fig. 2.7I). With moderate demand growth expected over the 45-year modeling period and ample water storage and treatment capacity under baseline conditions, increases in water availability were inconsequential to Cary. Durham and OWASA, by contrast, showed wider ranges of performance outcomes due to hydrologic change (Fig. 2.7(A and B)). Interestingly, LULC change alone (red) led to cases of worse indicator performance for both Durham and OWASA than model evaluations with climate change (blue and green) despite being an overall larger hydrologic contributor to increased water availability. For Durham, performance outcomes were degraded by LULC change scenarios because substantial increases in runoff due to LULC change in the water supply drainage areas do not accelerate until 2030 (Fig. 2.6(B)).

Similarly, OWASA saw performance indicators negatively impacted by LULC change, but to a lesser degree than Durham (Fig. 2.7(A)(1)). OWASA indicator degradation relative to baseline results was also primarily driven by early-term water availability (Fig. 2.6(A)(1)); OWASA's baseline indicators of restriction use and infrastructure investment under development pathway 1 were already well-performing (Fig. 2.7(A)(1), black), and small changes to reservoir inflow persistence from LULC change without substantial increase in drought flows during 2015-2030 drove slight increases in restriction use frequency and heightened risk-of-failure, driving small increases to infrastructure investment (Fig. 2.7(A)(1), red). An increase in impervious surface cover as a result of LULC change can lead to increased "flashiness" of runoff from lands that are highly impervious; larger amounts of runoff are likely immediately following precipitation events, but these events are followed by periods of reduced runoff. Large events may also not be completely retained as reservoir storage if inflows are too great over a short period of time and must be spilled out of the reservoir. Reduced consistency of base flow into reservoirs can exacerbate drought, resulting in lower rates of reliability even compared to baseline conditions in some cases.

The perceived impact of droughts to utilities is also dependent upon what metrics utilities judge their performance by. Reliability and use restriction frequency were relatively sensitive metrics to hydrologic change in this work, while infrastructure investment was not. Infrastructure investment is triggered not only based on risk-of-failure (like use restrictions) but also by the availability of infrastructure options to be built, limiting its range of outcomes. That being said, investment is a useful indicator of utility performance as a proxy for long-term financial health, something not provided by indicators of reservoir inflows or reliability.

2.4.3 Influence of utility decision-making on performance outcomes

A primary takeaway from our results is that changes to utility development pathways – decisions made by utilities regarding when to implement water transfers, use restrictions, and expand infrastructure – can influence performance outcomes and either mute or amplify the effects of hydrologic change on management outcomes for utilities. Both the type (climate vs. LULC) and timing (before or after 2030) of hydrologic change caused different interactions with utility decision-making and drought mitigation, leading to a range of performance outcomes for Triangle utilities that were heavily dependent on the risk preferences and infrastructure availability of the development pathway modeled. Infrastructure expansion after 2030, specifically, was found to strongly influence the reaction of performance outcomes to hydrologic change. Where storage capacity could be expanded sufficiently, the rate of storage failures dropped. In other cases large infrastructure expansion was unnecessary, as increased runoff due to urbanization ensured growing demands could be offset in the long-term. The degree to which infrastructure expansion was available, as well as what type of hydrologic change was occurring, impacted management outcomes.

One consideration to note is that development pathways applied in this study were previously identified through modeling under stationary hydrologic conditions (Zeff et al., 2016). This is consistent with regional planning where future infrastructure sequences were developed based primarily on projections of demand growth and limited consideration of changes to hydrologic conditions. Reliance on infrastructure sequencing developed a priori without consideration of hydrologic change runs the risk of over-investment and increased financial burden on local utilities (and their customers) should water availability increase, as well as under-investment and supply provision risk should water availability be reduced more than expected.

What is clear is that the common practice of evaluating future water availability alone neglects or overly simplifies the operational abilities of humans to mitigate water scarcity. However, because this study focuses on a region projected to become wetter in the future rather than drier, the value of including utility water supply management operations is not immediately obvious. When more water is available, outcomes measured both in terms of water availability or utility performance indicators tend to improve, leading to the potential conclusion that the additional step of accounting for utility decision-making is unnecessary. This is not the case – without an evaluation of utility supply and financial reliability under different hydrologic conditions, important operational factors are overlooked. There is clear need for more explicit representation of water management systems in future analyses of water availability, especially in regions not expected to become wetter. Due to the ability of water managers and utilities to effectively mitigate periods of water scarcity, studies of water availability should more rigorously consider management systems if they mean to accurately assess vulnerability to future hydrologic changes.

2.4.4 Additional considerations

While shifts in hydrologic patterns caused by climate or LULC effects appear likely to increase reservoir inflows regionally, they may also introduce new risks such as flooding from impervious surfaces, increased groundwater levels, and greater stormwater pollutant loading of water supply reservoirs. Though not a focus of our analysis – the water supply modeling framework presented here is meant to assess supply and financial risks that result due to water scarcity and drought – increases in flooding events would likely have ecological consequences as well. Increased flash flooding could increase nutrient loading into surface waterways and water supply reservoirs, degrading drinking water quality, which is an issue of current major concern and debate in the Triangle.

With respect to this analysis of water scarcity, however, the impact of flooding is muted in surface water dependent systems of reservoirs like those in the Triangle that cannot hold more water than their capacity allows. From a water supply modeling standpoint, and the standpoint of concerns over water scarcity, whether a reservoir receives enough inflow to fill to its capacity or a much greater volume of inflow, with most of it passing immediately downstream via spill structures, is largely irrelevant as both provide for the same volume of available water supply.

That said, high-flow flooding events and stormwater pollution in reservoirs like Jordan Lake, which is operated by the US Army Corps of Engineers to manage water quality and flooding along with water supply, are areas of concern for future work in water resources management.

An increase in water availability does not automatically alleviate all regional worries of future water scarcity under hydrologic change. Both climate and LULC change may affect the variability of water availability, changing the frequency of both drought and flooding as well as the persistence of wet and dry conditions. One week of heavy rain followed by four weeks of dry weather may produce the same amount of reservoir inflow as five weeks of steady, less extreme precipitation, but a "flashy" hydrologic regime would create difficult operating conditions for a utility trying to balance flood risk and water supply reliability when holding or releasing inflows.

Extrapolating results from this study to other locations should also be done with caution, as the geographic, hydrologic, and institutional conditions of the Triangle are not the same across the US or globe. As well, despite results suggesting the region will become wetter as a result of climate change, significant uncertainty remains about whether that will actually occur (IPCC, 2014b; Program, 2017). The six GCM projections used in our study represent a broad perspective on the potential impacts of climate change in the Triangle region, but their disagreement on outcomes for this region of the Southeastern US demonstrate non-negligible uncertainty regarding future climate conditions. We chose RCP 6.0 to be consistent with land-use/landcover projections of county level population, housing, employment, forest product demand and forest change of previous regional studies and to evaluate climate change vulnerability along a "moderate" trajectory. The choices of our six representative GCMs were made due to their collective spanning of the wide precipitation and temperature CMIP5 projections in the Research Triangle, as well as the differences in seasonal change trajectories relative to each other. Together, those two factors provided a diverse set of GCMs, showcasing a range of potential climate futures.

At the same time, generating thousands of hydrologic scenarios was done in part to address an overall shortcoming of all downscaled GCM analyses in underrepresenting drought extremes and the innate hydro-climatic variability where the calibration process focuses on a limited record of observed streamflows that are not a strong representation of extreme quantiles (i.e., drought flows). Because this work focused on the demonstration of our modeling framework and consistency between modeling components, our focus was not on expanding the range of RCP scenarios included, though this process should be used for future work. Although RCP 6.0 is a somewhat moderate scenario, our results highlight significant changes in how drought extremes will evolve.

We have also quantified an additive effect between climate and LULC change in terms of water availability – future scenarios with either effect isolated showed increased reservoir inflows relative to baseline conditions, and both effects together further increased water availability. However, the same positive interaction between LULC and climate change may not materialize in other regions. In the Triangle, land use trends toward urbanization and general climate trends toward warming and increased rainfall were complementary in terms of water availability, but in other places like the Southwest US will see decreased rainfall as a result of climate change. We emphasize that results of combined modeling are not necessarily generalizable, but the methods are, considering the incorporation of best available regional LULC and climate change projections.

Furthermore, while the intricacies of results from this work tend to be region-specific, it would be difficult to demonstrate the value of the analysis framework without considering regional decision-making and its impact in the case at hand; where past work has omitted the impact of actions by management actors in an effort to provide generalizability, it has often overlooked the importance of these small factors that can noticeably affect the regional vulnerability under a given future scenario. We note that this includes both utility decision making, and local forms of urbanization. This does, in some ways, impact generalizability, but inclusion of these considerations also makes the important point that they can be critical, even if a bit "messy". This work serves to introduce a comprehensive framework for assessing water supply vulnerability and provide an example of the integration of global scale products downscaled and used in specific decision making context. Applying this under different climates and development trajectories will be the goal of future work.

2.5 Conclusions

This study demonstrates an extensive effort to integrate important factors – including climate and land use change effects, as well as utility management and infrastructure planning, on water supply availability – which have typically been considered in isolation for their effects on water supply management. This connectivity allows for previously overlooked insights for governing a region's ability to provide water where and when it is needed. In the Triangle region, landcover and climate change are both likely to increase water supply availability, however improvements as a result are non-uniform across management system performance indicators, highlighting the need for consideration of financial and management-based interests in evaluation of vulnerability to hydrologic change. Furthermore, utility decision-making can hold notable influence over the impact of hydrologic change through both short-term (e.g. conservation use) and longer-term (infrastructure investment) actions, in some cases even countering the beneficial effects of additional water supply. The effectiveness of infrastructure development to mitigate water scarcity is also strongly sensitive to climate and land-use change influences as well as the timing and sequencing of infrastructure planning. As a result, this work underscores the need to consider adaptive management system responses and decision-relevant performance measures when assessing the impacts of hydrologic change on water availability.

CHAPTER 3 : EXPLORING TREATMENT AND CAPACITY-SHARING AGREEMENTS BETWEEN WATER UTILITIES[2]

3.1 Introduction

Water utilities have the unenviable task of having to predict the future. Utilities are responsible for meeting future water demands of their customers in an environment rich with uncertainty that includes changing population, per-capita use, and economic growth all of which impact future demands. In communities with positive growth, keeping up with demand often requires infrastructure investment years or decades before future use projections materialize, resulting in large amounts of spare capacity paid for but unused in the interim.

One way utilities can manage and share the financial risk of a large capital commitment before expected demands materialize is to partner with adjacent utilities through the creation of regional utilities or cooperative agreements offering a means of sharing infrastructure costs by sharing project capacity (EFC 2009, Tran et al. 2019). Given the need to rely on long-term demand projections when planning structural expansions, however, capacity sharing approaches and agreements can also be a source of financial and supply risk if future demands diverge from predictions. Questions of facility management can further complicate matters. Are agreement partners co-owners of a facility? Does only one manage day-to-day operations? Was a regional authority created to serve all parties? These and others concerns can potentially strain the willingness for agreement partners to amiably cooperate. To underline the importance of

[2] This work has been published: Gorelick, D. E., Zeff, H. B., Hughes, J., Eskaf, S., & Characklis, G. W. (2019). *Journal-American Water Works Association*, 111(9), 26-40.

understanding risks within capacity sharing agreements, we quantify the risks of cooperative agreements under a range of future demand scenarios, using a test case in the Research Triangle of North Carolina, to better inform utilities considering such agreements.

Implementing capacity sharing agreements. The approach for sharing capacity is often made possible through state law in the United States allowing a diverse range of customized water provider models (i.e. authorities, joint management agencies), cooperative contracts, financial policies, or interlocal agreements. A combination of provider models, policies and agreements can be used to structure numerous capacity sharing approaches. Due to the range of natural, regulatory, and institutional environments across the US, it is impossible to detail in this work the complete scope of capacity sharing agreements available to partnering utilities. Based on our observations of some of the most common elements of capacity sharing agreement structures place across the US (Fig. 3.1), this paper weighs the relative merits of each by identifying sources of risk inherent in each contract structure.

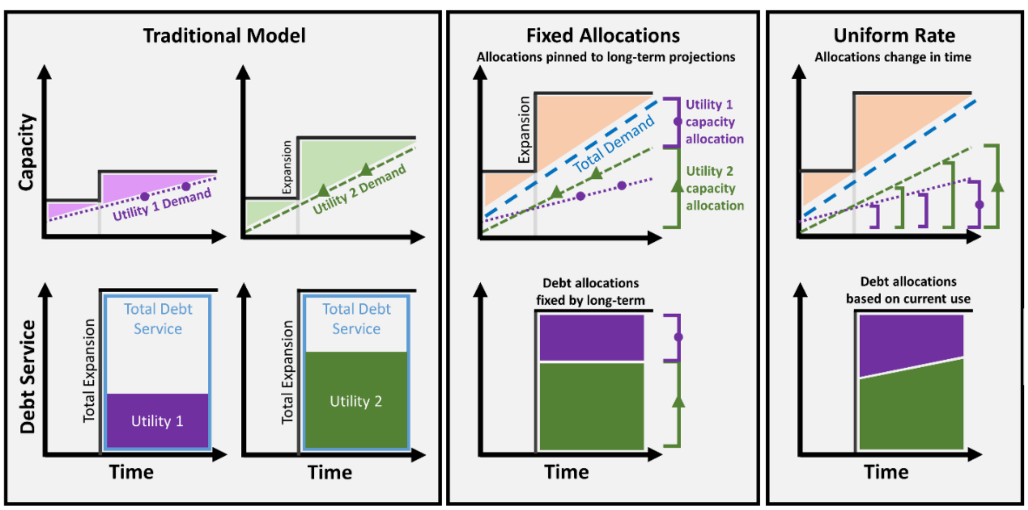

Figure 3.1: Schematic of capacity-sharing agreements, comparing a traditional, no-cooperation infrastructure development model with two cooperative agreement types. Third-party agreements (not pictured) can be added to reduce excess capacity (top row, shaded) when available through sales to additional partners, lowering debt service obligations proportionately (bottom row).

Fully reserved fixed capacity allocations. One way to understand differences between capacity sharing agreements is in the context of different approaches to paying for unused project capacity. Traditionally, without any sort of inter-utility cooperation, a water utility anticipating future growth would invest in additional system infrastructure, paying debt service on the entire project even though most of its capacity remains unused as demands grow (Fig. 3.1, left panel). There are many examples of this type of situation, where utilities plan and acquire the water or wastewater capacity they need on their own without any type of partnership. However, in many situations going it alone is infeasible financially (paying for capacity that goes unused for years) or from a regulatory standpoint (e.g. limited number of available withdrawal or effluent permits).

In other cases, a partnership offers attractive economies of scale (e.g. capital costs of a single 100 MGD facility may be significantly lower than the costs of three smaller facilities that together equal 100 MGD). The most basic form of capacity sharing consists of multiple utilities jointly developing infrastructure, deciding what percent of the facility they wish to reserve, and agreeing to pay the proportional costs for the capacity regardless of when or whether they use their full amount (Fig. 3.1, center panel). In some ways, this is the structural equivalent to partner utilities building separate, smaller facilities, but ideally with lower costs than having multiple, separate facilities as utilities are able to incur operational benefits by sharing costs.

A partnership approach can be implemented in several ways. Often, they take the form of a fixed capacity allocation, through joint ownership or long term capacity reservation agreement on an infrastructure project (Fig. 3.1, center column). Each utility reserves a stake in the total capacity of the project and provides financing relative to the proportion of total capacity allocated, receiving treated water at a wholesale price in return. This type of agreement was implemented in 2014 in the North Carolina Research Triangle; three water utilities – serving the towns of Cary, Apex, and Morrisville, NC – opened the Western Wake Water Reclamation Facility (WWWRF), a wastewater treatment facility operated solely by Cary but shared by all three (Apex et al. 2015). Each utility has a fixed capacity share, entitling them to a fixed amount of wastewater treatment capacity. All debt financing and fixed operating costs (separate from volumetric costs incurred directly from wastewater treatment) are borne in proportion to the capacity allocation of each utility in the plant.

A hallmark of this fixed allocations approach to a cooperative agreement is the simplicity. Permanent capacity share divisions can be easily explained and financing easily calculated, a benefit for utility officials when convincing a governing board or the general public that such an agreement is sensible. On the other hand, being locked into an allocation set based on long-term demand projections forces utilities to pay for presently unused capacity. Furthermore, if projections for one of the partners is much less accurate than for the others, having a fixed allocation can quickly become a problem: projections that underestimate growth can leave a utility short of capacity to meet demands; overestimating growth leaves the utility with relatively large debt service payments, for excess capacity that will not be used, with limited revenues generated by the slow growth. In a worst case scenario, this approach can lead to one or more partners suffering so much disproportional financial hardship that their ability to remain in the partnership may suffer and expose the entire agreement to financial risk.

Uniform rate payments. In the case of WWWRF, the agreement involves independent utilities using a contract to create the capacity sharing framework. In others situations, a new entity such as an authority may be created to structure the sharing framework and then, in turn, enter into additional agreements with other utilities. For example, utilities may be reliant upon an over-arching regional authority for provision of water or wastewater services at wholesale rates, which utilities can then distribute to customers. In Florida, the Tampa Bay Water Authority follows this format through agreements with the communities of Tampa, St. Petersburg, New Port Richey, as well as Hillsborough, Pinellas and Pasco Counties. Formed in 1998 in response to environmental concerns, area governments sold all groundwater wellfields to Tampa Bay Water. As part of the agreement, each member government (with the City of Tampa, also maintaining other water supply sources, as an exception) agreed to exclusively purchase water from Tampa Bay Water. In exchange, Tampa Bay Water is obligated to meet all member government demands (Asefa 2015). Because this region expects to grow into the future, the terms of the agreement leaves Tampa Bay Water charged with developing additional water supply infrastructure to meet future demands, as well as maintain existing wellfields. Utilities that rely on Tampa Bay Water for water could have entered into some type of allocation structure similar to what was done in the Triangle, however the utility partners instead chose a very different approach. Tampa Bay Water recovers all of its capacity capital costs as well as operating costs through a uniform volumetric rate on water sales to member governments.

Based on the total demands from member utilities in a given year, the uniform rate is set in order to recover any expected fixed costs, including any financial commitments to structural rehabilitation or expansion by Tampa Bay Water. As a result, the uniform rate paid by member utilities can vary year-to-year (Fig. 3.1, right column). As opposed to the fixed allocation agreement model of WWWRF in which member utilities must pay fixed costs that cover both their used and unused capacity in the project, the Tampa Bay Water uniform rate structure allows costs to partnering utilities to shift in time according to changes in aggregate demand. This approach provides benefits to growing utilities that do not yet require the water supply capacity they will need in the far future by essentially spreading the cost of unused capacity among agreement partners based on current use. In the example of a uniform rate agreement in Fig. 3.1, Utility 1 (purple) and Utility 2 (green) have about the same demand when repayment begins on incurred debt, but Utility 2 grows faster than Utility 2. Under the uniform rate agreement structure, the two utilities have almost equal shares of debt service initially, but Utility 2 is responsible for more and more debt as repayment continues and demands grow.

The relative impact of the uniform rate approach on different partners can vary based on their initial capacity projections/requirements and their actual growth patterns. If expected growth for a utility never materializes, for instance, then the other utility partners will end up paying higher volumetric rates to cover the fixed costs of the unused capacity originally reserved for the utility. Furthermore, with Tampa Bay Water obligated to meet any demands, there is reduced incentive for member utilities to encourage conservation. Member utilities have fixed costs of their own distribution systems, meaning reduced retail water sales increases the volumetric price they need to charge their end users to cover distribution. Any utility conserving much more water than others on the agreement would experience reduced revenues in their own system while paying wholesale rates driven by infrastructure development to meet demands of other, non-conserving partners. So long as costs of new capacity is shared volumetrically among members, faster growth in individual systems results in lower costs to end users in those systems while slower growth increases end user costs.

Temporary capacity sharing through third-party contracts. When infrastructure investment based on long-term demand projections results in long periods of time with capacity that is not needed, as could be the case for the WWWRF or for future supply options developed by Tampa Bay Water, another option for facility owners is to make this spare capacity available through temporary contracts with outside partners. In Colorado, the Water, Infrastructure and Supply Efficiency (WISE) Partnership (between the Cities of Aurora and Denver and parties to the South Metro Water Supply Authority, SMWSA) leveraged excess capacity in its existing Prairie Waters Project through contracted water sales between Aurora (and Denver) and SMWSA (Commissioners 2013). By entering into "take-or-pay" agreements with SMWSA, Aurora delivers water annually, sold at a set volumetric rate, as excess capacity is available, but is obligated to deliver a fixed amount of water over each decade of the contract. When Aurora makes water available SMWSA must either (a) purchase water at the current volumetric rate, or (b) make a "minimum payment" to compensate Aurora for the right to purchase water.

An agreement of this nature can provide a stable source of revenues for the selling party, in this case Aurora, as well as a consistent source of water for the buyer over the long term. The same obligations that make this an appealing agreement structure, however, also generate risk for both parties. In any given year, there may be no guarantee of water deliveries to the buyer. Even if a minimum allowable sale per time period is specified, a multi-year drought combined with unexpected rapid growth may leave the seller at the end of a ten-year period obligated to sell large quantities of water that no longer would be considered excess capacity. The buyer, even in cases where water is not needed or wanted, would be required to purchase at least some of any supply made available. Because of the uncertain nature of deliveries guaranteed under take-or-pay contracts or minimum purchase agreements, it is imperative that water buyers be in a situation that allows for the risk of water delivery volatility. For instance, groundwater users (making up all of the buyers under the WISE partnership) are able to draw water as needed in the absence of available water deliveries and have the operational flexibility necessary to enter into such an agreement.

Not as restrictive as take-or-pay agreements, an agreement might also take the form of a volumetric contract without obligations of delivery or provision for either party. The City of Durham, NC, for instance, maintains a mutual aid agreement with neighboring Chapel Hill, NC to provide water through shared interconnections in times of scarcity (OWASA & Durham 2009). Should either party request an emergency transfer of water at any volume, the other would attempt to fulfill the request, and be compensated at a volumetric rate for water transferred, but is not obligated to do so. In the context of Durham and Chapel Hill, this interlocal agreement covers emergency conditions only; more generally, this agreement structure could be applied between utilities under any conditions and be used to transfer water when spare reservoir capacity became available.

For communities within the same geographic area – and therefore often experiencing similar climate and weather patterns – the right to refuse or reduce the volume of water transferred as a result of an agreement of this nature may be beneficial should the entire region fall into drought. Just as the take-or-pay agreements introduce risk to either party due to their more stringent clauses, though, a voluntary agreement is risky for the inverse. In a voluntary agreement, there is no assurance that any given transfer request will be completely or partially fulfilled. Ideally, neither party would rely on such an arrangement as a primary source of water supply or revenues.

*Partially reserved capacity allocations with periodic adjustments***.** The Water and Sewer Authority of Cabarrus County (WSACC), a North Carolina wholesale wastewater utility formed to serve other utilities (similar to the Tampa Bay Water Authority) developed an innovative debt distribution policy to allocate capital costs to capacity holders in a unique manner (WSACC 2004). Initially, each retail wastewater provider was required to request and reserve capacity in the WSACC treatment facility. The debt service obligations of each purchaser were proportional to the percentage of their allocation over the total allocated amount. Capacity that was formally reserved could be allocated in the future but until that time occurred would be covered by the fixed payments of the current allocation holders. If, in the future, a utility exceeded their reserved allocation, they were obligated to revise their reserved capacity and were responsible for paying an adjusted amount of debt service for that year. Not only would current and future payments be based on updated allocations, but payment obligations would become retroactive as if the updated allocations had been fixed over the lifetime of the agreement to date. Utilities with increasing allocations relative to others would thus be made to compensate other agreement members for their increased share through ”Square One Adjustment” payments, while members with allocations shrinking relative to others would be paid by other utilities in proportion to the reduction.

Through WSACC’s Square One payments, debt service responsibilities can be adjusted to scale with changing allocations, offering a flexibility not available under long-term, fixed allocation agreements. Depending on the scale of change to allocations of participating partners, retroactive “true-up” payments could range from minimal to substantial. In the case of WSACC, adjustments appeared to become so small that WSACC discontinued the retroactive portion of the agreement after several years.

*Additional considerations for capacity sharing agreements***.** The agreement structures presented above are only the tip of the iceberg when it comes to the shape agreements may take. An agreement can be bolstered or undone by its own unique context and, to differing degrees, not perform as expected.

Beyond the structural components of an agreement (when water is transferred, when payments must occur, flexibility of capacity allocations, etc.), external sources of uncertainty can also impact the effectiveness of an agreement. One such example is the interlocal agreement between the Karengnodi Water Authority (KWA) and local communities in eastern Michigan. The KWA, formed by several units of government including Genesse County and the City of Flint, MI, began construction of a pipeline capable of delivering water from Lake Huron to Genesse County, Flint and a host of surrounding populations. Construction of the pipeline to provide water to interested communities was the founding purpose of the KWA (City of Flint 2013).

To allocate pipeline capacity and financing, KWA sold annual allocations in increments of 1 MGD "units" (up to 85 MGD permitted for the pipeline) on a first come, first served basis (Authority 2010). Each unit carried a monthly fee for the capacity reservation, combined with a uniform volumetric rate on water sold to ensure all KWA costs (including payments on debt for pipeline construction) could be met (Authority 2010).

However, the agreement structure for KWA pipeline allocation carried high levels of risk for both the KWA and any community relying on the pipeline for supply. A capacity "buyer" in the KWA pipeline was not obligated to purchase water (when available) from KWA and could modify or exit any agreement with KWA after one year. Without guaranteed revenues from water sales, KWA was forced to turn to limited tax pledges by its founding members to secure a general obligation bond for the project. At the same time, if KWA was unable to attract a large enough pool of capacity buyers, the wholesale rate would become expensive if only a fraction of the pipeline capacity was reserved.

To make matters more complicated, the KWA pipeline was constructed as a preferred lower cost alternative to an existing regional water supply source, the Great Lakes Water Authority (GLWA). Realistically, this places an upper bound on the rate KWA could charge utilities purchasing capacity in the pipeline without losing customers to the GLWA. Political risk also surrounds this project. Primarily owing to Flint's recent water crisis, local officials became wary of shifting the City's water supply again away from Detroit to a different source (Colomer 2017). As a result Flint, having initially purchased a stake in the KWA pipeline, chose in the future not to purchase pipeline capacity, instead entering a long-term agreement with the GLWA (Colomer 2018). While the eventual terms of the agreement with GLWA shifted some of this responsibility to GLWA, the loss of Flint as a significant KWA pipeline partner could result in costs being absorbed by other partners. In partnering with Flint under the structure of the original agreement, Genesse County therefore took on significant counterparty risk through the KWA that they may not have taken on if other approaches had been followed.

3.2 Case Study and Methods

To offer a quantitative perspective on the impact the initial capacity sharing approach can have on partners' costs and risk allocation, we applied different combinations of the capacity sharing approaches discussed above to a project currently under consideration in the Research Triangle (Triangle) of North Carolina. The Triangle is one of the nation's fastest-developing areas, and municipalities within the region are concerned with the effective allocation of Jordan Lake, the largest water source in the Triangle, in order to meet future demand growth. Five local government utilities– Pittsboro, Chatham County, Orange Water and Sewer Authority (OWASA), Orange County, and Durham – have partnered to begin planning and eventually finance a new water treatment plant on the west side of Jordan Lake (WJLWTP) that will help to meet each utility's future demands (Governments 2014). Most of the plant's initial demands are expected to come from Durham, currently by far the largest user among the partners, and shift toward the other utilities by 2060 – Pittsboro and Chatham County are presently relatively small but have the fastest projected demand growth in the region. Other utilities in the area are currently not formal partners but could be interested in acquiring either long term or short term capacity from the plant. Given all factors in play, an agreement should be designed that (1) adequately allocates capacity and costs among partners, and (2) can adapt to unexpected future conditions (i.e. shifts in demand growth from projections).

*Agreement structures and demand scenarios***.** To address both of these points, we evaluate a handful of agreement structures and approaches under different future growth scenarios (Fig. 3.2). We assume three cost sharing structures based on the approaches and examples described above: (1) fixed capacity allocations; (2) fixed capacity allocations with volumetric third-party sales and take-or-pay contracts available to other utilities; (3) uniform rate payments that are adjusted each year based on actual usage. Each approach is subjected to several future scenarios of demand growth (with demand growing as projected for each utility unless otherwise mentioned): (a) demand grows as projected for all utilities; (b) all regional utilities grow slower than expected; (c) Pittsboro and Chatham County experience slower-than-anticipated demand growth; (d) Pittsboro and Chatham County demand rises rapidly over a short period (ex: large commercial or mixed-use development occurs), then levels off slowly; (e) Durham and OWASA demands slow and gradually plateau after 20 years. Comparing the resultant costs to utilities in each combination of agreement and demand scenario can offer insight to the issues and tradeoffs utilities may face when implementing cooperative agreements.

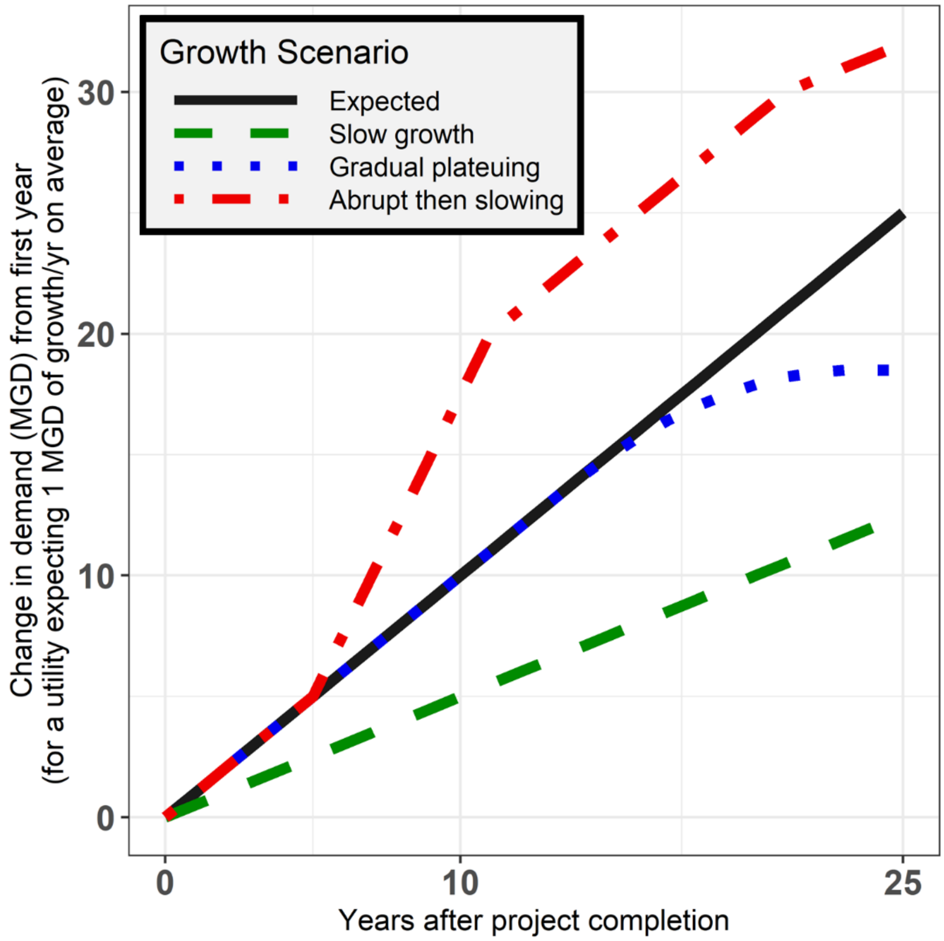

Figure 3.2: Modeled demand scenarios over lifetime of debt repayment

*Modeling description***.** A Microsoft Excel model of the WJLWTP project was constructed to simulate water demands to the WTP and financial payments by utilities annually over a twenty-five-year period. The WJLWTP project was assumed to be debt financed, repaid after twenty-five years with constant, equal annual payments over the life of the bond. Additional costs could occur as well, such as both fixed and variable (relative to amount of water treated at the plant) operations and maintenance (O&M) as well as payments between utilities for water delivered as a part of volumetric or take-or-pay contracts. Different components of the WJLWTP project are split into stages within the model described in further detail in Appendix 2; for simplicity, each stage was constructed on the same year. Based on estimates of future use by JLP (2014), Chatham County, Durham, Orange County[3], OWASA, and Pittsboro were assigned fixed allocations in the WJLWTP of 30.3%, 51.5%, 3.0%, 6.1%, and 9.1% of built treatment capacity. These values were only applied to modeled agreements where treatment capacity allocations were fixed. Initial capital costs ($243.3 million total), and estimates of O&M costs were based on a preliminary study by JLP (2014). Evaluation of results is based on costs incurred from the project to each utility, converted and presented as levelized, "unit" cost ($/kgal) of water treatment per utility (the total financing obligation for a utility divided by sum of its total water demand over the lifetime of the project) and the net present value cost per utility (the sum of present-valued annual costs to a utility over the financing period of the project). Additional detail, including the year-to-year calculation of allocations, costs, and water demands, can be found in Appendix 2.

3.3 Results

Three cost sharing approaches (fixed allocations, fixed allocations with a 2 MGD minimum purchase agreement with another utility and uniform rate), were tested under four different future demand conditions. Differences between combinations of cost sharing approaches and demand scenarios are outlined here based on unit costs per thousand gallons of water treated (Figures 3.3 and 3.4), which include fixed and variable operations and maintenance costs. Present valuation over the 25-year WJLWTP project assumes a 2.7% discount rate.

*Variation in Outcomes***.** Depending on the approach modeled, utilities experienced notable differences in capital commitment and unit costs (Fig. 3.3). With fixed allocations,

[3] Based on conversations with Triangle officials, it is possible that Orange County is no longer actively pursuing an allocation stake in the WJLWTP.

Chatham County and Pittsboro would see higher unit cost of water treatment than Durham, Orange County, and OWASA when demands grow as anticipated regionally (Fig. 3.3, left panel). When another utility is available as a buyer for unused treatment capacity through minimum purchase agreements in early years of the project, the unit cost of water treatment for all utilities drops relative to an agreement structure with fixed allocations and no third-party sales (Fig. 3.3, center vs. left panels); this reduction in unit costs is felt more strongly by Chatham County and Pittsboro, whose small water demands in early years relative to large allocation stakes anticipating future growth expose them to high unit cost of treatment unless another utility can provide compensation for some of their unused capacity.

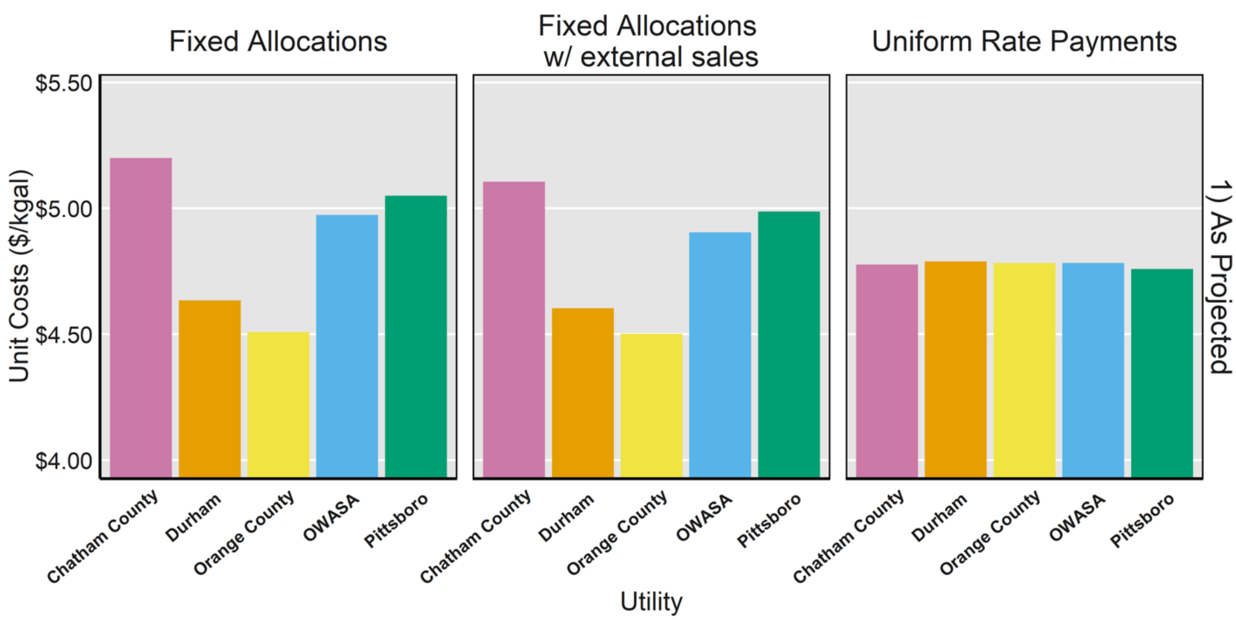

Figure 3.3: Unit costs of treated water for agreement member utilities across three tested approaches under expected demand growth conditions. Costs shown are those accrued over a 25-year debt repayment period.

True to name, uniform rate payment agreements lead to nearly even unit cost of treatment for participating utilities (Fig. 3.3, right panel). The small utilities of Chatham County and Pittsboro that requested relatively large fixed capacity allocations benefit from having a uniform rate agreement; this occurs because the uniform rate agreement weights annual payments by member utilities based on observed demands, not future expectations. Until Chatham County and Pittsboro "grow" into their expected long-run demands, utilities with already large demands pay the bulk of debt service on the project. Because of this, Durham, Orange County, and OWASA unit costs increase because their demands are initially greater than the other two utilities but do not grow at as fast into the future. Table 3.1 summarizes the general characteristics of utilities in the Triangle and the contract structure likely to benefit each based on regional expectations of future growth.

Table 3.1: Triangle utility classification and outcomes under expected conditions

Utility	Relative Size (2010 population)	Expected Demand Growth	Lowest Unit Cost Agreement	Primary Risk Source
Chatham County	Small (10,200)	Fast	Uniform Rate	Low demand growth
Durham	Large (227,100)	Slow	Fixed Allocations	Counterparty over-projection of demand
Orange County	Small (100)	Slow	Fixed Allocations	Counterparty over-projection of demand
OWASA	Large (79,400)	Slow	Uniform Rate	Counterparty mis-projection of demand
Pittsboro	Small (3,700)	Fast	Uniform Rate	Low demand growth

*Consequences of demand growth scenarios***.** The future demand trends of member utilities too have a substantial impact on the financial outcomes of each agreement structure. To summarize the influence of changes in demand growth, we will focus on the changes to unit cost and net present value cost fluctuations for Pittsboro (Fig. 3.4). When Pittsboro growth falls below expectations, unit costs rise under fixed allocation agreements even when third-party sales are available (Fig. 3.4, left/center panels). This pronounced increase in costs is because Pittsboro chooses to reserve a large allocation stake relative to its initial demand, making marginal reductions in demand growth especially costly. Conversely, rapid early growth in Pittsboro reduces unit costs for the utility. Both effects indicate that sales agreements in concert with fixed allocations cannot entirely insulate a utility on this project from the financial risk of demand uncertainty.

