A Practical Approach to Developing Climate Change Scenarios for Water Quality Models

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ABSTRACT

Climate model output is often downscaled to grids of moderately high spatial resolution (~ 4 – 6 -km grid cells). Such projections have been used in numerous hydrological impact assessment studies at watershed scales. However, relatively few studies have been conducted to assess the impact of climate change on the hydrodynamics and water quality in lakes and reservoirs. A potential barrier to such assessments is the need for meteorological variables at subdaily time scales that are downscaled to in situ observations to which lake and reservoir water quality models have been calibrated and validated. In this study, we describe a generalizable procedure that utilizes gridded downscaled data; applies a secondary bias-correction procedure using equidistance quantile mapping to map projections to station-based observations; and implements temporal disaggregation models to generate point-scale hourly air and dewpoint temperature, wind speed, and solar radiation for use in water quality models. The proposed approach is demonstrated for six locations within New York State: four within watersheds of the New York City water supply system and two at nearby National Weather Service stations. Disaggregation models developed using observations reproduced hourly data well at all locations, with Nash–Sutcliffe efficiency greater than 0.9 for air temperature and dewpoint, 0.4–0.6 for wind speed, and 0.7–0.9 for solar radiation.

1. Introduction

The effects of climate change are evident across the globe including in the contiguous United States, where many temperature and precipitation extremes are becoming common. The number of high-temperature records set in the past two decades far exceeds the number of low-temperature records, and heavy precipitation events in most parts of the United States have increased in both intensity and frequency since the 1900s (USGCRP 2017). Subsequent impacts on the water supply are being investigated (e.g., Whitehead et al. 2009), particularly during

extreme meteorological events such as floods and droughts (e.g., Delpla et al. 2009) common to both managed and unmanaged hydrologic systems (Ficklin et al. 2018). Potential impacts on water supply systems include a generally longer lake stratification period (Komatsu et al. 2007), increased sediment erosion (e.g., Mukundan et al. 2013a) leading to higher turbidity (Gelda et al. 2009; Rossi et al. 2016), increased nutrient loading (Mooij et al. 2005; Van Vliet and Zwolsman 2008), and dominance of cyanobacteria (Arheimer et al. 2005). Other constituents of concern in water supply systems that may be impacted by climate change are pathogens, disinfection byproducts precursors, and organic and inorganic micropollutants (Delpla et al. 2009).

The water quality impacts of climate change can be modeled by linking models of climate, watershed hydrology, and water quality. Global climate models (GCMs) are the primary tool used in providing the meteorological drivers required by both the watershed and receiving water quality models. It is desirable that 1) watershed and receiving water models

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include the constituents of concern and are validated at the study site, and 2) GCM output is adjusted to the spatial and temporal scale of watershed and receiving water models.

Typically, watershed models [e.g., Soil and Water Assessment Tool (SWAT); Neitsch et al. 2011] use daily maximum and minimum air temperatures and precipitation to simulate hydrologic processes, for example, stream discharges, and associated sediment and nutrients loading. Lake and reservoir water quality models (e.g., CE-QUAL-W2; Cole and Wells 2013) use hourly air and dewpoint temperatures, wind (speed and direction), and solar radiation to simulate a broad range of water quality impacts. Furthermore, water quality models perform better with local station-based meteorological drivers as compared to using gridded data. The depth of thermocline in lakes and reservoirs is affected by the mechanisms of wind mixing and nighttime convective cooling, requiring accurate and diurnal specifications of local wind and temperature in the models (Cole and Wells 2013). Most climate projections datasets as discussed below are coarsely gridded with daily time scales; as such, these datasets are not suitable for water quality models. The central question addressed here is how to adjust the future climate projections from coarse-scale GCM output to the spatial and temporal scales required by water quality impact assessment models.

There are several climate projections datasets publicly available for download covering North America, which include climate variables that are statistically and/or dynamically downscaled to different grid resolutions, for example, 1) Climate North America (ClimateNA; <https://sites.ualberta.ca/~ahamann/data/climatena.html>; Wang et al. 2016), 2) Localized Constructed Analogs (LOCA; <http://loca.ucsd.edu/>; Pierce et al. 2014), 3) Multivariate Adaptive Constructive Analogs (MACA; <https://climate.northwestknowledge.net/MACA/index.php>; Abatzoglou and Brown 2012), 4) North American Regional Climate Change Assessment Program (NARCCAP; <http://www.narccap.ucar.edu/data/>), and 5) NASA Earth Exchange (NEX) Downscaled Climate Projections (NASA-NEX-DCP30; <https://esgf.ncs.nasa.gov/projects/nex-dcp30/>). These datasets all differ in terms of the procedures used to downscale GCM output, spatial and temporal scales of available output, and variables provided. These and other similar climate projections have been used in numerous hydrological impact assessment studies at the watershed scale because such studies require only coarse-scale temperature and precipitation information (e.g., Ficklin et al. 2018). In contrast, climate change applications of hydrodynamic and water quality models remain limited (e.g., Jeznach and Tobiason 2015;

Buccola et al. 2016). This difference is mainly due to inadequacies in existing downscaled climate projection data including 1) biases between gridded fields and point-scale observations to which water quality models are often calibrated and validated, 2) insufficient temporal resolution of meteorological forcing data for lake and reservoir water quality models that often require hourly resolution, and 3) omission of variables in downscaled climate model output that is critical for water quality models such as dewpoint temperature, wind speed, and solar radiation.

