-Nicholas School of the Environment MEM Master's Project Report -

Duke University

Quantifying how Drought and Increases in Water Demand may Impact Municipal Water Supplies for Durham, North Carolina

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Water Resources Management Concentration

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EXECUTIVE SUMMARY

Objectives

- Create a model that determines the risk of experiencing a water storage loss.
- Assess how water storage risks may change in the future.

Report Overview

In 2007, North Carolina experienced its worst drought in the past 112 years of record. North Carolina has also seen a steady increase in population growth with the Triangle area acting as one of the fastest growing metropolitan areas in the country. With a prevalence for extreme drought coupled with a growing demand for water, city water managers are left with the dilemma of how to best plan for future water needs. An important part of the water planning process is to assess the level of risk for running out of water during the different seasons of the year. This project performed a quantitative risk assessment to measure how water supplies may respond to increasing water demands in the future. This was done by creating a hydrologic model which used historic climate and water use data along with future water demand projections to identify how water shortage risks may change over time for the City of Durham's water supplies.

Focus Area

The City of Durham gathers its water supply from two storage reservoirs, the 3,606 million gallon (MG) capacity Lake Michie Reservoir and the 4942.35 MG capacity Little River Reservoir. Durham currently uses approximately 9,769 MG of water a year, which makes water usage dependent on each reservoir recharge. At the end of the 2007 drought, Durham had only one month's worth of water left between its reservoir supplies.

Project Design

The model created was designed to quantify Durham's the risk of having the city's total reservoir supply reach either a failure level of 20% storage capacity or a total water loss storage capacity within the next year's time. This model analyzes historic reservoir system input and output for the following data: incoming river discharge volumes, precipitation on the reservoir surface, previous reservoir storage, reservoir evaporation, and municipal water withdrawal volumes. Projected water demands for Durham were then used in the model to assess how reservoir failure and total reservoir depletion risk levels may change through time. In developing water management plans, managers can decide on a certain percentage of risk they are comfortable with for experiencing, this is called a critical threshold. For determining reservoir failure and total depletion risks, this study modeled three separate critical threshold levels to see which monthly reservoir volumes would trigger each critical threshold. The critical threshold levels used were: 2% risk, 5% risk, and 10% risk.

Deliverables

This project produced a series hydrologic models that can be used to determine Durham's risk of experiencing any selected reservoir storage volume. A chart was produced for Durham's water managers to use every month in order to check current reservoir volumes and see whether current storage volumes are located below or over their chosen critical threshold volume. This chart also depicted future water demand projections to show managers how risks may change through time.

Findings

This study had found that as Durham's water demands increase in the future, risks also will increase for experiencing a water supply failure or total water loss. Results show that in 2020 and 2040, that months in winter and early spring will face the greatest changes in risk with some of these months becoming vulnerable to risk for the first time. It was also found that when reservoir volumes are low, as in times of drought, the risk of experiencing a reservoir failure or total supply loss will increase as storage levels decrease.

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INTORDUCTION

From the time when society began to establish permanent settlements, there has been a voracious need for a community water supply. Around 1900 BCE, the Mesopotamians constructed an aqueduct system which revolutionized how domestic water was used (AHE 2015). Since these ancient aqueduct times, human expansion around the world has been dependent on the accessibility of water. Whether it has been stream water used to drive grist mill turbines for milling corn in the 1800's or it is coolant water used for conveying heat from modern day nuclear reactors, our society's water needs have developed around the availability of having immediate access to large volumes of water. This high demand for water has led communities to establish around steady water sources. When water demands surpass natural storage volumes, a nearby river can be dammed to create a water storage reservoir to meet water demands. These reservoirs offer a sense of security when creating a large scale water budget and allow for communities to plan out their growth capacity.

As of 2010, approximately 78% of U.S. water withdrawals were from surface water sources which mostly consist of reservoirs (Maupin 2014). These reservoirs can provide a steady volume of stored water that allow communities to plan for their future water allocations for their residents and occupants. Water managers within these communities rely on historic precipitation and stream discharge data to determine the amount of water they can safely withdrawal from their reservoirs in order to meet the demands of the community. Managing these storage reserves during seasonal change in precipitation requires the understanding of the hydrology for a reservoir's contributing watershed, along with knowing the quantity of water needed by the community. Since these water demands are crucial for the functionality of the local community, understanding the risks of experiencing a shortage in water reserves is very important for water managers.

Water withdrawals are taken by a community's water department with the assumption that these water reserves will become naturally replenished in a short period of time. During times of drought or natural disaster, storage levels in a reservoir may become depleted below the necessary volume needed by the community and fail to refill at a rate needed to meet upcoming water demands. To better understand the risk of this occurrence of reservoir depletion, historic precipitation and river discharge data can be analyzed to determine the probability of having a reservoir experience a storage shortage or complete loss in supply. Water managers can use hydrologic models to determine their current level of reservoir storage risk based on the current volume of water in their reservoir(s).

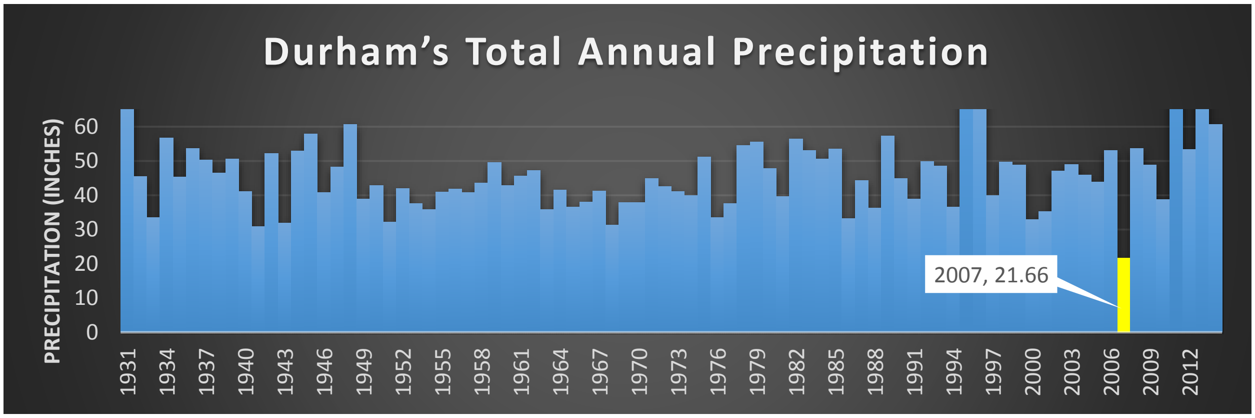
Quantification of the risks associated with water supply is crucial to rationally anticipate, plan for, and adapt to potential future water storage changes. This is especially important considering that the demand for water may rise with increase in population. Other future changes that may directly affect water supply risks include changes in land use / land cover and climate change. For water managers to plan for the future, predictions on water input and demand from the local reservoir is important. Reservoir levels reflect the current status of water availability and understanding of the demand determines how stored water is released. As such, understanding the principles that affect demand is imperative for properly controlling this release.

Today, determining reservoir depletion risk is becoming more difficult because of increasing climate volatility and rapid population growth in select regions. Even with modern technological advancements that allow for water use to be more efficient, the future still faces unprecedented challenges in securing steady water supplies with surface water sources being most vulnerable for experiencing change. To address these upcoming challenges, it is important for water managers to assess how the risk of experiencing reservoir storage failure will change for growing communities with increasing water demands. These changes in climate and in population can affect the rate at which reservoirs store water, which in turn alters previous reservoir storage depletion risk forecasts. Water managers can incorporate future projection figures for climate change and/or community water demands into their current hydrologic models to simulate how water reserves in their reservoir(s) may change.

This report will explore how a hydrological model can be created to use historic data to determine the risk of a reservoir reaching a critically low volume and then use future water demand projection figures to examine how these risks may change over time. The focus site for this study is the City of Durham, North Carolina. Durham acts as an ideal study site for modeling reservoir storage due to the city's dependence on reservoir water, available historic data, and the city's rapidly growing population.

Study Area Background

Durham's municipal water supplies are made available from two reservoir storage facilities located north of the city. The first reservoir is the Lake Michie Reservoir (LMR) which was built in 1926 and dams up the Flat River to create the 3,606 million gallon (MG) body of water called Lake Michie (Durham DWM 2015). The second reservoir is the 4942.35 MG Little River Reservoir (LRR) built in 1988 which receives water from the Little River (Durham DWM 2015). Between the years 2000 – 2011, the state of North Carolina had experienced three significant droughts with 2007 having the worst recorded drought in 112 years (Boyles 2008). Figure 1 shows a comparison with other years for how low Durham's annual precipitation was in 2007 (NOAA 2014, Weather Underground 2015). In December of 2007, Durham's reservoirs levels were so low that only one month's worth of water remained in storage (Greeley 2015). Durham and its surrounding area is also one of the nation's fastest growing metropolitan areas (Koebler 2011). If growth rate trends continue in Durham, the area's population may double over the next 50 years (U.S. Census Bureau 2015). Reoccurring drought and population growth will affect how water managers plan for furture water supplies and how resevoir depletion risk is assessed.


Durham’s Total Annual Precipitation

2007, 21.66

Figure 1: Durham’s annual precipitation in inches (NOAA 2014, Weather Underground 2015).

Understanding the risks of experiencing reservoir storage failure throughout the different times of the year is important for water managers for multiple reasons. One reason is to recognize at what appropriate reservoir volume, managers should implement conservation measures for the community. After the 2007 drought, Durham’s Water Department drafted a new Water Shortage Response Plan to be used in times when reservoir supplies decreased below average (Durham DWM 2009). Management plans such as these require risk assessments for reservoir storage volumes in order to design a response plan in times of drought. Another reason why discerning risk levels is beneficial is because water managers can analyze when current storage facilities become inadequate for meeting expected demands, which in turn presents the need for additional water supply sources and infrastructure. To meet the steadily increasing population trends in the Durham area, Durham and neighboring cities are beginning to discuss options for constructing a new water intake system from the Jordon Lake located southwest of Durham (Greeley 2015).

This study focuses on water demand challenges by performing a risk assessment on the probability of having Durham’s two reservoirs fail to provide adequate water supplies for municipal use. Through the use of hydrologic modeling, simulations were performed for both the LMR and the LRR to model how each reservoir receives their water supply. The use of historic water demand and precipitation data dating back to 1926 was used for modeling reservoir failure and total depletion risk. Simulations were conducted for a series of monthly recharge intervals which in turn produced a sensitivity table for analyzing storage loss. These models were then used to create simulations for a series of scenarios that examine future water demands projections. A new reservoir supply risk assessment was modeled to reflect these new water demand projections. This new supply risk forecast can provide the City of Durham with information that can assist the planning for future water allocation during times of drought.

METHODS

In order to model reservoir supply risk and examine how population growth and drought may impact Durham's future water planning, a series of hydrologic simulations were performed. A model was created to take any reservoir volume and determine what the probability would be for that volume of experiencing a reservoir failure or a total depletion within the next year. A reservoir failure can be interpreted to mean different volumes, so for this study the Palmer / Characklis definition was used signifying a reservoir accessible capacity of 20% as the risk of failure mark (Palmer and Characklis 2009). For this study, two separate risk assessments were performed: 1) experiencing a reservoir failure or 20% of accessible storage capacity, and 2) experiencing a total storage depletion or 0% of accessible storage capacity. The term depletion in this study will refer to total accessible volume loss in the reservoir system.

In both the LMR and LRR, the intake value in which the City of Durham withdrawals their water demands from is located towards the bottom of each reservoir. Beneath this intake value is a storage area referred to as 'dead storage' which is an area designated for collecting sediment. Since this dead storage is inaccessible for withdrawing supply, the total reservoir storage volume is different than the accessible storage volume. Since this project is interested in accessible storage and all references to 'reservoir storage' refers only to this accessible reservoir storage zone (see figure 2). At full capacity, the LMR has 2,811.5 MG of accessible storage and the LRR has 3,569.19 MG of accessible storage (Durham DWM 2015).