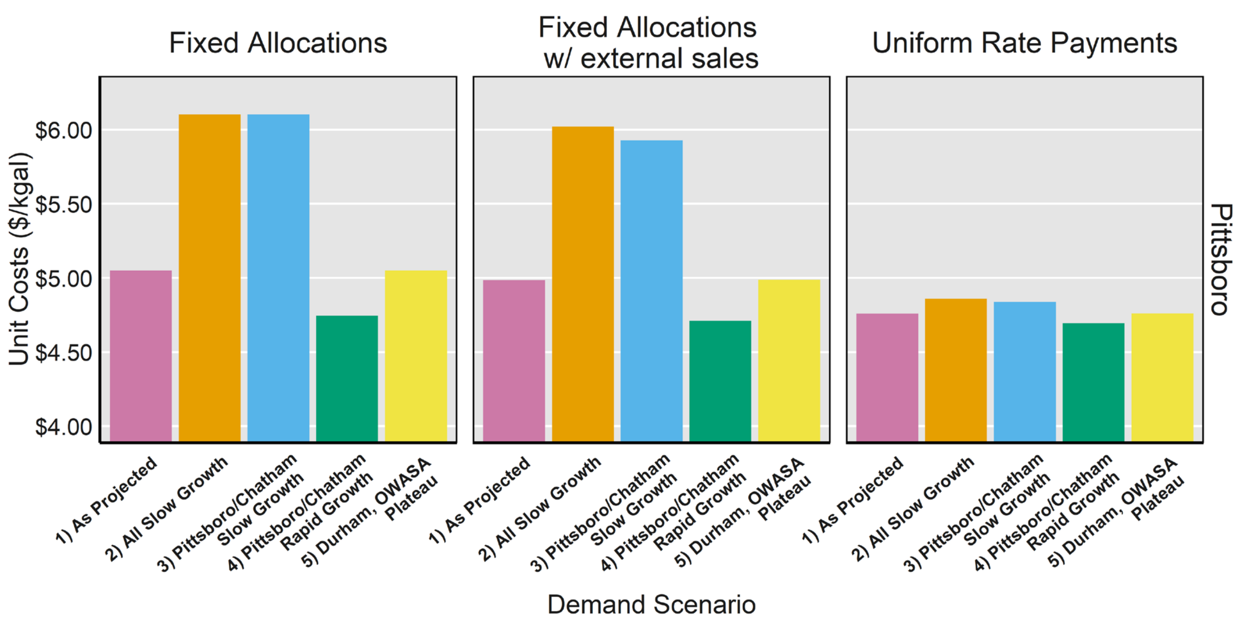

Figure 3.4: Unit costs of treated water for Pittsboro across three tested contract structures under five demand growth scenarios.

To a smaller degree, changing demand growth by other utilities like Durham and OWASA can also influence Pittsboro. A plateauing of Durham and OWASA demand marginally raises unit costs for Pittsboro and other utilities by increasing the share of costs borne by Pittsboro under a uniform rate agreement (Fig. 3.4, right panel). However, a fixed allocation agreement structure prevents Pittsboro from experiencing counterparty risk as a result of incorrectly-projected demands by other utilities in this example, as capacity allocations and payments by utilities on them are fixed regardless of demand growth trends. While debt service payments and costs related to fixed allocation sizes do not affect Pittsboro net present value costs between demand scenarios, changes in variable O&M or volumetric-based treatment costs also impact the net present value costs of the project for Pittsboro. Under a uniform rate agreement, net present value costs for Pittsboro are able to scale as demand changes, spreading the financial risk of over-projecting future demands among project partners and reducing unit costs. This “cost spreading” feature of a uniform rate agreement is likely appealing to initially small utilities like Pittsboro hoping to grow rapidly but may not have capital on hand to cover payments on a large fixed capacity allocation before demands mature.

3.4 Discussion and Conclusions

While each of the agreement approaches discussed above has appealing elements, they can also carry notable risk for utilities taking part in them. Uncertainty in future demands may cause fixed allocation agreements to become unpalatable, especially for utilities like Pittsboro or Chatham County who are small but expect to contribute the majority of demand growth among partner utilities. However, a uniform rate agreement may not seem as fair for a relatively large utility like Durham, already contributing the largest portion of funding for a project, having to cover potential shortfalls in future demand that Pittsboro may experience through an increase in payments and paying for unused capacity reservations for Pittsboro while the utility grows (even if growth occurs as projected). Having flexible allocation agreements, like the uniform rate structure presented here, can be a useful way to spread risk of demand uncertainty among agreement partners, but for the same reason it may be advantageous as well to lock into a fixed allocation instead. Though it did not prove to be a perfect solution in our modeling to demand mis-projection, having third-party agreements in place with other utilities such as minimum purchase or take-or-pay contracts can provide flexibility for utilities owning fixed capacity in a project to lease portions of unused capacity temporarily, limiting financial exposure of demand uncertainty.

Along with unit costs of a potential agreement, changes in net present value costs to each utility are also important to consider (Fig. 3.5). Durham, with the greatest demands among participating utilities, is always responsible for the bulk of costs across all agreement structures. Under most demand scenarios, Chatham County and Pittsboro contribute the second and third largest amounts toward covering project costs. Relative to an agreement with fixed allocations (Fig. 3.5, left panel), sales to other utilities through minimum purchase agreements reduce the net present value costs of the project to all participating utilities. Even a modest 2 MGD minimum purchase agreement can reduce collective costs to member utilities by tens of millions of dollars (Fig. 3.5, Raleigh costs, center panel). Implementation of a uniform rate agreement structure has different impacts depending on the evolution of demands for each utility (Fig. 3.5, right panel), but under expected demand conditions Durham covers more costs than it would with fixed allocations because other member utilities are using much smaller portions of treatment capacity for most of the 25-year bond repayment period. Smaller utilities – most notably Chatham County – pay less than they would have given fixed allocations for the same reason.

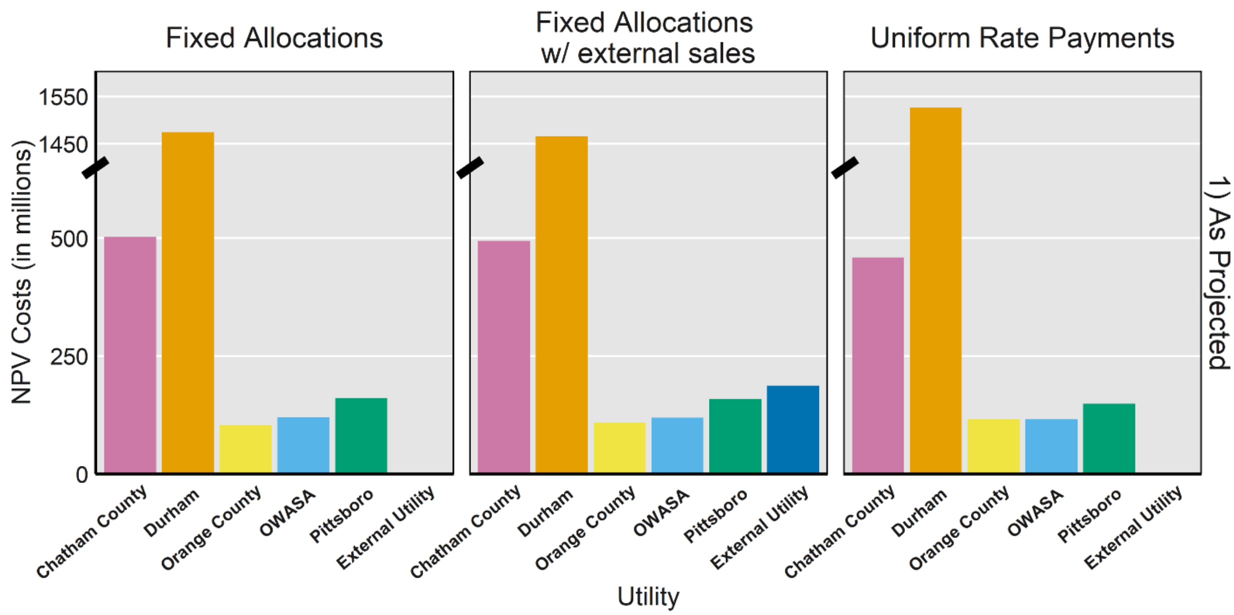

Figure 3.5: Net present-valued costs for each member utility across agreement structures under expected future demand growth. Cost estimates aggregated over debt repayment period of 25 years with discount rate of 2.7%.

Just as cooperative agreements can be mutually beneficial, they also subject utilities to counterparty risk. In a fixed allocation agreement, for example, a utility expecting to grow considerably might be incentivized to underestimate its growth when requesting an allocation, if it felt that political intervention to correct any supply shortfalls would occur or that it could enter a temporary contract with another utility with a capacity allocation to purchase its spare capacity. Both options could save a utility by avoiding debt service obligations of owning a larger capacity stake in the project (potentially placing a heavier burden on other stakeholders) while still offering a pathway to fulfilling demands. Similarly, one out of several utilities paying a uniform rate to receive water from a regional authority might be incentivized to overestimate future demands if the regional authority is obligated to provide supply to each member utility. Any costs of additional infrastructure built would be spread among all utilities uniformly, even if the others have no need for future supply increases.

Another important facet of any cooperative agreement is how ownership of structural assets is organized. Direct ownership by a utility of a stake in a water treatment plant or reservoir, as is the case with the WWWRF, can have benefits. On the other hand, relying on a regional authority to provide water and develop infrastructure – leaving utilities as wholesale customers rather than operators of water supply – may be preferred.

There are any number of ways neighboring utilities may choose to cooperate through cooperative agreements. As such, it is imperative to weigh the costs and benefits of different methods when designing and agreeing to any contract. By identifying and evaluating a range of designs already in place, this work offers guidance to utility managers and regional planners on the risks of infrastructure planning and management coordinated between multiple partners.

CHAPTER 4 : IMPACT OF INTER-UTILITY AGREEMENTS ON COOPERATIVE REGIONAL WATER INFRASTRUCTURE INVESTMENT AND MANAGEMENT PATHWAYS[4]

4.1 Introduction

Water utilities anticipate a range of risks to future water supply reliability and the provision of affordable services (AWWA, 2018). Hydrologic changes, resulting from climate and land use-landcover (LULC) changes, will likely lead to increasing uncertainty in the quantity and timing of surface and groundwater availability in many regions world-wide (IPCC, 2014b; USGCRP, 2018; World Bank, 2016; WUCA, 2016). Water demand growth is also expected to be a significant driver of future water scarcity (AghaKouchak et al., 2015, 2021). Spending on maintenance of aging water and wastewater infrastructure is also increasing (CBO, 2015, 2018), further straining the budgets of utilities trying to ensure reliable water supply while keeping customer rates affordable.

Increasingly, utilities are turning to 'portfolio' strategies that couple supply expansion with water use restrictions, and, increasingly, water transfers to address water supply risks (Brown et al., 2015; Loucks & van Beek, 2017; Lund, 2015). These techniques can be effective, but face challenges; as one example, supply-side capacity expansion has traditionally been the favored option for meeting long-term demand growth (AWWA, 2011; Gleick, 2003), however the rate of new dam and reservoir construction has declined in recent decades as the number

[4] This chapter has been submitted for publication: Gorelick, D.E., Gold, D.F., Reed, P.M., & Characklis, G.W. (2021). Impact of inter-utility agreements on cooperative regional water infrastructure investment and management pathways. In review. *Water Resources Research*. https://www.essoar.org/doi/abs/10.1002/essoar.10507429.1

cost-effective sites has dwindled and regulatory approval has become more onerous (Perry & Praskievicz, 2017). Short-term, drought mitigation measures such as water use restrictions (demand-side action) enjoy widespread use (Kenney et al., 2004; Milman & Polsky, 2016), but frequent implementation can be unpopular with customers and restrictions may not meet their desired reduction targets (Olmstead & Stavins, 2009a). Similarly, water transfers have shown promise as a short-term tool to alleviate scarcity (Gupta & van der Zaag, 2008; Lund & Israel, 1995; NRC, 1992), but typically involve additional costs, sometimes in the form of expanded conveyance infrastructure, which can discourage their implementation (Characklis et al., 2006a; Israel & Lund, 1995). Water transfers may also occur intermittently and at varying magnitude, adding complexity.

Water transfer purchases and water use restrictions are often motivated by drought and are thus implemented at unexpected intervals such that the cost increases and revenue reductions, respectively, can also carry unexpected financial risk (Barr & Ash, 2015; Baum & Characklis, 2020; Lund, 1993; Tiger et al., 2014). Mismatch between a utility's primarily fixed costs – debt service owed on infrastructure and fixed operating expenditures – and volumetric water sales can destabilize utility cashflow, potentially leading to budget shortfalls. Even if this does not occur, any elevated risk of non-performance with respect to debt payments can result in lower credit ratings and a higher cost-of-capital, a particular concern in the capital-intensive water utility sector, culminating in higher rates for customers (Hughes et al., 2014; Hughes & Leurig, 2013; Raftelis, 2005).

As an alternative, water utilities are more frequently considering inter-utility agreements, leveraging proximity and surplus capacity with neighboring utilities to provide additional operational and planning flexibility (EFC, 2009; Kurki et al., 2016; Reedy & Mumm, 2012;

Silvestre et al., 2018; Sjöstrand et al., 2018, 2019; Tran et al., 2019). Inter-utility agreements between utilities (sometimes termed inter-local agreements) can take a variety of forms that offer a range of benefits (EPA Office of Water, 2017): economies of scale in development and operation of regional water supply infrastructure (Apex et al., 2015); emergency or intermittent access to additional water supply (OWASA & Durham, 2009); and consistent sources of revenue from leasing of excess water supply or treatment capacity (Commissioners, 2013; Reedy & Mumm, 2012). However, despite widespread use, and long-standing institutional structures allowing inter-local agreements to facilitate cooperation in US states (e.g. NC General Statutes, 1971), quantitative assessment of their ability to mitigate both supply and financial risk is limited. In addition, differences in the legal definition of an inter-local agreement across U.S. states, as well as internationally, hamper the ability of past research to offer generalizable takeaways regarding agreement performance.

Several studies have reviewed the breadth and efficacy of regional agreements in practice (Silvestre et al., 2018; Tran et al., 2019), often via survey or data collection from utilities or resource managers engaged in existing partnerships (Bendz & Boholm, 2019; Kurki et al., 2016). A handful of studies have attempted to quantify economic costs and benefits (Arena et al., 2014; Sjöstrand et al., 2018, 2019) or financial outcomes (Gorelick et al., 2019) of agreements through scenario modeling of regional case studies, but are limited in the sources of uncertainty addressed and do not consider dynamic adaptive response by utility managers to mitigate time-evolving risks (i.e., droughts). Other studies of regional utility-scale decision-making under broad hydrologic and operational uncertainties include dynamic risk management by system actors (Gold et al., 2019; Mortazavi-Naeini et al., 2014; Tian et al., 2018; Trindade et al., 2019); however, inter-utility agreement structures have not been the primary focus of these studies, and alternative agreement structures were not considered. Important questions therefore remain regarding the structure of inter-utility agreements, particularly as relates to their performance under uncertainty.

While inter-utility cooperation has advantages over independent utility financing and operation, agreements may also bring about unintended consequences (Bendz & Boholm, 2019; Feiock, 2013). Cooperative control over water supply and operations can expose agreement partners to the risks of other partners (their counterparties) with whom they share financial and operational ties. The risk of supply failure may increase if partnerships involve consolidation of supply or treatment capacity to a single facility (Sjöstrand et al., 2018). The structure of an agreement involving commitment to fixed or variable capacity or joint financing may also limit its effectiveness if external conditions (e.g., demand growth) diverge from projections (Gorelick et al., 2019). In addition, costs and benefits of a regional partnership may not be shared equitably between individual partners (Dinar et al., 1992; Dinar & Howitt, 1997; Parrachino et al., 2006); collective action that requires compromise between utilities may be short-lived if an agreement becomes impractical for one or more participants as conditions change, even if it results in a better aggregate outcome at the regional scale (Madani & Dinar, 2012; Read et al., 2014).

Broadly, there are a number of ways in which counterparty risk may evolve under hydrologic and demand growth uncertainty. Many studies have considered the influence of endogenous (e.g., utility decision-making) and exogenous (e.g., population growth) factors may have on individual or regional utility performance (Borgomeo et al., 2018; Gold et al., 2019; Herman et al., 2015). However, little attention has been given to how increasing institutional connectivity via cooperative agreements may degrade utility (or regional) outcomes by partially exposing an individual utility to a partner's risks. Furthermore, despite recognition of demand growth as an important factor in water utility performance outcomes (Donkor et al., 2014; Herman et al., 2014; Trindade et al., 2019), projections of future growth in practice are often reduced to simplistic, linear trends (TJCOG, 2014; Walker, 2013) that exclude potential year-to-year uncertainty in growth rate. Quantifying the success of inter-utility agreement structures will require not only consideration of the flexibility of the agreement, but also contextual factors such as agreement partners, alternative supply projects, hydrologic and demand growth conditions.

This research represents the first application of dynamic adaptive water supply and management modeling and multi-objective optimization to evaluate the impact of inter-utility agreements in regional contexts. Specifically, this work explores the factors contributing to the benefits as well as the financial risks in inter-utility agreements through modeling cooperative regional infrastructure investment and water portfolio management that impacts six adjacent water utilities in the North Carolina Research Triangle (Triangle). Two inter-utility agreement structures are tested across a range of demand futures to assess their robustness under demand growth uncertainty. Through a comparison of supply and financial performance across agreement structures, at both a regional and individual utility scales, results respond to the questions: (1) how do differences in inter-utility agreement structure impact supply and financial risk across multiple utilities, and (2) to what degree do demand growth uncertainty and counterparty risk influence the viability of regional cooperation?

4.2 Methods

This work assesses the impact of different inter-utility agreement formulations on regional and individual utility performance in the Triangle through multi-utility regional modeling of decision-making, evaluating both water supply and financial outcomes under uncertainty. Multi-objective optimization is included in the modeling framework to understand the optimal tradeoffs for each agreement structure.

4.2.1 Region of Focus

The Triangle is a rapidly growing region with a recent history of drought that has raised concerns about water supply reliability. Home to more than two million residents, the Triangle historically refers to the three major cities of the region, Raleigh, Durham, and Chapel Hill. Growth patterns in the larger Triangle area have also spread to nearby towns of Cary, Pittsboro, and regions of Chatham County. This study broadens beyond prior published studies of the Triangle by integrating water utilities from all six areas – Town of Cary Water Resources Department, Chatham County Public Utilities, City of Durham Department of Water Management, Orange Water and Sewer Authority (OWASA; Chapel Hill), Town of Pittsboro Public Utilities, and Raleigh Water (Figure 4.1) – into our regional modeling framework.

Water demands in the Triangle are expected to grow considerably in the future (Table 4.1), however demand growth is anticipated to be asymmetric geographically. Utilities for larger population centers Raleigh, Durham, Cary, and OWASA do not expect rapid growth, while Pittsboro plans for demand increases of nearly an order of magnitude by 2060 (relative to 2015). Chatham County has three water service areas, however the County projects the vast majority of population and water demand growth to occur in its North System (Hazen and Sawyer, 2020). As a result, Chatham County North is the only water service area included in regional planning and therefore the only County system considered in this analysis.

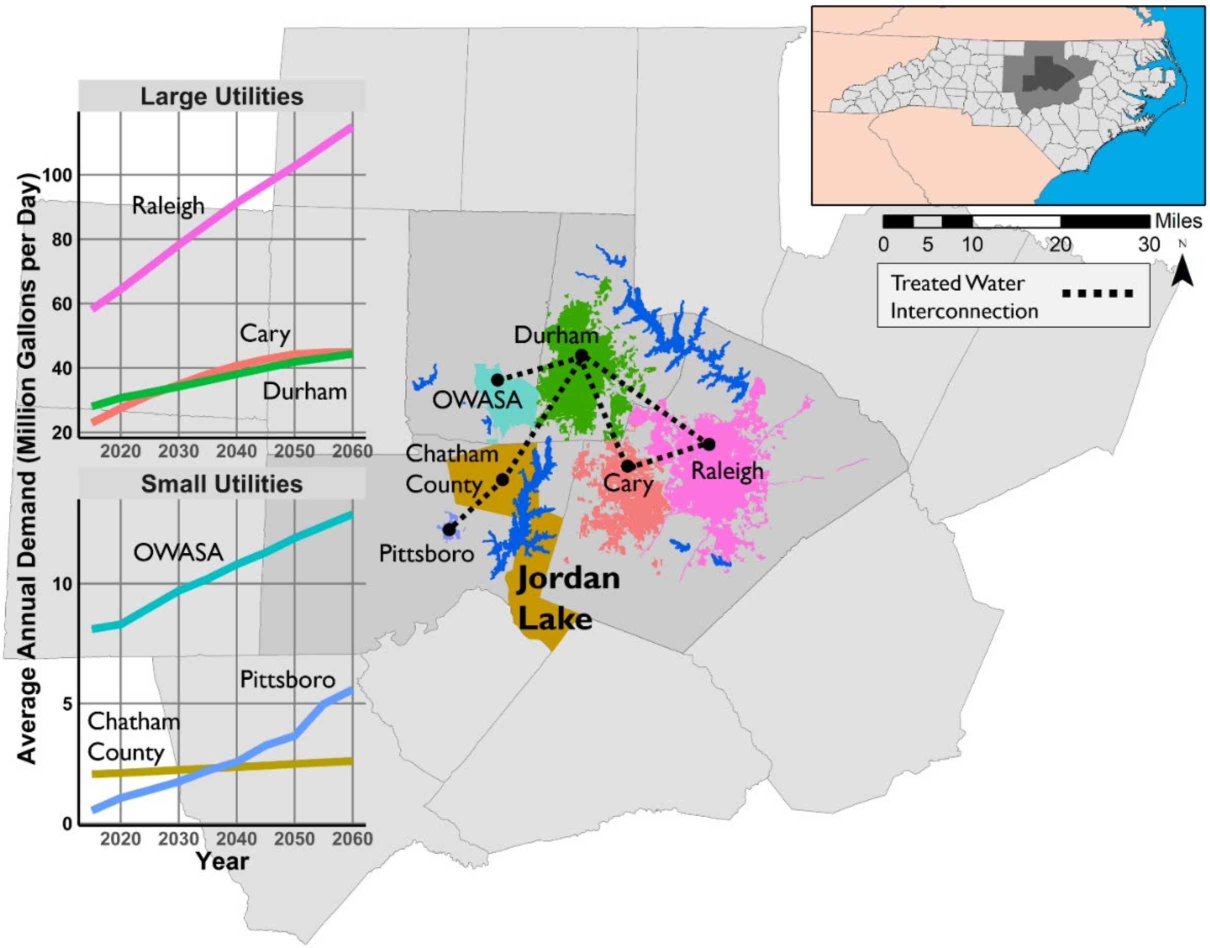

Figure 4.1: Six population centers (colors) of this study in the Research Triangle of North Carolina. Water demands (in annual average millions of gallons per day) are given from 2015 to 2060 on inset plots based on utility projections (TJCOG, 2014; Hazen and Sawyer, 2020).

Table 4.1: Projected Research Triangle water demands in millions of gallons per day (MGD).

Triangle Utility	**2020**	**2040**	**2060**
Cary**	27.5	40.7	45.0
Chatham County (North System)*	2.1	2.4	2.6
Durham	30.7	38.1	44.4
OWASA	8.3	10.8	12.9
Pittsboro*	1.1	2.6	5.6
Raleigh	64.4	91.3	115.0
Total (avg MGD)	134.1	185.9	225.5

* Pittsboro and Chatham County demands from 2019 projections by Hazen and Sawyer (2020)
** Represents sum demands of Towns of Cary, Apex, and Morrisville

Given demand growth projections, the Triangle utilities plan to expand water supply infrastructure (Table 4.2). A range of potential projects are under consideration by each utility or group of utilities to secure reliable water supply, differing in size (supply or treatment capacity), capital cost, earliest year construction may begin (represented here as the required permitting period for a project before it may be constructed), and whether the project is cooperative across multiple utilities.

Regional interconnections between utility water distribution systems also allow utilities to transfer quantities of treated water upon request. Durham, OWASA, and Raleigh can purchase treated water transfers from Cary's water treatment plant (WTP) that are then piped via interconnection to the purchasing utility. Durham can also sell water to Chatham County via transfer through a shared interconnection, as can Pittsboro through a separate interconnection. Transfers via these interconnections have been used in the past as alternative sources during times of high demand and/or low supply (OWASA & Durham, 2009); other interconnections in the Triangle are used to regularly supply water that meets a utility's demands. Triangle utilities also employ conservation to manage water demand, implementing both voluntary and mandatory water restrictions if necessary to reduce water use. Each Triangle utility maintains one or more reserve (contingency) funds to mitigate financial disruptions, such as cost and revenue fluctuations from restriction or water transfer use.

Table 4.2: Available infrastructure expansion options for Triangle utilities. Based on regional planning documents and consulting reports (TJCOG, 2014).

Project	Utility	Capacity (MG or MGD)	Capital Cost ($USD millions)	Earliest Availability (year)
Cary-Apex WTP Upgrades*	Cary	8.0, 16.0	121.5†, 243.0†	2015
Cape Fear River Intake in Harnett County	Cary	12.2	221.4	2032
Allocated Treatment Capacity in Sanford, NC WTP^	Cary / Sanford[a]	10.0	56.0	2015
Allocated Treatment Capacity in Sanford, NC WTP*^	Chatham County / Pittsboro / Sanford[a]	1.0, 2.0 / 3.0, 9.0	7.9, 11.2 / 49.6, 69.3	2022, 2028
Western Jordan Lake Regional WTP*^	Chatham County / Durham / OWASA / Pittsboro	33.0, 54.0	243.3, 316.8	2020, 2022
Reuse of Reclaimed Water*	Durham	2.2, 11.3	27.5, 104.4	2022
Teer Quarry	Durham	1315.0	22.6	2022
Lake Michie Reservoir Expansion*	Durham	2500.0, 7700.0	158.3, 203.3	2032
Cane Creek Reservoir Expansion	OWASA	3000.0	127.0	2032
Stone Quarry Expansion*	OWASA	1500.0, 2200.0	1.4, 64.6	2037
University Lake Expansion	OWASA	2550	107	2032
Haw River Intake and WTP Expansion*	Pittsboro	2.0, 4.0	18.6, 27.9	2017, 2020
Falls Lake Reallocation	Raleigh	5637	142	2022
Little River Reservoir	Raleigh	3700	263	2032
Neuse River Intake	Raleigh	16	225.5	2032
Richland Creek Quarry	Raleigh	4000	400	2055

* project that may be implemented in multiple stages, stage capacity and costs are cumulative
^ cooperative project between utilities
[a] utility not included in modeling
† costs not included in modeling (project occurs immediately after start of modeling period but is not ROF-triggered)

4.2.2 Problem Formulation

4.2.2.1 Regional Water Supply Simulation Model

To simulate water supply system planning and management through 2060 by Triangle utilities, this study develops a utility-scale computational model of the regional system using the WaterPaths stochastic simulation software. WaterPaths was developed specifically to enable computationally-efficient representation of multi-actor water systems under deep uncertainty (Trindade et al., 2020). WaterPaths offers computational flexibility to simulate the broad suite of decision-making options available for water utilities to adapt to evolving risks. The simulation framework is able to efficiently scale with high numbers of regional actors (utilities), incorporate a wide range of uncertainties (i.e. of hydrology, demand, and additional deeply uncertain factors), and facilitate simulation as well as optimization of water supply infrastructure planning policies. This study contributes an extension of a prior WaterPaths Triangle system implementation, expanding from four to six regional utilities (Gorelick et al., 2020) and exploring a wider range of uncertainties (detailed below).

4.2.2.2 Risk-of-Failure (ROF) Based Adaptive Management

Within WaterPaths, utility decisions to develop infrastructure, request water transfers, and implement use restrictions are made via state-aware rules, resulting in adaptive 'pathways' of action by utilities taken in response to changing risks. Decisions are triggered based on risk-of-failure ($ROF_{U,t}$), the dynamically-updating probability of supply storage falling below 20% of capacity or demands exceeding 90% of treatment capacity for a utility U at time t over the following (a) year for short-term ROF or (b) 1.5 years for long-term ROF (H. B. Zeff et al., 2016).

When short-term ROF rises above a trigger threshold $ROFT_{U,action}$, actions to implement use restrictions or purchase water transfers are taken to reduce water supply and/or treatment capacity risk. Long-term ROF is used to trigger infrastructure development of any project $IP_U \in \overrightarrow{IP}$, where $\overrightarrow{IP}$ is the set of all potential projects (Table 4.2 in this case). The sequencing of infrastructure project development for a utility is determined by the availability of each project (Table 4.2, right column) at the time a decision is triggered as well as a project's predetermined preference relative to other potential projects. WaterPaths also tracks revenues for each utility from weekly water sales, as well as utility contingency (reserve) funds that can be used to meet unexpected revenue reductions due to restrictions or increased costs arising from water transfers. All infrastructure projects, water portfolio instruments, and ROF-based rules have been specified in collaboration with the Triangle utilities. For more on WaterPaths functionality, see Trindade et al. (2020).

4.2.2.3 Sampling States-of-the-World for Monte Carlo Simulation

Risk-of-failure evolves based on reservoir capacity dynamics that change depending on hydroclimatic conditions, human demands, and path dependent management actions (i.e., short-term weekly portfolio management combined with long-term annual infrastructure investments). To fully exploit the adaptive nature of ROF-based decisions, we expose candidate infrastructure investment and water portfolio policies to a broad set of plausible future states-of-the-world (SOWs). This represents an exploratory modeling centered approach for identifying infrastructure investment and water portfolio policy rules that effectively adapt to highly challenging conditions (Bankes, 1993; Moallemi et al., 2020). Uncertainties that comprise future SOWs can be categorized as being either a “well-characterized” uncertainty (WCU), with a known probability distribution or large amounts of historical data, or a deep uncertainty (DU), without a known probability and limited historical data (Kwakkel et al., 2016; Marchau et al., 2019). In this study, hydro-climatic internal variability is treated as a stationary WCU (i.e. synthetic stochastic hydrology, described in section 4.2.2.3.1 below). DUs included in this study include water demands, economic factors, climate change along with deeply uncertain management and policy factors, within our modeling framework. For this work, five hundred SOWs, each representing one set of future conditions, were generated using a Latin Hypercube Sampling (LHS) approach (Figure 4.2).

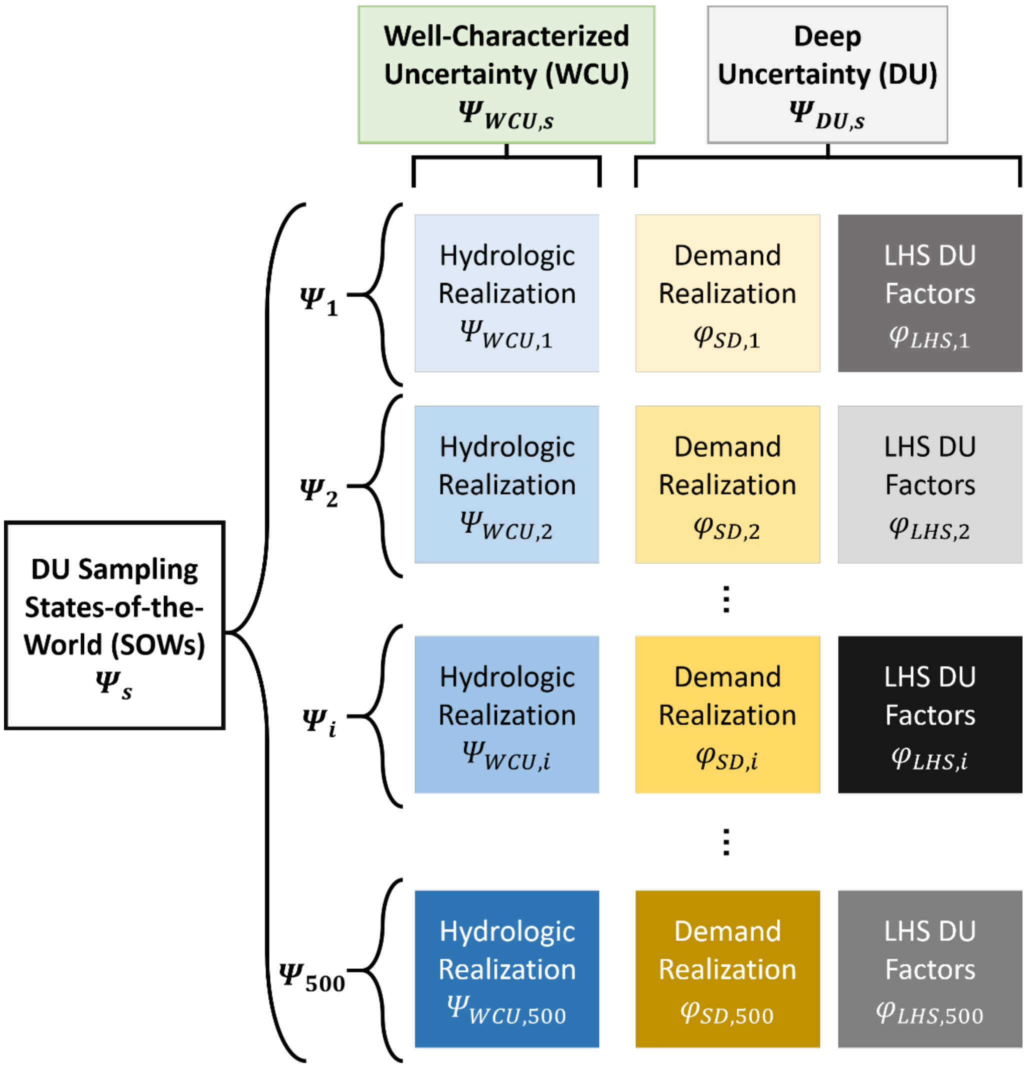

Figure 4.2: Visualization of DU sampling of SOWs, including timeseries realizations of hydrologic (reservoir inflow) and utility water demand along with DU factors sampled via LHS. Timeseries samples of hydrologic and demand WCUs are coupled with DU factor samples to form the set of SOWs.

Table 4.3: Description and ranges of deeply uncertain factors

Factor	Description	Range (multiplier factor)
Bond Term (B_{term})	affects number of years over which infrastructure capital costs are repaid as debt service	0.8-1.2
Bond Interest Rate (B_{rate})	factor adjusts fixed interest rate on bonds for infrastructure	0.6-1.2
Discount Rate (D_{rate})	applied to the discount rate, affecting how future infrastructure investment is discounted to 2015	0.6-1.4
Restriction Efficacy (RE_U: 6 factors, 1 per utility)	impacts how effective use restrictions are at reducing water demand	0.8-1.2
Lake Evaporation I	controls the rate water is evaporated from regional reservoirs	0.9-1.1
WJLWTP Permitting Period (PP)	brings forward or delays the year after which the WJLWTP can be constructed	0.75-1.5
WJLWTP Construction Time (CT)	lengthens the construction time that would be needed to build WJLWTP	1.0-1.2
Sinusoidal Demand Variables		
α	controls amplitude of sinusoidal function	0.000001-0.13
β	affects shape and periodicity of sinusoidal function	3000-6000
ρ	shifts sinusoidal function period	600-1200

Each row of panels in Fig. 4.2 denotes a single SOW, Ψ_i, in the set of all sampled SOWs, $\boldsymbol{\Psi_s}$, generated through the combined sampling of both well-characterized and deeply uncertain factors. WCU in hydrology ($\boldsymbol{\Psi_{WCU}}$) is sampled from synthetic records of hydroclimatic conditions, generated from patterns in historical observations (described in the following sub-sections). Additionally, Table 4.3 lists the DU factors included in our analysis, their relevance, and testing ranges, which were based on values used in previous Triangle research by Trindade et al. (2017; 2019). Each SOW contains one set $\Psi_{DU,i}$ of sampled DU factors $\boldsymbol{\Psi_{DU}} \ni [\boldsymbol{\varphi_{SD}}, \boldsymbol{\varphi_{LHS}}]$, containing demand growth realizations $\boldsymbol{\varphi_{SD}}$ (development described in section 4.2.2.3.2) and multiplicative factors $\boldsymbol{\varphi_{LHS}} \ni \left[\vec{B}_{term}, \vec{B}_{rate}, \vec{D}_{rate}, \boldsymbol{RE}, \vec{E}, \overrightarrow{PP}, \overrightarrow{CT}, \vec{\alpha}, \vec{\beta}, \vec{\rho}\right]$ applied to perturb financial parameters of utility debt financing – bond term length B_{term}, bond flat interest rates B_{rate}, and discount rate D_{rate} – along with use restriction efficacy for each utility RE_U, rate of lake evaporation E, permitting period PP and construction time CT, and sinusoidal effects on demand growth α, β, and ρ (detailed in 4.2.2.3.2).

4.2.2.3.1 Hydrologic Realization Development

The WCU samples of hydrology account for the internal variability of the hydrological record by generating synthetic timeseries of regional reservoir inflows. The full ensemble of synthetic inflows are developed through statistical resampling of the historical record (represented as full natural inflows, developed by HydroLogics, 2011) that preserves autocorrelation and spatial correlation patterns of the past through Cholesky decomposition while producing a wider range of extreme events than what is present in the historical record (Kirsch et al., 2013); this expanded evaluation of extreme conditions holds value as evaluation based on historical data alone can miss extreme events and overestimate the robustness of a potential development pathway or policy (Herman et al., 2016; Quinn et al., 2017; Vogel & Stedinger, 1988). For additional detail on water supply modeling in the Triangle, risk-of-failure policy, or synthetic generation of streamflows, see Gorelick et al. (2018) and Herman et al. (2016).

4.2.2.3.2 Demand Realization Development

Future water demand is based on projections of population and per-capita water use (TJCOG, 2014; Hazen and Sawyer, 2020), and week-to-week fluctuations are modeled through a joint probability distribution with inflows (as a proxy for the relationship between weather conditions and water demand; hot, dry days see higher outdoor water use, as an example) (Zeff & Characklis, 2013). Though per-capita water use has been in decline, Triangle utilities anticipate that population growth increases will more than offset this effect leading to overall increased future water demand for the region. Consistent with the ensemble of hydrologic realizations used, 500 realizations of demand ($\boldsymbol{\varphi_D}$) with seasonal variation and response to hydrologic conditions are generated to match, using a joint probability distribution between historical water demand and reservoir inflows as a proxy for hydrologic conditions (as described by Zeff et al., 2013, 2014).