Often simplifying assumptions have been made to overcome these limitations in studies linking climate to water quality at both the national (Johnson et al. 2012; Fant et al. 2017) and local scales (e.g., Jeznach and Tobiason 2015). Earlier large-scale studies (Johnson et al. 2012; Fant et al. 2017) have been useful for the purpose of informing policy but suffer from several shortcomings including use of few GCMs (e.g., ≤ 5), coarse spatial scale GCM output, important meteorological variables (solar radiation, wind, and relative humidity) derived from historical data, and uncalibrated water quality models. In local studies, climate scenarios have been developed using “change factors” by systematically altering historical observed data (Jeznach and Tobiason 2015; Rossi et al. 2016) but without regard to future changes in frequency of extreme events or occurrences of precipitation days. Buccola et al. (2016) used three GCMs coupled with a regional climate model to generate 15-km spatial scale climate variables. Only air temperature was further bias-corrected using quantile mapping, and disaggregated; however, it was not confirmed if disaggregation reintroduced the bias.

Here we propose simple, practical methods for overcoming the aforementioned data limitations to help water quality modelers develop realistic future climate scenarios for impact assessment studies. We utilize high spatial resolution (~ 4 -km grid cells) output of existing downscaled daily climate projections, apply a secondary bias-correction procedure using equidistance quantile mapping, and implement simple temporal disaggregation models to generate projections of point-scale hourly air and dewpoint temperatures, wind speed and direction, and solar radiation. To further increase confidence in the modeling analysis, it is recommended that 1) an ensemble of multiple GCMs be used to address the overall uncertainty that is inherent in GCMs and gained during downscaling, and 2) projected trends in various climate indicators be compared with the observed trends at the scale of interest, as the recent weather observations have already begun to show the effects of climate change. The proposed approach is demonstrated for six

locations within New York State, four of which are within watersheds of the New York City (NYC) water supply system. The methods of bias correction and temporal disaggregation presented in this study are not limited to water quality models, but will be useful for other models of watershed hydrology, ecology, and agriculture where subdaily meteorological data at point scale are desirable.

2. Study system, data, and methods

a. Study system

The NYC drinking water supply, managed by NYC Department of Environmental Protection (NYC DEP), composed of a network of 19 reservoirs and three controlled lakes, is located to the north and northwest of the city (Fig. 1). The contributing watersheds are grouped into the Delaware System (2624 km²) and Catskill System (1476 km²), both situated to the west of the Hudson River, and the Croton System (926 km²) to the east of the Hudson River (Fig. 1). The Delaware System includes 4 reservoirs (Cannonsville, Pepacton, Neversink, and Rondout), the Catskill System includes 2 reservoirs (Schoharie and Ashokan), and the Croton System includes 12 reservoirs. Water from the Catskill and Delaware systems is delivered to a terminal reservoir (Kensico) before entering into NYC's distribution system. The six Catskill and Delaware systems reservoirs supply approximately 90% of the water to more than 9 million consumers averaging about 1 billion gallons (3.8 million m³) per day (NYC DEP 2017).

While water supplied from these reservoirs is of consistently high quality and does not require filtration, large runoff events in the watershed can cause elevated turbidity in individual reservoirs. Under such circumstances, NYC DEP exploits the operational flexibility offered by the system by drawing water from reservoirs with lower turbidity so as to meet regulatory turbidity limits. When operations alone are not adequate, alum is added to water entering Kensico Reservoir, the terminal reservoir for the Catskill and Delaware Systems, to enhance settling of turbidity-causing particles and to avoid violation of source water turbidity standards. For example, alum treatment was required for 260 days following tropical cyclones Irene and Lee in 2011, when the total precipitation exceeded 33 cm, and turbidity in the west basin of Ashokan Reservoir exceeded 3000 nephelometric turbidity units (NTU; Klug et al. 2012).

Water supply is not the only purpose of these reservoirs. For example, water releases from reservoirs into the Delaware River are used to manage drought, mitigate flooding, protect the cold-water fishery and other habitat needs, and limit saltwater intrusion in

FIG. 1. Study area map with boundaries of watersheds within the NYC water supply system and locations of meteorological stations. Areas shown are watershed areas. The inset shows the map of New York State.

the estuary downstream. Similarly, releases from the Catskill System's Ashokan Reservoir provide environmental, recreational, and economic benefits to the lower Esopus Creek region (Fig. 1).

Potential impacts of climate change on the availability of high-quality water in sufficient quantity, and the other beneficial purposes that these reservoirs serve, are of long-term concern to NYC DEP. To that end, NYC DEP initiated the Climate Change Integrated Modeling Project (CCIMP; NYC DEP 2013), utilizing a suite of watershed and reservoir models driven by a range of climate scenarios to quantify the impacts of future climate. Though based on relatively simple methods, the first phase of CCIMP provided early insights into the future trends in temperature, precipitation, runoff, reservoir stratification and water quality, and water supply system operation. Noteworthy findings were that the timing of the annual peak runoff was projected to shift from late March and April to a more uniformly distributed pattern of runoff between autumn and winter due to smaller contribution from snowmelt to peak flows

(Zion et al. 2011; Pradhanang et al. 2013), and consequently, patterns in sediment (Mukundan et al. 2013b) and nutrient loading, and in-reservoir responses were also projected to change (Samal et al. 2013; Matonse et al. 2013).

