Evaporation and Modeling Water Availability in the Savannah River Basin

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Evaporation and Modeling Water Availability in the Savannah River Basin

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the Graduate School of
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In Partial Fulfillment
of the Requirements for the Degree
Master of Science
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by
Ryne Chamberlain Phillips
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Accepted by:
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Abstract

Four methods for estimating lake evaporation are presented and compared. Three are mass transfer methods that incorporated high resolution satellite imagery obtained from the MODIS sensor on the Terra and Aqua satellites. The fourth is the traditional pan method, which used monthly derived pan coefficients and pan evaporation measurements from a Class A evaporation pan located in Clemson, SC.

The four evaporation methods were used to estimate lake evaporation from the five major lakes in the Savannah River Basin for a period of more than one decade. Analysis of the evaporation rates clearly illustrated the uncertainty in daily, monthly, and yearly lake evaporation estimates derived from using different evaporation parameterizations. Results showed significant differences in the seasonal evaporation patterns between the mass transfer methods, which produced peak evaporation in the early fall months, and the pan method, which showed peak evaporation in the middle of the summer. In fact, there was virtually no correlation between the daily pan and daily mass transfer evaporation rates. Monthly and yearly evaporation estimates started to become more correlated, though the extent of the correlation varied from lake-to-lake, with the correlation increasing with decreasing lake depth.

Uncertainty in lake evaporation estimates was present. The effect of this uncertainty and its role in water-availability predictions within the Savannah River Basin were evaluated. Basin hydrologic modeling under historical and future water use scenarios were simulated for 70 and 57 years, respectively. The results showed significant uncertainty in the predicted available water during low-flow conditions, which corresponds to basin drought periods. Under normal-flow conditions, uncertainty in lake evaporation estimates did not show uncertainty in the water-availability predictions, due to an abundant supply of water during these conditions. For all lakes and evaporation methods presented, uncertainty in water availability increased with increasing water consumption.
Basin scale return periods were determined for an extreme hydrologic event, defined as each lake falling within 50% of the annual available storage volume. Under the historical water use scenario, the observed uncertainty in the predicted return periods was approximately 7 years, while the future water use scenario experienced an uncertainty of 22 years. This represents a 214% increase in the uncertainty in predicted water availability, due to population and industry growth, along with uncertainty in evaporation estimates. This type of uncertainty limits the predictive capabilities of the current basin model and will ultimately constrain the development of resilient drought and water-management plans within the Savannah River Basin.
Dedication

To the Blue Ridge Mountains of Clemson University, my dear friends, and family. Your determined spirit, love, and continued support has brought me many blessings.
Acknowledgments

First and foremost, I would like to thank my advisers, Dr. John R. Saylor and Dr. Nigel B. Kaye, for their invaluable support and continued spirit throughout this research. This thesis, as well as my advancement and success as a researcher, is a direct result of their guidance and mentorship. In spite of confusion or difficulties, they have always provided the necessary encouragement and resources.

I especially thank Dr. James G. Gibert for his efforts to mold and polish me into the forceful, multidisciplinary scientist I am today. Over the years he has been both a teacher and friend. His dedication, both in and out of the classroom, has been a blessing and always taught me to never give up.

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Success throughout this research required pan evaporation data and the Savannah River Basin’s water availability model. I would like to thank Seann Reed of the National Oceanic and Atmospheric Administration (NOAA) for his kind assistance in providing all of the digitized United States’ evaporation atlas maps. Additionally, I would like to thank the United States Army Corps of Engineers (USACE) for providing the current water availability model and all necessary data.

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Chapter 1

Introduction

Drought conditions and fluctuating lake levels have been persistent within the Savannah River Basin (SRB). However, at the time of this thesis research, the 2006 - 2009 southeastern drought marked the most devastating historical drought period for this basin. In an attempt to conserve the basin’s water supply throughout this period, reservoir and drought management plans were revised and placed into immediate effect by the United States Army Corps of Engineers (USACE). Even with such strategic management, the basin fell to less than 25% of its conservation storage by December of 2008, while Lake Hartwell and Lake Russell experienced their lowest observed pool elevations in history [49].

The SRB’s reservoir network can be, and usually is, under severe hydrologic stress during drought periods. Decreases in precipitation lower observed stream flows and increase restrictions in daily discharges from many of the lakes and reservoirs. This effect ultimately lowers reservoir elevations. As water levels fall below normal-flow conditions, less water is available for drinking water, industrial applications, and hydro-power generation. Furthermore, during periods of drought, water withdrawals are subject to increase, due to increased irrigation for agricultural and turf applications. Therefore, strategic management and drought plans are paramount for the economic well being and survival of the inhabitants of the SRB. However, a strong understanding of the hydrologic cycle, also known as the water budget, and its components is the key to developing effective and resilient management and drought plans.

The hydrologic cycle begins with evaporation of water from open-water surfaces (i.e. lakes, reservoirs, streams, rivers, etc.), soil, and plants. As the evaporated water vapor is transported by
air, the vapor is condensed to form clouds. From this point, precipitation may result in the form of rain, snow, or ice. Much of the water that reaches Earth’s surface will reside in the soil surface, while the remaining will percolate to become part of the groundwater or continue on to reach rivers, streams, and lakes [32].

Each year approximately 1 - 2 meters of precipitation falls within the SRB [18]. Much of the same water that results from precipitation in turn evaporates into the atmosphere. As a result, evaporation represents a considerable amount of available water for human consumption and has a major impact on water management. Therefore, understanding the mechanics of evaporation and its role on water supply within the SRB will only aid in strengthening reservoir and drought management.

1.1 Problem Statement

Growing demands on water resources in the SRB will ultimately constrain economic growth in South Carolina and Georgia. While water resources in this basin are currently plentiful, the growth in population, industry, and recreational activity will eventually consume more water than is available. Plans for the siting of additional hydro-power plants along the SRB will only exacerbate this emerging problem, due to the water-withdrawal requirements of such plants. As the basin’s water supply becomes more constrained, demands for more accurate and sophisticated predictions will be needed of the basin scale water cycle.

Current models used to simulate the SRB rely on historically observed monthly pan evaporation estimates derived from Class A evaporation pans. Using these data, reservoir evaporative loss is predicted for the SRB and the total water availability is evaluated. It is believed that estimates of lake evaporation derived from evaporation pans may introduce error in these models, due to the time resolution associated with the pan observations, as well as the thermal and climatic differences between the pan and actual lake environments.

The abundance of available water in the SRB is located within lakes and reservoirs. During drought and low-flow periods, lake evaporation represents a much larger fraction of available water, when compared to normal-flow periods. As a result, inaccuracies associated with lake evaporation estimates will only be magnified. Furthermore, if population and industry growth, along with more frequent and severe droughts, continue to rapidly grow, South Carolina and Georgia water
use will continue to increase to the point where evaporation will represent significantly larger and larger portions of the river flow at the ocean. Therefore, a thorough understanding of the effect of uncertainty in lake evaporation on the aforementioned water-availability model is essential to the safe and proper management, operation, and allocation of the SRB’s water supply.

1.2 Research Approach and Objectives

The primary objective of this thesis research was to explore the pan and mass transfer methods of estimating lake evaporation within the SRB. Uncertainty in predicted lake evaporation, resulting from uncertainty in lake evaporation, were evaluated with the current water-availability model used by USACE. In the research presented here, uncertainty in predicted evaporation and water-availability estimates will be used to denote the overall difference in the among the observed predictions.

With the use of the USACE water-availability model, several sets of historical lake evaporation estimates were generated and used as an input. The effect of increased water consumption, along with lake evaporation, was then coupled within the model and evaluated. The specific objectives of this thesis research were to:

1. Develop historical estimates of lake evaporation using physics-based, mass transfer models, along with high resolution, remotely sensed, surface temperature measurements for each of the major SRB lakes.

2. Compare and analyze the evaporation estimates obtained from high resolution mass transfer evaporation models using the traditional pan method as a baseline.

3. Evaluate the effect of uncertainty in the lake evaporation estimates on the basin’s water availability using the current reservoir model and historical water consumption data.

4. Investigate the role of increased water consumption on predictions of water availability coupled with the uncertainty in evaporative loss.
Chapter 2

Literature Review

In this chapter, literature is reviewed, which is pertinent to the Savannah River Basin hydrological setting, lake evaporation and modeling techniques, and water-availability modeling. More specifically, several methods of estimating lake evaporation are examined and reviewed, while the three distinct mass transfer methods implemented in this thesis research are presented. Additional information presented includes unimpaired flows and their use in water-availability modeling in the Savannah River Basin, as well as the incorporation of remote sensing technology in evaporation research.

2.1 Savannah River Basin

The Savannah River Basin (SRB) originates in the Blue Ridge Mountains of Georgia, North Carolina, and South Carolina. Within the Blue Ridge Mountains, the Tugaloo and Seneca rivers meet to form the Savannah River at Lake Hartwell. From that point on, the Savannah River forms the Georgia-South Carolina border and stretches more than 300 miles to the Atlantic Ocean [18]. The headwaters of the Seneca River are the Keowee River and Twelve-Mile Creek, while the Tugaloo River is formed by the confluence of the Tullulah and Chattooga Rivers [48]. The upper Savannah River is governed by the United States Army Corps of Engineers (USACE), which operates three multipurpose reservoirs: 1) Lake Hartwell, which was completed in 1962; 2) Lake Russell (Richard B. Russell), which was completed in 1985; and 3) Lake Thurmond (J. Strom Thurmond), which was completed in 1954. Additionally, Duke Power’s Keowee-Toxaway project, located above Lake
Hartwell, is composed of three separate reservoirs: 1) Bad Creek Reservoir, which was completed in 1991; 2) Lake Jocassee, which was completed in 1973; and 3) Lake Keowee, which was completed in 1971. Full pool elevations of Bad Creek, Jocassee, Keowee, Hartwell, Russell, and Thurmond are 704 m, 338 m, 244 m, 201 m, 145 m, and 101 m, respectively. Additional small lakes located within the SRB are the Issaqueena and Toxaway lakes.

A map of the basin and its main reservoirs are presented in Figure 2.1, while the major SRB lake geometric data is provided in Table 2.1. It is important to note that the volume and size of Bad Creek Reservoir, Lake Issaqueena, and Lake Toxaway are negligibly small, compared to the remaining lakes in the SRB. As a result, lake evaporation and water-availability analyses of Lake Jocassee, Lake Keowee, Lake Hartwell, Lake Russell, and Lake Thurmond were only examined in this thesis research.

Table 2.1: SRB major lake geometry information.

<table>
<thead>
<tr>
<th>Lake</th>
<th>Surface Area (km²)</th>
<th>Mean Depth (m)</th>
<th>Max Depth (m)</th>
<th>Shoreline Length (km)</th>
<th>Volume (Mm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jocassee</td>
<td>30.6</td>
<td>48.1</td>
<td>99.4</td>
<td>121</td>
<td>1,490</td>
</tr>
<tr>
<td>Keowee</td>
<td>75.0</td>
<td>16.0</td>
<td>90.5</td>
<td>483</td>
<td>1,070</td>
</tr>
<tr>
<td>Hartwell</td>
<td>227</td>
<td>14.0</td>
<td>53.6</td>
<td>1,550</td>
<td>3,130</td>
</tr>
<tr>
<td>Russell</td>
<td>108</td>
<td>12.1</td>
<td>44.8</td>
<td>869</td>
<td>1,260</td>
</tr>
<tr>
<td>Thurmond</td>
<td>283</td>
<td>11.3</td>
<td>43.3</td>
<td>1,930</td>
<td>3,070</td>
</tr>
</tbody>
</table>

*a Calculated at full pool elevation.
*b Data supplied by S.C. Department of Health and Environmental Control.
*c Data supplied by USACE.

The diverse ecological systems within the basin include agricultural, upland forests, bottomland hardwood stands, pine plantations, free-flowing streams, surface impoundments, swamps, and freshwater and maritime marshes. The basin contains approximately 7,810 km of streams, 723 km² of lakes, and 13.6 km² of estuarine areas [45]. The river basin has a total drainage area of approximately 27,400 km², of which approximately 11,900 km² are in South Carolina, 15,100 km² are in Georgia, and 453 km² are in North Carolina [48]. The basin serves a total 2010 population of approximately 778,000 in South Carolina, 1.35 million in Georgia, and 3,950 in North Carolina. Along the SRB, there are 9 hydroelectric power-generating facilities that deliver more than 3,300 megawatts for industrial and residential purposes.
Figure 2.1: Major lakes of the SRB. North Carolina, South Carolina, and Georgia counties are represented as dark grey, white, and light grey, respectively. Data courtesy of the South Carolina Department of Natural Resources (SCDNR) and the United States Bureau of the Census.
2.2 Evaporation

Evaporation is the phenomenon by which a substance is converted from the liquid state into vapor [9]. Evaporation, or vaporization, of water requires an energy input to convert water molecules from the liquid state to a vapor state [35]. This energy input is commonly denoted as the latent heat of vaporization of water. A commonly used empirical relationship is [33]

\[ h_w = 2.501 - 0.002361 T_w \] (2.1)

where \( h_w \) is the latent heat of vaporization of water in J/kg and \( T_w \) is the temperature of water in °C. The latent heat of vaporization of water serves as the minimum input into a hydrologic system to initiate the evaporation process. The energy absorbed by water molecules will increase particle energy and the gap between particles, causing the inter-molecular forces that hold the molecules together to grow weak and the kinetic energy to increase. If there is a large enough increase in kinetic energy, water molecules will be able to “escape” from the liquid-water surface as water vapor. The motion of the water molecules from the liquid-water vapor layer above the water surface produces a pressure known as vapor pressure. As the molecules continue to “escape,” they will collide with water molecules suspended in the air, causing many molecules to fall below to the water surface. When the number of molecules escaping a fluid equals the number of molecules returning to the fluid, an equilibrium is reached between the vapor pressure from the colliding molecules and the atmospheric pressure, also known as the saturation vapor pressure [12].

In the famous paper written by John Dalton in 1802, Dalton summarized the theory of surface evaporation and stated that the rate of evaporation from a water surface is proportional to the difference in vapor pressure at the surface of the water and that in the surrounding air [29]. Dalton developed this understanding through the first mathematical model of evaporation, known as Dalton’s Law, given as [14]

\[ E = \alpha (e_o - e) \] (2.2)

where \( E \) is the evaporation from a water surface, \( \alpha \) is a coefficient, which depends on different factors not taken into account and affecting evaporation, \( e_o \) is the pressure of saturated water vapor at the air-water interface, and \( e \) is the actual vapor pressure in the air. Dalton’s Law did not take into
account all of the variables that affect evaporation. However, much progress in evaporation research and many of the mathematical methods used to estimate evaporation still continue to follow this law.

As previously stated, evaporation requires a source of energy. Some of these energy sources are radiation, including both long- and short-wave radiation, from the sun, heat exchange with layers below the evaporating surface, due to heat storage from radiation, and the exchange of sensible heat with the air above the evaporating surface [35]. The amount of heat storage is negligible in the case of shallow bodies of water, but with larger and deeper bodies of water, such as lakes, reservoirs, and oceans, heat storage plays a large role in evaporation.

Numerous methods have been developed to estimate evaporation from water surfaces, such as lakes and reservoirs. While there are many equations and techniques, there are four general methods that are commonly applied in lake and reservoir studies: 1) Pan method; 2) Water balance method; 3) Energy balance method; and 4) Mass transfer method. A general overview of each method is presented in the following sections. However, a greater emphasis is placed on the pan and mass transfer method, as these two methods were used in this thesis research.

2.2.1 Pan Method

Perhaps the most commonly used method for estimating lake evaporation is achieved using pan evaporation measurements [32, 54] from registered National Weather Service (NWS) Class A evaporation pans. Using this method, lake evaporation is obtained using a calculated pan coefficient, defined as the ratio of lake evaporation to pan evaporation [9, 21],

\[ K_p = \frac{E_L}{E_p} \]  

(2.3)

where \( K_p \) is the pan coefficient, \( E_L \) is the evaporation of a water body, such as a lake or reservoir, and \( E_p \) is the evaporation from the pan. There are various types of pans that can be incorporated to predict lake evaporation. However, the most commonly used evaporation pan in the United States is the standard NWS Class A pan [16], which is shown in Figure 2.2.

The standard Class A pan is an unpainted galvanized pan with a diameter of 122 cm and a depth 25.4 cm. The Class A pan is mounted on top of a wooden base to allow for air circulation underneath the pan. Initially the pan is filled with water to a depth of 18 cm and is re-filled when
the water level falls to a depth of 7 cm [32]. Evaporation from the pan is measured on a daily basis, using a fixed-point gauge, and is adjusted for rainfall events [16]. Standard Class A evaporation pans are placed throughout the United States by numerous agencies and measurements are reported to the NWS. Once data are received and validated, pan evaporation measurements are published online.