Demand growth is also infamously difficult to accurately forecast at decadal time-scales (Walker, 2013). Previous studies that treat demand growth rate as deeply uncertain have been limited to examination of ranges of constant, linear growth projections (Herman et al., 2015; Trindade et al., 2019). However, water demand growth rate is often non-constant and non-monotonic, and the assumption of constant linear growth may lead water managers to mischaracterize risks associated with demand growth. In this study, we account for potential non-monotonic demand growth through a sinusoidal factor approach. This sinusoidal scaling approach has previously been applied by Quinn et al. (2018) and Trindade et al. (2020) to emulate hydrologic variability in synthetic streamflow projections. Deeply uncertain sinusoidal factors are repurposed here to stress utilities under temporally varying demand growth rate changes.

Equation (12) below describes how DU factors α, β, ρ control demand growth. These sampled sinusoidal factors $m_{s,t}$ are mapped to individual demand realization, impacting the shape and rate of water demand growth in each SOW.

$$m_{s,t}(\alpha, \beta, \rho) = 1 + \alpha \sin\left(\frac{2\pi t}{\beta + \rho}\right) - \alpha \sin(\rho) \tag{1}$$

Trindade et al. (2020) calibrated α, β and ρ to increase or decrease streamflow means no more than 20% compared to historical conditions. Similarly, in this study, we chose sinusoidal factor ranges of α, β and ρ to ensure future annual average demands could not be more than 25% different than utility demand projections. Our approach for synthetic demand realization generation is demonstrated in Figure 4.3. Panel A shows a demand growth projection without the sinusoidal factor multiplier applied. Panel B demonstrates how the factor may be used to generate two very different demand projections and the bottom panel shows the time-varying sinusoidal factors used to generate the records in panel B. By applying sinusoidal factors to demand realizations that follow existing utility projections of demand growth, this study can explore the impacts of both long-term and shorter-term changes in how demand projections on utility planning. Mathematically, the generation of sinusoidal demand timeseries $\boldsymbol{\varphi_{SD,s}}$ of each SOW can be written as

$$\boldsymbol{\varphi_{SD,s,t}} = m_{s,t}(\alpha, \beta, \rho) * \varphi_{D,s,t} \tag{2}$$

for all weeks t in each SOW s.

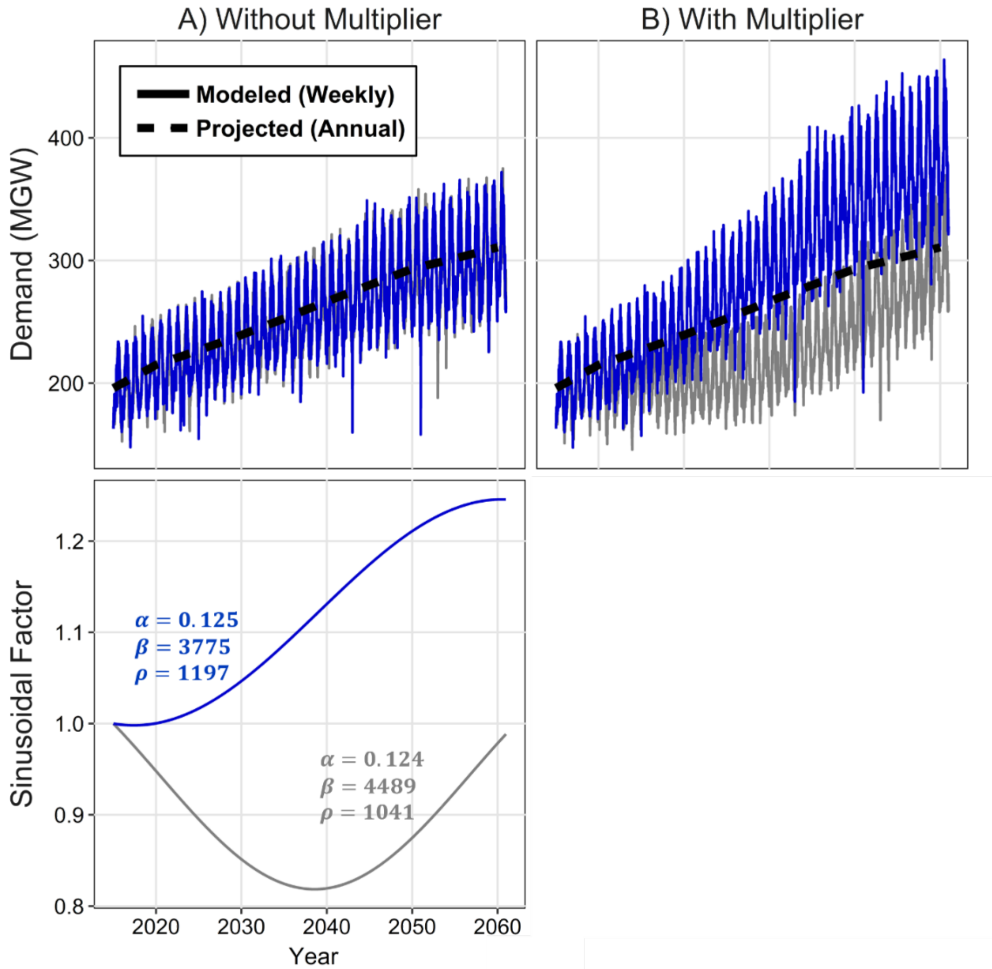

Figure 4.3: Deeply uncertain sinusoidal factors used to generate diversity between two example demand realizations. Parameters in bottom panel generate the factor timeseries plotted using Equation (1), with t changing across time, and the outcome sinusoidal demand realizations described in Equation (2).

4.2.2.4 Deeply Uncertain Optimization Framework

Many-objective optimization is performed to search for model parameters (decision variables) that provide the best possible outcomes across utility objectives. Recent work has found that including deep uncertainty in the many-objective search can improve the robustness of candidate alternatives (Bartholomew & Kwakkel, 2020; Eker & Kwakkel, 2018; Trindade et al., 2017; Watson & Kasprzyk, 2017). Our research employs a DU Optimization framework

(Trindade et al., 2017) to search for Pareto approximate regional agreements that are robust to a wide range of plausible future scenarios. In DU optimization, each candidate regional agreement is evaluated across 500 DU SOWs, generated using the sampling strategy shown in Figure 4.2. The terminology Pareto approximate refers to high quality approximation representations of tradeoffs where improvements in performance in any single objective comes at the cost of performance in one or more of the remaining objectives. The optimization problem can be mathematically described as a search for a set of Pareto-optimal policies $\boldsymbol{\theta}^*$ which minimize the objective function vector $\vec{F}$ such that

$$\boldsymbol{\theta}^* = \min_{\boldsymbol{\theta}} \vec{F} \tag{3}$$

where

$$\vec{F}(\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{\Psi_s}, a) = [-f_{Rel}, f_{RF}, f_{NPC}, f_{PFC}, f_{WCC}, f_{UC}] \tag{4}$$

In Equation (2), the objective function vector $\vec{F}$ contains six regional supply and financial objectives: f_{Rel} is the objective of supply reliability (negated above, as maximizing reliability is equivalent to minimizing failure in this problem); f_{RF} is the restriction use frequency objective; f_{NPC} represents the net present cost of infrastructure investment; f_{PFC} is the peak financial cost objective; f_{WCC} gives the objective of worst-case cost; f_{UC} describes the unit cost of service objective. Each objective is described in further detail below. Objective values in Equation (4) are conditioned based on

$$\boldsymbol{\theta} = \left[\overrightarrow{ROFT}_{action}, \overrightarrow{IP}_{rank}, \overrightarrow{CFC}, \overrightarrow{JLA}, \overrightarrow{DP}, \overrightarrow{\overline{TCA}_{\tau}}\right] \tag{5}$$

$$\boldsymbol{X} = [\vec{x}_{LTROF}, \vec{x}_{STROF}] \tag{6}$$

$$\boldsymbol{\Psi}_{s} = \begin{cases} \boldsymbol{\Psi}_{WCU} \\ \boldsymbol{\Psi}_{DU} \ni [\boldsymbol{\varphi}_{SD}, \boldsymbol{\varphi}_{LHS}] \end{cases} \tag{7}$$

where $\boldsymbol{\theta}$ is a candidate set of decision variables, $\boldsymbol{X}$ represents the time-varied state of both short- and long-term ROF ($\vec{x}_{LTROF}, \vec{x}_{STROF}$), $\boldsymbol{\Psi}_{s}$ contains vectorized sampled sets (s) of both (a) well characterized uncertainties (WCU; Ψ_{WCU}) and (b) deeply uncertain (DU) variables (Ψ_{DU}), and $a \in [a_{fixed}, a_{adjustable}, a_{none}]$ indicates the tested inter-utility cooperative formulation (described in detail in section 4.2.3.3).

In Equation (5), $\overrightarrow{ROFT}_{action}$ is the vector of all risk-of-failure triggers for each regional utility for potential $action \in [water\ transfers, restrictions, infrastructure]$, $\overrightarrow{IP}_{rank}$ is a vector of ranking variables for each potential infrastructure project IP, $\overrightarrow{CFC}$ is a vector of annual utility contingency fund contributions (specifically the fraction of annual revenues contributed), $\overrightarrow{JLA}$ is a vector containing each regional utility's Jordan Lake water supply allocation, $\overrightarrow{DP} = \left[r_{proj}, l_{proj}, \vec{b}\right]$ is the vector holding regional demand projection variables where $\vec{b}$ is the vector of demand buffers for all utilities, and $\overrightarrow{TCA}_{\tau}$ is the vector of initial WJLWTP treatment allocations for each partner utility.

Equation (7) above details the set of deeply uncertain factors $\boldsymbol{\Psi_s}$, containing both (a) WCU from sampling hydrologic realizations, as well as (b) realizations of water demand and vectors of key DU factors.

4.2.2.4.1 Regional Performance Metrics

Assessment of utility performance from each model evaluation is based on values generated across six regional objectives:

1. Water supply reliability (f_{Rel}); frequency of annual supply failure ($F_{r,U,y} = 1$ if any week during a calendar year $y \in \boldsymbol{Y} = [2015,2060]$ in which storage drops below 20% of supply capacity or demand exceeds 90% of treatment capacity, 0 otherwise) across $N_r = 500$ states-of-the-world (r) is quantified to measure the ability of a utility (U) to maintain reliable water service. To determine a regional objective value, the maximum objective value across the set of all utilities ($\vec{U}$) is taken.

$$f_{Rel} = \max_{U \in \vec{U}} \left[\frac{\max_{Y}\left(\sum_r F_{r,U,y}\right)}{N_r} \right] \tag{8}$$

2. Restriction use frequency (f_{RF}); utilities have incentive to limit the amount of time restrictions are implemented, as it can be politically unpopular and reduce utility revenues (Hughes et al., 2014); the fraction of years ($N_y = 46$) with at least one week of use restrictions in place over a model evaluation is therefore another important performance metric. Restriction use indicator $R_{r,U,y} = 1$ when year y of realization r has at least 1 week of restrictions implemented by utility U, and is 0 otherwise.

$$f_{RF} = \max_{U \in U} \left[\frac{\sum_r \sum_y R_{r,U,y}}{N_r N_y} \right] \tag{9}$$

3. Infrastructure net present cost (f_{NPC}); large infrastructure investments often force water utilities to increase water rates, a step they would prefer to defer or avoid altogether. When population and water demand growth are projected to exceed existing capacity, however, supply infrastructure expansion may become necessary. Quantifying net present infrastructure investment – present-valued debt service $DS_{r,u,y}$ based on a discount rate d, summed across SOWs r and years y for each utility U – can be compare with and without inter-utility agreements to demonstrate their ability to reduce overall infrastructure investment.

$$f_{NPC} = \max_{U \in U} \left[\frac{\sum_r \sum_y \frac{DS_{r,U,y}}{(1+d)^{y-1}}}{N_r} \right] \tag{10}$$

4. Peak annual costs (f_{PFC}); tracking the peak annual sum of drought mitigation costs and debt service paid across each realization offers more detail on the financial health of a utility in each model evaluation, where a utility's goal is to minimize peak costs relative to revenue streams. This objective returns the average of each realization's worst year, in terms of the fraction of utility annual volumetric revenue (AVR) required to cover annual debt service DS, contingency fund contribution CFC, revenue losses to restriction use RC, and costs of purchasing water transfers TC.

$$f_{PFC} = \max_{\overrightarrow{U \in U}} \left[\frac{\sum_r \max_{y \in [2015,2060]} \left(\frac{DS_{r,U,y} + CFC_{r,U,y} + RC_{r,U,y} + TC_{r,U,y}}{AVR_{r,U,y}} \right)}{N_r} \right] \quad (11)$$

5. Worst-case cost (WCC); while infrastructure spending over the full planning period is important, financial volatility due to drought mitigation in any given year is also a key utility concern. Specifically, water utilities are concerned with years where revenue losses from restrictions and costs of water transfers cannot be met with existing contingency funds (CF). To identify the worst-case costs a utility could face, this objective quantifies the 99th percentile highest annual cost across all SOWs (r).

$$f_{WCC} = \max_{\overrightarrow{U \in U}} \left[P_{99} \left(\max_{y \in [2015,2060]} \left(\frac{RC_{r,U,y} + TC_{r,U,y} - CF_{r,U,y}}{AVR_{r,U,y}} \right) \right) \right] \quad (12)$$

6. Unit cost of infrastructure expansion (UC); similar to objective 3, this objective quantifies present-valued debt service paid relative to water demand growth over the planning period, offering an assessment of how financially-efficient a utility is able to be when mitigating supply risk.

$$f_{UC} = \max_{\overrightarrow{U \in U}} \left[\frac{\sum_r \sum_y \frac{\frac{DS_{r,U,y}}{(1+d)^{y-1}}}{\left(D_{r,Y,y} - D_{r,Y,2015}\right)}}{N_r} \right] \quad (13)$$

4.2.2.5 Cooperative Formulations of Inter-Utility Agreement

Five of the six Triangle utilities (Raleigh excluded) have water supply allocations from Jordan Lake, the region's largest water source. Only Cary and Chatham County have direct access to their Jordan Lake allocations through independent WTPs, necessitating that other regional utilities access their own allocations through purchases of treated Jordan Lake water from either Cary or Chatham County. In 2018, partially in response to this bottleneck of Jordan Lake water supply access, regional utilities formed the Triangle Water Supply Partnership to determine how shared infrastructure on Jordan Lake could have regional water supply benefits. As a result, the development of a shared WTP on Jordan Lake is being considered by Chatham County, Durham, OWASA, and Pittsboro (Table 4.2B, Western Jordan Lake Regional WTP, or WJLWTP). These four partnering utilities in the development would be allocated treatment capacity in the WJLWTP, from which they may pipe treated water directly to their respective distribution systems (TJCOG, 2014; JLP, 2014). As a part of such an infrastructure project, an agreement between Triangle water utilities to finance and operate the WJLWTP would be required. Inter-utility and capacity-sharing agreements are common across the U.S. and globally (Silvestre et al., 2018; Tran et al., 2019). Differences in how an agreement is structured, however, can have significant impacts on the water supply and financial outcomes for participating partners (Gorelick et al., 2019; Sjöstrand et al., 2018).

Assessment of inter-utility agreement formulations within our water supply modeling framework requires each formulation be evaluated under identical conditions for comparison of performance, as well as against a formulation without agreement that contains only independent infrastructure planning by utilities. Therefore, this paper tests three model formulations:

1. Regional utilities have the option to develop the WJLWTP with fixed treatment capacity and financing allocations (4.2.3.5.1)
2. The WJLWTP may be developed with adjustable treatment capacity and financial allocations (4.2.3.5.2)
3. No cooperative agreement is reached, and Triangle utilities do not develop a joint WJLWTP (4.2.3.5.3).

4.2.2.5.1 Fixed Capacity Treatment Allocations

Fixed allocation inter-utility agreements are common. For example, the Cary-Apex WTP serves the towns of Cary, Apex, and Morrisville where each hold a fixed capacity allocation while Cary operates the plant (Cary-Apex WTP Agreement, 2015). Under such an agreement, treatment capacity allocations (in terms of maximum quantity of water treated per day) for each partner utility are fixed when the WTP comes online after construction. Each partner's share of the capital costs of construction are set based on the fraction of capacity allocated to each. Conveyance and other variable costs of water treatment or transfer, which are relatively small in comparison to capital costs, are not considered within the agreement structures evaluated in this research. The allocation of treatment capacity and debt service on capital expenditures for the WJLWTP under a fixed allocation agreement is described by (14) and (15) below:

$$TCA_{U,y} = TCA_{U,\tau} \tag{14}$$

$$DS_{WJLWTP,U,y} = \frac{TCA_{U,\tau}}{\sum_{u \in \vec{U}} TCA_{u,\tau}} * DS_{WJLWTP,y} \tag{15}$$

Here, τ is the year in which the WJLWTP begins operating, $TCA_{U,y}$ is the treatment capacity allocation for utility U in year $y \geq \tau$, $\vec{U}$ is the set of WJLWTP partner utilities, $DS_{WJLWTP,y}$ is the total debt service owed for capital costs and interest on the WJLWTP in year y to be disbursed among agreement partner utilities. Debt service is modeled for this work for each utility such that $DS_{p,U,y}$ for any future infrastructure project p (Table 4.2B) is equal in all repayment years $y \in Y_p$ where Y_p is the set of years from project p beginning operation (and debt repayment begins) to the year of debt maturity for that project.

4.2.2.5.2 Adjustable Treatment Allocations

Alternatively, an inter-utility agreement with flexibility in allocations may be beneficial to partner utilities. An adjustable capacity agreement is designed to ensure that the unit cost of treating water in a given year is equal between partners, no matter how much use occurs in aggregate; as an example, this type of accounting is used to cover costs of development by Tampa Bay Water Authority, which charges a uniform rate for supply to its six wholesale customers by scaling water supply production for each customer to match their respective levels of demand each year (Asefa, 2015). This work abstracts an adjustable capacity agreement structure, in which the rate of water can be set annually based on water use by all partners and costs – debt service, in this case – to be recovered over the year. Capacity allocations for WJLWTP partners are adjusted based on expected near-term water demand, allowing allocations to be adjustable year-to-year. The treatment capacity allocation under this agreement structure is described by (16) and (17):

$$TCA_{U,y} = \begin{cases} TCA_{U,\tau} & when\ y = \tau \\ TCA_{U,y-1} + \left(WSF_{JL,U,y} * DGR_{U,y}\right) & when\ y > \tau \end{cases} \tag{16}$$

$$DGR_{U,y} = f\left(r_{proj}, l_{proj}, b_U\right) \tag{17}$$

Under an adjustable agreement, capacity allocations in each year $y > \tau$ are based on the previous year allocation for utility $U \in \vec{U}$, adjusted based on estimated annual demand growth rate $DGR_{U,y}$ and the fraction of water supply drawn from Jordan Lake $WSF_{JL,U,y}$. Each utility's reliance on Jordan Lake is, in part, governed by the water supply allocation JLA_U awarded to the each utility in Jordan Lake by the US Army Corps of Engineers that operates the reservoir. Demand growth estimates for a utility are a function of how often re-projections of demand are done (r_{proj}), the length of the recent historical record (l_{proj}) used to estimate future demand, and any buffer (safety factor hedge against high growth) a utility may add (b_U). Debt service allocations are, like in a fixed agreement, proportionate to treatment capacity allocations.

4.2.2.5.3 No Cooperative Agreement

Though Triangle utilities intend to develop the WJLWTP, it remains possible that no agreement is reached and the facility is not constructed or financed. This potential alternative is also tested as a cooperative formulation in our work.

4.2.2.6 Computational Experiment and Multi-Objective Optimization Search

In this study, we employed the Borg multi-objective evolutionary algorithm (MOEA), which has demonstrated as an effective tools for identifying high-quality Pareto approximate solutions to non-linear, complex problems such as those in water supply management (Hadka & Reed, 2013). Optimization runs for each formulation were run on The Cube Cluster of the Cornell University Center for Advanced Computing and the Stampede2 Cluster of the Texas Advanced Computing Center (TACC) Extreme Science and Engineering Discovery Environment (XSEDE). Borg MOEA optimization seeds were allowed to progress for a maximum of 150,000 function evaluations. A single reference set of solutions was identified after combining individual reference sets from each seed across all inter-utility agreement formulations. Runtime diagnostics were performed using hypervolume and visual analytics to confirm convergence; more detailed discussion of the Borg MOEA optimization diagnostics and validation of reference set performance using an-out-of-sample set of SOWs is shown in Supplement A.

4.2.2.6.1 Defining Satisfactory Regional Performance

To identify management portfolios that produce satisfactory utility water supply and financial performance under uncertainty, reference set solutions identified in DU optimization are screened based on three key management criteria. The criteria of satisfaction are based on feedback from Triangle utilities' personnel, previously used to screen results from similar past research in the region (Herman et al., 2015; H. B. Zeff et al., 2014):

1. Reliability ≥ 99%: to meet demands, utility water supply storage cannot fall below 20% of capacity more than once in 100 years.

2. Restriction Use Frequency ≤ 20%: to maintain their efficacy and avoid public frustration, regional utilities hope to implement use restrictions less than 1-in-5 years on average.
3. Worst-Case Cost ≤ 5% AVR: unplanned financial disruptions of more than 5% AVR in a given year would be ruinous for regional utilities' budgets – only states-of-the-world that can minimize worst-case cost below this threshold, a function of hydrologic, demand, and utility decision-making factors, are acceptable.

4.3 Results

Results from DU optimization of three potential inter-utility cooperative formulations – where a shared WTP on Western Jordan Lake (WJLWTP) is (1) developed with fixed treatment allocations for each utility; (2) with adjustable capacity allocations; (3) not built, and no agreement is made – are presented below. Beginning with outcomes at a regional objective level (section 4.3.1), results span both regional and individual utility (4.2.2) objective performance for Pareto-approximate solutions under all formulations. Key relationships between decision variables and objective outcomes (4.2.3), as well as characteristics of representative solutions (4.2.4), are further explored to quantify differences in utility behavior and performance between cooperation formulations.

4.3.1 Regional Objective Outcomes

Figure 4.4 is a parallel axis plot of the Pareto-approximate reference set of solutions across all cooperative formulations. Each line across the six vertical axes represents regional objective results for a single solution of the reference set. The lower a solution crosses an objective's vertical axis, the better its performance in that objective. Solutions of the Pareto-approximate reference set (Fig. 4.4, light grey, $n = 29{,}654$) include non-dominated solutions across all optimizations performed (one for each formulation). Objective values represented for a solution are the "minimax" objective value across all utilities – the worst-performing utility, in terms of each objective, represents the regional objective value for that solution. These results are shown in two panels on Figure 4.4: Figure 4.4(I) visualizes the objective outcomes of the 588 solutions that meet utilities' performance criteria; Figure 4.4(II) identifies one high-performance representative solution under each cooperative formulation – meeting stricter performance criteria of greater than 99.2% reliability, less than 5% restriction use frequency, and less than 2% AVR worst-case cost – for subsequent exploration in this section.

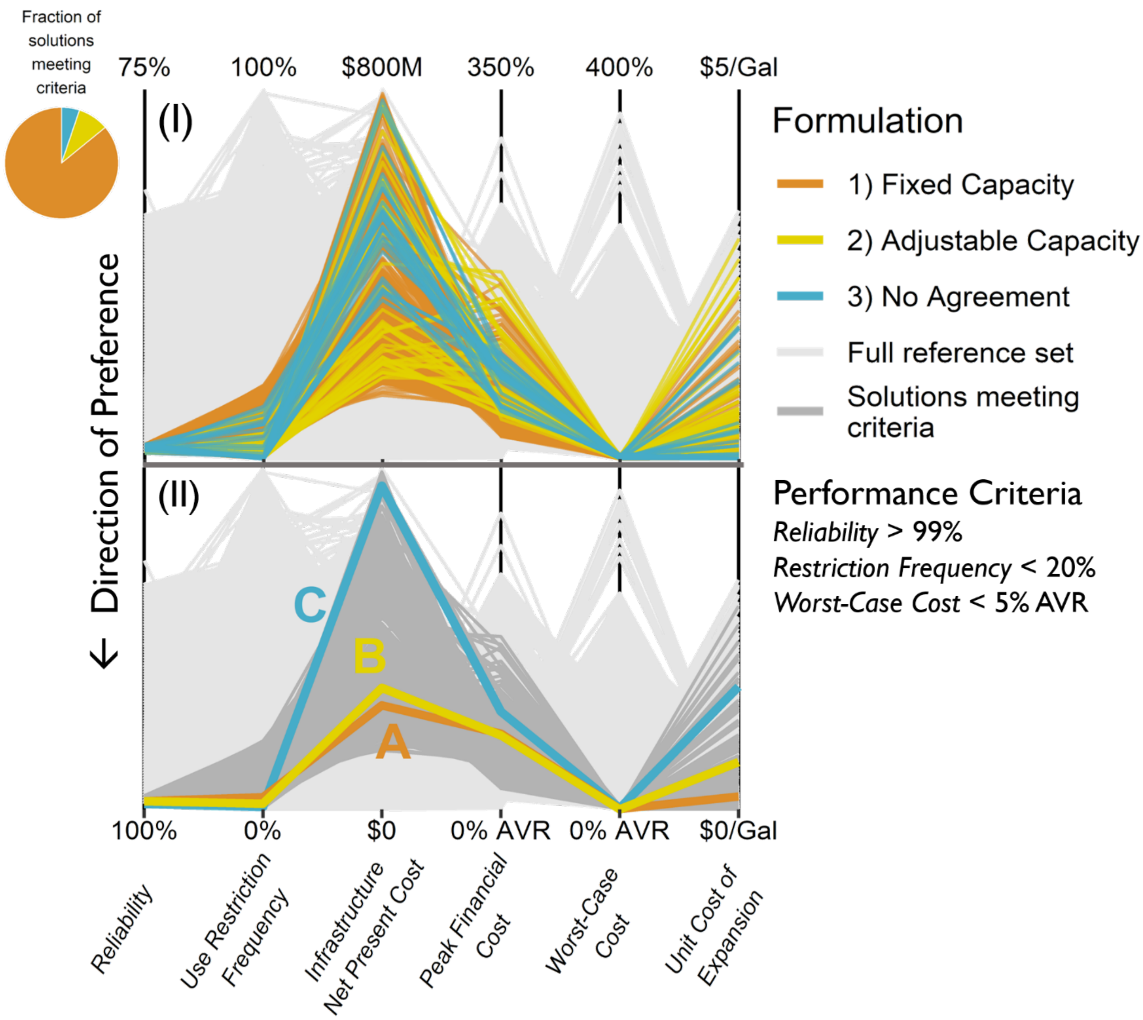

Figure 4.4: Parallel axis plot of the Pareto-approximate reference set of solutions (light grey), with solutions meeting utility performance criteria in color. Solution performance is shown across management objectives (from left to right). Each colored line represents objective results for a single solution. Solution performance is better if its line is closer to the bottom of the plot across each objective. Panel (I) compares the full reference set of solutions to those meeting criteria; panel (II) identifies three representative high-performance solutions meeting utility criteria, used for detailed comparison in subsequent results.

Imposing the utilities' performance criteria on the reference set yields a smaller suite of tradeoff solutions with high reliability, limited restriction use, and low worst-case costs, shown on Fig. 4.4(I) in color. Of the 588 solutions that meet the utilities' criteria, 506 include a fixed capacity agreement for development of the WJLWTP (Fig. 4.4(I), orange), 52 use an adjustable capacity WJLWTP agreement (Fig. 4.4(I), yellow), and only 30 had no cooperative agreement and no development of the WJLWTP (Fig. 4.4(I), blue). The relatively limited number of solutions able to meet utility performance criteria without an inter-utility agreement indicates that inter-utility agreements contribute planning flexibility and regional performance benefits through both the fixed and adjustable capacity variants. This is especially apparent in terms of net present cost of infrastructure (Fig. 4.4, third vertical axis), where the highlighted solutions meeting the utilities' performance criteria without an inter-utility agreement required relatively high investment in infrastructure expansion; solutions with an agreement could meet performance criteria at lower levels of infrastructure investment.

4.3.2 Individual Utility Objective Outcomes

Objective performance of Pareto-approximate solutions in Fig. 4.4 show only regional outcomes; however, identifying differences in individual utility performance is key to understanding how inter-utility agreements may benefit utilities asymmetrically. Figure 4.5 shows for which solutions of Fig. 4.4 that an individual utility was the 'driver' of that solution's objective value, answering the question: how often, for a particular objective, was each utility the worst-performing?

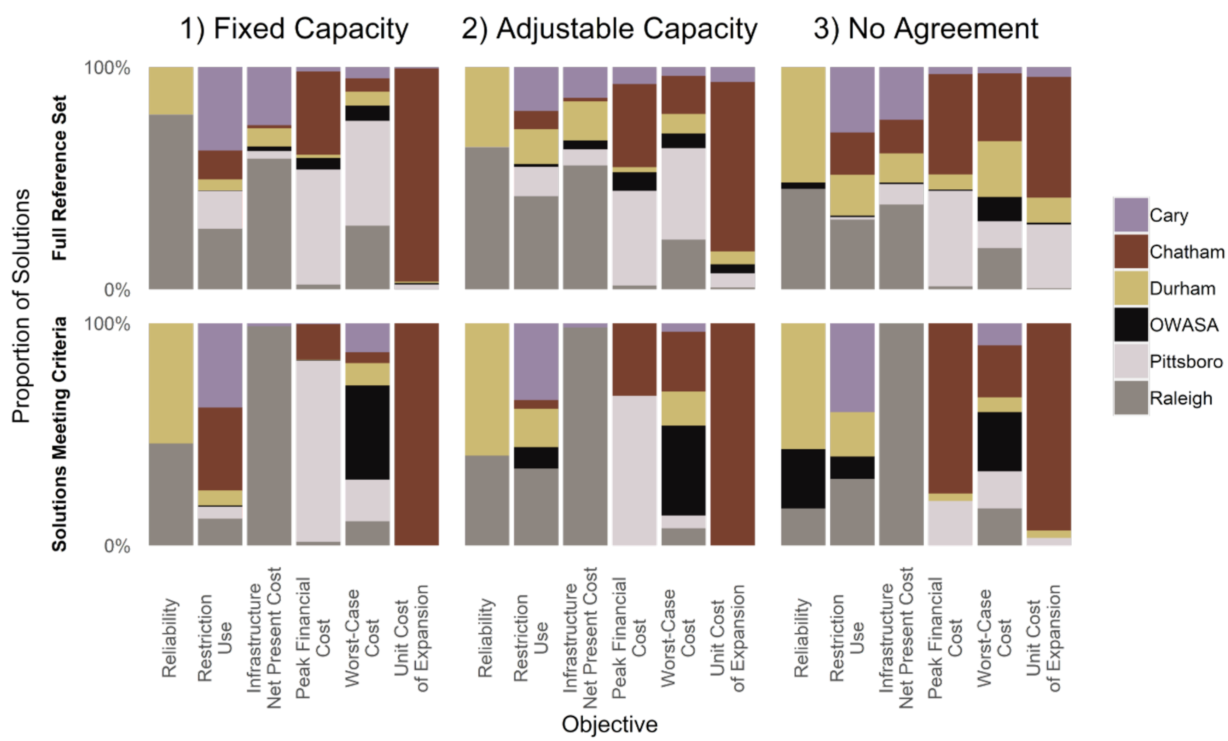

Figure 4.5: Fraction of solutions – in the (top row) Pareto-approximate reference set and (bottom row) solutions meeting utility criteria – for which an individual utility (color) represents the worst-performing of the region for a particular objective (x-axis), by formulation (rows).

Across the full reference set of solution (Fig. 4.5, top row of panels), a handful of differences between solutions with an inter-utility agreement (Fig. 4.5(1,2), top panels) and those without (Fig. 4.5(3), top panel) emerge. When an inter-utility agreement is available across all solutions, allowing Triangle partnering utilities to develop the WJLWTP, Durham (yellow) is less-frequently the utility of lowest reliability (Fig. 4.5, first column of top panels), with Raleigh (dark grey) becoming the most frequent utility to attain the lowest reliability. Only in solutions without any inter-utility agreement does OWASA (black) appear as the worst-performing utility in terms of reliability.

Financially, a larger share of solutions with inter-utility agreement show Pittsboro (light grey) as the worst-performing utility for both peak financial and worst-case cost objectives (Fig.

4.5, fourth and fifth columns of each panel), compared to solutions without an agreement. Whether or not cooperation via the WJLWTP is possible, Chatham County is the worst-performing utility in terms of unit cost of infrastructure expansion (Fig. 4.3B, sixth column) across almost all solutions.

Between the full set of solutions and solutions meeting utilities' performance criteria (Fig. 4.5, bottom row of panels; corresponding with solutions of Fig. 4.4(I) in color), other shifts in distribution of worst-performing regional utilities are apparent. These differences indicate which utilities may act as a "limiting factor" for regional performance as criteria for satisfactory performance become increasingly strict. For example, Raleigh was the utility of greatest infrastructure net present cost (Fig. 4.5, third column in each panel) across all solutions meeting utility performance criteria under fixed and adjustable cooperative formulations (Fig. 4.5(1,2)). Similarly, OWASA (black) became the worst-performing utility most frequently as measured by worst-case cost in solutions meeting performance criteria, and Pittsboro or Chatham County were almost exclusively responsible for the regional peak financial cost objective value in the same solutions.

4.3.3 Cooperative Formulation Differences on Jordan Lake

When evaluating the benefits of the cooperative inter-utility agreement formulations, it is important to distinguish the impacts across the partnering utilities for a WJLWTP – Chatham County, Durham, OWASA, and Pittsboro. Figure 4.6 shows the ranges of the utilities' objective outcomes for solutions meeting the regional performance criteria under each agreement formulation.

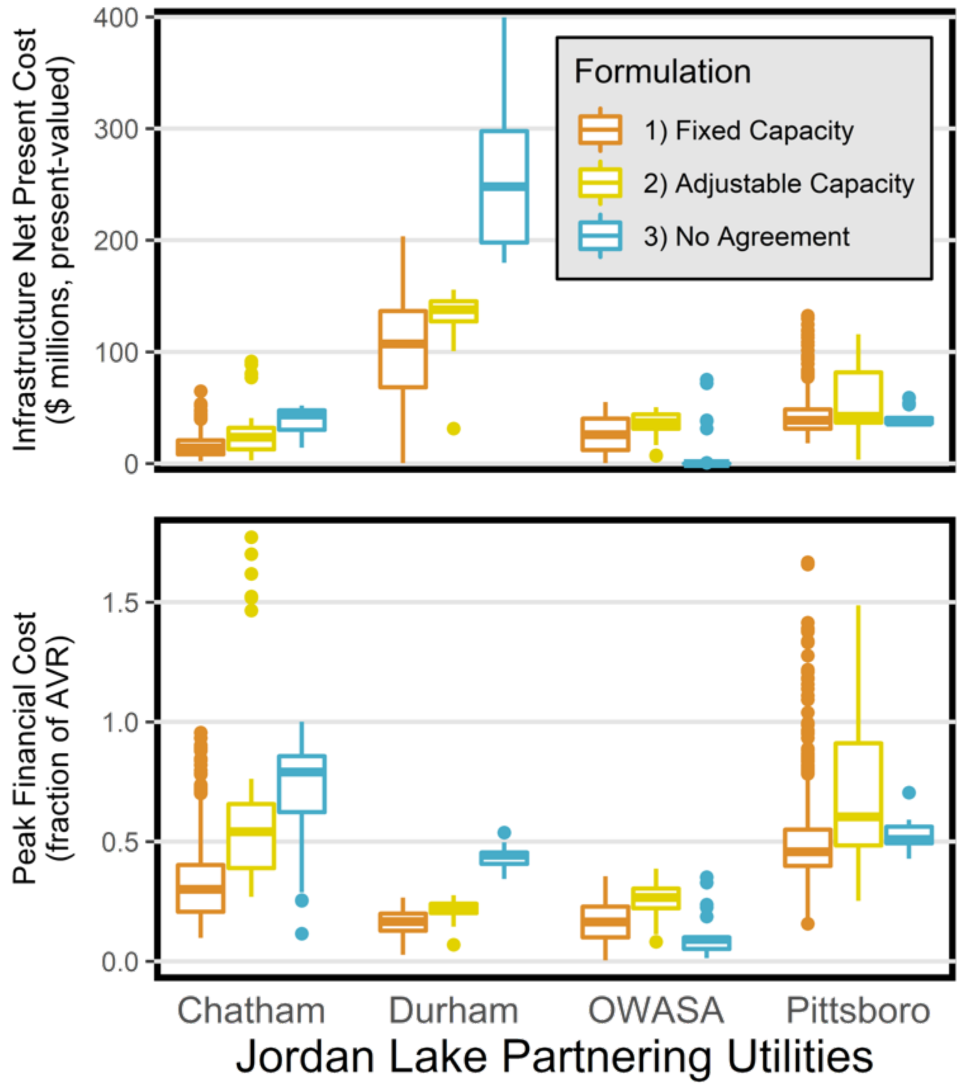

Figure 4.6: Range of (top panel) infrastructure net present cost and (bottom panel) peak financial cost objective values across Pareto-approximate reference set solutions meeting utility performance criteria, for utility partners to a WJLWTP agreement (x-axis) under each cooperative formulation (color).

Broadly, infrastructure net present cost (Fig. 4.6, top panel) and peak financial cost objective values (Fig. 4.6, bottom panel) improve for Chatham County and Durham under inter-utility cooperation formulations with the WJLWTP included (Fig. 4.6, orange and yellow), versus solutions without a WJLWTP agreement made (Fig. 4.6, blue). By contrast, OWASA and Pittsboro generally experience the worst financial objective outcomes when a WJLWTP is constructed. As the largest utility partner to the WJLWTP, Durham invests more than other partners in infrastructure net present costs regardless of formulation. Chatham County and Pittsboro are relatively small utilities, so they experience larger variability in peak financial cost than OWASA and Durham. On average, a fixed allocation WJLWTP agreement (Fig. 4.6, orange) formulation resulted in lower objective values than under an adjustable capacity agreement (Fig. 4.6, yellow), but solutions with adjustable capacity agreements could out-perform fixed capacity allocation agreements in some cases. Also, fixed capacity allocation agreements more frequently resulted in poor-performance (i.e., high objective values), in comparison to adjustable capacity agreements (Fig. 4.6, longer tails and outliers on upper bounds of boxplots).