The work we describe here is a fundamental component of the second phase of CCIMP to develop a complete, robust set of future local climate scenarios for use in watershed and reservoir models using state of the art procedures that allow better representation of model uncertainty. Here we adopt the latest climate projections from 20 different GCMs from phase 5 of the Coupled Model Intercomparison Project (CMIP5) of the World Climate Research Programme (compared to four CMIP3 GCMs climate projections in Phase I of CCIMP), use a statistical downscaling method (compared to “delta change factor” method in Phase I; Anandhi et al. 2011), and perform temporal disaggregation of the meteorological variables from daily to subdaily, including variables required for reservoir water quality models (not done in Phase I). A comparison of the differences between the findings of Phase I and II of CCIMP for NYC water supply system is beyond the scope of this study.

b. Data

Observations of hourly average air temperature, relative humidity (or dewpoint), wind (speed and direction), and solar radiation (or cloud cover) used in reservoir water quality models were obtained from National Weather Service (NWS) stations located at Albany (site 5) and White Plains airports (site 6) for 1986–2015, and four stations owned by NYC DEP located on the shores of Cannonsville, Pepacton, Neversink, and Rondout reservoirs (Fig. 1) for 1995–2015. Precipitation is typically not an input to reservoir water quality models and as such, it was not used from these stations.

We used the recently developed high spatial resolution (~ 4 -km grid cells), statistically downscaled climate projections dataset covering the conterminous United States, made available for download by the University of Idaho (<https://climate.northwestknowledge.net/MACA/index.php>), and also the U.S. Geological Survey (USGS GeoData Portal: <http://cida.usgs.gov/gdp/>). This Multivariate Adaptive Constructed Analogs (MACA-Version 2 MetData) dataset, referred to hereafter as MACA, comprised the latest CMIP5 climate projections from 20 GCMs (see the online supplemental material) of daily values of minimum ($T_{\min}$) and maximum ($T_{\max}$) temperature T , precipitation, minimum ($RH_{\min}$) and maximum ($RH_{\max}$) relative humidity (RH), specific humidity (SH), solar radiation (SR_{avg}), and zonal (w_x)

and meridional (w_y) components of wind. It included data for the historical GCM simulations (1950–2005) and for future Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios (2006–99), which correspond to greenhouse gases (GHG) emission scenarios resulting in a change of radiative forcing of 4.5 and 8.5 W m^{-2} , respectively, at the end of century relative to preindustrial values (Van Vuuren et al. 2011). MACA was chosen over other downscaled datasets due to its output including the full set of variables needed for water quality modeling across a broad set of climate models.

c. Overall strategy

MACA data includes a bias correction (based on the empirical statistical technique of quantile mapping) after developing the spatial downscaling as a linear superposition of 10 patterns across the contiguous United States. This bias correction is used to ensure that the distribution of downscaled data for the historical simulation experiments (1950–2005) match those of the training data for each ~ 4 -km grid cell, with the same bias correction applied to RCP4.5 and RCP8.5 scenarios (2006–99). We extend this methodology to point-scale observations. The first step in this process is to extract daily gridded output collocated with a point-scale observation of interest that was used during calibration and validation of hydrologic and reservoir models. We use equidistant quantile mapping (EQM) method (Li et al. 2010) to bias correct downscaled climate model output to point-scale observations. This process was done on monthly time scales (e.g., all days in March are pooled and bias corrected), thus ensuring the statistical attributes of historical climate match those of the observed climate record, and that differences between future and historical data are preserved along quantiles. In the second step, the secondary bias corrected data are then temporally disaggregated from daily to hourly values using simple, established methods, which then can be used by lake and reservoir models.

Projections from various GCMs can be quite different due to uncertainty in the drivers of anthropogenic change and due to differences in model framework, assumptions, complexity, and climate sensitivity. Although efforts have been made to rank GCMs (Rupp et al. 2013; Ahmadelipour et al. 2017) based on accuracy and performance, no consensus has emerged among the scientific community regarding how to achieve this. If the computational demand is high, a subset of GCMs may be considered in an impact assessment study, but no less than 10 is recommended (Mote et al. 2011). We developed scenarios using output

additive bias correction, c_τ at quantile level, $\tau = x_{o,b} - x_{m,b}$
 multiplicative bias correction, c_τ at quantile level, $\tau = x_{o,b} \div x_{m,b}$
 bias-corrected future value, $x_{m,f,adj} = x_{m,f} + c_\tau$
 or, in case of multiplicative, future value, $x_{m,f,adj} = x_{m,f} \times c_\tau$

FIG. 2. Illustration of equidistant quantile mapping method for secondary bias correction: (a) CDF for future modeled values of variable x , (b) CDF for observed values of x for the baseline period (i.e., historic), and (c) CDF for modeled values of x for the baseline period. Correction factors are calculated by matching quantile levels in the three CDFs. It is shown here for a value of $x_{m,f}$ corresponding to quantile level τ in (a).

from all 20 GCMs available through MACA (see supplemental material).

d. Secondary bias correction

Despite being downscaled at high spatial resolution, MACA data may not be free from bias when compared to point-scale observations data, particularly for regions with complex terrain, where interaction of the atmospheric circulation with the physiographic gradients contribute to spatial variability (e.g., Fowler et al. 2007). Biases may also be present due to the limitations of the observations dataset used in the development of MACA data. The gridded observations (4-km resolution) used for training data in MACA were developed by combining different data sources (Abatzoglou 2013). However, substantial differences often exist between gridded and point-scale observations of daily meteorological data (e.g., Bishop and Beier 2013). Moreover, reservoir water quality models are calibrated using the point-scale and not the gridded observations. Specification of representative wind speed, as obtained from the point observations, is particularly

critical for these models as the turbulent mixing in reservoirs is dominated by wind shear on the water surface. The biases between MACA and point-scale observations are identified and corrected for using a simple, effective EQM method (Li et al. 2010). This step is described here as secondary bias correction.

