Climate Change Integrated Modeling Project

Phase I Assessment of Impacts on the New York City Water Supply

West of Hudson Water Quantity, Schoharie Turbidity and Cannonsville Eutrophication

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Executive Summary

This report describes the first phase of the Climate Change Integrated Modeling Project (CCIMP) to evaluate the effects of future climate change on the quantity and quality of water in the NYC water supply. The project is an element of DEP's Climate Change Action Plan released in 2008. The CCIMP is designed to address three issues of concern to NYC: (1) overall quantity of water in the entire water supply; (2) turbidity in the Catskill System of reservoirs, including Kensico; and (3) eutrophication in Delaware System reservoirs.

In CCIMP Phase I an initial estimate of climate change impacts is made using available GCM data sets and DEP's present suite of watershed, reservoir and system operation models. Phase I focuses on water quantity in the West of Hudson (WOH) System, turbidity in the Schoharie Reservoir and eutrophication in the Cannonsville Reservoir. An important component of Phase I is the development of methodologies and tools for linking models and data. These tools will be needed in further studies as we proceed into Phase II of the project.

The modeling and data components for Phase I include: output from four Global Climate Models (GCM); transformation of these results into data sets appropriate for model input and analysis; use of the Generalized Watershed Loading Function model, variable source area version (GWLF-VSA) to generate watershed hydrology and water quality inputs to the reservoir and water supply system models; a one-dimensional reservoir eutrophication model (UFI-PROTBAS); a two-dimensional reservoir turbidity transport model (CE-QUAL-W2); and the OASIS system operations model for the overall water supply. These models are connected and run in series with outputs from one model feeding inputs to other models. A number of system indicators of water supply quantity and quality were developed and used to measure climate change effects, including elements such as total water quantity, probabilities of refill, system wide drought warnings, keypoint turbidity levels, reservoir phosphorus and chlorophyll *a* concentrations, and phytoplankton functional group biomass.

General Findings of Phase I

The timing of the spring snowmelt is predicted to shift from a distinct peak in late March and April to being more evenly distributed throughout the winter and fall due to increased temperatures causing less precipitation to fall as snow, decreased snow accumulation and earlier snowmelt. The consequent shift in streamflow drives many of the findings obtained from applications of the water supply system and reservoir water quality models.

Increased winter stream flow leads to the WOH reservoirs filling earlier in the year, and increased amounts of water being spilled from the reservoirs during the winter-spring period.

For the WOH System, drought seems to be less prevalent in the future as the GCM scenarios used in this study tend to predict an increase in precipitation throughout the year, which compensates for the loss of snow water storage and increased evapotranspiration due to higher temperatures.

The shifting seasonal pattern in streamflow similarly affects the turbidity loads into Schoharie Reservoir and impacts Schoharie withdrawals, with increased turbidity in the fall and winter and decreased turbidity in the spring.

The nutrient loads to Cannonsville Reservoir also exhibit shifts similar to the streamflow shifts noted above. However, despite increased nutrient loads during the winter and fall, the response of the phytoplankton is small, presumably since unfavorable algal growth conditions coincide with the increased loading. The thermal structure of the reservoir is impacted by the warmer temperatures of the future climate with thermal stratification beginning earlier in the spring and lasting longer into the fall, and reservoir water temperatures increasing.

The findings presented in this report could be considered the “first cut” estimates of potential effects of climate change. Issues to be addressed in later phases of the project include:

- The use of more GCMs to gain a better understanding of the uncertainty in future climate predictions;
- Development of more sophisticated downscaling of GCM output to the scale of local watershed and reservoir model inputs, which will allow a more robust analysis including changes in storm timing in addition to storm event magnitude;
- Improvement of model linkages to allow for better feedback between water supply system operations and reservoir water quality;
- Better estimation of water quality loads to the reservoir through the use of more sophisticated watershed models that will better account for the climate change effects on critical biogeochemical and sediment transport processes;
- Feedback between climate change and potential changes in future land use, watershed management practices, and future water demand dynamics; and
- Better understanding of the robustness of the models and the potential errors associated with model applications under future climate conditions that may be different from the conditions for which the models were developed and calibrated.

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1. Introduction

The New York City (NYC) Water Supply (Figure 1.1) is composed of a system of reservoirs and conveyances that deliver more than 1 billion gallons (3.8 million cubic meters) of unfiltered drinking water per day to NYC and surrounding communities. The Climate Change Integrated Modeling Project (CCIMP) is a long term effort to evaluate the effects of future climate change on the quantity and quality of water in this supply, and to evaluate how climate change could influence the use and operation of the water supply. Projected future changes in air temperature and precipitation due to climate change may alter the availability and quality of water in the future by altering water supply hydrology (Brekke et al., 2009; Milly et al., 2005; Seager et al., 2007), including changes in the total amount and seasonal timing of flow entering the reservoirs; changes in seasonal patterns of reservoir storage; alteration of the partitioning of streamflow between hydrologic components; changes in the quantity and timing of transport of nutrients and other materials into and within the reservoir system; and possible alteration of ecosystem health and function, which could in turn affect both flow quantity and water quality.

Figure 1.1 Overview of the New York City water supply.

The nature and details of the potential impacts of climate change on the availability of high quality water is a primary long-term concern to the NYC Department of Environmental Protection (DEP) (DEP, 2009), and a critical question is whether a sufficient quantity of high quality water can continue to be provided under future climate conditions by the present water supply system and operating constraints. If water supply goals are not expected to be met in the future, changes to the system operation or infrastructure need to be addressed. The complexity of the

NYC water supply gives the system operators some degree of flexibility in choosing when to move water between different parts of the system in order to optimize reservoir storage and delivered water quality. This flexibility has been instrumental in DEP's ability to provide high quality drinking water to NYC and is expected to play an important role in adapting to future uncertainty related to climate change. This project is designed to provide the strategy, framework and tools to help in evaluating the effects of climate change on the NYC water supply.

Project Overview

Background

The CCIMP was an outgrowth of the DEP Climate Change Task Force. Project planning took place during 2006-2007. A series of meetings which included members of the DEP Bureau of Water Supply Water Quality Modeling Program, the Strategic Services Unit, the Bureau of Environmental Planning and Assessment, and the Columbia University Center for Climate Systems Research was used to develop an overall project strategy and plan (Major et al., 2007), which was evaluated by a leading group of climate change and water science experts. The work specified by this plan became an integral part of the task to "Quantify the Potential Climate Change Impacts on NYC Water Systems" in the NYC DEP Climate Change Program Assessment and Action Plan (DEP, 2008a). The CCIMP work is being performed as a joint effort between DEP in-house scientists and DEP-funded post-doctoral researchers from the City University of New York (CUNY) Hunter College.

Goals

The CCIMP was designed to be carried out in multiple phases. The first of these had the goal of making an initial estimate of climate change impacts using available Global Climate Models (GCM) data sets and DEP's present suite of watershed, reservoir and system operation models.

Phase I identified and addressed three issues of concern, the results of which are summarized in this report.

- Overall quantity of water in the entire water supply. Possible effects include altered inputs to the system, potential changes in the dynamics of the system (i.e., changes in the timing of inputs, spill, and drawdown), and resultant adjustments in reservoir operations. This study focuses on the West of Hudson (WOH) reservoirs, which supply approximately 90% of the City's supply.
- Turbidity in the Catskill System of reservoirs, including Kensico (Figure 1.1). Changes in the frequency, timing and intensity of precipitation may lead to increases in turbidity loading to Catskill System reservoirs. Increased turbidity inputs could become a water quality concern that would limit the use of Catskill System water, and could also require treatment of Catskill System water with alum. The Phase I turbidity simulations were run for Schoharie Reservoir and its watershed.
- Eutrophication in Delaware System reservoirs. Changes in the timing and magnitude of nutrient inputs to NYC reservoirs, as well as changes in reservoir thermal structure, could poten-

tially lead to future changes in reservoir trophic status. If the frequency and/or intensity of algal blooms increase, water use from some reservoirs may need to be adjusted, and water treatment could become more costly. The Phase I eutrophication studies were carried out for Cannonsville Reservoir.

Methodology

An added benefit of implementing Phase I was the development of methodologies and tools for linking models and data. The handling of large amounts of input data, the development of climate change scenarios, the complexity of connecting various climate, watershed, system and reservoir models, and the analysis of model results require significant time and resources. It has been critical, therefore, to produce tools and analysis methods that allow for repeating and refining the analysis as new climate data, improved models and more detailed questions are developed. For much of the Phase I work, the modeling group developed and improved model linkages and developed tools for running model simulations, manipulating data files and analyzing model results. These tools will continue to be valuable for further studies as we proceed into future phases of the project.

In Phase I, data from readily available GCMs were used to calculate delta change factors (Hay et al., 2000; Anandhi et al., 2009) representing mean monthly changes in the meteorological data needed to drive DEP's watershed and reservoir models. These models include: the Generalized Watershed Loading Function model, variable source area version (GWLF-VSA) (Schneiderman et al., 2002, Schneiderman et al., 2007); a 1-dimensional reservoir eutrophication model (Doerr et al., 1998; Owens, 1998; DEP, 2008b); a 2-dimensional reservoir turbidity transport model (CE-Qual-W2) (Cole and Buchak, 1995; Gelda and Effler, 2007); and the OASIS reservoir system operation model (HydroLogics, Inc., 2007; Gannett Fleming & Hazen and Sawyer, 2007). These four models can be connected as a system, with outputs from one model feeding inputs to other models (Figure 1.2). Together with the GCM based climate simulations, this modeling system made the first phase of the CCIMP feasible and readily obtainable. Watershed model simulations driven by climate change scenarios produce large data sets specifying watershed conditions and subsequent rates of hydrologic and nutrient loading to the reservoirs, while reservoir simulations produce detailed information on water quality and storage. A number of system indicators of water supply quantity and quality were developed and used to measure climate change effects.

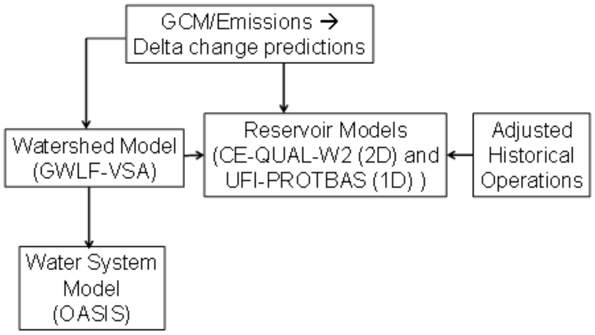


Figure 1.2 DEP's modeling system of water quality and supply system models used for Phase I simulations.

These indicators include elements such as total water quantity, probabilities of refill, systemwide drought warnings, turbidity levels at critical locations in the water supply system, reservoir phosphorus and chlorophyll *a* concentrations and phytoplankton functional group biomass.

Each aspect of this integrated program is described as follows:

Chapter 2 discusses the development of Phase I climate change scenarios utilizing the delta change factor method;
Chapter 3 discusses the GWLF-VSA watershed model simulations and results;
Chapter 4 presents results of the OASIS model for water quantity for the WOH System;
Chapter 5 investigates the climate change effects on turbidity in Schoharie Reservoir;
Chapter 6 describes the results of analysis of eutrophication in Cannonsville Reservoir.

2. Climate Change Projections

To examine the potential effects of climate change on the quantity and quality of water in the NYC water supply, future climate simulations are used as inputs to DEP's integrated suite of models (Figure 1.2). Global Climate Models (GCMs) are a good source from which future climate scenarios can be developed, since GCMs simulate the behavior of the global climate system, its components and their interactions. One difficulty encountered in using GCM simulations directly in our study is the mismatch of spatial scales between GCMs on the one hand, and local observations and local impact assessments in the NYC watershed on the other hand. For example, the area of typical GCM grid cells ranges between 40,000 km^2 and 90,000 km^2, while water quality model simulations are typically run on watershed areas of 25 to 1200 km^2.

Change Factors

A number of techniques have been employed to overcome the problem of mismatched spatial scales. Future climate scenarios have been derived (i) based on analogues with different climatic zones or historical time periods or (ii) from GCMs using simple manipulation of current climate observations (e.g., Change Factor Methodology, or CFM) and (iii) using more sophisticated statistical and dynamical downscaling methodologies (Wilby et al., 2000). Each has its own set of advantages and pitfalls (Semadeni-Davies, 2004). The CCIMP Phase I study used the second alternative—CFM. The major advantage in CFM (also referred to as delta change factor methodology) is the ease and speed of application, and the direct scaling of local observations to form a scenario based on changes suggested by the GCM simulations. Hence CFM is used in many climate change impact assessment studies (e.g., Semadeni-Davies et al., 2008) and programs across the world such as the US Global Change Research Program (http://www.usgcrp.gov/usgcrp/nacc/default.htm), and in a recent study of the effect of climate change impacts on lakes in Europe (CLIME, Schneiderman et al., 2009). However, there are some disadvantages to this approach. For example, the temporal sequencing of wet and dry days generally remains unchanged, so that the method may not be helpful in circumstances where changes in event frequency and antecedent conditions are important to the impact assessment (Gleick, 1986; Diaz-Nieto and Wilby, 2005).

Global Climate Models and Greenhouse Gas Emission Scenarios

The output from four GCMs was used in the Phase I climate change analyses: National Center for Atmospheric Research (NCAR), Goddard Institute of Space Studies (GISS), European Center Hamburg Model (ECHAM) and Canadian Centre for Climate Modeling and Analysis (CGCM3). Data and metadata from all of these models are available from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model data set. The NCAR, GISS and ECHAM results were supplied by Columbia University/GISS as part of a contract with DEP. The CGCM3 results were downloaded from the Canadian Centre for Climate Modelling and Analysis website http://www.cccma.bc.ec.gc.ca/.

The future emission greenhouse gas (GHG) emission scenarios used with the GCM models are from the Special Report on Emission Scenarios (SRES) (IPCC, 2000). These scenarios are derived based on how the greenhouse gases are projected to be emitted in the future, which in turn is based on how world population, economy, new technologies, energy resources, land use changes and political structure may evolve over the next several decades. The future climate is simulated by the GCM models for the various SRES scenarios for a period encompassing many decades into the future. The SRES A2, A1B and B1 emission scenarios representing future high, medium and low GHG concentrations were used to develop future climate change GCM simulations (IPCC, 2007), for two future time periods: 2046-2065 and 2081-2100. GCM simulations during the 1981-2000 period were used to represent current climate conditions. Table 2.1 lists the GCMs, the emission scenarios and the time slices used to develop the potential future climate scenarios to drive Phase I watershed and reservoir model simulations. The daily GCM results were downloaded for the grid box closest to the centroid of the WOH watershed. Daily GCM results representing six meteorological variables (precipitation, maximum, minimum and average temperature, wind speed and shortwave solar radiation) were obtained when available. Daily locally observed data for the same six meteorological variables were used to develop baseline model inputs and when combined with change factors (see below) were used to produce the future climate change scenarios for the NYC West of Hudson (WOH) watersheds.

Table 2.1: GCM, Emission Scenarios and Time slices used to develop potential future climate scenarios to drive Phase I watershed and reservoir model analyses.

GCM	Emission Scenarios	Time Slices	Watershed Modeling	System Modeling	Turbidity Modeling	Eutrophication Modeling*
ECHAM	A2 A1B B1	1981-2000 2046-2065 2081-2100	X	X	X	X
GISS	A2 A1B B1	1981-2000 2046-2065 2081-2100	X	X	X	X
NCAR	A2 A1B	1981-2000 2045-2064 2080-2099	X	X	X	
CGCM3	A2 A1B B1	1981-2000 2046-2065 2081-2100				X*

*For eutrophication simulations the CGCM3 model was used instead of the NCAR model since dew point temperature data needed for the reservoir model could not be obtained from the NCAR model results.

Change Factor Methodology

Change factors are based on the difference or ratio of a GCM result for a future time slice/ emission scenario combination compared to the current climate as simulated by the same GCM. This difference or ratio is then applied to a local observed data set, creating a new future climate time series that can be used as model input (Figure 2.1). For example, for an additive change factor (CF), one calculates the arithmetic difference between a GCM variable derived from a current-climate simulation and that derived from a future climate simulation taken at the same GCM grid location. This difference is then added to observed local values to obtain the modeled future values. The additive method, typically used for temperature (e.g., Hay et al., 2000; Akhtar et al., 2008), assumes that the GCM produces a reasonable estimate of the *absolute change* in the value of a particular variable regardless of the accuracy of the GCM's current climate simulation, or differences in the spatial scale between the GCM grid and the local measurement. Similarly, a multiplicative CF uses the ratio, rather than arithmetic difference, between the future and current conditions GCM simulations; the observed values are then multiplied by the CF. This method assumes that the GCM produces a reasonable estimate of the *relative change* in the value of a variable, and is used in our study for precipitation, wind speed and solar radiation.

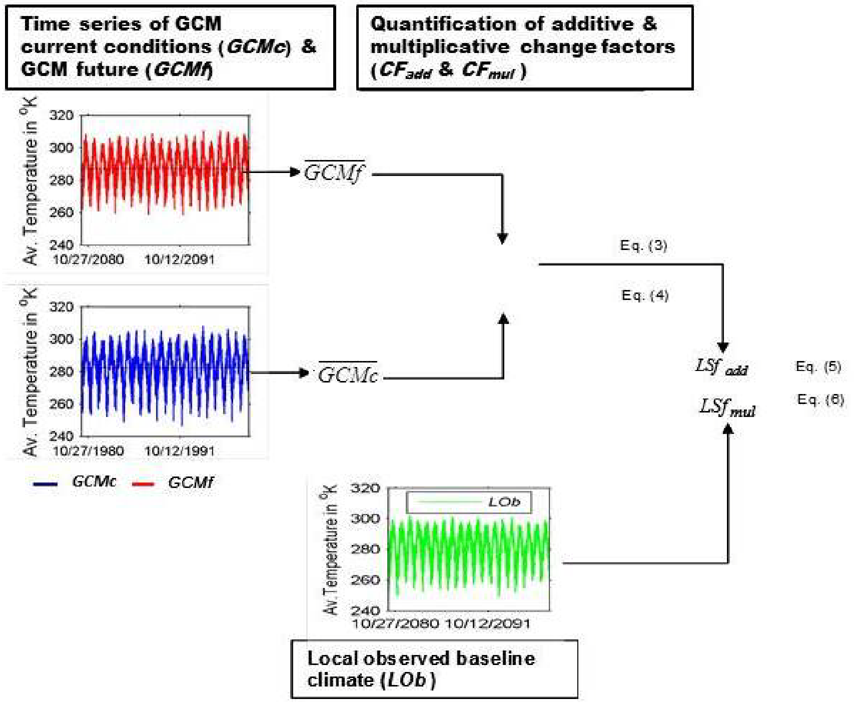


Figure 2.1 Methodology to estimate future scenarios using "Single additive" and "Single multiplicative" change factors.

When applying CFM the first step is to estimate the mean values of GCM simulated baseline and future climates:

$$\overline{GCMc} = \sum_{i=1}^{Nb} GCMc_i \Big/ Nc \tag{2.1}$$

$$\overline{GCMf} = \sum_{i=1}^{Nf} GCMf_i \Big/ Nf \tag{2.2}$$

where $\overline{GCMc}$ is the mean of a meteorologic data type as simulated by a GCM under current climate conditions for a particular averaging period, $\overline{GCMf}$ is the similar mean value based on a GCM future simulation. $GCMc_i$ are the daily simulated meteorologic data from the GCM for the current climate, $GCMf_i$ are the daily meteorologic data from the future GCM simulation, Nc is the number of data points in the averaging period for the current climate GCM simulation, and Nf is the number of data points in the averaging period for the future climate GCM simulation. In this study a single CF is estimated for each of the 12 months in a year. The temporal domain of $GCMc$ corresponds to the period 1981-2000, while the temporal domain of the two $GCMf$ time slices was 2046-2065 and 2081-2100. In Equations 2.1 and 2.2, the averaging period Nc would be equal to the number of days in all the January months during this time period 1981-2000. Nf would similarly be equal to either the number of days in all the January months during 2046-2065 or during 2081-2100 time periods depending on the time period the CFs are to be estimated.

Additive and multiplicative change factors (CF_{add} and CF_{mul}) can now be calculated:

$$CF_{add} = \overline{GCMf} - \overline{GCMc} \tag{2.3}$$

$$CF_{mul} = \overline{GCMf} \Big/ \overline{GCMc} \tag{2.4}$$

Future local climate time series ($LSf_{mul,i}$ and $LSf_{add,i}$) are then calculated by applying CF_{add} and CF_{mul} to a time series of locally observed baseline data:

$$LSf_{add,i} = LOb_i + CF_{add} \tag{2.5}$$

$$LSf_{mul,i} = LOb_i * CF_{mul} \tag{2.6}$$

An example of the application of the additive CFM for three months of a temperature time series is illustrated in Figure 2.2. The tabular data show how the CF is calculated as the difference in monthly average temperature for the future GCM time slice versus the current GCM period. The monthly CFs are then applied to the local observation (blue line) to produce the future climate scenario (red line).

	Jan	Feb	Mar
Current Period GCM Results	-5.4	-3.3	2.4
Future Time Slice GCM Results	-1.6	-0.2	4.0
Additive CF (Future-Current)	3.8	3.1	1.6

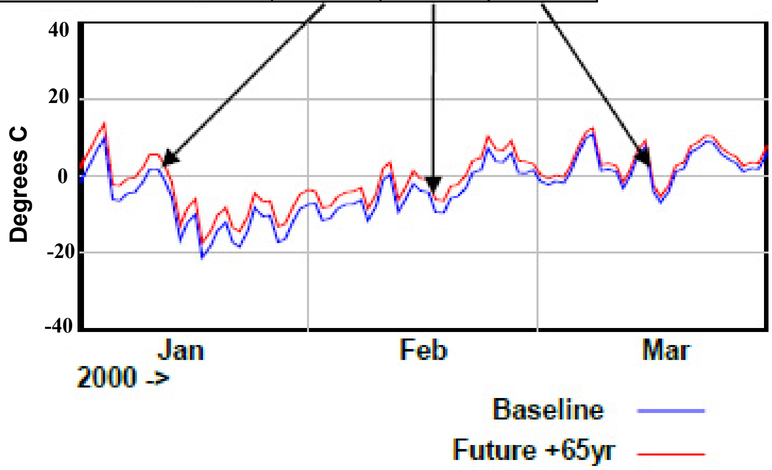


Figure 2.2 Application of an additive CFM for three months of a temperature time series. The tabular data show how the CF is calculated as the difference in monthly average temperature for the future GCM period versus the current GCM period. The CFs are then applied to the local observation (blue line) to produce the future climate scenario (red line).

Phase I Change Factor Results

Change factors representing mean monthly projected changes in precipitation, average, maximum and minimum air temperature, wind speed and solar radiation were calculated as described above. The monthly CFs are applied additively for air temperature and multiplicatively for precipitation, wind speed and solar radiation (Table 2.2) to daily historical data, generating a future climate scenario. The boxplots in Figure 2.3 show the range in the change factors associated with different GCMs and emission scenarios for air temperature, precipitation, wind speed and solar radiation for each of the future time periods.