A drawback of the pan method is the inaccuracy associated with estimating the pan coefficient. Pan coefficients were originally developed by the National Oceanic and Atmospheric Administration (NOAA) by computing the ratio of the free-water surface (FWS) evaporation to the pan
evaporation [16]. The FWS evaporation was computed using a mass transfer method and meteorological inputs observed at the Class A pan location. An important flaw in the pan method is that FWS evaporation is defined as the mean evaporation from a thin film of water having no appreciable heat storage, which is often thought to closely resemble evaporation occurring from natural water surfaces [16]. As a result of the considerable amount of heat storage in lakes and reservoirs, FWS evaporation is a valid indicator of lake evaporation only when heat storage within the lake or reservoir is negligible [16]. However, FWS has typically been assumed to be representative of actual lake evaporation [16]. Therefore, any heat stored or released from a lake or reservoir will cause errors in pan coefficients. Even larger errors are caused by the considerable amount of heat transfer through the sides and bottom of the Class A pan, due to advection of air and radiation exchange from the sun [27].

An additional problem associated with estimating lake evaporation from Class A pans is that many Class A pans are placed inland and away from the water body of interest. As a result, it is thought that the meteorological factors affecting the evaporation process observed at the pan location do not properly represent conditions believed to be present over surface waters [9]. Due to this phenomenon, the pan coefficient must be changed or adjusted. However, this is rarely done in many applications. Last of all, most pan evaporation estimates are provided only on a month-to-month basis, which causes many issues when trying to develop high temporal resolution estimates of reservoir and lake evaporation. Improvements in lake evaporation estimates obtained from evaporation pans would require implementation of floating pans at multiple locations on a lake. Such an approach would enable the pan to experience the same atmospheric and thermal conditions as the lake, but is costly and labor-intensive.

2.2.2 Water Balance Method

The water balance method of estimating evaporation uses mass conservation of all incoming, outgoing, and stored water in a lake or reservoir. A general expression for determining evaporation via the water balance method is given by [39]

\[ E = (P + I_{sf} + I_{gf}) - (O_{sf} + O_{gf}) + \Delta S \]  

(2.4)
where $P$ is the rate of precipitation over the lake surface, $I_{sf}$ is the surface-water inflow, $I_{gf}$ is the groundwater inflow, $O_{sf}$ is the surface-water outflow, $O_{gf}$ is the groundwater outflow, and $\Delta S$ is the change in storage.

The time resolution associated with the water balance method is quite poor, due to difficulties in quantifying many of the above variables over small time scales. When developing an evaporation model to use in determining water-availability predictions for reservoirs, lakes, or river basins, high temporal resolution evaporation estimates are necessary to quickly adapt water-management resources and decisions to changing climate and hydrological conditions, such as drought periods. Moreover, considerable error is associated with groundwater inflow and outflow measurements [32].

### 2.2.3 Energy Balance Method

The energy balance method of estimating evaporation is based on conservation of energy [21], and is commonly expressed as [9]

$$E = \frac{R_n - H - G}{h_w}$$  \hspace{1cm} (2.5)

where $R_n$ is the specific flux of net incoming radiation, $H$ is the specific flux of sensible heat into the atmosphere, and $G$ is the specific flux of heat conducted into the lake. This method can potentially provide greater temporal and spatial resolution of evaporation than that for the water balance method [21]. However, such a method is highly data-intensive [21]. Additionally, net radiometers, used to measure $R_n$, must be placed over the water surface at numerous points to truly represent the radiation exchange over that surface. Due to the difficulty of maintaining observation sites on lake and reservoir surfaces, many net radiometers are placed on adjacent inland surfaces, which is not necessarily representative of the water surface [32]. Last of all, the sensible heat flux, $H$, presented in Eq. (2.5) is calculated using empirical relationships and is often subject to error when quantifying heat exchange for large water surfaces.

### 2.2.4 Mass Transfer Method

The mass transfer method is an approach used to estimate lake evaporation, which can potentially provide much greater spatial and temporal resolution than the methods described above, where evaporation is parameterized in terms of a mass transfer coefficient, which itself is a function
of the wind speed, $f_D(\bar{u})$, and the driving force for evaporation, the vapor concentration or vapor pressure difference, $(e_*^s - e_a)$ [1,9,21,28,40,44]. Specifically, the evaporative flux is written in general terms as

$$\dot{m}'' = f_D(\bar{u})(e_*^s - e_a)$$ (2.6)

where $\dot{m}''$ is the net evaporative flux of water, $f_D(\bar{u})$ is a function of the mean wind speed $\bar{u}$, $e_*^s$ is the saturation vapor pressure of water at the temperature of the water surface, and $e_a$ is the vapor pressure of water in the ambient air. Estimating $\dot{m}''$ from Eq. (2.6) requires only four measurements: 1) Temperature of the evaporating surface, $T_s$; 2) Ambient air temperature, $T_a$; 3) Relative humidity, $\phi$; and 4) Wind speed, $\bar{u}$. When using the mass transfer method, $T_s$ is used to compute the saturation vapor pressure, $e_*^s$, while $T_a$ and $\phi$ are used to determine the vapor pressure in the ambient air, $e_a$.

Until recent years, the mass transfer method would have provided no greater temporal or spatial resolution than those methods previously described. However, due to growing trends in water-resources monitoring, there has been an increase in meteorological stations near water sources with greater data availability from government agencies. As a result of higher data availability and finer time scales, mass transfer methods provide an easy and simple approach of estimating evaporation from lakes and reservoirs with the promise of higher temporal resolution. However, many meteorological measurement stations are located inland and may not necessarily represent the climate observed over the evaporating surface.

Especially significant is the advent of high resolution satellite imagery, providing a unique and accurate approach for estimating $T_s$ for a reservoir with good resolution in both space and time. Consequently, three mass transfer methods, along with high resolution surface temperature measurements from NASA’s Terra and Aqua satellites, were selected to estimate surface evaporation from each of the major SRB lakes.

The three mass transfer methods presented herein were selected based on three general approaches by which the mass transfer transfer coefficients have been developed. Each of the models selected have been used in past evaporation studies [8,9,14,21,22,34,40,44,46]. The three methods used in this thesis research are as follows: 1) Turbulent boundary layer (TBL) method; 2) General aerodynamic (AERO) method; and 3) Heat transfer (HT) method. It is important to note that the
naming convention for each of the above methods was selected only based on the derivation and/or assumptions for which the final evaporation equation used in this thesis research was developed. The following sections serve as a derivation of each of the mass transfer methods used in this research.

2.2.4.1 Turbulent Boundary Layer (TBL) Model

A boundary layer is the layer of fluid in the immediate vicinity of a bounding surface where the effects of viscosity are significant [36]. Atmospheric researchers treat the air near the surface of the earth as a boundary layer, which is known as the atmospheric boundary layer (ABL) [9, 10]. Within the ABL, the motion of air is turbulent and is greatly affected by nature, as well as the properties of the air and surface, such as, molecular diffusivities, viscosity of air and water, and relative roughness lengths.

A relationship can be developed for the net evaporative flux of water from an open-water surface using the concept of an ABL and mass transfer theory. However, it is necessary to first develop an interfacial transfer coefficient, commonly referred to as the Dalton number, given by [9]

\[ Da_0 = \frac{\dot{m}''}{\rho_a u_* (q^*_s - q_{a,r})} \]  

where \( Da_0 \) is the interfacial Dalton number at the surface, \( \rho_a \) is the density of air, \( u_* \) is the friction velocity, \( q^*_s \) is the saturated specific humidity of water vapor at the temperature of the water surface, \( T_s \), and \( q_{a,r} \) is the specific humidity of water vapor in the ambient air, \( T_a \), at a reference height, \( r \), above the surface. Since the mass transfer of water vapor from the water surface to some reference point in the air is to be determined, accurate values of the saturated specific humidity, \( q^*_s \), at the water surface temperature are paramount. Therefore, throughout this research, high resolution values of \( q^*_s \) were achieved using remotely sensed \( T_s \) measurements from the MODIS sensor on the Terra and Aqua satellites.

A mass transfer equation for an evaporating surface can be formulated through the use of Eq. (2.7). However, implementation of the previous equation is often inefficient to develop, due to the costly and difficult nature of estimating the friction velocity. Therefore, a more general form of the mass transfer equation presented in Eq. (2.6) is often used and is given by [9]

\[ \dot{m}'' = C e_r \rho_a \bar{u}_r (q^*_s - q_{a,r}) \]  

13
where $C_{e_r}$ and $\bar{u}_r$ are the water vapor transfer coefficient and mean wind speed at a reference height, $r$, above the water surface, respectively. When using Eq. (2.8) to estimate the net evaporative flux, a proper water vapor transfer coefficient must be developed. As described by Brutsaert [9], the water vapor transfer coefficient can be formulated through similarity profiles and is given by

$$C_{e_r} = \frac{C_{d_r}^{1/2}}{Da_0^{-1} - a_v^{-1}C_{d_0}^{-1/2} + a_v^{-1}C_{d_r}^{-1/2}}$$  \hspace{1cm} (2.9)$$

where $C_{d_r}$ is the drag coefficient at a reference height, $r$, above the surface, which itself is a function of the reference wind speed, $u_r$, $a_v$ is the ratio of the von Karman constant for water vapor to that for momentum, typically assumed to be unity, and $C_{d_0}$ is the drag coefficient at the evaporating surface.

The use of Eq. (2.9) eliminates the need for friction velocity measurements or calculations, but still requires values for the surface drag coefficient and surface Dalton number. In the case of a smooth surface and relatively low wind speeds, Brutsaert obtained the following parameterization of the surface Dalton number and surface drag coefficient [8,9] expressed as

$$Da_0^{-1} - a_v^{-1}C_{d_0}^{-1/2} = 13.6Sc^{2/3} - 13.5$$  \hspace{1cm} (2.10)$$

where $Sc$ is the Schmidt number defined as

$$Sc = \frac{\nu}{D}$$  \hspace{1cm} (2.11)$$

where $\nu$ is the kinematic viscosity of air and $D$ is the diffusivity of water vapor in air. The approach used to obtain measurements of $C_{d_r}$ is presented in section 3.2.1. Substitution of Eqs. (2.9) and (2.10) gives

$$\dot{m}'' = \rho_a \bar{u}_r (q_s^* - q_{a,r}) \frac{C_{d_r}^{1/2}}{13.6Sc^{2/3} - 13.5 + C_{d_r}^{-1/2}}.$$

The equation presented above represents the net evaporative flux from a water surface and is based heavily upon the physics of mass transfer and TBLs.
2.2.4.2 General Aerodynamic (AERO) Model

A general form of the mass transfer equation for an evaporating water surface was previously defined. However, many scientists and engineers use an approximation of this equation by manipulating the specific humidity terms. A good approximation of specific humidity can be defined as

\[ q = 0.622 \frac{e}{P_a} \]  

(2.13)

where \( P_a \) is the atmospheric pressure. Substitution of this approximation into Eq. (2.8) yields the following expression for the net evaporative flux [9,21]

\[ \dot{m}'' = N \bar{u}_r (e^*_s - e_{a,r}) \]  

(2.14)

where \( e_{a,r} \) is the vapor pressure of water in the ambient air at a reference height, \( r \), and \( N \) is the aerodynamic bulk mass transfer coefficient defined as

\[ N = 0.622 \frac{C_e}{P_a \rho_a} \]  

(2.15)

where \( C_e \) is the general water vapor transfer coefficient. The \( C_e \) coefficient seen in Eq. (2.15) is representative of \( C_{e,r} \) in the TBL method. However, a different notation and the term general is used here to signify that throughout this research, the two coefficients were not estimated in the same manner.

Many researchers have generated estimates of an appropriate bulk aerodynamic mass transfer coefficient, \( N \), by calibrating Eq. (2.14) with reference to the energy balance method [9,21]. This is done by developing a plot of \( \bar{u}_r (e^*_s - e_{a,r}) \) against independent estimates of \( \dot{m}'' \) and taking \( N \) to be the slope of the line [9,21]. Although the bulk transfer equation can be generalized and reduced to fewer terms, there is still uncertainty in the general water vapor transfer coefficient, \( C_e \). As a result, there has been extensive research focused primarily on estimating accurate values of \( C_e \) for lakes and reservoirs of differing shapes, sizes, and climate conditions. For the AERO model, \( C_e \) was assumed to be a function of only the wind speed reference height, resulting in a constant \( C_e \) value for all values of \( \dot{m}'' \) and SRB lakes. The approach used to estimate a proper \( C_e \) value for the major SRB lakes is covered in section 3.2.1.
The AERO method is nearly identical to the TBL method. Nonetheless, the AERO method is quite simple and requires relatively few mathematical adjustments and parameterizations, as compared to the TBL method. Furthermore, it should be noted that a major assumption of using the AERO method is that the dimensionless transfer coefficient, $Ce$, remains constant for all wind speeds and lakes. However, it is clear that $Ce$ will depend on factors including, but not limited to, wind speed, atmospheric stability, and the underlying geometric characteristics of the lake, such as the length of fetch or the shoreline length [9].

### 2.2.4.3 Heat Transfer (HT) Model

Researchers have followed the present day notation of Dalton’s evaporation law in many previous evaporation and lake studies. [34, 40, 43]. Due to the analogous nature of heat and mass transfer [29], many of these equations have been employed in heat budgets of lakes and reservoirs [34, 46] and can generally be expressed to obtain estimates of heat loss due to evaporation. Although there are a large variety of proposed equations, all are of the general form [44] seen in Eq. (2.6). However, in the case of the lake heat studies mentioned above, the wind speed function, $f_D(\bar{u})$, is multiplied by the latent heat of vaporization of water, $h_w$, and is commonly referred to as an evaporative heat transfer coefficient.

An appropriate evaporative heat transfer coefficient must be implemented to determine the net evaporative flux by means of Eq. (2.6). Of the numerous functions available, the work of McMillan [34] has been extensively explored and used in many evaporation studies [44, 46] to estimate the evaporative heat transfer coefficient as a function of the wind speed.

McMillan [34] conducted a heat dispersal/cooling study and estimated the heat budget of Lake Trawsfynydd in North Wales. While researching the heat budget, McMillan postulated that the lake evaporation took the form of Eq. (2.6), but still needed to develop an appropriate evaporative heat transfer coefficient function to estimate the evaporative heat loss. Since all terms of the energy budget of the lake were directly measurable except those of the sensible and evaporative heat loss, McMillan decided to first perform an energy balance on the lake and estimate the combined sensible and latent heat loss. With the Bowen ratio, defined as the ratio of sensible heat transfer to evaporative (latent) heat transfer, the combined sensible and evaporative heat loss was defined in a
similar manner as Eq. (2.6) and expressed as

$$q''_e + H = h_e(\bar{u})(e_s^* - e_{a,r})(1 + B)$$  \hspace{1cm} (2.16)

where $q''_e$ is the net evaporative heat flux, $h_e$ is the evaporative heat transfer coefficient, and $B$ is the Bowen ratio, which is assumed constant, given as

$$B = \frac{0.61 P_a(T_s - T_a)}{(e_s^* - e_{a,r})}.$$  \hspace{1cm} (2.17)

An appropriate evaporative heat transfer coefficient was then developed by re-arranging Eq. (2.16) as

$$h_e(\bar{u}) = \frac{q''_e + H}{(e_s^* - e_{a,r})(1 + B)}.$$  \hspace{1cm} (2.18)

After calculating the energy budget of the lake for many years, the use of Eq. (2.18) allowed McMillan to estimate the evaporative heat transfer coefficient. Throughout the study, McMillan measured wind speed profiles at many different heights and locations across Lake Trawsfynydd. After an extensive analysis, the evaporative heat transfer coefficient function, Eq. (2.18), was plotted against the measured wind speed and a least squares fit was performed. Assuming the evaporative heat transfer coefficient was of the general form originally suggested by Stelling 1882 (see [9, 40]), McMillan was able to develop a general evaporative heat transfer coefficient function given as

$$h_e(\bar{u}) = C_1 (0.036 + 0.025C_2 \bar{u})$$  \hspace{1cm} (2.19)

where $C_1$ and $C_2$ are empirical constants that are a function of the height, $z$, at which the wind speed is measured over the water surface. These values are provided in Table 2.2.

Some time shortly after development of Eq. (2.19), Sweers [46] conducted an extensive analysis of many evaporative heat transfer coefficient functions. The evaporative heat transfer coefficients were calculated using the observed wind speeds at the research test sites in which each equation was calibrated and developed. Next, Sweers adjusted McMillan’s equation as needed, calculated the corresponding evaporative heat transfer coefficients, and compared the results. Sweers found that for small ($<1.5$ m/s) or large ($>6.0$ m/s) wind speeds, the evaporative heat transfer functions began to diverge [46]. Furthermore, when comparing functions, there were only a narrow
Table 2.2: Constants $C_1$ and $C_2$ as a function of the height $z$, in meters (m), above the evaporating water surface [34].