The EQM method is illustrated in Fig. 2. Cumulative density functions (CDFs) of point-scale observations and GCM-MACA data from the corresponding grid for a common historical period are prepared. Next, from these paired CDFs, a quantile map (or transfer function; Li et al. 2010) is prepared where at each quantile level τ ($0 \leq \tau \leq 1$), the bias between the observed and the modeled value is calculated as the difference between, or the ratio of (for precipitation only), the two quantities. Finally, bias at quantile level τ is applied to the future modeled value that corresponds to the same quantile level τ in its own CDF (Fig. 2).

Here, CDFs of the point-scale observations and the MACA data for the historical baseline and future periods, for $T_{\max}$, $T_{\min}$, $RH_{\max}$, $RH_{\min}$, w_x , w_y , and SR_{avg} ,

TABLE 1. Equations for disaggregating daily air temperature, relative humidity, wind speed, and solar radiation to hourly.

Equations	References
Hourly air temperature T_t (where $t = 1\text{--}24$ h; $t_{T_{\max}}$ and $t_{T_{\min}}$ are the times of day at which daily maximum and minimum temperatures occur):	Scharmer and Greif (2000)
$T_t = \begin{cases} \frac{T_{\max} + T_{\min}}{2} - \left(\frac{T_{\max} - T_{\min}}{2}\right) \cos\left[\frac{\pi(t_{T_{\min}} - t)}{24 + t_{T_{\min}} - t_{T_{\max}}}\right], & 0 < t \leq t_{T_{\min}} \\ \frac{T_{\max} + T_{\min}}{2} + \left(\frac{T_{\max} - T_{\min}}{2}\right) \cos\left[\frac{\pi(t_{T_{\max}} - t)}{t_{T_{\max}} - t_{T_{\min}}}\right], & t_{T_{\min}} < t \leq t_{T_{\max}} \\ \frac{T_{\max} + T_{\min}}{2} - \left(\frac{T_{\max} - T_{\min}}{2}\right) \cos\left[\frac{\pi(24 + t_{T_{\min}} - t)}{24 + t_{T_{\min}} - t_{T_{\max}}}\right], & t_{T_{\max}} < t \leq 24 \end{cases} \quad (1)$	
Hourly relative humidity (RH_t): $RH_t = RH_{\max} + \frac{T_t - T_{\min}}{T_{\max} - T_{\min}}(RH_{\min} - RH_{\max})$	Waichler and Wigmosta (2003)
Hourly wind speed w_t : $w_t = w_{\text{avg}} + \frac{1}{2} w_{\text{avg}} \cos\left[\frac{\pi(t - t_{T_{\max}})}{12}\right]$	Guo et al. (2016)
Hourly solar radiation (SR_t ; where $SR_{t,\text{ClearSky}}$ and $SR_{\text{avg},\text{ClearSky}}$ = hourly and daily average theoretical maximum solar radiation, respectively, for a specific day, time, and location):	Martin and McCutcheon (1999); Cole and Wells (2013)
$SR_t = SR_{\text{avg}} \frac{SR_{t,\text{ClearSky}}}{SR_{\text{avg},\text{ClearSky}}} \quad (4)$	

were developed on a monthly basis, for 1986–2015. Quantile maps for each specific combination of site, variable, month, and GCM model were computed at a quantile level resolution of 0.001 (from 0 to 1, inclusive). The use of high-resolution empirical CDFs minimized the interpolation over large differences in values, particularly at the tails of distributions. Therefore, fitting a theoretical parameter distribution to a CDF was not necessary and not considered in this study.

e. Disaggregation

Following the secondary bias correction, data are disaggregated from daily to hourly values. We adopt simple, parsimonious disaggregation models that do not require any calibration, for air and dewpoint (based on relative or specific humidity) temperatures, wind speed, and solar radiation (Table 1). These models also preserve daily $T_{\max}$, $T_{\min}$, $RH_{\max}$, $RH_{\min}$, w_{avg} , and SR_{avg} . Other disaggregation methods for temperature based on sinusoidal functions (Debele et al. 2007) and for wind based on stochastic distributions (Donatelli et al. 2009) may be explored for other applications. However, the users must ensure that the selected methods do not reintroduce bias in the daily values.

The performance of the selected disaggregation models prior to applying to the MACA data was evaluated using historical hourly observations at sites 1–6

(Fig. 1). These are the same data used in the development and validation of water quality models for these reservoirs (Gelda and Effler 2007; Gelda et al. 2009, 2012). Data from Albany Airport (site 5; Fig. 1) supported the development of water quality models for Schoharie and Ashokan reservoirs, whereas White Plains Airport data were used for Kensico Reservoir model (Gelda et al. 2012). Data for a common period of hourly records (2000–15) were used for all six sites. Solar radiation observations were obtained from the North American Land Data Assimilation System (NLDAS; <https://ldas.gsfc.nasa.gov/index.php>) and were corrected for known overestimation (Zhao et al. 2013) by applying a factor (= 0.9, estimated from paired NLDAS and onsite solar radiation data on an annual mean basis) uniformly.

The disaggregation models were evaluated using historical hourly observations in three steps. First, the observed hourly time series was transformed into time series of daily values of observations of $T_{\max}$, $T_{\min}$, $RH_{\max}$, $RH_{\min}$, w_{avg} , and SR_{avg} . Next, using the proposed disaggregation methods (Table 1), the observed daily values from the first step were disaggregated into hourly values. Wind direction could not be disaggregated because no diurnal pattern was detected in the observations. Furthermore, w_x and w_y are directional quantities and cannot be averaged to identify any systematic diurnal cycle that would then become the basis to disaggregate daily w_x and w_y separately. Where a general

diurnal pattern in the wind direction exists, users can determine the dominant frequencies of wind direction at every hour and season to establish the pattern and then impose this pattern of wind direction while disaggregating such that the vector average of hourly winds results in the same value as the starting daily average value.