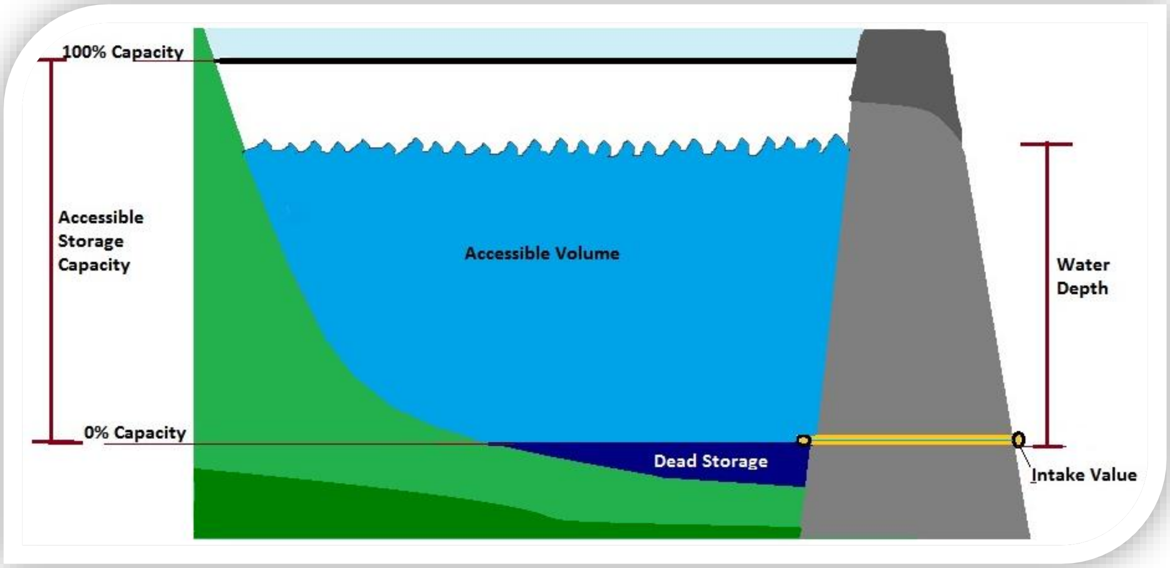


Figure 2: Description of reservoir volume terms.

This model used 89 years of historic reservoir input and output data to simulate reservoir volumes using a monthly time interval. In order to find the probability of experiencing a reservoir failure or total depletion, each model selected a starting reservoir volume and ran this volume through the 89 years of data to see whether this reservoir volume would ever experience a reservoir failure or a total depletion during a one year period. This was done by setting the reservoir at the starting volume after every year for the 89 years of data and seeing whether during each 1 year period whether the reservoir would reach 20% or 0% capacity. To capture seasonal variation in system recharge, the model was replicated 12 different times with each of these 12 models representing a different month as the reset month for the 1 year probability period. For example: out of the 12 models, if we are using the July model with the selected starting reservoir volume set at 70% capacity, this 70% volume will be used as the reservoir volume every July and seen whether there exists an occurrence of the reservoir system dropping down to 20% or 0% capacity during every 1 year period between July and the following June during the 89 years of data.

Durham predominately receives most of its water supply from the LMR and LRR, which function as an integrated supply system. The city withdrawals water from each of these reservoirs throughout the year and this combined volumetric use makes these two reservoirs act as one unit in terms of total storage. Modeling a comparative hydrologic response for each of these reservoirs in a comparable format is important to conduct for a uniform risk assessment. Each reservoir was individually modeled with their final outputs being coalesced together to determine whether or not this combined volume fell below the failure level or total depletion level. Demand withdrawals were modeled in a joint ratio system so that each reservoir drew down in volume at a uniform rate as the other. This meant that the reservoir failure level of 20% or depletion level of 0% would be approached simultaneously for both the LMR and LRR.

Identifying Water Sources

In quantifying Durham's water supply, identifying the source and watershed boundary was needed. With LMR and LRR acting as the storage locations, it is possible to identify each water source flowing into each reservoir and then locating the contributing area of all streams and rivers that feed into each reservoir. This was done by performing a watershed delineation for each watershed using ESRI ArcGIS, PIHM, and QGIS using a 10 meter resolution Digital Elevation Model (DEM) for the combined area of northern Durham County, Person County, and eastern Orange County (USGS 2014). DEMs for each of these counties were downloaded from the USGS National Map Platform and then spliced together to form a continuous dataset (USGS 2014). A point layer for the LMR was then placed within this DEM in ESRI ArcGIS to perform the watershed delineation to reveal the Lake Michie Watershed. This step was repeated using PIHM and QGIS using a LRR point layer to determine the Little River contributing area. Both watersheds boundaries are shown in figure 3.

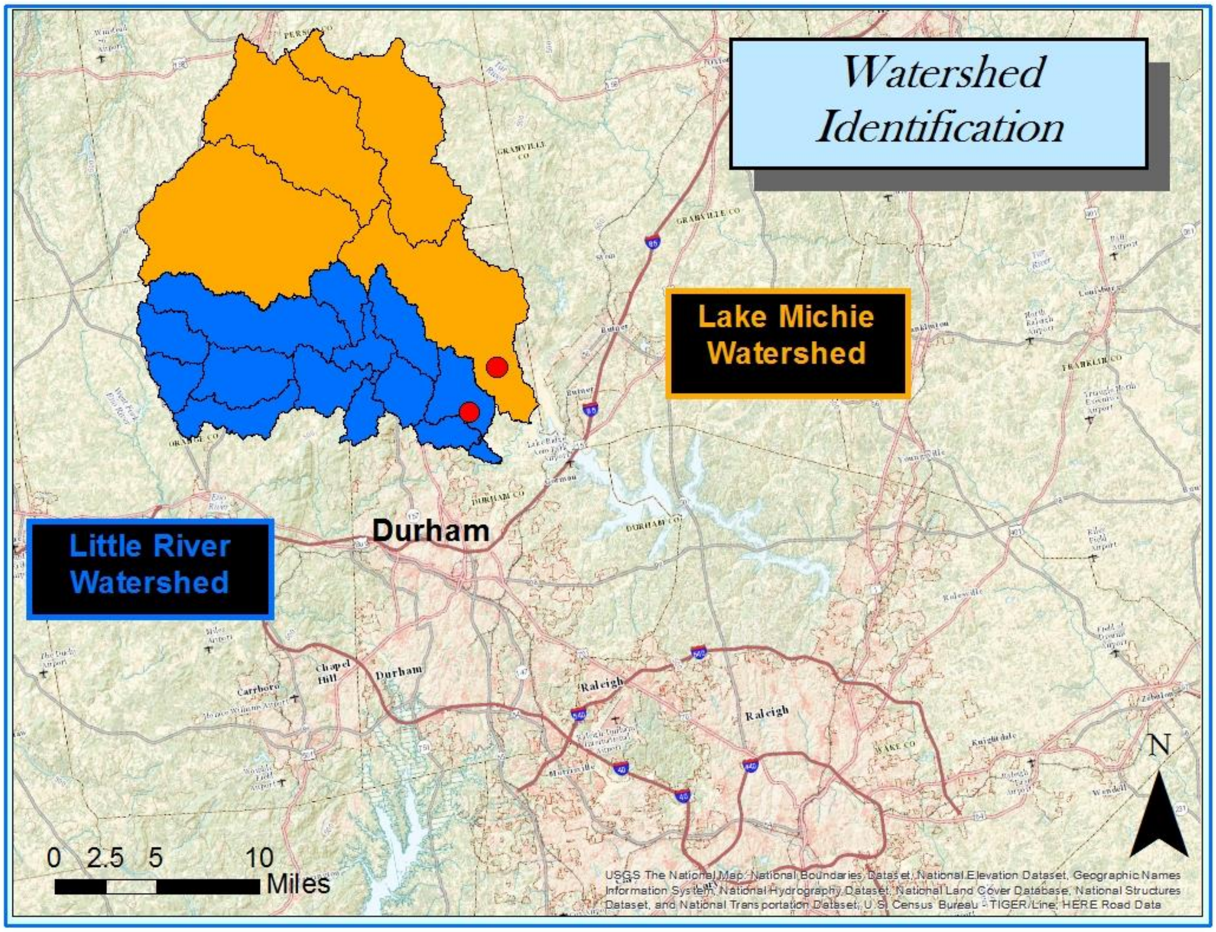


Figure 3: Map identifying watersheds for both of Durham's reservoirs. Red dots represent each reservoir.

Model Design

Microsoft Excel was used in developing a series of models to simulate storage recharge for each of the focus watersheds. Inputs used will be a function of precipitation and storage while outputs used will be a function of evaporation loss and public / private water demand over time. To simulate water usage by each reservoir, the water balance equation (equation 1) was used to model water inputs and outputs for both reservoir systems (Hornberger 1998). Table 1 shows the sources of data for each variable used in equation 1.

Equation 1: Water Balance Equation

Reservoir Water Volume = River Discharge + Previous Water Storage + Precipitation on the Reservoir Surface - City Water Demand – Evaporation

Table 1: Data Sources for the Hydrologic Model

River Discharge Inputs	Reservoir Capacity Information	Precipitation	Historic Water Demand for Durham	Evaporation
USGS gage 02085500 located on the Flat River at Bahama, NC; USGS gage 02085220 and gage 208521324 on the Little River at SR1461 Near Orange Factory, NC	Durham Department of Water Management	NOAA Weather Station at Lake Michie, Weather Underground stations at RDU airport, Horace Airport, and Lake Michie Forest Location	Durham Department of Water Management	NSRDB -NREL (Radiation), Weather Underground and NSRDB -NREL (Temperature), NSRDB (Relative Humidity)

For river discharge inputs, data in cubic feet per second (cfs) were taken from the USGS for each reservoir as shown in Table 1. Discharge data were then converted to million gallons per month (MGM) using average daily cfs (USGS 2014). For LMR river data, the USGS gage on the Flat River at Bahama was used for all 89 years providing all the needed data for LMR. For LRR river data, the USGS gage on the Little River near Orange Factory was used for years 1961 – 1987. From 1987 – 2014, a different gage was used which is located near the former gage site at mark SR1461 on the Little River near Orange Factory. Since the LMR dates back 62 years prior to the completion of the LRR, data for Little River discharge was not available. Data for the Little River flow discharge was only recorded by the USGS starting in 1961, so the remaining years back to 1926 were needed to match LMR's data. Both of the USGS monitoring stations for these two rivers are relatively close to each other, so a simple linear regression was performed on both of the river's daily discharge data from 1961 – 2014, (sample size of 19,497). A high correlation in discharge from the Flat River and Little River was found with a R^2 of 0.92 (see figure 4). The slope equation for the correlation's fitted line was then used to extrapolate the remaining values for the Little River dating back to the start of LMR's discharge data in 1926.

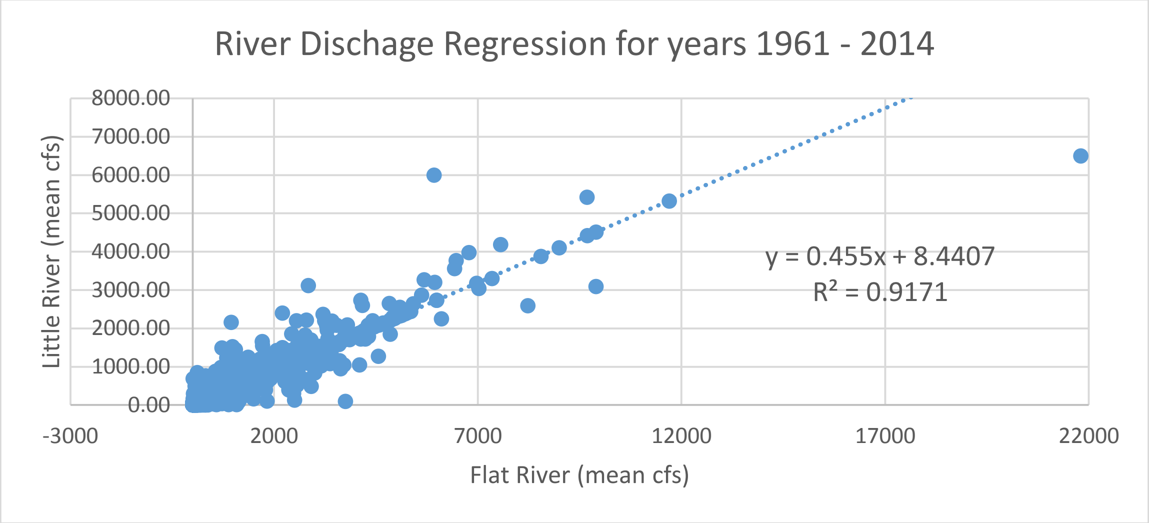


Figure 4: Regression with an R^2 of 92% showing how the Flat River and Little River are correlated.