The effects of inter-utility agreements on an individual utility's objective performance are not only tied to the agreement formulations but also to differences in a utility's exposure to the decisions of its counterparties (other WJLWTP partner utilities). Figure 4.7 explores the statistical relationships observed between initial treatment capacity allocations for each utility partnering on the WJLWTP and utility financial objective outcomes. Under a fixed capacity allocation agreement (Fig. 4.7, top row of panels), each utility's WJLWTP initial treatment capacity allocation is strongly positively correlated (green) to that utility's financial objective outcomes, with the exception of Chatham County who maintain a minimal initial allocation across most solutions. When allocations are fixed, the objective outcomes for a single utility are not strongly correlated with the initial allocations of other utilities.

Under an adjustable capacity agreement (Fig. 4.7, bottom row of panels), however, a utility's objective performance is more substantially correlated to the treatment allocations of other utilities – OWASA offers a particularly clear example (Fig. 4.7, bottom row, third column of panels), where OWASA objective outcomes are strongly positively correlated to its own WJLWTP allocation size, but also strongly negatively correlated (purple) with Chatham and Pittsboro treatment allocations. Increased sensitivity to other utilities' adjustable allocations appears for Durham and Chatham as well; in fact, Durham's financial objective outcomes (Fig. 4.7, second row, second columns of panels) become more correlated to Chatham County and Pittsboro allocations than to the City's own allocation. Though the utilities do have statistically significant impacts on the objective outcomes of their partners through fixed agreements (i.e., Durham and Pittsboro), the correlations are positive and relatively weak, indicating that initial fixed allocations of one partner may impact another adversely, but only to a small degree.

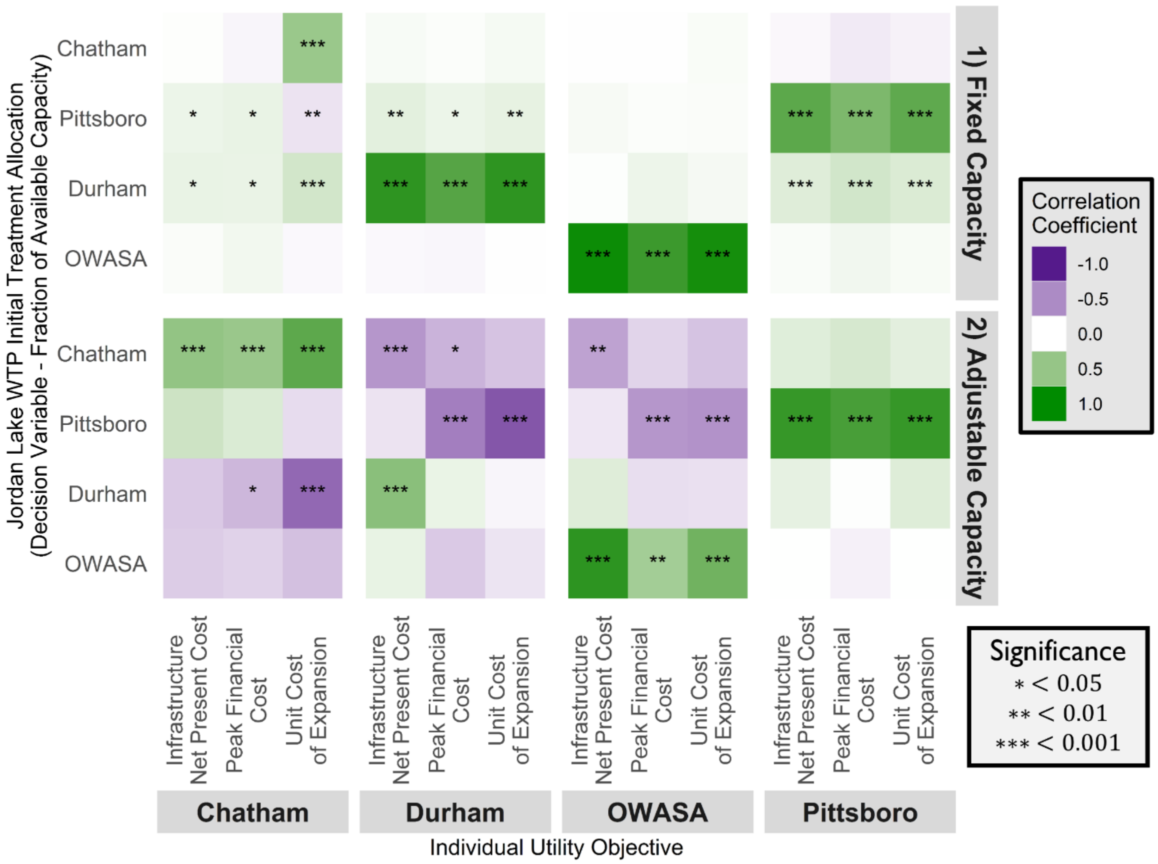

Figure 4.7: Spearman correlation coefficients (color) and p-value statistical significance (asterisks) between (rows) individual utility financial objective values and (columns) initial treatment capacity allocations in the WJLWTP for Pareto-approximate solutions meeting utility performance criteria under each cooperative formulation (rows of panels).

4.3.4 Demand Growth Influences on Infrastructure Pathways

Cooperation on the WJLWTP has significant influence on regional performance despite being just one potential infrastructure project within a larger set of investment options for the utilities to develop. Fig. 4.8 details how infrastructure pathways evolve across SOWs of three high-performance example solutions that meet utility performance criteria (Fig. 4.4(II)), chosen for their similar initial treatment allocations in the WJLWTP.

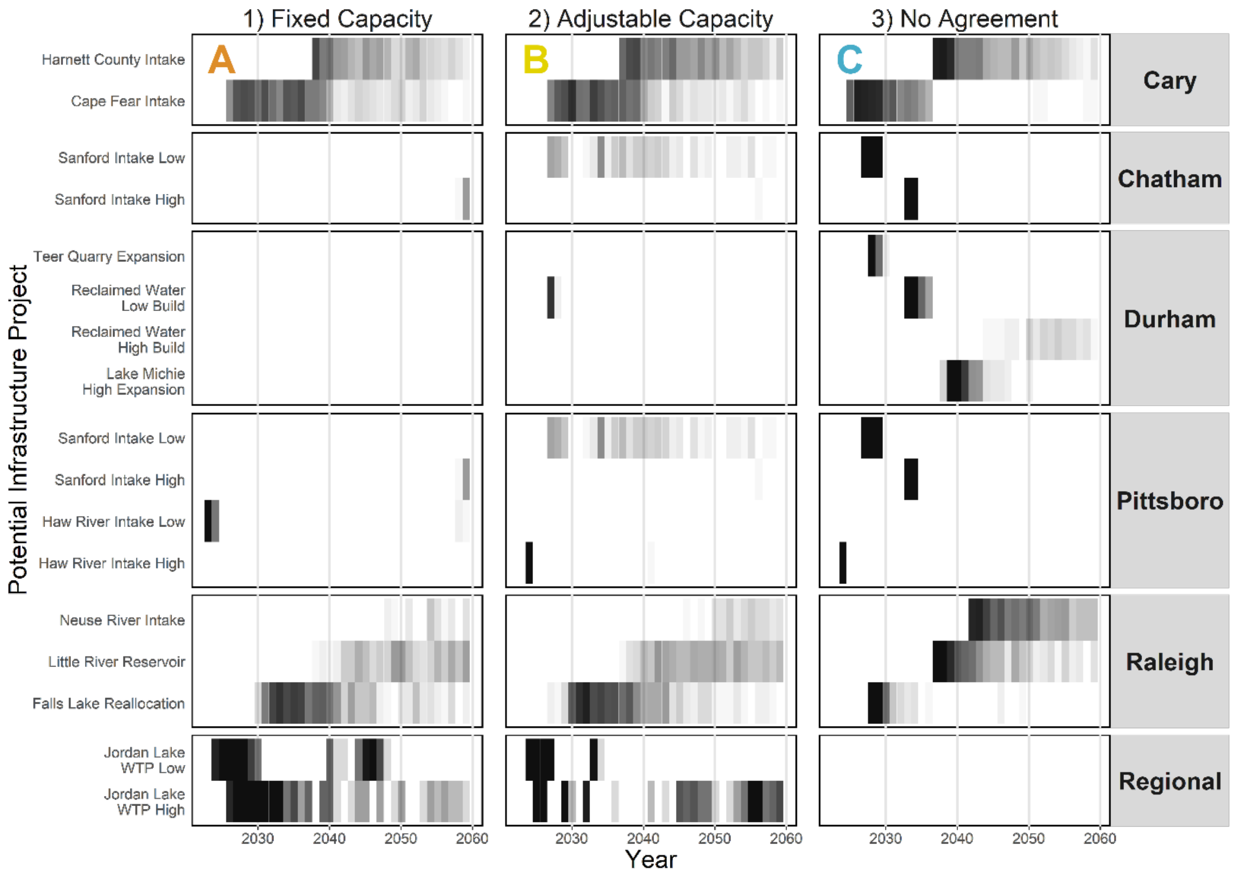

Figure 4.8: Infrastructure development pathways from 2015-2060 (x-axis) by utility across example solutions (shown in Fig. 4.4(II)) in each cooperative formulation (columns). Darker shading indicates a higher fraction of SOWs where an infrastructure option (y-axis) is constructed.

When the WJLWTP (Fig. 4.8, Regional) is utilized under a fixed or adjustable capacity allocation formulation, it is constructed and/or expanded before 2035 in the majority of SOWs. Implementation of the WJLWTP has consequences for agreement partners, especially Durham who avoids constructing up to four independent infrastructure options (Fig. 4.8(3), Durham). Pittsboro is able to avoid a large/high expansion of its Haw River Intake project with a fixed WJLWTP agreement. The Haw River Intake is built in almost all SOWs when no WJLWTP agreement is made. When the WJLWTP is constructed, Pittsboro instead blends the use of a small/low expansion of the regional WJLWTP with deferred construction of a Sanford intake.

Chatham County, when the WJLWTP is available, can similarly defer construction of a Sanford intake (a shared project with Pittsboro) and/or reduce the scale of Sanford intake required. OWASA, the fourth partner utility on the WJLWTP, has no representation in Fig. 4.8, indicating no other infrastructure is built by OWASA other than the WJLWTP.

Differences in pathways between cooperative formulations can be attributed, in part, to how each WJLWTP agreement formulation responds to demand growth and allocates treatment capacity and debt service among partners. Fig. 4.9 visualizes how treatment allocations are set year-to-year for the WJLWTP under two example SOWs of high and low demand under each WJLWTP cooperative formulation (A and B from Fig. 4.4(II)).

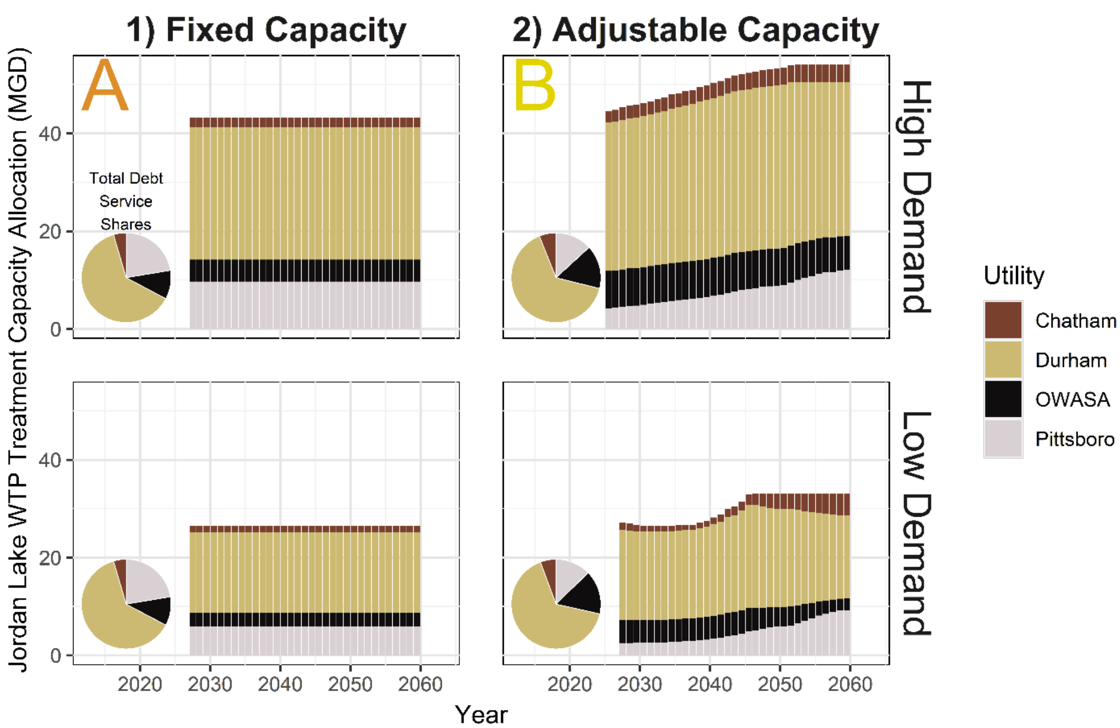

Figure 4.9: Year-to-year treatment allocations in the WJLWTP for each utility (color), under (1) fixed and (2) adjustable capacity allocation agreement formulations, under two example SOWs of high (top panels) and low (bottom panels) demand growth. Relative shares of debt service paid by each utility over the course of capital repayment for each utility is shown by inset pie charts for each realization.

Aspects of Fig. 4.9 demonstrate the relative benefits and drawbacks of each cooperative agreement formulation, in terms of treatment capacity availability and financial responsibility. Under a fixed capacity agreement (Fig. 4.9, left column), utility treatment capacity and debt service (pie charts) are steady over time, though differences in demand growth (Fig. 4.9, panel rows) impacts the initial sizing of WJLWTP construction. When an adjustable capacity agreement is used (Fig. 4.9, right column), annual treatment capacity allocations increase as water demands grow, which results in reduced overall debt service paid by smaller partner Pittsboro (light grey), primarily at the expense of larger partners Durham (yellow) and OWASA (black). When capacity is available, an adjustable agreement also allows Chatham County (brown) to accumulate a larger share of treatment capacity as it grows, compared to the fixed allocation agreements. If initial treatment capacity allocations sum to less than the total available capacity, and no additional partners join the project, an adjustable agreement can adapt to make use of that excess capacity as demands shift, while a fixed agreement cannot.

4.4 Discussion

Contextualizing results of this study within the two primary research aims – (1) how may differences in inter-utility agreement structure impact utility supply and financial risk, and (2) to what degree do demand growth uncertainty and counterparty risk influence the viability of regional cooperation – requires interpretation of regional (4.4.1) and individual (4.4.2) utility performance, as well as what effects counterparty risk (4.4.3) and demand growth uncertainty (4.4.4) may have to influence performance under cooperative agreement formulations.

4.4.1 Regional performance with inter-utility agreements

Inter-utility cooperative agreements for the WJLWTP offer the Research Triangle region substantially more planning flexibility to meet utility performance criteria of high reliability, low restriction use frequency, and low worst-case costs compared to futures without any cooperation to develop a shared WTP on Jordan Lake. That flexibility specifically offers partner utilities (Chatham County, Durham, OWASA, Pittsboro) the ability to defer or avoid other infrastructure projects they might have had to build otherwise.

While it is possible for the Triangle to meet regional performance criteria without a cooperative agreement, such solutions exhibited significantly higher infrastructure investment (indicated by high infrastructure net present cost objective values) and peak financial costs. The behavior of non-agreement solutions indicates a strong tradeoff between reliability, restriction use, worst-case costs, and infrastructure investment; substantially increasing supply and treatment capacity through infrastructure expansion, increasing infrastructure net present cost, which can then increase reliability and decrease restriction frequency. Worst-case costs are similarly reduced, as the frequency of water transfer purchases and restriction implementation is reduced due to higher levels of treatment or supply capacity available to a utility. Use of an inter-utility agreement, in comparison, can reduce the severity of this tradeoff through economies-of-scale, offering the region the potential to reduce infrastructure investment without compromising water supply or financial performance.

4.4.2 Individual utility tradeoffs to meet regional performance criteria

Inter-utility cooperative formulations offer clear water supply and financial objective performance benefits regionally, relative to solutions without an agreement, but differences in performance between fixed and adjustable capacity allocation agreement formulations were not as obvious at a regional scale. To identify the diverse impacts that inter-utility agreements can have across the multi-actor Triangle system, individual utility outcomes across water supply and financial objectives in solutions that meet utility performance criteria are most informative.

This analysis finds that the worst-performing utility in terms of each performance objective, which drives the regional objective value, varied by objective. For some objectives an individual utility is the worst-performing for all solutions meeting utility criteria, such as Raleigh driving regional outcomes of infrastructure net present cost. Related to infrastructure spending, Raleigh also shows to be the worst-performing utility in cooperative solutions meeting utility performance criteria in terms of water supply reliability, with Durham being the only other utility exhibiting worst regional reliability outcomes; Raleigh, not being a partner to Jordan Lake WTP development, is forced to respond to low reliability levels through substantial independent investment in its own infrastructure projects. However, when no agreement is used, Durham is most frequently the worst-performing utility in terms of reliability. This discrepancy between cooperative formulation is due to inter-utility agreement on the WJLWTP, allowing Durham a lower-cost pathway to expanding water supply and treatment capacity earlier. Cooperation via the WJLWTP also reduces Durham exposure to drought and demand growth that later result in reduced reliability, a pathway that does not exist without Jordan Lake cooperation.

Chatham County and Pittsboro almost exclusively represent the region's worst-performing utilities for peak financial cost in solutions meeting regional utility performance criteria. Because both Chatham County and Pittsboro have the smallest demands – and projected demands – of Triangle utilities, financial fluctuations of debt service paid on infrastructure expansion have an outsized impact on them compared to other utilities. While about 15% of solutions meeting utility criteria under a fixed allocation agreement show Chatham County to be the worst-performing utility in terms of peak financial cost, this percentage rises to more than 25% of solutions under an adjustable capacity agreement. Pittsboro, the faster-growing of the two smallest partners, has an incentive to reserve an allocation in the WJLWTP much larger than its projected demands would suggest if allocations are fixed and cannot be revised later as demands grow. However, reservation of a large fixed allocation results in Pittsboro more often being the worst-performing utility, paying debt service on the WJLWTP as a higher percentage of their annual revenues in early years before demands have grown. Chatham County, being small and projected to grow slowly, reserves very small fixed WJLWTP allocations and (mostly) avoids the financial risk outcomes seen by Pittsboro. Under an adjustable agreement where treatment allocations can grow in time with demand, Chatham County still has incentive to request a small initial allocation in a WJLWTP; however, Pittsboro now does as well, which means that the same treatment allocation between agreement formulations for Chatham County can result in a larger share of debt service owed under an adjustable agreement.

4.4.3 Counterparty effects of cooperative infrastructure development

Regional supply and financial outcomes may improve as a result of inter-utility cooperation but impacts to individual utilities may go unnoticed, due to the asymmetric size and growth trends of each partner utility. One example of this is that inter-utility cooperation offers clear financial benefits to Durham and Chatham County relative to futures without cooperation, reducing infrastructure investment and peak financial costs, while cooperation simultaneously has negative effects on OWASA and (to a lesser degree) Pittsboro. Because Chatham County, OWASA, and Pittsboro are relatively small utilities in the Triangle, their increased financial risk or levels of infrastructure investment as a result of cooperation may not negatively impact regional financial objective outcomes; instead, larger utilities Cary, Durham, or Raleigh can, conversely, have an outsized impact on regional objectives.

When comparing fixed and adjustable cooperative formulations, generally better performance for solutions was attained under a fixed allocation agreement formulation. In part, adjustable agreement solutions resulted in less-effective cooperation because of the counterparty exposure each partner utility faces as result of decisions made by other partners, as demonstrated by the increased strength of correlation between partner utility objective outcomes and other utilities' initial treatment allocations when allocations are adjustable. When allocations are fixed each utility can more effectively control its own objective outcomes. With adjustable allocations, a tradeoff in financial performance appears between larger (Durham and OWASA) and smaller (Chatham County and Pittsboro) WJLWTP partners – with smaller initial treatment allocations for Durham and OWASA comes increased financial costs for Chatham County and Pittsboro, and vice versa. While adjustable capacity agreements can offer financial benefits to smaller partners 'growing into' their treatment allocations as demands rise, the counterparty effects can constrain the overall value of an adjustable inter-utility agreement.

4.4.4 Infrastructure pathway adaptation via inter-utility agreement

Cooperation between partner utilities on Jordan Lake could not only impact the decision-making and infrastructure pathways of partners but also those of other regional utilities like Cary and Raleigh. When a WJLWTP is constructed, Cary less frequently chooses to build a Harnett County Intake, or defers doing so until after 2035, compared to SOWs where no regional agreement is reached. The changes to Cary infrastructure pathways are due to (a) more frequent requests of water transfers from Cary to Durham, OWASA, and Pittsboro during periods of water scarcity when no Jordan Lake agreement is available; (b) the capacity of Cary's water supply allocation in Jordan Lake, which can be susceptible to lower levels in the 2050s as demands grow and raise Cary's risk of supply failure. Regional cooperation on a shared WTP is able to relieve pressure from Cary to reduce its effective treatment and supply capacity to meet regional transfer requests, giving Cary more flexibility to defer or avoid medium-to-long-term infrastructure expansion – as a result, regional cooperation does not only offer benefits to partner utilities, but other actors in the region as well.

Raleigh also appears to benefit from the existence of a WJLWTP agreement, despite not being a partner, as the agreement often keeps it from investing in the Neuse River Intake after 2040 when Jordan Lake cooperation is ongoing. However, Raleigh is the utility with the greatest infrastructure net present cost in all solutions meeting regional performance criteria, but not all of those cooperative formulation solutions saw less infrastructure investment than solutions without cooperation. With the WJLWTP built, Durham and other partners can more easily achieve the performance criteria of 99% supply reliability, putting the onus of regional improvement on Raleigh; as a result, maintaining a regional reliability of at least 99% requires Raleigh to balance (over)investment in infrastructure against increased risk-of-failure. In some states of the world, Raleigh can do so without expanding infrastructure to the extent necessary when no WJLWTP exists, but that is not always the case.

While cooperation is regionally beneficial, this study documented how individual utilities may simultaneously experience unintended financial consequences. This may be most apparent for OWASA, who do not opt to invest in independent infrastructure options in almost all solutions meeting regional performance criteria. This implies that OWASA is unlikely to be the

WJLWTP partner to trigger construction of the project and doesn't experience elevated risk-of-failure levels that would necessitate infrastructure expansion of any project before 2060.

4.4.5 Additional considerations

Just as infrastructure expansion was not limited to cooperative development on Jordan Lake, other aspects of the Research Triangle management and planning system could impact the results of this work. One example could be how satisfactory regional performance is quantified. Regional water managers were polled to determine the performance criteria, used to screen our Pareto-approximate set for management policies that were robust under uncertainty, with a preference for risk-averse solutions. Should performance criteria be relaxed (or tightened), different conclusions could be drawn about the ability of management policies or cooperative agreements to meet utility goals. However, the regional benefits of cooperation compared to scenarios without cooperation under the selected reliability, restriction use, and cost performance criteria are a strong indicator that inter-utility agreements are a broadly useful technique to reduce water supply and financial risk.

Similarly, the minimax approach for objective calculation used here can well identify solutions that improve overall regional outcomes in a multi-actor system but does not always explicitly reveal conflict and tradeoffs among the objectives of the individual participating actors. Future work to improve or locate shortcomings of a minimax approach in the Triangle system should include re-analysis of solutions identified here, re-optimized for individual utility objectives.

Though this work applied a sinusoidal factor method to subject water utilities to greater uncertainty in demand growth than in past studies of this nature, our research still falls short of quantifying system dynamics under two important uncertainties: (a) spatial asymmetry of demand growth; and (b) management response to realized vs. projected demand. Sinusoidal factors were applied to all utility demand projections uniformly, meaning changes to demand growth rate were regionally correlated. Even within a single region, however, demand growth can react differently spatially (i.e. in suburbs where growth is planned vs. already urbanized areas, an economic recession having different impacts based on development type and zoning, etc.). By anchoring sinusoidal factor perturbations to long-term demand projections of each individual utility, our work is partially able to account for spatial disparities in growth rate, but future work to better assess spatial asymmetry in growth among regional actors would be valuable to the water systems management literature. Secondly, this study was able to test utility performance under realized demand growth changes, but not changes in how utilities project long-term growth; because utilities generally make decisions on infrastructure development at a decadal scale, based on projections, this work has only addressed one "side of the coin" in terms of decision-making under demand growth uncertainty. The authors hope future work into demand growth uncertainty will investigate not only the impacts of changes in demand growth over time, but also of changes to how utilities dynamically project demands and choose to develop infrastructure as a result.

4.5 Conclusions

Cooperation between urban water utilities is increasingly common. Partnerships can offer lower costs via economies of scale through shared ownership or use of a supply, water treatment plant, or other facility. However, cooperation may also expose partners to counterparty risk. Under agreements made based on highly uncertain long-term projections of demand growth and water availability, unexpected changes can introduce both supply and financial risk. Risks may also be compounded by the structure of the agreement itself. This work demonstrates both the benefits that inter-utility cooperative agreements can provide, as well as the added counterparty risk that may jeopardize the effectiveness of cooperation. To identify key differences in cooperative strategy, both individual and regional utility objectives must be considered under a broad range of conditions. Results of this work can inform regional decision-makers considering cooperative partnerships to manage risk and provide general guidance for the development of robust regional water supply management strategies under uncertainty.

4.6 Acknowledgements and data availability statement

The authors would like to thank and acknowledge the Triangle Water Supply Partnership, especially Ruth Rouse (OWASA), Syd Miller (Durham), and Ed Buchan (Raleigh) for their feedback and support of this work. All WaterPaths modeling code used to simulate Triangle water supply decision-making can be found at https://github.com/bernardoct/WaterPaths/tree/JLWTPAgreementsModel. Additional code for input data preparation and results visualization is being prepared for sharing now and will be made available before acceptance of this manuscript.

CHAPTER 5 : THE POTENTIAL OF DYNAMIC ADAPTIVE RISK MITIGATION ACROSS WATER UTILITY INSTITUTIONAL STRUCTURES

5.1 Introduction

Water utilities in growing urban regions must constantly adapt to meet increasing water demands (AWWA, 2018). To provide reliable water supply during shorter-term drought, utilities adopt a range of strategies, including temporary water use restrictions (Kenney et al., 2004; Milman & Polsky, 2016; Zeff et al., 2020), transfers of water from adjacent utilities or agricultural users (Characklis et al., 2006; Gorelick et al., 2018; Lund & Israel, 1995; Palmer & Characklis, 2009), and cooperation between water systems (Jensen et al., 2020; Kurki et al., 2016; Tran et al., 2019) to mitigate the risk of supply failure. Over longer planning horizons, utilities primarily meet growing demands through investment in supply infrastructure improvement and expansion (Gleick, 2003; Krueger et al., 2019; Padowski et al., 2016; Perry & Praskievicz, 2017). However, the high cost of a new reservoir, water treatment plant, or other capital project (e.g. pipeline, aqueduct) to shield against water supply shortage can strain utility budgets, often leading to water rate hikes (Boyle, 2014; Zhong et al., 2019).

Water managers must therefore balance investment to expand water supply with affordability for end users (Ajami et al., 2018; Baird, 2010; Dickinson et al., 2015; Hughes et al., 2014; Schwartz et al., 2017). Many innovative strategies to aid utilities in the simultaneous mitigation of water supply risks and financial risks have been studied, including adaptation of reservoir operations to changing supply and demand conditions (Benson, 2018; Castelletti et al., 2020), use of financial instruments to preserve utility budgets in years of water scarcity (Baum &

Characklis, 2020; Coleman et al., 2015; Denaro et al., 2020), implementation of alternative water rate structures (J. Beecher, 1999; Boyle, 2014), and consolidation or inter-utility partnership (Klien & Michaud, 2019; Silvestre et al., 2018). Development of modeling frameworks that identify policies or sequences of actions (pathways) that perform well under uncertainty have also been applied to quantify the combined outcomes of differing adaptation options (Herman et al., 2015; Hoekstra et al., 2018; Kwakkel et al., 2012; Trindade et al., 2020).

While financial outcomes have more recently begun to be considered alongside supply performance (Baum et al., 2020; Zeff & Characklis, 2013), no studies of future water utility planning and management have directly quantified the financial impacts of water supply system adaptation in terms of decision-relevant metrics used by utilities. Debt covenants, which typically include one or more measures of financial health, are often required of utilities by creditors seeking assurance that debt issued through bonds for infrastructure expansion will be repaid (Raftelis, 2005; TBW, 2018b), represent a key factor in utility budgets (Alegre et al., 2016; AWWA, 2011; Beecher et al., 1993; Hughes et al., 2014; Jordan et al., 1996; Wirick et al., 1997). However, it is uncommon in the research literature to see a direct quantification of a utility's ability to maintain covenants as a result of infrastructure investment, even though it is an important measure of a utility's financial health. Previous work has quantified utility financial performance in other ways: the fraction of utility revenues devoted to drought mitigation and debt service on infrastructure expansion (Gold et al., 2019; Gorelick et al., 2020; Zeff et al., 2014); revenue and cost fluctuations due to demand management and water rate changes (Sahin et al., 2018); infrastructure and budgetary policy impacts on consumer affordability (Gorelick et al., 2019; Jensen et al., 2020; Rehan et al., 2015); cost/benefit analysis of potential infrastructure projects (Furlong et al., 2017). Nonetheless, such reflections of financial standing only capture subsets of the budgetary response of a utility to changing system conditions, and are not those focused on by groups such as the credit ratings agencies whose assessments directly impact the interest utilities pay on debt. Studies able to quantify utility performance in terms of debt covenant metrics, such as debt service coverage or operating ratios, have been limited to surveys of historical utility budgets (Iovino, 2020; Marques & Monteiro, 2001; Tsagarakis, 2013). Yet no studies have calculated covenant ratios in concert with simulations of utility operations and planning, nor have any modeled utility budgets in a manner that allows for dynamic reactions to swings in costs and revenues that threaten violation of covenant thresholds. The latter are critical to utility senior management (e.g., CEO, CFO) as they must be met to ensure good standing with creditors and maintain low financing costs on debt, which can constitute more than 20% of a water utility operating budget (NACWA, 2015).

Even without explicit consideration of financial adaptation by existing water supply management efforts, such frameworks proposed in the literature have had little success being understood, adopted, and applied by decision-makers (Smith et al., 2019). Though studies emphasizing collaboration between practitioners and researchers – “double” or “triple-loop” learning, to evaluate and improve upon existing understanding of water management systems – are increasingly common (Johannessen et al., 2019; McLoughlin et al., 2020), adoption of recommendations by researchers in practice is less prevalent (Lawrence & Haasnoot, 2017). One reason for lack of uptake is differences between modeling frameworks used by academic studies to assess management conditions and those of practitioners. However, to this point no studies of water supply management have emphasized either (a) decision-relevant quantification of financial status within modeling frameworks in use by practitioners, or (b) coordination with practitioners (in this case utility managers and personnel) to adopt modeling updates and recommendations.

This study develops a coupled adaptive water supply and financial risk assessment framework for use by the Tampa Bay Water Authority (TBW) in Florida, the Southeast U.S.' largest water wholesaler, tasked with collectively meeting the demands of six retail water utilities in the Tampa Bay region (Asefa, 2015; Asefa et al., 2014; Wang et al., 2020). Developed as a collaborative effort between TBW personnel and external researchers, results of this work provide insight into the value of detailed financial modeling in long-term forecasting as well as the ability of coupled adaptive supply and financial modeling to improve water utility decision-making in practice.

5.2 Methods

This research summarizes the benefits of adaptive management for improving water supply reliability and financial modeling capabilities of the Tampa Bay Water Authority (5.2.1). Existing TBW modeling, used for weekly operational and long-term infrastructure planning (5.2.2), is coupled with a financial risk assessment model (5.2.3). System performance across relevant supply and financial performance indicators (5.2.4) is evaluated through Monte Carlo simulation of hydroclimatic and demand growth uncertainty (5.2.5). Improvements allow for consideration of decision-relevant water supply and financial utility objectives and demonstrate the value of adaptive management (or learning) in a real-world system.

5.2.1 Case Study Region

This study centers on the Tampa Bay, FL region in the southeastern U.S. (Figure 5.1). More than 2.5 million people reside within the three cities (City of Tampa, City of St. Petersburg, City of New Port Richey) and three counties (Hillsborough, Pasco, Pinellas) of the Tampa Bay region served by the Tampa Bay Water Authority (TBW). Formed in 1998 through interlocal agreement between regional member governments, TBW is obligated to meet drinking water demands of these six governments through wholesale and delivery of treated water to their respective water utilities until 2038. One of the six utilities served by TBW, the City of Tampa (CoT), self-supplies a portion of its water demand with infrastructure developed independently.

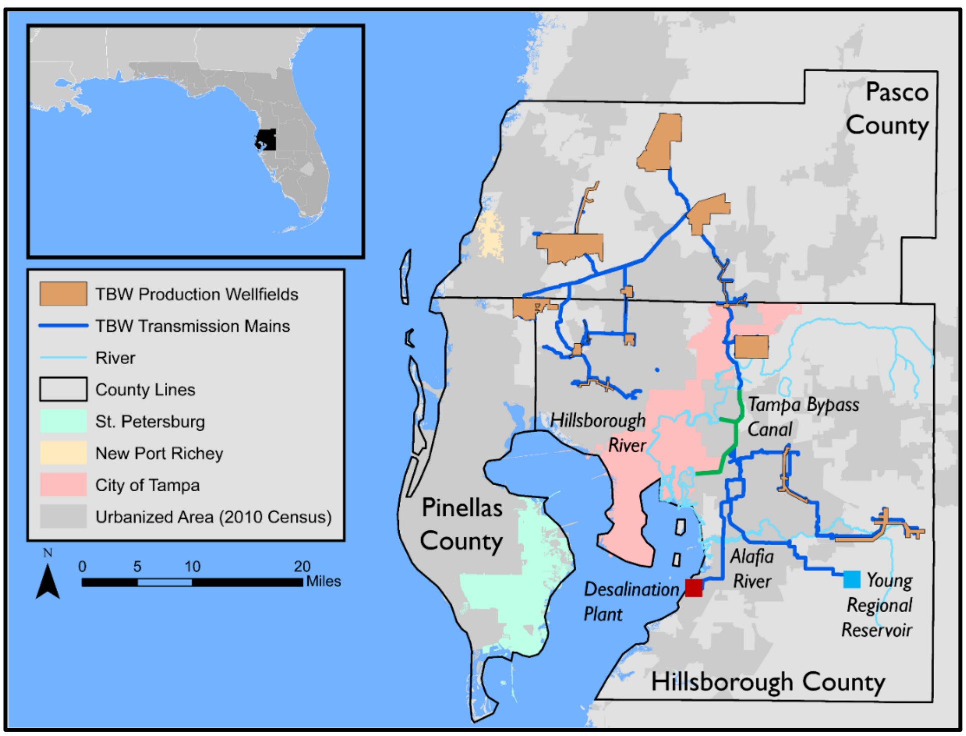

Figure 5.1: Counties and municipalities served by Tampa Bay Water and major components of TBW water supply infrastructure.

Tampa Bay Water was created primarily to resolve regional issues of groundwater over-withdrawal, which had degraded environmental conditions and lowered the regional? water table due to inadequate action by member governments to reduce pumping. As part of its agreement to meet regional water demands, TBW assumed ownership of regional groundwater production wellfields and has expanded supply infrastructure to include surface water and desalination sources. Surface and desalination currently make up over 50% of TBW water supply under normal hydroclimatic conditions. TBW expects system-wide demands to meet or exceed 200 million gallons per day (MGD) under dry conditions by 2030, and 210 MGD by 2040, while current supply capacity under dry conditions is approximately 190 MGD (TBW, 2018b).

Existing TBW supply infrastructure includes 13 groundwater production wellfields, a regional surface water treatment plant (SWTP) with sustainable treatment capacity of 90 MGD, the 15.5 billion gallon (BG) C.W. Bill Young Regional Reservoir (off-stream; water is pumped in and out, not naturally filled via streamflow), the Tampa Bypass Canal – originally constructed by the US Army Corps of Engineers to divert floodwaters from the Hillsborough River into Tampa Bay – with a maximum withdrawal permit of 258 MGD, a pump station on the Alafia River with a withdrawal permit maximum of 60 MGD (subject to minimum flow constraints), the Tampa Bay Desalination Plant (with a maximum production rate of 20 MGD), and over 150 miles of treated water transmission mains linking all facilities and delivery points to member governments. Groundwater withdrawals are permitted under three separate agreements: (a) Consolidated Well Use Permit (CWUP) with a 90 MGD permitted capacity; South-Central Hillsborough County wellfields (SCH) with a 24 MGD capacity; Brandon Urban Dispersed wellfields (BUD) with a 6 MGD permitted capacity.

Though existing surface and groundwater withdrawal permit volumes exceed TBW's expected long-term needs, other factors such as environmental flow requirements, seasonality of surface water availability, water temperature and level at TBW's desalination facility, as well as asymmetry in regional demand growth leave TBW with a need to expand supply and transmission infrastructure to deliver enough water to meet regional demands. TBW is considering several supply expansion and operation adjustment pathways to meet demands expected by 2040 and demand growth over the next 10 years driven by rapid growth in South Central Hillsborough County (SCH), where water infrastructure delivery capacity may be exceeded as soon as 2025. Based on screening of infrastructure expansion options to meet SCH demands, outlined in TBW's 2018 Long-Term Master Water Plan, a subset of development pathways were identified for further study (Table 5.1).

Table 5.1: Delivery capacity (in Million Gallons per Day) and estimated costs (in millions of USD) of potential water supply expansion or operational changes under consideration by TBW to meet future demands.

Infrastructure Pathway	**Pipeline to South Central Hillsborough County (est. capital, annual operating cost)**	**Expansion of Surface WTP (est. capital, operating cost)**
1 (baseline)	12.5 MGD ($151.7M, $0.7M)	-
2	12.5 MGD	20 MGD ($88.2M, $1.6M)

Primarily to ensure demand growth in South Central Hillsborough County can be met, TBW is planning to construct a transmission pipeline that will connect its existing distribution system to a delivery point in SCH. To further aid in meeting SCH demands, and in preparation of demand growth across all member governments, TBW is also considering expansion of their surface water treatment plant by 20 MGD.

5.2.2 Tampa Bay Water System-Wide Reliability Evaluation (SWRE) Framework

TBW curates a suite of water supply reliability models to assess the status and future needs of its system; this collection is referred to as the System-Wide Reliability Evaluation

(SWRE). SWRE is a simulation-optimization modeling framework used for utility operational support and long-term planning, primarily composed of two component models – the Operational Modeling System Version 1 (OMS1; section 5.2.2.1) and the Optimized Regional Operations Plan (OROP; 5.2.2.2). Together, the coupled OMS1 and OROP evaluations are able to project the effects of meeting regional water demands from 2021 to 2040 (TBW's planning horizon) on groundwater levels, surface water storage, and desalination plant production, including whether withdrawal permits or capacity limits may be violated in order to do so.