In the final step, the disaggregated hourly values were compared with the actual observed hourly values ($n \approx 140\,000$; 16 years of hourly values). The performance of the methods in reproducing hourly values was evaluated by three measures [mean absolute error (MAE), Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970), and Pearson correlation coefficient r]. The same equations in Table 1 were then applied to secondary bias-corrected daily MACA data to predict point-scale hourly values. These data represent climate scenarios that will be used in the water quality impact assessment models.

3. Results

a. Secondary bias correction

Monthly boxplots of $T_{\max}$ for a 30-yr interval (1986–2015) at Albany Airport for a selected MACA dataset (GCM named CanESM2 available from the Canadian Centre for Climate Modeling and Analysis) is presented in Fig. 3, juxtaposed with secondary bias corrected data. Bias computed as the modeled minus observed statistic refers to bias in median statistic here; biases in other statistics (e.g., 75th percentile) can be visually assessed from the boxplots in Figs. 3 and 4. Bias is evident in most months, with modeled median temperature about 1°C warmer than observations for the 30-yr period (Fig. 3a). The bias was reduced to 0.03°C (Fig. 3b) by the secondary correction. Other GCMs produced varying but always positive bias, that is, over predicted the observed $T_{\max}$ (by 0.25°C – 1°C) for this location attributable to the gridded training data in MACA also being generally warmer. The maximum bias found was 2°C for the Cannonsville Reservoir site perhaps partly due to microscale climate features. In addition, the training dataset in the development of MACA included data from 1950 to 2005, but here we adopted data from the 1986 to 2015 interval. Biases in $T_{\max}$ at all sites 1–6 before and after correction are compared in Table 2.

The character of biases in $T_{\min}$, $\text{RH}_{\max}$, $\text{RH}_{\min}$, w_x , w_y , and SR_{avg} is illustrated in the same graphical format of monthly boxplots in Figs. 4a–4f (before correction) and Figs. 4g–4l (after correction). Biases in $T_{\min}$ (0.03°C ; Fig. 4a), and w_x (-0.03 m s^{-1} ; Fig. 4d) were negligible, and secondary correction had no effect (Fig. 4g and

FIG. 3. Evaluation of and correction for bias between the observed and the modeled (CanESM2–MACA) daily maximum temperature $T_{\max}$ for Albany Airport for 1986–2015.

Fig. 4j, respectively). $\text{RH}_{\max}$ was modestly under predicted during March–August with an overall bias of -2.6% (Fig. 4b), which was effectively corrected by EQM (1.6% ; Fig. 4h). Other noteworthy bias was detected in SR_{avg} (15 W m^{-2} ; Fig. 4f), which was reduced to -0.8 W m^{-2} after secondary bias correction. This bias in SR_{avg} is a direct outcome of the overestimation of solar radiation by the gridMET (Abatzoglou 2013) dataset, where solar radiation is adopted from NLDAS2 without correcting for known bias (Zhao et al. 2013). Biases in $\text{RH}_{\min}$ (-2.39% ; Fig. 4c) and w_y (0.12 m s^{-1} ; Fig. 4e) were also reduced to 1% (Fig. 4i) and 0.02 m s^{-1} (Fig. 4k), respectively. See Table 2 for a comparison of the biases in these variables at other sites. Relatively large biases in w_x and w_y at reservoir sites 1–4 are important to note (Table 2). The biases are likely due to the use of the observations of w at the reservoir sites that reflect features of local terrain and station siting (hills, mountains, vegetation) not adequately represented in the training dataset for MACA. Accurate specification of wind is critical in hydrodynamic and water quality models of inland waterbodies as wind stress is the most important driver of large-scale circulation as well as turbulence and vertical mixing (Fischer et al. 1979), further underscoring the need for secondary bias correction. The bias correction done independently for w_x and w_y also reduced bias in w quite effectively (Table 2). Results of bias correction for other GCMs are summarized in the supplemental material.

FIG. 4. Example of evaluation of and correction for bias between the observed and the modeled (CanESM2–MACA) monthly values of selected weather variables for Albany Airport for 1986–2015. Modeled data (left) before and (right) after secondary bias correction. The variables are (a),(g) $T_{\min}$; (b),(h) $RH_{\max}$; (c),(i) $RH_{\min}$; (d),(j) w_x ; (e),(k) w_y ; and (f),(l) SR.

Examples of the correction factors c_τ (see EQM method, Fig. 2) for various variables (Albany Airport site), expressed as averages of January–December, for the CanESM2–MACA dataset are depicted in Fig. 5. These factors are additive for all variables. Employing multiplicative c_τ to RH and w did not reduce bias more than it did with additive c_τ . If the bias correction resulted in $RH > 100$ or $RH < 0$ then it was forced to be 100 or 0, respectively. The pattern of c_τ is nonlinear, and the

absolute magnitude is generally higher at the extremes of distributions because the observed empirical probabilities of occurrence of the extreme values of $T_{\max}$, $T_{\min}$, w_x , w_y , $RH_{\max}$, and $RH_{\min}$ deviate more significantly from the modeled probabilities. Differences in probabilities could arise, in part, due to incomplete representation of natural, decadal scale variability in climate models output. Greater c_τ for $\tau = 0.2$ – 0.4 for solar radiation (Fig. 5b) corresponded to SR_{avg} of

TABLE 2. Mean bias (modeled – observed; CanESM2–MACA) in average values of seven weather variables, before and after secondary bias correction, for six locations in New York for 1986–2015.