<table>
<thead>
<tr>
<th>$z$(m)</th>
<th>$C_1$</th>
<th>$C_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.05</td>
<td>1.18</td>
</tr>
<tr>
<td>2</td>
<td>1.02</td>
<td>1.06</td>
</tr>
<tr>
<td>3</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>4</td>
<td>0.99</td>
<td>0.96</td>
</tr>
<tr>
<td>5</td>
<td>0.97</td>
<td>0.93</td>
</tr>
<tr>
<td>6</td>
<td>0.96</td>
<td>0.91</td>
</tr>
<tr>
<td>8</td>
<td>0.95</td>
<td>0.89</td>
</tr>
</tbody>
</table>

range of wind speed observations available at which each function was developed [46]. However, within this range, agreement between McMillan’s and other functions were generally good [46]. As a result, Sweers concluded that McMillan’s general function yields the best results for practical applications [46] of estimating the evaporative heat transfer coefficient.

McMillan’s evaporative heat transfer coefficient function was believed to provide the most accurate estimates of $h_e$ for this research, since the average wind speed measurements obtained from regional airports in the SRB, described in section 3.1.1, were generally within the range at which Sweers conducted his analysis (i.e. $1.5 \text{ m/s} < u < 6.0$). As a result, the combination of Eqs. (2.6) and (2.19) yields a reasonable expression, in the form of Eq. (2.6), for the net evaporative flux given as

$$\dot{m}'' = f_D(\bar{u})(e_s^* - e_{a,r})$$

(2.20)

where $f_D(\bar{u})$ is expressed as

$$f_D(\bar{u}) = \frac{h_w(\bar{u})}{h_w}. \quad (2.21)$$

The net evaporative flux of water can be calculated for an open-water surface with the use of Eqs. (2.20) and (2.21), and the tabulated coefficients presented by McMillan [34]. However, only when the wind speeds are measured at the same reference height, $r$, as the water vapor term, $e_{a,r}$.

2.2.4.4 Summary of Methods

The aforementioned mass transfer methods take on two general forms and the transfer coefficients/functions are all derived from varying techniques and experimental procedures. Although
each parameterization and derivation may seem quite different, each of the equations used to estimate
the net evaporative flux can be reduced to the general form given by

\[ \dot{m}'' = h_m(q_s' - q_{a,r}) \]  \hspace{1cm} (2.22)

where \( h_m \) is the general evaporative mass transfer coefficient given as

\[
\begin{align*}
    h_m &= \left\{
    \begin{array}{ll}
    \rho_a \bar{u}_r (C_d r^{1/2}/(13.6 S c^{2/3} - 13.5 + C d_r^{1/2})) & \text{for TBL,} \\
    \rho_a \bar{u}_r C e & \text{for AERO,} \\
    Pa C_1 (0.025 + 0.036 C_2 \bar{u}_r)/(0.622 h_w) & \text{for HT.}
    \end{array}
    \right.
\end{align*}
\]  \hspace{1cm} (2.23a-b-c)

It is easy to see that each of the parameterizations for estimating the net evaporative flux
from an open-water surface has an identical form when presented in the form of Eq. (2.22). The main
underlying difference in each approach is associated with estimating an appropriate and accurate
evaporative mass-transfer coefficient, \( h_m \). Moreover, it is important to note that the TBL method
is non-linear in wind speed, due to \( C_d r \), the AERO method is linear in wind speed, and the HT
method is linear in wind speed with an additive term.

## 2.3 Unimpaired Flows

The use of unimpaired flows by water-resources managers is a common practice in developing
drought-contingency and water-management plans [19, 30, 47]. As described by ARCADIS U.S.,
Inc. [3], unimpaired flows are the flows which would have historically occurred within the main
branches of rivers comprising a river basin, had the flows not been influenced or altered by humans.
Therefore, the key component and underlying advantage of unimpaired flows is that the influence of
mankind and construction (i.e. dams and reservoirs) have been removed from the naturally occurring
river basin flows.

For the proper development of drought plans, water managers want to model a reservoir
network in response to as many drought-occurring periods as possible. This creates a problem for the
SRB, as the full reservoir network is relatively young. For example, the last reservoir constructed
in the basin was Bad Creek in 1991, while the first reservoir completed was Lake Thurmond in
1954. As a result, there are few drought periods that naturally cover the entire system, and to properly model the system response to major notable drought periods, all reservoirs must be present. Therefore, unimpaired flows provide a viable method for drought planning in the SRB. Since human influences, such as reservoir net evaporation, pre-reservoir runoff, and water consumption, have been added back to the naturally occurring flows, the entire reservoir system can be “virtually” created prior to reservoir construction with the use of a reservoir modeling program, such as HEC-ResSim. Consequently, water-resources managers can successfully model the SRB network under the influence of more naturally occurring drought and hydrologically stressed periods using unimpaired flows, especially since the current SRB period of record (POR) is January 1939 - December 2008. These reservoir model programs and unimpaired flows can and will be used to develop sound operational water-management and drought-contingency plans.

Unimpaired flows are one of the major input time series used for modeling and analyzing the SRB and play a major role in the development of how the basin’s water supply is managed. Although these flow data sets attempt to remove the influences of mankind from historically observed flows, they do not necessarily remove all effects of humans, due to land-use change, undocumented ground- and surface-water uses, etc. As a result, unimpaired flows will not provide an exact solution to modeling a reservoir network. However, water managers are able to grasp a greater understanding of a reservoir network’s response to drought conditions, as well as increased water usage, with the use of unimpaired flows than without unimpaired flows.

The original unimpaired flow data set for the SRB was developed by ARCADIS, U.S., Inc. as part of the Surface Water Availability Modeling and Technical Analysis for Statewide Water Management Plan prepared for the Georgia Department of Natural Resources [3]. As a result of this study, unimpaired flows for the SRB are given by [3]

\[
UIF = LIF + NETEVAP_F + NETWU
\]  

(2.24)

where \(UIF\) is the local unimpaired incremental flow, \(LIF\) is the local incremental flow, \(NETWU\) is the net water consumption, resulting from municipal, industrial, and agricultural uses, as well as and groundwater pumping, and \(NETEVAP_F\) is the flow due to reservoir net evaporation effects.
given by [3]

\[
NETEVAP = [(EV - P) \cdot A + ROC \cdot P \cdot A]
\]  

(2.25)

where \( EV \) is the rate of surface evaporation, \( P \) is the rate of precipitation, \( A \) is the reservoir surface area, and \( ROC \) is the sub-basin runoff coefficient.

A general overview discussing the details of the process is provided in Appendix A. However, a complete and detailed description of the UIF computation process can be obtained from ARCADIS U.S., Inc. [3].

2.4 HEC-ResSim Model

As a result of increasing water demands in the United States, water-management plans have been developed using various modeling programs. In the case of the SRB, the current computer modeling program that is utilized by the USACE Savannah District is HEC-ResSim, which is a reservoir network simulation computer program developed by the USACE Hydrologic Engineering Center Institute for Water Resources. The HEC-ResSim model used by USACE was developed and completed by HDR Engineering, Inc., an engineering and consulting firm based out of Portland, Maine. A general view of the model reservoir network within HEC-ResSim is presented in Figure 2.3.

The HEC-ResSim model used by USACE incorporates physical reservoir data, such as, net evaporation, net evaporation plus runoff in this case, and stage-storage relationships, as well as stream routing steps, dam flow properties, diverted outlets, and power-plant operations for each of five major SRB lakes, including Bad Creek reservoir. Although each of these components play an intricate part of the model, the key lies within the operational rules embedded in the reservoir model.

The current model contains the operational rules and data sets for the 2006 Drought-Contingency Plan (2006-DCP), as well as the current water-management plan. As a result, this model will be referred to as the 2006-DCP model herein. Within the 2006-DCP model, Lake Jocassee, Lake Keowee, and Bad Creek, operate under the storage-balance rule set imposed by Duke Energy, requiring safe operating levels for the Oconee County Nuclear Plant. Lake Hartwell, Lake Russell, and Lake Thurmond operate under the 2006-DCP developed by USACE. A complete and
Figure 2.3: View of the SRB HEC-ResSim model reservoir network.
detailed description of the operation rule sets defined within the 2006-DCP model is beyond the scope of this thesis. However, in general, the 2006-DCP model contains zone rules for reservoir flood, conservation, and drought levels. These rules ensure proper reservoir levels for adequate fish spawning, safe power-generation, and human, industrial, and agricultural water use.

The 2006-DCP model contains rules and physical properties of the SRB stream and reservoir network. Through mass conservation, the reservoir network can be modeled over a period of days, months, or years, providing simulated reservoir elevations, storage volumes, power generation, etc. Within the 2006-DCP model, there are three fundamental inputs that govern the final result: 1) UIF data sets, developed by ARCADIS U.S., Inc.; 2) Reservoir pool evaporation; and 3) Human water consumption.

The current UIF data sets incorporated in the 2006-DCP model include the following daily local flow time series: 1) Bad Creek Reservoir; 2) Lake Jocassee; 3) Lake Keowee; 4) Lake Hartwell; 5) Lake Russell; 6) Lake Thurmond; 7) Augusta; and 8) Clyo. Similarly, human water consumption time series are represented by diversions and include data for the following locations: 1) Lake Jocassee; 2) Lake Keowee; 3) Lake Hartwell; 4) Lake Russell; 5) Lake Thurmond; 6) Woodlawn; 7) Stevens Creek; 8) North Augusta; 9) Augusta; 10) Augusta Canal Return; 11) Girard; 12) Millhaven; and 13) Clyo. Finally, reservoir pool evaporation for each of the major lakes is currently represented with monthly time series that remain constant from year-to-year.

Each of the above inputs determine the output of the 2006-DCP model. In a general sense, when any simulation in 2006-DCP model is generated and run, UIF time series are routed downstream. Then, a water balance is computed, using stage-storage-area relationships, power-plant operations, spillway properties, reservoir operational rules, and mass conservation. Evaporation and human water consumption are removed from each reservoir’s storage volume. Additional human water consumption is then removed from the UIF at the remaining diversions.

The 2006-DCP model currently serves as the main tool for simulating the SRB reservoir network. Water-availability predictions can be developed under a variety of conditions using this model. USACE and local governments can then work closely to develop proper reservoir management guidelines from the model results, under normal- and low-flow conditions. Consequently, the 2006-DCP model was used as a tool to evaluate effects of evaporation estimates and increased human water consumption in the SRB.
2.5 Remote Sensing in Evaporation Research

Remote sensing is an increasingly useful approach for monitoring hydrologic and climate data from polar-orbiting and geostationary satellites [21]. The main advantage of incorporating remote sensing in hydrology and climate research is the increased spatial and temporal resolution provided by these satellites [37]. Although there are numerous remote sensing platforms around the world, each of these systems typically obtain data in three forms: 1) Images as photographs; 2) Analog signals; and 3) Digital signals [21].

Remote sensing cannot be used to directly measure evaporation from water surfaces. However, critical variables needed to estimate evaporation can be measured and/or estimated by remote sensing platforms [21]. Of the variables needed to estimate evaporation from lakes and reservoirs, surface temperature is one of the most heavily remotely sensed. Researchers can now estimate and monitor surface temperatures at higher spatial and temporal scales by using remotely sensed, thermal-infrared (TIR), imagery collected from sensors on satellites [2,42].

Throughout this thesis research, surface temperature was used to estimate the saturated specific humidity at the air-water interface, $q^*_s$. An approach was then applied to estimate lake evaporation, based off of remotely sensed surface temperature measurements. Therefore, the following sections are presented to familiarize the reader with common satellite platforms used to estimate water surface temperatures from lakes and reservoirs around the globe.

2.5.1 Landsat Platform

Starting in the early 1970s, there have been a series of polar-orbiting satellites observing the Earth known as the Landsat Program. Over the years, numerous Landsat missions have been launched, administered, and monitored jointly by NOAA, the National Aeronautics and Space Administration (NASA), and the United States Geological Survey (USGS) to provide the imagery necessary for monitoring and modeling water resources around the globe.

Of the numerous Landsat missions, the Landsat-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper (ETM) are the most frequently used to measure lake and reservoir surface temperature. Surface temperature values are found using a TIR sensor on each satellite and have been found to be within $\pm 1.47 \, ^\circ C$ and $\pm 0.98 \, ^\circ C$ of observed measurements, respectively [31].

A benefit of the Landsat satellites is the high spatial resolution provided by the TIR sensor.
For example, the TIR sensor on the Landsat-5 TM provides a spatial resolution of 120 m, while the TIR sensor on the Landsat-7 ETM data has a 60-m resolution. As a result, Landsat missions can provide the resolution needed to estimate surface temperature over much smaller lakes and reservoirs.

Although TIR data from Landsat platforms can provide the spatial resolution needed to effectively monitor water surface temperatures over lakes and reservoirs, these instruments have a typical temporal resolution of 16 days [31]. Furthermore, water surface temperature data sets are not directly available through these instruments and have not been corrected for atmospheric contamination. For example, the data is received in the form of TIR imagery, in which each image pixel is assigned a digital number. Digital numbers must then be converted to spectral radiance values and effective surface temperatures, using calibration constants and equations available in the Landsat data users handbooks.

### 2.5.2 NOAA Platform

NOAA launched its first series of polar-orbiting satellites in 1978, commonly known as the NOAA satellites. On the NOAA satellites is the Advanced Very High Resolution Radiometer (AVHRR) sensor, which allows for surface temperature measurements over lakes and reservoirs. The AVHRR sensor is similar to the TIR sensor on the Landsat platforms in that it does not directly provide surface temperature measurements. However, the sensor does provide the necessary data needed to determine surface temperature values.

The AVHRR sensor provides surface radiance values at a spatial resolution of 1.09 km and a temporal resolution of approximately 12 hours. Radiance values must then be corrected for atmospheric interference and converted to brightness temperatures using a split-window algorithm to obtain actual surface temperature measurements. There have been many split-window algorithms developed to estimate surface temperature values using AVHRR data, and it has been found that these algorithms can estimate surface temperatures within approximately ± 1.64 °C - 2.29 °C of observed values [41].

The spatial resolution of the AVHRR sensor on the NOAA satellites is less than that of the TIR sensor on the Landsat satellites. However, AVHRR-derived surface temperatures have a much higher temporal resolution and can allow researches to monitor and evaluate diurnal cycles of surface temperature over lakes and reservoirs [24]. Therefore, incorporating AVHRR data sets
can provide greater insight in evaporation cycles over larger lakes and reservoirs. A downfall of
using AVHRR-derived surface temperature measurements is the significant amount of orbit drift in
afternoon overpasses of satellites NOAA-7, -9, -11, and -14, which make AVHRR surface temperature
temporally in-homogeneous [25].

2.5.3 Terra & Aqua Platform

A newer generation of satellites frequently used to estimate surface temperatures during lake
studies are NASA’s Terra and Aqua satellites. The Terra and Aqua satellites have marked a new
revolution of remote sensing technology and were launched in 1999 and 2002, respectively. Each of
these satellites carry the Moderate Resolution Imaging Spectroradiometer (MODIS), which provides
high resolution and accurate surface temperature measurements over land and water surfaces.

The MODIS sensor acquires TIR data at a spatial and temporal resolution of 1 km and 12
hours, respectively. However, MODIS TIR data is retrieved only in clear-sky conditions to ensure
that the derived surface temperatures are not mixed with cloud-top temperatures [50]. Once the
sensor obtains TIR data, surface temperature values are computed using a generalized split-window
land surface temperature (LST) algorithm. During the split-window algorithm, surface temperatures
are corrected to account for atmospheric and surface emissivity effects for land and water surfaces of
known band emissivities [51]. The generalized split-window algorithm is a technique often applied
to obtain land and surface water temperatures from other satellite sensors. The key difference is
that the split-window algorithm is applied prior to publishing data. As a result, surface temperature
measurements are directly available in the form of MODIS LST products.

MODIS LST data sets have been studied and found to accurately produce surface tempera-
ture values within ± 1 °C of field measurements [50,51]. An advantage of MODIS data is that little
processing is required to obtain surface temperature measurements. Furthermore, incorporation of
both data sets can improve diurnal characterizations of surface temperature and evaporation esti-
mates over lakes and reservoirs, due to differences in satellite data acquisition (i.e. overflight pass)
times between Terra and Aqua satellites. As a result, the MODIS instrument on the Terra and Aqua
satellites was used to obtain surface temperature and \( q_s^* \) measurements for each of the major lakes
within the SRB.
Chapter 3

Methods

This chapter details the approach taken to estimate surface evaporation from each of the five major SRB lakes using remotely sensed surface temperature data with the three mass transfer methods presented in Chapter 2, as well as the traditional pan method. Furthermore, this chapter outlines the procedures used to model the SRB reservoir network and determine water-availability estimates as a function of the aforementioned lake evaporation estimates, using both historical and future water consumption data.