5.2.2.1 Operational Modeling System, Version 1 (OMS1)

The Operational Modeling System, Version 1 is a MATLAB-based water routing model, used by TBW to simulate daily surface water availability for TBW based on surface water inflows and City of Tampa demands. Surface water can be withdrawn by TBW via the Tampa Bypass Canal (TBC), Alafia River pump station, or C.W. Bill Young Regional Reservoir, for treatment and delivery to member governments. The City of Tampa may self-supply with water from its own Hillsborough River Reservoir, and during drought the City may also purchase additional water from TBW. TBW can deliver treated water to the City of Tampa with regional transmission mains or through sales of untreated water pumped from the Harney Canal (a component of the Tampa Bypass Canal) to the Hillsborough Reservoir, a process known as Harney Augmentation. OMS1 simulates surface water inflows and City of Tampa demands at a daily timestep, providing Harney Augmentation, reservoir, and TBC storage levels. See Fig. 7.3 in Appendix 4.3 for a visual description and details on the system configuration of OMS1.

5.2.2.2 Optimized Regional Operations Plan (OROP)

The Optimized Regional Operations Plan Model (OROP) is an optimization model, run at a daily timestep in connection with OMS1, identifying the least-cost strategy for delivering water to member governments (see Fig. 5.4 in Appendix 4.3 for visualization of the OROP system model). As surface water availability is estimated at withdrawal points by OMS1, OROP optimizes the routing of available surface, groundwater, and desalination supply within the TBW system of transmission mains to members' points of connection. Before the entire SWRE (OMS-1 and OROP) can advance to the next day of water supply simulation, OROP must identify a routing strategy based on cost minimization, with different costs assigned to each water source and transmission main segment. If no feasible solution can be found, routing is accomplished with slack variables; water withdrawal permit capacities at groundwater wellfields and surface water intakes may be temporarily exceeded to meet demand growth across the system. Choices made by OROP to meet each day's demands are transferred back to OMS1 to inform initial conditions of the subsequent timestep.

5.2.2.3 Combining OROP and OMS1 for TBW Water Supply Reliability Evaluation

To evaluate the impact of water supply infrastructure and operational change on the TBW system, structural improvements (Table 5.1) can be implemented within OROP and OMS1 as pre-specified changes that activate on specific timesteps. As TBW expects demands in South Central Hillsborough County to exceed its capacity to deliver water to the area by 2028, all infrastructure improvements tested within the SWRE modeling framework are assumed to come online at the end of 2027. Other than OROP optimization in each daily timestep of modeling to locate least-cost water delivery routing by TBW to its member governments, SWRE is not dynamically adaptive to changing hydroclimatic or demand conditions; water shortage mitigation action (e.g., use restriction) or infrastructure expansion cannot be triggered during an SWRE framework evaluation. Future infrastructure projects, as described above, may come online during an evaluation, but the date must be pre-specified.

5.2.3 Implementation of the Financial Risk Assessment Tool (FRAT)

This work introduces the Financial Risk Assessment Tool (FRAT), a financial forecasting tool for tracking key financial funds and flows across future fiscal years (Fig. 5.2). Daily simulation of water supply deliveries to member governments within SWRE are passed to FRAT and used to estimate monthly water sales revenues across the modeling horizon (2021-2040). Sales may occur via two operations: (a) sales of treated water by TBW to member governments, delivered through TBW's network of transmission mains, charged a volumetric Uniform Rate set by TBW; (b) sales of untreated water to the City of Tampa through the Tampa Bypass Canal (Harney Augmentation), which are charged a separate, smaller volumetric rate.

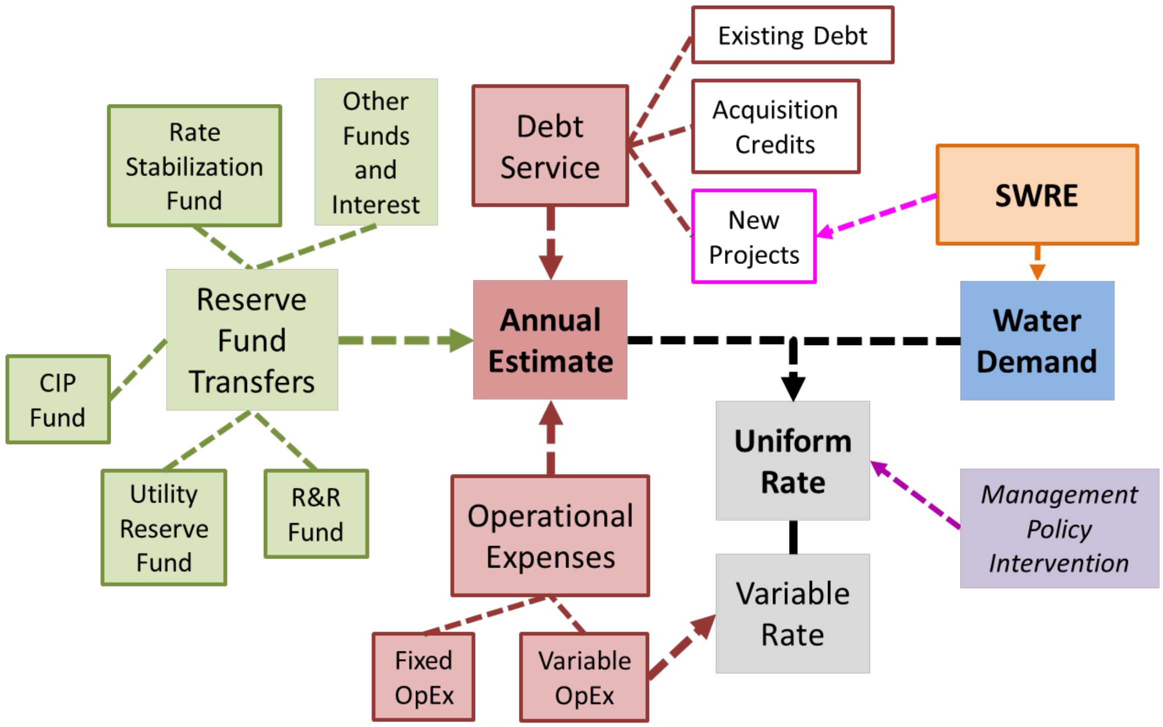

Figure 5.2: Flowchart linking SWRE (orange) outputs of water deliveries and infrastructure expansion timing to annual financial model flows of FRAT.

The Uniform Rate, set annually for the next FY at the end of each current fiscal year (FY), is estimated based on projected water demands and TBW's Annual Estimate, which is the sum of projected next-FY operating expenses, debt service, and required transfers into reserve funds. Dividing the Annual Estimate by projected water demand, the Uniform Rate per unit of water sold can be calculated for an upcoming FY. The Uniform Rate itself is split into two portions: (a) a fixed rate charge levied monthly to member governments in proportion to their previous FY demands, designed to offset all TBW fixed operating expenses; (b) a variable rate, set to cover TBW variable operating expenses, that is charged monthly based on water deliveries to member governments in the current FY.

Debt service is tabulated annually within FRAT as a sum of existing debt held by TBW on bonds previously issued for capital improvements (CIP), rehabilitation and renewal (R&R),

and large investments for supply infrastructure, remaining Acquisition Credits – debt owed to member governments on water supply assets ceded to TBW during its 1998 formation – and debt on new supply infrastructure projects (including those in Table 5.1). Debt on future large supply projects assumes a 30-year amortization schedule on bonds issued and a flat 4% interest rate, consistent with rates of recently issued bonds by TBW (TBW, 2019). Based on TBW plans to maintain debt service at or below approximately $80 million annually, only interest is paid on debt incurred through financing of new infrastructure projects until FY 2032, after which payments on principal also begin. FRAT also tabulates balances and transfers of CIP, R&R, rate stabilization, utility reserve, and other TBW funds in each FY, based on historical trends of reserve fund transfer policy, the current FY Uniform Rate, debt service owed, water deliveries, additional miscellaneous revenues and costs, and required transfers to meet TBW regulations.

At the end of each FY, FRAT combines historical trends of budgetary policy (i.e. inflation and demand growth rates, etc.) with realized outcomes (actuals) from the current FY to project a budget for the subsequent FY. Budget estimation accounts for debt and rate covenants (described in 5.2.4), reserve fund requirements (set in accordance with TBW's Master Bond Resolution), future water demand growth, management of the Uniform Rate (e.g. ensuring rate does not rise too quickly year-over-year), as well as new and existing debt service. The budget estimation process culminates in setting of the Uniform Rate based on a budgeted Annual Estimate and projected water demands. Differentiation between budget estimation and actuals in each FY allows FRAT to better approximate the "real-world" budget-setting process and avoid an assumption of "perfect foresight" through which budget estimation and actuals of each FY would be equal (for example, the water demand projection used to set a FY budget by FRAT may not equal deliveries over that FY observed in SWRE). FRAT directly calculates TBW rate and debt covenants, as well as all reserve fund balances and the Uniform Rate, for all future fiscal years across the planning horizon (2021-2040).

5.2.4 Coupled SWRE and FRAT Modeling

Despite the capability of TBW to model the effects of supply infrastructure changes and its ability to meet future demands, SWRE alone does not include consideration of financial processes or metrics in such changes nor long-term fiscal modeling of demand growth impacts to Authority budgeting. To make adaptive financial and budgetary assessment possible in connection with water supply system changes, this work develops the FRAT as a financial component to the SWRE to translate the impacts of hydroclimatic change, demand growth, and infrastructure expansion into financial outcomes (Fig. 5.3). The coupled SWRE-FRAT framework is able to model financial responses by TBW that adapt to changing environmental and demand conditions as well as to year-to-year changes to the Authority's budget.

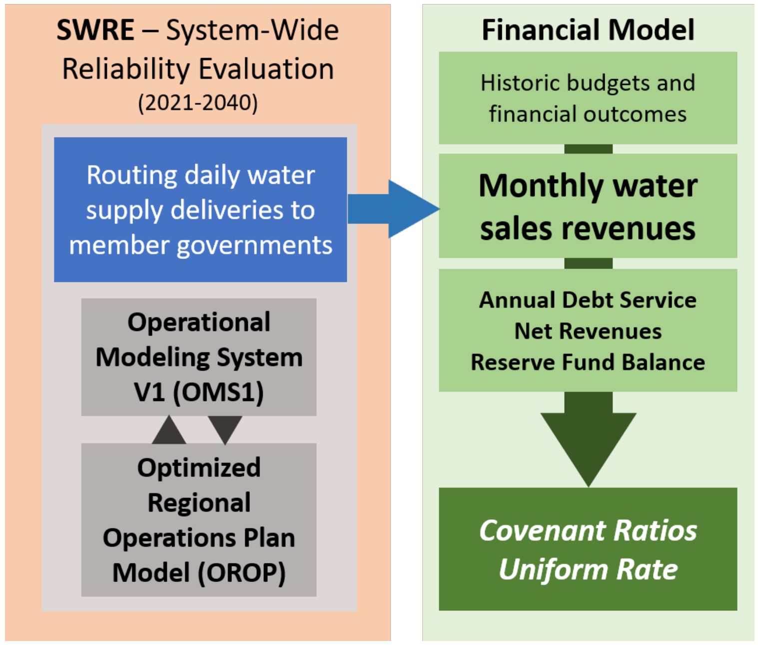

Figure 5.3: Description of coupled water supply-financial assessment framework, combining existing TBW SWRE modeling with a financial component.

Development of the SWRE-FRAT framework was necessary to address a key TBW management goal of quantifying future system performance beyond the current scope, expanding assessment to also include financial health. TBW evaluation of system conditions using SWRE has historically been done based on a user-defined Level of Service (LoS) threshold, with LoS being a metric quantified as the percent of Monte Carlo realizations of future hydroclimatic and demand conditions that meet regional demands (Asefa et al., 2014). A LoS level of 99%, for example, is linked to the greatest regional water demand that could be met in 99% of tested realizations. Demand is 'met' for LoS if a realization never experiences a 1-month-or-longer period of demand exceeding delivery capacity without violation of withdrawal permits. Short-term, one-month (30 day) periods where demands are not met in SWRE are assumed by TBW as able to be mitigated through short-term water use restrictions or other drought mitigation action that TBW or regional utilities could implement.

While Level of Service can offer an indication of overall system reliability, it does not reflect vulnerability or resiliency of the TBW water supply system, nor financial outcomes related to infrastructure expansion. In response, this work expanded upon LoS to identify several key reliability and financial indicators that offer TBW a more comprehensive view of system performance, answering the questions: (a) how often can TBW expect future supply shortfalls; (b) where will shortfalls manifest within the supply system; (c) how severe will supply shortfalls be; (d) how do planned future infrastructure investments impact TBW financial performance (f) under hydroclimatic and demand growth uncertainty; (e) how can management intervention influence financial stability?

5.2.4.1 Supply reliability performance metrics

Water supply system performance is assessed based on three proposed metrics of water supply shortfall, supply shortfall asymmetry, and shortfall severity, quantifying reliability, vulnerability, and resiliency of the TBW supply system. While Level of Service can only be calculated based on a summary of performance across all realizations, each performance metric below is quantified on more granular temporal scales (i.e. per year or fiscal year).

5.2.4.1.1 Supply shortfall

For TBW, as with all water supply authorities, being able to reliably meet demands is a primary objective (Asefa et al., 2014; AWWA, 2018). Though TBW anticipates they are able to mitigate up to 30 consecutive days of permit violation through drought management programs, it remains key for the utility to monitor the overall potential for shortfalls in future years. Supply shortfall (or reliability) R_r is defined for TBWA as the fraction of realizations r containing at least one period of 30 or more consecutive days in which demand cannot be met without water supply deliveries exceeding withdrawal permit levels:

$$R_r = \frac{1}{N_r} \sum_{r \in N_r} \lambda_r \tag{1}$$

$$\lambda_r = \begin{cases} 1 & \max(\boldsymbol{SD_r}) \\ 0 & else \end{cases} \tag{2}$$

where $\boldsymbol{SD_r}$ is the set of shortfall durations in a given realization.

5.2.4.1.2 Shortfall asymmetry

Within regional water supply systems, it is common for demand, population growth, hydroclimatic conditions, and other factors to vary asymmetrically in space and time (Gold et al., 2019; Herman et al., 2014; TJCOG, 2014); this reality complicates planning for TBW, which is considering large-scale system enhancements in response to demand growth of one sub-region (TBW, 2018b). As a result, regional supply shortfall asymmetries are a second objective of interest.

Shortfall asymmetry magnitude M_{SRC} is defined for each TBW system point SRC where withdrawal permit violations or demand shortfalls are 'allowed' by slack variables in SWRE modeling – surface water withdrawal from the Alafia River and Tampa Bypass Canal; groundwater withdrawal from wellfields under the CWUP and SCH permits; supply delivery shortfalls to SCH. This metric annually tracks the level to which permit capacities are exceeded or deliveries fall short of demands for the system points named:

$$M_{SRC,y} = \max_{\mathrm{d}\in\{1..365\}}\left(MOV_{SRC,d}\right) \tag{3}$$

$$MOV_{SRC,d} = \frac{1}{30}\sum_{i=0}^{29} V_{SRC,d+i} \;\; \forall\, d \in \{1{,}365\} \tag{4}$$

where $V_{SRC,d}$ is the magnitude of violation of a given day, in MG of permit capacity exceeded or unmet demand for a given source, and MOV_{SRC} is the 30-day moving average of such violations.

5.2.4.1.3 Shortfall severity

Along with supply-side capability to meet water demand, TBW engages is demand-side management and cooperation with member governments to encourage water conservation during periods of scarcity and drought (TBW, 2017). As a result, TBW is resilient in its ability to recover from short periods of supply shortfall. Considering that shortfalls found in SWRE modeling do not consider short-term drought mitigation response, a final supply metric of interest to TBW is the longest continuous period of supply shortfall S_y in each future year:

$$S_y = \max\left(\boldsymbol{\varphi}_{\boldsymbol{y}}\right) \tag{5}$$

where $\boldsymbol{\varphi}_{\boldsymbol{y}}$ is a vector containing the length (in days) of each continuous period of supply shortfall within a given year. Supply shortfall is calculated as the sum of withdrawal permit and delivery shortfall magnitude per day across the TBW system; any day with shortfall > 0 is counted as a day of shortfall when calculating S_y.

5.2.4.2 Financial performance metrics

Water utilities must consider both water supply and financial goals in decision-making (Baum & Characklis, 2020; Gorelick et al., 2020; Zeff et al., 2014). This is true of Tampa Bay Water – maintaining financial stability is a core component of the Authority's strategic goals that must be accounted for (TBW, 2018b); however, like most utilities, TBW water supply and financial stability have been largely pursued separately. As TBW plans infrastructure expansions to meet future system water demands, the Authority must also maintain good standing in terms of its financial metrics lest it raise concerns with ratings agencies and/or the municipal bond market. These benchmarks, or covenants, are defined as: (a) debt covenant,

$$C_{Debt,FY} = \frac{Revenue_{net,FY}}{DS_{FY} + Deposit_{CIP,FY} + Deposit_{R\&R,FY}} \tag{6}$$

where C_{Debt} in fiscal year FY is the ratio of FY net revenues against the sum of debt service and budgeted deposits into CIP and R&R reserve funds, and (b) rate covenant

$$C_{Rate,FY} = \frac{Revenue_{net,FY} + Fund_{Reserve,FY}}{DS_{FY}} \tag{7}$$

for which C_{Rate} is the ratio of net revenues and utility reserve fund balance relative to debt service. Tampa Bay Water is required to maintain a debt covenant ratio of at least 1.0 and a rate covenant ratio of at least 1.25 in each fiscal year by the utility's Master Bond Resolution, developed between TBW and its constituent member governments, indicating the Authority is financially stable and capable of meeting any debt obligations (TBW, 2019). Should covenants be violated, TBW risks credit rating downgrades and subsequent increased interest rates on future debt issued for supply infrastructure. Net revenues for covenant calculations are equal to the sum of TBW FY water sales revenues, unencumbered funds remaining from the previous fiscal year, non-sales revenues and additional funds made available from the Authority's Rate Stabilization reserve fund, less Acquisition Credits owed, necessary deposits to reserve funds, and all operating expenses.

To meet covenant thresholds, TBW is able to make budgetary adjustments such as changing the Uniform Rate of water sales to generate revenues in line with changing operating costs. Setting the Uniform Rate is done each fiscal year based on expectations for the following year; to provide quantitative context on how TBW budgets adapt to future conditions, the Uniform Rate is also presented in this work alongside covenant ratios. The Uniform Rate UR_{FY} is estimated as

$$UR_{FY} = \frac{AE_{FY}}{DE_{FY}} \tag{8}$$

where AE_{FY} is the Annual Estimate for a particular fiscal year; the Annual Estimate, made at the end of each FY, is the estimate of total costs for the following FY, including fixed and variable operating costs, debt service, Acquisition Credits owed, and deposits to reserve funds. DE_{FY} is the TBW estimate of water demand for the given FY. Water demand is estimated based on the previous FY water demand and a demand growth rate (assumed at 1.5%, consistent with historical demand growth).

5.2.5 Problem Formulation

This research presents a stochastic computational framework for simultaneous adaptive financial and water supply system performance assessment, by contrasting current TBW SWRE framing of infrastructure expansion impacts on supply reliability with a coupled and expanded SWRE-FRAT framework (Fig. 5.4). This coupled framework is used to simulate both water supply effects of infrastructure development alongside the financial ramifications for future TBW covenants and water rates.

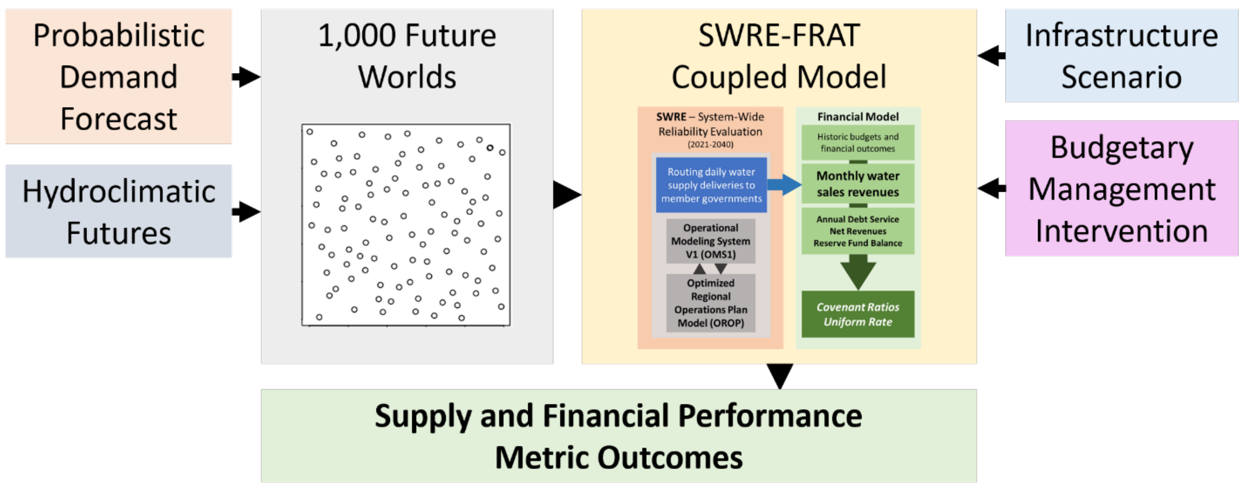

Figure 5.4: Flowchart of computational experiment.

5.2.5.1 Probabilistic Demand Forecast

Since 2009, TBW has evaluated and updated its future demand forecasts based on newly-observed trends. In parallel, TBW also annually updates a probabilistic Monte Carlo ensemble of synthetic demand realizations across the planning horizon to 2045 (TBW, 2018a). This study applies TBW's 2021 long-term probabilistic demand forecast, designed for planning purposes over 20-30 year time horizons, to test regional performance under future demand uncertainty.

Demand projections are developed independently in each of TBW's six water demand planning regions (3 cities and portions of 3 counties), based on changes to "drivers" of water demand within each region. Drivers include single and multi-family residences, as well as non-residential properties; the future demand forecast will increase based on expectation that the number of residences (drivers) in a particular planning region will increase. A single "point" forecast to 2045 is developed based on best estimates of explanatory variables of demand (i.e. rainfall, temperature, housing unit density, market penetration of new high-efficiency water fixtures, etc.). The forecast is calibrated using data from 2001-2013 and validated over the period 2014-2018, with corrections applied for each calendar month to address discrepancies between model performance and observed demands over the validation period.

A probabilistic forecast is also developed, realized with an ensemble of 1,000 daily demand records through 2045. This forecast is generated using a "rate-of-use-times-driver" approach. Demand is partitioned into three sectors: single family homes, multi-family homes and non-residential. Sector specific models estimate the average monthly demand, known as the "rate of use" for each water consuming entity, called a "driver unit". Rate of use is estimated using variables including price, efficiency factors and weather variables. These variables are projected independently and not correlated with one another. Uncertainty in exploratory variables is represented by fitting distributions to the estimated rate of use and driver units for the three sectors. Then, single values of each parameter are jointly sampled to construct the ensemble of Monte Carlo realizations. Estimation of driver units begins by establishing point projections for income, population, persons per household and price using data from the Florida Bureau of Economic and Business Research (BEBR), Moody's Analytics, and the Florida Department of Transportation. Ranges of uncertainty and probability density functions are ten estimated though data from population projections from the BEBR and socioeconomic variables from Moody's Analytics. Population projections from the BEBR utilize multivariate normal distributions for each county and each year. Distributions derived from Moody's Analytics data include data on the number of households, fraction of single-family homes, median household income and employment. Joint distributions for these parameters are constructed considering cross-correlations between variables. BEBR and Moody's distributions are sampled independently of one another. Real marginal price of water is assumed to be normally distributed and independent between Water Demand Planning Areas. Efficiency is estimated using a uniform distribution across a range of plausible values derived from examining a set of 49 possible efficiency scenarios. Weather variables are simulated using a bootstrapping method. Model uncertainty is included through bootstrapping from historical model residuals. More information on TBW's demand forecasting methodology, see Appendix 4.1.

5.2.5.2 Hydroclimatic Futures

The Flow Modeling System, Version 2 (FMS2) Model, developed by Hazen & Sawyer for use by TBW (TBW, 2018), combines rainfall models at the three rainfall stations in the Tampa Bay region to generate synthetic realizations of future streamflow. FMS2 applies historical rainfall data to develop synthetic daily surface water flow records in the Hillsborough and Alafia Rivers, and Tampa Bypass Canal (TBC), the main sources of TBW and the City of Tampa surface water supplies.

From FMS2 records, 1,000 stochastic rainfall timeseries were then synthetically generated for TBW (Hazen and Sawyer, 2010) to simulate a range of future surface water inflow conditions in the Hillsborough and Alafia Rivers. These flow timeseries are based on rainfall observations from the three gaging stations (Plant City, St. Leo, and Cypress Creek). Each of the 1,000 timeseries was generated for 100 years, with the first 22 years taken for simulation in TBW's 2018 Long-Term Master Water Plan (2018-2040) and first 20 years are used for this study (2021-2040). Monthly streamflows were generated synthetically and then dis-aggregated to a daily timestep. Monthly generation is best to capture rainfall-streamflow correlation, but daily is needed to match the scale of water use permits. Dis-aggregation was done using a "multivariate non-parametric" k-nearest neighbor approach (Lall & Sharma, 1996). Additional steps were taken to account for month-to-month transitions of flow, temporal autocorrelation, and spatial correlation of streamflow. For more detail on FMS2 validation and development of synthetic hydroclimatic futures, see Appendix 4.2.

5.2.5.3 SWRE-FRAT Pathways and Performance Outcomes

The ensembles of 1,000 demand and 1,000 hydroclimatic realizations, described above, are combined through Latin Hypercube Sampling (LHS) to form a joint Monte Carlo assessment of TBW system performance under hydroclimatic and demand uncertainty. Of 1 million possible demand and hydroclimatic pairs of conditions (1,000 demand times 1,000 hydroclimatic realizations), 1,000 paired realizations of demand and hydroclimate are identified by LHS and passed to the SWRE-FRAT framework, where TBW performance is determined according to metrics described in section 5.2.4.

The Monte Carlo ensemble evaluation is repeated for two infrastructure pathways (Table 5.2A) – a (1) baseline pathway with development of a pipeline to South Central Hillsborough County, and (2) a pathway with both a SCH pipeline and SWTP expansion completed in 2028. Evaluation is also done under a range of potential financial management interventions; TBW has maintained a Uniform Rate of $2.559 per thousand gallons (kgal) of water delivered over the last 10 fiscal years, but this may be subject to change in future budgets (TBW, 2019). Financial outcomes are tested here under conditions of (a) a "hands-off" Uniform Rate set based on the Annual Estimate and water demand projections of SWRE-FRAT without intervention by managers, (b) fixed Uniform Rate at present-day level, and (c) a Uniform Rate with gradual, controlled growth where the Uniform Rate rises steadily within a range of 0.5-1% per year. Differences between the above rate-setting policies will elicit the ability of TBW to financially adapt when revenues from water sales are constrained (or not).

5.3 Results

Results across 1,000 LHS realizations of hydroclimatic and demand conditions from 2021-2040 are developed, comparing supply reliability and financial performance metrics under a baseline infrastructure pathway (Table 5.1, pathway 1; 5.3.1), results across infrastructure pathways (5.3.2), and the contrasting implications of demand growth on water supply and financial outcomes (5.3.3).

5.3.1 Performance metric outcomes under baseline infrastructure pathway

5.3.1.1 Supply shortfall (water supply reliability)

Quantifying supply shortfall, or system-wide reliability, provides a generalized view of Tampa Bay Water's ability to meet regional demands in future years. Fig. 5.5 details TBW reliability in terms of the percentage of SWRE realizations without a supply shortfall in each future year, under the baseline infrastructure pathway.

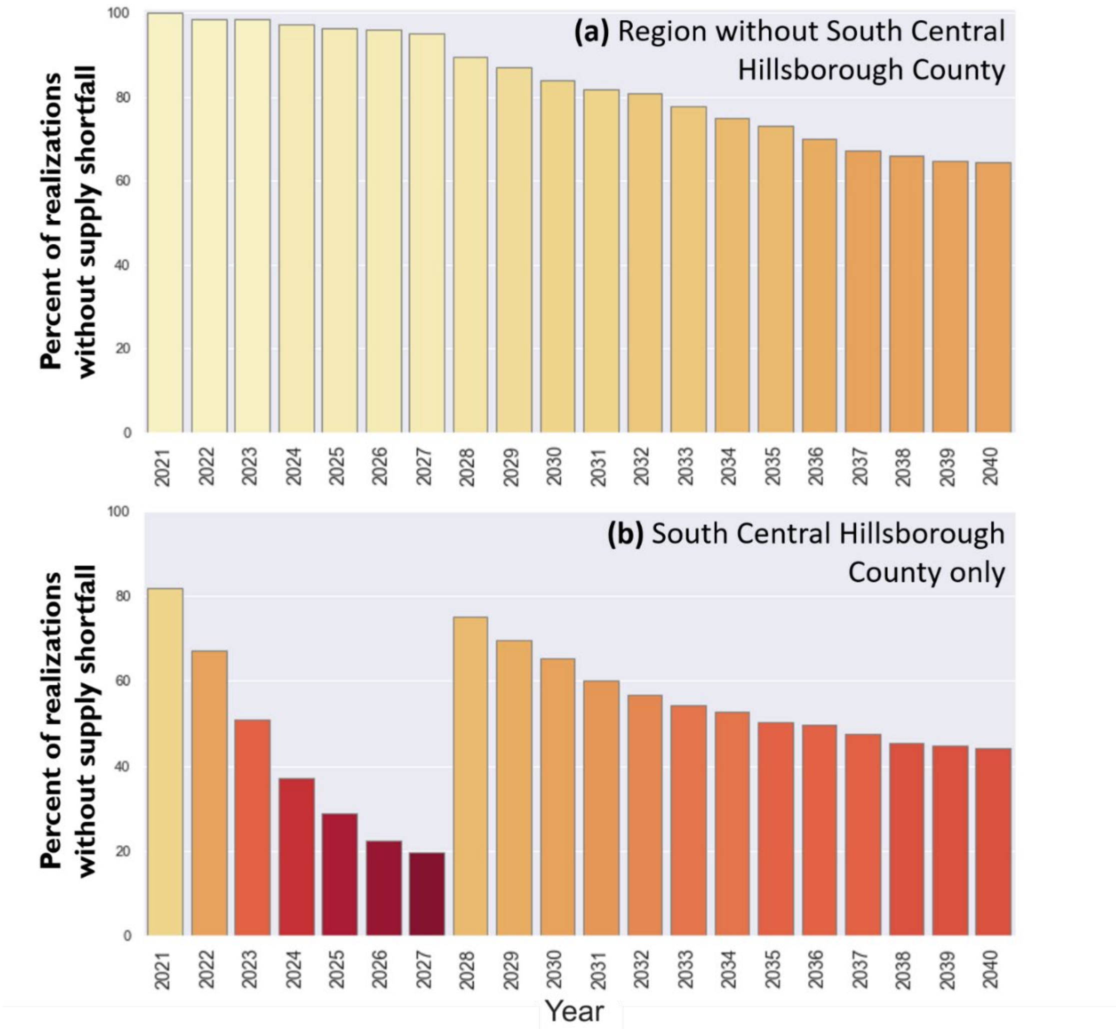

Figure 5.5: Fraction of realizations in SWRE-FRAT evaluation of baseline infrastructure pathway without supply shortfall in each future year for (a) TBW's service area other than South Central Hillsborough County and (b) South Central Hillsborough County only.

Tampa Bay Water expects to expand delivery capacity of its distribution system in 2028, to meet growing demands of South Central Hillsborough County (SCH) that cannot be met with delivery capacity of the existing transmission mains operated by TBW. In the baseline infrastructure pathway, this is achieved with development of the SCH pipeline project. As a result, SWRE shows a large increase in reliability – realizations without supply shortfall – after

2028 for the SCH region (Fig. 5.5(b)). While demand growth before 2028 has significant negative impacts to SCH water supply reliability, the remainder of the TBW service area does not see the same large reductions in supply reliability, due to a water distribution capacity "bottleneck" in SCH severely limiting water delivery to the sub-region (Fig. 5.5(a)). However, as regional demand continues to grow in the 2030s, supply shortfall becomes more common across SWRE realizations for both SCH and the region as a whole.

5.3.1.2 Shortfall asymmetry

Regional supply shortfalls and reliability offer one picture of TBW system performance, however the metric is unable to capture dynamics between different system points. Fig. 5.6 quantifies the magnitude (in MGD) of supply shortfalls at five key system points: withdrawal permit violations of Alafia River and Tampa Bypass Canal (TBC) surface waters; withdrawal permit violations of South Central Hillsborough County and Consolidated Well Use permits (CWUP) for groundwater; delivery shortfalls to SCH.

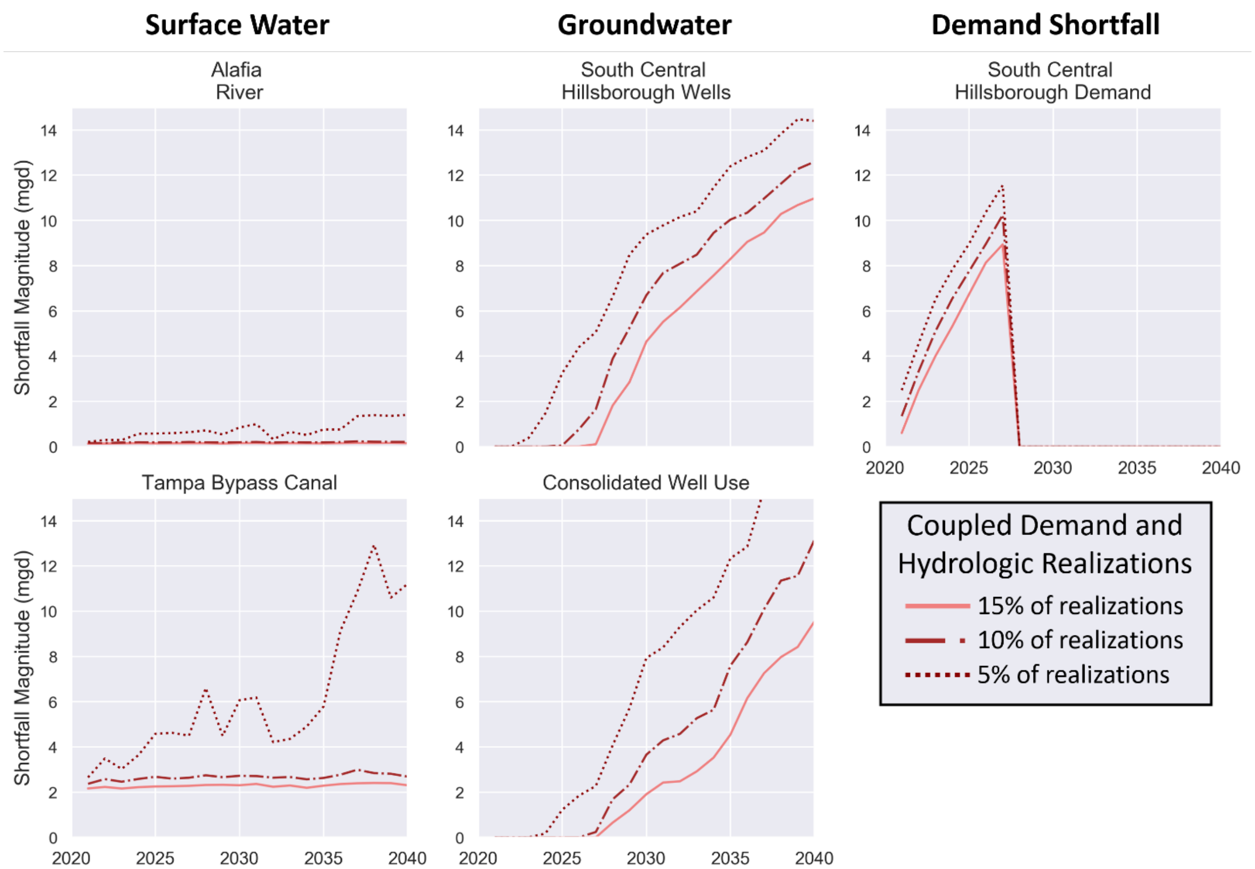

Figure 5.6: Shortfall magnitude at key surface water (left column), groundwater (center column), and delivery (right column) system points. Lines indicate the magnitude of shortfall reached in the worst-performing 15% (solid), 10% (dot-dash), and 5% (dotted) realizations of SWRE under a baseline infrastructure pathway.

Asymmetry in system shortfalls is presented, in terms of the 15th, 10th, and 5th percentiles of shortfall magnitude across all 1,000 SWRE realizations tested, providing perspective on TBW system performance under dry hydroclimatic conditions and/or high demand growth futures. Consistent with the degradation in reliability for SCH from 2021 to 2027 (Fig. 5.5(b)), this trend is reflected by a growing magnitude of delivery shortfalls to South Central Hillsborough County (Fig. 5.6, top right panel). After 2028, SCH shortfalls are reduced with the introduction of a new pipeline to deliver water to the sub-region. For the majority of the TBW system, however, shortfalls of the TBW system continue to increase in dry and high-demand realizations after 2028, primarily manifesting through violation of SCH and CWUP groundwater permits (Fig. 5.6, center column). While shortfalls do occur for some realizations at the Tampa Bypass Canal and Alafia River surface water withdrawal points, this behavior was only significant in the worst-performing 5% of SWRE realizations.

5.3.1.3 Covenant response to Uniform Rate management intervention

The financial risk experienced by TBW under a baseline infrastructure pathway can vary widely based on management intervention to control the Uniform Rate, responsible for the vast majority of TBW annual revenues. Fig. 5.7 shows future rate and debt covenant outcome ranges under three different uniform rate-setting policies for TBW across 1,000 hydroclimatic and demand realizations – (a) "hands-off" Uniform Rate set based on the Annual Estimate and water demand projections of SWRE-FRAT without additional intervention by managers (green), (b) fixed Uniform Rate at present-day level (blue), and (c) a Uniform Rate with gradual, controlled growth where the Uniform Rate rises steadily within a range of 0.5-1% per year (red).