Site	Name	Before/after correction	$T_{\max}$ (°C)	$T_{\min}$ (°C)	$RH_{\max}$ (%)	$RH_{\min}$ (%)	w_x (m s ⁻¹)	w_y (m s ⁻¹)	w (m s ⁻¹)	SR_{avg} (W m ⁻²)
1	Cannonsville Reservoir	Before	1.96	0.32	-5.86	-7.96	2.13	2.37	2.94	15.4
		After	-0.1	0.24	-0.35	1.08	-0.04	-0.07	0.09	-0.2
2	Pepacton Reservoir	Before	0.98	-0.65	-3.84	-7.32	2.17	1.68	3.48	15.7
		After	-0.08	0.28	-1	0.77	-0.05	-0.03	0.06	-0.3
3	Neversink Reservoir	Before	1.77	-0.4	-5.14	-8.05	2.44	2.54	2.14	16.8
		After	0.07	0.18	-0.05	0.14	-0.06	0	0.03	-0.5
4	Rondout Reservoir	Before	1.66	0.41	-8.34	-9.2	1.89	3.84	0.14	16.9
		After	-0.1	0.11	-0.3	-0.38	-0.06	-0.17	0.18	-0.4
5	Albany Airport	Before	0.98	0.03	-2.59	-2.39	-0.03	0.12	0.5	15.4
		After	0.03	-0.15	1.59	1.01	-0.04	0.02	0.09	-0.8
6	White Plains Airport	Before	1.11	0.48	-5.62	-4.16	0.41	0.46	1.23	17.1
		After	0.02	-0.03	1.21	0.79	-0.15	0.16	0	-1.3

50–150 W m⁻² in the cooler months, which could be due to the tendency of the original MACA output to overpredict SR_{avg} (Fig. 4f).

b. Disaggregation

Performance of the disaggregation methods is evaluated in terms of three goodness-of-fit statistics, MAE, NSE, and r , and is summarized in Table 3 for sites 1–6. Additionally, a typical example of the model performance is shown in Fig. 6 where hourly observations of the four variables are compared with the predicted values for three selected consecutive days at Albany Airport. Analysis of hourly observations yielded typical values of $t_{T_{\max}}$ as 1500 LT and $t_{T_{\min}}$ as 500 LT [Eq. (1); see Table 1 for all equations] for the study region. Excellent NSE (>0.9) and r (≥ 0.97) were achieved for T and T_{dew} at all sites while MAE ranged from 1.5° to 1.9°C (Table 3). These results are generally consistent with other studies (Waichler and Wigmosta 2003; Safeeq and Fares 2011). Considering minor seasonal variations in $t_{T_{\max}}$ and $t_{T_{\min}}$ did not improve the overall performance of the disaggregation models, though it may be important

in other geographical locations. Note that hourly T_{dew} was computed from hourly T and RH or SH assuming that daily $RH_{\max}$ and $RH_{\min}$ coincide with daily $T_{\min}$ and $T_{\max}$, respectively. The observed diurnal patterns in T and T_{dew} were simulated well by these simple methods, with maximum values observed during mid-afternoon (Figs. 6a,b). Discontinuity in the predictions at midnight hour is due to the application of the method on a daily basis (Figs. 6a,b).

The simple cosine model for disaggregating daily w did not perform as well, particularly at sites 5–6 (NSE < 0.45 , $r \leq 0.7$; Table 3). The geographic variations in diurnal wind patterns can be large and a function of differential heating patterns and local topographical features, causing them to be more difficult to simulate with a simple disaggregation model (e.g., Fig. 6c). However, the typical pattern of increasing wind during day time and then a decreasing pattern during the midafternoon through nighttime hours was captured adequately by this simple model. An alternative wind disaggregation model using random numbers (Debele et al. 2007; Donatelli et al. 2009) was investigated and

FIG. 5. Correction factors c_r (averages of January–December) as functions of quantile levels, derived from quantile mapping between the observed and the modeled (CanESM2–MACA) cumulative density functions of (a) $T_{\max}$, $T_{\min}$, and w_x and w_y , and (b) $RH_{\max}$, $RH_{\min}$, and SR for Albany Airport for 1986–2015.

TABLE 3. Disaggregation models performance statistics.

Site	Name	Air temperature			Dewpoint temperature			Wind speed			Solar radiation		
		MAE (°C)	NSE	<i>r</i>	MAE (°C)	NSE	<i>r</i>	MAE (m s ⁻¹)	NSE	<i>r</i>	MAE (W m ⁻²)	NSE	<i>r</i>
1	Cannonsville Reservoir	1.85	0.93	0.97	1.57	0.95	0.97	0.80	0.54	0.74	38.0	0.91	0.95
2	Pepacton Reservoir	1.93	0.93	0.97	1.56	0.95	0.98	0.52	0.57	0.76	69.3	0.74	0.87
3	Neversink Reservoir	1.57	0.95	0.98	1.49	0.95	0.98	0.99	0.62	0.79	69.7	0.74	0.87
4	Rondout Reservoir	1.64	0.95	0.98	1.54	0.95	0.98	1.33	0.59	0.78	51.7	0.84	0.92
5	Albany Airport	1.62	0.95	0.98	1.60	0.95	0.98	1.45	0.43	0.70	36.2	0.92	0.96
6	White Plains Airport	1.48	0.95	0.98	1.69	0.95	0.97	1.47	0.35	0.68	39.0	0.90	0.95

did not perform as well. Wind direction was assumed to be uniform through the day. Short-term diel variations in wind direction are usually not important for water quality models. It is the longer-term sustained winds along the long axis of a waterbody that cause the greatest mixing and therefore affect the water quality the most.