3.1 Data Collection

As discussed in the previous chapter, four main parameters are needed to estimate lake evaporation via mass transfer methods: 1) Ambient air temperature, $T_a$; 2) Surface temperature of the lake, $T_s$; 3) Relative humidity, $\phi$; and 4) Wind speed, $\bar{u}$. Accurate methods must be used to estimate and measure each of these parameters when developing reliable evaporation estimates for the lakes in the SRB. Furthermore, hydrologic and reservoir data used to model the lakes and reservoirs in the basin are paramount to quantifying uncertainty in the 2006-DCP model with respect to varying evaporation parameterizations. As a result, this section serves to discuss the specific data sources used to estimate lake evaporation and model the SRB reservoir network under historical and future water use scenarios.
3.1.1 Weather Data

The parameters $T_a$, $\phi$, and $\bar{u}$ were all obtained from the Automated Surface Observing Systems (ASOS) program through the Southeast River Forecast Center (SERFC) at the University of North Carolina - Chapel Hill from 2002 - 2012. The ASOS program is a joint effort between the National Weather Service (NWS), the Federal Aviation Administration (FAA), and the Department of Defense (DOD), in which the primary function is to provide minute-by-minute observations and to generate the Aviation Routine Weather Report (METAR) and Aviation Selected Special Weather (SPECI) report [38]. In the case of evaporation research, the ASOS program provides basic hourly weather observations ($T_a$, $\phi$, and $\bar{u}$) at regional airports across the United States.

Three regional airports within the SRB were selected to obtain the parameters $T_a$, $\phi$, and $\bar{u}$: 1) Oconee Country Regional Airport (ICAO:KCEU); 2) Anderson Regional Airport (ICAO:KAND); and 3) Augusta Regional Airport (ICAO:KAGS). The Greenville-Spartenburg Regional Airport (ICAO:KGSP) was an additional weather station that was considered. However, weather data from this airport were not included, due to the distance from local water bodies. The locations of the regional airports are presented in Figure 3.1. It is important to note that none of the above airports are located directly on any of the major SRB lakes. As a result, it was assumed that weather data from these airports is representative of the climate conditions observed over each lake.

Air temperature observations reported through the ASOS program are measured 2 meters above the ground surface using a modern version of the fully automated “HO-83” hygrometer [38]. Using a Resistive Temperature Device (RTD), the “HO-83” hygrometer is capable of measuring the ambient air temperature within 0.1 °F with a maximum error of approximately 2 °F - 4 °F [38]. The RTD measures ambient temperature at 5-minute intervals over each hour in degrees Fahrenheit and then converts to degrees Celsius, rounding to the nearest 0.1 °C. Five-minute interval measurements are then averaged over each hour to provide the hourly ambient air temperature reported by the ASOS program [38].

Relative humidity measurements reported by the ASOS program are calculated using the 5-minute averaged ambient air temperature measurements described above, along with dew-point temperature measurements. Dew-point temperature measurements are determined using the same hygrometer instrument used to measure ambient air temperature. However, a mirror is chilled until dew forms [38]. Once dew has formed, a similar RTD, as previously described, measures
Figure 3.1: Major lakes of the SRB and nearby regional airports. North Carolina, South Carolina, and Georgia counties are represented as dark grey, white, and light grey, respectively. Data courtesy of the South Carolina Department of Natural Resources (SCDNR) and the United States Bureau of the Census.
the mirror temperature. The recorded temperature is assumed to be the dew point temperature. Relative humidity measurements are determined 2 meters above the ground surface and reported as a percentages.

Wind speeds reported by the ASOS program are measured using a modern automated version of the “F420” series anemometer, located 10 meters above the ground surface [38]. The automated anemometer uses electro-magnetic signals generated by the rotating cup and wind vanes to measure and report wind speeds [38]. The wind speeds are measured using 2-minute intervals, and then averaged over each hour to provide hourly wind speed measurements. Hourly ASOS wind speed measurements are initially measured and reported in knots with an accuracy and resolution of 2 knots and 1 knot, respectively [38]. However, values obtained from the SERFC were reported in meters per second.

3.1.2 Satellite Data

An intricate component of this work was the use of the mass transfer method, where $q_s^*$, the saturation specific humidity at the water surface temperature, was computed at high spatial and temporal resolution through satellite measurements of $T_s$. As noted in the previous chapter, $T_s$ was obtained from the MODIS sensor on NASA’s Terra and Aqua satellites.

Daily MODIS LST level 3, 1-km nominal resolution data for Terra (MOD11A1, version 5) and Aqua (MYD11A1, version 5) were obtained from the NASA Earth Observing System Data and Information System (EOSDIS) in the form of satellite images from July 2002 - December 2012. The MOD11A1 and MYD11A1 LST products are generated from MODIS bands 31 (11 $\mu$m) and 32 (12 $\mu$m) using a split-window algorithm designed for a variety of surfaces, including land and inland water surfaces [51]. An advantage of MODIS products is that the LST data is pre-processed to account for atmospheric and surface emissivity effects, requiring little post-processing upon retrieving data. Furthermore, a cloud mask is incorporated when estimates of LST for inland water surfaces are developed. The cloud mask allows LST values to be generated when there is 66% or greater confidence of clear-sky conditions [13, 51, 51]. As a result, effects of cloud-top temperatures are excluded from the data, allowing for more accurate surface temperature measurements.

Each Terra and Aqua satellite has a sun-synchronous, near-polar, circular orbit, with a temporal resolution of approximately 12 hours and a 1-km nominal spatial resolution (0.928 km actual at Nadir). The Terra satellite has a local equatorial crossing time of approximately 10:30
A.M. and 10:30 P.M. in a descending and ascending node, respectively, while the Aqua satellite has a local equatorial crossing time of approximately 1:30 A.M. and 1:30 P.M. in a descending and ascending node, respectively.

3.1.2.1 Image Processing

A shoreline mask was generated using ERDAS Imagine, a geographic information system (GIS) used for spatial analysis and image processing/analysis, and Landsat 7-ETM imagery to process the MODIS LST imagery. The shoreline mask was used to develop an algorithm to extract land-free pixels containing surface temperature measurements and data acquisition times from each of the major SRB lakes. The high resolution associated with the Landsat imagery successfully allowed identification of all available land-free pixel locations. Sample MODIS LST delineated pixels for Lake Jocassee stacked with Landsat 7-ETM TIR imagery are presented in Figure 3.2. The number of available land-free pixels were 6, 1, 12, 3, and 19 for lakes Jocassee, Keowee, Hartwell, Russell, and Thurmond, respectively.

Pixel data sets extracted from the MODIS LST imagery were scaled measurements and required further processing to obtain usable data. For example, MODIS overflight data acquisition times are recorded in the range of 0 - 240, while surface temperature measurements are recorded in the range of 7500 - 65535. As a result, the time measurements required scaling by a factor of 10 to obtain the data acquisition hour on a scale of 0 - 24, while the surface temperature measurements required scaling by a factor of 50 to obtain measurements in Kelvin. As stated earlier, MODIS LST data is generated using a split-window algorithm, which removes cloud contaminated pixels. Any data acquisition times contaminated from cloud cover are stamped with a value of 255 to signify no data is available. Similarly, surface temperature measurements are stamped with a value of 0 if contaminated from cloud cover. It is important to note that individual pixel values were averaged for each daily satellite overflight to provide an average representative surface temperature measurement. If any cloud contamination occurred in the overflight pixel measurements, those pixels were ignored in the averaging process.

As a result of cloud contamination and miscellaneous satellite malfunctions occurring over the image acquisition period, gaps were present in each MODIS LST data set. A sample plot of available surface temperature observations extracted for Lake Hartwell is presented in Figure 3.3.

From Figure 3.3, it is apparent that a little more than half of the daily observations from
Figure 3.2: MODIS LST pixels identified for Lake Jocassee stacked with Landsat 7-ETM TIR imagery.
Figure 3.3: Available surface temperature measurements for Lake Hartwell.
each MODIS LST data set was available. This presents difficulty in developing an accurate and continuous daily evaporation data set. Consequently, some degree of temporal interpolation was used for filling the missing surface temperature measurements.

### 3.1.2.2 Temporal Interpolation of Surface Temperature

A type of Fourier (harmonic) analysis was used to estimate missing surface temperature measurements for each MODIS LST data set. A typical Fourier analysis requires the original time series data, MODIS LST data in this case, to be equally spaced in time. Cloud contamination and atmospheric effects cause MODIS LST data to be unequally spaced in time and create difficulty when attempting to perform a traditional Fourier transform. As a result, the Harmonic ANalysis of Time Series (HANTS) algorithm was used to estimate missing MODIS LST data.

The HANTS algorithm was originally developed by Wout Verhoef at the National Aerospace Laboratory (NLR) in The Netherlands and was intended for filling and smoothing Normalized Difference Vegetation Index (NDVI) image time series. Over time, the HANTS algorithm has been used in other remote sensing applications and has proved its validity in reconstruction of surface temperature data sets [26, 53]. The overall basis of the algorithm is generated by replacing the traditional discrete Fourier time series analysis, known as the Fast Fourier Transform (FFT), with the classical Fourier analysis and attaching weights to the different observations. In this approach, the Fourier analysis is treated as a curve fitting problem and the parameters describing the Fourier terms are found from a weighted least squares fit.

In general, the HANTS algorithm is based on a weighted least squares curve fit. However, the curve fitting approach is applied in an iterative manner. First, the least squares curve is determined based on all available data points of the time series. Next, the observations estimated from the curve fit are compared to the original time series data. Values that are clearly much higher or lower than the curve are determined as outliers and removed from the time series. The curve fitting procedure is then repeated until all of the remaining data points are within an error tolerance or the remaining number of original data points is too low.

The HANTS algorithm is controlled by five main parameters: 1) Number of frequencies (NOF), which describes how many terms to keep of the Fourier fit; 2) Hi/Lo/None suppression flag, which indicates whether high or low values, outliers, should be rejected during the curve fitting procedure; 3) Invalid data threshold range, which gives the range of valid data values; 4) Fit error
tolerance (FET), which expresses the absolute difference in data values from the curve fit and the original data; and 5) Degree of overdeterminedness (DOD), which designates the minimum number of original data points for which the curve fit can be completed.

NOF, FET, and DOD were the most important parameters to estimate for controlling the output of the HANTS algorithm. The remaining parameters were relatively easy to determine. For this research, the suppression flag was set to none, while the invalid data threshold range was set to 0 - 100. This indicated that no outliers would be rejected during the curve fit between the range of 0 °C - 100 °C, which corresponds to the valid data range of the MODIS LST data.

A parametric study was conducted to estimate appropriate values for NOF, FET, and DOD. During this study, the HANTS algorithm was performed with variations of NOF, FET, and DOD for each of the MODIS LST data sets. Coefficients of determination were calculated using the HANTS and MODIS derived LST values to ensure an accurate fit. Visual inspection of each HANTS derived LST time series also ensured the fit was reasonably accurate. After performing the study and analyzing the HANTS derived LST data sets, appropriate values for NOF, FET, and DOD were selected. The parameter values selected for this thesis remained constant and did not vary by lake. NOF values selected for the HANTS Algorithm were 225, 200, 225, and 175 for Aqua day, Aqua night, Terra day, and Terra night satellites data sets, respectively. FET and DOD values selected for the HANTS algorithm were 5 and 6, respectively, for each satellite overpass. The calculated coefficient of determination for each lake MODIS LST data set is presented in Table 3.1.

<table>
<thead>
<tr>
<th>Lake</th>
<th>Aqua Day</th>
<th>Aqua Night</th>
<th>Terra Day</th>
<th>Terra Night</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jocassee</td>
<td>0.94</td>
<td>0.92</td>
<td>0.93</td>
<td>0.92</td>
</tr>
<tr>
<td>Keowee</td>
<td>0.93</td>
<td>0.95</td>
<td>0.94</td>
<td>0.92</td>
</tr>
<tr>
<td>Hartwell</td>
<td>0.95</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>Russell</td>
<td>0.94</td>
<td>0.94</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>Thurmond</td>
<td>0.95</td>
<td>0.93</td>
<td>0.94</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Once the five HANTS parameters were selected, the algorithm was applied to each MODIS LST data set. The HANTS derived surface temperature data sets were then used to fill the missing MODIS LST data of each lake. A sample HANTS output and original MODIS LST data for Lake Hartwell’s Aqua daytime overpass are presented in Figure 3.4.
Figure 3.4: Lake Hartwell MODIS and HANTS derived surface temperature estimates from the Aqua daytime overpass.

3.1.3 Pan Evaporation Data

The 2006-DCP model used by USACE incorporates the use of NOAA pan evaporation measurements, evaporation atlas map data, and Hamon potential evapotranspiration (PET) daily time series to estimate pool evaporative loss. These values were determined by ARCADIS, U.S., Inc. and a description of their calculation process is presented in Appendix A. The use of PET estimates to generate pool evaporation suggests there may be error associated with reservoir evaporation estimates. As a result, daily pan evaporation data measured in Clemson, SC were obtained and downloaded from NOAA’s National Climatic Data Center (NCDC) in order to remain as close to reservoir evaporation estimates obtained from actual pan evaporation data. Additionally, digitized monthly pan evaporation atlas maps were obtained from NOAA. The Clemson Class A pan period of record (POR) was 1949 - 2012 at the time of this thesis research.

The digitized evaporation maps are raster data sets, which represent long-term, monthly daily mean, free-water surface (FWS) evaporation estimates for the contiguous 48 United States.
The original evaporation atlas maps were developed by NWS by collecting pan evaporation and weather data from all registered Class A pan observation stations located within the United States. The POR used in atlas preparation was 1956 - 1970. NOAA was then able to develop long-term FWS evaporation contour maps for the United States using available climate data and pan evaporation measurements. Recently, NOAA digitized the FWS evaporation atlas as part of an ArcView application called the Calibration Assistance Program (CAP).

Daily mean FWS evaporation estimates for each month were generated for the five major SRB lakes using ESRI’s ArcMap interface.

### 3.1.4 Reservoir Modeling Data

It is necessary to use the most up to date reservoir simulation model and UIF data set to properly analyze water availability within the SRB. As a result, the current 2006-DCP model was obtained from the USACE Savannah District, located in Savannah, GA. Additionally, all UIF, LIF, NETEVAPF, and NETWU data sets, as well as the precipitation time series, P, area time series, A, and runoff coefficient values, ROC, were obtained from the Georgia Environmental Protection Division (GAEPD).

### 3.1.5 Future Water Use Data

Accurate predictions of future water use must be incorporated within the current 2006-DCP model to properly evaluate the effect of industry and population growth coupled with varying evaporation parameterizations. Due to the difficult and timely manner required to generate accurate future water use projections, water use projections were obtained from an HDR Engineering, Inc. report that was developed as part of Duke Energy’s Keowee-Toxaway Hydroelectric Re-licensing Project.

During the Keowee-Toxaway Re-licensing study, HDR Engineering, Inc. developed water use predictions based on four main water use categories: 1) Agricultural and Irrigation; 2) Thermal-Electric Power; 3) Public Water Supplies and Wastewater Utilities; and 4) Direct Industrial. A general approach was applied to generate the projections, in which historical water use data, where available, population growth predictions, developed by each state, power consumption per person data, and future plans of industry growth/decline were considered [23]. Projections were then
developed by using the data mentioned above, starting with a base year, 2010. Then, average-annual
rates were computed for each diversion in ten-year increments from 2016 - 2066 [23]. Furthermore,
the re-licensing water study was limited to withdrawals and returns that were greater than or equal
to 379 cubic meters per day, allowing for greater focus on significant water users along the basin.
Projected net withdrawal rates for each diversion in the SRB are presented in Table 3.2.