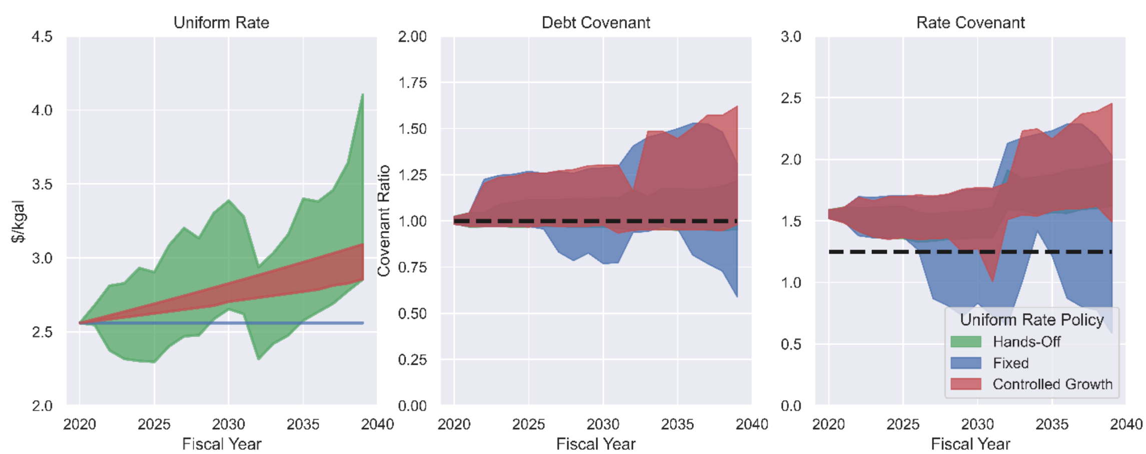

Figure 5.7: FRAT estimates of uniform rate (left), debt (center) and rate (right) covenant levels in future fiscal years, based on three rate-setting policies (colors). Dashed lines show covenant ratios that must be maintained by TBW.

Maintenance of the current uniform rate (Fig. 5.7, blue), which has not changed in the previous 10 fiscal years, would subject TBW to significant financial risk of covenants falling below required thresholds (dashed lines) while paying down existing debt. After fiscal year 2032 most existing debt held by TBW has matured, including Acquisition Credits expiring after FY 2028, resulting in a visible jump in projected rate covenant levels and reduction in the Uniform Rate (Fig. 5.7, green). Debt covenant drops below the 1.0 required threshold in a fraction of realizations under all Uniform Rate policies, but only a fixed Uniform Rate constrains TBW budgets from quickly rebounding to rectify it. Even with a controlled growth policy, capping Uniform Rate growth at 1% annually, TBW could largely avoid consistent or severe violations of debt and rate covenant thresholds (Fig. 5.7, red).

5.3.2 Performance differences across infrastructure pathways

Tampa Bay Water is considering a 20 MGD expansion of its surface water treatment plant (SWTP), alongside construction of a pipeline to increase delivery capacity to South Central Hillsborough County. Results below explore the impact of additional 2028 SWTP expansion on supply shortfall and financial metric outcomes.

5.3.2.1 Shortfall severity

Shortfall outcomes from SWRE modeling do not account for demand management and conservation that TBW or member governments can implement during periods of scarcity. As a result, TBW estimates that continuous periods of shortfall lasting less than 1 month can be mitigated through demand management. Fig. 5.8 shows shortfall severity, in terms of the longest period of days with supply shortfall in each future year, in the worst-performing percentiles of

SWRE realizations under the infrastructure pathway 2 with both a SCH Pipeline and SWTP expansion in 2028. In practice, the "worst-performing" percentiles of coupled hydroclimatic and demand realizations primarily include high-demand, dry conditions.

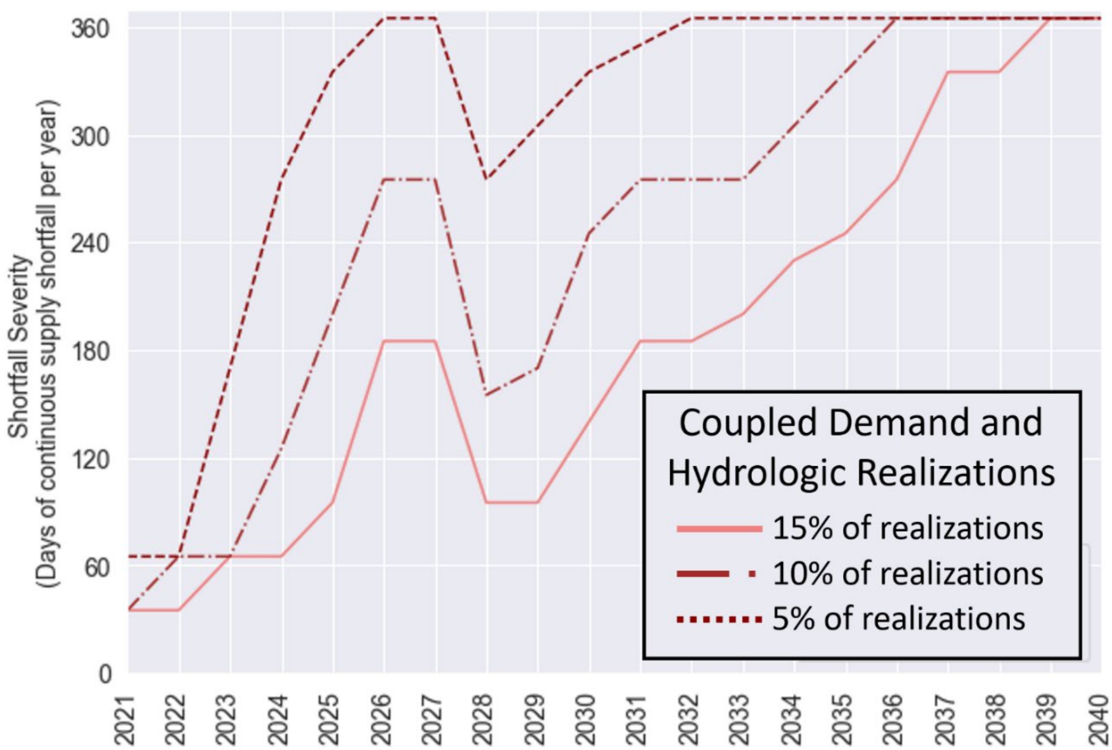

Figure 5.8: Shortfall severity of realization percentiles of SWRE under infrastructure pathway 2. Lines indicate the severity of shortfall reached in the worst-performing 15% (solid), 10% (dot-dash), and 5% (dashed) realizations.

Results show that, by 2027, more than 15% of tested realizations see at least six consecutive months (180 days) of supply shortfall (i.e. groundwater overdraft), far beyond the levels that TBW estimates can be mitigated with demand management. Infrastructure expansion in 2028 is able to reduce shortfall severity significantly; however, by 2031 the worst 10% of realizations all experience shortfall in 9 of 12 months (270 days), and by 2036 experience shortfall every day of the calendar year.

5.3.2.2 Probability of un-manageable shortfall (1 month or longer)

Due to TBW's concern over supply shortfall periods lasting more than one month (30 consecutive days), comparison of infrastructure pathways was done to also identify the first year of each SWRE realization in which this threshold is violated, resulting in an exceedance curve of growing risk of shortfall over the planning horizon (Fig. 5.9).

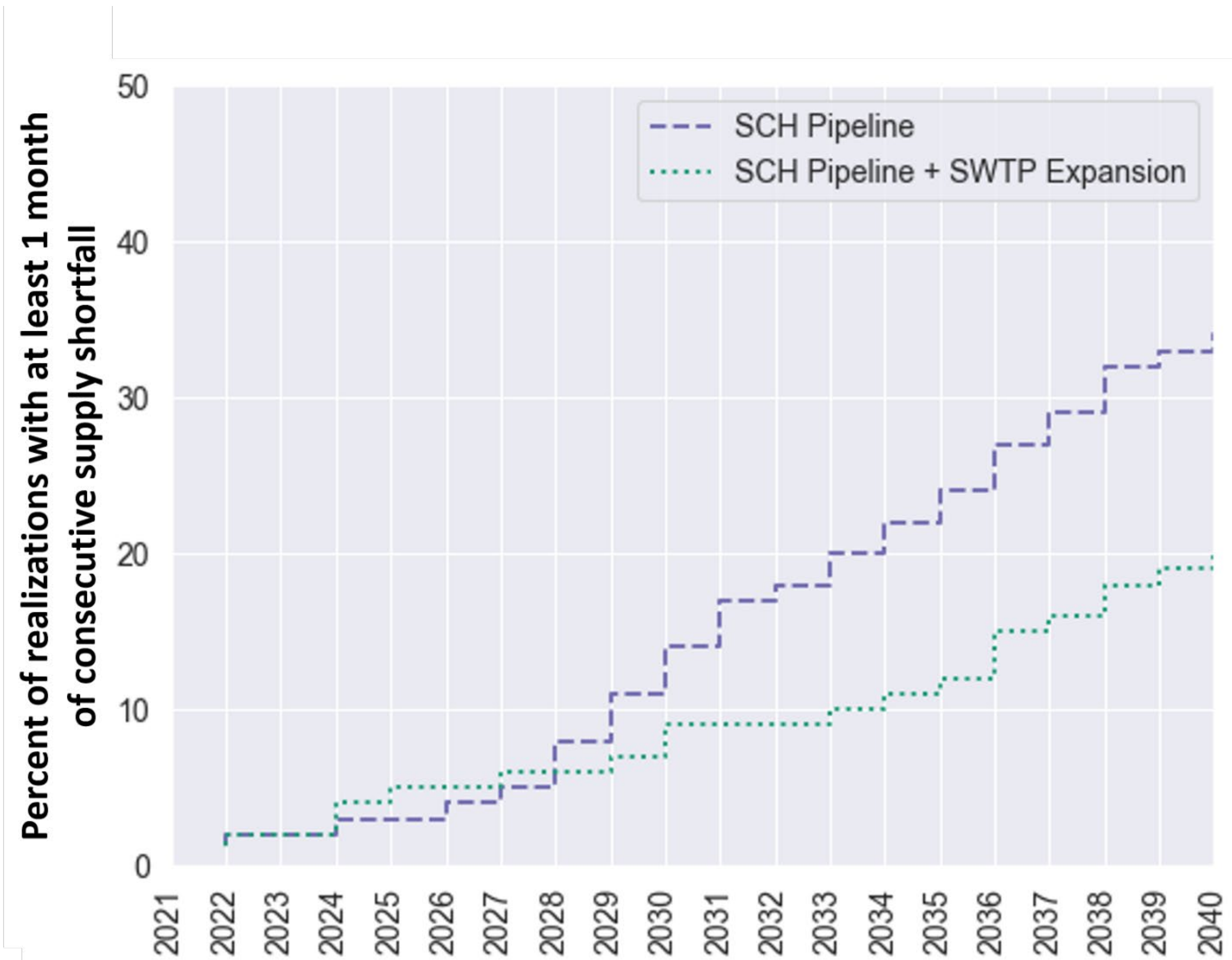

Figure 5.9: Percent of SWRE realizations seeing at least one month of consecutive daily supply shortfalls per year, separated by infrastructure pathway (color and line type).

Prior to 2027, before any substantial infrastructure expansion is possible, about 5% of tested hydroclimatic and demand realizations experience at least one consecutive month of supply shortfall within an annual period (Fig. 5.9). However, implementation of the SCH pipeline, as well as the addition of the SWTP expansion infrastructure in 2028, stabilizes shortfall severity until the early 2030s (Fig. 5.9, green dotted). Construction of only the SCH pipeline in 2028 (Fig. 5.9, blue dashed) – the baseline infrastructure pathway – is unable to prevent demand growth from causing a steep increase in 1-month-or-longer supply shortfalls after 2028, showing 20% of future realizations experiencing such conditions by 2033 and continued increase in shortfall prevalence across realizations to 2040.

5.3.2.3 Probability of covenant violation

Like in Fig. 5.9, visualization of how often financial covenants are violated in future infrastructure pathways offers a useful comparison of performance. Fig. 5.10 shows the frequency of covenant violations across Uniform Rate setting policies (colors) under each infrastructure pathway (boxes).

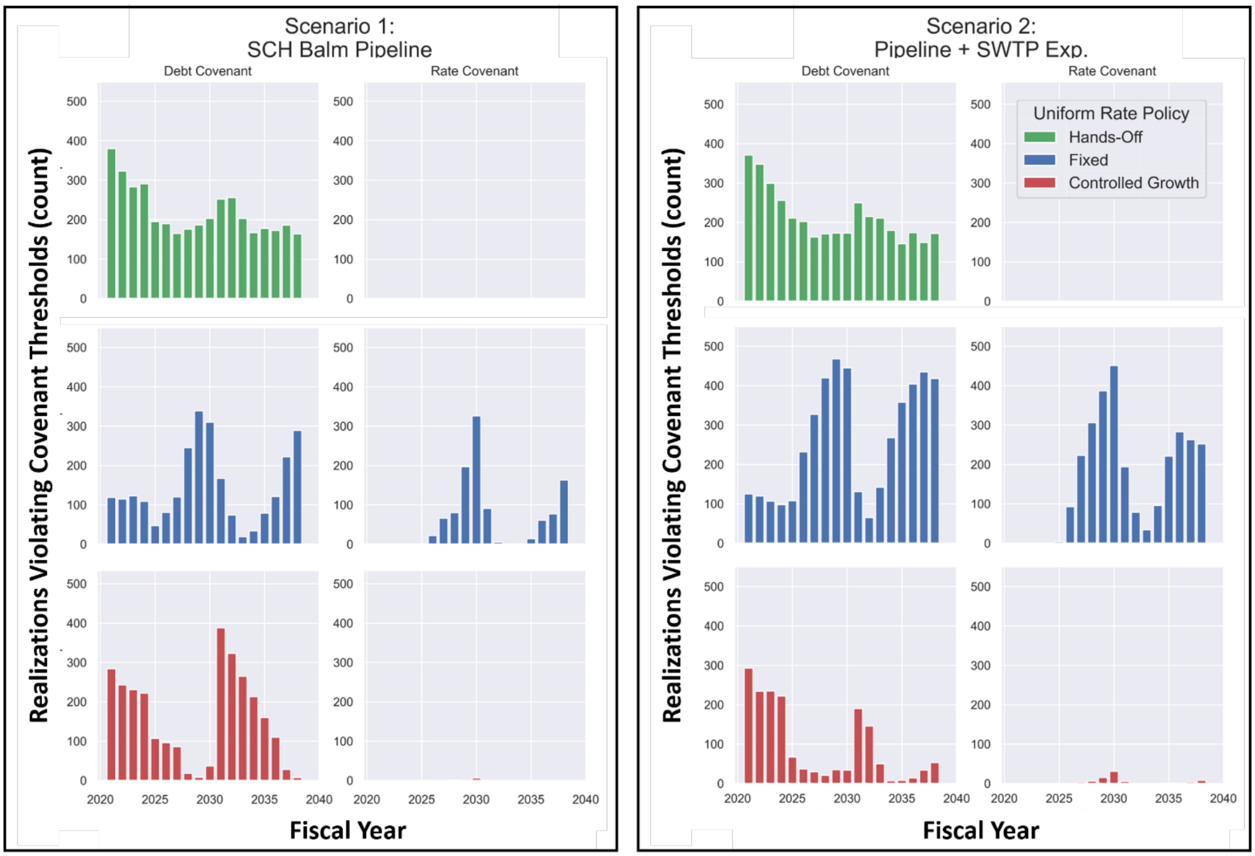

Figure 5.10: Count of realizations (out of 1,000 total per evaluation) with debt (left column of panels in each box) and rate (right column in each box) covenant violations under each infrastructure pathway (large boxes), by Uniform Rate setting policy (color and rows of plots).

Debt covenant violations for TBW are much more common in future simulation than rate covenant violations (Fig. 5.10, left columns of panels in each box), owing primarily to management of the TBW budget over historical fiscal years preceding FY 2021 when debt covenant ratio levels were maintained close to the 1.0 threshold and rate covenant ratio levels were held high relative to the 1.25 threshold. Almost all observed rate covenant violations occur when the Uniform Rate is fixed to current levels until 2040, regardless of infrastructure pathway (Fig. 5.10, blue, right columns of panels); for reference, TBW has not raised the Uniform Rate over the last 10 years. Fewer debt and rate covenant violations were observed under a fixed

Uniform Rate policy for the baseline infrastructure pathway, relative to infrastructure pathway 2 with expansion of the SWTP included (Fig. 5.10, blue, left vs. right boxes).

Frequency of debt covenant violations under a “hands-off” policy (Fig. 5.10, green) generally decreased year-over-year during the planning horizon, except for small increases in FYs 2032 and 2033 as TBW’s budget reacts to principal repayment beginning on debt issued to build new water supply infrastructure in 2028. Violations under a controlled growth Uniform Rate policy (Fig. 5.10, red) were most common under the baseline infrastructure pathway and peaked between FYs 2031-2033, also in connection to increases in new debt service obligations during those fiscal years. Peaking of violations under fixed Uniform Rate policy occurred at different periods, during FYs 2026-2030 and FYs 2038-2040, where a combination of rising demands and operating costs plus steady or increasing debt service was unable to be matched by reduced revenues from a fixed Uniform Rate.

5.3.3 Contrasting supply and financial risks of high vs. low demand growth

Coupling supply and financial modeling also offers insights to the “double-edged sword” of risks faced by TBW and other water utilities, in terms of susceptibility to uncertainty in future water demand. Fig. 5.11 depicts TBW Uniform Rate response under low-demand, relatively wet realizations (Fig. 5.11, blue) for infrastructure pathway 2 (SCH pipeline and SWTP expansion in 2028) against all realization outcomes under a controlled growth Rate policy (grey). By contrasting the below results to those of high-demand, relatively dry realizations exhibited in Fig. 5.8, risks to both water supply and financial stability are observed for TBW.

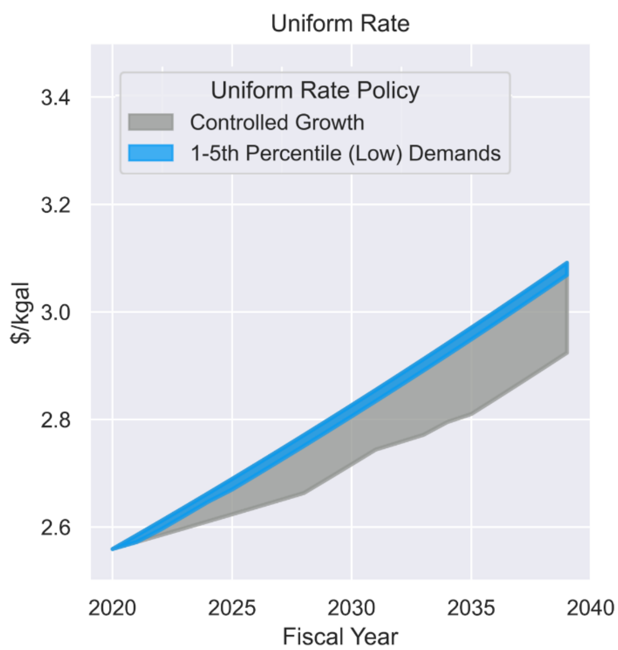

Figure 5.11: Example of financial risk facing TBW under low water demand conditions for infrastructure pathway 2 with both an SCH pipeline and SWTP expansion in terms of Uniform Rate levels under a controlled growth Rate policy, highlighting realizations with 5th percentile-or-smaller demands.

In contrast to results shown in Fig. 5.8 – supply shortfall spanning the majority of months per year by the 2030s in high-demand, dry realizations – Fig. 5.11 shows that Uniform Rate increases, and therefore TBW financial risks, are greatest under low demand realizations (Fig. 5.11, blue). Rate increases necessary to pay down infrastructure investments and match operating costs under these low demand futures are projected to grow the FY 2040 Uniform Rate by almost 20% relative to FY2020. By investing in substantial supply infrastructure expansion, TBW may experience severe financial risk should demands fall below projections; at the same time, TBW faces supply reliability risk from potential rapid demand growth that requires significant infrastructure investment to mitigate.

5.4 Discussion

5.4.1 Adaptive modeling to develop multi-criteria performance assessment

Adaptive modeling using a multi-criteria performance assessment for Tampa Bay Water provides value through quantification of supply resilience and financial stability alongside supply reliability (which is already provided as Level of Service in past TBW evaluation). Changes in system reliability indicate that infrastructure expansion to meet South-Central Hillsborough County (SCH) demand growth should be implemented by 2028, if not sooner, and that a second stage of infrastructure expansion should be considered in the 2030s to improve supply reliability. However, reliability alone is unable to reveal asymmetries in TBW system shortfalls or system behavior under extreme supply and demand conditions.

Quantifying shortfall severity by consecutive days with supply shortfall also reveals a balance between TBW's supply risk tolerance and infrastructure investment costs. The 2030s will bring significant increases to supply shortfall severity – periods that cannot be totally mitigated through demand management and conservation – and may require additional infrastructure expansion by TBW. However, safeguarding against shortfalls that might occur in 95% of potential futures, as opposed to 90% of futures, could mean a difference of 3-4 years in timing (not to mention scale) of infrastructure expansion. The Authority's chosen level of acceptable risk (in terms of supply shortfall) will inevitably influence the timing and cost of future infrastructure projects. Should infrastructure expansion occur earlier, additional debt service will be incurred across more years when TBW already carries significant existing debt; this could result in an increased water rate or depleted reserves over the late 2020s, or deferred, large debt service payments in later years that will complicate the Authority's decision-making on financing of additional projects as demands grow. Alternatively, the tradeoff from delaying implementation of supply expansion would reduce the need for rate increases and financial risk in the short term, but also decrease the reliability of water supply and risk demands rapidly rising to levels than the existing system can meet.

5.4.2 Financial balance of infrastructure development and Uniform Rate

Balancing infrastructure investment and supply reliability in future years cannot be done without an integrated parallel assessment of financial status, made possible for TBW using our proposed SWRE-FRAT framework. Tampa Bay Water carries significant existing debt, which they expect to pay off annually at a rate of about $70-80 million until after fiscal year 2031 (when most existing debt has matured). As with the maturation of existing debt, the addition of new debt to finance a SCH pipeline and SWTP expansion will influence TBW Uniform Rate and covenant values. Without management policy intervention to control the Uniform Rate, reduction of existing debt will greatly reduce annual operating costs for TBW and, all else being equal, allow a drop in the Uniform Rate without risking severe financial consequences. However, it is unlikely that the Uniform Rate would be allowed to vary widely or decline, as evidenced by the last 10 fiscal years having the same Rate. Even so, results indicate that TBW should consider a management policy that allows at least a gradual increase in the Uniform Rate to generate enough revenues to match rising operating costs without drawing frequently from reserve funds.

Across varying realizations of demand, a range of budgetary factors also influence TBW financial outcomes. Because the Uniform Rate is set before each fiscal year begins, it is based on projections of demand growth rather than actual demands of that FY. This discrepancy between projected and realized demand creates uncertainty in revenue generation, which subsequently leads to fluctuations in reserve funds to compensate. Subsequently, TBW policy on the size of, deposits to, and withdrawals from Rate Stabilization, CIP, R&R, and other reserve funds will directly influence covenant outcomes; as such, differences between projected and realized demands can lead to ‘downstream’ financial distress throughout the TBW budget. This analysis also assumed interest rate and repayment period of new debt issued to fund TBW projects, however in practice the maturity and interest rates on issued debt vary, as does the repayment schedule for each issuance (i.e. delayed principal repayments). Changes in debt policy, such as renegotiation of existing debt into FYs 2030 and beyond or shortened timelines for repayment (TBW itself is only authorized to operate until 2038), may have significant impacts to financial status but fell outside the scope of this analysis. As well, the assumed inflation rate in operating expenses holds considerable influence over financial outcomes in far future fiscal years; changes in inflation, or in the difference between budgeted and realized operating costs (TBW generally sees operating costs in a given FY realized about 15% less than projected), could further disrupt financial stability of TBW.

5.4.3 Additional considerations

One drawback of this analysis is the lack of demand management representation within SWRE modeling. Outside of selling low-flow fixtures to businesses and households in the Tampa Bay area and encouraging conservation, TBW must rely on member governments and the Southwestern Florida Water Management District (SWFWMD) to officially declare water shortages and implement restrictions or other demand management actions during drought. This shortcoming means that SWRE outputs likely represent a low-end representation of TBW’s ability to manage scarcity. On the other hand, optimization of SWRE’s routing of water deliveries from supply sources, where shortfalls are generated when slack variables are used to locate feasible solutions, does not preserve slack deficiencies between timesteps; this behavior means SWRE may present a "best-case" view of shortfalls and day-to-day system conditions. Furthermore, this framework contains no dynamic relationship between hydroclimatic conditions and demand (i.e. demands are not reduced during abnormally wet conditions, as has often been observed for retail water demand).

5.5 Conclusion

Sustainable water supply management under uncertain future conditions requires broad consideration of the impacts to water utility performance, including both supply reliability and financial conditions. Working with practitioners of the Tampa Bay Water Authority, major contributions of this work include the quantification of financial performance integrated with adaptive modeling of water supply operations, capabilities not apparent in any previous studies of utility performance. Expansion of utility assessment to include both water supply and financial metrics was able to reveal key tradeoffs, consequences of under-investment to meet demand, and potential impacts on water affordability not possible with previous analysis. Findings here are valuable to water managers, at both TBW and other utilities, as guidance on how similar frameworks may be effectively applied within different supply systems, and to inform research through lessons learned in a practical setting that can be accounted for in development or adjustment of modeling frameworks in the future.

5.6 Acknowledgements

The authors would like to thank Tampa Bay Water for funding this research. As well, we thank TBW finance (Maribel Medina and Christina Sackett), planning (Solomon Erkyihun and

Ken Herd), and information technology (Brian Kyle) staff for their constant assistance in accessing data, interpreting findings, and troubleshooting all modeling and technical issues.

CHAPTER 6 : CONCLUSIONS

This dissertation focuses on a broad set of risks and uncertainties faced by urban water utilities. Between climate and land use change, demand growth, cooperative agreements, and adaptive financing, it describes several key discoveries which are summarized and expanded upon below. Furthermore, this work exposes the need for additional study in a number of areas within the field of water resources planning and management, topics which are also briefly discussed herein.

6.1 Key takeaways for urban water supply and financial risk management under uncertainty

Water utilities worldwide share the same mission: to provide a reliable source of high-quality water to customers. Doing so requires utilities to constantly adapt to uncertain future conditions, mitigating water supply risk through both short-term drought management and long-term infrastructure planning. However, management and planning are challenging – ensuring robust, reliable water supply in an uncertain future necessitates careful decision-making for infrastructure implementation and financial planning. These are interrelated, as infrastructure and management decisions generate financial risks to water utilities if drought mitigation incurs unexpected cost and revenue fluctuations, or if long-term choices on infrastructure to service rising water demands must be built earlier than expected. As a result, water supply management to meet utilities' missions must also consider the financial implications; the joint modeling and mitigation of supply risk and financial risk are the subject of this dissertation.

Key to understanding, and subsequently managing, evolving risks is the identification and proper quantification of the major uncertainties that strain water utility operations and financing. Chief among these uncertainties are hydrologic variability arising from climate and land use change; climate change is expected to impact (and already has to some degree) water supply availability through changes in evapotranspiration and precipitation in watersheds feeding water supply reservoirs, while land use change and urbanization will influence the timing and magnitude of surface water runoff. Though climate and land use change uncertainties are consequential to water supply, and well-studied across academia and industry, there is limited research of their combined effects on water supply systems and few studies that rigorously account for adaptive infrastructure investment and management interventions in response to these uncertainties, as well as the resulting financial impacts. As a result, past work falls short in representing key aspects of reservoir operations, utility decision-making, and financing, offering an incomplete picture of vulnerability to external stressors. In some cases, this leads to simply equating more (or less) water from climate and land use change to better (or worse) outcomes. By contrast, this study describes an extensive effort to integrate important factors – including climate and land use change effects, as well as utility management and infrastructure planning, on water supply availability – which have typically been considered in isolation for their effects on water supply management. Chapter 2 of this dissertation therefore provides a novel methodological contribution to the water resources management field by coupling state-of-the-art hydrological modeling of climate and land use change with an adaptive water utility decision-making model to quantify water supply vulnerability to hydrologic change. Through a regional application in North Carolina, this new modeling connectivity allows for new insights into governing a region's ability to provide water, in a cost-effective and financially-sustainable manner, where and when it is needed.

Though landcover and climate change are both likely to increase water supply availability in North Carolina's Research Triangle, improvements in utility performance are non-uniform, highlighting the need to consider financial and management-based performance when evaluating vulnerability to hydrologic change. Furthermore, utility decision-making can notably reduce the impact of climate and land use change through both short-term (e.g. conservation) and long-term (infrastructure) actions, in some cases even countering the beneficial effects of additional water supply. The effectiveness of supply infrastructure development in reducing supply risk is also strongly sensitive to climate and land use change influences, as well as the timing and sequencing of infrastructure planning. Altogether, this work underscores the need for water utilities to consider adaptive management system responses and decision-relevant performance measures when assessing the impacts of climate and land use change uncertainty on water availability.

Beyond hydrologic change, utilities face additional risk to water supply reliability and affordability as a result of demand growth uncertainty. For utilities in rapidly growing regions, demand growth also can pose a significant financial risk; near-term investment may be necessary to meet future demand levels but must be paid for by the current, smaller customer base. For utilities in regions that are more densely populated, one cost-reducing alternative are inter-utility agreements. These cooperative agreements – now commonplace among neighboring utilities and municipalities in the US and worldwide – can reduce costs via economies of scale and help limit environmental impacts as more resource-efficient substitutes for independent investments by individual utilities. However, uncertainty in demand growth (i.e. deviations from the projections that underpin a cooperative agreement) can introduce both supply and financial risk to utility partners. These risks may be compounded by asymmetric growth in demand across partners, or if the structure of the agreement itself limits adaptive responses by each utility. As such, water utilities considering inter-utility agreements must be informed on the benefits and drawback of potential agreements, as well as the impacts of both hydrologic and demand growth uncertainty on their performance.

Through a pair of studies, this research details a range of agreements currently in use by utilities across the US, and the potential water supply and financial risks of different agreements under demand growth uncertainty are quantified through an example in the Research Triangle. Despite the increasing prevalence of inter-utility agreements in practice, no previous research has quantified the financial risks of inter-utility agreement to partnering utilities under demand growth, hydrologic, and institutional (i.e. independent decision-making by a utility and its partners) uncertainty. As a result, Chapters 3 and 4 of this dissertation demonstrate an innovative application of adaptive water supply and financial modeling to explore the benefits and drawbacks of inter-utility partnerships. This involved comparing joint financing of a water treatment plant through fixed or adjustable capacity shares to independent infrastructure planning for each regional utility. Inter-utility agreements, coupled with structured financing for partnering utilities, can significantly improve regional supply reliability and financial outcomes versus independent planning by individual utilities, providing financial flexibility to address water supply risks should demands fluctuate. Improvements in performance, measured as regional supply reliability and financial volatility, mask tradeoffs among individual agreement partners. Adjustable treatment capacity allocations may add flexibility to inter-utility agreements, but also increase the financial risk of each utility as a function of the decision-making of the other partners. It is important to note that even regional utilities that do not plan to participate in an inter-utility agreement can still benefit from the agreement. In showcasing the significant benefits of carefully designed and evaluated inter-utility agreements, this work provides a template to aid decision-makers considering water supply partnerships in other regions, especially in the face of wide-ranging uncertainties.

The final focus of this dissertation centers on how utilities financially adapt to meet uncertain future conditions related to supply, demand, and financial status. Despite debt financing for infrastructure being a central component of utility budgets, few studies have directly quantified decision-relevant financial outcomes (and the associated risks) of water supply system adaptation under uncertainty. Covenants, often required of utilities by creditors seeking assurance that debt will be repaid, represent a key factor in utility budgets, as most major water supply infrastructure is debt-financed. However, no previous studies have (a) calculated covenants in simulations of future utility operations and infrastructure planning, nor (b) modeled utility budgets to dynamically adapt to swings in costs and revenues with covenants as triggers of adaptive financial responses to supply infrastructure expansion that preserve budget stability. This work develops an integrated adaptive operational and financial modeling framework for the Tampa Bay Water Authority (TBW) to characterize the impacts of long-term infrastructure planning decisions, representing the first methodological advancement in the water resources management field to mechanistically forecast water utility financial adaptation to water supply decision-making. The coupled water supply-financial modeling framework is able to track TBW budgetary decisions in response to future water demand shifts and infrastructure expansion, quantifying the effects of infrastructure planning decisions and demand growth on changes to water rates, a key utility concern, that must be made to satisfy covenants. These results, for the first time, directly quantify adaptive financial response (e.g., financial risk mitigation) by a water utility to infrastructure expansion, providing a template for future assessments of supply and financial risks by water utilities.

In total, the research described in this dissertation fills several gaps in the field of water resources planning and management, showcasing a range of methodological and applied advances in coupled supply and financial modeling for water utilities. In doing so, this document provides a blueprint for future studies of water utility risk assessment as well as for sustainable water utility planning by managers themselves.

6.2 Recommendations for improved water supply and financial systems modeling, and future challenges (and opportunities) for urban water utilities

Throughout the conduction of this research, many more interesting questions arose than could be fully explored. Below, I would like to quickly discuss several of the most interesting topics, as well as potential pathways for future research.

Perfect foresight in demand growth uncertainty modeling. One aspect of water supply system modeling with which I constantly struggled was the relationship between how utilities project water demand growth and how that growth materialized (or didn't) in reality. It is no secret that demand growth is very difficult to project with long-term accuracy for a utility service area, especially given uncertainty in zoning rules, water rates, climatic conditions, annexation or incorporation of new communities, hardening of demand after drought and conservation measures, and more. These uncertainties call into question (a) whether it is appropriate to use water demand and population growth projections derived from water utility master plans, the US Census, or by another authority, as the basis for demand growth in water resource systems research, and (b) whether designing experiments to test utility robustness under demand growth uncertainty around projections implies that utilities have a degree of "perfect foresight." As research in this field continues, I look forward to seeing further investigation into reducing demand uncertainties, specifically with respect to the distinctions made between demand projection and demand realization uncertainties, as well as which utilities actually react to when making long-term planning decisions for infrastructure.

Generalizability of systems modeling for utility risk assessment. Successful modeling of water supply systems requires careful balance between the site-specific intricacies (read: accuracy) of a regional model and its generalizability; in my experiences, the former quality allows for practitioners (water managers and utilities) to make practical use of findings, while the latter quality justifies the work academically. In this work, however, I felt both the greatest academic and practical contributions were made through collaboration with practitioners at Tampa Bay Water on research that emphasized site-specific details and regionally-tailored modeling about generalizability. Working directly with utility staff quickly led to identification of interesting (and unique) focus areas that contributed to utility objectives (exploring impacts of infrastructure development for supply planning decisions) as well as academic progress (novel adaptive financial modeling to support water supply decision-making). As a result, I suggest that future research on regional water utility risk mitigation focus less on ensuring a generalizable analysis framework, and instead (a) emphasize details of the case at hand, even if more complex modeling is required, and (b) elicit constant feedback from stakeholders (i.e. utility planning and executive staff) to learn what information is most useful as well as what details are unnecessary.

Accounting for accounting. Directly related to the importance of capturing case-by-case nuance within water supply systems models, I was surprised to find that successful modeling of financial risks and the dynamic adaptation of utility budgets to infrastructure investment required a well-nuanced understanding of financial accounting practices and terminology. Without the daily assistance of (and detailed data from) TBW's financing staff to enhance my understanding of the utility's operating budget, it would have been impossible to construct an accurate model of TBW's finances that could directly link every key element of their budget (covenants, water rate, debt service, reserve funds, etc.) and form the framework to provide adaptive financial modeling. It would benefit future modeling efforts that intend to accurately model utility response to financial risk to consult not only utility financing and accounting staff, but to also take academic courses in this area.

Avenues for future research. One of the most interesting angles for continuing research in this field relates to how regulatory and institutional uncertainty will impact water supply and financial risks in urban regions. Inter-utility agreement structures are "the tip of the iceberg" in this sense, and I will be interested to see how increased prevalence (and diversity) of cooperative agreements will generate (or alleviate) regional water supply challenges. This is particularly compelling within the context of the Tampa Bay Water Authority, formed to resolve legal conflict between utilities of the Tampa Bay region that could not agree to cooperate on sustainable groundwater use. Incorporating such uncertainties – the degree to which partners cooperate; agreement clauses to incentivize cooperation; state or federal regulatory change impacts on regional supply management – will be a computational challenge.

Another financial uncertainty that could be better accounted for in future research is the growing creativity in debt financing mechanisms. Utilities can now find flexibility in the debt scheduling of individual bond issuances (timing of principal repayment, date to maturity, refunding bonds, etc.). "Green" bonds offer benefits for environmentally-friendly projects, such as landscaping for stormwater flow reduction, where investors can earn greater returns if the project performs well. As well, government-subsidized financing (i.e. the federal US Water Infrastructure Finance and Innovation Act (WIFIA)) provides another potential financing outlet. Because water utilities operate with a large fraction of their budget dedicated to debt service (especially larger utilities that can juggle many debt-financed projects), their mix of available funding sources may have a significant impact on financial stability under other uncertainties.

Finally, a major shortcoming of this work (and much of the work in the water systems field) is the lack of consideration of water supply quality and how it will influence utility financial risk. In North Carolina and many other places, emerging contaminants in surface and groundwater (i.e. PFAS and Gen-X) pose a threat to water quality and therefore are a financial risk to water utilities who must provide safe drinking water. As such contaminants are assigned threshold concentrations for safe human consumption – and utilities become legally responsible for ensuring that emerging contaminant concentrations in drinking water falls below those levels – it will require a financial investment in water treatment for many utilities. While this may be a larger problem for smaller utilities without the revenues to afford retrofitting or replacement of existing treatment infrastructure, urban utilities will not be immune.

6.3 Final thoughts

Despite the outstanding questions and interesting tangents that remain, I feel this dissertation makes a significant contribution to both the academic literature of water supply resource management, as well as the overall body of knowledge related to water utility management. By developing state-of-the-art frameworks for assessment and consideration of hydrologic and demand growth uncertainties, cooperative water supply management, and adaptive financial risk mitigation, this work provides a launching point for future research. I look forward to seeing how this work is built upon by future students to drive further innovation in water resources management and planning.

APPENDIX 1: CHAPTER 2 SUPPLMENTARY MATERIAL

Introduction. Supplemental information provided here gives additional detail on the selection (S1) and calibration/validation (S2) of eco-hydrologic modeling from this study as well as technical detail and validation results of stochastic streamflow and evapotranspiration record generation (S3).