Hourly solar radiation estimated by Eq. (4) from daily SR_{avg} was in good agreement with the observations at all of the six sites (Table 3). NSE was >0.9 for sites 1, 5, and 6 (corresponding $r \geq 0.95$); at other sites NSE ranged from 0.7 to 0.8 and $r \sim 0.9$. MAE was also low varying from 36 to 70 W m⁻² (Table 3). Examples of excellent performance are shown in Fig. 6d for three days in July 2005 for site 5 (Albany Airport).

c. Climate scenarios

1) ANNUAL CYCLE

To illustrate the changes in climate, the recent observed annual climatological cycles (1986–2015 average) of T_{max} , T_{min} , RH_{max} , RH_{min} , w_x , w_y , and SR_{avg} are compared with the projected cycles (2041–60 average; RCP8.5) at Albany Airport site in Fig. 7. Projections are represented as ranges (minimum and maximum) derived from the ensemble of 20 GCMs. An individual ensemble member corresponds to average climatology projected by that particular GCM. Ensemble average (i.e., average of the 20 GCMs) can also be computed and can be considered as the most likely future scenario (Fig. 7). The increase (= ensemble average – observed) in T_{max} and T_{min} is expected to be largely uniform throughout the annual cycle, with both expected to rise typically by 1°–4°C (Figs. 7a,b). RH_{max} , RH_{min} , w_x , w_y , and SR_{avg} do not exhibit any systematic change in the future, as illustrated by their respective ensemble ranges capturing the recent observations (Figs. 7c–g). Projected ensemble averages of these variables (not shown here) closely track the recent observations, although a particular GCM may show a systematic change in the future. Annual averages and standard deviations of these variables at sites 1–6 for the recent and future time

periods are compared in Table 4. The magnitude of projected change in annual average T_{max} and T_{min} is similar at the six locations ($\sim 2.7^\circ\text{C}$). The joint interannual and intermodel variability is 1.2°C attributed to the warming trend of the midcentury as well as varying climate sensitivity of GCMs (Table 4). No significant changes in other variables are projected in this region (Table 4; decrease in RH_{max} and $RH_{min} < 1\%$, no change in w_x and w_y , increase in $SR_{avg} \approx 5 \text{ W m}^{-2}$).

2) LONG-TERM TRENDS

Observations for 1986–2015 are compared with the range of projections from 20 GCMs for 1986–2060 for

FIG. 6. Performance of the disaggregation models for four weather variables shown here as a comparison of the observed and the predicted hourly values for selected days in July 2005 for Albany Airport.

FIG. 7. Annual climatological cycles of selected weather variables as represented by the average of daily observations (1986–2015) and as the range of daily projected (2041–60; RCP8.5) averages derived from an ensemble of 20 GCMs for Albany Airport. The variables are (a) $T_{\max}$, (b) $T_{\min}$, (c) $RH_{\max}$, (d) $RH_{\min}$, (e) w_x , (f) w_y , and (g) SR. For $T_{\max}$ and $T_{\min}$,

the seven variables at Albany Airport (Fig. 8). The inclusion of the results for the historical period (1986–2015) offers a form of verification of and a measure of confidence in, the GCMs, the primary downscaling method, and the secondary bias correction method. Any one particular GCM is not expected to match the observed annual average values, but the ensemble of 20 GCMs is expected to encompass the observed variability. For example, observations of $T_{\max}$ for 1986–2015 are well within the bounds of simulated values from 20 GCMs (Fig. 8a). Both $T_{\max}$ and $T_{\min}$ are expected to gradually increase; $T_{\max}$ rising from the recent average of 14°C to within a range of 15°–20°C in 2060, and $T_{\min}$ from 4.5°C to within a range of 5°–10°C (Fig. 8a). As mentioned earlier, no long-term trend in RH, w_x , w_y , and SR_{avg} is evident, however, a wide intermodal range is projected, particularly in w_x and w_y (Figs. 8b–e). Decreases in the observed RH in the recent years need further investigation.

4. Discussion and concluding remarks

Our analysis emphasizes that even though several high spatial resolution climate projections are readily available now, such datasets still require thorough assessment of and correction for any bias prior to using them in impact studies. Biases among different GCMs and for different climate variables can be highly variable and may depend on various metrics of evaluation. All statistical downscaling methods rely on variants of homogenized, gridded historical climate observations to account for local climate and topographic features. Uncertainty in the gridded datasets exists due to errors related to measurements as well as interpolation techniques used. This can propagate to the output of bias-corrected GCMs during downscaling, and potentially alter the future climate trends, particularly in regions of complex topography. Effects of overall uncertainty, both inherent in GCMs and gained during downscaling may be reduced by using an ensemble of multiple models. Moreover, as the recent weather observations are beginning to show the effects of climate change, the confidence in climate projections can be increased by comparing projected trends to the observed trends in various climate indicators at the scale of interest.

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the average of the ensemble of 20 GCMs is also shown. For other variables, the ensemble averages closely track the observations, and hence they are not shown.

TABLE 4. Projections of seven weather variables for 2041–60 compared to current (1986–2015) observations for six locations in New York. Projections are shown for the GHG emission scenario RCP 8.5. The standard deviation (SD) represents interannual (30 years) variability in the case of observations, and joint interannual (20 years) and intermodel (20 GCMs) variability in the case of future projections.