Table 2.2: List of meteorological variables used to create scenarios for Phase I analyses.

Meteorological variable	CF Type	GWLF-VSA	CE-Qual-W2	UFI-PROTBAS
Mean daily air temperature	Additive	X	X[1]	X
Max daily air temperature	Additive		X[1]	
Min daily air temperature	Additive		X[1]	X[2]
Mean daily precipitation	Multiplicative	X		X
Mean daily wind speed	Multiplicative			X
Mean daily solar radiation	Multiplicative			X

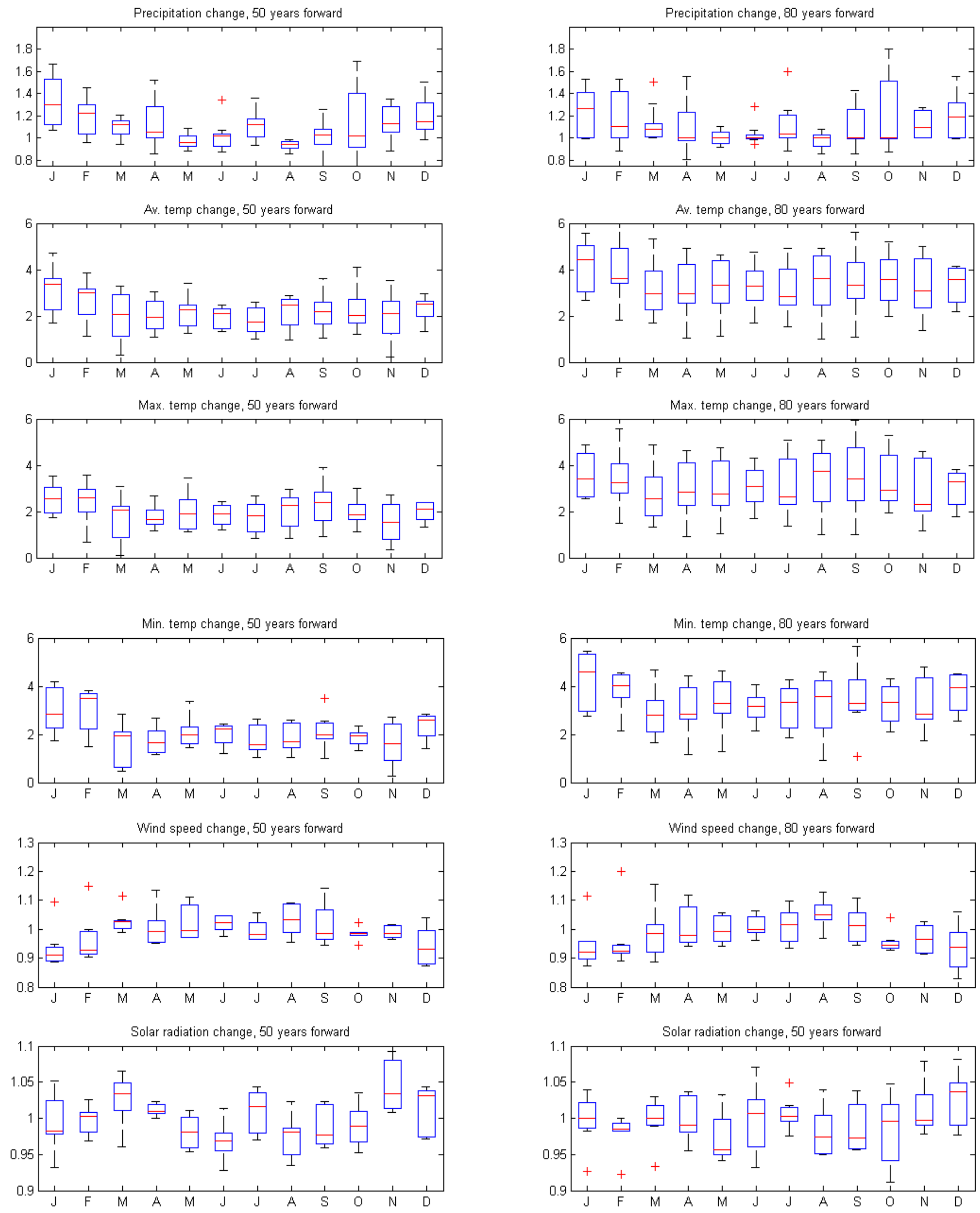
[1] Used to develop diurnal hourly variations in air temperature as described in Chapter 5. For Phase I simulations using the CE-Qual-W2 model, only air temperature was changed in the climate scenarios used to drive the model.

[2] Minimum daily air temperature was used as a proxy for mean daily dew point temperature when developing future scenarios of driving data for the UFI-PROTBAS model.

The CF values generally point to greater precipitation for most months and most scenarios; however there are some small decreases in most months for at least one GCM simulation. For temperature the CFs are positive for all months and more positive for the 2080-2100 simulations. The CFs for wind speed tend to imply decreases in winter values with more simulations indicating increases in spring and summer; however, most months have simulations with both increases and decreases. Solar radiation CFs show wide variability during each of the months with no clear trend.

The level of confidence in these initial projections is somewhat increased by employing an ensemble of GCMs and emission scenarios. It is not uncommon for output from different GCMs for the same geographic area to differ not just in magnitude but even in the direction of future change for some climate variables, reflecting different assumptions for key processes among the climate models. More confidence can be placed in projections when all future simulations of an ensemble agree in the direction of future change, and even more confidence can be inferred when the variability of the ensemble projections tightens. In this regard, projected increases in mean air temperature throughout the year are clearly more certain than the projected increases in precipitation, for which most months had at least one of the future simulations projecting no change or decreasing precipitation.

All monthly change factors used to create Figure 2.3 were applied to historical meteorological time series (using Equations 2.5 and 2.6) to produce 22 future climate scenarios (Table 2.1) for each meteorological variable needed as a driver for the watershed and reservoir models.


Precipitation change, 50 years forward

Precipitation change, 80 years forward

Av. temp change, 50 years forward

Av. temp change, 80 years forward

Max. temp change, 50 years forward

Max. temp change, 80 years forward

Min. temp change, 50 years forward

Min. temp change, 80 years forward

Wind speed change, 50 years forward

Wind speed change, 80 years forward

Solar radiation change, 50 years forward

Solar radiation change, 50 years forward

Figure 2.3 Monthly delta change factors for precipitation, temperature, wind speed and solar radiation. The box plots show the variability in the change factors calculated using data from multiple GCMs combined with multiple future emission scenarios. The mid-way line (red line) in the boxes shows the median value (50th percentile), the extent of the boxes show the interquartile range (25th (Q1) to 75th (Q3) percentile) of the change factors. The whiskers represent the lowest and highest values within the lower (Q1-1.5(Q3-Q1)) and upper (Q1+1.5(Q3-Q1)) limits, respectively. Points beyond the whiskers are displayed using '+'.

Future Work

Selection of GCMs and emission scenarios is an important consideration when using an ensemble of climate simulation results to address uncertainty in climate model output. The four GCMs selected for Phase 1 (Table 2.1) were in a sense chosen as an ensemble of opportunity—we obtained what was readily available at the start of the project. Presently the availability of GCM output has greatly increased. There are currently 23 climate modeling centers that produce GCM output. One professed strategy of the climate modeling community is to use the entire available ensemble to best account for uncertainty in climate model projections. Another strategy, to limit the number of models in the selected ensemble due to computing time constraints, is to select a subset of the available GCM models that best represents local historical conditions as evidenced by the relative match of current conditions GCM simulations to these historical measurements. Furthermore, the available ensemble is itself evolving as the climate model centers increase their focus on ESMs (Earth System Models), which more dynamically simulate atmospheric chemistry and the ecology of land and oceans at higher spatial and temporal resolutions. These ongoing developments underscore the preliminary nature of the Phase I analyses. Ongoing work will evaluate a wider range of GCM models and methods for determining the relevance of these data to the NYC water supply.

The change factor methodology for downscaling GCM output that we employed accounts for seasonal variation of climate change impacts, but does not consider changes in the intensity, frequency, or duration of storm events. One approach to capturing these impacts is the application of statistical change factors which represent varying changes in meteorological variables depending on the probability of occurrence of events of a given size (Anandhi et al., 2011). This and other potential improvements are being pursued as part of future phases of this project.

3. Watershed Hydrology

Before proceeding to an examination of the potential effects of climate change on supply system water quantity, Schoharie Reservoir turbidity, and Cannonsville Reservoir eutrophication, we present a discussion of the effects of future climate air temperature and precipitation changes on the various hydrologic processes that are the components of watershed water balance: precipitation; snowfall; snowpack development; direct runoff; baseflow; evapotranspiration (ET); streamflow; and soil moisture. This preliminary inquiry is important because projected changes in these processes are used as input to other watershed and reservoir models to drive the simulated changes in water quantity, turbidity, and eutrophication that are described in subsequent chapters. The chapter also introduces the GWLF-VSA model, which was employed by DEP to model these hydrologic processes, using daily time series of air temperature and precipitation as input.

We proceed first to a description of the GWLF-VSA model. From there we present a summary of the projected changes in critical model forcing inputs: air temperature and precipitation. We conclude with a review of the projected changes in water balance as reflected in changes to their hydrological components.

GWLF-VSA Model

GWLF-VSA (Schneiderman et al., 2007), a variant of GWLF (Haith et al., 1992; Haith and Shoemaker, 1987), is a lumped-parameter continuous simulation watershed model that simulates daily watershed water balance components including streamflow, snowpack and evapotranspiration (ET) based on daily inputs of precipitation, air temperature, solar radiation and relative humidity. Input precipitation is first determined to be either rain (liquid) or snow based on air temperature. Snow is accumulated in a snowpack which melts based on a degree-day formulation. Rain plus snowmelt is partitioned into direct runoff (i.e., surface runoff) and infiltration using a SCS Runoff Curve Number-based calculation. This partitioning is calculated separately for different combinations of land use and a soil wetness index based on the TOPMODEL soils-topographic index (Bevin and Kirkby, 1979; Schneiderman et al., 2007). The infiltration is then partitioned into two lumped (i.e., averaged over the whole catchment) subsurface reservoirs: an unsaturated soil zone from which water can be lost by ET and a deeper saturated zone that maintains baseflow. Streamflow is the sum of the direct runoff and baseflow. Potential evapotranspiration (PET) is calculated using the Priestley-Taylor method (Priestley and Taylor, 1972). Actual ET is either equal to PET under wet conditions or less than PET during dry conditions depending on the unsaturated zone soil water content.

Watershed Characteristics Input

The model requires temporally constant information about the soil properties, land use/land cover and topographic information. Land cover and land use (LC/LU) data for model input were derived from a combination of sources including an LC/LU classification derived from LandSat imagery from 2001, information from the New York City Watershed Agricultural Program to refine total agricultural areas, and New York State Department of Transportation GIS road data (DEP, 2006a). Sixteen land use classes are distinguished in the model classification: deciduous forest, coniferous forest, mixed forest, brushland, non-agricultural grass, cropland, permanent hayland, pasture, barnyard, rural roads, residential pervious and impervious, commercial/industrial pervious and impervious, wetland and water. Soils data, including available water capacity, saturated hydraulic conductivity and soil depth, are derived from the digital Soil Survey Geographic (SSURGO) Database (NRCS, 2005). Soils-topographic index values used in the GWLF-VSA were derived with the GIS from the soils data and a 10-meter digital elevation model (USGS, 1998).

Baseline Input

The baseline scenario represents the input forcing time series of the historical meteorologic model precipitation and air temperature forcings. The required daily precipitation and daily minimum and maximum temperature data were developed from cooperator stations recognized by the National Climate Data Center and were obtained from the Northeast Regional Climate Center (Figure 3.1). The daily precipitation station data are averaged for the each reservoir watershed using a Thiessen polygon method (Burrough, 1987). A reservoir watershed estimate of daily minimum and maximum air temperature was calculated based on an inverse distance weighting to four cooperator stations (Cooperstown, Liberty, Slide Mountain, and Walton) and an environmental lapse rate of $6^{o}C{\cdot}km^{-1}$ was applied to adjust for the difference in station elevation versus basin average elevation. Daily input times series were developed from 1927 through 2004.

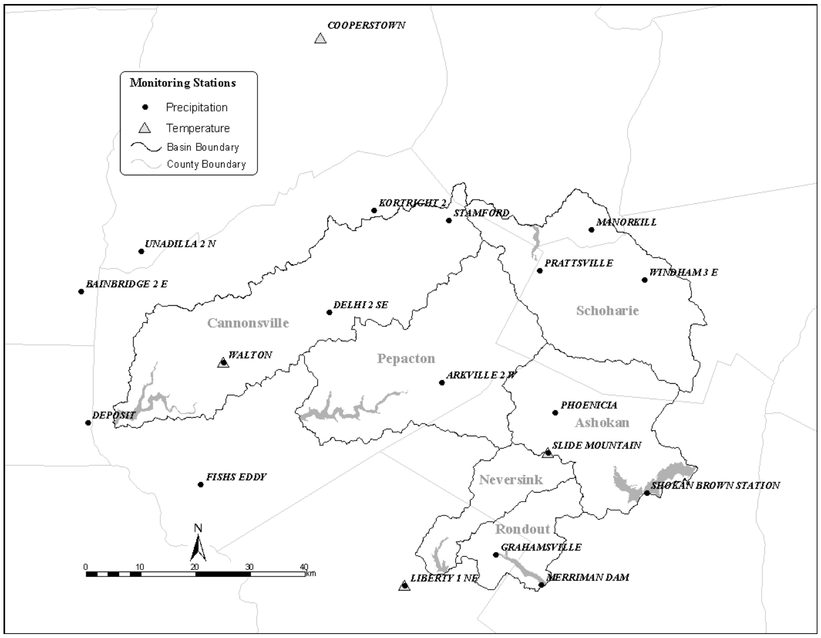
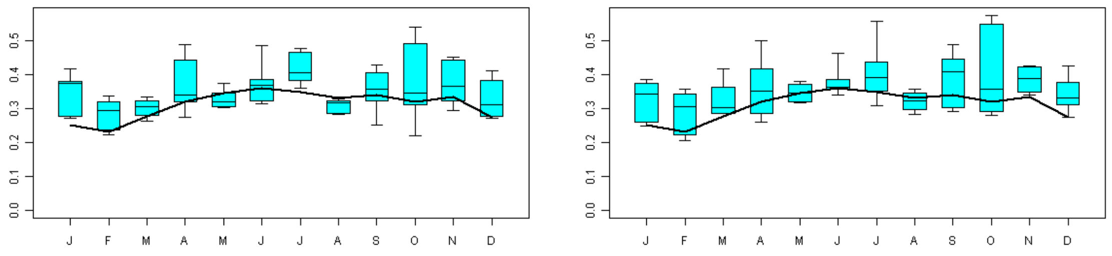


Figure 3.1 Location of daily precipitation (dots) and temperature (triangles) stations used for GWLF model input.

Future climate scenarios of air temperature and precipitation input time series were estimated for each reservoir watershed using the change factor method as described in Chapter 2. The simulations reported here were based on the ECHAM and GISS GCMs with the A1B, A2, and B1 emission scenarios, and the NCAR GCM with the A1B and A2 emission scenarios for two time slices (2045-2065 and 2081-2100) (Table 2.1). The locally observed baseline data set to which change factors were applied used the watershed-specific inputs of precipitation and air temperature from 1927 through 2004 described above. In total, 16 future climate scenarios (8 GCM/emission combinations x 2 time slices) for each model input variable were developed.

Figure 3.2 summarizes the projected changes in mean monthly precipitation and air temperature. Although each reservoir watershed has a unique climate, the graphs here depict the values areally averaged for all WOH watersheds. Mean monthly precipitation generally increases throughout the year. This increase tends to be more variable in the later time slice (2081-2100). Mean monthly air temperature consistently increases throughout the year, becoming more pronounced in the 2081-2100 time slice.

a) Precipitation (cm day^{-1}) 2046-2065 b) Precipitation (cm day^{-1}) 2081-2100



c) Average Daily Temperature (^{o}C) 2046-2065 d) Average Daily Temperature (^{o}C) 2081-2100

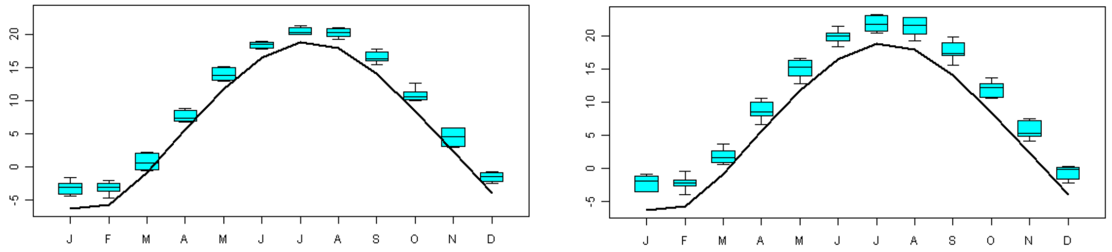
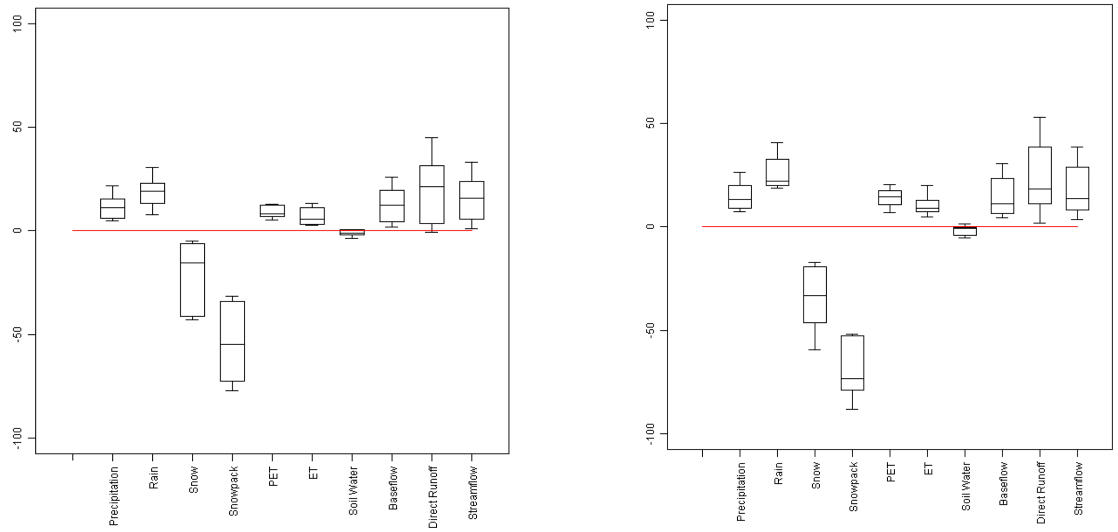


Figure 3.2 Monthly mean input precipitation (a,b) and input average daily temperature (c,d) for baseline and eight scenarios for the future 2046-2065 (a,c) and 2081-2100 (b,d) time slices, areally averaged over all WOH watershed. The line on the graph shows the baseline data, the midway line in the boxes shows the median value for the climate scenarios, the extent of the boxes shows the range of the middle six scenarios, and the whiskers show the range of all eight scenarios.

Projected Changes in Watershed Hydrology

To analyze the watershed water balance, the model was run for each reservoir watershed, using as input the baseline time series and the 16 daily time series of climate changed precipitation and air temperature generated as described above. This resulted in 17 scenarios for each of the modeled hydrological processes: one for baseline time series and 8 for each future time slice. The model results of the future climate simulations are compared to the simulation results using the baseline input to understand the potential effects of future climate change. Although the model was run separately for each reservoir watershed, the results presented here show the areal average of the water balance components for all WOH watersheds combined.

Annual water balance results from the GWLF-VSA model runs are summarized in Figure 3.3. On the whole, they show a general enhancement of the water cycle. As precipitation increases, streamflow increases, with both direct runoff and baseflow increasing. Similarly, as temperature increases, PET and ET are enhanced. The exceptions to these increased water balance components are snowfall and snowpack, which decrease due to increased winter temperatures. In addition, soil moisture tends to decrease slightly.



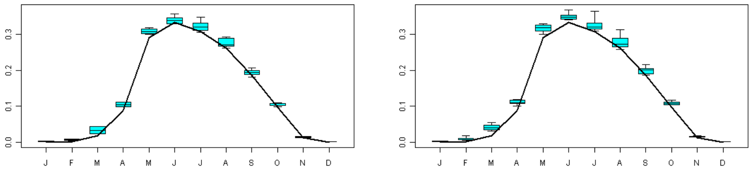
a) 2046-2065

b) 2081-2100

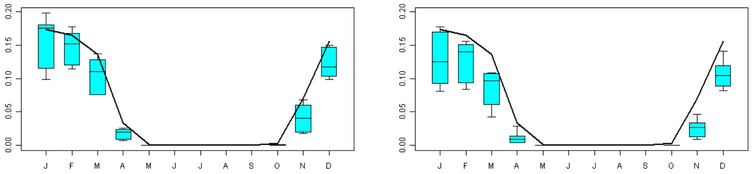
Figure 3.3 Percent changes in annual water balance results for eight scenarios for (a) the future 2046-2065 and (b) the future 2081-2100 time slices, areally averaged over all WOH watersheds. For each graph, the red line represents no change from baseline results, the midway line in the boxes shows the median value for the climate scenarios, the extent of the boxes shows the range of the middle six scenarios, and the whiskers show the full range of all eight scenarios.

Figure 3.4 shows the results for monthly means of the critical water balance components. Snowfall and snowpack are greatly decreased during the winter months, because increased temperature causes more of the precipitation to fall as rain, while the snowpack that does develop tends to melt faster and earlier in the year. These changes in snowpack accumulation and melt can be observed in the results for streamflow, which is projected to increase primarily in the late fall and early winter. This is due to the decrease in snow and increase in precipitation falling as rain. This seasonal shift in streamflow has already been found in recent streamflow trends in Catskill region streams (Burns et al., 2007; Zion et al., 2011). The peak magnitude of the traditional spring melt, however, is about the same or less than baseline conditions, since the accumulated snowpack leading into the spring is considerably reduced. In essence, the present day high flows of March and April are shifted to earlier in the year.