For river flow input for each reservoir, the total drainage area must be taken into consideration. The USGS gage at Bahama, accounts for 150 square miles of drainage, yet the LMR watershed has a drainage area of approximately 170 square miles (Carter 1999). This difference in drainage area can produce a drainage ratio of 170/150 or 1.13 which was used as a multiplier for calculating total LMR river input (Carter 1999). The USGS gage on the Little River accounted for 80 square miles while the actual LRR watershed has an area of 120 square miles (Carter 1999). This made a drainage ratio of 120/80 or 1.5 which was used as a multiplier for the LRR total river input (Carter 1999).

Water demand data was provided by the Durham Department of Water Management (Durham DWM 2014). This data had only accounted for years 1990 – 2013, so a monthly average of the data was used to fill the remaining time frame back to 1926. The data provided accounts for the total demand and considers both reservoirs as a combined system. For purposes for this study, individual demand volumes were needed for each reservoir model. Individual demands were distributed for each reservoir by applying a storage ratio to the total demand data given which then split the total demand into a demand figure for each reservoir. This ratio considered total volume for the combined reservoirs and the individual reservoir volume for the given month. Equations 2 and 3 were used in computing the storage ratio for distributing the demand data for both reservoirs.

Equation 2: LMR Volume + LMR input / Total LMR & LRR Volume

Equation 3: LRR Volume + LRR input / Total LMR & LRR Volume

For evaporation, the radiation based Turc method (see equation 4) was used to calculate estimated evaporation loss for each reservoir (Lu et al. 2005).

Equation 4: Turc Evapotranspiration Method

$RH < 50\%$ $PET = 0.013\ (T / T+15)(R_s + 50)(1 + [(50-RH)/70])$

$RH > 50\%$ $PET = 0.013\ (T / T+15)(R_s + 50)$

In calculating evaporation, relative humdity (RH) figures were obtained from the National Renewable Energy Laboratory's (NREL) National Solar Radiation Data Base (NSRDB) using the site at the Raliegh- Durham International Airport (RDU) during the dates 1961 – 2010 and then from the Weather Underground's Bahama site for dates 2010-2014 (NREL 2015, Weather Underground 2015). The monthly average RH of the existing data was used for the remaining dates back to 1926. Temperature data was taken from the same sources for RH, yet data for dates 1931 – 1973 were obtained from the NOAA weather station on Lake Michie (NOAA 2014). For the remaining 5 years back to 1926, the average monthly temperature from the existing temperature data was used. Radiation data was gathered from from the NSRDB site at RDU for dates 1961 – 2010 (NREL 2015). Average monthly figures from the existing NSRDB data were used for the remaining radiation data.

Evaporation was calculated and applied to the lake surface area. A regression analysis can be done to determine the equation for each reservoir's surface area which can be expressed as a function of storage (Carter 1999). Equation 5 and 6 were used for calculating the

LMR and LRR surface area for each reservoir volume in order to compute evaporation loss (Carter 1999).

Equation 5: LM Area = 0.132 x LM Volume + 48.3 (Units in MG)

Equation 6: LR Area = 0.1 x LR Volume + 72.25 (Units in MG)

Precipitation data was collected from 4 locations near the reservoirs: 1) the NOAA weather station on Lake Michie for dates 1931 – 1972, from 2) the Weather Underground KIGX site at the Chapel Hill Airport for dates 1973 – 1993, from 3) the Weather Underground RDU station for dates 1994 – 2005, and from 4) the Weather Underground Forest near Lake Michie station for dates 2005 – 2014 (NOAA 2015, Weather Underground 2015). Average monthly precipitation from the existing data was used for dates 1926 – 1931. Precipitation inputs on each reservoir were then found by using equation 5 and 6.

Once all the data and calculations were prepared, a series of simulations were performed for 10 reservoir volumes: 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and 100%. Modeling his full spectrum of reservoir volumes examines how risk changes during various volumes of water supply. Covering this range of storage levels also covers the majority range of possible water supply volumes during times of drought. When future water demand projections are modeled under this full range of reservoir capacities, all drought condition scenarios for future water demands projections will be examined to see how reservoir failure and total depletion risk levels will change. Equation 1 was used to determine each month's storage level for every storage capacity level listed. Table 2 shows every model combination simulated to cover drought scenarios, which was done for both reservoirs and for both the reservoir failure risk and total depletion risk.

Table 2: Combinations for each model simulation, done for LRR and LMR

	12 month simulation period												
		Jan-Dec	Feb-Jan	Mar-Feb	Apr-Mar	May-Apr	June-May	July-June	Aug-July	Sept-Aug	Oct-Sept	Nov-Oct	Dec-Nov
Initial Volume	100%	X	x	X	X	X	X	X	X	x	X	X	X
	90%	X	X	X	X	X	X	X	X	X	X	X	X
	80%	X	X	X	X	X	X	X	X	X	X	X	X
	70%	X	X	X	X	X	X	X	X	X	X	X	X
	60%	X	X	X	X	x	X	X	X	X	x	X	X
	50%	X	X	X	X	X	X	X	X	X	X	X	X
	40%	X	X	X	X	X	X	X	X	X	x	X	X
	30%	X	X	x	X	X	X	X	X	X	X	X	X
	20%	X	X	X	X	X	x	X	X	X	X	X	X
	10%	x	X	X	X	X	X	x	x	X	X	X	X

<u>Critical Threshold</u>

In planning for water failure and total depletion risk, water managers must determine a certain percentage rate for which they are comfortable with for experiencing risk. This comfortability rate or ‘Critical Threshold’ is how managers can determine whether their daily risk is trivial or requires attention. Once a significant drop in reservoir volume occurs that breaches the critical threshold level, managers then know to implement conservation initiatives and other water conservation strategies. For this study, three critical thresholds were simulated, a 2% risk, a 5% risk, and a 10% risk of experiencing the reservoir failure or a total depletion. These three thresholds were used to simulate which reservoir volumes would trigger each critical threshold level during each month. The results were then displayed in terms of elevation in feet above sea level to show the reservoir volume. Checking the reservoir water height is the standard way to measure reservoir volume (Durham DWM 2015).

<u>Future Demand Model</u>

With the model built and fully functional, future demand projection figures can be implemented into the model to see how risk may change in the future. Future water demand projections were obtained from a *Triangle J Council of Governments* report from 2012 about Central North Carolina's Water Supply Plan (Triangle J 2012). Projection figures for Durham's total demand are shown in table 3.

Table 3: Projected total annual water demands for the Durham, NC (Triangle J 2012)

Year	2020	2030	2040	2050	2060
Project Water Use (MG per year)	9,831	13,293	14,837	16,319	17,319

This report used an Urban Growth Area boundary method to predict Durham's future water demand needs (Triangle J 2012). For this study, a short term and long term projection were used to model how failure and total depletion risk may change in the future. The year 2020 was chosen for the short term range and year 2040 was chosen for the long term range. Since these projected demand figures are in annual terms, a monthly ratio was calculated from the existing data and applied to the projected demands to create monthly projection demand figures. Short term future demands were then modeled by replacing each existing year of demand data in the model with the short term projected figures. The same was replicated for long term demands.

The final tool produced in these methods were a series of hydrologic models that use future water demand projections alongside drought like reservoir conditions for the purpose of modeling future reservoir failure and reservoir total depletion risk.

RESULTS

The model created for this study is capable of analyzing Durham's risk for experiencing any reservoir volume. For this study, the reservoir failure volume and reservoir total depletion volume were modeled with the results shown below.

Results for Reservoir Failure Risk

At current water demands, results show that as reservoir volumes decline (as in times of drought), the risk of experiencing a reservoir failure increases at every month besides February (see figure 5 and table 4). Figure 5 and table 4 show how Durham's risk of experiencing a reservoir failure within the next year increases as reservoir storage volumes decline. Figure 5 and table 4 also show that risk changes during each month, with failure risk being the greatest in late summer.

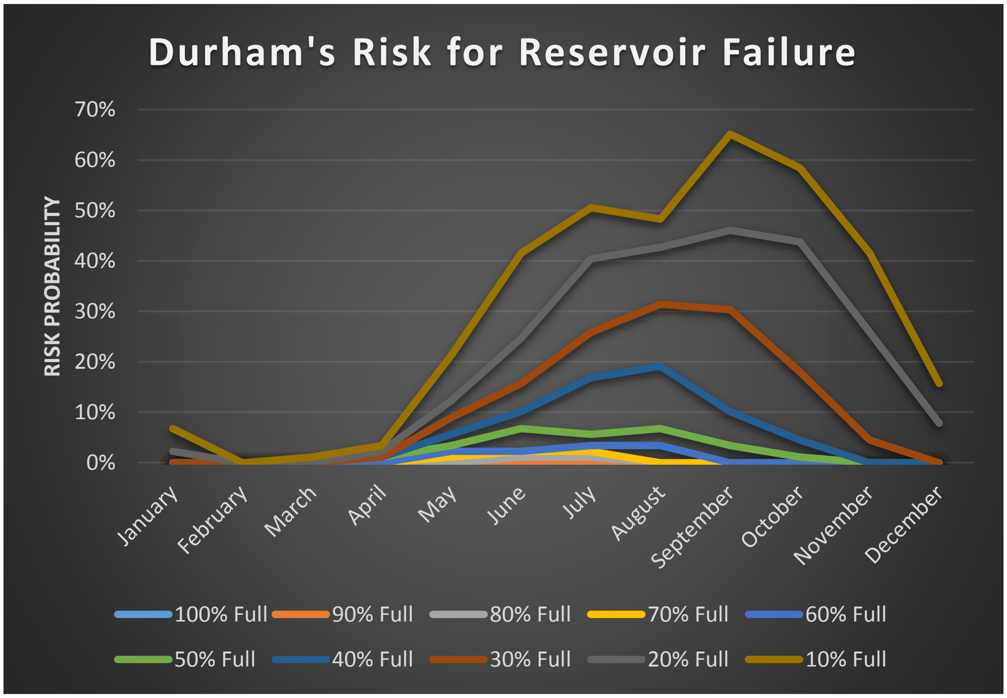


Figure 5: Monthly risk of reservoir failure for 10 different storage volumes.

Table 4: Monthly risk of reservoir failure for 10 different storage volumes shown.