Site	Name	Time periods	Avg (SD)						
			$T_{\max}$ (°C)	$T_{\min}$ (°C)	RH _{max} (%)	RH _{min} (%)	w_x (m s ⁻¹)	w_y (m s ⁻¹)	SR _{avg} (W m ⁻²)
1	Cannonsville Reservoir	1986–2015	12.8 (0.9)	2.8 (0.8)	93.8 (2.4)	53.8 (2.8)	−0.1 (0.0)	−2.1 (0.2)	143.8 (3.8)
		2041–60	15.5 (1.2)	5.7 (1.1)	92.9 (1.2)	52.9 (3.3)	−0.2 (0.1)	−2.1 (0.1)	148.3 (4.3)
2	Pepacton Reservoir	1986–2015	13.0 (1.1)	2.8 (0.8)	93.0 (3.2)	53.3 (3.5)	−0.1 (0.0)	−1.4 (0.2)	144.7 (3.6)
		2041–60	15.7 (1.2)	5.7 (1.1)	91.2 (1.4)	52.2 (3.3)	−0.1 (0.1)	−1.4 (0.1)	149.3 (4.2)
3	Neversink Reservoir	1986–2015	12.5 (0.8)	3.4 (0.8)	91.6 (1.8)	53.8 (2.0)	−0.2 (0.0)	−2.7 (0.3)	152.1 (3.7)
		2041–60	15.2 (1.2)	6.0 (1.0)	90.8 (1.3)	52.2 (3.2)	−0.2 (0.1)	−2.7 (0.1)	156.9 (4.3)
4	Rondout Reservoir	1986–2015	13.5 (1.0)	4.0 (0.8)	92.8 (2.4)	55.4 (3.2)	−0.3 (0.0)	−3.9 (0.5)	153.0 (3.6)
		2041–60	16.0 (1.2)	6.5 (1.0)	91.8 (1.2)	53.3 (3.1)	−0.3 (0.1)	−4.0 (0.1)	158.1 (4.3)
5	Albany Airport	1986–2015	14.3 (0.8)	4.4 (0.8)	89.4 (2.8)	49.8 (2.4)	1.1 (0.3)	0.1 (0.2)	148.4 (4.7)
		2041–60	17.1 (1.2)	7.0 (1.1)	90.1 (1.3)	48.9 (2.9)	1.0 (0.2)	0.1 (0.2)	152.4 (4.4)
6	White Plains Airport	1986–2015	15.5 (0.7)	6.6 (0.7)	87.5 (2.3)	48.3 (2.2)	0.9 (0.2)	−0.6 (0.3)	163.6 (4.5)
		2041–60	18.1 (1.2)	9.0 (1.0)	88.0 (1.4)	47.6 (2.5)	0.8 (0.2)	−0.4 (0.2)	168.7 (4.5)

Among the limitations of the EQM method, the bias between the modeled and the observed data is dependent on the choice of baseline period and is assumed to be time-invariant. The same limitations also exist in other statistical downscaling methods. Choosing a recent and long-term (e.g., 30 years) period for baseline observations and then adjusting near-future projections (e.g., 2050s) may reduce the uncertainties associated with this method. Farther-term end of the century climate projections may be inherently more uncertain as the uncertainty associated with the forcing conditions is large.

Disaggregation methods assume idealized diurnal patterns for temperature, wind, and solar radiation. While these patterns persist normally, synoptic-scale weather (e.g., a low pressure system) may produce anomalous diurnal patterns. We do not view this as a shortcoming as we have demonstrated good performance of these methods in reproducing diurnal variations over a long time interval. Furthermore, the potential impact on water quality variables may be assessed in a probabilistic format at a coarse scale such as monthly and thus characterize any systematic change. Disaggregation of precipitation was not considered in this study. Watershed models can simulate stream discharges adequately using daily precipitation values. Where required (e.g., hydraulic modeling involving designs of stormwater management facilities, flood protection structures, etc.), precipitation may be disaggregated at subdaily scale using methods of Rupp et al. 2009, for example.

Application

For the application of the reservoir hydrodynamic-water quality model, CE-QUAL-W2, we plan to run the

model for each scenario independently, generate an ensemble of water quality predictions, and then represent the results in a probabilistic format. Besides meteorological drivers, CE-QUAL-W2 also requires stream inputs—inflow, inflow temperatures, and inflow water quality. For the NYC water supply watersheds, inflows will be simulated with the Generalized Watershed Loading Function (GWLF; Haith and Shoemaker 1987) using meteorological drivers ($T_{\max}$, $T_{\min}$, and precipitation) developed for the same 40 scenarios. Preliminary results of the effect of bias correction on inflow from Esopus Creek, a tributary to Ashokan Reservoir (Fig. 1), indicated that the secondary bias-corrected meteorological data predicted median flow in the Creek lower by ~9% than using MACA directly (unpublished results). Stream temperatures and water quality variables will be estimated using empirical models (e.g., Morrill et al. 2005), or alternatively, using distributed watershed models (e.g., SWAT; Ficklin et al. 2013). The methods for secondary bias correction and disaggregation presented here are easily transferable to other applications of CE-QUAL-W2, and other impact assessment models elsewhere.

Future work will focus on the application of previously developed models or those currently under development, to assess the potential impacts of climate change on water supply reliability from the perspective of both the quantity and quality. Currently, the areas of interest are thermal stratification, ice phenology, turbidity, dissolved organic carbon and disinfection by-product precursors, and eutrophication. Additionally, we plan to assess what, if any, changes in reservoir operation strategy would be necessary in order to continue to fulfill NYC DEP's

FIG. 8. Long-term trend in annual average (a) air temperature ($T_{\min}$ and $T_{\max}$), (b) relative humidity ($RH_{\min}$ and $RH_{\max}$), (c) w_x , (d) w_y , and (e) SR for Albany Airport. Observations for 1986–2015 are compared with a range of hindcasts and future projections from an ensemble of 20 GCMs for 1986–2060.

mission of supplying high-quality water in sufficient quantity.

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