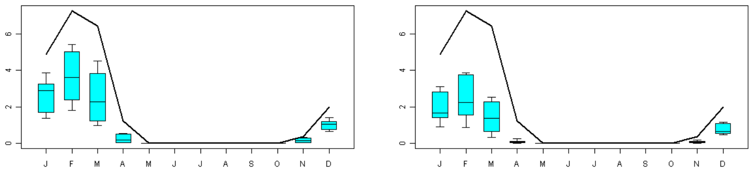
a) Evapotranspiration (cm day^{-1}) 2046-2065   b) Evapotranspiration (cm day^{-1}) 2081-2100



c) Snowfall (cm day^{-1}) 2046-2065   d) Snowfall (cm day^{-1}) 2081-2100



e) Snowpack (cm) 2046-2065   f) Snowpack (cm) 2081-2100



g) Unsaturated zone soil water (cm) 2046-2065   h) Unsaturated zone soil water (cm) 2081-2100

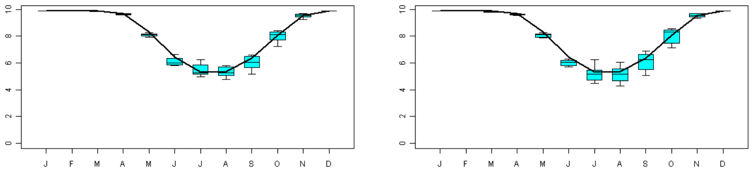
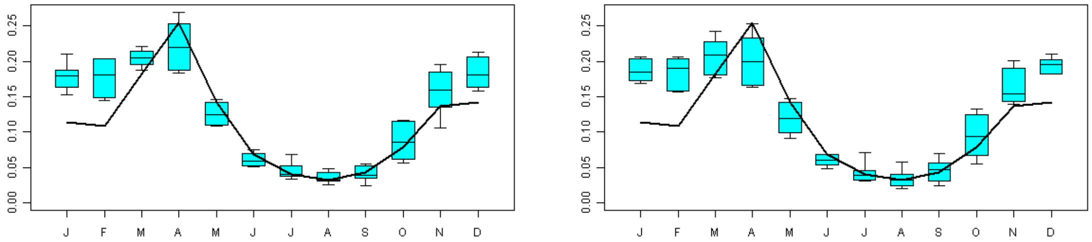


Figure 3.4 Monthly mean evapotranspiration (a,b), snowfall (c,d), snowpack (e,f) and unsaturated zone soil water (g,h) for the baseline and eight scenarios for the future 2046-2065 (a,c,e,g) and future 2081-2100 (b,d,f,h) time slices, areally averaged for all West of Hudson watersheds. Snowfall and snowpack values are in snow water equivalent (SWE) depths.

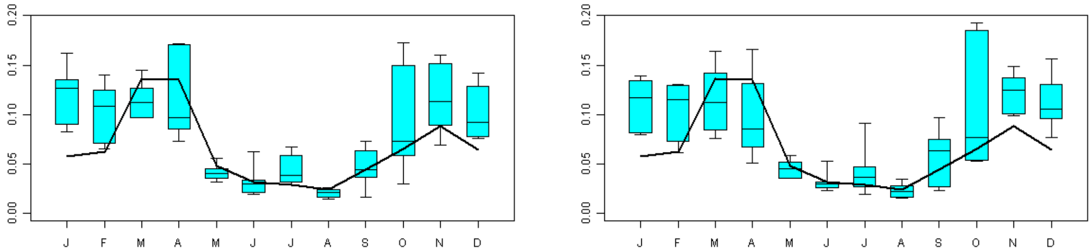
i) Baseflow (cm day^{-1}) 2046-2065

j) Baseflow (cm day^{-1}) 2081-2100



k) Runoff (cm day^{-1}) 2046-2065

l) Runoff (cm day^{-1}) 2081-2100



m) Streamflow (cm day^{-1}) 2046-2065

n) Streamflow (cm day^{-1}) 2081-2100

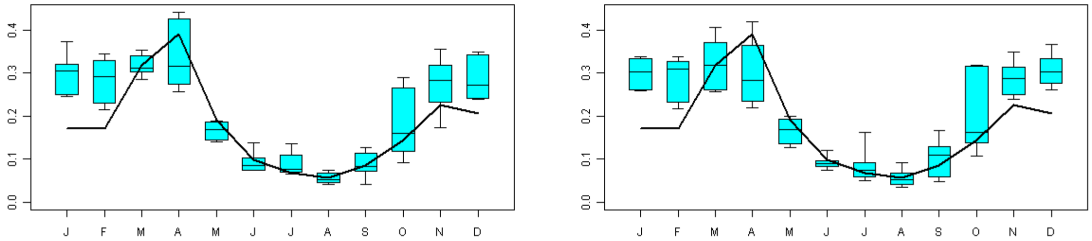


Figure 3.4 (cont.) Monthly mean baseflow (i,j), direct runoff (k,l), and streamflow (m,n) for the baseline and eight scenarios for the future 2046-2065 (i,k,m) and future 2081-2100 (j,l,n) time slices, areally averaged for all West of Hudson watersheds. Flows in cm day^{-1} represent per unit watershed depth values (flow volume divided by watershed area).

During the growing season, increased ET is balanced by increased precipitation and the mean monthly streamflow is largely unchanged. Despite increased precipitation, the average unsaturated zone soil moisture decreases slightly during the spring months. This is because the soil has a limited storage. The increased precipitation, therefore, does not increase the maximum soil moisture storage, but the increased ET rate in the future climate scenarios tends to enhance the decrease in soil moisture storage during inter-storm periods.

These results indicate that water balance will be affected in a number of ways due to increases in temperature and precipitation. Some of these predictions, however, can be made with greater confidence than others. Thus, there is a greater degree of certainty associated with the climate predictions for temperature, which are quite consistent between different GCM simulations (with temperatures increasing throughout the year in all cases) than with those for precipitation, whose changes are less consistent from month to month and from GCM to GCM (i.e., although precipitation increases in most months and in most future simulations, for each month there is at least one simulation that indicates decreased precipitation). The greater confidence in temperature predictions, in turn, suggests that the shift in spring streamflow timing and changes in ET, both of which are mainly due to the increase in temperature, should be treated with greater confidence than the apparent overall increase in annual streamflow, which is due mainly to the increase in precipitation.

4. Water Storage, System Operation, and System Performance

The management of large systems like the NYC Water Supply is complex, as it depends on watershed hydroclimatologic characteristics, reservoir capacities, reservoir operating rules, and system demands. Operational complexity is a consequence of the large number (19) of interconnected reservoirs and a decision-making process that includes meeting often competing goals to satisfy demand, balance storage in different parts of the system so as to maximize water availability and minimize spills, meet regulatory flow requirements, and maintain water quality standards imposed on the system. Spills are uncontrolled water losses over dams and other structures, whereas releases are deliberate (often regulated) losses. The term "withdrawals" refers to water taken for supply purposes.

The Catskill and Delaware Systems form the portion of the NYC water supply that is located west of the Hudson River (WOH) (Figure 4.1). This portion of the system supplies about 90% of the NYC water demand. Regulatory rules require the Delaware System to deliver water to the lower Delaware River that serves New Jersey and Pennsylvania. The Croton System provides the east of Hudson (EOH) portion of the water supply (approximately 10% of the total).

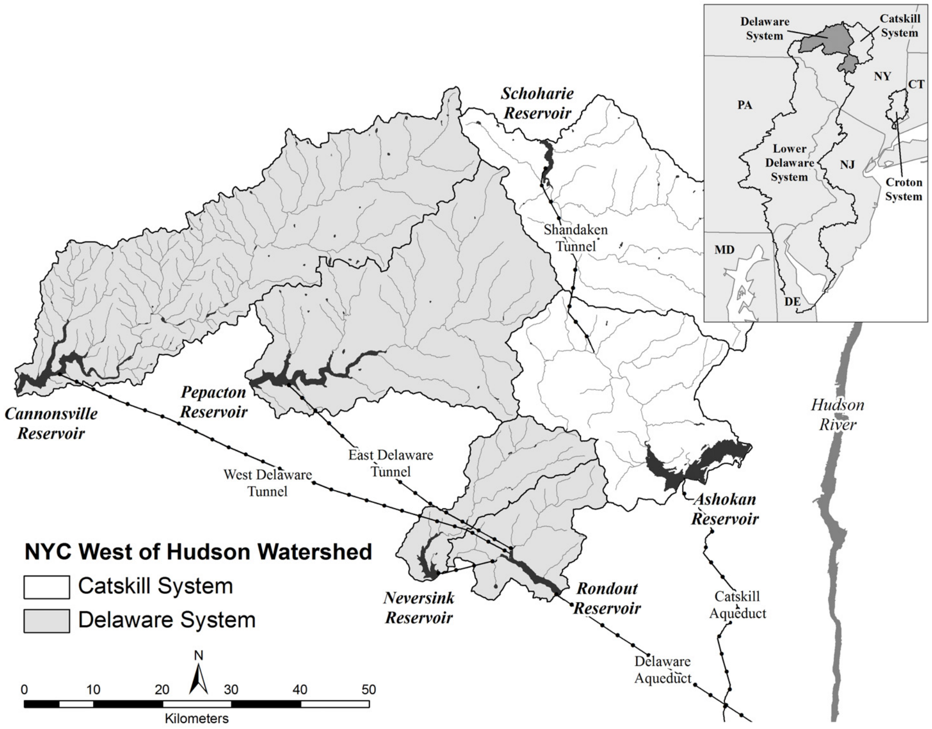


Figure 4.1 The West of Hudson (WOH) watershed, showing reservoirs and aqueducts for the Catskill and Delaware Systems. The inset map displays the East of Hudson (EOH) and Lower Delaware (LD) Systems. Mandated release to the LD affects water supply operation.

To investigate the effects of climate change on the operational state of the system and the quantity of water stored within it, Phase I of the CCIMP examined future scenarios for reservoir storage, inflow, release, and spill, indicators that provide important information for daily operation of the system. A further set of indicators was used to evaluate the system's overall performance based on these projections of system status. The performance indicators—drought status; probability of refill by June 1; system resilience, reliability, and vulnerability—provided assessments of the system's ability to satisfy demand under changing conditions over seasonal and longer time scales.

Methodology

Two models—the GWLF-VSA model described in Chapter 3 and the OASIS system model—were employed for this purpose. OASIS is a reservoir system model which simulates water supply system operations and provides assessments of supply status based on a set of rules that represents current system operating policies. These rules are based on empirical knowledge accumulated during years of operating the system, and target multiple objectives, including meeting water demands, meeting regulatory release requirements and Surface Water Treatment Rule turbidity standards, and balancing diversion from the Delaware, Catskill, and Croton Systems.

For this study, OASIS used as inputs the inflow scenarios produced by running the ECHAM, GISS, and NCAR precipitation and temperature climate change projections (Chapter 2) through the GWLF-VSA model (Chapter 3). Future water demands were assumed to be the same as current demands, and system rules were left unchanged from current conditions. The simulated results for the various water supply indicators are described below. The storage, release, spill, drought conditions, and probability of refill scenarios were simulated directly by OASIS, while the analysis of projected system resilience, reliability, and vulnerability were derived from calculations based on those simulations. Although projections of future inflow have previously been described in Chapter 3, those descriptions were based on an average of all WOH watersheds, and focused on the effects that future changes in the components of watershed hydrology might have on the volume and seasonal pattern of streamflow. Here, we look more closely at the projected changes in streamflow volume and seasonality, and their impact on NYC water supply management, by examining each WOH system separately (Catskill and Delaware) and by describing the patterns of variability in the various indicators of the system operational status and long-term performance associated with the inflow scenarios produced by the three GCMs.

Results

Inflow, Storage, Spill, and Release

Figure 4.2 presents boxplots of the annual inflows to the Delaware and Catskill Systems of the WOH portion of the water supply. The values used to generate the boxplots for each scenario are the means, for all reservoirs in the system, of the mean annual inflows for each year of the time slice.

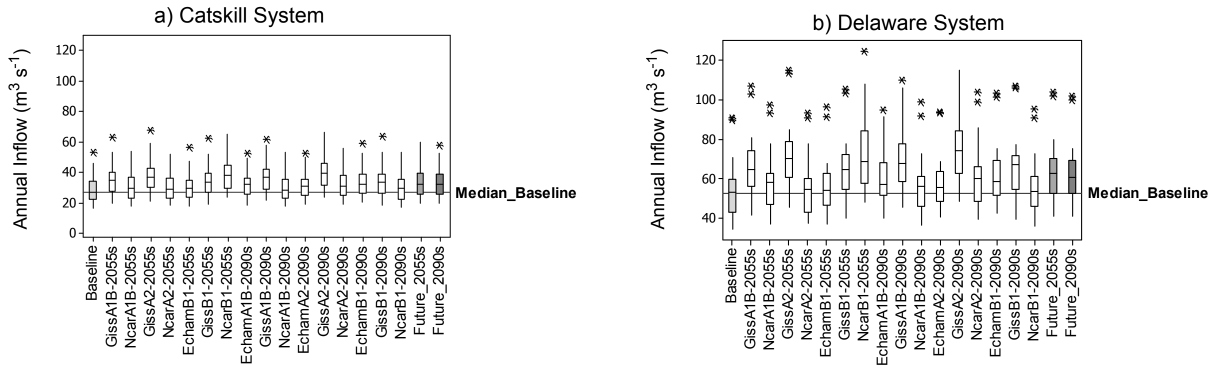


Figure 4.2 Annual inflow for baseline (light grey boxplots) and different future climate scenarios (white boxplots) for the Catskill and Delaware Systems. The medium and dark gray boxplots (at the right side in both graphs) represent the mean of all scenarios for the future 2046-2065 (2055s) and 2081-2100 (2090s) time periods**.** The lower and upper bounds of the boxes represent the 25th (Q1) and 75th (Q3) percentiles, the whiskers the lowest and highest values within the lower (Q1-1.5(Q3-Q1)) and upper (Q3+1.5(Q3-Q1)) limits, respectively. The stars are outliers. The horizontal lines within the boxes are the medians. The horizontal lines extending across the entire width of the graphs represent the median for the baseline scenarios.

On an annual basis, most future streamflow scenarios indicate an increase in median projected inflow as well as a relatively large range in variability in future flow levels. Although the magnitude of Delaware inflows is greater due to a larger watershed area, the patterns of inflow variability given by most of the three GCM models used in the analysis is similar for both the Catskill and Delaware Systems. As between the GCMs, the results are mixed, but the GISS model does have a tendency to produce somewhat greater inflows. For both systems, no significant difference (α=0.05) could be found between the aggregate flow volumes simulated to occur in the 2046-2065 and 2081-2100 periods (Matonse et al., 2012).

Seasonal patterns in reservoir inflows are shown in Figure 4.3 for the Delaware and Catskill Systems. These results indicate an increase in inflow from October through February, with larger increases for the second time slice (2081-2100). During this period, the reservoirs are fuller (Figure 4.4a,b) and releases appear to increase (Figure 4.4c), consistent with the high inflows predicted for this period. The plots for April, May, and June indicate a decrease in future inflow followed by a three-month period with relatively minor changes in inflow volume between baseline and future predictions. As discussed in Chapter 3, earlier snowmelt and greater streamflow associated with higher winter temperatures (see also Figures 3.2 and 3.3) explain these seasonal changes in inflow.

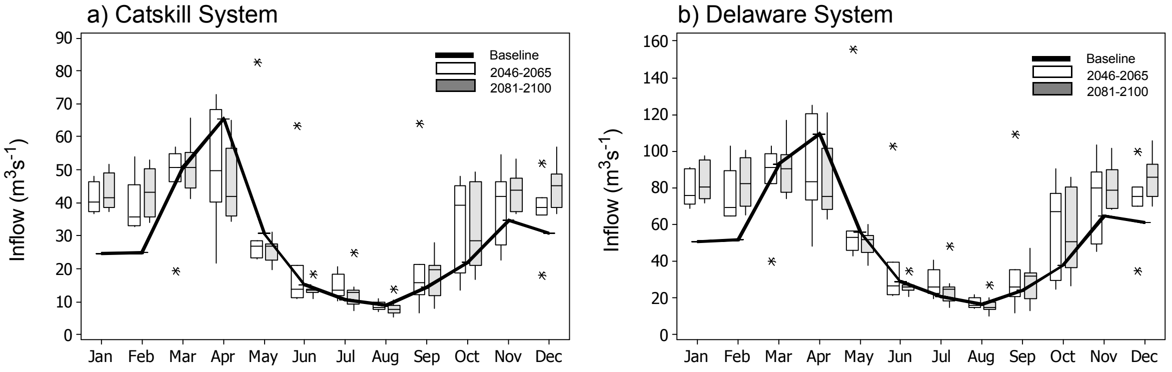


Figure 4.3 Average monthly inflow for the baseline (solid line), future 2046-2065 (white boxplots), and future 2081-2100 (gray boxplots) time periods. The boxplots represent the mean monthly values calculated for the different climate scenarios. For the boxplot description, see Figure 4.2.

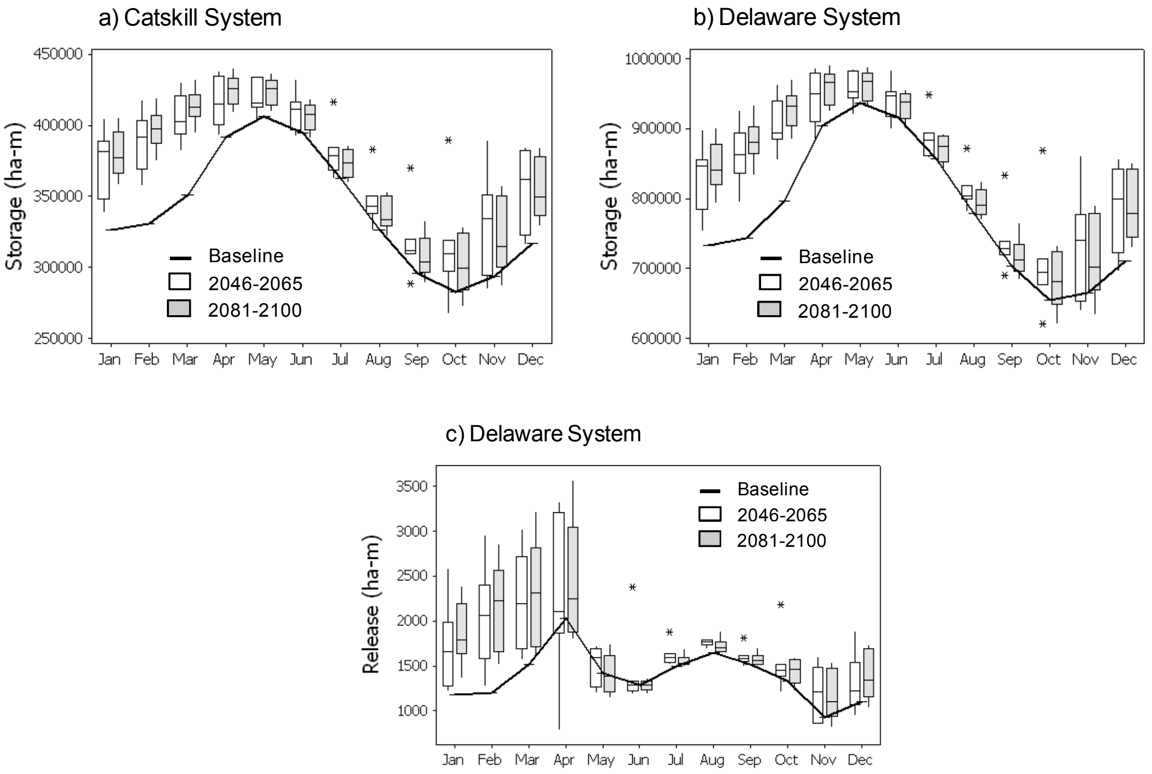


Figure 4.4 Storage patterns for (a) the Catskill System, (b) the Delaware System, and (c) the Delaware release for the baseline (solid line), future 2046-2065 (white boxplots), and future 2081-2100 (gray boxplots) scenarios. For the boxplot description, see Figure 4.2.

Changes in the magnitude and distribution of inflows to the reservoir systems were calculated by comparing the relative bias between baseline and future inflows using the values of 10th, 25th, 75th, and 90th percentiles derived from the empirical distributions of daily inflows to the Delaware and Catskill Systems. Relative bias was calculated according to equation 4.1:

Relative Bias = (Future scenario - Baseline scenario)/Baseline scenario (4.1)

The boxplots in Figure 4.5 suggest an overall average increase in inflows, with higher relative increases in the lower 25th percentile of the flow distribution curve. Increases in these lower flows may be caused by an increase in the inflows during the summer months, particularly during July (Figures 3.4m,n and 4.3).

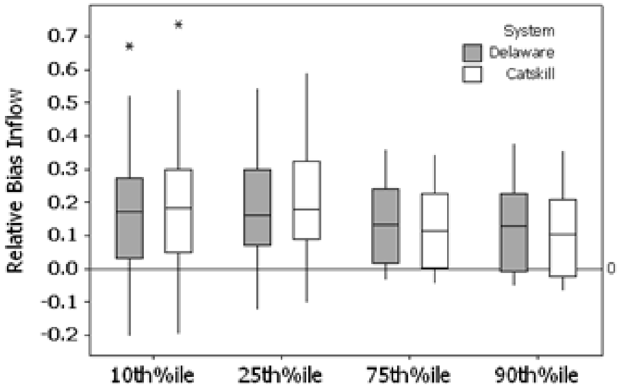


Figure 4.5 Relative bias of inflow by percentile for the Delaware and Catskill Systems. For the boxplot description, see Figure 4.2.

The range in the simulated average storage among the different future scenarios is greater during late fall and earlier winter, and reflects the cumulative effects of the simulated variability in snow accumulation, melt and winter streamflow (Figure 4.3). The relationship between snowpack, snowmelt, and reservoir releases is complex (Matonse et al., 2012). Higher projected winter inflows cause the reservoirs, which under present conditions reach their 90% storage capacity in April, to fill to the 90% level one to two months earlier for the 2046-2065 and 2081-2100 scenarios (Figure 4.6). Under the rules guiding its simulations, OASIS attempts to maintain a void in reservoir storage equal to 50% of the estimated watershed snow water equivalent, but as a result of the predicted higher winter inflows, OASIS releases will increase in order to maintain the required void. However, since the snowpack is also projected to decrease in the future, the size of the required void will also decrease, making it possible to maintain reservoirs at a higher level. The overall effect will be an increase in controlled releases during winter and early spring, and, at the same time, higher levels of water storage (Figure 4.4).

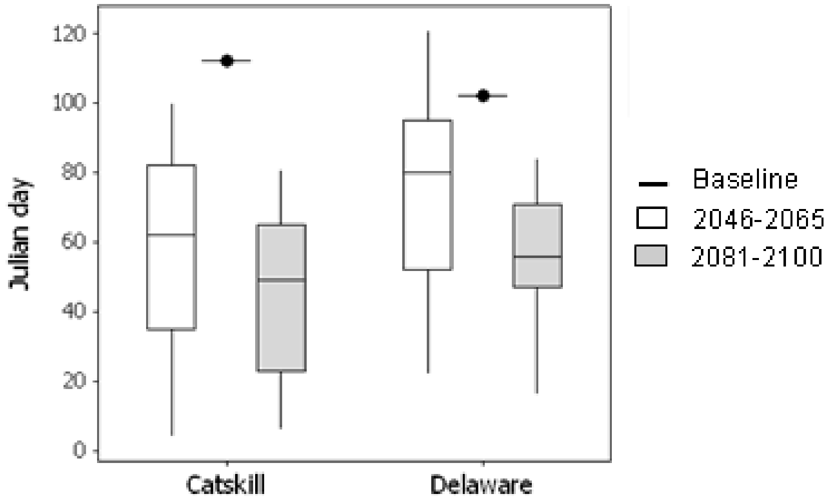


Figure 4.6 First Julian Day when reservoirs in the Catskill and Delaware Systems pass the level of 90% of total storage capacity. The lines with dark dots represent the average baseline values. The boxplots represent simulated data by time period. Boxplots show the variation in the timing of reaching the 90% level associated with the different GCMs and emission scenarios. For the boxplot description, see Figure 4.2.