Month	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
January	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.25%	6.74%
February	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
March	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%
April	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	1.12%	2.25%	3.37%
May	0.00%	0.00%	0.00%	1.12%	2.25%	3.37%	5.62%	8.99%	12.36%	21.35%
June	0.00%	0.00%	1.12%	2.25%	2.25%	6.74%	10.11%	15.73%	24.72%	41.57%
July	0.00%	0.00%	1.12%	2.25%	3.37%	5.62%	16.85%	25.84%	40.45%	50.56%
August	0.00%	0.00%	0.00%	0.00%	3.37%	6.74%	19.10%	31.46%	42.70%	48.31%
September	0.00%	0.00%	0.00%	0.00%	0.00%	3.37%	10.11%	30.34%	46.07%	65.17%
October	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	4.49%	17.98%	43.82%	58.43%
November	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.49%	25.84%	41.57%
December	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.87%	15.73%

This reservoir failure model was used to model short term and long term future water demand projections which are shown in the appendix (Figures A & B and Tables A & B). With the reservoir failure risk modeled for the present and future, a critical threshold risk level can be selected and used to determine which reservoir volume would trigger this threshold each month. Figures 6 and 7 depict this by setting a 5% critical threshold for both reservoirs. Figures 6 and 7 can be read by Durham Water Managers to see if current water elevations either fall below or above the present day risk line during the current month. If the current reservoir elevation is over the threshold line, then risk of reservoir failure is not yet 5%. If the current elevation is below the threshold line for the given month, then there exists at least a 5% risk of the reservoir witnessing a reservoir failure during the next year. Results for a 2% and 10% critical threshold were also modeled for each reservoir and are shown in the appendix (figures C, D, E, & F). All critical threshold figures show an increase in risk as time increases.

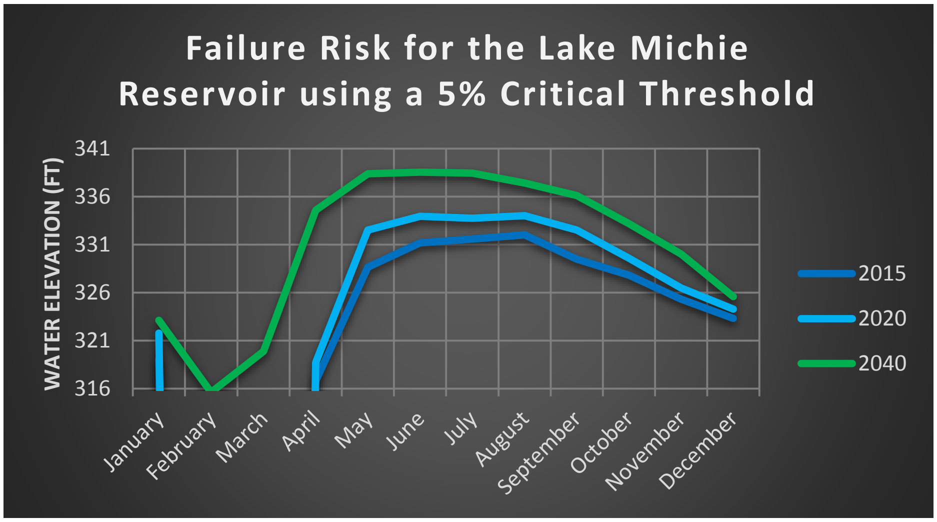


Figure 6: Lake Michie Reservoir failure risk for current and projected water demands.

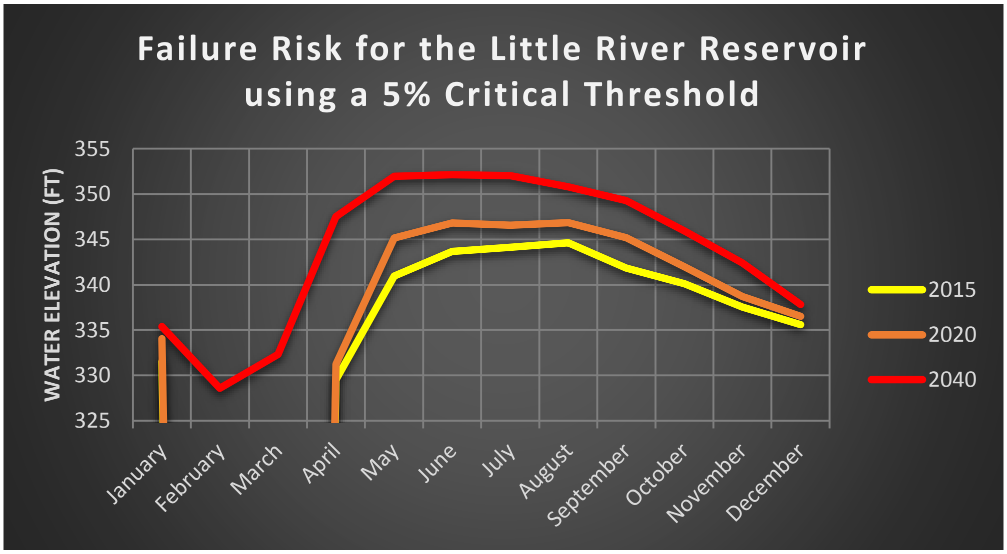


Figure 7: Little River Reservoir failure risk for current and projected water demands.

Results for Reservoir Total Depletion Risk

Results for total depletion risk are similar to the reservoir failure results. At current water demands, results show that as reservoir volumes decline, depletion risk increases during every month besides January, February, and March (see figure 8 and table 5). Figure 8 and table 5 show how Durham's risk of experiencing a total reservoir depletion within the next year increases as the staring reservoir volume declines. Figure 8 and table 5 also show that risk changes during each month with total depletion risk being the greatest in late summer.

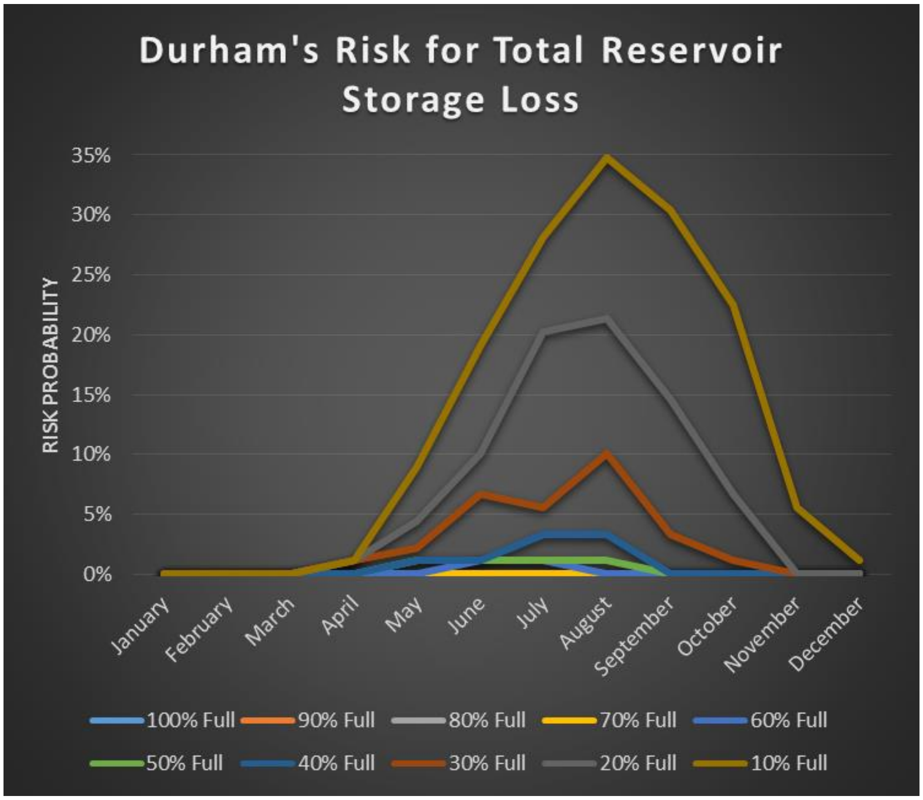


Figure 8: Monthly risk of reservoir depletion for 10 different storage volumes.

Table 5: Monthly risk of reservoir failure for 10 different storage volumes shown in a table.

Month	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
January	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
February	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
March	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
April	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	1.12%
May	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	2.25%	4.49%	8.99%
June	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	1.12%	6.74%	10.11%	19.10%
July	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	3.37%	5.62%	20.22%	28.09%
August	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	3.37%	10.11%	21.35%	34.83%
September	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.37%	14.61%	30.34%
October	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	6.74%	22.47%
November	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.62%
December	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%

Like the reservoir failure model, short term and long term future water demand projections were modeled to show total reservoir depletion risk (Appendix Figures G & H and Tables C & D). Critical threshold risk levels were modeled to determine at which reservoir volume threshold would be reached. Figure 9 and 10 depict this by showing a 5% critical threshold set for both reservoirs. Results for a 2% and 10% critical threshold were modeled for each reservoir and are shown in the appendix (Figures I, J, K, & L). All critical threshold figures show an increase in risk as time increases.

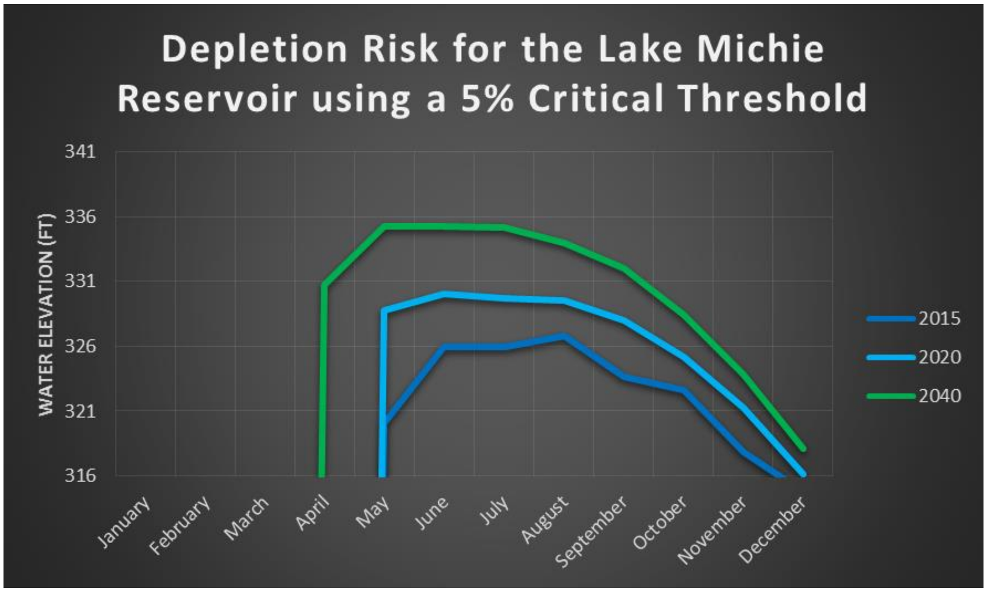


Figure 9: Lake Michie Reservoir Depletion risk for current and projected water demands.