Table 3.2: SRB projected annual-average net withdrawal rates for major diversions, in cubic meters per second (cms), in descending elevation [23]

<table>
<thead>
<tr>
<th>Reservoir/Diversion</th>
<th>2010</th>
<th>2016</th>
<th>2026</th>
<th>2036</th>
<th>2046</th>
<th>2056</th>
<th>2066</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bad Creek Dam</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Jocassee Dam</td>
<td>0.20</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>Keowee Dam</td>
<td>2.80</td>
<td>3.26</td>
<td>3.88</td>
<td>4.90</td>
<td>5.49</td>
<td>6.09</td>
<td>6.77</td>
</tr>
<tr>
<td>Hartwell Dam</td>
<td>1.08</td>
<td>1.67</td>
<td>1.95</td>
<td>2.58</td>
<td>2.80</td>
<td>3.00</td>
<td>3.23</td>
</tr>
<tr>
<td>Russell Dam</td>
<td>-0.14</td>
<td>-0.17</td>
<td>0.20</td>
<td>0.14</td>
<td>0.08</td>
<td>0.45</td>
<td>0.40</td>
</tr>
<tr>
<td>Thurmond Dam</td>
<td>0.76</td>
<td>0.82</td>
<td>1.33</td>
<td>1.42</td>
<td>1.56</td>
<td>2.12</td>
<td>2.32</td>
</tr>
<tr>
<td>Woodlawn</td>
<td>-0.08</td>
<td>-0.11</td>
<td>-0.20</td>
<td>-0.28</td>
<td>0.00</td>
<td>-0.14</td>
<td>-0.34</td>
</tr>
<tr>
<td>Stevens Creek</td>
<td>0.68</td>
<td>1.10</td>
<td>1.64</td>
<td>1.76</td>
<td>2.27</td>
<td>2.38</td>
<td>2.49</td>
</tr>
<tr>
<td>North Augusta</td>
<td>0.93</td>
<td>1.08</td>
<td>1.30</td>
<td>1.61</td>
<td>1.95</td>
<td>2.41</td>
<td>2.94</td>
</tr>
<tr>
<td>Augusta Canal Diversion</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Augusta Canal Diversion Return</td>
<td>3.68</td>
<td>3.71</td>
<td>3.71</td>
<td>3.71</td>
<td>3.65</td>
<td>3.57</td>
<td></td>
</tr>
<tr>
<td>Augusta</td>
<td>-0.85</td>
<td>-0.85</td>
<td>-0.51</td>
<td>-0.62</td>
<td>-0.74</td>
<td>-0.85</td>
<td>-0.99</td>
</tr>
<tr>
<td>Girard</td>
<td>1.47</td>
<td>3.48</td>
<td>3.34</td>
<td>3.23</td>
<td>3.09</td>
<td>2.94</td>
<td>2.80</td>
</tr>
<tr>
<td>Millhaven</td>
<td>0.14</td>
<td>0.17</td>
<td>0.17</td>
<td>0.17</td>
<td>0.59</td>
<td>0.59</td>
<td>0.59</td>
</tr>
<tr>
<td>Clyo</td>
<td>0.31</td>
<td>0.31</td>
<td>0.28</td>
<td>0.68</td>
<td>1.10</td>
<td>1.08</td>
<td>1.05</td>
</tr>
<tr>
<td>Below Clyo</td>
<td>-0.34</td>
<td>-0.42</td>
<td>0.08</td>
<td>0.28</td>
<td>0.45</td>
<td>0.93</td>
<td>0.91</td>
</tr>
</tbody>
</table>

The average-annual net withdrawal rates developed by HDR Engineering, Inc. provided
some indication of future water use along the SRB. However, daily net water withdrawals needed to
be generated for use in the 2006-DCP model. As a result, inter-year average-annual net withdrawal
rates were interpolated using the data presented in Table 3.2 and an elliptical based interpolation
function. This provided a continuous yearly average net withdrawal rates from 2010 - 2066. The pro-
jected withdrawal rates determined by HDR Engineering, Inc. were average-annual rates and were
assumed to be representative of each day within the calendar year. Consequently, daily projected
water use rates were developed based on the average-annual rates.
3.2 Evaporation Modeling

The preferred method of estimating reservoir evaporation within the SRB was through the use of the three mass transfer methods, TBL, AERO, and HT, presented in section 2.2.4. Incorporation of hourly ASOS data and MODIS derived $T_s$ measurements was thought to help capture the diurnal variation of reservoir evaporation and provide more accurate estimates of lake evaporation. Therefore, the following sections detail the approach taken to estimate reservoir evaporation within the SRB using the three mass transfer methods. Additionally, one of the objectives of this research was to compare estimates of lake evaporation obtained via mass transfer methods using estimates obtained from the pan method as a baseline. Consequently, the technique applied to estimate lake evaporation using the standard pan method is also covered.

3.2.1 Mass Transfer Estimates

Ambient air temperature and relative humidity measurements obtained from the ASOS program are reported at a 2-m reference height above the ground surface, while wind speed measurements are reported at a 10-m reference height. Accordingly, the wind speed measurements were adjusted to a 2-m height. This was achieved for the TBL model by using the logarithmic boundary layer velocity profile given by [9]

$$\bar{u}(z) = \frac{u_*}{k} \ln \left( \frac{z}{z_{0m}} \right)$$

(3.1)

where $z$ is the height above the surface at which the wind speed is measured, and $z_{0m}$ is the momentum roughness length. For all wind speed height measurements, the von Karman constant and friction velocity were assumed to be constant, which allowed for a relation of wind speeds between two heights as

$$\bar{u}_2 = \frac{\bar{u}_1 \ln \left( \frac{z_2}{z_{0m}} \right)}{\ln \left( \frac{z_1}{z_{0m}} \right)}$$

(3.2)

where $z_1$ and $z_2$ refer to heights of the wind speeds for levels 1 and 2, respectively. However, using the above approach required appropriate values of $z_{0m}$.

Equation (3.1) can be used to estimate $z_{0m}$ for the wind speeds reported by the ASOS program, but friction velocity estimates, $u_*$, were required. For the case of the TBL model, Brutsaert
has defined the drag coefficient term, $C_d_r$ as [8,9]

$$C_d_r = \frac{u_s^2}{\bar{u}_r^2}$$

(3.3)

which can be re-arranged to obtain the friction velocity,

$$u_s = \bar{u}_r C_d^{1/2}.$$  

(3.4)

Various researchers have conducted experiments to obtain $C_{d10}$ values under neutral and near-neutral conditions. After examination of existing experimental results, Brutsaert concluded that a $C_{d10}$ value of $1.4 \times 10^{-3}$ appears to be a good overall average for relatively low wind speeds [9]. As a result of the relatively low wind speeds observed from the ASOS weather stations, the aforementioned $C_{d10}$ value was selected and assumed constant for all wind speeds. As a result, surface roughness values were calculated using the above $C_{d10}$ value, $\bar{u}_{10}$ measurements, and Eqs. (3.4) and (3.1). Next, Eqs. (3.2) and (3.3) were implemented to obtain scaled wind speed and drag coefficient values corresponding to a 2-m reference height.

Wind speed adjustments for the AERO and the HT method were obtained based on a simplified adjustment using the power law wind speed profile given by [21]

$$\bar{u}_2 = \bar{u}_1 \left( \frac{z_2}{z_1} \right)^{0.2}.$$  

(3.5)

The relationship in Eq. (3.5) is an empirical formulation that is often used to describe wind speeds at various heights within the atmospheric boundary layer (ABL), as well as general boundary layers. The exponent presented in Eq. (3.5) is an empirical constant, which corresponds to the relative roughness length of open-water surfaces [32]. The use of Eq. (3.5) provided an easy approach for estimating scaled wind speed measurements within the ABL [10] for both AERO and HT methods.

$C_1$ and $C_2$ values of 1.02 and 1.06 were selected from Table 2.2 and used for the 2-m height adjustment needed in the HT method. The general water vapor transfer coefficient, $C_e$, presented in the AERO method was approximated for a 2-m height using a power law function given by

$$C_e(z) = 0.00246z^{-0.355}$$

(3.6)
which gives a value of $1.92 \times 10^{-3}$ at a 2-m height.

Equation (3.6) was developed based on aggregating accepted values of field measurements and experiments at various locations and measurement heights [4, 21, 22]. This result is presented in Figure 3.5. Assuming that the values obtained from other researchers at the numerous testing sites are representative of the general physics of an evaporating surface, such as a lake or reservoir, the power law function presented in Eq. (3.6) was generated and found to have a coefficient of determination of 0.87, when compared to researchers accepted values.

![Figure 3.5: Accepted values of $Ce(z)$ for the AERO method.](image)

ASOS weather data provided hourly measurements of $T_a$, $\phi$, and $\bar{u}$. However, MODIS derived $T_s$ values were only available at the four overflight times corresponding to the Terra day/night and Aqua day/night overpasses. The polar orbiting nature of the Terra and Aqua satellites provides nearly constant daily overflight times, with minor fluctuations, associated with the $T_s$ data. Each MODIS $T_s$ data set was taken as having a constant overflight time while developing evaporation estimates. Averaging all available overflight times associated with each of the four MODIS data sets provided a good overall constant acquisition time for each lake $T_s$ data set. Overflight times for the
Terra and Aqua satellites, along with Lake Thurmond $T_s$ measurements, are presented in Figure 3.6. As a result, the assumed $T_s$ measurement times were 11 A.M., 1 P.M., 10 P.M., and 2 A.M. for Terra day, Aqua day, Terra night, and Aqua night MODIS data sets, respectively.

Figure 3.6: Data acquisition times for $T_s$ measurements obtained from Terra and Aqua satellites. $T_s$ measurements for Lake Thurmond are indicated by color in °C.

Due to the lack of available ASOS weather stations located within the SRB, an appropriate station thought to be representative of the weather data for each lake was selected. Based on the proximity of the ASOS stations to the SRB lakes, the ICAO:KCEU weather data was used for Lake Jocassee and Lake Keowee, ICAO:KAND was used for Lake Hartwell and Lake Russell, and ICAO:KAGS data was used for Lake Thurmond. Using the appropriate weather station, evaporation rates for each reservoir were calculated at the four MODIS overflight times. This was achieved by using $T_s$ values from the LST data and the corresponding hourly $T_a$, $\phi$, and $\bar{u}_2$ measurements. It is important to note that the evaporation rates obtained by the TBL, AERO, and HT methods were computed by scaling the hourly net evaporative flux by the water density calculated at $T_s$. Finally, the four hourly evaporation rates obtained from each method were averaged to give a daily estimate.
of reservoir evaporation.

No steps were taken to fill missing ASOS data. As a result, some gaps were present in $T_a$, $\phi$, and $\bar{u}$ data, resulting in missing daily evaporation estimates for several reservoirs. These gaps were filled using an elliptical based interpolation function, allowing for a continuous daily evaporation time series for each lake from July 2002 - December 2012.

3.2.2 Class A Pan Estimates

Measured pan evaporation values must be multiplied by a calculated pan coefficient, $K_p$, to appropriately estimate lake evaporation via the pan method. Pan coefficients for registered Class A pan evaporation observations have been developed by government agencies, researchers, and engineers, all concluding that a pan coefficient value of 0.70 is a good overall standard estimate [7, 16, 17]. Although a coefficient of 0.70 may provide a good initial estimate of lake evaporation, it has been found that pan coefficients can experience strong monthly variations [7, 16, 17]. Consequently, a monthly pan coefficient time series was developed for use with the pan method. Furthermore, due to geographical and geometric differences between each or the major SRB lakes, it was assumed that each lake would need its own set of unique monthly pan coefficients.

The pan coefficient, by definition, is described as the ratio of FWS evaporation to the measured pan evaporation [16]. Therefore, the monthly daily mean evaporation values obtained from the FWS grids and daily Clemson Class A pan observations could be used in determining monthly pan coefficients for each lake within the SRB. As a result, a technique was applied to obtain monthly varying pan coefficients for the Clemson Class A pan that describes individual lake evaporation estimates using the digitized FWS grids and daily Clemson Class A pan observations.

The FWS evaporation grids were developed using pan and pan observed meteorological data obtained from 1956 - 1970. Therefore, the monthly daily mean pan evaporation values corresponding to this date range were generated from the Clemson Class A pan evaporation measurements. Next, the monthly pan coefficients were estimated as

$$K_p = \frac{FWS_{\text{grid}}}{E_{\text{pan}}},$$

where $K_p$ is the monthly pan coefficient, January - December, $FWS_{\text{grid}}$ is the monthly daily mean FWS evaporation rate obtained from the digitized evaporation atlas maps, and $E_{\text{pan}}$ is the monthly
daily mean evaporation from the Clemson Class A evaporation pan.

Application of Eq. (3.7) resulted in a monthly pan coefficient time series to describe evaporation from each of the major SRB lakes using Clemson Class A pan observations. The monthly pan coefficients are presented in Figure 3.7, along with the monthly average evaporation for each SRB lake corresponding to the Clemson Class A pan POR. Figure 3.7 shows a large seasonal variation in \( K_p \). However, the overall average lake evaporation from each of the major SRB lakes were approximately equal with little variation in magnitude, which is a major downfall of using Class A pan measurements to estimate lake evaporation. Since the pan does not take into account the thermal behavior of the lake, regional variations of lake evaporation cannot be accounted for.

![Figure 3.7: Monthly derived pan coefficients, \( K_p \), (a) and average monthly lake evaporation corresponding to Clemson Class A POR (b): Jocassee (\( \triangle \)); Keowee (\( \bigcirc \)); Hartwell (\( \times \)); Russell (\( \square \)); and Thurmond (\( \bigtriangleup \)).](image)

A daily evaporation rate time series was developed for each of the major SRB lakes using the monthly derived pan coefficients. Some gaps occurred in the daily lake evaporation estimates, due to missing observations in the Clemson Class A pan data. As a result, daily lake evaporation time series obtained by pan observations were filled using a linear interpolation function.

### 3.3 Basin Hydrologic Modeling

Differences in the parameterization of the four evaporation methods, presented in Chapter 2, will ultimately lead to uncertainty in the overall estimates of reservoir evaporation along the SRB. These evaporation estimates play a significant role in modeling the hydrologic cycle, assessing water availability, and developing water-management and drought-contingency plans. As a result, a
proper understanding of the effect of uncertainty in evaporation estimates on basin water-availability predictions is paramount. Therefore, a method was applied to understand the response of the SRB reservoir network to the evaporation estimates described in sections 3.2.1 and 3.2.2.

3.3.1 Unimpaired Flow Development

An unimpaired flow represents the flow that would have naturally occurred without the influence of mankind, as discussed in section 2.3. A component of the UIF, and the motivation of this thesis, is the NETEVAP\textsubscript{F} occurring from each reservoir. The NETEVAP\textsubscript{F} time series currently used by USACE were developed by ARCADIS U.S., Inc. using NOAA pan evaporation observations, along with Hamon PET estimates. Consequently, the current UIF is not representative of the TBL, AERO, HT, and pan evaporation estimates described in section 3.2.

Although the UIF data in the current 2006-DCP model is not representative of the TBL, AERO, HT, and pan evaporation estimates, a UIF set independent of any one evaporation parameterization should be developed and used in the 2006-DCP model, mainly since the UIF is dependent upon the evaporation estimates used to develop NETEVAP\textsubscript{F}. Furthermore, the goal of this research was to understand the effect of uncertainty in evaporation estimates on the total water availability in the SRB. As a result, a single UIF data set for the basin was used as a baseline, while pool evaporation varied within the 2006-DCP model.

Developing a UIF data set independent of any one of the four evaporation methods was achieved by first generating NETEVAP\textsubscript{F} estimates for each of the evaporation methods. However, TBL, AERO, and HT evaporation estimates were not available until July 2002 and NETEVAP\textsubscript{F} data sets for each of the reservoirs required evaporation estimates at reservoir completion. Although, the TBL, AERO, and HT estimates were not available at reservoir completion, pan evaporation estimates were available starting in 1949, spanning the life of each reservoir. As a result, an approach was applied to project the MODIS derived evaporation estimates back to reservoir completion using pan based evaporation estimates.

A series of adjustment factors was developed for each of the three mass transfer evaporation time series to project MODIS-derived lake evaporation estimates back to reservoir completion. First, monthly evaporation rates were computed for each of the four evaporation methods using the daily evaporation rates described in section 3.2. A time series of monthly adjustment factors was then
developed for each of the SRB lakes from July 2002 - December 2012 given by

\[ K_{MT} = \frac{1}{n} \sum_{i=1}^{n} \frac{Em_{MT}(i)}{Em_{P}(i)} \]  

(3.8)

where \( K_{MT} \) is the monthly mass transfer evaporation adjustment factor, \( Em_{MT} \) is the monthly evaporation total estimated by the mass transfer method (i.e. MODIS derived \( T_s \) measurements), \( Em_{P} \) is the monthly evaporation total estimated from the pan method, and \( n \) is the total number of monthly ratios. Adjusted daily mass transfer estimates of lake evaporation were extended to reservoir completion for each mass transfer method given by

\[ Ed_{MT} = Ed_{P} \cdot K_{MT} \]  

(3.9)

where \( Ed_{MT} \) is the adjusted daily mass transfer evaporation estimate and \( Ed_{P} \) is the original daily pan evaporation estimate, as described in section 3.2.2.

\( NETEVAPE_F \) and \( UIF \) time series were then generated for each lake, as described in Eqs. (2.24) and (2.25), using the adjusted mass transfer evaporation estimates, pan evaporation estimates, \( ROC \) data, lake precipitation data, \( P \), and \( LIF \) data. This resulted in four \( UIF \) data sets for each of the five SRB lakes (i.e. TBL, AERO, HT, and pan). However, the current 2006-DCP model incorporates three additional \( UIF \) time series, aside from Jocassee, Keowee, Hartwell, Russell, and Thurmond. These time series are Bad Creek, Augusta, and Clyo.