Figure 4.7 shows boxplots of the total reservoir spill volume between November 1 and March 1 for both baseline and future scenarios. The volume of spill during this period increases in both the Catskill and Delaware Systems under the future scenarios, slightly more so for the 2081-2100 period. This increase, an indicator of water no longer available to the water supply, is not directly related to flooding (whose effects were not evaluated as part of the study), but rather to greater winter flows (Figure 4.3) that cause the reservoirs to fill earlier and spill more. That, in turn, is a consequence of the projected increase in snowmelt and a decreased amount of water stored in the snowpack. The projected increase in spill could also be a function of the higher winter inflows, which may occasionally result in elevated turbidity; under extreme circumstances, this could trigger a reduction in the use of the Catskill System, resulting in greater spills.

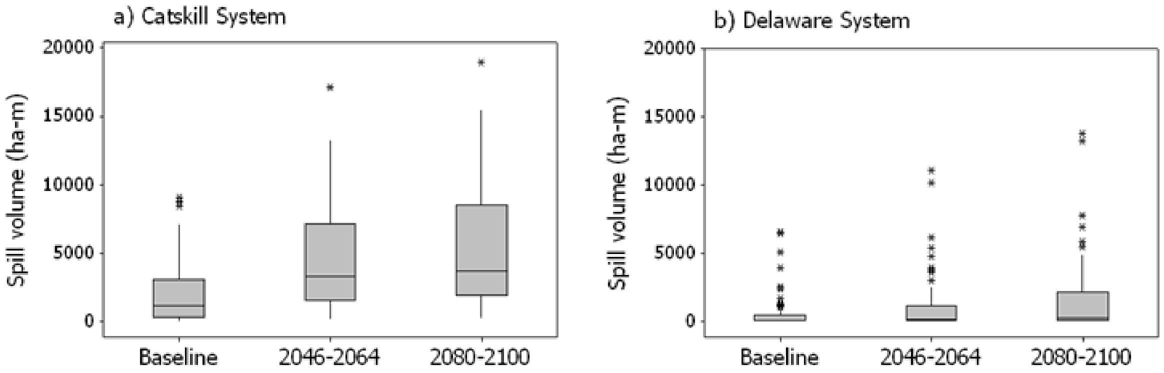


Figure 4.7 Yearly volume of spill from November 1 to March 1 for (a) the Catskill and (b) the Delaware Systems for the baseline and future periods. Boxplots show the median (horizontal line) and interquartile range, whiskers show the extent of the upper and lower limits, and the asterisks represent outliers. For the boxplot description, see Figure 4.2.

Figure 4.8 displays baseline and future estimates of the storage of water in the reservoir and the snowpack in the WOH reservoir system, and the combination of the two. From these data it is apparent that, while future scenarios predict that the reservoir system will fill earlier, this outcome occurs at the expense of snowpack storage. While it might appear that the earlier fill and snowpack decrease, combined with greater levels of evapotranspiration later in the year, might lead to decreased reservoir storage during summer, this is not the predicted result. Instead, total reservoir and snowpack storage levels are predicted to increase in the future (Figure 4.8) as a result of an overall increase in precipitation and resulting inflow (Figure 4.3).

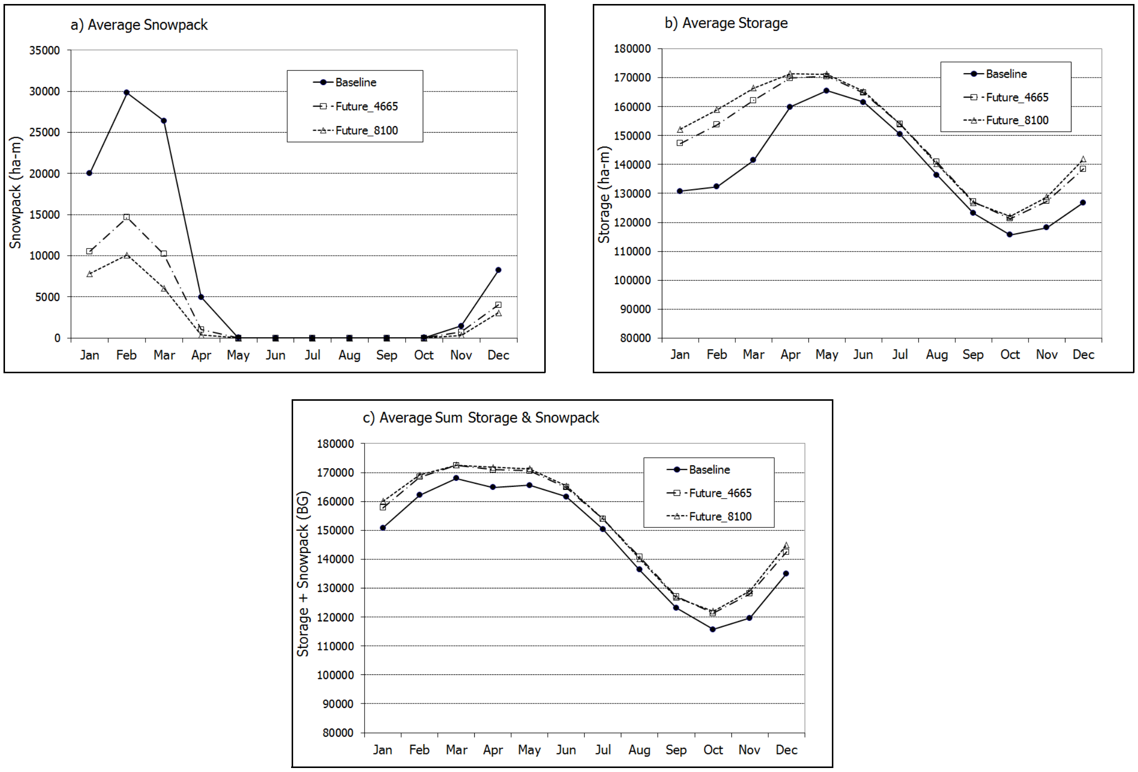


Figure 4.8 Seasonal variations in (a) baseline and future snowpack, (b) reservoir storage, and (c) total storage in the reservoirs and snowpack, for the WOH system. Monthly values are the mean for the baseline scenario and the combined mean for all GCM/emission scenarios.

Drought Status

A measure of the water supply system's performance is the number of days per year that the WOH system is under the three drought levels—watch, warning, and emergency—defined by DEP and calculated from the OASIS model. These levels, in addition to serving as an indicator of system status, trigger progressive water conservation measures. The classification is based on a comparison of the current total storage with average seasonal storage patterns under normal and drought level conditions. In Figure 4.9, the future scenarios (gray bars) indicate an average decrease in the total number of drought days compared to baseline conditions (white bars). The largest drop is for the emergency level, with about a 75 and 80% drop for the Delaware and Catskill Systems, respectively. Changes in inflow patterns, including increases in winter streamflow at the lower streamflow percentiles (Figures 4.3 and 4.4), contribute to the less frequent drought occurrences. However, there is a relatively large level of variability in the number of days under emergency, warning, and watch drought conditions. One source of uncertainty in these calculations is the use of historical drought patterns as a reference, since such patterns may change in the future.

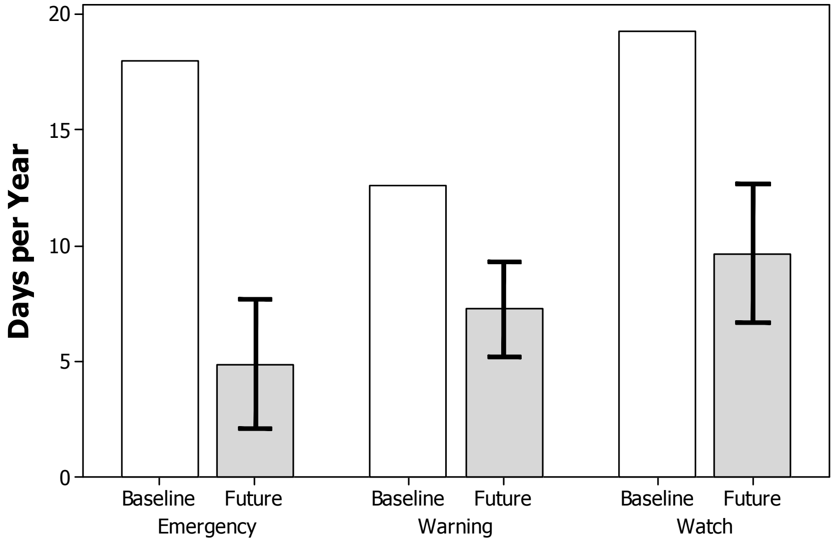


Figure 4.9 Number of days per year the WOH system is under watch, warning, and emergency drought conditions. The bars show baseline conditions (white) and simulated future climate conditions (gray) for the 2081-2100 time period. The interval bars represent the 95% confidence interval for the mean. Variation in future drought status is the result of differences in GCM/emission simulations.

Probability of System to Refill by June 1

The probability of refill by June 1 (PR) is a statistic used by the engineers operating the water supply system to track the state of the system on any given day of the year, and is important because of the high desirability that the system be full by June 1, once the seasonally high spring streamflow has occurred. PR is a function of (1) the current day's storage deficit, (2) expected system withdrawals (diversions) and releases (determined using average historical data values from 1987 to 2004), and (3) systemwide inflow forecasts between the current day and June 1 (also determined using historical data values). The indicator can assume values from 0 to 1, representing the probability that the reservoirs will be close to full on June 1. For example, a PR value of 1 indicates that it is virtually certain that the reservoirs will be close to full on June 1, while a value of 0 indicates that it is practically impossible for the reservoirs to fill up by that date.

Based on the 20-year baseline scenario and the combined results of all future scenarios in both of the two future time periods, estimates of the fraction of each month when the Delaware System probability of refill will fall below 90%, 80%, 60%, and 40% were calculated (Figure 4.10). Clearly, a June 1 refill is more likely for most of the months under future climate scenarios than under baseline conditions. In other words, under future conditions there are fewer months when it is predicted that the reservoir system will not fill at a given probability level; under these conditions, PR values will be higher. The difference in probability between baseline and future conditions becomes more pronounced as the refill threshold value is lowered. These future changes in PR are consistent with the declining number of drought days predicted under future scenarios, since drought days are triggered at lower PR values, not the higher ones expected under future conditions.

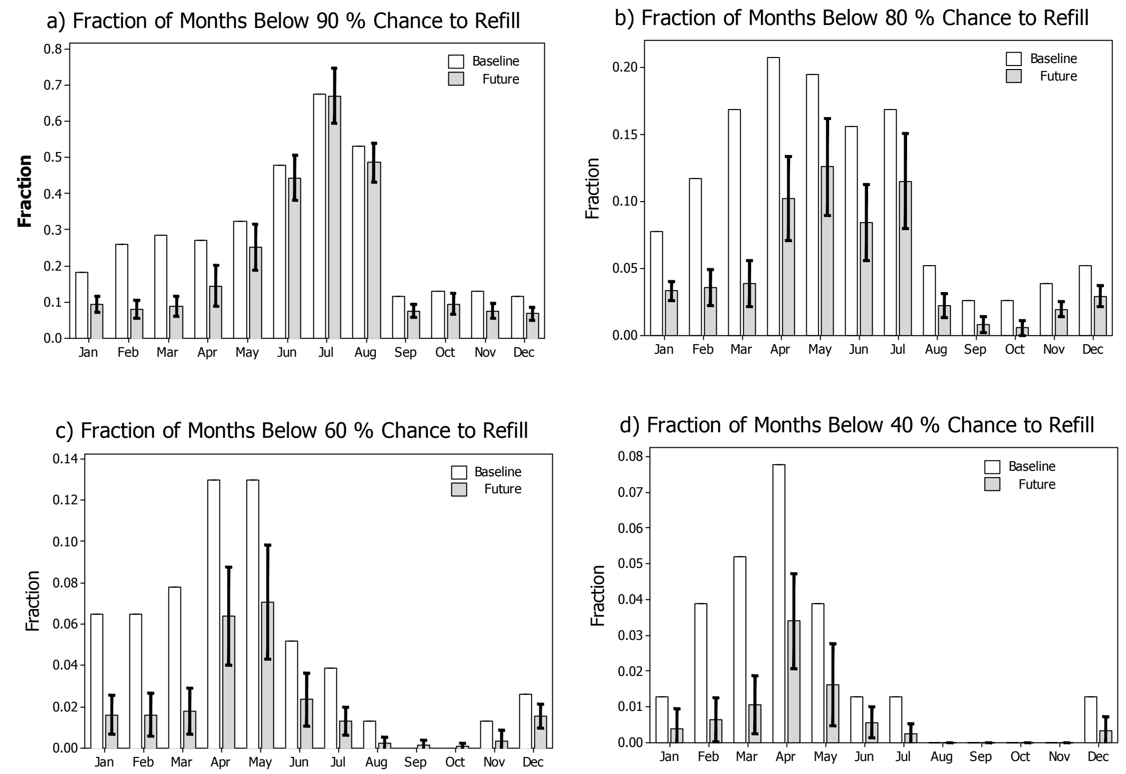


Figure 4.10 Fraction of months where the chance of refilling by June 1 for the Delaware System is below 90, 80, 60, and 40%. White bars are baseline conditions; grey bars are scenarios run for both future time periods. Variation in future refill is the result of differences in GCM/emission simulations. The interval bars represent the 95% confidence interval for the mean.

System Resilience, Reliability, and Vulnerability

Resilience, reliability, and vulnerability are indicators that have been used to evaluate the long-term performance of water supply systems. All are linked to drought conditions and PR in that they are related to the likelihood of a particular system experiencing a failure (extreme drought) and recovering after the failure has occurred. A failure for any given year is defined as the inability of a water system to supply the anticipated annual demand (Vogel et al., 1999; Vogel et al., 1995). Calculation of these indicators is described in detail by Hashimoto et al. (1982), Vogel and Bolognese (1995), and Vogel et al. (1999), and their use in evaluating the performance of the NYC water supply is further discussed by Matonse et al. (2012). The resilience index (*r*) (Hashimoto et al., 1982) is the probability that a reservoir system will deliver its stated yield in a year following a failure (Vogel et al., 1999); its optimal value is 1. The index was calculated for the NYC system and the results indicate that levels of resilience under future climate scenarios will somewhat exceed the already high levels characteristic of baseline conditions (Figure 4.11). Reservoir system vulnerability D is an indicator of the average number of consecutive years a reservoir system could potentially fail to deliver an expected yield; a unity vulnerability (i.e., $D = 1$) can be interpreted as a failure state that will last one year on average (Vogel et al., 1999). Projected future climate scenarios indicate that high resilience of the NYC reservoir system will continue to be associated with low vulnerability ($D \approx 0.1$), meaning that if a system failure occurs it will last for far less than a year.

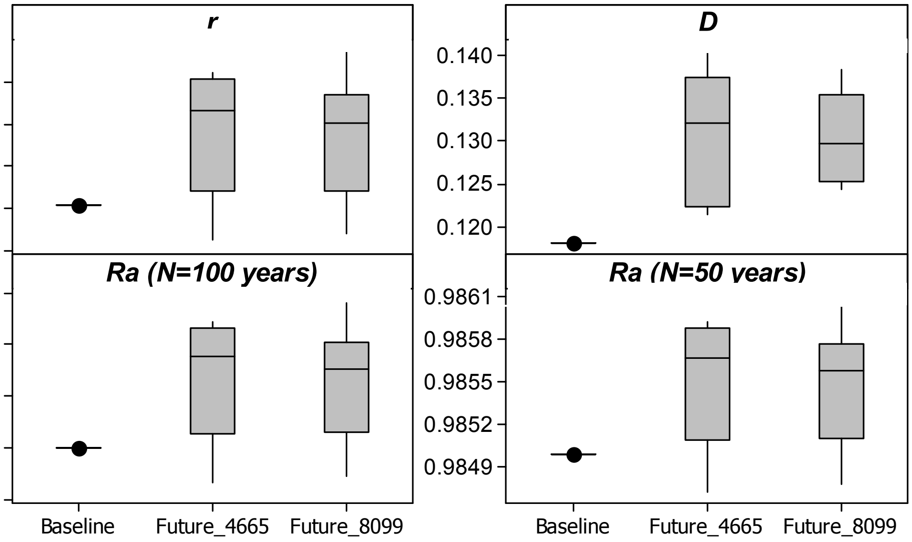


Figure 4.11 Baseline and future calculated resilience (r), reliability (R_a for 50- and 100-year planning horizons (N)), and vulnerability (D) for the NYC water supply.

For the design of hydraulic structures for flood control it is a standard practice to employ the average return period of a flood as the design event. Similarly, an index showing the average return period N of a reservoir system shortage can be used for the design of a water supply system (Vogel, 1987). The corresponding probability that a reservoir will deliver a constant yield Y, without failure, over N years is known as no-failure reliability R_a with a return period of N (Vogel et al.,1999).

Annual reliability of reservoirs across the United States is generally between 0.97 and 0.985 (Vogel et al., 1999). The baseline scenario revealed values for WOH reservoirs both within (50-year planning horizon) and slightly above (100-year horizon) the upper limit of this range. Based on the results displayed in Figure 4.11, it appears that future changes in climate will result in no substantial change in annual reliability. The variability among the different model scenarios was less than 0.0015.

Overall, estimated values of D, r, and R_a are within the range found in previous studies for this region (e.g., Lane et al., 1999; Vogel et al., 1999). That suggests that the NYC water supply is resilient and reliable and has a low level of vulnerability, a condition which, based on the models and data applied for this Phase I study, is predicted to continue under future simulated changes in climate.

Conclusions

Future changes in seasonal patterns of streamflow will result in greater flow volumes entering the reservoirs during winter. As a result, the reservoirs will fill earlier in the year and lose greater volumes of water as spill earlier in the year. Less water will be stored in the snowpack and what there is will be lost earlier. Any loss of snow storage or increased spill will apparently be compensated for by increased precipitation occurring throughout the year, since system indicators of drought status and reservoir storage are simulated as being more favorable in the future. Metrics of reservoir system resilience and reliability are high under baseline conditions and are simulated to continue at high levels in the future.

While most GCMs are in good agreement with each other in predicted changes in air temperature, simulated snow accumulation and winter-spring streamflow, the forecast for increased summer precipitation was far less certain, casting some doubt on the predicted favorable changes in drought status. Such doubts will to some extent be reduced in the next phase of this work, which makes use of a greater variety of GCM data and improved downscaling methods. Other assumptions used in these simulations that will need to be eliminated or relaxed in future simulations include the assumptions that (1) water demands, as well as EOH and lower Delaware flows, are fixed at present levels, and (2) certain system indicators, such as drought level and probability of reservoir refill, can be calculated based on historical patterns of reservoir storage, when in fact historical storage patterns may no longer represent the true variability of reservoir storage under future conditions.

5. Turbidity in Schoharie Reservoir

Storm-generated turbidity (see Glossary for definition of turbidity) in the NYC water supply watersheds—particularly in the Catskill System consisting of Schoharie and Ashokan Reservoirs and their respective watersheds—is an important and persistent water quality issue that can constrain the operation of the water supply. One of the primary goals of the CCIMP is to estimate the potential effects of climate change on turbidity in the water supply system. As an initial step towards this goal, Phase I of the project focused on Schoharie Reservoir. Water stored in Schoharie Reservoir is utilized by conveying it through the Shandaken Tunnel to Esopus Creek which drains to Ashokan Reservoir (Figure 5.1). Operation of the Shandaken Tunnel is a dynamic process of adapting to changing conditions to balance sometimes competing goals related to meeting water demand, maintaining low turbidity in the system, meeting regulatory requirements and accommodating environmental concerns. The complexity of the water supply system gives the system operators some degree of flexibility in choosing when to move water to or from different parts of the system to optimize reservoir storage and delivered water quality. This flexibility has been instrumental in DEP's ability to provide high quality drinking water to NYC and is expected to play an important role in adapting to future uncertainty related to climate change.

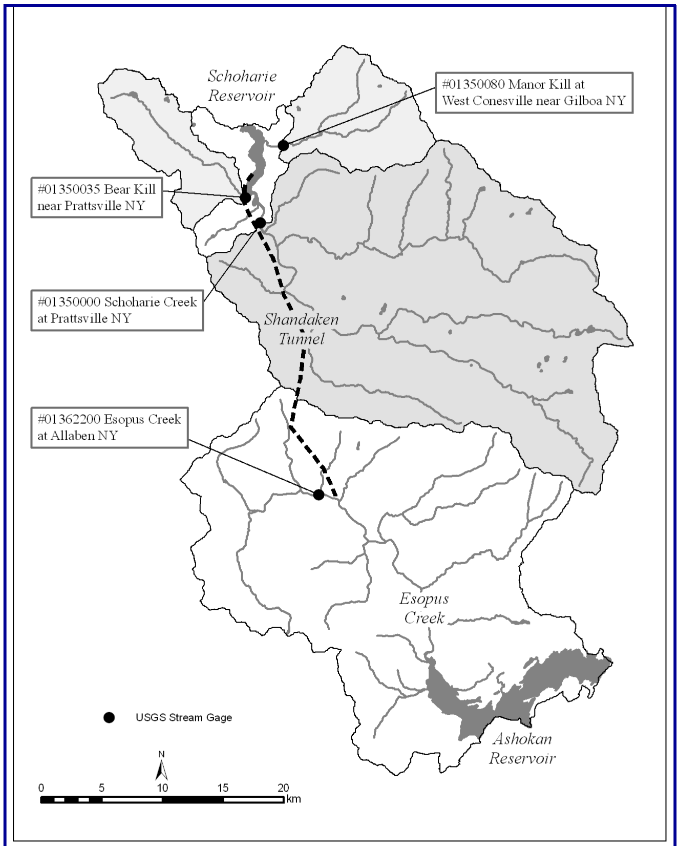


Figure 5.1 The Catskill System of the New York City Water Supply. The numbers represent the USGS gauge numbers.

Watershed Turbidity Modeling

Climate scenarios were developed from the output of three GCMs: GISS, NCAR and ECHAM (see Table 2.1). Streamflow inflows to Schoharie Reservoir from Schoharie Creek were simulated for each scenario using the GWLF-VSA model (Chapter 3). This model was previously calibrated and tested against Schoharie Creek at Prattsville USGS gage flow data (DEP, 2007) (Figure 5.1). For each scenario the GWLF-VSA model was driven by the climate scenario daily time series of precipitation and air temperature, in order to produce future inflow scenarios for the

Schoharie Creek watershed (see Chapter 3). Inflows for the two other main tributaries to Schoharie Reservoir (Manor Kill and Bear Kill) and for the remaining catchment area were scaled from the Schoharie Creek simulations using empirically-derived scaling factors.