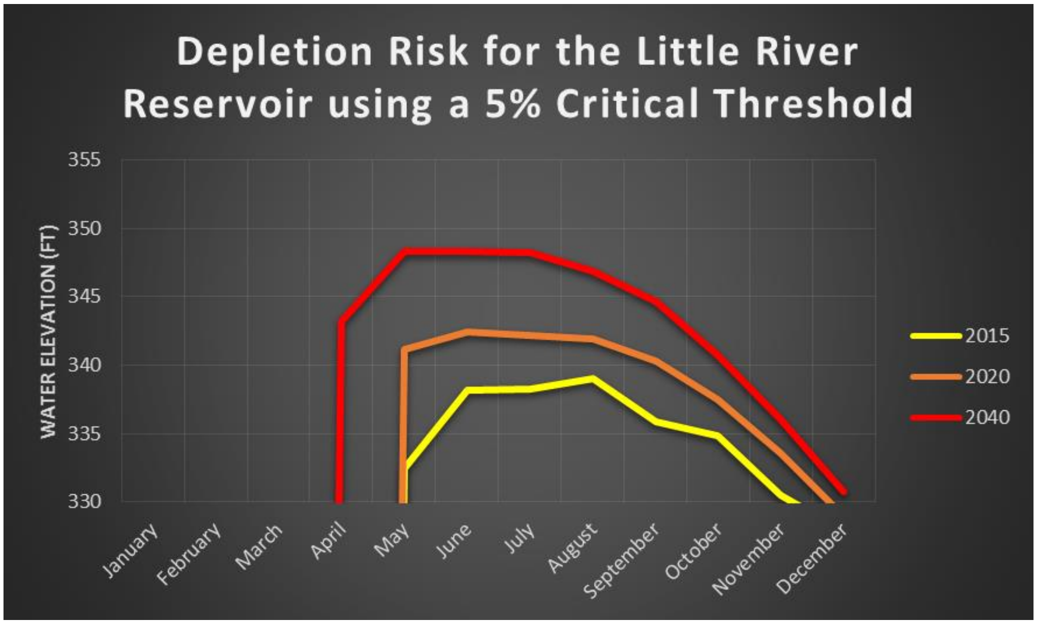
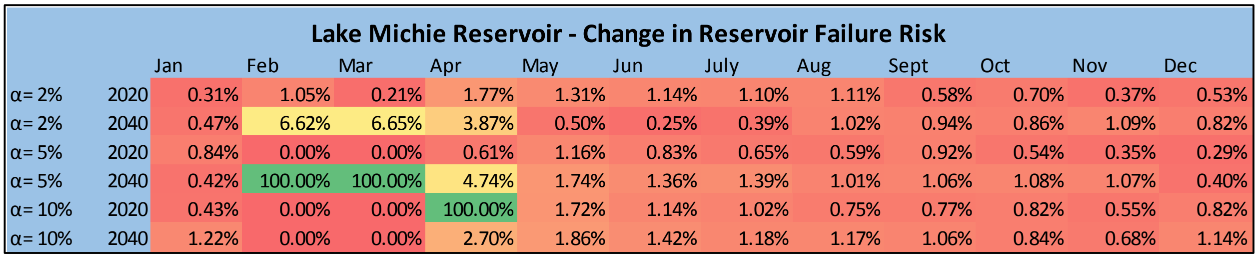


Figure 10: Little River Reservoir depletion risk for current and projected water demands.

<u>Change in Risk during each Future Demand Projection</u>

With each short term and long term projection modeled using three different critical thresholds, it can be seen that as time increases, reservoir failure and total depletion risk levels increase as well. Tables 6-9 show the percentage change in risk for each reservoir. Each month's change in risk is colored to depict the extremity of change with red representing a minor change around 1%, yellow representing approximately a 5% change, and green representing a significant change. The months depicting green cells show a 100% change representing that previously, this month had no risk of failure or total depletion. As water demands increase, these months shown in green will become vulnerable for the first time for experiencing a reservoir failure or total depletion. For change in reservoir failure risk (shown in tables 6 & 7), the greatest amount of change is seen between the months: February, March, and April. For change in total reservoir depletion risk (shown in tables 8 & 9), the months: January, February, March, and April in 2040 show a great amount of risk change. The month of December in 2020 is the only significant change shown during this year for depletion risk.

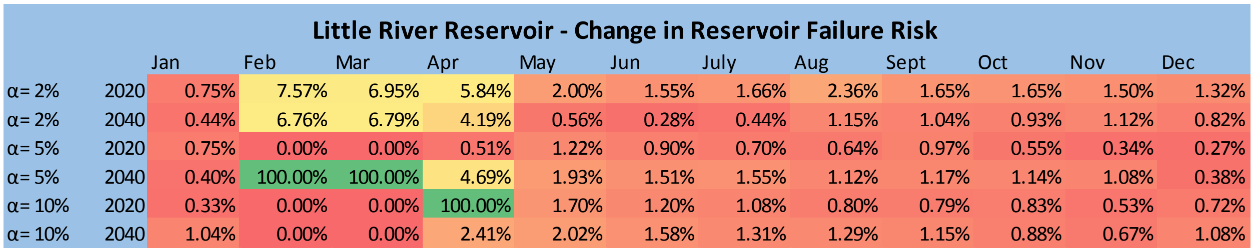
Table 6: Quantifying reservoir failure risk change in the short term and long term time period for LMR



Lake Michie Reservoir - Change in Reservoir Failure Risk

		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
α= 2%	2020	0.31%	1.05%	0.21%	1.77%	1.31%	1.14%	1.10%	1.11%	0.58%	0.70%	0.37%	0.53%
α= 2%	2040	0.47%	6.62%	6.65%	3.87%	0.50%	0.25%	0.39%	1.02%	0.94%	0.86%	1.09%	0.82%
α= 5%	2020	0.84%	0.00%	0.00%	0.61%	1.16%	0.83%	0.65%	0.59%	0.92%	0.54%	0.35%	0.29%
α= 5%	2040	0.42%	100.00%	100.00%	4.74%	1.74%	1.36%	1.39%	1.01%	1.06%	1.08%	1.07%	0.40%
α= 10%	2020	0.43%	0.00%	0.00%	100.00%	1.72%	1.14%	1.02%	0.75%	0.77%	0.82%	0.55%	0.82%
α= 10%	2040	1.22%	0.00%	0.00%	2.70%	1.86%	1.42%	1.18%	1.17%	1.06%	0.84%	0.68%	1.14%

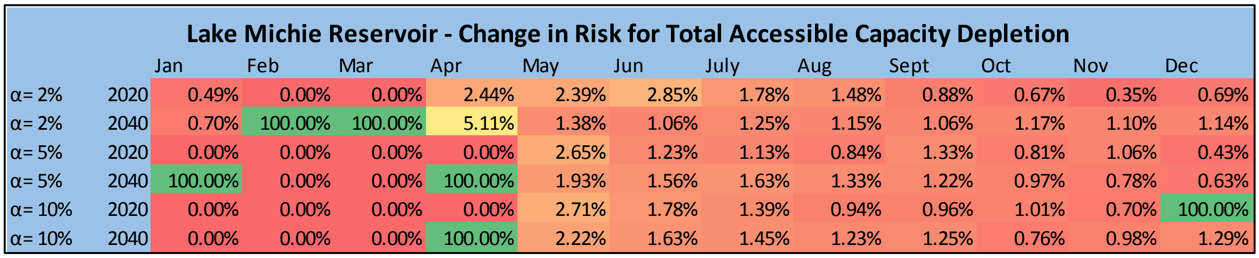
Table 7: Quantifying reservoir failure risk change in the short term and long term time period for LRR



Little River Reservoir - Change in Reservoir Failure Risk

		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
α= 2%	2020	0.75%	7.57%	6.95%	5.84%	2.00%	1.55%	1.66%	2.36%	1.65%	1.65%	1.50%	1.32%
α= 2%	2040	0.44%	6.76%	6.79%	4.19%	0.56%	0.28%	0.44%	1.15%	1.04%	0.93%	1.12%	0.82%
α= 5%	2020	0.75%	0.00%	0.00%	0.51%	1.22%	0.90%	0.70%	0.64%	0.97%	0.55%	0.34%	0.27%
α= 5%	2040	0.40%	100.00%	100.00%	4.69%	1.93%	1.51%	1.55%	1.12%	1.17%	1.14%	1.08%	0.38%
α= 10%	2020	0.33%	0.00%	0.00%	100.00%	1.70%	1.20%	1.08%	0.80%	0.79%	0.83%	0.53%	0.72%
α= 10%	2040	1.04%	0.00%	0.00%	2.41%	2.02%	1.58%	1.31%	1.29%	1.15%	0.88%	0.67%	1.08%

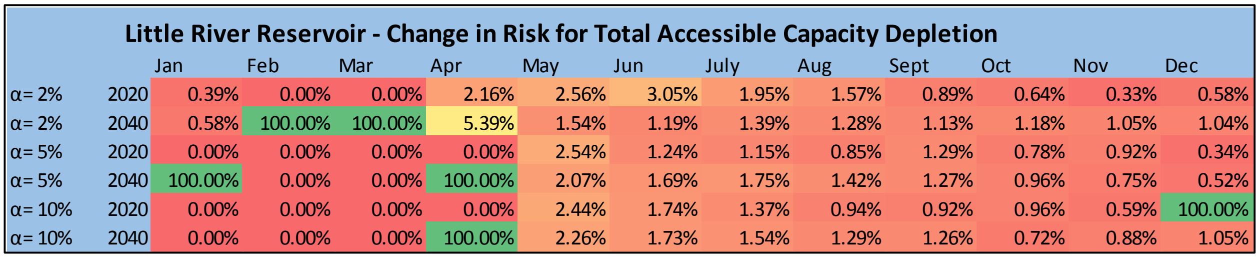
Table 8: Quantifying reservoir depletion risk change in the short term and long term time period for LMR



Lake Michie Reservoir - Change in Risk for Total Accessible Capacity Depletion

		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
α= 2%	2020	0.49%	0.00%	0.00%	2.44%	2.39%	2.85%	1.78%	1.48%	0.88%	0.67%	0.35%	0.69%
α= 2%	2040	0.70%	100.00%	100.00%	5.11%	1.38%	1.06%	1.25%	1.15%	1.06%	1.17%	1.10%	1.14%
α= 5%	2020	0.00%	0.00%	0.00%	0.00%	2.65%	1.23%	1.13%	0.84%	1.33%	0.81%	1.06%	0.43%
α= 5%	2040	100.00%	0.00%	0.00%	100.00%	1.93%	1.56%	1.63%	1.33%	1.22%	0.97%	0.78%	0.63%
α= 10%	2020	0.00%	0.00%	0.00%	0.00%	2.71%	1.78%	1.39%	0.94%	0.96%	1.01%	0.70%	100.00%
α= 10%	2040	0.00%	0.00%	0.00%	100.00%	2.22%	1.63%	1.45%	1.23%	1.25%	0.76%	0.98%	1.29%

Table 9: Quantifying reservoir depletion risk change in the short term and long term time period for LRR



Little River Reservoir - Change in Risk for Total Accessible Capacity Depletion

		Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
α= 2%	2020	0.39%	0.00%	0.00%	2.16%	2.56%	3.05%	1.95%	1.57%	0.89%	0.64%	0.33%	0.58%
α= 2%	2040	0.58%	100.00%	100.00%	5.39%	1.54%	1.19%	1.39%	1.28%	1.13%	1.18%	1.05%	1.04%
α= 5%	2020	0.00%	0.00%	0.00%	0.00%	2.54%	1.24%	1.15%	0.85%	1.29%	0.78%	0.92%	0.34%
α= 5%	2040	100.00%	0.00%	0.00%	100.00%	2.07%	1.69%	1.75%	1.42%	1.27%	0.96%	0.75%	0.52%
α= 10%	2020	0.00%	0.00%	0.00%	0.00%	2.44%	1.74%	1.37%	0.94%	0.92%	0.96%	0.59%	100.00%
α= 10%	2040	0.00%	0.00%	0.00%	100.00%	2.26%	1.73%	1.54%	1.29%	1.26%	0.72%	0.88%	1.05%

DISCUSSION

The models created for this study have produced results that clearly show that as Durham's water demands increase in the future, the risk in experiencing a reservoir failure or reservoir total loss also increases. The models also show that when reservoir volumes resemble drought like conditions, that reservoir failure risk and total depletion risk increase as reservoir storage volumes decrease. These findings were expected since as the rate of water withdrawals increase, the rate of reservoir storage drainage should increase, ultimately affecting the chances of reaching a low reservoir volume. An interesting finding from this study is how reservoir and total depletion risks may have the greatest change during the months of January, February, March, April, and December. These months historically represent low to zero levels of risk which may mean that there exists a larger availability for risk expansion during these times. In 2020 and especially in 2040, these 5 months are expected to experience greater risks for reaching reservoir failure or total depletion volumes. Some of these months are becoming vulnerable for the first time for experiencing these risks. This can infer that in the future, as water demands increase, every month in the year will become vulnerable to some degree of having water supplies reach a critically low level or running out of water completely.

The models created for this study can be used by Durham's water managers as tools for monitoring the current risk of experiencing reservoir failure or total reservoir depletion within the next year. Current model parameters can be easily altered in order for managers to assess the risk of experiencing any desired water volume level. This model was designed to display the reservoir volume elevation for which the critical threshold risk exists during each month. This can allow water managers to easily check current reservoirs elevations each day and see whether this elevation height is below or above the selected critical threshold mark. This accessibility in monitoring can assist water managers in quickly knowing when they need to make decisions regarding water conservation plans. In times of drought, making timely decision can be very important.