Within the 2006-DCP model, Bad Creek flows are defined as 1% of Jocassee’s original \( UIF \), while the final Jocassee flows are defined as 99% of Jocassee’s original \( UIF \). Consequently, Bad Creek and final Jocassee \( UIF \) time series were computed by taking 1% and 99% of the previously described Jocassee \( UIF \) data set, respectively. Augusta and Clyo \( UIF \) time series do not incorporate \( NETEVAPE_F \) time series. Therefore, Augusta and Clyo flows were not altered. The final \( UIF \) time series used within the 2006-DCP model were obtained by averaging the four \( UIF \) data sets for each of SRB lakes. The result was a single \( UIF \) time series for Bad Creek, Jocassee, Keowee, Hartwell, Russell, and Thurmond, which was not solely dependent upon any one evaporation method.

3.3.2 Pool Evaporation

When the 2006-DCP model runs, the surface area of each reservoir is calculated using the simulated lake level and area-stage relationships. Next, the pool evaporation rates are multiplied
by the calculated surface area to obtain the pool evaporation flow, \( NETEVAP \). These values are then subtracted from the \( UIF \) data sets to simulate the addition of the reservoirs within the basin. As a result of the development process of the \( UIF \) described in section 2.3, the pool evaporation data used in the 2006-DCP model is actually represented as the net evaporation runoff rate given by

\[
NETEVAP_R = EV - P + ROC \cdot P
\]  

(3.10)

where \( NETEVAP_R \) is the net evaporation runoff rate.

The pool evaporation for each reservoir can be implemented as a constant monthly time series or a daily time series. Incorporating a daily time series within the model would generate more accurate results. However, since the SRB is modeled over the entire POR, “virtual” lakes are implemented prior to reservoir completion. Specifying a look-back elevation (i.e. the reservoir elevation the day prior to the simulation start date) constitutes the addition of each reservoir in the 2006-DCP model prior to the actual completion date. Since the lakes are “virtually” simulated prior to construction, the runoff flows that resulted from the land surface inundated by each reservoir must be subtracted out of the historically observed flows. The runoff flow concept is satisfied by \( ROC \), as seen in Eq. (3.10). However, a small problem still resides with the concept of the “virtual” lake.

Each lake is simulated and “added” into the SRB many years before the actual completion date. As a result, no surface temperature measurements exist for the lakes prior to completion. Moreover, pan evaporation estimates do not span the entire POR (1939-2008). Therefore, there is no way to predict reservoir evaporation using the aforementioned mass transfer method adjustments, as shown in Eq. (3.9), and a daily time series of pool evaporation cannot be implemented. Consequently, a constant monthly pool evaporation time series was incorporated into the 2006-DCP model for the entire simulated period, which is also currently done by USACE.

The first step in developing pool evaporation estimates for the 2006-DCP model was to identify POR years in which MODIS and pan derived evaporation estimates coexist. This time period was from July 2002 - December 2008. Next, daily lake \( NETEVAP_R \) time series were developed using the pan and mass transfer evaporation estimates described in section 3.2. The daily \( NETEVAP_R \) time series were then summed to generate monthly \( NETEVAP_R \) values. Lastly, the monthly rates
were averaged to produce the final monthly $NETEVA\overline{P}_R$ time series for each evaporation method and lake. It is important to note that monthly $NETEVA\overline{P}_R$ values were required for Bad Creek in the 2006-DCP model. The focus of this thesis research was on the major SRB lakes and the size of Bad Creek is negligibly small when compared to these lakes. As a result, the monthly $NETEVA\overline{P}_R$ values for Bad Creek were assumed to be equal to that of Lake Jocassee, due to the proximity of Bad Creek to Lake Jocassee.

3.3.3 Historical Reservoir Simulations

Reservoir simulations can be run over any date range from January 1939 - December 2008 using the historical $UIF$, $NETWU$, and monthly $NETEVA\overline{P}_R$ time series. As a result, historical simulations were run over the entire POR for each of evaporation methods (i.e. pool evaporation estimates). This was done to encompass as many historical drought periods as possible.

First, a new alternative within the 2006-DCP model was developed. The alternative was developed using the current 2006-DCP reservoir operational rules, routing steps (i.e. streams and reservoir routing computation methods), and general computation methods currently employed by the USACE. Time series inputs for the new alternative included the $UIF$ time series described in section 3.3.1 and daily $NETWU$ data. As stated in Chapter 2, the current 2006-DCP model used by USACE incorporates constant monthly net water use data at each diversion or constant daily discharge values. However, daily net water use data, where available, was incorporated in the new alternative. Daily net water use time series were available for Hartwell, Russell, Thurmond, Clyo, Augusta, and Millhaven diversions, while net water use was represented by constant monthly time series or a constant daily flow rate at the remaining diversions, as specified by USACE.

A simulation was developed for each of the four evaporation methods using the new alternative. The start and end date selected for each simulation was January 02, 1939 and December 31, 2008, respectively, while the look-back date was set to January 01, 1939. Each simulation was then computed using the $NETEVA\overline{P}_R$ monthly time series for each lake. This was done to ensure each simulation was identical in every aspect, excluding evaporation estimates.
3.3.4 Future Reservoir Simulations

The effect of future water use coupled with varying evaporation parameterizations was evaluated by implementing the daily projected water use time series, described in section 3.1.5, into the 2006-DCP model. It was assumed that the future hydrologic setting would remain similar to that of the historical alternative. As a result, a greater focus is placed upon the effect of future water use only without changing the hydrology settings along the basin. Consequently, the UIF data set described in section 3.3.1 was used with the future water use projections. Since the historical UIF data set was used with the future water use data, and water use projections were only provided for 57 years, a set of corresponding historical dates was selected for running future simulations. The date range selected for the analysis was 1952 - 2008, which corresponds to projected years for 2010 - 2066.

Similar to the historical simulations, a new alternative was developed in the 2006-DCP model. The future alternative incorporated the same operational and computational rules as the historical alternative. However, the UIF data implemented within the new alternative corresponded to the UIF time series from 1952 - 2008, not 1939 - 2008. Next, the projected daily water use time series for each diversion was placed into the alternative.

Three diversions defined in HDR’s projected net water withdrawals were not present in the 2006-DCP model and needed to be evaluated: 1) Below Clyo; and 2) Augusta Canal Diversion; and 3) Augusta Canal Diversion Return. During this thesis research, the Below Clyo diversion was not included, simply because the 2006-DCP used herein ends its hydrologic routing steps at the Clyo diversion. Additionally, the water use projections of the Augusta Canal Diversion were not included, due to their negligibly small nature (see Table 3.2).

The Augusta Canal Diversion Return presented some difficulty, as the 2006-DCP model incorporates an Augusta Canal Return, not an Augusta Canal Diversion Return. Unlike the remaining diversions mentioned in section 2.4, the Augusta Canal Return is a function of the flow at North Augusta, which removes flow from North Augusta, and does not remove water from the entire SRB system. Instead of changing the Augusta Canal Return operation and creating an Augusta Canal Diversion Return, the Augusta Canal Diversion Return water use time series were added to the Augusta Diversion water use time series. The final time series was applied at the Augusta Diversion.
After development of the future alternative, four simulations were developed and computed using the four monthly *NETEVAP* time series described in previous sections. The start and end date of each simulation was set to January 02, 1952, and December 31, 2008, respectively, while the look-back date was set to January 01, 1952. The future simulation represented the SRB behavior from January 2010 - December 2066.
Chapter 4

Results and Discussion

The previous chapter covered the details of estimating lake evaporation within the SRB using two general methods: 1) the Mass transfer method, along with high resolution surface temperature, $T_s$, obtained from the MODIS sensor; and 2) the Pan method, along with monthly derived pan coefficients. The reservoir network was then modeled with monthly $NETEVAP_R$ using historical and future water scenarios.

In this chapter, results of the lake evaporation estimates generated for the basin and their effect on water availability predictions are presented and discussed. Two sections are presented. The first presents an analysis of lake evaporation estimates from the three mass transfer models and the pan method. The second section examines the impact of uncertainty in lake evaporation estimates on water availability predictions.

4.1 Evaporation Analysis

In the first stage of this research, a continuous daily time series of evaporation rates was generated for each of the five major SRB lakes using all four evaporation models. The daily evaporation rates, in millimeters, generated for Lake Hartwell are presented in Figure 4.1, while results for Lake Jocassee, Lake Keowee, Lake Russell, and Lake Thurmond are presented in Appendix B. For all of the major SRB lakes, the pan method resulted in lake evaporation with a fairly smooth variation over time and with less scatter when compared with the TBL, AERO, and HT rates. However, the footprint of an underlying pattern was present in all four of the daily evaporation rates.
Long-term monthly averages were computed from the daily time series using the entire duration of the MODIS data set to reduce the effect of scatter on the method comparisons. Figure 4.2 shows that the general patterns of long-term monthly average evaporation among the three mass transfer methods were in good agreement. However, there were major differences between the underlying seasonal patterns associated with the pan and mass transfer based results. In general, the pan method showed greater evaporation during the summer months, while the mass transfer methods tended to show lower values during this period. Pan evaporation rates had a single peak during the year, while the mass transfer rates typically peaked in the spring and fall (i.e. April and September/October). The peak noted above is likely the result of heating, overturning, and stratification effects of each lake, effects which evaporation pans are not sensitive to.

Figure 4.2 also reveals that the mass transfer methods exhibited different seasonal trends for each lake. For example, Lake Keowee had two clear peaks during the year (i.e. spring and
Figure 4.2: Long-term average monthly evaporation corresponding to MODIS POR for TBL (□), AERO (△), HT (○), & Pan (○): (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond.
fall), while Lake Hartwell had only one clear peak, which was during the fall. When using the pan method, the underlying physics associated with a particular lake or reservoir cannot be properly accounted for. As a result, pan based evaporation rates for each of the lakes were very similar. It stands to reason that the differences in the physical and geometric properties of the lakes within the SRB result in different thermal and hydrological behavior over the course of the year, and that these features affect the evaporation rate from each lake.

The long-term average monthly lake evaporation for the TBL, AERO, and HT methods were scaled by average monthly pan evaporation rates to clearly show the difference between the mass transfer and pan rates. This result is presented in Figure 4.3, which was given by

\[ \alpha = \frac{E_{mm}}{E_{mp}} \]  

where \( E_{mm} \) and \( E_{mp} \) are the monthly mass transfer and pan evaporation rates, respectively.

Inspection of the ratios presented in Figure 4.3 helped to highlight the differences between the long-term average lake evaporation rates produced by the mass transfer methods and the pan method. In general, the mass transfer based evaporation rates tended to be slightly lower than pan based rates for the summer months, while the fall and winter months tended to be much higher. Jocassee, Keowee, and Hartwell showed very large seasonal differences between the mass transfer methods and the pan method, while Russell and Thurmond produced more constant ratios throughout the year.

Overall, the TBL method produced the highest \( \alpha \), followed by the HT and the AERO method. Although \( \alpha \) was slightly different for each of the mass transfer methods, the seasonal patterns associated with each method were nearly identical for a given lake. Figure helps 4.3 to reiterate the fact that differences in lake evaporation on a regional basis occurred and clearly demonstrates differences in the long-term seasonal patterns of lake evaporation within the SRB.

Yearly patterns were also compared during this thesis research. From the daily evaporation rates, yearly evaporation totals were calculated for each of the four evaporation methods. Yearly evaporation for each of the major SRB lakes is presented in Figure 4.4. It is important to note that since the MODIS study period did not begin until July of 2002, yearly evaporation totals for 2002 were excluded.

The yearly evaporation rates calculated for each of the major SRB lakes showed differences
Figure 4.3: Long-term average monthly evaporation ratio, $(\alpha)$, corresponding to MODIS POR for TBL (□), AERO (∆), & HT (◇): (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond.
Figure 4.4: Yearly evaporation corresponding to MODIS POR for TBL (⊙), AERO (△), HT (◊), & Pan (○): (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond.
from lake-to-lake among the mass transfer methods. However, a general pattern was present among all four evaporation methods. Each of the four methods showed an almost monotonic increase in yearly evaporation from 2003-2007. From 2007-2009 there was a decrease in evaporation, an increase from 2009-2011, and a slight decrease through the end of 2012. The TBL rates remained the highest, followed by HT and AERO methods, respectively. The yearly rates produced from the pan method appeared to remain nearly constant for each of the lakes, slightly increasing with the downstream lakes. This result is also presented in section 3.2.2. Furthermore, pan evaporation rates did not seem to consistently agree with any one of the three mass transfer methods for any of the lakes.

Average yearly rates were computed using the 2003-2012 yearly evaporation totals. These results are presented in Figure 4.5. Average yearly evaporation rates confirmed that the pan method

![Figure 4.5: Long-term yearly average evaporation.](image)

did not consistently agree with any one of the three mass transfer methods. The results presented in Figure 4.5 reveal differences between pan and mass transfer based lake evaporation rates that ranged from as little as 0.20 mm/yr. to as much as 500 mm/yr. (approximately 5 in/yr. and
This amount of evaporation equates to a considerable volume of water when displaced over the surface area of the larger lakes within the SRB, such as Hartwell and Thurmond. For example, while maintaining the full pool elevation of Lake Hartwell, the above amount of evaporation comes out to an estimated water volume of 28.8 million m$^3$ and 115 million m$^3$, equivalent to a total uncertainty of 86.2 million m$^3$.

The seasonal evaporation patterns were significantly different for the mass transfer methods and the pan method. However, similarity in the patterns between pan and mass transfer methods presented in Figure 4.4 suggests that as the measurement time scale increases, the two methods begin to approach the same behavior, although with different magnitudes. Consequently, scatter plots of the pan and the mass transfer evaporation rates were generated from the daily, monthly, and yearly evaporation time series to further explore the result noted above. For each time scale, lake, and mass transfer method, correlation coefficients were then computed between the mass transfer estimates and pan estimates. Sample plots for Lake Hartwell are presented in Figure 4.6, while the calculated correlation coefficients for each of the lakes are presented in Table 4.1. Results for Lake Jocassee, Lake Keowee, Lake Russell, and Lake Thurmond are presented in Appendix B.

Table 4.1: Daily, monthly, and yearly evaporation rate correlation coefficients between the three mass transfer methods and the pan method.

<table>
<thead>
<tr>
<th></th>
<th>Jocassee</th>
<th>Keowee</th>
<th>Hartwell</th>
<th>Russell</th>
<th>Thurmond</th>
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<tr>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>TBL</td>
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<td>0.23</td>
<td>0.27</td>
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<tr>
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<td>Monthly</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>TBL</td>
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<tr>
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<td>0.63</td>
<td>0.66</td>
<td>0.57</td>
</tr>
<tr>
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<td>0.63</td>
<td>0.63</td>
<td>0.66</td>
<td>0.57</td>
</tr>
<tr>
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<td>0.73</td>
<td>0.66</td>
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Overall, the pan and mass transfer evaporation rates started to become more correlated with an increasing measurement time scale. As shown in Table 4.1, there seemed to be little to
no correlation between the daily evaporation rates obtained from the three mass transfer methods and the pan method, the maximum correlation coefficient being only 0.38. However, from the daily to monthly evaporation rates, there was a large increase in the correlation between the pan and the mass transfer methods. Increasing the averaging period from monthly to yearly continued to strengthen these correlation coefficients. For each of the lakes and time scales, the HT method had the highest correlation with the pan method, followed by the AERO and the TBL method.

The result presented above is extremely important to consider when developing drought- and water-management plans. For example, many water managers may develop long-term drought plans on a yearly basis. In this case, implications of using one of the three mass transfer methods or the pan method may not be as severe, given that the yearly patterns were quite similar. However, the ability to model and monitor reservoir systems on a smaller time scale is becoming increasingly
important, due to changing and variable climatic conditions. When comparing the daily evaporation rate correlation coefficients, it is quite clear that neither of the three mass transfer estimates were in good agreement with the pan estimates. As a result, one particular method of estimating lake evaporation cannot be blindly used to model the SRB reservoir network.

Although the correlation coefficients increased with increasing averaging time, there was still significant variation from lake-to-lake at the monthly time scale. There are two possible explanations for this: 1) Misrepresentation of the weather observed over the lake surface; and 2) the Thermal inertia of the lakes. As a proxy for how well the climate data used in this thesis research represented actual weather observed for each lake, the distances from the nearby ASOS station to the point of the lake where the surface temperature measurements were recorded and plotted against the correlation coefficients for each model and time scale. These results are presented in Figure 4.7 Distances from the nearby ASOS stations to the lakes are 15.4 km, 18.1 km, 33.9 km, 45.8 km, and 46.5 km for Keowee, Hartwell, Jocassee, Russell, and Thurmond, respectively. Figure 4.7 reveals that there was no clear relationship between the distance from the nearest ASOS station to the lake and the correlation coefficient for each time scale. This suggests that representation of the ASOS weather data is not the cause of lake-to-lake variations in the correlation coefficients presented in Table 4.1. Even though there was no clear relationship between the evaporation correlation coefficients and the ASOS station distance, there is still a possibility that the stations used in this thesis research may not entirely represent surface conditions over each of the major SRB lakes. As a result, a comparison of the actual surface conditions, obtained from floating weather stations, of each SRB lake and weather data from the ASOS station used to represent those conditions is suggested. Only this comparison will disprove misrepresentation of the ASOS weather data.