Turbidity inputs were derived from estimates of total suspended solids concentration (TSS), with the latter being estimated using a sediment rating curve for the outlet of the Schoharie Creek watershed at Prattsville (DEP, 2006a) (Figure 5.2):

$$S_d = \begin{cases} 147.4 Q_d^{\,1.2} & \text{for } Q_d \geq 12.13\ \text{m}^3/\text{sec} \\ 1.651 Q_d^{\,3.0} & \text{for } Q_d < 12.13\ \text{m}^3/\text{sec} \end{cases} \qquad (5.1)$$

where, S_d is the daily total suspended solids load (kg/day) and Q_d is the mean daily streamflow (m^3/sec). The numerical factors, exponents, and flow threshold in equation 5.1 were estimated by calibration, based on flow and stream monitoring data collected along Schoharie Creek. The TSS input time series, derived by applying the rating curve, was transformed to a turbidity input time series using an empirically-derived relationship between TSS and turbidity (Tn, as measured in Nephelometric Turbidity Units, NTU) for Schoharie Creek (Gannett Fleming & Hazen and Sawyer, 2007). See Glossary for an amplification of "NTU".

$$Tn = 1.31032 \left(\frac{S_d}{86.4 Q_d} \right)^{0.85971} \qquad (5.2)$$

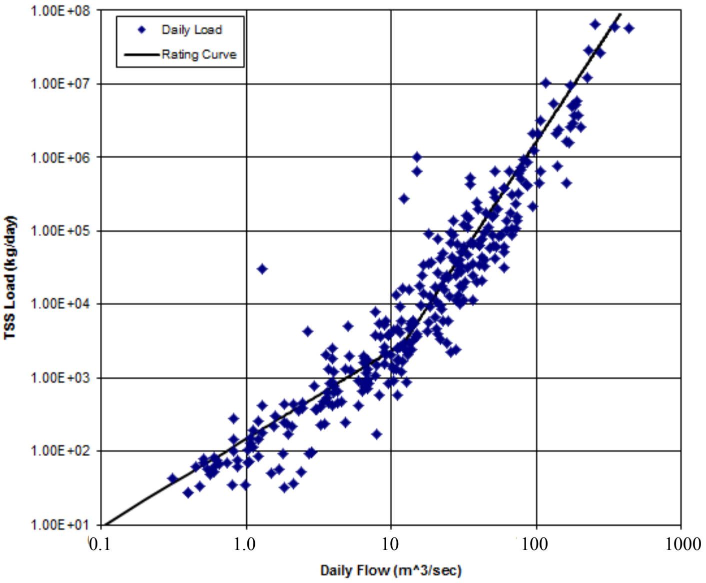


Figure 5.2 Rating curve, showing relationship between TSS daily load and mean daily flow for USGS streamflow gauge located at Schoharie Creek at Prattsville.

Reservoir Turbidity Modeling

The fate of the turbidity loads (see Glossary) entering Schoharie Reservoir was determined using the CE-QUAL-W2 model (Cole and Buchak, 1995) which has been adapted, calibrated and rigorously tested for Schoharie Reservoir (Gelda and Effler, 2007). This model is a two-dimensional reservoir hydrodynamic and water quality model that simulates thermal structure, storages and fluxes of water and turbidity along vertical and longitudinal dimensions within the reservoir as well as spill over the Schoharie Dam. Given a time series of turbidity inputs, water inputs, and operational withdrawals, this model simulates the transport and distribution of turbidity within the reservoir, including turbidity levels at key locations such as the Shandaken Tunnel withdrawal.

Driving data for the CE-QUAL-W2 model include time series of daily inflow volumes, with associated water temperature and turbidity; local meteorology; and operational withdrawal volumes via the Shandaken Tunnel. Inflow volume and turbidity were simulated using the GWLF-VSA model as described above. Water temperatures of stream inputs to the reservoir were derived from an empirical hourly temperature model for Schoharie Creek that was previously developed to support Schoharie CE-QUAL-W2 model applications (Gelda and Effler 2008). The temperature model calculates hourly water temperature as a function of air temperature three hours earlier, and daily streamflow using multiple non-linear regressions that were developed for individual months.

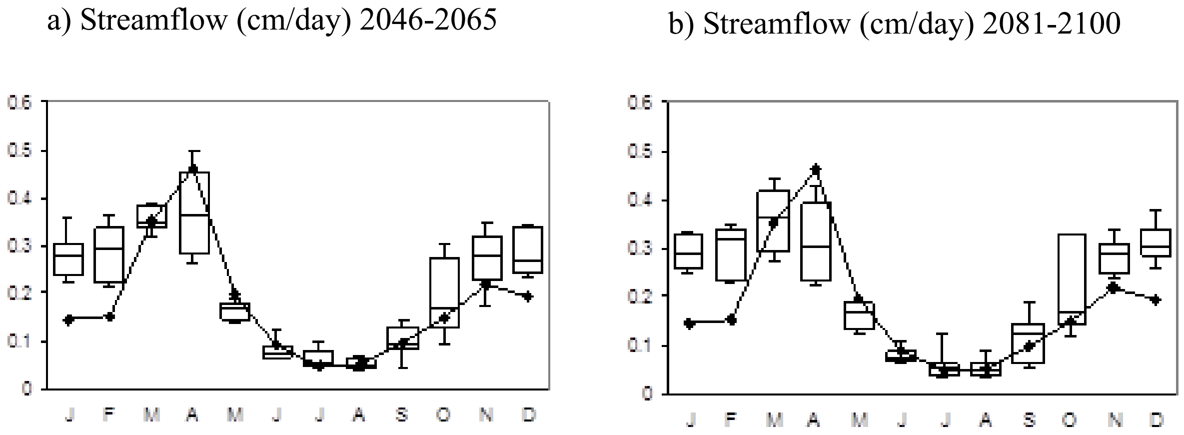
In order to develop future scenarios of hourly air temperature from the daily scenarios that were calculated as described in Chapter 2, the maximum air temperature change factor was applied to the hour(s) in that day with the highest temperature, the minimum change factor was applied to the hour(s) with the lowest temperature, and a linearly interpolated change factor was applied to each of the remaining hours' air temperatures. In this way diurnal variation in projected future air temperatures was applied and carried through to water temperature projections. In addition to air temperature, other meteorological input time series required by the CE-QUAL-W2 model include solar radiation, relative humidity, wind speed and direction. In the Phase I simulations these were not adjusted for the future climate scenarios.

The CE-QUAL-W2 model is a descriptive model driven by tightly coupled historical stream inflows and operational withdrawals. Use of the model for climate change scenarios involves adjusting stream inflows. Adjusted inflows are still somewhat coupled to historical operational withdrawals because the change factor methodology employed for generating future inflow scenarios maintains the same historical pattern in meteorological and streamflow data. However, adjusting inflows does introduce the possibility of drawing the reservoir below physically-possible levels in the CE-QUAL-W2 model simulations. To preclude this, the operational withdrawal data were run through a simple preprocessor that calculates a daily reservoir water balance and, if necessary, reduced the Shandaken Tunnel flow so that tunnel withdrawals would not exceed available reservoir storage.

Future Turbidity Scenarios

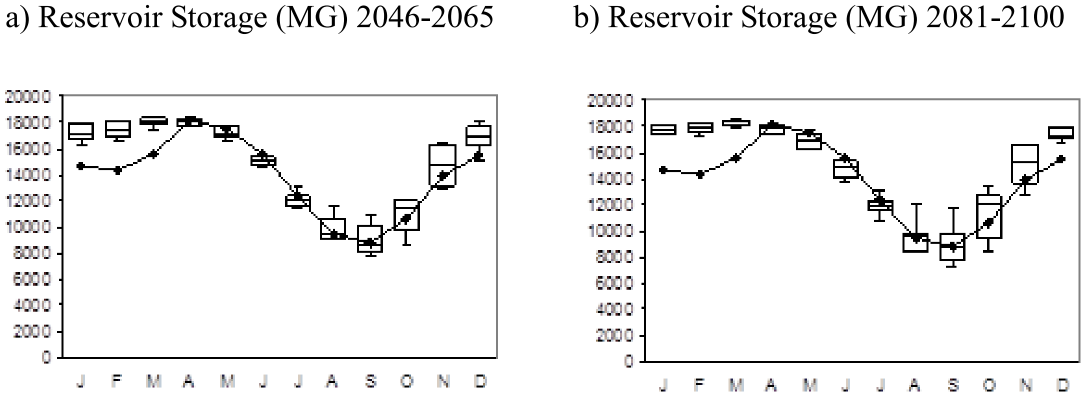
Results of climate scenarios with linked watershed-reservoir models shows the cascading effects of projected changes in future meteorology on watershed inflows and loads, reservoir storage and turbidity in the Shandaken Tunnel. As discussed in Chapters 2 and 3 of this report, air temperature increases throughout the year for all future scenarios, with greater increases in the 2081-2100 scenario. Precipitation projections are more variable among the different GCM/Emission scenarios, with winter increases somewhat more pronounced than summer. Annual snowfall and snowpack are projected to decrease; annual precipitation, streamflow and streamflow components (baseflow, runoff) to increase; annual evapotranspiration (potential and actual) to increase; and annual soil water to decrease.

On a monthly basis, projected streamflow inputs to Schoharie Reservoir, as predicted by the GWLF-VSA model, reflect the interplay of increased air temperature and precipitation through their effects on snowpack and evapotranspiration (Figure 3.4). Increased winter precipitation, along with higher temperatures, reduces snow and increases snowmelt, thus pushing the peak streamflow events historically associated with the spring snowmelt back into the winter. Increased evapotranspiration keeps summer streamflows near historical levels despite increased precipitation (Figure 5.3). Projected changes in reservoir inflows translate into changes in future reservoir storage and spill over the Schoharie Dam, assuming the historical pattern of operational flows for the Shandaken Tunnel holds in future simulations (Figure 5.4). Increased winter streamflow tends to fill the reservoir earlier and increase spill in the winter, consistent with the results described in Chapter 4.


a) Streamflow (cm/day) 2046-2065

b) Streamflow (cm/day) 2081-2100

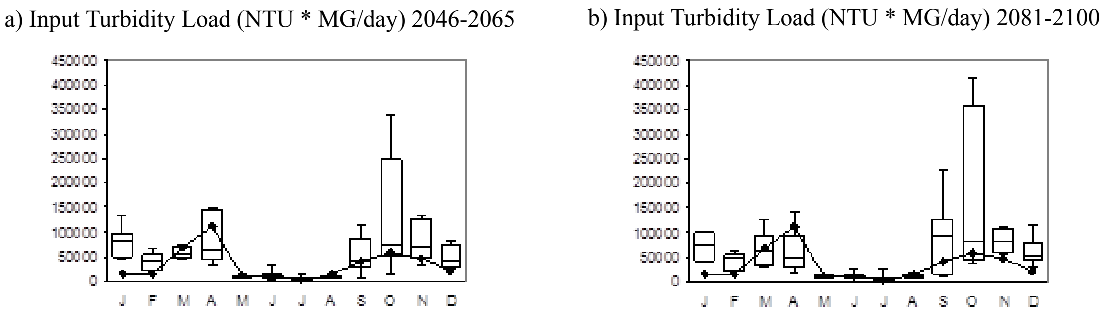
Figure 5.3 Monthly mean streamflow (expressed as cm/day) for baseline (black line) and 8 climate scenarios for the future 2046-2065 and 2081-2100 time slices for the Schoharie watershed. The boxplots show the median (horizontal bar within the box), the upper and lower quartiles (top and bottom of box), with the whiskers representing the maximum and minimum values.


a) Reservoir Storage (MG) 2046-2065

b) Reservoir Storage (MG) 2081-2100

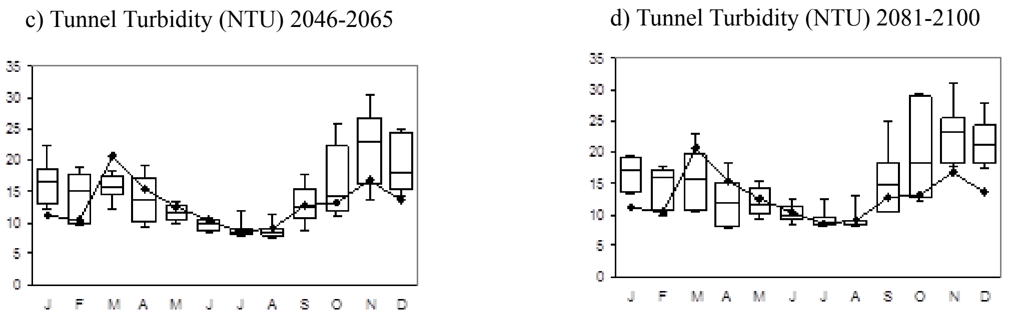
Figure 5.4 Monthly mean Schoharie Reservoir storage (millions of gallons (MG)), for baseline and 8 climate scenarios for the future 2046-2065 and 2081-2100 time slices. The boxplot descriptor is given in Figure 5.3. MG = million gallons

The mean monthly turbidity load for the baseline and climate change scenarios is shown in Figure 5.5 (a and b). Similar to the streamflow pattern (Figure 5.3), turbidity loads increase in the late fall and early winter. Turbidity loads are especially increased in the fall, due to relatively large and variable increases in streamflow. Figure 5.5 (c and d) shows the effects of the increased load on Shandaken Tunnel turbidity, with increases in late fall and early winter, and decreases in the late winter and early spring these results are directly related to the changes in streamflow timing due to the changes in snowpack development and melting.



a) Input Turbidity Load (NTU * MG/day) 2046-2065

b) Input Turbidity Load (NTU * MG/day) 2081-2100



c) Tunnel Turbidity (NTU) 2046-2065

d) Tunnel Turbidity (NTU) 2081-2100

Figure 5.5 Monthly mean input turbidity load (NTU*MG/day) to Schoharie Reservoir and turbidity (NTU) in the Shandaken Tunnel for baseline (black line) and 8 climate scenarios for the 65 future 2046-2065 (a) and 2081-2100 (b) time slices. The boxplot descriptor is given in Figure 5.3. MG = million gallons.

Conclusions

The analysis presented here suggests that climate change may result in a shifting seasonal pattern of turbidity in Schoharie Reservoir withdrawals, with increased turbidity in the fall and winter and decreased turbidity in spring. These projections closely follow those for streamflow inputs to the reservoir, driven by projected increases in precipitation particularly in winter along with reduced snow and increased snowmelt due to higher temperatures that shifts the historically high snowmelt-driven spring flows earlier into winter. The future scenarios also project winter increases in reservoir storage and spill.

The results presented here are a reasonable expectation of what may occur. However, in the case of all climate simulations, and in particular turbidity simulations which may be affected by processes occurring over relatively small spatial scales, it is important to keep in mind the assumptions, simplifications and limitations inherent in the modeling.

Our analysis is based on several important simplifying assumptions. The analysis assumes unchanging operation of the Shandaken Tunnel and thus does not consider the adaptive response of reservoir management to climate change. The simple GCM downscaling method employed does not consider future changes in storm event frequency, intensity, and duration. The use of an historically-based sediment rating curve to estimate future turbidity loads to the reservoir does not consider potential effects of climate change on the rating curve itself. These assumptions limit the scope of results to a broad characterization of potential impacts. Nevertheless, this analysis, conducted with resources that are within reach of many water utilities (historical input and systems operations data, watershed and reservoir models) is a useful first step to broadly identify potential impacts. The next phase of the project will address many of the simplifying assumptions of this Phase I analysis.

6. Eutrophication in Cannonsville Reservoir

Introduction

Reservoir eutrophication due to excessive nutrients has been a significant water quality problem and continues to be a potential concern for the NYC water supply. The Cannonsville watershed has the greatest amount of agricultural land use compared to all other WOH reservoir watersheds, and there are also a number of wastewater treatment plants contributing effluent to the West Branch of the Delaware River, the major water source to the reservoir (Figure 6.1). These factors in the past have led to high point and non-point nutrient loading to the reservoir, high average chlorophyll concentrations and frequent phytoplankton blooms (Effler and Bader, 1998; Upstate Freshwater Institute, 2003). Starting in 1992 the implementation of wastewater treatment upgrades, and an aggressive program of agricultural, stormwater and other best management practices, have reduced nutrient inputs, improved trophic status and reduced the occurrence of phytoplankton blooms (DEP, 2006b; 2011). Due to eutrophication of the reservoir, and its ongoing recovery, Cannonsville has been a focus for the development, testing and application of nutrient-phytoplankton models, and was chosen as the location for CCIMP Phase I simulations of the effects of climate change on reservoir eutrophication and phytoplankton.

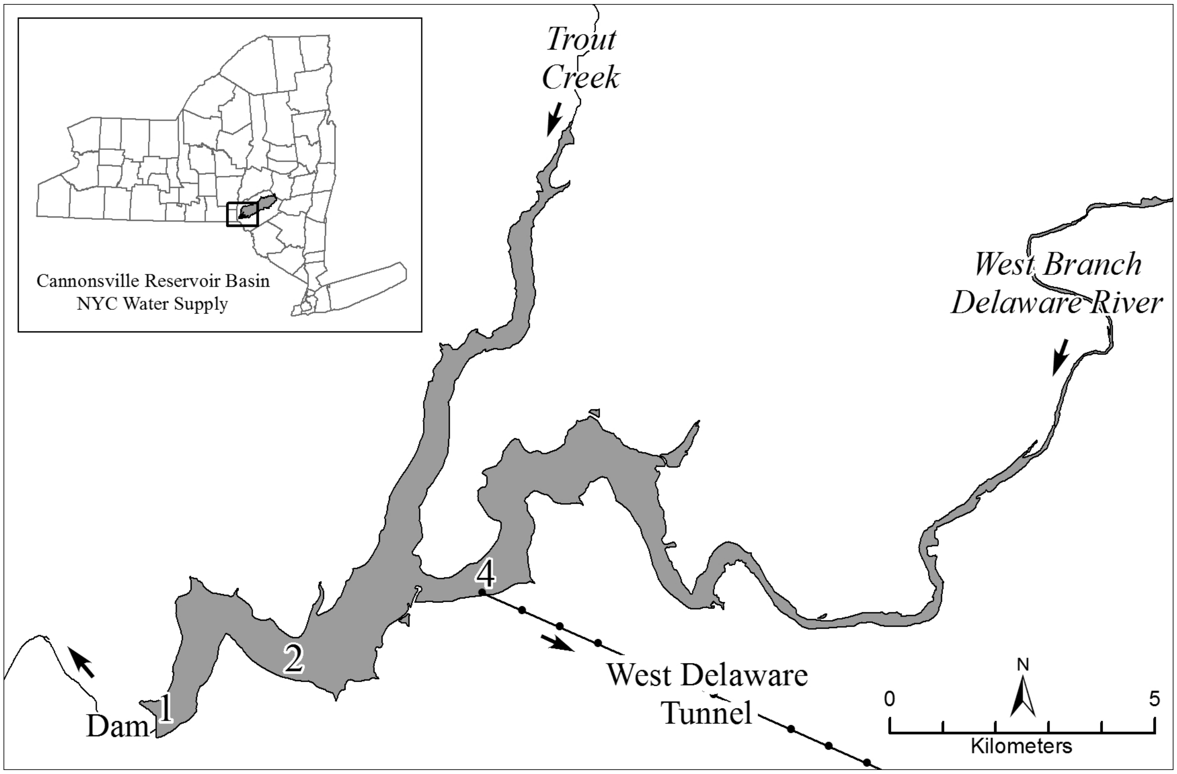


Figure 6.1 Cannonsville Reservoir in New York State and sampling stations 1, 2 and 4. Arrows show the direction of water flow.

Phase I of the CCIMP had the goal of evaluating climate change impacts on the trophic status of Cannonsville Reservoir by examining future effects on hydrodynamics and in-reservoir processes that influence trophic status, as well as the effects on watershed hydrology and nutrient transport from the watershed to the reservoir. Climate change impacts were judged by the simulated effects on reservoir thermal structure, reservoir nutrient concentrations, total phytoplankton biomass as chlorophyll *a,* and the biomass of key phytoplankton functional groups.

To accomplish this evaluation it was necessary to simulate: the watershed processes that regulate the hydrologic and nutrient loads entering the reservoir; reservoir hydrodynamic processes that control reservoir thermal structure, mixing and the vertical distribution of inflows; and the in-reservoir processes that affect phytoplankton growth.

Watershed simulations were made with the GWLF-VSA model (Chapter 3), and reservoir hydrodynamic and phytoplankton growth were simulated using the 1D reservoir eutrophication model (UFI-PROTBAS) currently used to simulate trophic conditions in Cannonsville Reservoir (DEP, 2008b). When simulating future climate conditions, a preprocessing program was used to adjust historical operations and inflowing stream water temperature (Figure 6.2). A baseline scenario, 18 future scenarios and two combinations of future and historical conditions were used for the model simulations. These provided information on:

1. The current condition of Cannonsville Reservoir (Figure 6.2a), including the variability in reservoir conditions that would be associated with long term variations in the hydro-meteorological data driving the watershed and reservoir models.

2. Simulations that looked at possible effects of climate change on Cannonsville Reservoir (Figure 6.2b), including those related to changes in watershed loading as simulated by the GWLF-VSA model and changes in reservoir thermal structure that could be expected due to changes in air temperature humidity (dew point temperature), wind, solar radiation, and changes in the inflowing stream water temperature.

3. Simulations which only examined the effects related to future changes in watershed loading (Figure 6.2c). To separate watershed from reservoir hydrothermal effects, only future changes in watershed inputs were simulated by GWLF-VSA, which was driven by future climate scenario data. The UFI-PROTBAS model was driven by baseline meteorological and stream inflow temperature data so that the simulation results were only affected by future changes in hydrologic and nutrient inputs.

4. Simulations which only examined the effects related to future changes in reservoir hydrodynamics (Figure 6.2d). Converse to the above set of simulations, the inputs to the reservoir generated by GWLF-VSA were based on simulations driven by baseline conditions, while reservoir inflow temperatures and the meteorological data input to the UFI-PROTBAS model were derived from future climate scenarios.