Text S1: Technical detail of eco-hydrologic modeling. RHESSys is a spatially explicit and distributed eco-hydrologic process-based model; spatially distributed LULC data, as well as elevation, soils, impervious surface cover, forest LAI, urban canopy LAI, forest type, and computation of stomatal physiology, carbon assimilation and allocation, are directly incorporated in the modeling spatial unit at the same spatial resolution of LULC data used in this study. RHESSys is used for simulation of streamflow generation in the urbanized and forest area of the Triangle, and to generate information to modulate demand for outdoor water use (not described in this paper). The model must balance computational cost and accuracy of RHESSys representation of the complex Triangle area over the wide array of tree species with distinct water use traits. Using local measurements at Duke Forest (e.g. Pataki & Oren, 2003; Pataki et al., 1998), we adapt RHESSys forest parameterization with tree density weighted ecophysiological parameters for deciduous and evergreen canopy types. This approach approximates the region's distribution of tree species based on the dominant species in each forest type (from the FIA based imputations). We have previously shown that this locally weighted parameterization can significantly improve watershed ecohydrological predictions (Lin et al., 2018). Daily precipitation and temperature, along with estimated radiation and vapor pressure deficit (by Running et al., 1987) are spatially distributed into hillslopes and patches based on elevation, slope, and aspect. Model hydrologic processes then redistribute the precipitation into evapotranspiration, surface detention, soil moisture, shallow and deep groundwater at the patch level, and simulate water movement among patches along topographic flow paths, yielding streamflow in the receiving channel network.

SWAT modeling occurs at the hydrologic response unit (HRU) spatial scale, a zonal classification of LULC, slope, and soil. Unlike RHESSys, SWAT is a lumped model at the sub-basin level, in which all HRUs directly contribute to the total sub-basin runoff by a time-lag water release function. SWAT incorporates LULC change in the Haw River basin at the sub-basin level, with projected LULC changes centralized around existing developed area.

Both SWAT and RHESSys models have been calibrated and validated to produce consistent hydrologic outputs between different modeled basins in response to climate change and LULC change despite variation in model sensitivities (E. Morán-Tejeda et al., 2013; Enrique Morán-Tejeda et al., 2015). For example, SWAT is more sensitive to climate change than RHESSys, while RHESSys is more sensitive to LULC change than SWAT. While SWAT is a lumped (semi-distributed) model, calculating model processes at the HRU level, RHESSys is a distributed model using pixels as the processing unit. This, as well as differences in equations governing water balance, impacts parameter sensitivities to LULC change between SWAT and RHESSys and requires different model calibration and bias correction strategies. More detail on RHESSys and SWAT model development for this study can be found in subsections 2.2.3.2 and 2.2.3.3 of the main text as well as the following section of the supplementary material.

Text S2: Eco-hydrologic model bias correction detail. Both RHESSys and SWAT models were calibrated and validated at the USGS catchments nested inside the reservoir drainage basins, e.g., USGS Little River for the Little River reservoir, USGS Flat River for the Lake Michie, USGS Cane Creek and Morgan Creek for Cane Creek reservoir and University Lake, respectively. Calibrated parameters of the New Hope and Morgan Creek subbasins (within University Lake drainage area) were used for the urban areas surrounding Jordan Lake. Total inflow to Jordan Lake was calculated as the combined outflow from the Haw River, Morgan Creek and New Hope basins, as well as un-gaged tributaries surrounding Jordan Lake. When estimating inflow to the reservoir by these eco-hydrological models, we included the ungauged area within the reservoir drainage basin into the model. The ungauged areas in the Little River reservoir and Lake Michie drainage basins are small as the gauges are immediately upstream of the reservoirs. The ungauged areas in the Cane Creek and University Lake watersheds include surrounding urban landscape and further downstream areas. The Jordan Lake watershed is the largest in our study, including the Haw River drainage basin and all the surrounding areas near Jordan Lake (e.g., New Hope, Cary, Morrisville, Apex, and part of Holly Spring and Durham drainage areas).

Water supply management modeling done by Triangle utilities made use of estimated reservoir inflow products (Kirsch et al. 2013), records previously used to develop and calibrate our modeling of the region. Therefore, RHESSys / SWAT daily inflow to reservoirs were statistically corrected by the previously-estimated daily reservoir inflow records from 1945 to 2009. To account for differences between modeled and estimated historical inflows, current and historical LULC, and modeled and observed conditions, we utilized a quantile bias correction method based on the historical period of reservoir inflows (1940-2011). This was done following the widely-used bias-correction method of quantile mapping, a methods particularly common in climate change studies mapping modeled meteorological time series to the locally observed records (J. H. Christensen et al., 2008; Maraun et al., 2010). For each day of a year (Julian day; j), daily inflow (Q_j) data were gathered from multiple years, as well as within a 15-day window (7-day prior and 7-day after), to construct cumulative inflow distributions: one for RHESSys/SWAT inflow ($F_{model,\ Qj}$) and another one for the previous estimation ($F_{record,\ Qj}$). For any particular day (i) and its corresponding year day (j), the cumulative value ($F_{model,\ Qj}[q_i]$) is calculated for RHESSys / SWAT inflow (q_i) and used to map onto the previous inflow estimations used in water supply modeling ($F^{-1}_{record,\ Qj}[F_{model,\ Qj}[q_i]]$). The difference between q_i and $F^{-1}_{record,\ Qj}[F_{model,\ Qj}[q_i]]$ is used to adjusted the RHESSys/SWAT inflow to the previous reservoir inflow. Results from calibration and validation are included below in Table S2.1 in terms of Nash-Sutcliffe Efficiency coefficient. Parameter selection for SWAT and RHESSys models was further refined by closely matching the 60-year weekly inflow auto-correlation between the modeled and historical (empirical) references.

There are multiple realizations in each modeling components, representing uncertainty. For climate change, we used six different CMIP5 RCP 6.0 GCMs to project the future change. For LULC change, we used six projected realizations of 30-m resolution LULC change (each projected realization contains 6 chronic LULC representing the decadal changes), and each realization further has 3 levels of urban canopy projections in the developed area. For ecohydrological models, we selected four parameter sets at each of the six USGS gaged catchments that produced the best model predictions on streamflow in calibration-validation period and long historical period. In this study, multiple realizations of climate and LULC change are input into the ecohydrologic models that were parameterized using different parameter sets. Thus, multiple inflow timeseries were generated from these multiple climate-LULC input and ecohydrological model settings for each scenario and represent the uncertainty in this multi-step process. In all, 24 combinations of model parameter sets, LULC realizations, GCMs and urban canopy levels were selected for simulation in this work (Table S2.2). Numbered sets within LULC realizations and parameter sets indicate unique organizations of LULC or model parameters in Table S2.2. See Figure S2.1 for further illustration of model linkages before water supply management modeling is considered in the analysis framework.

Text S3: Synthetic generator description and validation. To comprehensively evaluate water utility objective performance under future hydrologic scenarios, a wider range of weekly future realizations from 2015-2060 than could be provided by eco-hydrologic modeling alone are needed. To do so, this work built upon the Kirsch-Nowak synthetic generator, an existing semi-parametric stochastic streamflow generator for stationary hydrology (previously applied by Giuliani, Quinn, Herman, Castelletti, & Reed, 2017 and Quinn, Reed, Giuliani, & Castelletti, 2017). Rather than creating synthetic records of a stationary historic record of hydrology, as in the two aforementioned studies, non-stationary synthetic records are generated by sampling from decadally-shifting eco-hydrologic modeling outputs (from RHESSys and SWAT) to generate concurrent, transient records of reservoir inflow and lake net evaporation at seven sites (four sets of reservoir inflow and three sets of net evapotranspiration). Synthetic outputs were validated through comparison of flow duration curves, and spatial and temporal autocorrelation structures to contemporaneous eco-hydrologic modeling records. Eco-hydrologic modeling records of 2010-2020 flows were previously bias corrected to be in line with empirically-estimated reservoir inflow data of the same period.

Based on the methodology of Kirsch et al. (2013), records of reservoir inflow and net lake evaporation from eco-hydrologic modeling of each hydrologic scenario were first aggregated to a monthly timestep before sampling to produce synthetic records occurs. Sampling at a monthly level was preferred to weekly or daily aggregations for more consistent preservation of an inter-annual, or seasonal, signal. Records are then log-transformed (net evaporation records, which can take positive or negative absolute values, were first exponentiated) and first and second-order moments are removed from the data, providing de-trended residuals for sampling that follow a standard normal distribution. For each decade of synthetic data generated for each site, 120 months (ten years) of monthly residuals are sampled from the available record; the same set of random numbers is used to select residuals across sites in order to preserve spatial correlation. This process is repeated in time to produce each realization of synthetic data from 2015-2060. For example, to produce a single synthetic realization of 2010-2030 inflows, 120 monthly residuals are randomly sampled from the eco-hydrologic record of 2020-2029 inflows and appended to 120 monthly random samples of the available 2010-2019 residual record. For each hydrologic scenario, one-thousand 46-year synthetic realizations across all seven sites are generated. Once residuals for each realization have been sampled, temporal autocorrelation structures of eco-hydrologic records are applied to the randomly-selected synthetic residuals through Cholesky decomposition and the synthetic realizations are subsequently back-transformed into real space by applying monthly means and standard deviations to the residual data and exponentiating it. To preserve intra-annual autocorrelation Cholesky decomposition was done in two steps: (1) as described and (2) shifted six months forward. Finally, the first six months of data in each synthetic year from the original set and the months 7-12 from the shifted set are concatenated to form the final synthetic realization with temporal autocorrelation preserved (see documentation for the Kirsch-Nowak generator on GitHub for further explanation of this step).

Following sampling, monthly sets of synthetic streamflows for a given decade across all sites are disaggregated to a daily level using a k-nearest neighbor (kNN) method (detailed in Nowak et al., 2010). For a given month in the synthetic record, flow of the month at each site is compared across all observed records for the same calendar month, including monthly periods beginning ± 7 days from the start of that month (i.e. for February flows, aggregations of flow from the last week of January to the penultimate week of February, as well as aggregations of from the second week of February to the first week of March), Euclidean distance between observed and synthetic flows is calculated for each site and summed to determine observed months of the record most closely resembling synthetic flow results across all sites simultaneously. Using a Kernel estimator to assign probabilities to each distance estimate (Lall & Sharma, 1996), one month is probabilistically-selected from k nearest neighbors where k is taken to be the square root of the number of observed years on record (Lall et al., 1996; Nowak et al., 2010). Once a month has been selected, the observed daily patterns in flow of that monthly period across sites is used to proportionately disaggregate synthetic record flows such that all synthetic monthly flow is disaggregated amongst days in the month to match the patterns observed on record in the selected monthly period. To match the weekly time step required by the water resources modeling in this paper, daily values were then aggregated to a weekly level assuming a 52-week year. Disaggregating monthly values to daily levels, followed by re-aggregation to weekly time step, was done due to the incongruity between daily and weekly records. Fifty-two weeks do not fit evenly into 12-month periods, but can be synthesized properly based on summation of each seven days of flow.

To then construct a single realization of 2015-2060 flows for a single hydrologic scenario at one site, decadally-sampled synthetic flows for each decade in 2010-2060 are appended, then clipped to capture the 46-year period desired for water supply modeling. As stated previously, this process is done 1,000 times per scenario per site to generate a comprehensive set of hydrologic futures, allowing water supply modeling to capture influence of each hydrologic scenario on utility management objectives.

To validate generator performance, flow duration curves, temporal autocorrelation, and spatial correlation were examined across monthly and weekly time steps of each decadal period for both observed (RHESSys and SWAT projections) and synthetic records (Figures S3.1-S3.8). Monthly results are shown here for each scenario – both aggregation levels displayed high levels of agreement across all scenarios. Red lines in the plots represent observed record values, while grey and blue lines and boxplots show the range of synthetic flow records. Synthetic records were generated for four reservoir inflow sites (at Jordan Lake [Haw River], Cane Creek Reservoir [Cane Creek; CCR], Little River Reservoir [Little River], and Lake Michie [Flat River]) and three lake evaporation timeseries (at Cane Creek Reservoir, Jordan Lake, and Lake Michie).

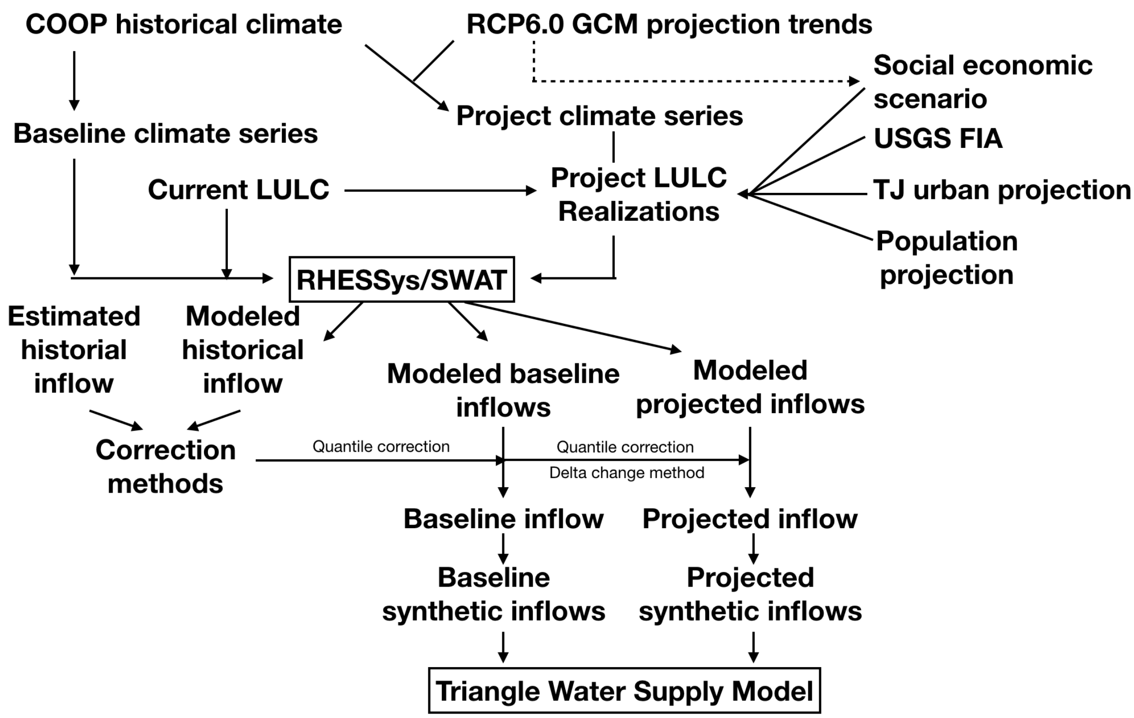

Figure 7.1: Conceptual diagram of linkages between components of the modeling framework, emphasizing modeling steps before water supply management modeling occurs (climate and land use projections informing eco-hydrologic modeling)

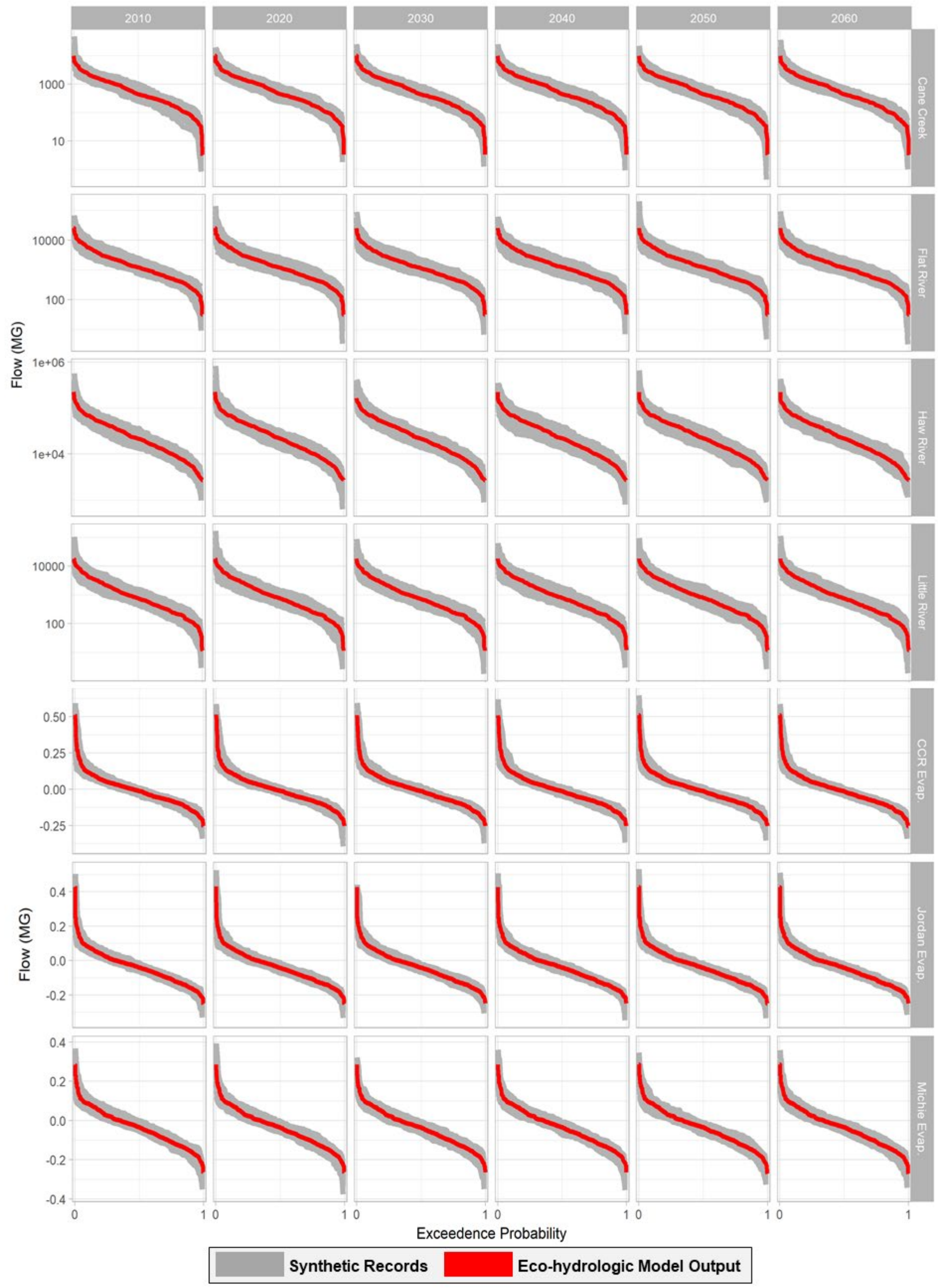

Figure 7.2. Synthetic generator validation of monthly flow duration curves for the baseline hydrologic scenario (scenario 1). Synthetic records (grey) are shown against eco-hydrologic model outputs (red) by site (row) and decade (column) for four reservoir inflow records (top four rows) and three evaporation sites at regional reservoirs (bottom three rows). Synthetic records show steady ability to retain probabilistic monthly flow trends of eco-hydrologic modeling of reservoir inflows (red lines centered among many grey lines) while simultaneously providing a wide range of variability between synthetic realizations (thickness of grey area).

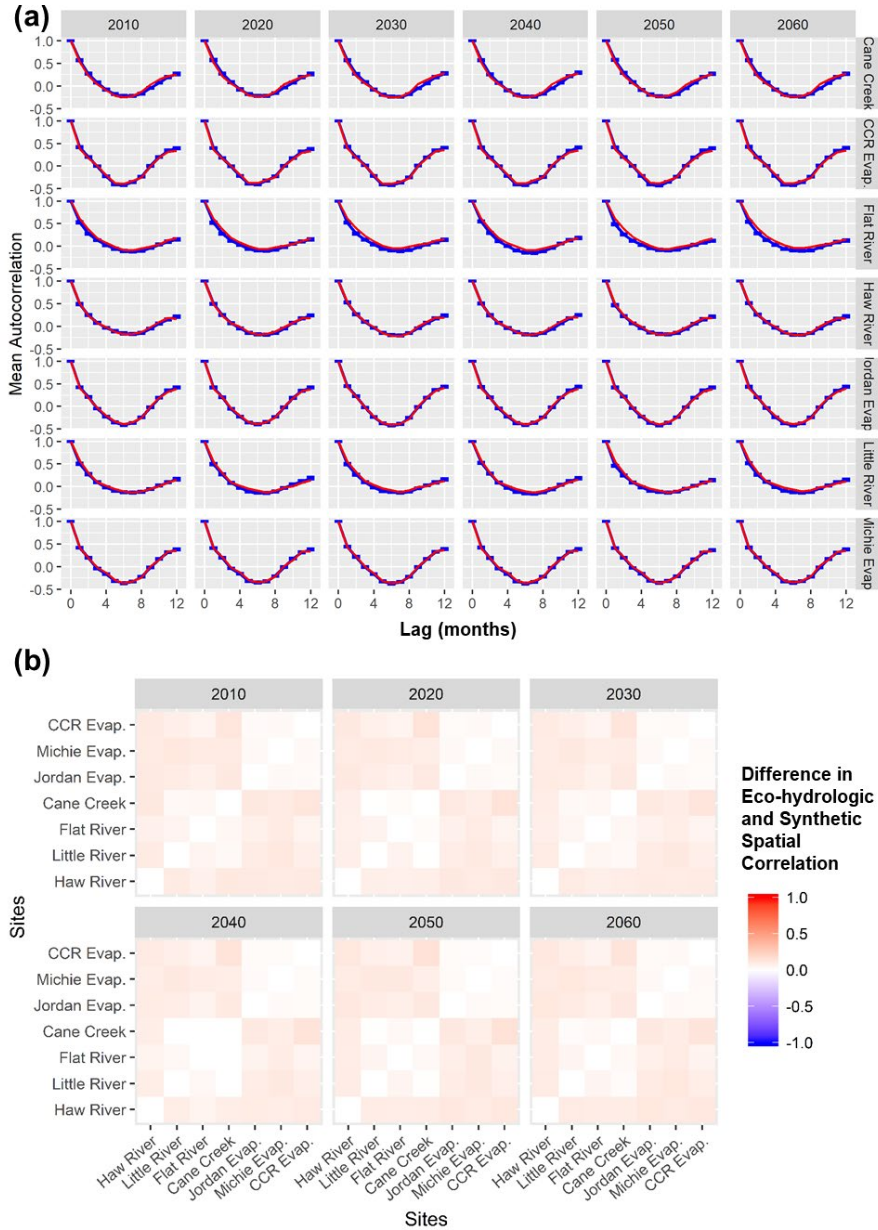

Figure 7.3. Synthetic generator validation of the baseline scenario 1 of: (a) monthly temporal autocorrelation at each regional site (row) for each decade (column) modeled. Red line depicts eco-hydrologic model output temporal autocorrelation across 12 months of lag, and blue boxplots show the range of autocorrelation observed across all synthetic realizations statistically constructed from eco-hydrologic records. Synthetic records are observed to preserve eco-hydrologically modeled autocorrelation well across all sites and time periods. (b) spatial correlation comparisons across sites by decade (facets). Colors show the difference between spatial correlation in flows between eco-hydrologic model outputs and averages across all synthetic realizations. Colors are close to white, indicating a close agreement between synthetic and eco-hydrologic records, with eco-hydrologic records tending to preserve slightly more the intra-site correlations in flow.

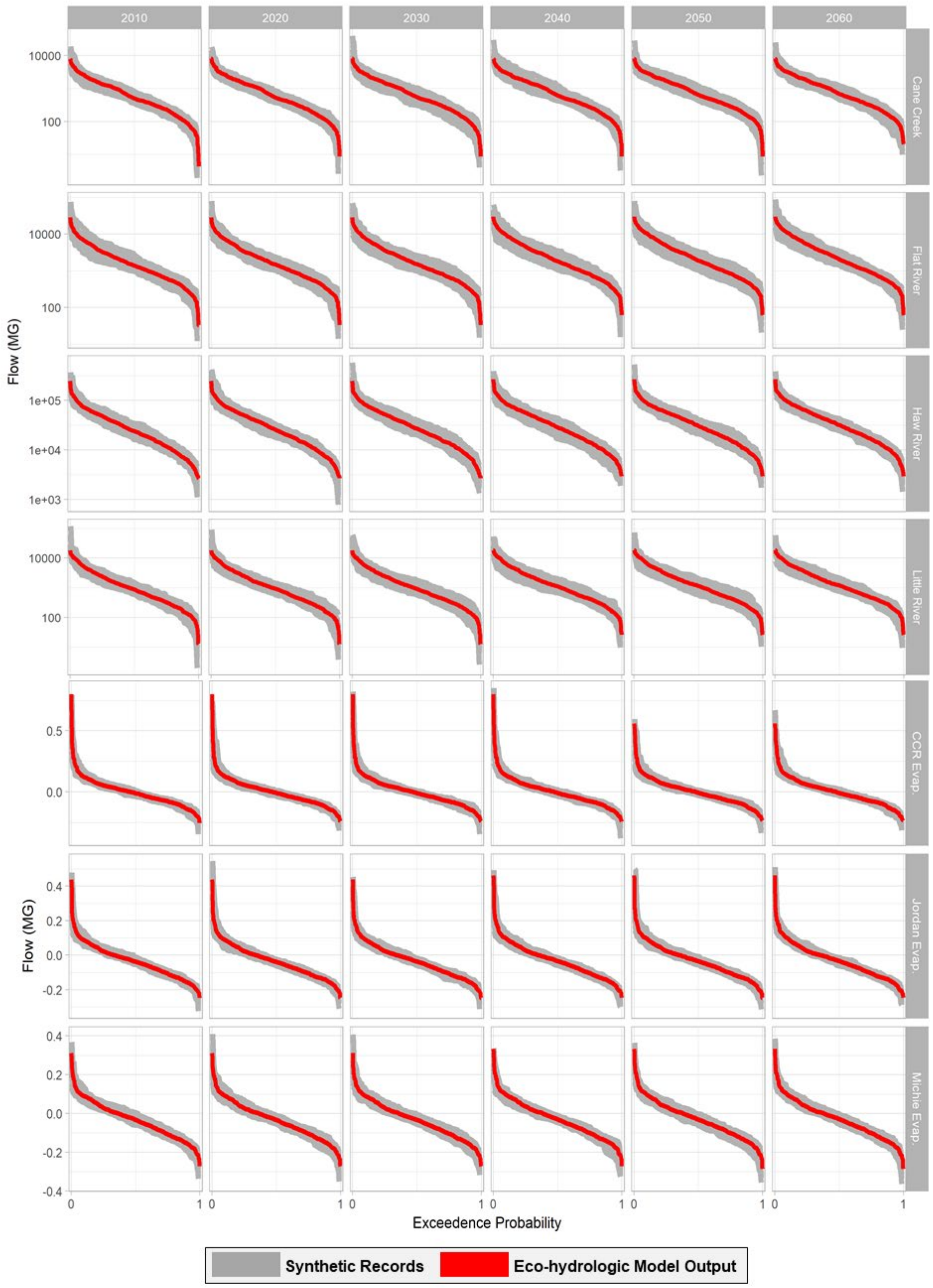

Figure 7.4. Synthetic generator validation of monthly flow duration curves for the climate change hydrologic scenario (scenario 2). Synthetic records (grey) are shown against eco-hydrologic model outputs (red) by site (row) and decade (column) for four reservoir inflow records (top four rows) and three evaporation sites at regional reservoirs (bottom three rows). Synthetic records show steady ability to retain probabilistic monthly flow trends of eco-hydrologic modeling of reservoir inflows (red lines centered among many grey lines) while simultaneously providing a wide range of variability between synthetic realizations (thickness of grey area).

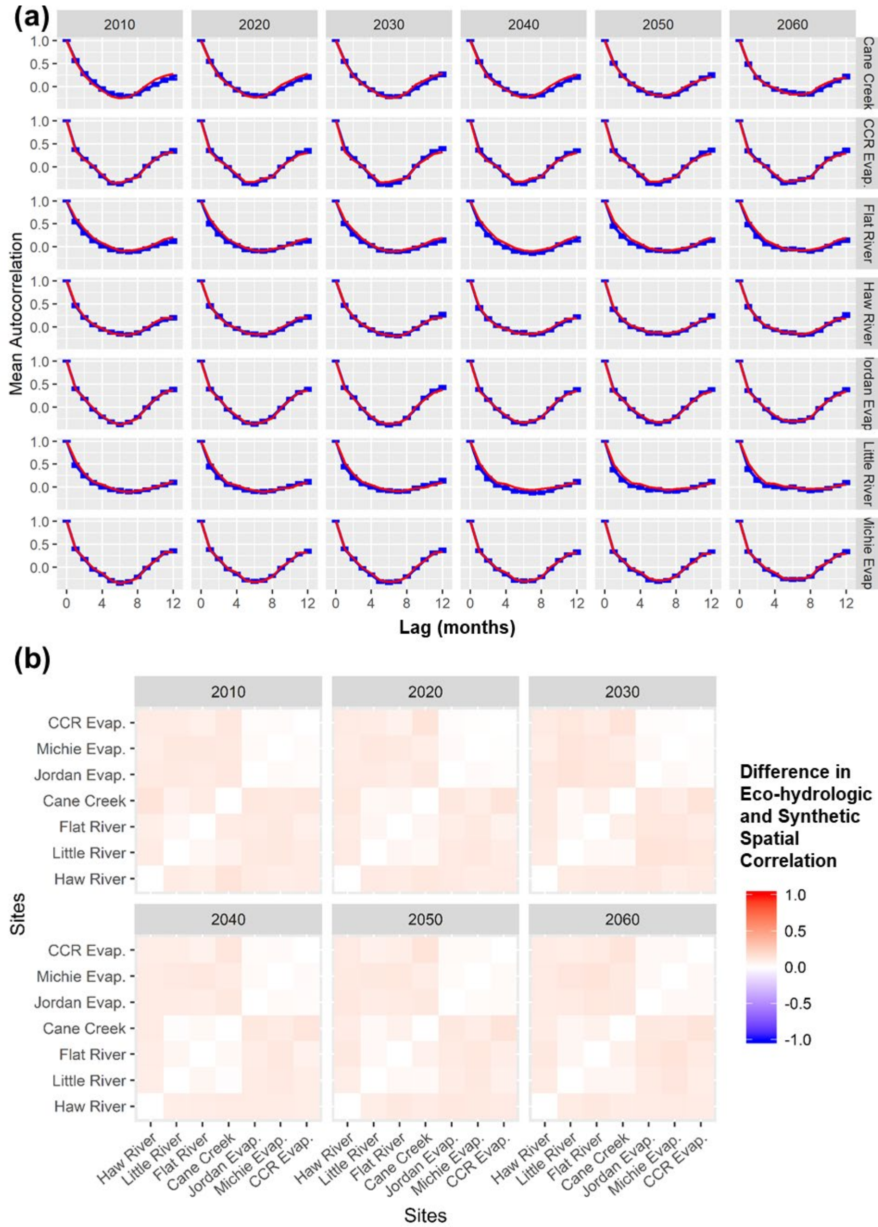

Figure 7.5. Synthetic generator validation of the climate change scenario 2 of: (a) monthly temporal autocorrelation at each regional site (row) for each decade (column) modeled. Red line depicts eco-hydrologic model output temporal autocorrelation across 12 months of lag, and blue boxplots show the range of autocorrelation observed across all synthetic realizations statistically constructed from eco-hydrologic records. Synthetic records are observed to preserve eco-hydrologically modeled autocorrelation well across all sites and time periods. (b) spatial correlation comparisons across sites by decade (facets). Colors show the difference between spatial correlation in flows between eco-hydrologic model outputs and averages across all synthetic realizations. Colors are close to white, indicating a close agreement between synthetic and eco-hydrologic records, with eco-hydrologic records tending to preserve slightly more the intra-site correlations in flow.

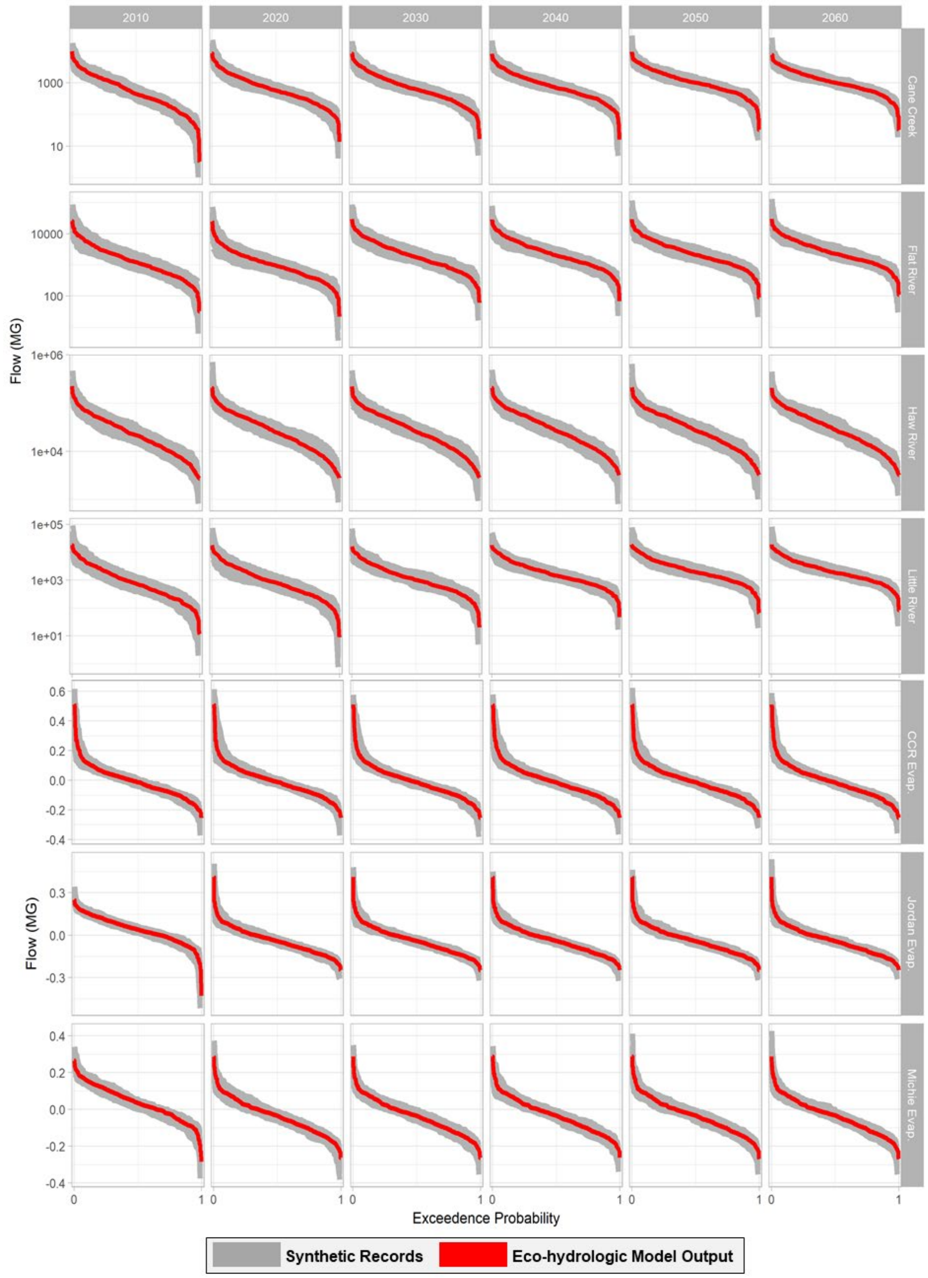

Figure 7.6. Synthetic generator validation of monthly flow duration curves for the land use hydrologic scenario (scenario 3). Synthetic records (grey) are shown against eco-hydrologic model outputs (red) by site (row) and decade (column) for four reservoir inflow records (top four rows) and three evaporation sites at regional reservoirs (bottom three rows). Synthetic records show steady ability to retain probabilistic monthly flow trends of eco-hydrologic modeling of reservoir inflows (red lines centered among many grey lines) while simultaneously providing a wide range of variability between synthetic realizations (thickness of grey area).

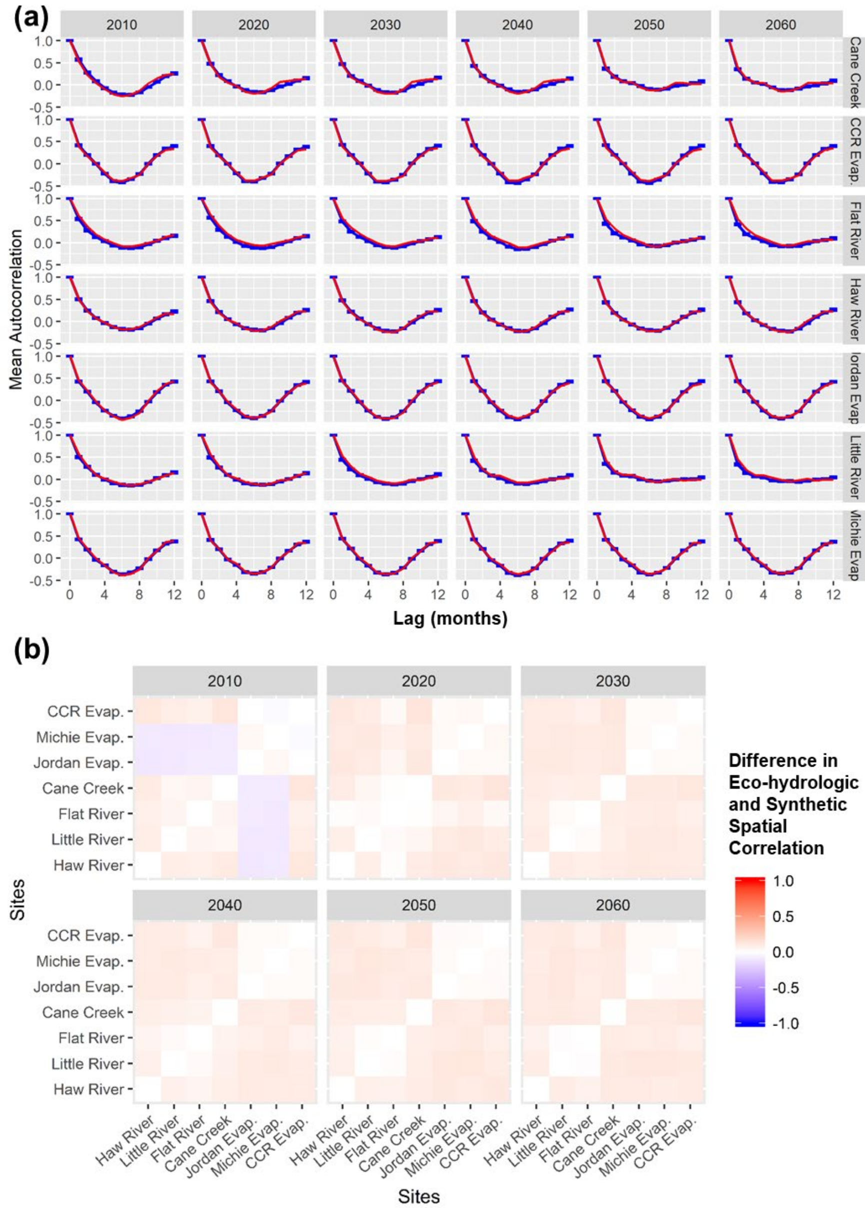

Figure 7.7. Synthetic generator validation of the land use scenario 3 of: (a) monthly temporal autocorrelation at each regional site (row) for each decade (column) modeled. Red line depicts eco-hydrologic model output temporal autocorrelation across 12 months of lag, and blue boxplots show the range of autocorrelation observed across all synthetic realizations statistically constructed from eco-hydrologic records. Synthetic records are observed to preserve eco-hydrologically modeled autocorrelation well across all sites and time periods. (b) spatial correlation comparisons across sites by decade (facets). Colors show the difference between spatial correlation in flows between eco-hydrologic model outputs and averages across all synthetic realizations. Colors are close to white, indicating a close agreement between synthetic and eco-hydrologic records, with eco-hydrologic records tending to preserve slightly better the intra-site correlations in flow, save two evaporation sites in the first decade.