Limitations

In setting up this study, limitations had occurred which created some obstacles. These obstacles consisted of gaps in the historic data which led to assumptions being made. One assumption that was made was for the water demand data prior to 1990. Demand data was only available for 1990 to the present, so a monthly average demand was used for the rest of the years back to 1926. This doesn't create a significant issue since reservoir recharge from the hydrological cycle is key for determining accessible water supplies.

Another limitation may have been the temporal scale used. A monthly interval was used to capture seasonal variation, where as a weekly interval may have been more appropriate. A weekly interval could possibly do a finer job at capturing discharge peaks throughout the year which would give a closer representation of annual risk. A monthly interval was chosen for this study because this was the time unit the demand data was provided in. All other data was given in at least daily units, which could allow this model to be restructured to use a weekly interval, granted the demand data was segmented correctly.

Durham's two reservoir system was modeled by having withdrawals taken evenly from each reservoir. In practice, Durham does not withdrawal their water evenly from each reservoir (Nelson 2014). Individual reservoir demands were unavailable when acquiring Durham's demand data which led to the use of this even distributed withdrawal method. This withdrawal method still can accurately represent how water demand outputs are used since the reservoir system was modeled in a combined system. This combined system captures total accessible volume between both reservoirs which is important for analyzing risk and is still representative of how actual volumes are withdrawn by the city.

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APPENDIX

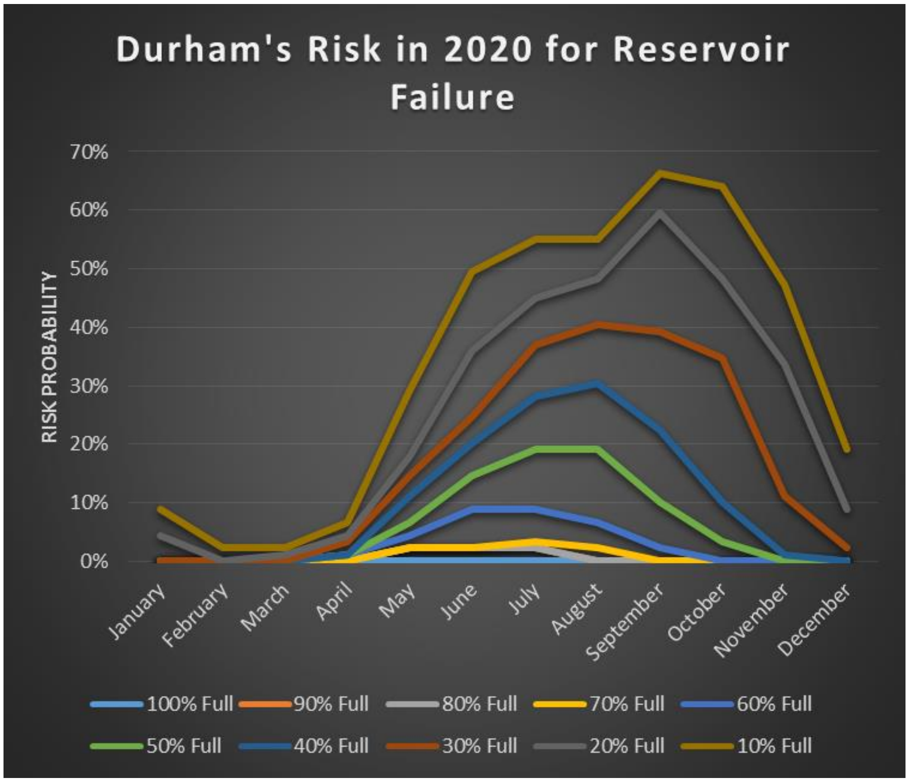

Figure A: Durham's monthly risk in 2020 for reservoir failure at 10 different storage volumes.

Table A: Durham's risk in 2020 of reservoir failure for 10 different storage volumes shown numerically.

Month	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
January	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.49%	8.99%
February	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.25%
March	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	2.25%
April	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	1.12%	3.37%	4.49%	6.74%
May	0.00%	2.25%	2.25%	2.25%	4.49%	6.74%	11.24%	14.61%	17.98%	29.21%
June	0.00%	2.25%	2.25%	2.25%	8.99%	14.61%	20.22%	24.72%	35.96%	49.44%
July	0.00%	2.25%	2.25%	3.37%	8.99%	19.10%	28.09%	37.08%	44.94%	55.06%
August	0.00%	0.00%	0.00%	2.25%	6.74%	19.10%	30.34%	40.45%	48.31%	55.06%
September	0.00%	0.00%	0.00%	0.00%	2.25%	10.11%	22.47%	39.33%	59.55%	66.29%
October	0.00%	0.00%	0.00%	0.00%	0.00%	3.37%	10.11%	34.83%	48.31%	64.04%
November	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	11.24%	33.71%	47.19%
December	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.25%	8.99%	19.10%

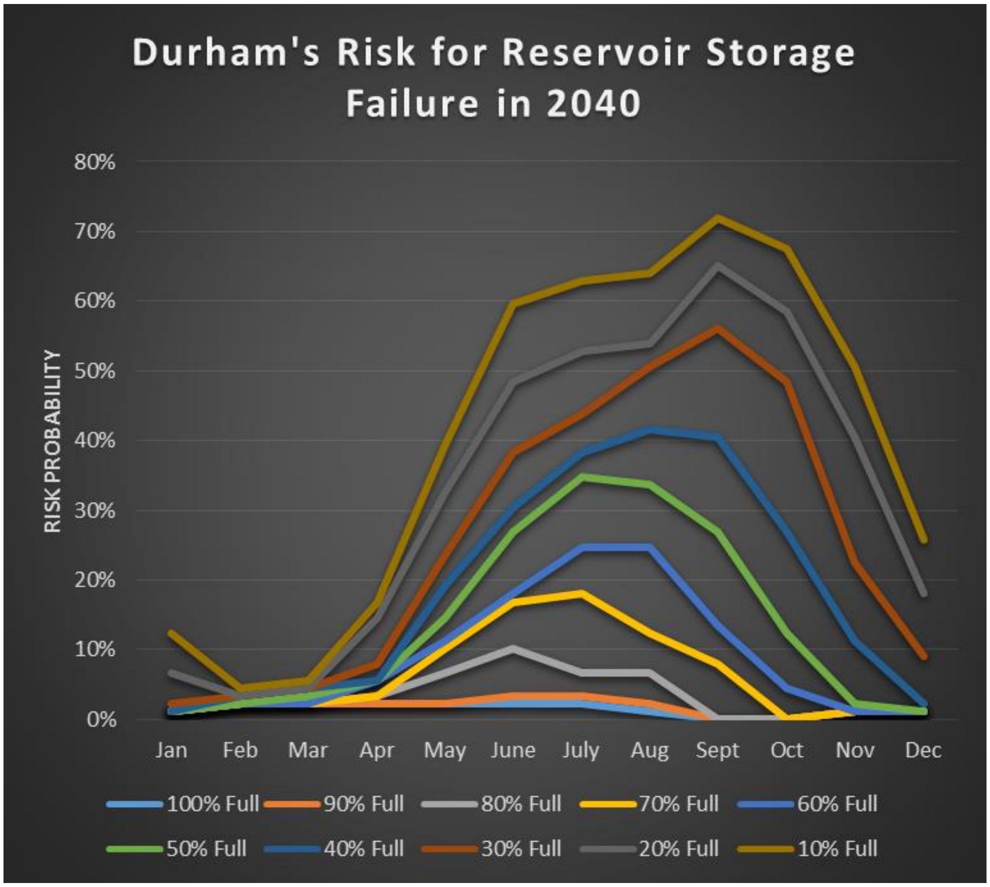

Figure B: Durham's monthly risk in 2040 for reservoir failure at 10 different storage volumes.

Table B: Durham's risk in 2040 of reservoir failure for 10 different storage volumes shown numerically

	Probability of reaching 20% capacity									
	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
Jan	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	2.25%	6.74%	12.36%
Feb	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	3.37%	3.37%	3.37%	4.49%
Mar	2.25%	2.25%	2.25%	2.25%	2.25%	3.37%	4.49%	4.49%	4.49%	5.62%
Apr	2.25%	2.25%	3.37%	3.37%	5.62%	5.62%	5.62%	7.87%	14.61%	16.85%
May	2.25%	2.25%	6.74%	10.11%	11.24%	14.61%	19.10%	23.60%	32.58%	39.33%
June	2.25%	3.37%	10.11%	16.85%	17.98%	26.97%	30.34%	38.20%	48.31%	59.55%
July	2.25%	3.37%	6.74%	17.98%	24.72%	34.83%	38.20%	43.82%	52.81%	62.92%
Aug	1.12%	2.25%	6.74%	12.36%	24.72%	33.71%	41.57%	50.56%	53.93%	64.04%
Sept	0.00%	0.00%	0.00%	7.87%	13.48%	26.97%	40.45%	56.18%	65.17%	71.91%
Oct	0.00%	0.00%	0.00%	0.00%	4.49%	12.36%	26.97%	48.31%	58.43%	67.42%
Nov	1.12%	1.12%	1.12%	1.12%	1.12%	2.25%	11.24%	22.47%	40.45%	50.56%
Dec	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	2.25%	8.99%	17.98%	25.84%

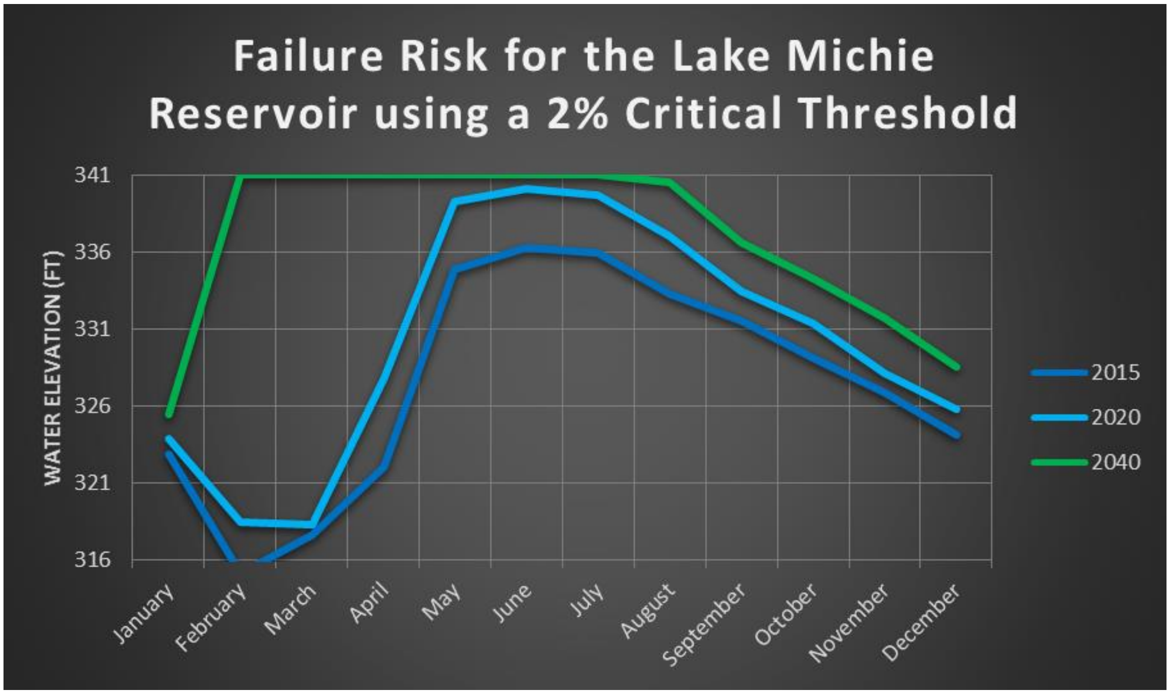

Figure C: Lake Michie Reservoir failure risk for current and projected water demands