The thermal behavior of a lake depends, in part, on its depth. For this thesis research, two depths were used as a proxy for the lake thermal inertia, the mean and maximum lake depth. The above depths are provided in Table 2.1 and it is important to note that both depths decrease when moving from Lake Jocassee downstream to Lake Thurmond. As a result, the correlation coefficients were plotted against the mean and maximum lake depths for all three mass transfer models and averaging times. These plots are presented in Figure 4.7. The results show that the pan and the mass transfer evaporation rates started to become less correlated for daily and monthly time scales, as the mean and maximum lake depth increased. Correlation coefficients for the yearly time scale appeared to remain fairly constant for each model and depth measurement. The daily and monthly
Figure 4.7: Pan to mass transfer model correlation coefficients for TBL (□), AERO (△), and HT (○): (a) Distance from nearby ASOS station; (b) Mean lake depth; and (c) Maximum lake depth.

results may be tied to the larger thermal inertia associated with the lake compared to the Class A evaporation pan. As the lake depth increases, an increased thermal inertia would result, while the Class A evaporation pan has negligible thermal inertia. It can therefore be argued that as the mean/maximum depth of the water body decreases, the lake should approach Class A pan behavior, and the correlation between pan and mass transfer evaporation rates should increase as observed in Figure 4.7.

4.2 Water Availability Analysis

The 2006-DCP model used in this thesis research allowed for the development of a continuous daily water surface elevation time series for each of the major SRB lakes with respect to the four pool evaporation estimates described in Chapter 3. Sample simulated Lake Hartwell daily water
surface elevations for the historical water use alternative are presented in Figure 4.8. Historical simulated reservoir elevations for Lake Jocassee, Lake Keowee, Lake Russell, and Lake Thurmond are presented in Appendix C.

Lake Hartwell’s daily simulated lake level showed a very clear pattern in the daily simulated water surface elevation, under normal hydrologic conditions (i.e. non-drought periods). The daily reservoir elevation results were directly related to the operational data sets that make up the 2006-DCP model. For example, during the fall, and under normal flow conditions, the virtual water manager, HEC-ResSim in this case, lowers Hartwell’s lake elevation from 201 m to 200 m from October to January, while raising the lake elevation from 200 m to 201 m from January to April. These levels are maintained throughout normal-flow conditions to account for heavy rainfall during the fall/winter and lighter rainfall during the summer. As a result, the pattern seen in Figure 4.8 was controlled by the operational and water-management plan built into the 2006-DCP model. Since
2006-DCP model imposes annual-minimum lake elevation regulations, annual-minimum reservoir elevations were only examined throughout this thesis research and the discussion of the remaining daily simulated reservoir elevations is not needed.

Evaluating uncertainty in water-availability predictions within the SRB requires the definition of total available water. In the case of municipal, industrial, and thermal power applications, the amount of water that is usable is that which lies above the critical intake elevation for each lake. Therefore, throughout this thesis research, the available water from each of the lakes was defined as the amount of water located above the critical intake elevation. The critical intake lake elevations for the major SRB lakes are presented provided in Table 4.2.

The annual-minimum distance from the critical intake elevation was computed for each of the SRB lakes and evaporation methods using the data provided in Table 4.2 and the daily simulated lake elevation data sets. This result was given by

$$\delta_C = z_{\text{min}} - z_{\text{intake}}$$  \hspace{1cm} (4.2)

where $\delta_C$ is the annual-minimum distance to the critical intake, $z_{\text{min}}$ is the simulated annual-minimum reservoir surface elevation, and $z_{\text{intake}}$ is the critical intake elevation. A physical representation of Eq. (4.2) is presented in Figure 4.9.

Throughout this thesis research, $\delta_C$ was used as a proxy for the amount of available water within each lake, while differences in the observed $\delta_C$ values were used as a proxy for the uncertainty in water-availability predictions. Furthermore, the objective of the availability analysis was not to evaluate whether any one method of estimating lake evaporation was more correct than the other, but to assess the uncertainty in water-availability predictions with respect to varying evaporation parameterizations, using the pan method as a baseline. As a result, the maximum, minimum, and average $\delta_C$ among the four evaporation methods presented herein were computed to illustrate this uncertainty. Results from the historical water use alternative are presented in Figure 4.10.

Figure 4.10 displays plots of $\delta_C$ versus the year for each of the five major lakes in the SRB based on historical water consumption. Presented are the maximum, minimum, and average values of $\delta_C$ for each evaporation model. The above results reveal the overall range of uncertainty in $\delta_C$ among the four evaporation methods. In general, each of the lakes showed some degree of uncertainty in the predicted $\delta_C$. However, the magnitude of the uncertainty was often minimal in
Table 4.2: Major SRB lake critical intake elevation summary [23].

<table>
<thead>
<tr>
<th>Lake</th>
<th>Critical Intake Elevation (M AMSL)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jocassee</td>
<td>329</td>
<td>Hydropower operations limitation .</td>
</tr>
<tr>
<td>Keowee</td>
<td>242</td>
<td>Oconee Nuclear Station Limitation.</td>
</tr>
<tr>
<td>Hartwell</td>
<td>194</td>
<td>Clemson University Central Energy Facility intake (Note: Although Clemson University’s Musser Fruit Farm irrigation intake is higher @ 197 m, in the event this intake is exposed, the facility can purchase water from the City of Seneca. Due to the alternate water source, the Musser Fruit Farm intake @ EL 197 m is not considered as the critical intake.</td>
</tr>
<tr>
<td>Russell</td>
<td>143</td>
<td>Hydro-power operations limitation .</td>
</tr>
<tr>
<td>Thurmond</td>
<td>95</td>
<td>Columbia County Water Utility (GA) and McDuffie County - City of Thomson (GA) raw water intake elevation (2nd highest of 3 intakes; if highest intake is exposed, the remaining two intakes are capable of meeting water demands, thus making the second highest intake the critical intake elevation); Hydro-power operations limitation.</td>
</tr>
</tbody>
</table>
Figure 4.9: Physical representation of an individual lake's water availability, $\delta_C$. 
Figure 4.10: Historical simulated yearly maximum (○), minimum (△), and average (□) $\delta C$ from 1939-2008: (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond. The $z_{intake}$ level is represented by a solid horizontal line and the revised Keowee $z_{intake}$ level is represented by a dashed horizontal line.
specific lakes. For example, Lake Keowee and Lake Russell showed minimal uncertainty, while Lake Jocassee, Lake Hartwell, and Lake Thurmond exhibited higher magnitudes of uncertainty. For all lakes, any observed uncertainty in $\delta_C$ did not seem to be residual and only existed for approximately 1-2 years, in most cases.

It is apparent from Figure 4.10 that Lake Keowee frequently fell below the critical intake elevation, provided in Table 4.2, during the historical simulates. This was due to the operational rules imposed on the Keowee reservoir within the 2006-DCP model. For example, the current water management plan in the 2006-DCP model maintains Lake Keowee above the elevation of 242 m (i.e. critical intake elevation), and allows Lake Keowee to fall to 240 m under drought conditions. The 2006-DCP management rule explains why negative values were observed in $\delta_C$ at Lake Keowee in Figure 4.10. Consequently, the 240 m critical intake elevation for Lake Keowee was used to calculate $\delta_C$ throughout the remainder of this thesis research.

The magnitude and degree of uncertainty in the predicted $\delta_C$ showed the effect of varying evaporation parameterizations on water-availability predictions. However, the time at which differences in predicted $\delta_C$ are observed in Figure 4.10 was an interesting result. Notable drought occurrences during the SRB POR (1939-2008) were 1938-44, 1950-57, 1965-70, 1976-78, 1980-82, 1985-90, 1993, 1995, 1998-2003, and 2006-09 [5, 15, 49]. While examining the results, it was clear that many of the periods when uncertainty was observed in the predicted $\delta_C$ corresponds to the above drought years, which makes logical sense. For example, it can be argued that under normal-flow conditions, uncertainty is minimized, due to the large amount of available water within the basin. However, under low-flow periods (i.e. drought periods), uncertainty in water-availability predictions, due to uncertainties in evaporation estimates, is magnified for many of the SRB lakes.

The range of uncertainty observed during several of the drought periods represented a significant fraction of available water within the basin and warrants further investigation by water-resources managers to achieve efficient and effective reservoir management during drought periods. For example, during 1988, Lake Jocassee, Lake Keowee, Lake Hartwell, Lake Russell, and Lake Thurmond experienced uncertainty in the simulated $\delta_C$ of 1.75 m, 0.03 m, 0.48 m, 0.05 m, and 0.43 m, respectively. Although these $\delta_C$ seem quite low, they represent a considerable volume of water. For example, the $\delta_C$ value of 0.03 ended up representing a total uncertainty in the predicted volume of available water of 1.93 million m$^3$ of water. According to water reports prepared by Greenville Water Systems, the City of Greenville, SC, population of 60,379 (U.S. Census Bureau
2011), pulled an approximate daily average of 102,000 m$^3$ from Lake Keowee during the 2012 fiscal year [20]. Consequently, an uncertainty in $\delta C$ by only 0.03 represents the City of Greenville’s daily water withdrawal from Lake Keowee for approximately 19 days.

Uncertainty in the predicted $\delta C$ of each lake was more prevalent during drought periods. During drought periods, water managers (i.e. Duke Energy and USACE) decrease the outflows of many reservoirs within the SRB to maintain an adequate water, causing many of the SRB lakes to experience lower reservoir elevations (i.e. smaller $\delta C$). Under the above conditions, the net evaporative loss from each reservoir now begins to represent a larger fraction of the total available water within the basin, when compared to normal-flow conditions. Consequently, the reservoir level and $\delta C$ is more heavily influenced by the evaporation occurring over the lake surface. In order to characterize this result, the annual range of $\delta C$ was plotted against the average annual $\delta C$ and is presented in Figure 4.11. The results presented in Figure 4.11 were given by

$$\Delta \delta C = \delta C_{max} - \delta C_{min}$$

and

$$\bar{\delta C} = \frac{1}{n} \sum_{i=1}^{n} \delta C(i)$$

where $\Delta \delta C$, $\delta C_{max}$, $\delta C_{min}$, $\bar{\delta C}$ are the annual range, maximum, minimum, and average $\delta C$, respectively, among the four evaporation methods, and $n$ is the total number of $\delta C$ values (i.e. one for each evaporation method).

Figure 4.11 shows a degree of scattering in the results. However, in general, as the reservoir pool elevation decreased from the full pool elevation, the observed uncertainty, $\Delta \delta C$, increased. Lake Keowee seemed to be the only lake that did not exhibit this behavior. In contrast, Lake Jocassee showed the largest range of results, while Lake Keowee and Lake Russell exhibited much smaller ranges. The Lake Jocassee result was coupled to the Lake Keowee result in that Jocassee is heavily managed in the 2006-DCP model (i.e. raised and lowered) to maintain Keowee at a nearly constant pool elevation, as needed for adequate power-plant operations. Each of the lakes, with the exception of Lake Russell, are lowered each year to a target minimum elevation, due to the absence or presence of rainfall. Lake Russell is kept at a nearly constant full pool elevation of 145 m, due to the critical intake elevation of the lake located at 140 m. As a consequence of water-management

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Figure 4.11: Historical simulated $\delta_C$ variation: (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.
and operational rules, $\delta C$ values for Jocassee, Keowee, Hartwell, and Thurmond were never equal to the full pool elevation. This result demonstrates that effective water-resources management under drought conditions requires a more detailed understanding of lake evaporation in the SRB.

Up till now, the results of the uncertainty in water-availability predictions, due to differences in evaporation estimates, have been presented only for the historical water use alternative. Now, the effect of industry and population growth on this uncertainty is presented for each evaporation method.

The distribution of $\delta C$ for each lake and evaporation method was computed to demonstrate the change in availability due to increased water demand. This was done for both the historical and the future water use scenario. While the distribution of $\delta C$ were being generated, only the last 57 years of data for each reservoir simulation scenario were used, corresponding to the years 1952-2008 and 2010-2066 for the historical and future scenario, respectively. The above interval was selected because future industry and population growth data was available only for 57 years, while the historical data was available for 70 years (i.e. the historical POR was from 1939-2008). Moreover, the future water use scenario incorporated the historical UIF data set from 1952-2008.

Sample histograms for Lake Hartwell’s $\delta C$ distribution are presented in Figure 4.12, while the summary statistics of each lake’s $\delta C$ distribution are presented in Table 4.3. Histograms for the remaining lakes are presented in Appendix C.

![Histograms](image_url)

Figure 4.12: Lake Hartwell $\delta C$ histogram: (a) Historical water use; and (b) Future water use. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.

The general patterns and shifts in the $\delta C$ distributions between historical and future water
Table 4.3: Summary statistics of $\delta_C$: (a) Historical water use; and (b) Future water use

<table>
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<tr>
<th></th>
<th>Model</th>
<th>Mean (m)</th>
<th>Std (m)</th>
<th>CoV</th>
<th></th>
<th>Model</th>
<th>Mean (m)</th>
<th>Std (m)</th>
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</tr>
</tbody>
</table>
use scenarios were very similar for all five lakes. Overall, the mean $\delta_C$ decreased for the future water use scenario, while the standard deviation (StD) and coefficient of variation (CoV) increased significantly. For example, Lake Hartwell’s mean $\delta_C$ for the TBL model decreased from 4.93 m to 4.72 m from the historical to future water use scenario. The standard deviation (StD) and coefficient of variation (CoV) increased from 0.68 m and 0.14 to 0.94 m and 0.20, respectively, from the historical to future water use scenario. Therefore, it can be argued that under the future water use scenario, uncertainty in the predicted available water increased.

During the development of water-resources plans and management schemes, engineers and scientists often evaluate the risk of failure by assigning an exceedence probability, $P_e$, to hydrologic events [11]. The exceedence probability is used as an indicator of the risk of failure of the system in any given year, while the average number of years between events is called the return period, $T$, given by

$$T = \frac{1}{P_e}. \quad (4.5)$$

Evaluating the return period of extreme events allows water-resources managers to assess the reliability of any hydrologic system. As a result, return periods were used as a proxy for the sensitivity of water availability predictions with respect to evaporation parameterizations coupled with increased water consumption. In Figure 4.13, the return periods are presented for each of the five major SRB lakes and evaporation method. The return periods presented in Figure 4.13 were generated by first computing an empirical cumulative density function (CDF) from each $\delta_C$ data set, as opposed to fitting probability distributions to each data set. This was done because each lake is heavily managed and this management negatively skews lake elevation data, making it difficult to fit distributions to the data. For this thesis research, an event was considered extreme when $\delta_C$ falls halfway between $z_{min}$ and $z_{critical}$. The extreme event can be thought of as 50% of the available water. Return periods, in years, were then computed using the extreme event distances, the empirically computed CDFs, and Eq. (4.5).

As shown in Figure 4.13, the AERO method generally produced the highest return periods for all lakes for both the historical and the future water use scenario. A clear pattern among the remaining methods was not present. In all cases, predicted return periods decreased when moving from the historical to the future water use scenario. In some instances, the overall observed
Figure 4.13: Lake return periods for falling within 50% of available $\delta_C$ under historical (black) and future (grey) water use scenarios: (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond.
difference between historical and future return periods was greater than individual return periods. For example, the distance observed between Lake Russell’s historical and future return periods for the AERO method was much larger than either of the return periods computed using the pan method.

For further illustrative purposes, the results of Lake Hartwell will be discussed. For Lake Hartwell, $\delta_C = 2.74 \text{ m}$ is half of the 5.49 m between $z_{\text{min}}$ and $z_{\text{critical}}$. Figure 4.13 illustrates that as water consumption increased, the return period for each evaporation method decreased. Furthermore, there was a considerable amount of uncertainty in the predicted return periods between the mass transfer methods and the pan method. For example, TBL, AERO, and HT methods had approximate historical return periods of 45, 58, and 56 years, respectively. The pan method produced a historical return period of 43 years. As a result, the return periods generated from the historical water use scenario had a total uncertainty of 15 years. However, uncertainty among the predicted return periods was only 7 years for the future water use scenario.

Figure 4.13 provides some indication of the uncertainty in the individual SRB lake’s water availability predictions as a function of uncertainty in evaporation estimates and increased water consumption. However, the SRB lakes are coupled and operate as a single network. As a result, the effect of one lake output will closely affect the operation and function of downstream and upstream lakes. Therefore, a complete basin evaluation is useful.