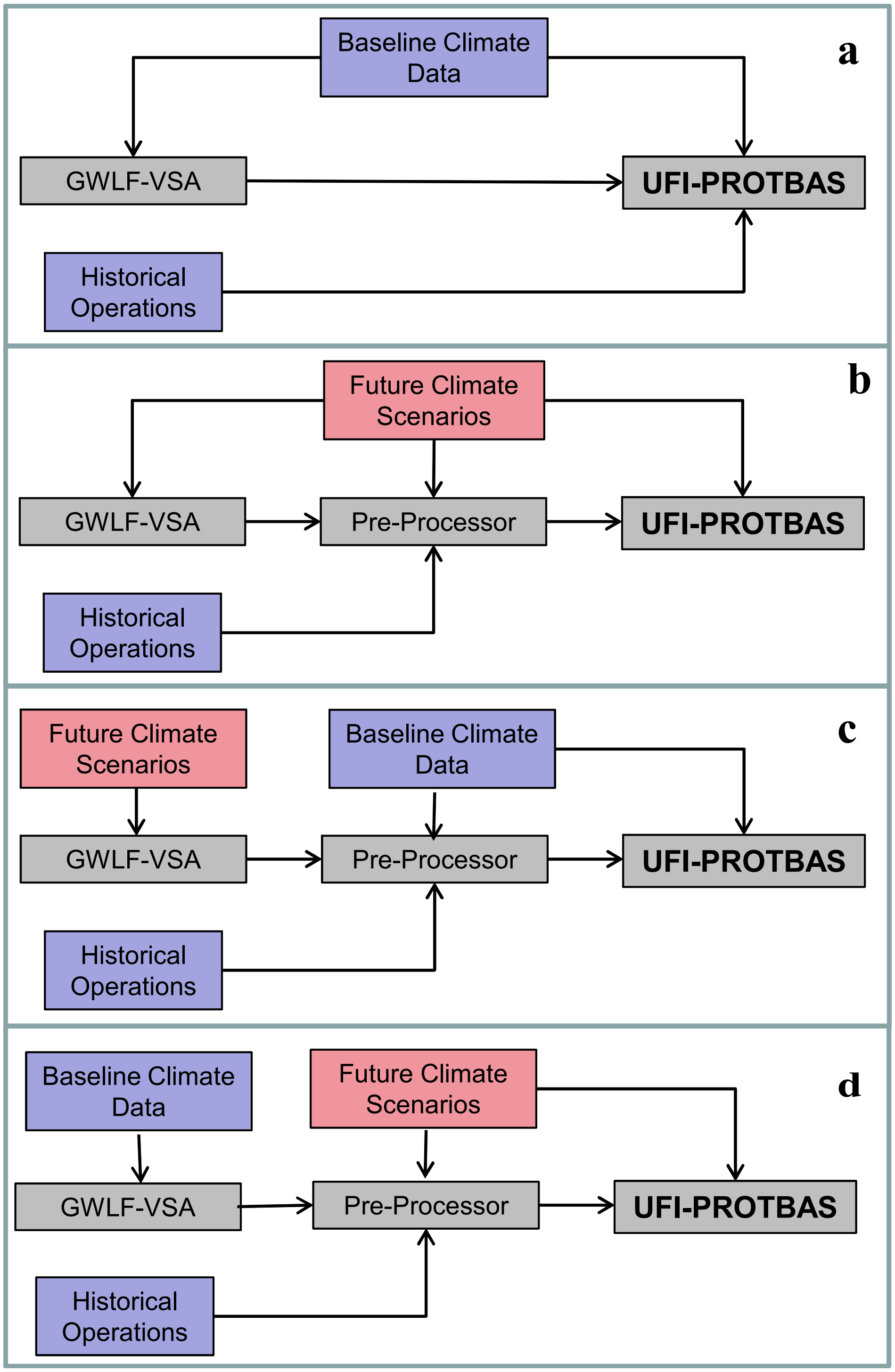


Figure 6.2 Schematic illustrating model coupling to baseline and future scenario climate data. a) Simulation of baseline conditions. b) Simulation of future conditions. c) Simulation of the effects of future climate on watershed loads only. d) Simulation of the effects of future climate on reservoir hydrothermal processes only.

The UFI-PROTBAS Model

The UFI-PROTBAS reservoir water quality model simulates reservoir nutrient dynamics and the biomass of phytoplankton functional groups, and is based on a robust hydrothermal model integrated with a thorough description of reservoir nutrient dynamics (Doerr et al., 1998; Owens, 1998; DEP, 2008b). An overview of the features in the model is given in Table 6.1. The hydrothermal portion of the model is driven by daily meteorological data (air temperature, humidity, wind speed, solar radiation) and data related to the reservoir water balance (river inflows, reservoir water elevation, aqueduct discharge, dam spill, tunnel outflow). The hydrothermal model is integrated with a water quality model to describe the cycling of phosphorus (P), nitrogen (N), carbon (C), dissolved oxygen (DO), and phytoplankton functional group biomass. The water quality part of the model requires daily inputs of nutrient loads (dissolved and particulate forms of P, N and C) (Doerr et al., 1998). The nutrients exist in both particulate and dissolved forms, with the proportion available to the phytoplankton being influenced by temperature-dependent hydrolysis, mineralization and nitrification (Figure 6.3).

Table 6.1: Overview of features in the UFI-PROTBAS water quality model.

Feature	UFI-PROTBAS model
Representation of phytoplankton	Carbon-based; constant stoichiometry; multiple (eight) algae classes
Nutrients	N, P, Si.
Zooplankton	Modeled.
Suspended solids	VSS = Detritus + Algal material.
Phytoplankton settling	Some phytoplankton settle. Others may actively move up or down.
Resuspension	Complete resuspension and entrainment of deposited algal particulates (Algal C) into the mixed layer
Deposition	In mixed layer no deposition occurs. Deposition below the mixed layer is determined by settling velocity.

The approach used to model multiple phytoplankton groups was first described in the PROTECH model (Reynolds et al., 2001), and later refined in the PROTBAS model (Markensten and Pierson, 2007). The present version of the model UFI-PROTBAS has been applied and tested for Cannonsville Reservoir (DEP, 2008b). Eight genera of phytoplankton (*Aulacoseira*, *Stephanodiscus*, *Aphanizomenon*, *Anabaena*, *Rhodomonas*, *Cryptomonas*, *Microcystis*, and *Ceratium*) are used in the model to represent phytoplankton functional groups spanning a range of sizes and also displaying the behaviors typical of freshwater phytoplankton in mesotrophic-eutrophic systems (Reynolds et al., 2001). PROTECH and PROTBAS use an allometric approach where the longest dimension and surface area to volume ratio for each species defines how growth rates depend on temperature and light (Reynolds et al., 2001). Such an approach recognizes the fundamental physical constraints which link nutrient uptake and light absorption to the ratio of phytoplankton surface area to volume. These growth characteristics were derived from extensive culture experiments as described by (Reynolds, 1989).

Including losses, the daily change in biomass, ΔB (g), is given by:

$$\frac{\Delta B}{\Delta t} = \Delta A - S - G - R - A_{out} + A_{in} \qquad (6.1)$$

Where ΔA is the increase in algal biomass due to growth over time interval Δt, S is the loss due to net settling, G the loss due to grazing (only species < 50 µm are grazed), R the loss due to respiration, A_{out} the loss due to basin outflow and A_{in} the gain due to river inflow, all of which are in the units of g day^{-1} (Reynolds et al., 2001). Each phytoplankton functional group is assumed to experience a constant respiration rate. Growth is dependent on the relationship between phytoplankton surface area:volume, and is adjusted to account for variations in water temperature and incident light. Growth rate is not directly affected by levels of ambient nutrients. However, growth is only allowed as long as there are available sources of soluble P, N and Si as required by the mass ratio of 83:82:12:10 for N:Si:P:Chl *a* (Stumm and Morgan, 1981). Each day the lake is fed with small inocula of phytoplankton to maintain a small seed population and prevent species extinction (Reynolds et al., 2001).

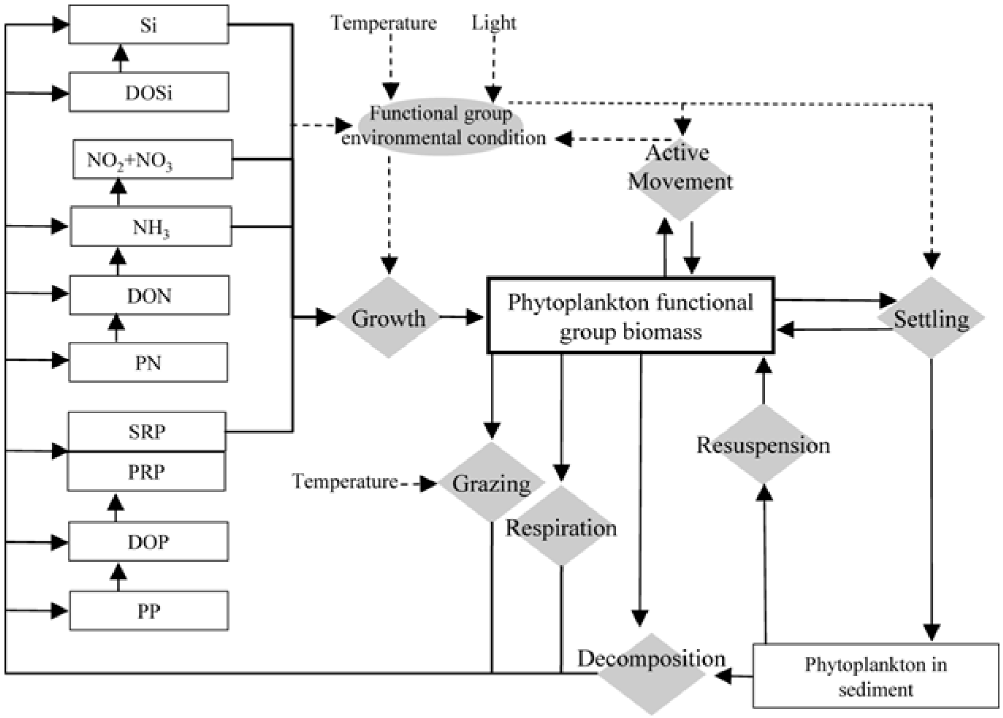


Figure 6.3 Conceptual phytoplankton and mass balance framework for UFI-PROTBAS nutrient/phytoplankton model for Cannonsville Reservoir, with multiple algal classes and modeled zooplankton grazing rate. State variables are contained within boxes. Solid arrows denote transformation between the state variables. Dashed arrows and shaded ovals are environmental variables influencing phytoplankton related processes. Processes affecting phytoplankton biomass are written within shaded diamonds.

Climate Scenarios

Future scenarios of model meteorological input data associated with the baseline scenario and 18 climate change scenarios based on the CGCM, ECHAM and GISS GCMs with the A1B, A2 and B1 emission scenarios (Table 2.1) were used as inputs to GWLF-VSA and UFI-PROTBAS models (Figure 6.2). For each of these GCM/emission scenario combinations, the 2046-2065 (65-year forward) and 2081-2100 (100-year forward) time slices were used to develop monthly change factors as described in Chapter 2. The baseline scenario used historical measurements (1966-2005) of precipitation, air temperature, dew point temperature, solar radiation and wind speed needed to drive the GWLF-VSA and UFI-PROTBAS models. The change factor methodology (Chapter 2) was applied to the baseline historical meteorological data to produce model inputs for the 18 climate change scenarios.

Simulated Hydrologic and Nutrient Inputs to Cannonsville Reservoir

GWLF-VSA was used to simulate the hydrologic and nutrient inputs to the UFI-PROTBAS model (Figure 6.2). The hydrologic component of GWLF-VSA, as well as the simulated hydrologic response to future climate scenarios has been presented in Chapter 3. When estimating reservoir nutrient inputs, non-point source loads of dissolved and suspended substances in streamflow are estimated at the watershed outlet by loading functions that empirically relate substance concentrations in surface runoff, suspended sediment and baseflow to watershed and land use specific characteristics. For example, the phosphorus load in surface runoff is calculated by multiplying land use specific surface runoff volumes by land use specific dissolved phosphorus concentrations. There is a seasonal adjustment of the nutrient concentrations in surface runoff from agricultural lands during the manure spreading season. A single rate of baseflow dissolved phosphorus export is calculated as the product of baseflow and a dissolved nutrient concentration assumed to be representative of baseflow exported from the basin as a whole. In addition, loads from septic systems are accounted separately and based on seasonal unsewered population estimates and estimates of failing septic system occurrence. Point source nutrient loads are added directly to obtain total reservoir loads. To estimate future changes in discharge and nutrient loading to Cannonsville Reservoir the GWLF-VSA model was run following the methodology described in Chapter 3, and simulations made use of the full nutrient output available from the model. GWLF-VSA parameterization was based on the assumptions used for the 2006 FAD program analysis (DEP, 2006b). Land use data were set to that considered representative of the 2000s decade, and the effects of present day watershed point and non-point source nutrient reduction programs were simulated.

Preprocessing Reservoir Model Input Data

Scenarios of meteorology together with river discharge, water temperature, soluble nitrogen, soluble phosphorus, particulate phosphorus and soluble silica loads obtained from GWLF-VSA simulations were used to drive the UFI-PROTBAS model. As in Chapter 5 above, a preprocessor program was developed which took as input GWLF-VSA simulations associated with a given future climate scenario, as well as the change factor modified meteorological data associated with the same future scenario, and input files were created for the reservoir model for that particular future climate scenario. The preprocessor program performed several functions:

1. Reformatted the daily hydrologic and nutrient loads output by GWLF-VSA so that they were compatible with the expected file format used by the 1D reservoir model.

2. Reformatted the meteorological data to a file format expected by the 1D reservoir model.

3. Calculated future stream water temperature based on projected future air temperature, and output these data in the file format expected by the 1D reservoir model.

4. Checked the reservoir water balance under future conditions and when using future GWLF-VSA inflows. When necessary, historical reservoir withdrawals were modified to maintain minimum water levels in the reservoir.

The reservoir model preprocessor program provided a convenient method to take data from a number of different sources and modify and/or reformat these so that they could be directly used by the reservoir model.

Results

Watershed Inputs to Cannonsville Reservoir

Changes in hydrology, as discussed in Chapter 3, clearly play a dominant role in controlling changes in the annual levels and seasonal patterns of nutrient loading. Greater levels of precipitation lead to greater levels of nutrient loading, with future increases in the annual rates of nutrient loading associated with the 18 future scenarios ranging between 3%-44% for soluble P, 3%-38% for soluble N and 4%-40% for soluble Si (Figure 6.4). More pronounced are the seasonal shifts in the timing of streamflow and nutrient loading simulated by the GWLF-VSA future scenarios. As a result of warmer winter temperatures, greater amounts of rain in the winter, and earlier snowmelt there is a seasonal shift in stream discharge, as described in Chapter 3, and consequently also in nutrient loading. Rates of loading at the time of contemporary spring snowmelt runoff (April) are reduced, and rates of loading in the winter months (November-February) are increased (Pierson et al., 2013). Slightly lower levels of streamflow during the summer lead to slight reductions in summer nutrient loads.

Changes in Reservoir Thermal Structure

Future changes in climate were found to lead to future changes in reservoir water temperature and thermal structure. On average, water temperatures increased throughout the year except during the winter months of January and February when the reservoir remained isothermal and at low temperatures (Figure 6.5). Temperature increases were greatest during spring and summer (April-September) when the reservoir was stratified and light conditions would also favor phytoplankton growth. The length of the thermally stratified period was simulated to be on average one week longer 100 years into the future, with the largest monthly changes in stratification occurring at the beginning (spring) and end (fall) of stratification. The effects on reservoir thermal structure can also be examined in greater detail by examining thermal isopleth plots of several representative years of the baseline run and a future simulation 100 years into the future (Figure 6.6). From these diagrams it is evident that the future scenario has a longer stratified period, warmer epilimnion temperatures and deeper mixing of warmer waters near the end of the stratified period (Samal et al., 2012). Verification of the UFI-PROTBAS model (DEP, 2008b) shows that changes in thermal structure can be predicted with a greater level of certainty than other more complex indicators of eutrophication.

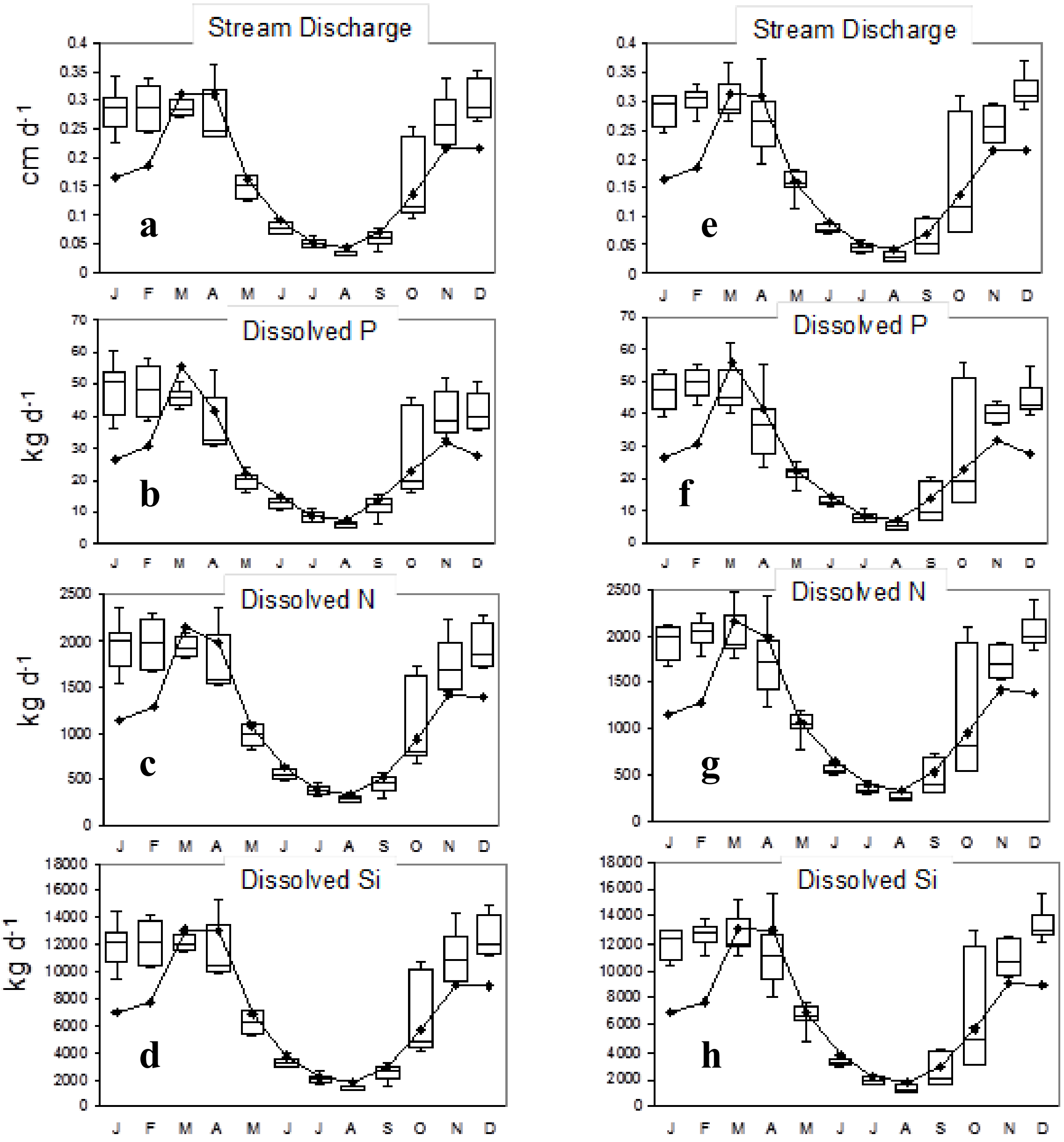


Figure 6.4 Average monthly rates of stream discharge (a and e), dissolved P loading (b and f), dissolved N loading (c and g), and dissolved Si loading (d and h) from the Cannonsville watershed, simulated with the GWLF model and serving as inputs to the UFI-PROTBAS model. Figures a-d are for future scenarios 65 years into the future, while e-h are for scenarios 100 years into the future. Mean monthly values of baseline simulations are shown as a line. Median and quartiles for future climate scenarios are shown in boxplots.

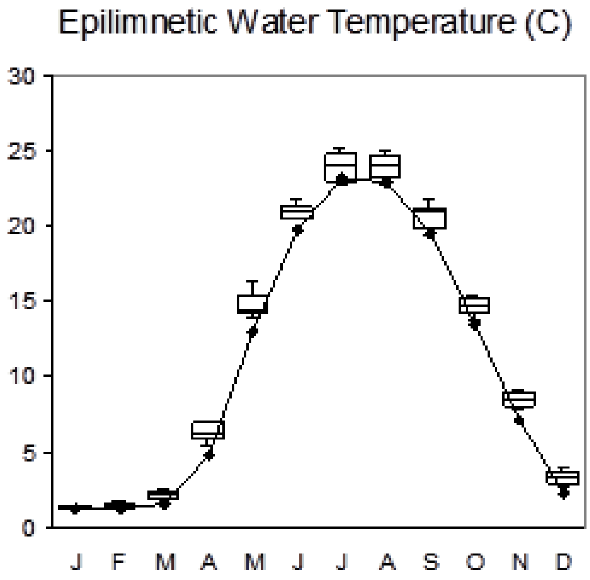


Figure 6.5 Cannonsville Reservoir mean monthly epilimnetic water temperature. Median and quartiles for nine future climate scenarios (+100 years) are shown in boxplots.

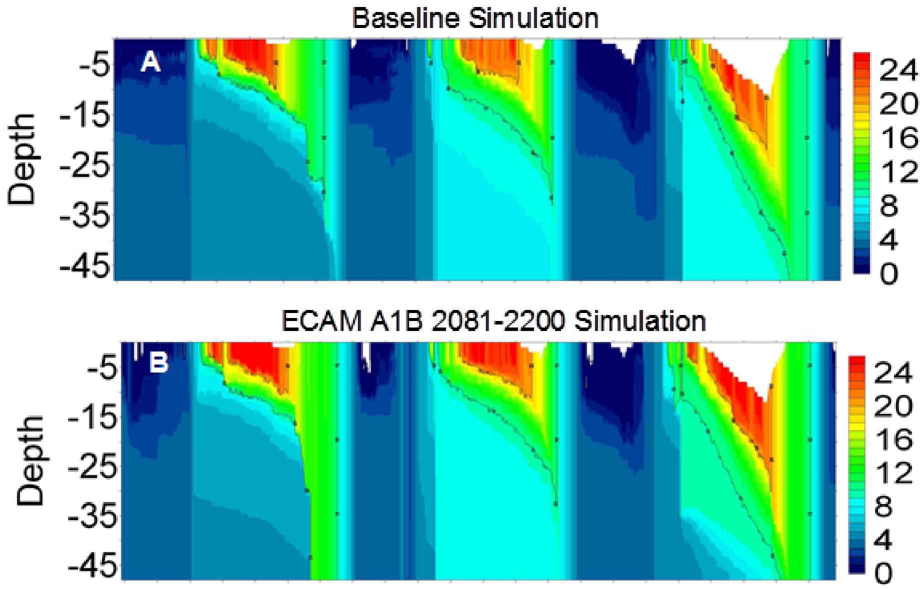


Figure 6.6 Thermal isopleth diagrams showing vertical temperature gradients over a three-year period for the Cannonsville Reservoir baseline simulation and a scenario based on the ECHAM A1B simulation 100 years into the future. Depths are relative to the elevation of the reservoir spillway. Changes in surface elevation are due to water drawdown.

Climate Change Effects on Phytoplankton

Average seasonal plots of chlorophyll and phytoplankton functional group biomass are presented in Figures 6.7 and 6.8 for baseline and future climate scenarios. Since the difference between 65-year and 100-year simulation results was not great, only the 100-year forward scenarios are shown. Simulations project that there will be only slightly higher monthly average total phytoplankton concentrations during May through October in the future climate scenarios compared to baseline conditions, and that the greatest changes will occur during the spring bloom period (Fig. 6.7a). When looking at the relative importance of climate change effects related to reservoir hydrodynamics/thermal structure versus effects related to watershed inputs (Figures 6.7b, c), it seems that future changes in water temperature more strongly influenced chlorophyll concentration in May, but during the other months the effect on chlorophyll is divided more equally between the influence from watershed and the reservoir thermal structure and mixing processes (Pierson et al., 2013).