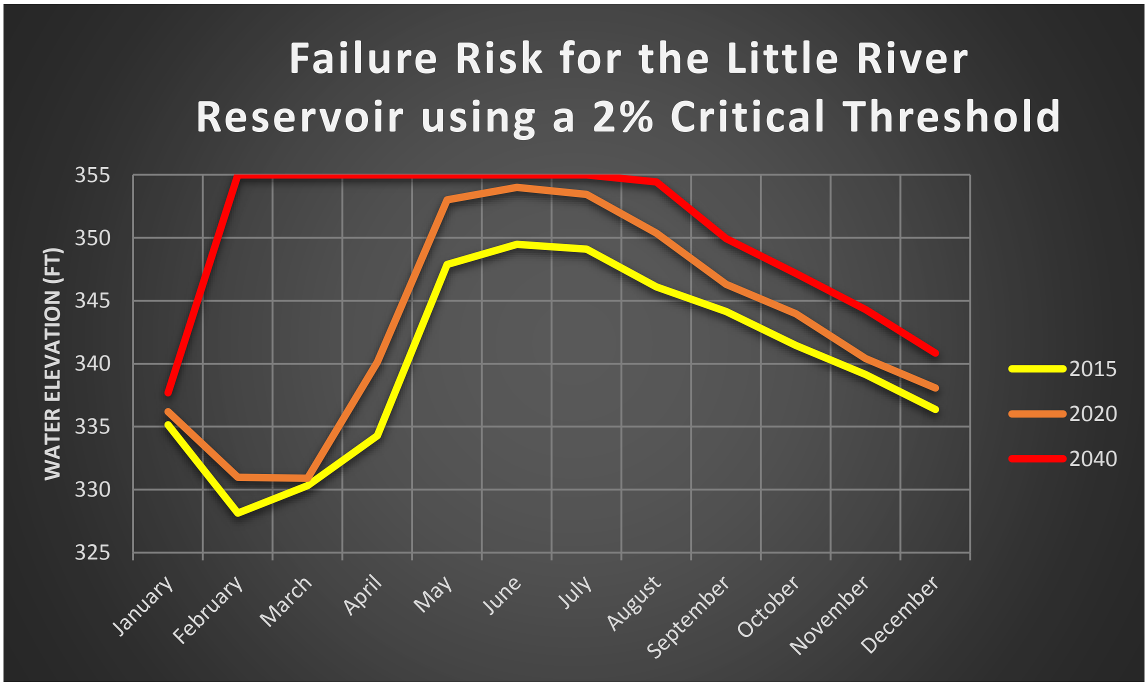

Figure D: Little River Reservoir failure risk for current and projected water demands.

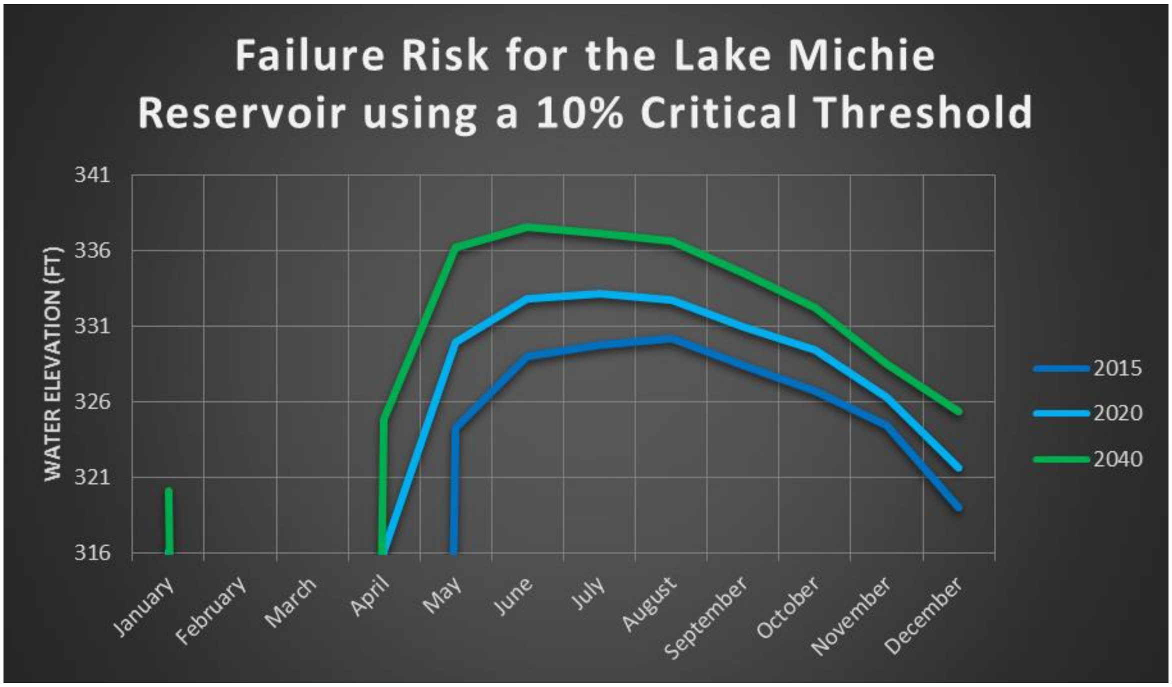

Figure E: Lake Michie Reservoir failure risk for current and projected water demands.

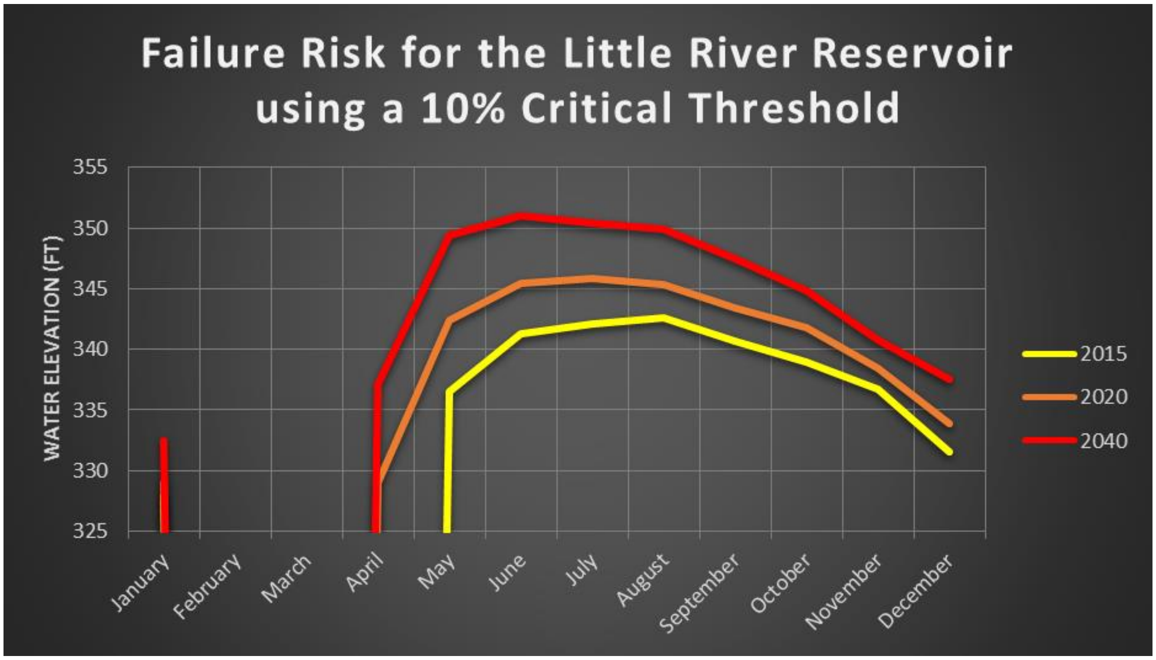

Figure F: Little River Reservoir failure risk for current and projected water demands.

Depletion Figures

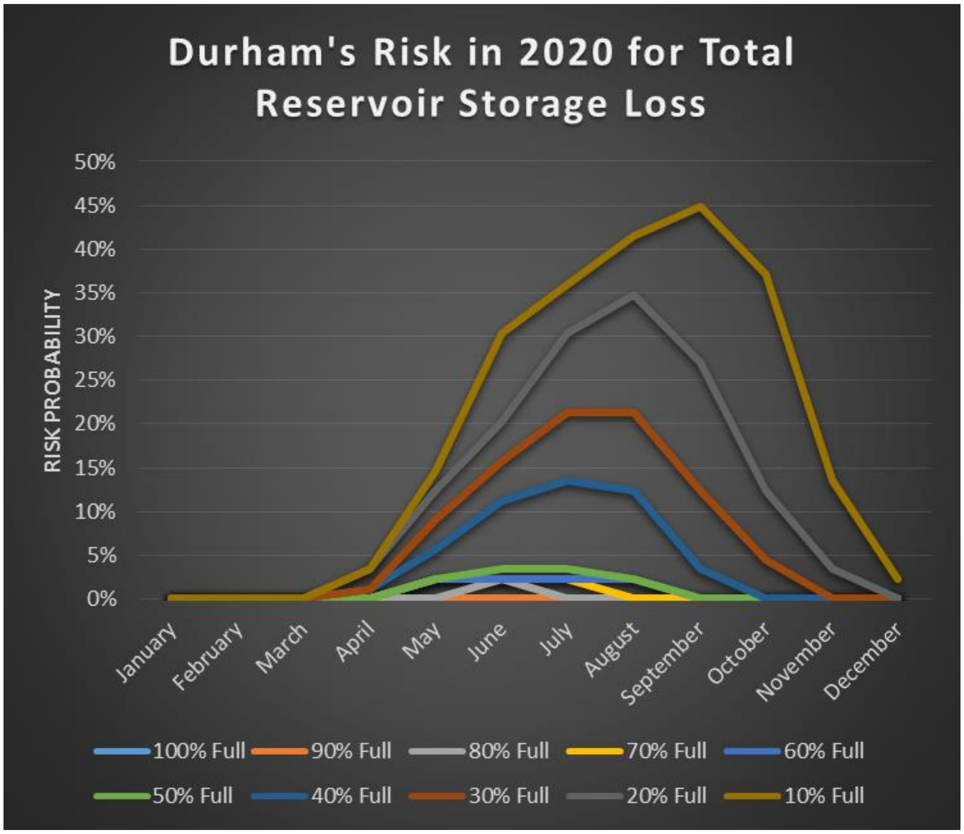

Figure G: Durham's monthly risk in 2020 for reservoir depletion at 10 different storage volumes.

Table C: Durham's risk in 2020 of reservoir depletion for 10 different storage volumes shown numerically.