Due to differences in the stage-storage relationship among each of the major SRB lakes, a basin $\delta_C$ distribution cannot be developed. As a result, the daily simulated available storage volume was computed for each lake and evaporation method for both the historical and the future water use scenario. These values were then used to determine the SRB annual-minimum storage volume for each evaporation model and water use scenario. Next, the ratio of the available annual target minimum storage volume was computed for each water use scenario. This ratio was given by

$$\forall_{\alpha} = \frac{\forall_a}{\forall_t}$$

where $\forall_a$ was the annual minimum storage volume and $\forall_t$ was the annual target minimum storage volume. The $\forall_{\alpha}$ ratios provided SRB water-availability distributions for the historical and future water use scenario. Figure 4.14 presents SRB histograms of $\forall_{\alpha}$, while summary statistics of $\forall_{\alpha}$ are presented in Table 4.4.
As shown in Table 4.4, the AERO, HT and pan method all experienced a decrease of 0.03 in the mean \( \forall \alpha \), while TBL’s mean fell by 0.04. Increased water consumption caused the standard deviation (StD) to increase anywhere from 0.03 to 0.05. However, the coefficient of variation (CoV) increased by a range of 0.04 to 0.06. This result encapsulates the SRB uncertainty and variation in water availability with respect to not only evaporation, but increased water usage, making evaporation research in the SRB a major priority for water-resources managers.

Table 4.4: Summary statistics of \( \forall \alpha \): (a) Historical water use; and (b) Future water use.

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean</th>
<th>StD</th>
<th>CoV</th>
</tr>
</thead>
<tbody>
<tr>
<td>TBL</td>
<td>0.89</td>
<td>0.16</td>
<td>0.18</td>
</tr>
<tr>
<td>AERO</td>
<td>0.91</td>
<td>0.13</td>
<td>0.14</td>
</tr>
<tr>
<td>HT</td>
<td>0.90</td>
<td>0.14</td>
<td>0.16</td>
</tr>
<tr>
<td>Pan</td>
<td>0.90</td>
<td>0.16</td>
<td>0.17</td>
</tr>
<tr>
<td>-------</td>
<td>------</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>TBL</td>
<td>0.85</td>
<td>0.19</td>
<td>0.23</td>
</tr>
<tr>
<td>AERO</td>
<td>0.88</td>
<td>0.16</td>
<td>0.18</td>
</tr>
<tr>
<td>HT</td>
<td>0.86</td>
<td>0.19</td>
<td>0.22</td>
</tr>
<tr>
<td>Pan</td>
<td>0.86</td>
<td>0.19</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Basin return periods were generated using the \( \forall \alpha_{\text{alpha}} \) for a 50% minimum basin storage volume. The return periods are presented in Figure 4.15. Similar to individual lake return periods, the figure shows that the AERO method produced the highest return period for both the historical and the future water use scenario, approximately 40 and 30 years, respectively. Under the historical water use scenario, the HT method fell within approximately 4 years of the AERO method, while the HT and the pan method predicted return period was approximately 34 years.

Uncertainty in the predicted historical return periods among the three mass transfer methods
and the pan method was relatively small. Increased water consumption within the SRB greatly affected this result. During the future water use scenario, the TBL and pan method both predicted return periods of approximately 9 years. However, the AERO and the HT method predicted future return periods of 31 and 20 years, respectively. The range of predicted return periods for the future water use scenario created a total uncertainty of 22 years, as opposed to 7 years for the historical water use scenario. The increase in the return period uncertainty from 7 years to 22 years represents a 214% increase. An increase in uncertainty by that amount alone could have devastating impacts on water resources management in the SRB and ultimately limit the resiliency of the system in response to a drought period.

Figure 4.15: SRB return periods for falling within 50% of the annual minimum storage volume for historical and future water use scenarios.
Chapter 5

Conclusions

The TBL, AERO, and HT methods presented herein yielded evaporation estimates that were different in magnitude, but showed similar qualitative patterns when plotted versus time for a given lake and averaging period. The pan method pattern was significantly different from the mass transfer methods in both magnitude and seasonal behavior. The mass transfer methods generally produced lower rates of lake evaporation during the summer and higher rates during the winter months, when compared to the pan method. Additionally, as the time averaging scale was increased from daily to monthly and yearly rates, correlation between the two methods (i.e. mass transfer and pan) increased. Furthermore, daily and monthly correlation between mass transfer and pan rates both decreased with increasing lake depths. This suggests that lake thermal behavior begins to approach that of a Class A evaporation pan with decreasing depth, causing mass transfer and pan based estimates to converge.

Uncertainty in water-availability estimates were defined as the overall difference in the predicted available water. Throughout this thesis research, $\delta C$ was used as a proxy for the annual available water within a given lake. Uncertainty in the predicted water availability was generally only observed during drought conditions. Results showed that as the reservoir levels fell from their full pool elevation, uncertainty in the predicted available water, due to uncertainty in lake evaporation estimates, increased. This result demonstrated that as drought periods occur, resulting in lower reservoir levels, uncertainty in evaporation estimate begin to impact predicted water availability much more, when compared to normal-flow periods. During normal-flow periods there is an excess supply, so the lakes oscillate between full pond and their target annual-minimum, regardless
of the evaporation method. However, in low-flow periods, there is a deficit of supply and the lake levels decline. In this case differences in approximations in the evaporation rate are integrated over long periods of time, which leads to large differences in predicted lake levels and hence predicted availability. Uncertainty in water-availability predictions was magnified when water consumption increased, due to industry and population growth.

Basin return periods for exceedence probabilities under severe hydrologic stress provided some indication of uncertainty in water-availability predictions on a basin scale. The observed uncertainty in the predicted return periods was approximately 7 years for the historical water use scenario, while the return periods for the future water use scenario had an estimated uncertainty of 22 years. This result not only demonstrated the result of uncertainty in evaporation estimates on basin water-availability modeling, but also shows that increased water consumption increased this uncertainty by 214%.

The observed uncertainty in water-availability predictions is a direct result of the uncertainty in evaporation estimates within the SRB. Under normal-flow conditions, the uncertainty is small due to an abundance of water. As a result, any one of the four evaporation methods presented in this thesis may be used to evaluate water availability. However, under drought conditions, the uncertainty in evaporation estimates caused significant uncertainty in the total available water. Increased water consumption from industry and population growth caused this effect to intensify. The resiliency of the SRB reservoir system is a function of proper drought planning and sound water-management plans. Under low-flow and drought conditions, efficient and effective reservoir management is essential to human, industrial, and agricultural life. Due to the uncertainty in predicted water availability estimates under these conditions, a successful and well constructed water management and drought-contingency plan will only be achieved with a greater understanding of the evaporative loss along the SRB. Such methods include validating the results presented herein using floating pans and weather station monitoring devices located throughout each of the major SRB lakes.
Appendices
Appendix A   USACE Unimpaired Flow Data Set

USACE currently uses a set of unimpaired flows that were developed by ARCADIS U.S., Inc. to model the SRB reservoir network. The general inputs and overall components of the unimpaired flow calculation are presented in Figure A.1. Throughout this section, the general approach and data used to arrive at the current (i.e. ARCADIS U.S., Inc. flows) UIF data sets will be examined. Additional information on the data collection, inputs, and overall calculation process can be obtained from ARCADIS U.S, Inc [3].

The unimpaired flow calculation process, conducted by ARCADIS U.S., Inc., for the SRB began with daily historical observed stream flow data obtained from the United States Geological Survey (USGS) gauge records. The USGS gauge records are commonly referred to as the impaired flows and continuous impaired flow data was required to develop time series for proper and accurate calculations of UIF. As a result of missing stream flow records, ARCADIS U.S., Inc. took reasonable methods to “fill” or interpolate the missing data. Such methods or ratios used to interpolate and fill data included: 1) Multiple linear regression analysis; 2) Mean flow ratios; 3) Drainage area ratios; and 4) Hydrologic modeling [3].

The next step taken by ARCADIS U.S., Inc. was to remove the effects of reservoirs within the SRB. Reservoir physical and operational data were collected for each of the major reservoirs within the basin. The reservoir physical data were obtained from respective agencies, which included stage-storage-area curves, dam and outlet works dimensions, rating curves, and operational limits. Additional private power reservoir data was obtained from Georgia Power and Duke Energy companies. Operational data were obtained from the Tennessee Valley Authority (TVA) and US-ACE. The operational data was composed of observed time series or computed reservoir inflows, outflows, pool elevations, and state variables.

The generation of holdout flows is the result of placing reservoirs within any river basin. Holdout flows represent the change in storage upstream of a reservoir and can be represented by a volume flow rate. As a result of the change in storage, holdout flows were added back to the historically observed stream flows to simulate the flow that would have occurred prior to reservoir development. Holdout flows were calculated using a continuity relationship defined as

\[ I - O = \Delta S \]  

(A.1)
where $I$ is the reservoir inflow, $O$ is the reservoir outflow, and $\Delta S$ is the rate of change in reservoir storage (i.e., holdout flow).

Holdout flows represent only a portion of the effects a reservoir had on the naturally occurring flows within the SRB. The remaining reservoir effect, which must be accounted for in the unimpaired flow calculation, is the net-evaporation. Traditionally, net-evaporation is described as evaporation minus precipitation. However, a different concept of net-evaporation was introduced by ARCADIS U.S., Inc. for the UIF computation. Throughout the development of the unimpaired flows and the water availability modeling presented in this thesis research, net-evaporation accounts for the traditional net-evaporation, evaporation minus precipitation, from the reservoir surface after reservoir construction, as well as the runoff that would have naturally occurred from the land area that was “consumed” as a result of reservoir construction [3]. This was extremely important because when the reservoirs are “virtually” added into the system using HEC-ResSim, the runoff that occurred over the land covered by the reservoir must be removed from the historically observed flows.

Mean areal precipitation (MAP) time series were obtained by the Southeast River Forecast Center (SERFC) and the Lower Mississippi River Forecast Center (LMRFC) to develop net-
evaporation effects on each reservoir. The MAP time series were then extended by ARCADIS U.S., Inc. to fill any missing precipitation values. These time series represented the historically observed precipitation that took place over the major reservoirs in the SRB. Additionally, Spatial Climate Analysis Service Parameter-Elevation Regressions on Independent Slopes Model (PRISM) was used to develop additional precipitation time series used in the UIF calculation. Finally, ARCADIS U.S., Inc. adjusted the above precipitation time series by the ratio of the PRISM time series to the MAP time series. This provided daily precipitation time series for each of the major lakes within the SRB for the entire period of record (POR) (1939-2008).

Daily evaporation time series were developed in cooperation with Georgia Environmental Protection Division (GAEPD). The evaporation time series were generated by combining monthly evaporation estimates and daily potential evapotranspiration (PET) estimates. The monthly evaporation estimates represent the long-term monthly free-water surface (FWS) evaporation. Long-term, SRB, monthly evaporation estimates were determined for each reservoir using geographic information system (GIS) tools, pan evaporation atlas maps from the National Oceanic Atmospheric Administration (NOAA), monthly pan evaporation data from National Climatic Data Center (NCDC), and assumed pan evaporation coefficients. Next, the long-term monthly evaporation estimates were converted to daily FWS evaporation estimates using PET estimates. Daily PET time series were generated by GAEPD staff through the use of the Hamon method. The Hamon method of calculating PET is affected by the daily minimum and maximum ambient air temperatures and required a daily temperature time series. The Hamon (1961) method [52] of PET is given

\[
PET = 0.55D^2Pt
\]  

(A.2)

where \(PET\) is potential evapotranspiration in inch/day, \(D\) is the hours of daylight for a given day in units of 12h and \(Pt\) is a saturated water vapor density term calculated as

\[
Pt = \frac{4.95e^{0.062T_a}}{100} 
\]  

(A.3)

where \(T_a\) is daily mean air temperature in °C.

The Hamon method takes in account transpiration of water from plants. As a result, the effects of transpiration from the PET time series were removed by combining daily PET and long-term monthly evaporation estimates. Transpiration effects were removed by first determining
monthly PET values for the periods corresponding to the long-term FWS evaporation time series. Adjustment factors were then computed by taking the ratio of FWS evaporation to PET for each month. Next, the monthly adjustment ratios were assigned to the 15th of each month and linearly interpolated to mid-month values to generate a daily time series of adjustment factors. Lastly, the daily time series of adjustment factors was multiplied by the daily PET time series to obtain the daily FWS evaporation time series. Overall, daily PET time series for each lake were scaled by the ratio of the long-term monthly PET values to long-term monthly NOAA pan lake evaporation estimates. This allowed for the development of daily lake evaporation time series from daily PET time series by removing transpiration effects.

A runoff coefficient was determined and selected for each of the reservoirs to account for the runoff that would have naturally occurred had a reservoir not been placed within the river basin. ARCADIS U.S., Inc. conducted an analysis in which the mean annual stream flow was divided by the drainage area for each sub-basin within the entire SRB. The above computation produced mean annual runoff depths. The ratio of the mean annual runoff depth to the mean areal precipitation represented the final runoff coefficients for each lake.

Overall, net-evaporation reservoir effects consisted evaporation over the reservoir minus the precipitation on the reservoir and the addition of the runoff that would have naturally occurred over the reservoir, had the reservoir not been constructed. Using the concept described above, \( NETEVAPE \) were generated for the major SRB lakes, as described in Eq. (2.25).

The final step in determining the \( UIF \) was to remove the effects of water use by humans. Monthly water use data, if available, was obtained through GAEPD. Missing water use data, if present, was filled using water use data from neighboring states. The final \( UIF \) for each reservoir was then determined using the local incremental flows, net reservoir effects, and net water consumption, as described in Eq. (2.24).
Appendix B  Evaporation Results

B.1 Daily Evaporation

Figure B.1: Lake Jocassee daily evaporation for MODIS POR: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure B.2: Lake Keowee daily evaporation for MODIS POR: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure B.3: Lake Russell daily evaporation for MODIS POR: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure B.4: Lake Thurmond daily evaporation for MODIS POR: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
B.2 Correlation Scatter Plots

Figure B.5: Lake Jocassee pan to mass transfer evaporation scatter plots: (a) Daily rates; (b) Monthly rates; and (c) Yearly rates.
Figure B.6: Lake Keowee pan to mass transfer evaporation scatter plots: (a) Daily rates; (b) Monthly rates; and (c) Yearly rates.
Figure B.7: Lake Russell pan to mass transfer evaporation scatter plots: (a) Daily rates; (b) Monthly rates; and (c) Yearly rates.
Figure B.8: Lake Thurmond pan to mass transfer evaporation scatter plots: (a) Daily rates; (b) Monthly rates; and (c) Yearly rates.
Appendix C  Water Availability Results

C.1  Daily Reservoir Elevation

C.1.1  Historical Water Use Alternative

Figure C.1: Lake Jocassee daily simulated reservoir elevation from 1939-2008: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.2: Lake Keowee daily simulated reservoir elevation from 1939-2008: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.3: Lake Russell daily simulated reservoir elevation from 1939-2008: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.4: Lake Thurmond daily simulated reservoir elevation from 1939-2008: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.5: Lake Jocassee daily simulated reservoir elevation from 2010-2066: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.6: Lake Keowee daily simulated reservoir elevation from 2010-2066: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.7: Lake Hartwell daily simulated reservoir elevation from 2010-2066: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.8: Lake Russell daily simulated reservoir elevation from 2010-2066: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
Figure C.9: Lake Thurmond daily simulated reservoir elevation from 2010-2066: (a) TBL; (b) AERO; (c) HT; and (d) Pan.
C.2 Future Observed $\delta C$

Figure C.10: Future simulated yearly maximum (◯), minimum (△), and average (□) $\delta C$ from 2010-2066: (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond. The $z_{intake}$ level is represented by a solid horizontal line and the revised Keowee $z_{intake}$ level is represented by dashed horizontal line.
C.3 Future Variation of $\delta_C$

Figure C.11: Future simulated variation in $\delta_C$: (a) Jocassee; (b) Keowee; (c) Hartwell; (d) Russell; and (e) Thurmond. Full pool and $z_{min}$ levels are represented by a solid and dashed vertical line, respectively.
C.4 Histograms of $\delta_C$

Figure C.12: Lake Jocassee $\delta_C$ histogram: (a) Historical; and (b) Future water use. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.

Figure C.13: Lake Keowee $\delta_C$ histogram: (a) Historical; and (b) Future water use. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.
Figure C.14: Lake Russell $\delta_C$ histogram: (a) Historical; and (b) Future water use. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.

Figure C.15: Lake Thurmond $\delta_C$ histogram: (a) Historical; and (b) Future water use. Full pool and $z_{\text{min}}$ levels are represented by a solid and dashed vertical line, respectively.
Bibliography