Differing although small effects on Cannonsville Reservoir phytoplankton functional groups become evident if the total phytoplankton concentration is split into groups of diatoms (*Aulacoseira* and *Stephanodiscus*), buoyant cyanobacteria (*Aphanizomenon*, *Anabaena*, and *Microcystis*) and flagellates (*Rhodomonas*, *Cryptomonas*, and *Ceratium*). In the future climate scenarios, diatom concentrations were similar to baseline conditions during all months but May, when they were slightly higher, and June, when they were slightly lower (Figure 6.8). When examining the effects of changes in reservoir thermal structure alone, there was a slight negative effect on diatom concentrations in all months except for a positive effect in May. Diatoms were not affected by the simulated future changes in watershed loading rates alone. Buoyant cyanobacteria, in contrast, thrived in the future climate scenario simulations, with higher concentrations during stratified conditions in May through October. Increases in future reservoir temperature influenced buoyant cyanobacteria more than the effects related to changes in watershed loading. Flagellates show little variation between present climate and the future scenarios.

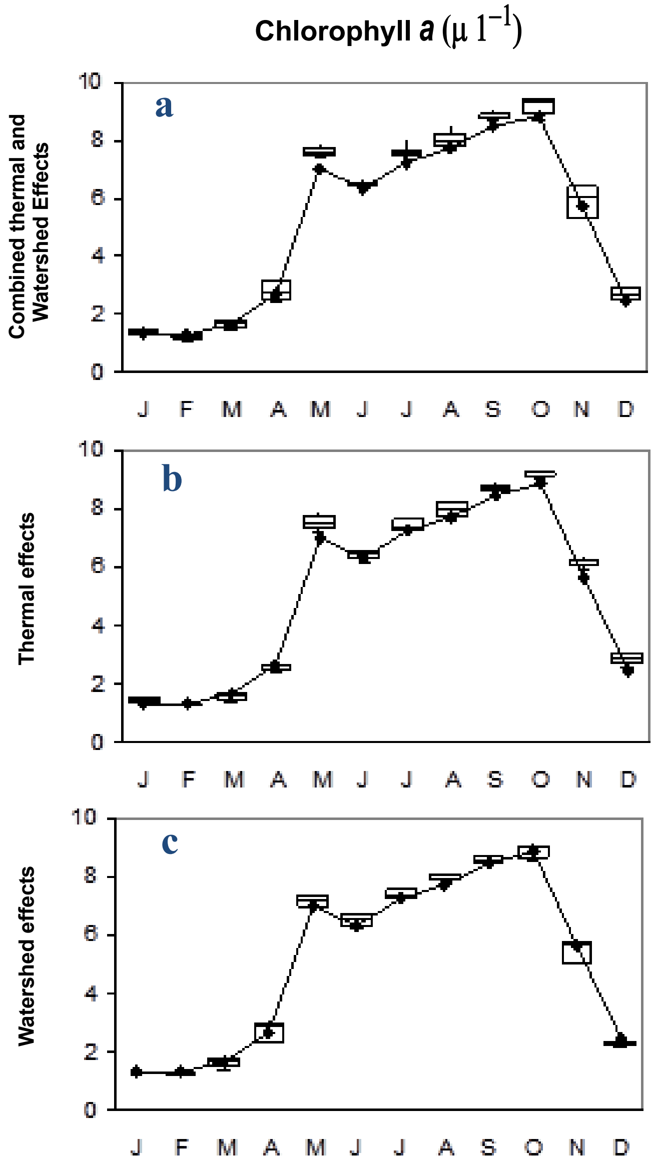


Figure 6.7 Simulated Cannonsville Reservoir epilimnion concentrations of chlorophyll *a,* 1966-2004 (line with dot symbols). Median and quartiles for nine future climate scenarios (+100 years) are shown in boxplots. Top panel (a) displays the combined watershed and thermal effects on chlorophyll *a* concentrations. Middle panel (b) displays the effect from a change only in thermal lake conditions, but with discharge and nutrient loading on the present day levels. Bottom panel (c) summarizes the effect of a change only in the discharge and nutrient loads.

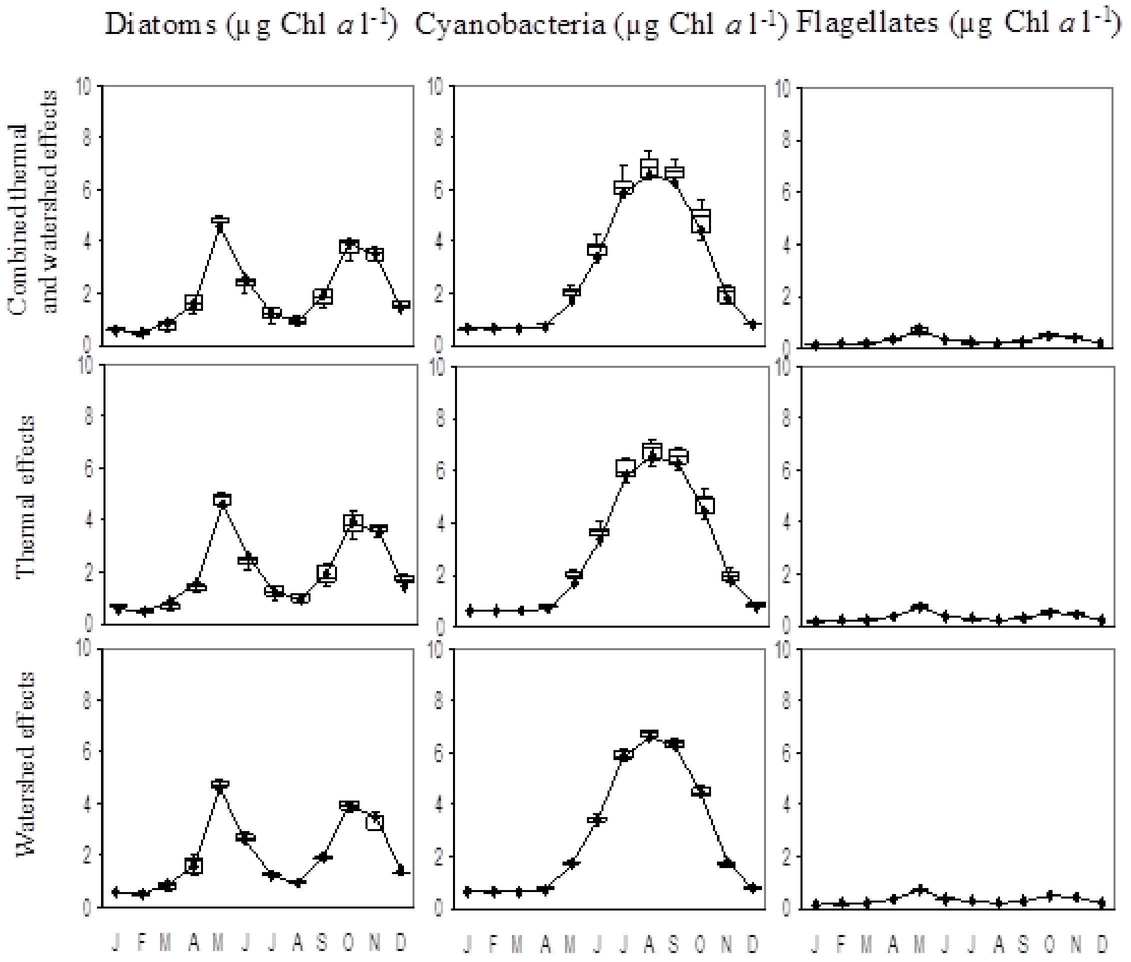


Figure 6.8 Cannonsville Reservoir epilimnion simulated concentrations of diatoms, cyanobacteria and flagellates, 1966-2004 (line with dot symbols). Median and quartiles for 18 future climate scenarios (+100 years) are shown in boxplots. Top panel (combined effects) displays the combined watershed and thermal effects on chlorophyll a concentrations. Middle panel (thermal effects) displays the effect from a change only in lake temperature alone, with discharge and nutrient loading on the present day levels. Bottom panel (watershed effects) summarizes the effects on three groups of phytoplankton from a change only in the discharge and nutrient loads.

Conclusions

One common expectation for water bodies in a warmer world is that spring phytoplankton biomass will increase (Gerten and Adrian, 2002) and cyanobacteria will dominate over the larger portions of the stratified season (Robarts and Zohary, 1987; Hyenstrand et al., 1998). Indeed, historical studies suggest that in some cases there was an increase in spring biomass and a tendency towards a dominance of cyanobacteria during the remainder of the year (Adrian et al., 1995, 1996). Other long-term studies found that increasing water temperature has led to stronger and longer lasting lake stratification, but trends in yearly biomass of phytoplankton were absent (Gerten and Adrian, 2002; Arnott et al., 2003). Overall, the literature suggests that future climate lake properties will be characterized by warmer water temperatures, earlier stratification, shorter ice-cover periods, and changes in annual phytoplankton biomasses, ranging from minimal to substantial (Marsh and Lesack, 1996; Frisk et al., 1997; Hamilton et al., 2002; Arheimer et al., 2005; Elliott et al., 2005).

The future climate scenarios for Cannonsville Reservoir projected a slight increase in total phytoplankton concentration and a shift towards buoyant nitrogen-fixing cyanobacteria dominance at the expense of diatoms, in line with conclusions from historical studies (Adrian et al., 1995; Adrian and Deneke, 1996) and future projections (Hassan et al., 1998; Arheimer et al., 2005). The relatively small simulated response of the phytoplankton in Cannonsville Reservoir to substantial projected increases in winter nutrient loading (Figures 6.4 and 6.7) seemingly demonstrates the importance of the timing of nutrient delivery in eutrophication impact studies. Even though there are increases in nutrient loading (Figure 6.4) these are projected to occur in the winter and fall when levels of temperature and light would not favor phytoplankton growth. Furthermore, there are significantly lower levels of nutrient loading simulated to occur during the spring and slightly lower levels of nutrient loading simulated to occur during the remainder of the growing season. Previous investigations of Cannonsville eutrophication indicate that phytoplankton growth tends to be relatively insensitive to winter and early spring loadings due to low seasonal residence time associated with the spring high flow period, but quite sensitive to loadings during the growing season (DEP, 2006b).

These initial results are generally encouraging for DEP, suggesting that climate change will not strongly impact reservoir eutrophication levels, and that any increases in eutrophication that do occur will generally be less than the water quality improvements that have resulted from FAD-mandated programs of watershed management (DEP, 2006b). However, while Phase I CCIMP results are reasonable, there are significant uncertainties associated with the Phase I projections. In particular, we are investigating the ability of our models to sufficiently simulate processes such as nutrient transformation and phytoplankton light adaptation that occur during the winter isothermal period.

7. Phase I Summary

This report presents the Phase I results for the Climate Change Integrated Modeling Project (CCIMP). The project is part of an ongoing effort to evaluate the effects of future climate change on the quantity and quality of water in the NYC Water Supply, and to evaluate how such effects could influence the use and operation of the water supply. Phase I focused on water quantity in the West of Hudson (WOH) portion of the system, turbidity in Schoharie Reservoir, and eutrophication in Cannonsville Reservoir. Phase I was designed specifically with the goal of making an initial estimate of climate change impacts using available GCM data sets and DEP's present suite of watershed, reservoir, and system operation models. During the course of these studies, the DEP modeling unit improved the tools it will use to carry out these and other similar analyses in the future.

Some of the general findings of Phase I were:

The timing of the spring snowmelt was predicted to shift from a distinct peak in late March and April to a more consistent distribution throughout the winter and autumn. This shift is a function of increased temperatures, which will cause less precipitation to fall as snow and faster melting of the snowpack that does develop. The consequent shift in streamflow drives many of the findings obtained from applications of the water system and reservoir water quality models.

Greater winter streamflow will cause the WOH reservoirs to fill earlier in the year, and for spill from the reservoirs to increase during the winter. The increased winter spill will come at the cost of lost storage in the spring snowpack.

For the WOH System, drought seems to be less prevalent, because the GCM simulations used in the study predict increased precipitation throughout the year, which compensates for lost snow storage and increased evapotranspiration due to higher temperatures.

The shifting seasonal pattern in streamflow will similarly affect the turbidity loads into Schoharie Reservoir, which in turn will impact the Schoharie withdrawals, resulting in increased turbidity in the autumn and winter and decreased turbidity in the spring.

The nutrient loads to Cannonsville Reservoir will also exhibit shifts similar to the streamflow shifts noted above. However, despite increased nutrient loads during the winter and autumn, the response of the phytoplankton will be small, presumably due to unfavorable growth conditions at this time of the year. The thermal structure of the reservoir will be impacted by the higher temperatures of the future climate, with thermal stratification beginning earlier in the spring and lasting longer into the autumn.

8. Future Planning

The findings presented in this report should be considered the "first cut" estimates of some of the potential effects of climate change, because many issues related to data limitations, uncertainties, and modeling assumptions remain to be resolved. At the same time, it should be remembered that there will always be a level of uncertainty associated with projected future climate data for which no validation is possible.

Some of the issues that will be addressed during future phases of the project are as follows:

Development of Improved Future Climate Scenarios

During Phase I of the project, an ensemble of GCMs and emission scenarios was used to understand some of the potential variability in results, given the uncertainty of future climate predictions. That variability is illustrated by the somewhat different results produced by different GCMs for the same geographic location and future time period, depending on the parameter of interest. For example, the four GCMs used in the Phase I study were all in agreement that temperature would rise throughout the year, but, while agreeing for the most part that annual average precipitation would increase, they differed with respect to the seasonal pattern of increase. To better account for this uncertainty, DEP plans to use more GCMs in future simulations. The four GCMs selected for Phase I were chosen due to the availability of processed GCM results at the time the Phase I project started; adding additional simulations, however, will introduce a more complete picture of the variability associated with future climate predictions.

Using the change factor methodology to downscale GCM output leaves long-term historical patterns of the timing of storm events unchanged, even as the magnitude of these events changes based on projected seasonal changes in climate. This makes the historical and climate change scenarios fairly consistent and more easily comparable, especially when using historical reservoir operations, as was done here for the reservoir turbidity and eutrophication analyses. On the other hand, the monthly change factor methodology does not account for changes in the frequency or duration of storm events or changes in inter-storm periods. Future work will investigate the use of other techniques for downscaling GCM results and developing climate change scenarios for model input, to help account for potential changes in storm frequency and magnitude, and inter-storm duration. One possibility is adjusting the change factor approach to use more factors that account for the changes in the frequency distribution of the parameter of interest. Other approaches include the use of complex statistical downscaling techniques and the use of regional climate model results.

Watershed Modeling

Clearly, changes in patterns of precipitation, evapotranspiration, snow accumulation, and snowmelt resulting from climate change can be expected to impact the NYC Water Supply. Consequently it is important that watershed models be responsive to spatial variations in precipitation and air temperature, and more accurately represent the spatial distribution of snow and snowmelt. Moreover, changes in watershed processes can be expected to affect future patterns in nutrient and turbidity loading. These processes are not, however, explicitly simulated in GWLF-VSA, or in the rating curve used to produce stream turbidity loads. GWLF-VSA is used to simulate the effects of changes in hydrology (water quantity and flow path) on water quality loads, but these applications assume that climate change will not alter the biogeochemical and sediment transport properties of the watershed.

Plant growth and nutrient uptake, decomposition, nutrient migration in soil, soil nutrient fluxes, storage and transformation, and related processes are temperature and/or moisture dependent. Climate change impacts on these processes may substantially influence spatial and temporal patterns of nutrient concentrations, and projected loads to a reservoir. As part of future work on the CCIMP, DEP is developing SWAT and RHESSys model applications, which more correctly simulate nutrient dynamics.

The turbidity analysis faces similar uncertainties. Changes to the flow regime of a watershed may change the shape of the rating curve because of changes in the frequency and magnitude of channel-altering flows. In addition, there is a large degree of uncertainty associated with turbidity rating curves themselves. Future work will investigate the use of improved sediment transport modeling to better explain the uncertainty in the rating curves and possibly gain an understanding of how the channels might react to future climate change.

Another assumption under the current Phase I analysis is that land use and management practices will remain static moving into the future, but changes in climate may affect these practices too, possibly altering the type and/or management practices of agriculture or altering the forest.

While projecting these changes is difficult, future work will attempt to address some of these issues.

System Modeling

A number of improvements could be implemented within the system model (OASIS) to further support climate change analyses. In the first phase of OASIS simulations, East of Hudson (EOH) and lower Delaware flows were not modified under future climate scenarios. Although these watershed areas have relatively small impacts on the operations of the West of Hudson (WOH) areas, these systems will be included in future work, which has the goal of examining the entire water supply system. The linkage of the OASIS system model with appropriate water quality models will be pursued in future analyses. This will allow more feedback between simulated water quality and system operations than can be achieved using the simple empirical water quality relationships presently embedded in the OASIS model. Additional benefits will be gained once linked OASIS water quality runs can be used to define reservoir operations under future climate scenarios, and the simple preprocessing programs described in Chapters 5 and 6 can be replaced.

Finally, Phase I analyses assumed unchanging demand on the water supply system, and a fixed operating rule set that was the same under present and future conditions. In future phases of the CCIMP these assumptions will be examined. Climate-induced changes in system inputs (inflows, volume, and turbidity to reservoirs) and driving forces (meteorology, inflow temperature) may trigger adaptive responses that cause the system to operate differently from the present using current day rules and demands. However, it will also be necessary to evaluate future changes in demand, and if better operational rule sets might be appropriate for future climate conditions.

Reservoir Modeling

Some of the uncertainty in the CCIMP Phase I predictions stems from the fact that the DEP modeling system has not been extensively evaluated to determine its suitability for providing simulations under future climate conditions. While validation of the models over a long time period of contemporary conditions has been successful, more extensive testing of the suitability of the watershed and reservoir models for use under future climate conditions is needed. So far, the clearest need for such testing was revealed through examination of the future reservoir eutrophication simulations. Despite significant changes in the timing of nutrient inputs to Cannonsville Reservoir (Chapter 6), only minor changes in phytoplankton biomass were predicted. While this could well be correct, further testing is needed to determine if in fact the UFI-PROTBAS model is correctly simulating the fate of nutrients under winter conditions, as well as phytoplankton adaptation and growth under low light/isothermal conditions typical of the winter. Such testing will be hampered by the fact that most model testing and calibration has until now focused on processes occurring during the stratified period, which is most important for reservoir water quality under present climate conditions.

Glossary of Terms

Baseflow. The part of streamflow that is related to slower delivery processes such as infiltrated precipitation that travels through sub-surface groundwater flow. Baseflow can be expressed as a flow volume per unit time (e.g., $m^3 s^{-1}$) or as a depth per unit time (e.g., cm day^{-1}) where the depth represents the flow volume divided by the watershed area. (See also, *Streamflow*)

Baseline climate scenario. A time series of locally observed meteorological data that represents baseline conditions. For the CCIMP we used data collected between 1927-2005. Reservoir model simulations used data measured at or close to the reservoir. Watershed model simulations used data from multiple stations in and adjacent to the watershed.

Change factor (aka *delta change factor).* A mechanism to translate GCM climate output from the large geographic scale of the GCM to a local spatial resolution. There are two basic forms: additive or multiplicative. In an additive change factor, the arithmetic difference is calculated between a GCM variable derived from a current condition (20C3M) GCM simulation and a future climate simulation using the same GCM and taken at the same grid location. This difference is then added to *observed* local meteorological data (aka baseline climate scenario) to obtain the modeled future climate scenarios. A multiplicative change factor is similar to an additive change factor (CF) except that the *ratio*, rather than the arithmetic difference, between the future and current condition GCM simulations is calculated; the observed local meteorological data are then multiplied by (rather than added to) the CF. Here, an additive CF is used for temperature, and a multiplicative CF is used for precipitation, to obtain local future climate scenarios. For simulations with DEP’s watershed and reservoir models, the observed meteorological data serve as the baseline scenario, whereas the CF-modified data serve as future scenarios. Change factors were developed by comparing 20-year GCM simulation periods.

Climate. A composite of weather conditions (i.e., air temperature, precipitation, wind, humidity) including both average values and inter- and intra-annual variability for a region over a period of years.

*Climate simulation (*aka *GCM simulation).* Time series of results obtained from a GCM simulation. For this report we used GCM results that were available at daily resolution from the CMIP3 data archive of the World Climate Research Program Coupled Model Intercomparison Project (http://cmip-pcmdi.llnl.gov/).

Current climate GCM simulation. The climate pattern of the period 1981-2000 as modeled by GCM simulations.

Direct runoff (aka *surface runoff* or *quickflow*). Liquid precipitation or snowmelt that travels quickly to the stream via overland flow or sub-surface storm flow. Direct runoff can be expressed as a flow volume per unit time (e.g., $m^3 s^{-1}$) or as a depth per unit time (e.g., cm day^{-1}) where the depth represents the flow volume divided by the watershed area. (See also, *Streamflow*)

EOH. The part of the New York City Water Supply that is east of the Hudson River

Evapotranspiration (ET). The part of the water balance dealing with the movement of water vapor from the land surface into the atmosphere. Evaporation can occur from open water bodies or from bare soil and transpiration is water movement via plants. Evapotranspiration is the sum of transpiration and evaporation.

Eutrophication. The process by which a body of water becomes enriched in dissolved nutrients (often from fertilizers or sewage), thereby stimulating the growth of aquatic phytoplankton and macrophytes. Eutrophication can have detrimental effects on the use of reservoir water including taste and odor issues, the presence of potentially toxic compounds (e.g., cyanobacteria), and the potential increase in disinfection by-products. The degree of eutrophication in a water body is commonly related to lake/reservoir nutrient levels, phytoplankton biomass (usually measured as chlorophyll *a*), phytoplankton primary production, phytoplankton community composition, water transparency measured by Secchi depth, reservoir thermal structure, and hypolimnetic oxygen depletion resulting from bacterial decomposition of excessive organic matter. Lake trophic status is most often classified by the available limiting nutrient, here total dissolved phosphorus, and levels of phytoplankton biomass as indicated by their chlorophyll *a* concentration.

Emission scenarios. These describe future releases into the atmosphere of greenhouse gases, aerosols, and other pollutants and, along with information on land use and land cover, provide inputs to climate models (see *Global climate models*). They are based on assumptions about driving forces such as patterns of economic and population growth, technology development, and other factors. For this report we used the A2, A1B and B1 emission scenarios representing future high, medium and low greenhouse gas concentrations, respectively.

Future climate simulations. The climate pattern of the future time periods as simulated by a GCM driven by different emission scenarios. In this report we have made use of model simulations for two future time slices (2046-2065 and 2081-2100) when GCM models were driven by three future emission scenarios (A2, A1B, and B2).

Future climate scenario. A time series of data produced by applying change factor downscaling to time series of locally measured (baseline) meteorological data. Future climate scenarios were produced for each of the time slice/emission scenario simulations available from each GCM model. (See also, *Change Factor*)

GCM time slice. The time period represented by a future climate simulation or scenario. For our analyses two time slices (or time periods) are used: 2046-2065 and 2081-2100.