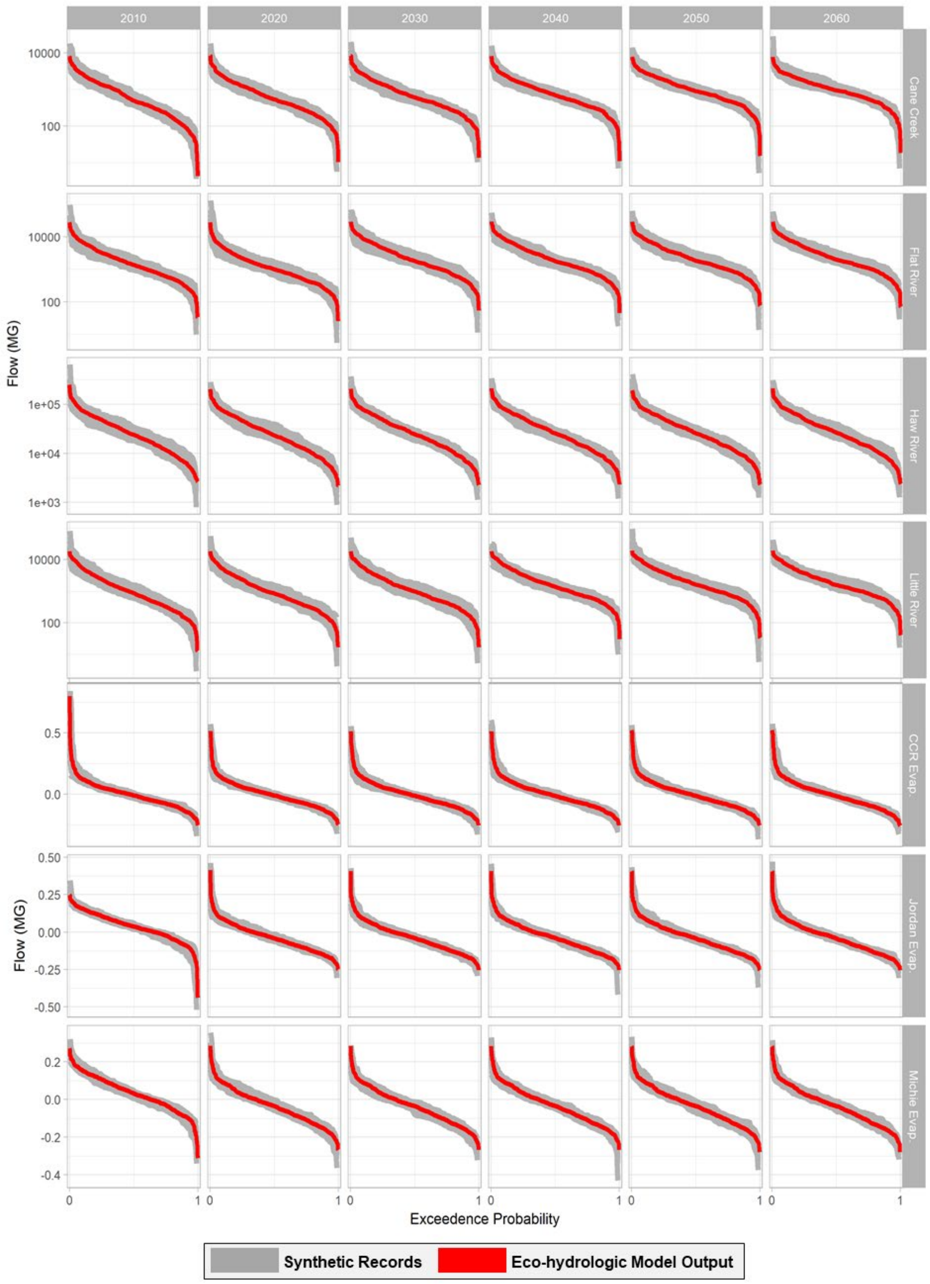

Figure 7.8. Synthetic generator validation of monthly flow duration curves for the climate and land use hydrologic scenario (scenario 4). Synthetic records (grey) are shown against eco-hydrologic model outputs (red) by site (row) and decade (column) for four reservoir inflow records (top four rows) and three evaporation sites at regional reservoirs (bottom three rows). Synthetic records show steady ability to retain probabilistic monthly flow trends of eco-hydrologic modeling of reservoir inflows (red lines centered among many grey lines) while simultaneously providing a wide range of variability between synthetic realizations (thickness of grey area).

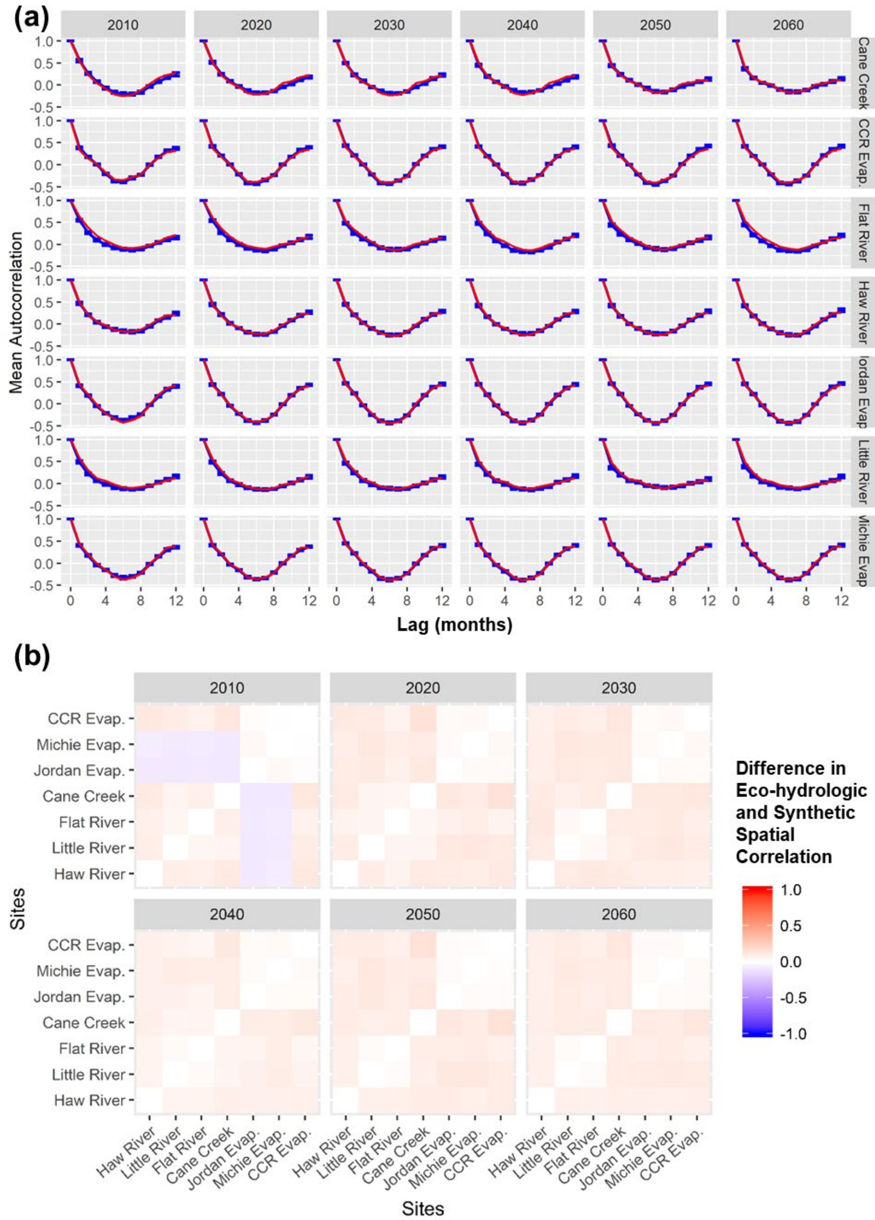

Figure 7.9. Synthetic generator validation of the climate and land use scenario 4 of: (a) monthly temporal autocorrelation at each regional site (row) for each decade (column) modeled. Red line depicts eco-hydrologic model output temporal autocorrelation across 12 months of lag, and blue boxplots show the range of autocorrelation observed across all synthetic realizations statistically constructed from eco-hydrologic records. Synthetic records are observed to preserve eco-hydrologically modeled autocorrelation well across all sites and time periods. (b) spatial correlation comparisons across sites by decade (facets). Colors show the difference between spatial correlation in flows between eco-hydrologic model outputs and averages across all synthetic realizations. Colors are close to white, indicating a close agreement between synthetic and eco-hydrologic records, with eco-hydrologic records tending to preserve slightly better the intra-site correlations in flow, save two evaporation sites in the first decade.

			Calibration period			Validation period		
Catchment	USGS ID	Area (sq. km)	weekly NSE	weekly log NSE	monthly NSE	weekly NSE	weekly log NSE	monthly NSE
Cane Creek	02096846	19.7	0.68±0.02	0.69±0.02	0.71±0.02	0.51±0.06	0.68±0.04	0.62±0.08
Morgan Creek	02097464	21.4	0.78±0.02	0.63±0.03	0.89±0.01	0.53±0.05	0.68±0.01	0.88±0.04
Flat River	02085500	385.1	0.70±0.02	0.60±0.02	0.78±0.02	0.49±0.02	0.48±0.03	0.68±0.04
Little River	0208521324	202.7	0.71±0.01	0.69±0.04	0.78±0.01	0.43±0.01	0.62±0.03	0.69±0.02
New Hope	02097314	198.9	0.74±0.03	0.51±0.01	0.74±0.01	0.48±0.02	0.61±0.02	0.69±0.03
Haw River	02096960	329.6	0.76±0.01	0.75±0.02	0.74±0.01	0.61±0.03	0.56±0.08	0.58±0.02

Table 7.1. RHESSys and SWAT calibration and validation statistics for Triangle catchments.

LULC Realization	GCM	Parameter Set	Urban Canopy Density
less-urban 2	GISS	set 1	mid
less-urban 3	CCSM	set 3	mid
less-urban 3	GISS	set 4	mid
less-urban 1	CCSM	set 3	high
less-urban 2	GFDL	set 4	high
more-urban 1	GISS	set 2	none
more-urban 2	GFDL	set 4	none
more-urban 2	GISS	set 4	mid
more-urban 1	CCSM	set 1	high
more-urban 3	GFDL	set 3	high
more-urban 3	GISS	set 2	high
less-urban 1	CSIRO	set 3	none
less-urban 1	MIROC	set 2	none
less-urban 2	MIROC	set 1	none
less-urban 2	CSIRO	set 4	mid
less-urban 1	HADG	set 2	high
less-urban 3	CSIRO	set 4	high
less-urban 3	HADG	set 3	high
more-urban 1	HADG	set 1	none
more-urban 3	CSIRO	set 2	none
more-urban 2	HADG	set 1	mid
more-urban 3	HADG	set 3	mid
more-urban 1	MIROC	set 2	high
more-urban 2	CSIRO	set 1	high

Table 7.2. Eco-hydrologic modeling simulations defined by the landcover realization, downscaled GCM data, parameter set, and urban canopy density driving simulation of water availability. Numbered sets within LULC realizations and parameter sets indicate unique organizations of LULC or model parameters.

APPENDIX 2: CHAPTER 3 MODELING METHODOLOGY

For each stage s of a project, the following parameters are specified: fixed treatment capacity C_s (in millions of gallons per day; MGD), upfront capacity expenses EXP_s, fixed annual operation and maintenance costs FOM_s, variable annual O&M costs VOM_s, construction year of the project stage y_s, bond term $B_{term,s}$ and interest rate $B_{rate,s}$, and a cost escalator term e_s (to approximate increasing annual fixed O&M into the future). A project with multiple utility partners, such as the WJLWTP, is parameterized within the model for each utility U through specification of: water use peaking factor f_U, initial total water demand $D_{U,0}$ (in MGD, based on 2010 levels), annual rate of demand growth rd_U (in MGD/year), number of customers of the utility NC_U, and a predefined growth scenario (detailed below). Each utility is also assigned a capacity share of the project for each project stage $CS_{U,s}$ along with any water a utility (in MGDs) is allocated to treat/buy per year through minimum purchase $MPA_{U,s}$ and take-or-pay $TPA_{U,s}$ agreements.

Demand growth scenarios are represented via annual growth units. For instance, expected growth would be a modeled with numbers sequentially ordered from 0 to 24, one per year of the 25-year modeling range, meaning that demand grew 1 unit per year for 25 years, with the first year having demand equal to initial demands. As such, demand $D_{U,y}$ in a future year y for utility U is calculated based on the "units" of annual demand growth $dgu_{U,y}$ that have occurred to that point following this formula of linear growth: $D_{U,y} = D_{U,0} + dgu_{U,y} * rd_U$. Under expected demand growth conditions, $dgu_{U,y} = y$ (demand grows at one annual unit per year).

To determine treatment capacities and water use by each utility per year, a number of steps are required. First, available project treatment capacity AC_y (capacity available for allocation) for current year y is determined, equal to $\sum_s C_s$ where $y \geq y_s$. Each utility's capacity share in the project, as well as any spot purchases made, and final total use of treatment capacity annually, are determined via the following steps:

1. Capacity shares $CS_{U,y}$ for each utility in the project each year are determined based on the agreement type. If allocations are fixed, they are equal to the portions specified above, mathematically set such that $CS_{U,y} = \sum_s CS_{U,s}$ $for\ all\ s\ where\ y \geq y_s$. If a uniform rate agreement is used, allocations are determined based on expected demand (including a peaking factor) of a utility relative to the other users, also factoring in minimum purchase agreements related to all active stages of the project:

$$CS_{U,y} = AC_Y * \frac{max(D_{U,y}f_U\ , MPA_U)}{\sum_U max(D_{U,y}f_U\ , MPA_U)}$$

2. Spot purchases $SP_{U,y}$ for a utility as part of any take-or-pay agreements each year are calculated. Assuming that excess treatment capacity is available ($AC_y > \sum_U \min(CS_{U,y}\ , D_{U,y}f_U)$), spot purchases take the minimum value between the following two equations:

$$max\left(\sum_s TPA_{U,s}\ , D_{U,y}f_U - CS_{U,y}\right)$$

$$\left(AC_y - \sum_U \min(CS_{U,y}, D_{U,y}f_U)\right) * \left(\frac{CS_{U,y}}{AC_y}\right)$$

3. Total use $TD_{U,y}$ by each utility each year is then calculated as the minimum value of either demand $D_{U,y}$ or the sum of a utility's raw capacity share and spot purchases $\left(\frac{CS_{U,y}+SP_{U,y}}{f_U}\right)$.

Finally, cash flows relating to the project are determined. Total debt service DSP_y, fixed and variable operation and maintenance FOM_y and VOM_y are calculated based on stages of project that are active and their component costs, as well as the capacity allocated to each utility and total use by each utility. Spot purchases by any utility are assumed to be paid out to utilities with allocations in proportion to their allocation stakes, and unit costs per available capacity:

$$Spot\ Payment_{U,y} = \frac{\left(\min\left(CS_{U,y}, D_{U,y} f_U\right)\right)}{\sum_U \min\left(CS_{U,y}, D_{U,y} f_U\right)} * \left(\sum_U SP_{U,y} - SP_{U,y}\right) * \frac{DSP_y + FOM_y}{AC_y}$$

APPENDIX 3: CHAPTER 4 MULTI-OBJECTIVE OPTIMIZATION DETAILS AND SOW VALIDATION

Runtime diagnostics on Borg optimization seeds were performed using hypervolume and visual analytics to confirm convergence (Fig. 10). Six random seeds for each formulation were run for 150,000 function evaluations (NFE). An additional test run of 50,000 NFE was also included in the reference set, as runtime diagnostics using the Hypervolume indicator (Zitzler et al., 2003) confirmed that the algorithm converged before 50,000 NFE.

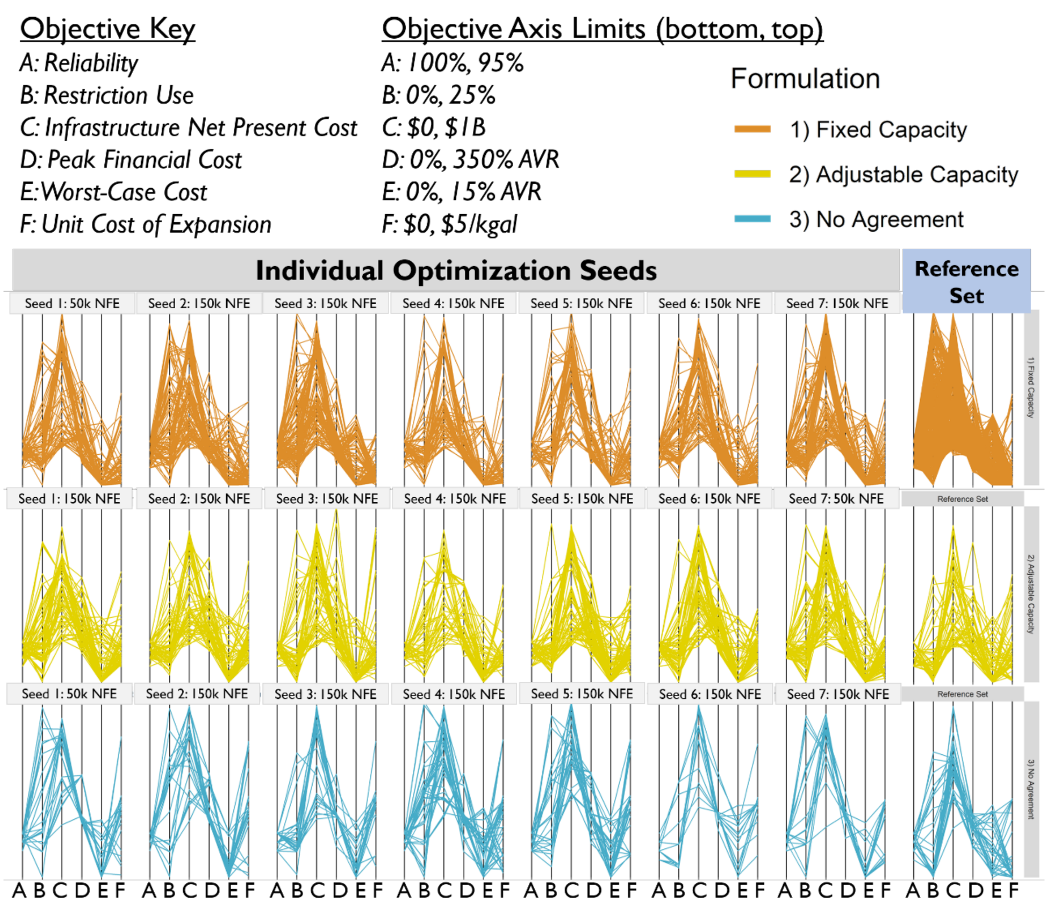

Figure 7.10: Visual analysis of Borg optimization seed convergence. Individual seed (panels) reference sets were screened for solutions satisfying utility reliability, restriction use, and worst case cost performance criteria for each formulation (rows) and compared to the full reference set of solutions across all seeds (right column of panels). Seeds with a maximum of both 50,000 and 150,000 function evaluations were able to successfully identify solutions meeting criteria.

Following DU optimization, Pareto approximate reference set solutions that meet utilities' performance criteria were re-evaluated under a separate set of 500 SOWs to validate robustness of solutions identified by the DU optimization and ensure representative solutions presented in results did not represent outlier solutions (i.e. satisfactory in initial DU optimization but not in re-evaluation. Fig. 11 shows the ability of solutions identified as satisfactory under both (a) the SOW set used in DU optimization, and (b) the re-evaluation SOW set to perform similarly, demonstrating the ability of DU optimization to successfully identify robust policy pathways.

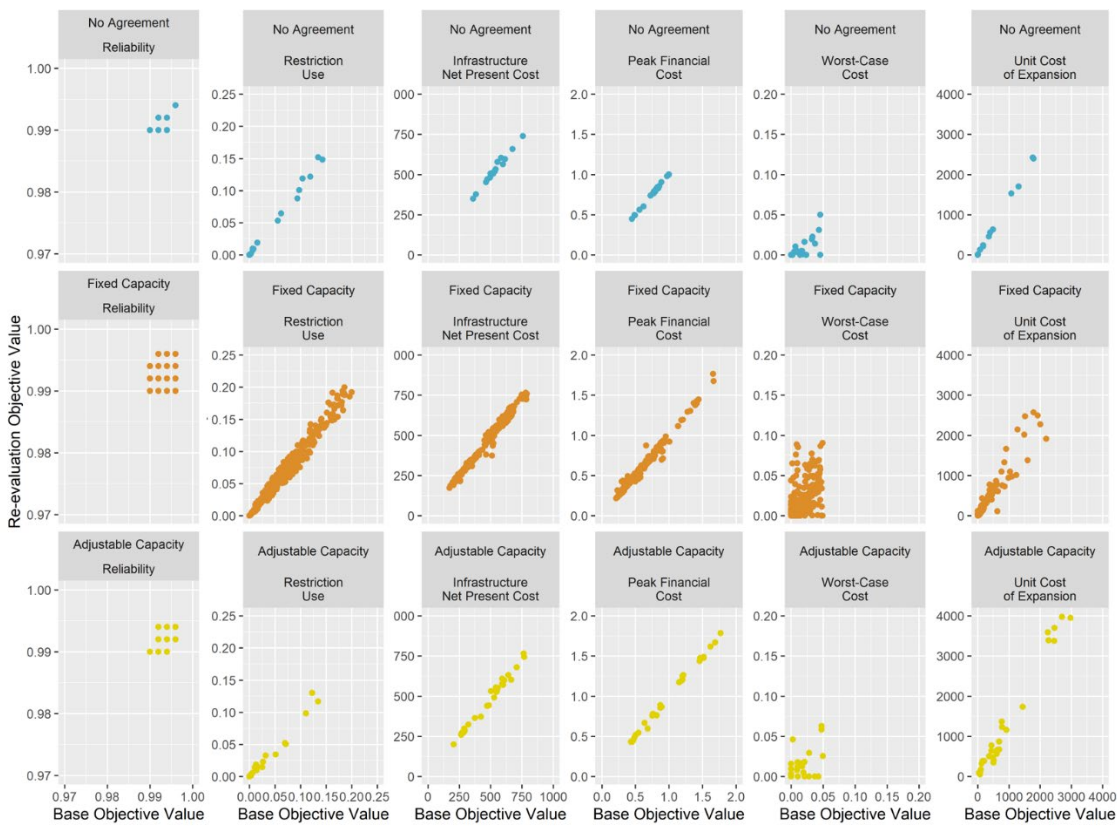

Figure 7.11: Comparison of regional objective performance by solutions identified by DU optimization as meeting utilities' performance criteria under base SOWs (x-axis) to performance of the same solutions under the re-evaluation SOWs set (y-axis). Colors and rows of panels separate inter-utility agreement formulations, columns separate the six regional objectives. Dots represent solutions that met performance criteria under both base and re-evaluation SOW sets.

Table 3 provides further detail on the ability of DU optimization satisfactory solutions to remain so under re-evaluation with different SOWs. Of 588 satisfactory solutions identified by DU optimization, 434 were also satisfactory in re-evaluation. When re-evaluation criteria of reliability satisfaction was loosened by 0.04%, the number of satisfactory solutions rises to 546. In all sets, the relative percentages of satisfactory solutions found under each inter-utility agreement formulation were consistent (parentheticals in Table 3), providing confidence that DU optimization correctly identified inter-utility cooperative agreements as robust options for improving regional performance. Furthermore, our re-analysis confirmed that representative solutions, used for example analysis in Fig. 4.4 of the main text, satisfied utility criteria in both SOW sets.

Table 7.3: Summary statistics comparing the number of solutions under both (a) the initial reference set identified by DU optimization, and (b) the re-evaluation of satisfactory solutions under new SOWs that meet utility performance criteria.

	Number of solutions meeting utility performance criteria by formulation (and percent of all solutions):			
States-of-the-World	**0: No Agreement**	**1: Fixed Capacity**	**2: Adjustable Capacity**	**Total**
Reference (with Reliability performance criteria of 99%)	30 (5%)	506 (86%)	52 (9%)	588 (100%)
Re-evaluation (with Reliability performance criteria of 99%)	19 (4%)	385 (89%)	30 (7%)	434 (74%)
Re-evaluation (with Reliability performance criteria of 98.6%)	26 (5%)	473 (86%)	47 (9%)	546 (93%)

APPENDIX 4: CHAPTER 5 SUPPLEMENTARY MATERIAL

5.1: Probabilistic Demand Forecasting Details

Tampa Bay Water's latest long-term demand forecasting model was developed in 2017 by Hazen & Sawyer. Retail water demand is modeled using three sector specific models, single family (SF), multi-family (MF) and non-residential (NR). Each model is used to generate demand forecasts fore each of the region's Water Demand Planning Areas (WDPAs). Each model uses a rate-of-use-times-driver approach for calculating demand. The sector-specific monthly mean, or rate-of-use is calculated per water consuming entity, multiplied by the number of driver units of the given entity. For example, the SF model defines a driver unit as one single family dwelling unit, it then calculates the monthly retail demand of a housing unit and multiplies it by the number of housing units in the WDPA. The MF model uses MF dwelling units as drivers and the NR model uses units of 1,000 square feet.

This model is then used to make a point forecast for regional demand through 2045, as well as a probabilistic forecast. The point forecast is created using best estimates for predictions of explanatory variables through 2045; explanatory variables included in each WDPA model include rainfall, temperature, real median household income, real marginal price of water, persons per household, housing unit density, fraction of use from reclaimed water services, non-residential square footage, and market penetration of high-efficiency water fixtures. Model estimates are adjusted to account for wholesale water purchases and unbilled water sales. The model is fit using data from 2001-2013 and evaluated over the period 2014-2018. Based on the performance in the validation set, multiplicative calibration factors are set to correct the discrepancies between forecasted values and observations during the validation period. A separate calibration factor is used for each sector, WDPA and month of the year.

The probabilistic forecast uses Monte Carlo simulation to generate an ensemble of probabilistic demand records through 2045. The forecast accounts for both uncertainty in the exploratory variables and in model parameters. Uncertainty in exploratory variables was accounted for by fitting distributions to each uncertain parameter and sampling. All input data aside from weather variables was assumed to be normally distributed, some data was sampled from multivariate normal distributions to account for cross correlations while variables were assumed to be independent. Weather variables were simulated using a bootstrapping method. Model uncertainty was accounted for by bootstrapping from historical model residuals. The overall forecast for TBW demand in 2018 had a -1.34% error, in aggregate across the three forecast models from all WDPAs.

5.2: Flow Modeling System V2 Hydroclimatic Realization Development

The Flow Modeling System, Version 2 (FMS2) Model, developed by Hazen & Sawyer consultants for use by Tampa Bay Water, combines rainfall models at the three rainfall stations in the Tampa Bay region to generate synthetic realizations of future streamflow. Rainfall models developed for rainfall stations at Plant City, St. Leo, and Cypress Creek wellfield were based on 106 years of available historical record (1901-2006); concurrent records at all sites are available from 1977-2006. Rainfall patterns from 1901-2006 are similar to the record from 1977-2006 in terms of total annual rainfall, though monthly totals (ex: comparing all Januarys on record to 1977-2006 Januaries) showed substantial changes, indicating shifting seasonality. They also observe that calendar month average flows could shift noticeably between any two arbitrary 30-year periods of the historic record. St. Leo and Plant City rainfall records, which span the entire 106-year record, were used for streamflow estimates. Records generated of rainfall are in inches of rain, while synthetic flow timeseries are in units of MGD (for daily flows) or average monthly MGD (for monthly flows).

Rainfall records are used to simulate monthly flow in the Hillsborough River at Morris Bridge, the Alafia River at Bell Shoals, and un-gaged groundwater inflows/runoff into the Tampa Bypass Canal (TBC) lower and middle pools. FMS2 was "specifically designed to maximize the explanatory power of rainfall inputs in determining source flows." These monthly estimates are disaggregated to daily levels with inter-month daily flow continuity. From these four sets of daily flow timeseries, other daily models were developed to simulate flows at the Hillsborough Reservoir, in Cypress Creek, Trout Creek, and un-gaged runoff (as net losses in runoff) into the Hillsborough Reservoir. Data limitations at monthly scale meant these timeseries were not developed at monthly levels. Hillsborough River flow at Morris Bridge at a daily scale was used to simulate flow at the additional sites, including using leading simulations of Morris Bridge flows to produce daily estimates of Hillsborough River flow at Zephyrhills (needed for simulation of Lower Hillsborough River Minimum flow requirements). These flows were simulated at major USGS gage locations from which historical data was available.

The process of developing flow records starts with the generation of an ensemble of rainfall records from historic data at/for the three stations already mentioned. Monthly rainfall was modeled with a Hidden Markov model that factored "wetness" of preceding states when probabilistically determining a given month's rainfall. Next, a seasonal-multivariate linear regression model was applied to generate ensembles of flow at Morris Bridge, un-gaged TBC flow, and Alafia River - Bell Shoals. The regression model accepts generated ensembles of rainfall records from the three rainfall sites as the only predictors. Spatial and temporal correlations are preserved by generating output for all three sites at the same time using concurrent timeseries. These 3 monthly ensembles are then disaggregated to daily levels (method given above). Remaining flow site ensembles of flow timeseries are then generated using regressions with some combination of daily level flows from the sites with existing data, always including Morris Bridge daily flow as an explanatory variable.

Separate models were built for each rainfall station and each calendar month to develop rainfall records (36 total models). Cypress Creek rainfall models did not perform (match historical distributions) as well as Plant City and St. Leo models. However, because rainfall models are univariate models, rainfall simulations are generated individually rather than as an ensemble of the region. There is also an inherent area of concern regarding the use of the 106-year rainfall record to develop rainfall (and flow) ensembles rather than the most recent 30 years on record. However, because every 30-year period on record shows different trends than the overall record, no climate change signal persistence could be confidently seen. It falls to future work to determine how to incorporate climate change into modeling.

One-thousand stochastic rainfall timeseries were synthetically generated for TBW (Hazen and Sawyer, 2010) to simulate a range of future surface water inflows in the Hillsborough and Alafia Rivers. These flow timeseries are based on rainfall observations from the three gaging stations (Plant City, St. Leo, and Cypress Creek). Each of the 1,000 timeseries was generated for 100 years, with the first 22 years taken for simulation in TBW's 2018 Long-Term Master Water Plan (2018-2040) and first 20 years are used for this study (2020-2040). Stochastic flow models developed as a part of FMS2 include all surface water source flows for City of Tampa and TBW. Monthly streamflows were generated synthetically and then dis-aggregated to a daily timestep. Monthly generation is best to capture rainfall-streamflow correlation, but daily is needed to match the scale of water use permits. Dis-aggregation was done using a "multivariate nonparametric" k-nearest neighbor approach (Lall and Sharma, 1996). Additional steps were taken to account for month-to-month transitions of flow, temporal autocorrelation, and spatial correlation of streamflow.

5.3: Systemwide Reliability Evaluation Visualizations

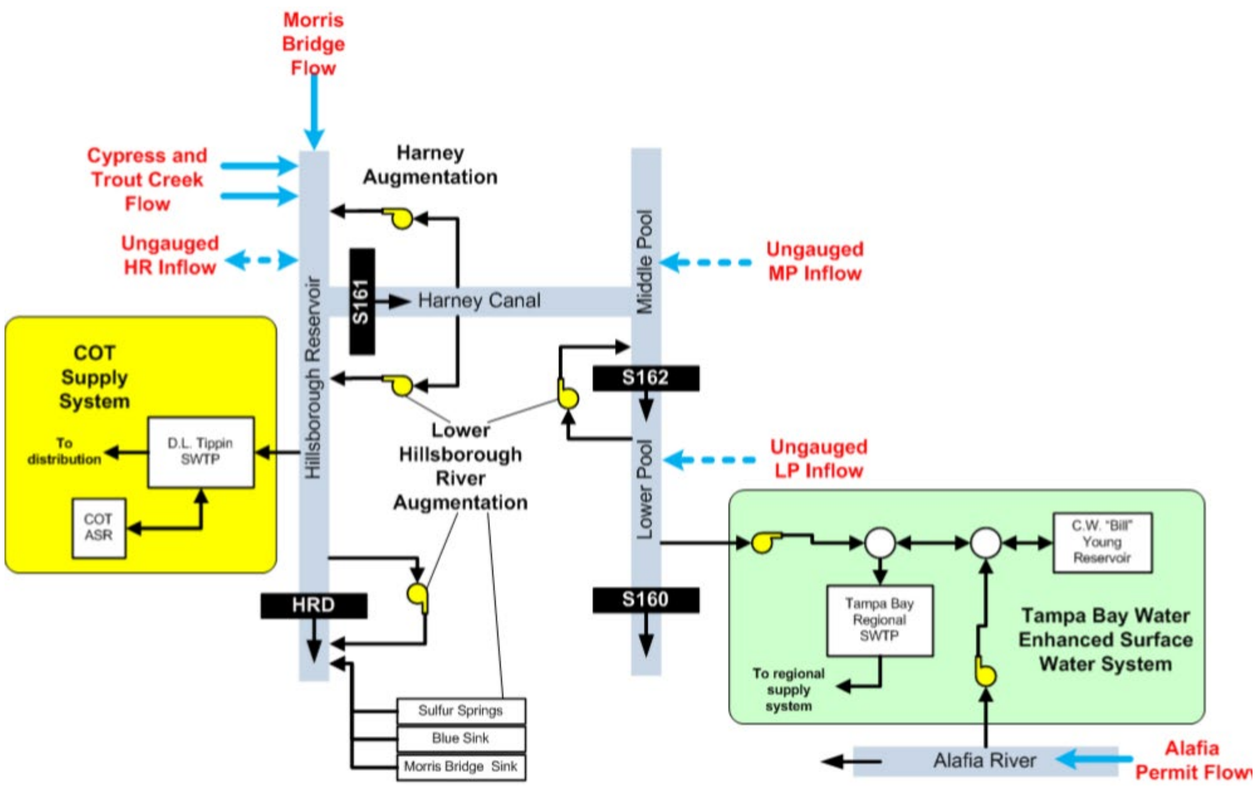

Figure 7.12: Visual description of OMS1-modeled TBW system components (from Hazen and Sawyer, 2010). Indicates the physical connections between TBW Enhanced Surface Water System (green box) that incorporates all surface water supply assets including the Young Reservoir, Regional Surface WTP, and water withdrawal intakes from the Alafia River and the Lower Pool of the Tampa Bypass Canal. The figure also depicts the ability of the City of Tampa (COT, yellow box) to self-supply water from the Hillsborough Reservoir, which is also connected to the Tampa Bypass Canal via the Harney Canal, which TBW may use to sell untreated water to COT. S160, S161, and S162 represent locks separating different pools of the Tampa Bypass Canal and Hillsborough Reservoir, and HRD is the Hillsborough River Dam. Arrows indicate direction of inflows and outflows from surface water sources.

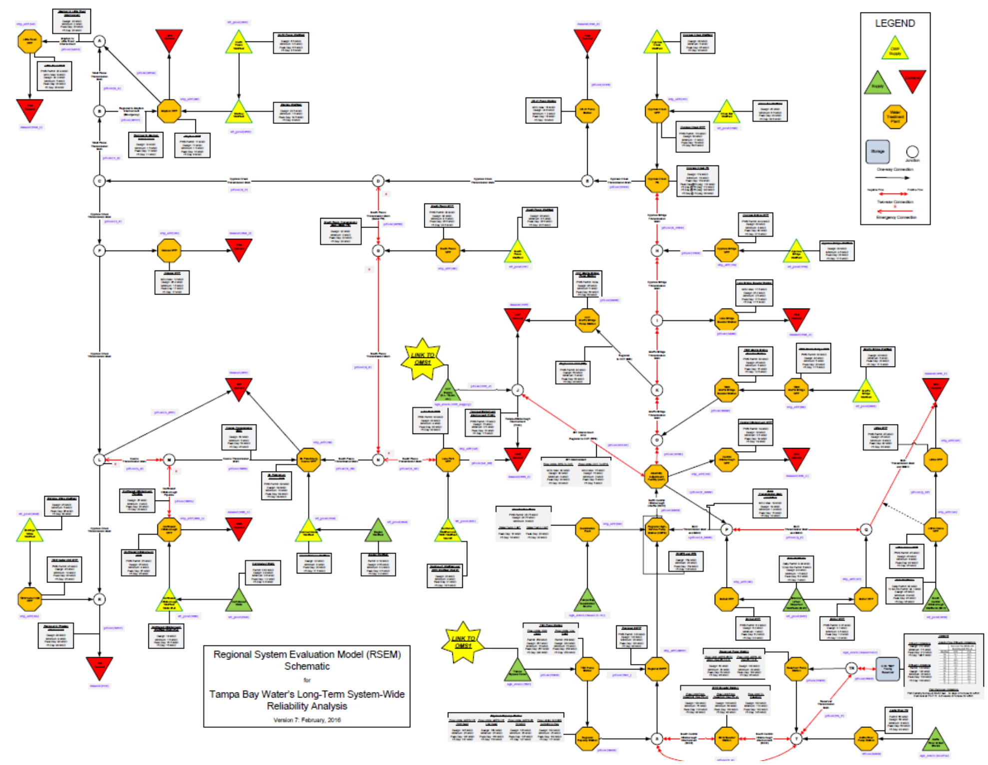

Figure 7.13: Schematic of the Optimized Regional Operations Plan Model. Green and yellow triangles indicate supply nodes, with yellow stars indicating supply sources estimated by the Operational Modeling System, V1. Orange nodes indicate water treatment plants, and red triangles indicate points of connection where deliveries to member government must be made to meet water demands. Lines indicate existing transmission mains.

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