Month	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
January	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
February	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
March	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
April	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	1.12%	3.37%	3.37%
May	0.00%	0.00%	0.00%	2.25%	2.25%	2.25%	5.62%	8.99%	12.36%	14.61%
June	0.00%	0.00%	2.25%	2.25%	2.25%	3.37%	11.24%	15.73%	20.22%	30.34%
July	0.00%	0.00%	0.00%	2.25%	2.25%	3.37%	13.48%	21.35%	30.34%	35.96%
August	0.00%	0.00%	0.00%	0.00%	2.25%	2.25%	12.36%	21.35%	34.83%	41.57%
September	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.37%	12.36%	26.97%	44.94%
October	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.49%	12.36%	37.08%
November	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.37%	13.48%
December	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.25%

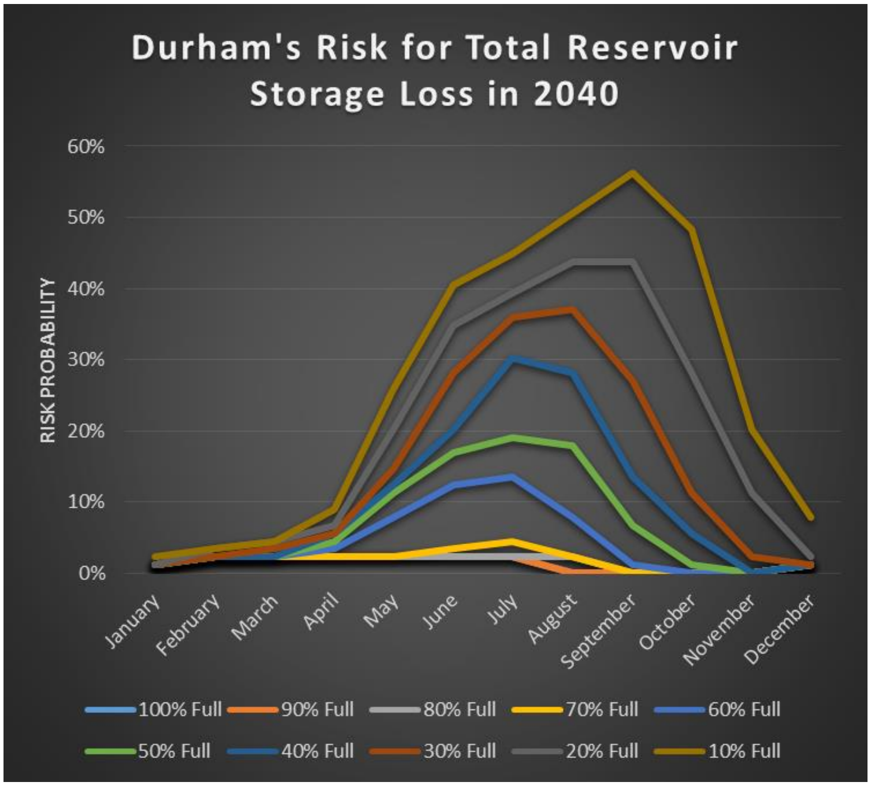

Figure H: Durham’s monthly risk in 2040 for reservoir depletion at 10 different storage volumes.

Table D: Durham’s risk in 2040 of reservoir depletion for 10 different storage volumes shown numerically.

Month	100% Full	90% Full	80% Full	70% Full	60% Full	50% Full	40% Full	30% Full	20% Full	10% Full
January	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	2.25%
February	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	3.37%	3.37%
March	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	2.25%	3.37%	4.49%	4.49%
April	2.25%	2.25%	2.25%	2.25%	3.37%	4.49%	5.62%	5.62%	6.74%	8.99%
May	2.25%	2.25%	2.25%	2.25%	7.87%	11.24%	12.36%	14.61%	20.22%	25.84%
June	2.25%	2.25%	2.25%	3.37%	12.36%	16.85%	20.22%	28.09%	34.83%	40.45%
July	2.25%	2.25%	2.25%	4.49%	13.48%	19.10%	30.34%	35.96%	39.33%	44.94%
August	0.00%	0.00%	2.25%	2.25%	7.87%	17.98%	28.09%	37.08%	43.82%	50.56%
September	0.00%	0.00%	0.00%	0.00%	1.12%	6.74%	13.48%	26.97%	43.82%	56.18%
October	0.00%	0.00%	0.00%	0.00%	0.00%	1.12%	5.62%	11.24%	28.09%	48.31%
November	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.25%	11.24%	20.22%
December	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	1.12%	2.25%	7.87%

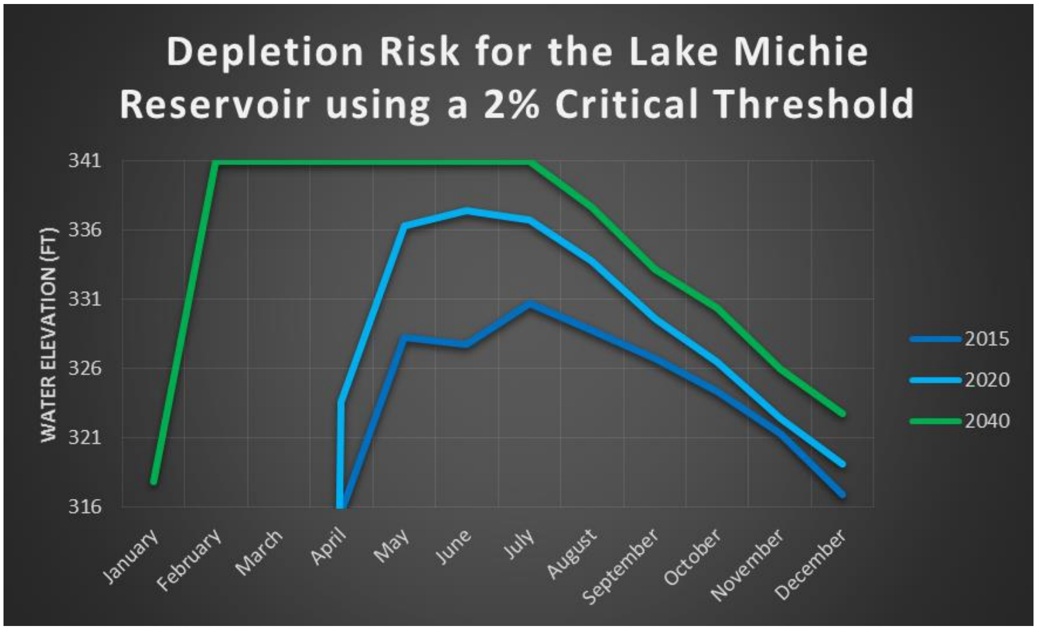

Figure I: Lake Michie Reservoir depletion risk for current and projected water demands.

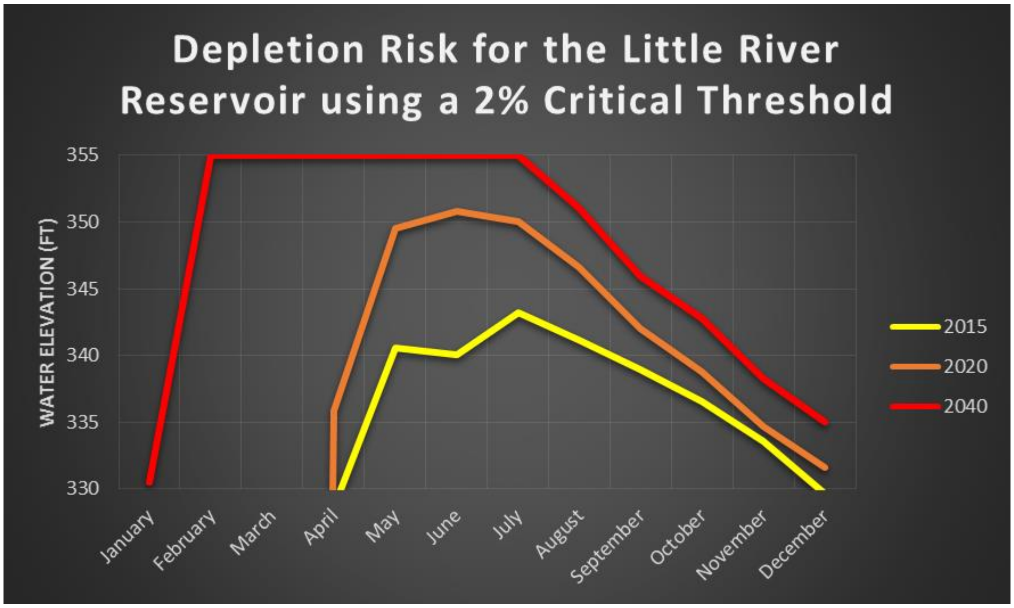

Figure J: Little River Reservoir depletion risk for current and projected water demands.

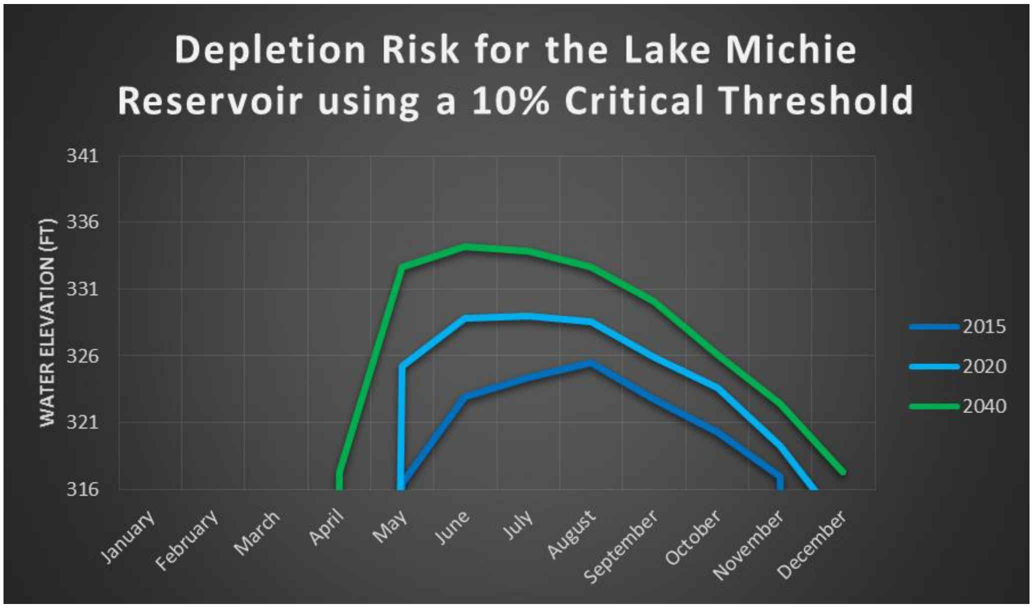

Figure K: Lake Michie Reservoir depletion risk for current and projected water demands.

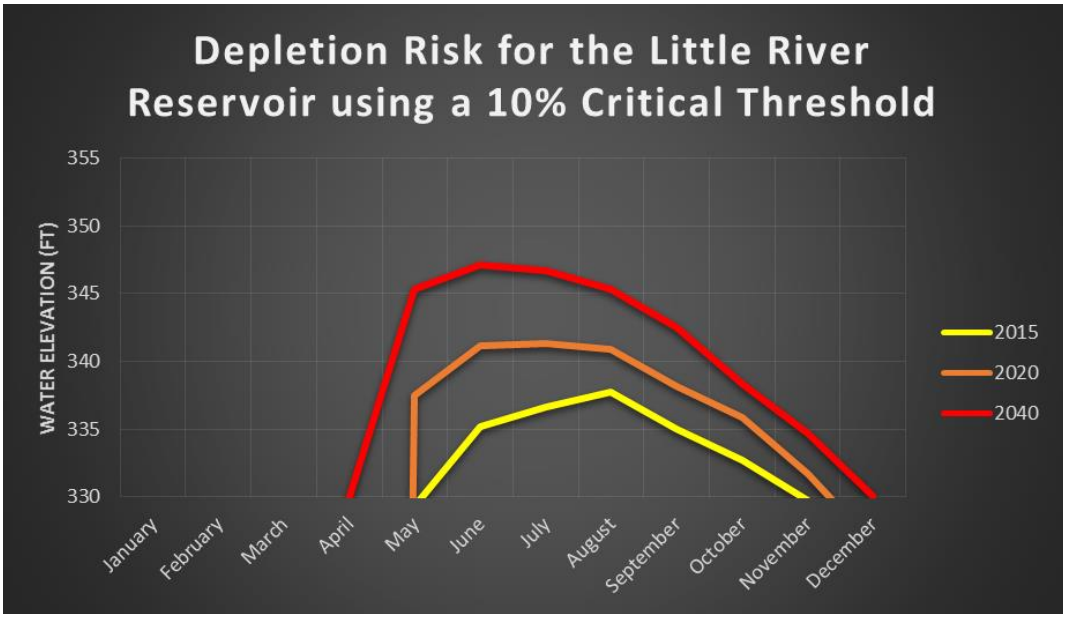

Figure L: Little River Reservoir depletion risk for current and projected water demands.