Global climate models (GCM). Complex computer codes that simulate the behavior of the global climate system, its components and their interactions. The models include mathematical representations of the earth's climate system based on physical, biological and chemical principles. There are multiple GCM models that have been developed independently by research groups around the world. Systematic comparisons and model output are available from the Coupled Model Intercomparison Project (http://cmip-pcmdi.llnl.gov/).

Potential evapotranspiration (PET). The maximum rate of evapotranspiration as limited by atmospheric forcing conditions (i.e., net solar and long wave radiation, humidity, wind speed and air temperature).

Reservoir release. Controlled water release from a reservoir to a downstream receiving water body.

Reservoir spill. Uncontrolled movement of water out of a reservoir to a downstream water body due to reservoir water surface elevation exceeding the spillway elevation.

Reservoir withdrawal (aka *reservoir diversion*). Controlled flow from a reservoir into aqueducts transporting water to other parts of the water supply system (i.e., to downstream reservoirs or to the distribution system).

Streamflow. Flow within a stream. This could be in units of volume per unit time (i.e., m^3s^{-1} or m^3/s). In other cases, streamflow may be expressed as a depth per unit time (i.e., cm/day) where the depth is the flow volume divided by the watershed area (i.e., *unit area streamflow* or *specific discharge*). Expressing flows in depth per time units allows direct comparison with precipitation inputs and also allows normalized comparison of water cycle components between different watersheds

Thermal stratification. A seasonal process of vertical lake thermal structure when warmer waters form a surface mixed layer (epilimnion) and a lower colder layer (hypolimnion). The zone separating the two layers is the metalimnion (the zone of the greatest vertical temperature gradient). Lake stratification generally occurs in the spring and continues through the fall.

Turbidity. The cloudiness of a water body (or sample) as measured in arbitrary Nephelometric Turbidity Units (NTU). It is measured, using an instrument called a Nephelometer, by assessing the light scattered in a cone centered on 90^o. The measurements obtained are instrument dependent but when assessed by the Hach 2100A or 2100AN instruments the values obtained are similar to the scattering coefficient, *b*, an inherent optical property of water. Excess turbidity is detrimental to drinking water quality because contaminants and pathogens can become associated with turbidity-causing particles thereby reducing the effectiveness of water disinfection. Regulatory requirements limit turbidity to 5 NTU for water entering a drinking water distribution system from an unfiltered water supply, as is the case with NYC.

Turbidity load. Mathematically, this is turbidity (NTU) x flow ($m^3 s^{-1}$). Strictly speaking it is not a true load (*sensu* mass x flow) but it is, nonetheless, a convenient and mathematically defensible tool in computations. Its use is becoming widespread in the literature and is justified based on the additive character of its components (i.e., Davies-Colley *et al*., 2003; Gelda *et al*., 2007).

Watershed. An area of surface water drainage defined by the topographic characteristics of land surface (km^2) (aka *catchment*).

WOH. The part of the New York City Water Supply that is west of the Hudson River.

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Appendix - Submissions from the CCIMP Expert Panel Members

After the compilation of a draft of this CCIMP Phase I report was completed, a panel of "Experts in their field" was invited to attend a workshop to discuss its contents with DEP's Water Quality Modeling Group, other DEP staff, and City University of New York Post-Doctoral Fellows working with the Modeling Group. This workshop was held in The Ashokan Center, Olivebridge, New York on 23-24 September, 2013.

At this workshop, each "Expert" was asked to provide a 5-10 minute verbal critique of the work documented in this report, and also to provide a one page written summary. They were also requested to provide suggestions for charting out future directions.

During the Workshop, 'break-out' groups were organized to discuss and develop the future course of climate change modeling by DEP's Water Quality Modeling Group and to highlight key issues. These outcomes of these group discussions were presented to the entire Workshop for additional comment.

The initial written summary comments of the Experts are presented in this Appendix.

Comments on this report by Peter M. Groffman, Cary Institute of Ecosystem Studies, Millbrook, NY 12545. groffmanp@caryinstitute.org

The basic approach of the project, where Global Climate Models (GCM) are linked to the Generalized Watershed Loading Function model (variable source area version), water supply system models, and reservoir eutrophication and turbidity models is very impressive. The fact that the model outputs are linked to monitoring data is also critically important. Ideas for future phases of the project, especially to address changes in storm frequency and intensity are strong. It would be nice to see more evaluation of how well the modeling system works, with comparison of model outputs with data over the past years and decades. Some more specific comments:

- I like the "climate factor methodology" approach for working with GCMs as it allows for exploration of extremes. I also agree that confidence in GCM predictions for the region is relatively high as the different models are quite consistent in their outputs. It will be very important to develop approaches to consider changes in the intensity, frequency, or duration of storm events in future phases of the project. It would be nice to see how predicted climate changes compare with trends that have been observed in the region over recent decades.

- I am a big fan of the GWLF-VSA model and am impressed with the approach to "get the water right" as the primary step in the analysis. I wonder about the assumption that evapotranspiration (ET) is going to go up given that atmospheric CO_2 is rising and recent observations about regional declines in ET. Again, it would be nice to see how predicted changes compare with trends that have been observed in the region over recent decades. Ideas for future work to improve then ability to simulate nutrient fluxes with SWAT and RHESSYS are sound.

- I am not qualified to evaluate the OASIS-based system operation modeling in detail, but the approach seems very sound to me. I wonder about the assumption that future water demands will be similar to current demands. It might be worthwhile to evaluate how significant increases or decreases in demand might affect the system. The intention to address the uncertainty in future summer precipitation in future phases of the project seems quite important.

- The analysis of turbidity in the Schoharie reservoir is also outside my area of expertise. However, the analysis appears to be sound and the acknowledgement that changes in storm event frequency, intensity, and duration will be important to consider in future analyses is very important. It would also be interesting to see how the model performed during several recent large events, e.g., Tropical Storm Irene.

- Some comments and questions on the Cannonsville eutrophication modeling:
  I note that estimates of nutrient input via septic systems are based on an estimate of how many systems are failing. This might be wrong as all septic systems contribute nutrients to the environment. Functioning systems are actually more efficient producers of inorganic forms of N and P than failing systems.
  - Just how do greater levels of precipitation lead to greater levels of nutrient loading? Is it a decline in residence time? If the inputs don't go up, this approach might be overestimating the increase.
  - The assumption of lower levels of streamflow in the summer are not being seen at other sites in the northeast, e.g., Hubbard Brook in NH. What have summer streamflow levels been doing in these streams over the past couple of decades?
  - Any ideas about how inputs are going to change in the next 50 – 100 years?

Comments on this report by Paul C. Hanson, Center for Limnology, University of Wisconsin, Madison. pchanson@wisc.edu

The CCIMP has provided a useful and reliable assessment of possible climate change effects on the quantity and quality of water quality in NYC reservoirs. The report articulates clearly future scenarios for water quantity, turbidity, and eutrophication, and provides an accessible description of the integrative modeling supporting those scenarios. Project personnel have identified key areas of uncertainty, such as the role of meteorological events in loading, and are devising strategies for addressing those uncertainties. Finally, a diversity of researchers and managers with responsibility for NYC water supply, as well as a number of outside collaborators, have been engaged in the evolution and evolution of this project. The commitment to exploring a diversity of issues and research avenues with management relevance, apparent in the fertile, positive and enthusiastic tone of discussions, increases the probability of success and broader adoption of the outcomes.

Specific Comments

The integrative modeling approach of CCIMP, from atmospheric processes through hydrologic and nutrient fluxes to reservoir hydrodynamics and water quality dynamics, is at the forefront of watershed integrative modeling. Project personnel have overcome many technical challenges in linking typically disparate models that consume complex data, much of which needs intensive interpretation and transformation. The outcome is a systems approach that has the flexibility to model a diversity of climate change and land use (and water use) scenarios and provide useful and reliable products that will aide in evaluation of the consequences of those changes. The comments that follow address issues already raised by the CCIMP, in some cases.

Basic information about the system: More basic information about the reservoirs, such as nutrient and phytoplankton distributions, hydrologic and chemical residence times, and system dynamics would be helpful in the report or in readily available in supplemental material. For example, an experienced limnologist will use key characteristics, such as morphology, residence time, and trophic state to evaluate the possible range of system behaviors. If that information is combined with visualizations of time series for key observed (not just modeled) variables, such as phytoplankton biomass (or chlorophyll concentration), then the reader has solid reference points from which to evaluate model predictions.

Model calibration: It would be easier to evaluate model performance if model predictions and observations were both included in the report, rather than in the cited literature. How well can observed data be predicted? What patterns can the models **not** recreate? Answering these questions would provide information on the scales of variability, as well as other system features, such as events, that can and cannot be represented adequately by the models.

Events can be very important to nutrient and carbon loads (long tailed distributions). How well are historical events captured? What are the system response/recovery times? What kind of future events might be important and how likely are they to occur? Addressing these questions will be important for prediction of future sediment loads (turbidity) and nutrient loads (eutrophication).

Uncertainty: Currently, all the uncertainty appears to be subsumed in the GCM scenarios. Understanding how other sources of uncertainty, such as observational, parameter and model uncertainty, contribute to uncertainty in the predictions is important. For example, the uncertainty due to the change factor methodology seems much smaller than the uncertainties due to selection of the particular GCM. Investigating various uncertainties in these kinds of systems models is a substantial undertaking that is of interest to the broader scientific community. This might be a topic to raise with outside collaborators who have experience in this area.

Broadening collaboration: This is a big project with many dimensions and many possible avenues to explore for the next phase. It will be challenging to determine which research avenues are within scope of the project and then how to prioritize the many recommendations for future work. One approach to addressing these issues would be to engage further the broader research community, providing leadership to other entities with similar research interests, while gaining additional expertise through the collaborative process. For example, the CCIMP has a need for reservoir carbon cycling models to better understand issues regarding disinfectant byproducts. Aquatic carbon cycling is an area of recent and intensive research in the academic community, and it seems likely that DEP could attract a diversity of scientists in a collaborative activity, such as a workshop to devise a dynamic reservoir carbon cycling model.

Breaking the system: What sequence of events would be required to lead to substantial, or even catastrophic, change in water quality or availability? Answering this question seems important, and applying the model toward that end would stimulate important discussions by stakeholders and might reveal additional and important research avenues not apparent in approaches that rely primarily on climate drivers to dictate system dynamics.

Comments on this report by Kenan Ozekin, Water Research Foundation, Denver, CO 80235. (kozekin@waterrf.org)

I read the “Climate Change Integrated Modeling Project - Phase I Assessment of Impacts on the New York City Water Supply” report with high interest. Water agencies have always faced uncertainty when planning for the future. Traditional planning methods are based on the assumption of hydrologic stationarity. However, there is substantial evidence that future climate and hydrologic conditions will be significantly different adding a layer of complexity for planning for the future. Phase I report prepared by NYCDEP shows how a utility can assess the impacts and evaluate the options for future planning.

When it comes to climate change, there are climate winners and losers. It is very clear from the Phase I report that NYCDEP is on the winner side as far as the precipitation concerned. However, being an unfiltered system complicates NYCDEP’s situation. For example, Phase I report does an excellent job explaining the importance of extreme events on turbidity. Unfortunately climate projections available at the report do not adequately quantify future changes in extreme rainfall intensity, despite qualitative evidence in current trends. One area that NYCDEP may focus in future studies to understand how frequency and intensity of extreme events may change in future.

Another area that is not addressed in Phase I analysis is how future climate may impact future demand which may be very different from the present because of changes in domestic use characteristics, economic growth, the emergence or decline of commercial or industrial water users, or other uncertainties. It is highly encouraged for NYCDEP to understand the impacts of demand and incorporate climate factors into the future demand calculations.

On the modeling side, GCM simulations during the 1981-2000 period were used to represent current climate conditions and simulations were run for two future time periods. It will be interesting to run the models for 2000- 2012 period to assess the sensitivity and accuracy of the predictions.

Finally, climate change may impact the nature and concentration of organic matter and the formation of disinfection byproducts. It will be important for NYCDEP to understand the organic matter loading to its reservoirs under future climate predictions.

Comments on this report by Dennis P Lettenmaier, University of Washington. dennisl@uw.edu

This phase 1 report summarizes results of what amounts to a pilot study to predict mid and end of century system performance of DEP's West of Hudson (WOH) reservoirs, as well turbidity impacts on the Catskill portion of the system, and eutrophication effects on the Delaware portion of the system. The study used existing hydrology, reservoir system, and stream and reservoir water quality models developed by or for DEP, all of which have been used in previous system studies. Climate scenarios came from delta method downscaling from four IPCC AR4 global models, each with run for three (two in the case of one of the models) global emissions scenarios.

Most of my concerns about the study are to be addressed in subsequent phases of the project, but I will summarize them nonetheless:

1. I think the key limitation in the Phase 1 study is that it is based on only four global models (GCMs), and they are now somewhat outdated (IPCC AR5 scenarios are now available for most of the participating models). Several of the key conclusions (reduced drought susceptibility due to increased precipitation and hence runoff, especially in the summer) may be to some extent an artifact of the four GCMs that were used, and in any event may not be the same for the AR5 results.
2. Some of the results come from models that are highly empirical, and the "tuning" to historical conditions may not be valid under future climate. This is the case especially for the turbidity modeling. From the description, I can't be entirely sure, but there seems to be an inconsistency between the stream temperature modeling (used in turbidity simulations) which is empirical, and the reservoir temperature and hydrodynamics, which seem to be physically based.
3. A key limitation of the AR4 GCM archive as contrasted with AR5 is that only monthly results were archived. This supports the delta method, which simply adjusts historical records, but (as indicated in the report) can't capture future predicted changes in storm characteristics. Given the size of the reservoir system, the delta approach may be OK for the reservoir system modeling (seasonal variations in storage levels and ability to meet demands) but more problematic for turbidity, which I assume must be related to specific storm events, as well as eutrophication, which seems to be driven primarily by summer storms. This needs to be better articulated in the report.
4. As in many similar studies, this one uses a chain of models, and suggests the obvious question of uncertainty, which isn't addressed, and should be in subsequent phases. The report does

indicate that alternate, more physically based models will be applied in subsequent phases of the eutrophication part of the study. They may want to consider either using alternate hydrology models, or attempting to characterize the differences in sensitivity that would result from alternate models. In such studies, uncertainty about future climate usually is the largest overall source of uncertainty, however contributions from the following other sources can be considerable as well (see Vano et al, 2013 for an example): a) hydrology model uncertainty; b) downscaling uncertainty, and c) water quality (stream transport and reservoir) response to changes in hydrology and climate. It would be useful to do some exploratory analysis to determine which of these is most important for the DEP system, and then attempt to characterize those contributions to future system performance.

Comments on this report by Francis J. Magilligan, Dartmouth College, Hanover, New Hampshire. Francis.J.Magilligan@dartmouth.edu

This is a very thoughtful and extremely well-written report. It does a fantastic job of conveying sophisticated scientific information yet being written in an approachable layperson's language. Moreover, it has done an exceptional job of condensing and distilling sophisticated scientific modeling into a few important bullet points that give it an even stronger resonance.

In terms of analysis of the Phase I portion, this phase has done a great job of covering the breadth of issues facing New York City's future water supply. As they layout in the document, there are many climate models, each with their specific strengths and weaknesses. Their selection of a “Delta change” approach is highly defensible as it captures the associated projected climate changes and represents it in a way that is very understandable.

As a fluvial geomorphologist and hydrologist who has spent the last 15 years evaluating the hydro-ecological impacts of dams, I will focus my comments primarily to geomorphic processes and reservoir regulation. And my comments are probably more about how to proceed in Phase II rather than as any criticism of Phase 1.

Major Points:

- Extreme events. The report mentions that peak flows should remain the same, but I am less convinced of that result. I think this needs to be explored more thoroughly. Peak flows have an important impact on channel erosion and subsequent sediment transfers. Moreover, planning needs to consider changes in the timing of extremes. Changes in the occurrence of large storms can have profound effects on sediment supply: e.g., big storms in June are different than big storms in August in part due to natural land cover conditions (trees not fully leafed out yet) combined with land use timings (recently plowed ag fields in June).

  Also, in terms of extreme events, there is no mention of changes in hurricane magnitude or frequency. These types of events are very hard to project and predict with current models, but there should at least be some discussion of their projected role.

- Consequences of increased spilling. One of the projected externalities of increased streamflow is the increased likelihood and volume of reservoir spilling. There is an associated economic cost of course associated with the increased spilling, but there may be some unknown impacts on downstream geomorphic processes and ecological integrity. The unknown costs and risks associated with increased spilling needs greater coverage in future efforts.

- Better understanding of geomorphic processes contributing sediment to reservoirs. Besides the material covered in the Phase I report, the 2-day workshop revealed how important erosion and sedimentation was to meeting water quality standards. NYC DEP has fantastic field personnel, and they have done a great job of restoring degraded stream reaches and in doing subsequent field monitoring. The changes in streamflow documented in the report will have important impacts on sediment delivery to the reservoirs. Future efforts may need to be directed at developing a whole basin sediment budget. This will require more field monitoring and data acquisition, but it may also need a detailed sediment sampling protocol and rainfall runoff-erosion model development.

- The section on drought needs greater elaboration. The report suggests that droughts will not necessarily be a major concern. Perhaps this issue can be scoped better. Modeling results indicate that low annual totals will not be a major concern. However, droughts reflect extended periods of below average precipitation, and just because it may be a wetter world in the future doesn't mean you can't have 5 consecutive years with below average rainfall. This might require better attention in the modeling.

Engagement with other institutions. How do the management schemes outlined in Phase I relate to or affect state and federal regulations? Many of the protocols and management schemes and alternatives outlined in the report may have repercussions with existing state and federal legislating and may be important boundary conditions for storage and release strategies. Does DEP need better institutional engagement with, for example, the Corps, NOAA or FWS?

Comments on this report by Radley Horton, Columbia University, New York, NY. rh142@columbia.edu

Key questions and recommendations:

Should you use CMIP3 or CMIP5 GCMs? CMIP5 seems the obvious answer, but you might explore how different CMIP3 and CMIP5 results are for the region and your specific applications.

How robust are your findings thus far about fall precipitation increases? I fear they may be highly dependent on the small (3 GCM) model sample size.

Don’t be wedded exclusively to GCM scenarios. For example, you might want to consider a scenario of increasing snow cover and snow events during the heart of winter, even if no GCMs project such an outcome.

Don’t overemphasize downscaling at the expense of other considerations. In terms of the downscaling, explore both BCSD and BCCA which are based on standardized algorithms. It will require a lot more resources, but also consider developing your own empirical approaches tailored to the region and questions of interest to you, by identifying key metrics.

Along the same lines, encourage process-based studies, and focus on extreme events in general. Look for example to the atmospheric rivers research along the West Coast, and ask what the equivalent large-scale events are here.

General comments:

I don’t think it will affect your results much, but I would consider applying a several day filter across all days, to avoid having the abrupt transitions at the beginning and end of each calendar month.

Continue to explore the growing paleoclimatology records for the region, and continue to ask yourselves how you should be treating the 1960s drought of record

Think about how you can contextualize the climate uncertainties relative to other uncertainties (e.g., those—stated or unstated—in systems operation).

How will you interact with NYC operational support tools. Can they be helpful and provide a means for increased collaboration?

For your eutrophication work, how have you addressed correlation between the solar, wind, T, and P terms?

Does turbidity affect solar absorption?

Is the analysis of stream temperature you described sufficiently sensitive to the volume of flow?

I think more work could go into validation and calibration of the hydrological models. How are they informed by observations? How well do you know what has actually happened in the reservoirs in the past

Delve deeper into why evapotranspiration seems to be dropping. Is it CO_2 levels, changes in vapor pressure?

Comments on this report (and Workshop Operations Group findings) by Richard Palmer, Department of Civil and Environmental Engineering, University of Massachusetts, Amherst, MA01003. palmer@ecs.umass.edu

The group of participants reviewing the Operations portion of the first phase of the Climate Change Integrated Modeling Project (CCIMP) agreed that the report represented an excellent first step in evaluating the effects of future climate change on the quantity and quality of water in the NYC water supply. The group's discussion led to comments on future activities, both related to broad goals and to specific activities.

The Operations review group recognized that "climate change studies" such as this one provide the opportunity to address a variety of stressors to a water resources system, and to place those concerns associated with climate change in balance with those posed by other factors. It was felt that upper management might well be more attentive to the stressors when viewed from a "climate impacts" lens and that this was a good opportunity for the DEP to engage stakeholders in investigating all the stressors impacting the water supply system.

Building upon this idea, the Phase II study presents the opportunity to have ongoing, inclusive interactions with a wide range of stakeholders, not only with the various units of DEP but also outside the agency. This will result in the opportunity to integrate the DEP's climate studies both with other studies focused on the watersheds within the agency and those being conducted by other research agencies, such as NOAA, NSF, and the Northeast Climate Science Center.

One broad challenge noted by the Operations review group is the need for scenario planning. The goal of scenario planning is to provide the most meaningful, easily understood, practical and applicable set of scenarios possible for planning purposes. For the Phase I study, a modest number of GCMs were used to generate potential futures. A structured decision making process was suggested to define the goals of the agency related to climate change and to determine how best to generate and identify those climate scenarios what would be the most valuable.

The review group also discussed the use of "virtual management exercises" (like those used by FERC) to derive new operating policies that could be incorporated into existing computer models of systems operations. It was noted that DEP is already a national leader in modeling their system and this suggestion simply encourages their continuing effort remain at the cutting edge of the water resources field. In addition to such exercises, the DEP is encouraged to continue its modeling efforts and sensitivity analyses and to identify those parameters that are the most critical to improved operations.

The Operations review group also identified some more specific actions that might prove valuable in future modeling. The group suggested that future research includes investigating the full range of demands that DEP will be required to meet in the future. This would include a better understanding and forecasting of future Municipal & Industrial demands currently met by DEP, future regional demand that may bring pressure on their system, significant shifts in regulatory standards, and future, more stringent requirements to provide environmental flows downstream of their facilities. In addition, the group noted the need to obtain forecasts of hydrologic futures that go beyond those that are available from current downscaling of GCMs.

Another issue noted was the need to process many hydrologic futures and operating rules quickly and to identify those of most interest and value from a planning perspective. It was suggested that there could be an important role for "screening" models that captured the primary characteristics of the system and could identify hydrologic sequences of value that would be further explored in DEP's sophisticated operations model. Another modeling suggestion was to attempt to incorporate more measures of system performance that are easily understood by management, so that the results of the model better resonate and provide more useful information in decision making. This would require continuing efforts on the part of the DEP modelers and systems operators. Some of the metrics suggested included days of supply remaining, frequency that treatment was needed, and spatial performance measures (those that illustrated the performance of individual reservoirs). The group was confident that this list could be improved upon and expanded by the modelers, operators, and managers.

The review group also noted the potential value of investigating multiple hydrologic models in capturing the impacts of climate change. It was recognized, however, that DEP has worked diligently in the development of specific models and that their models are performing well. In the same vein, it was suggested that more detailed results associated with the role of parameter estimation in their models be presented. Discussions with DEP indicated that this suggestion was appreciated. It was noted, however, that although not in the Phase I report, such studies had been documented elsewhere.

In conclusion, the group indicated that they were very impressed with the quality of the overall report and research effort and hoped that their suggestions could provide some value in defining the next stages of DEP's research.