AGU100 ADVANCING EARTH AND SPACE SCIENCE

Water Resources Research

RESEARCH ARTICLE
10.1029/2019WR025614

Accounting for Adaptive Water Supply Management When Quantifying Climate and Land Cover Change Vulnerability

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Key Points:
- Utility-scale decision making influences the impact of climate and land use change on both short- and long-term outcomes
- Timing and sequencing of infrastructure development is highly sensitive to hydrologic change as captured by utility performance indicators
- Impacts of hydrologic change are not uniform across performance indicators, utilities, or time, owing to management actions

Supporting Information:
- Supporting Information S1

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Citation:
Gorelick, D. E., Lin, L., Zeff, H. B., Kim, Y., Vose, J. M., Coulston, J. W., et al. (2020). Accounting for adaptive water supply management when quantifying climate and land cover change vulnerability. *Water Resources Research*, *56*, e2019WR025614. https://doi.org/10.1029/2019WR025614

Received 20 MAY 2019
Accepted 22 DEC 2019
Accepted article online 26 DEC 2019

Abstract Climate and land cover change strongly shape water resources management, but understanding their joint impacts is extremely challenging. Consequently, there is limited research of their integrated effects on water supply systems, and even fewer studies that rigorously account for infrastructure investment and management interventions. We utilize ecohydrologic modeling to generate watershed outflows under scenarios of climate and land cover change, which in turn drive modeled water utility-level decision making for the Research Triangle region of North Carolina. In the Triangle region, land cover and climate change are both likely to increase water supply availability (reservoir inflows) individually and in tandem. However, improvements from water supply increases are not uniform across management system performance indicators of reliability, conservation implementation frequency (i.e., water use restrictions), and infrastructure investment. Utility decisions influence the impact of hydrologic change through both short-term (e.g., use restrictions and water transfers) and longer-term infrastructure investment actions, in some cases offsetting the beneficial effects of additional water supply. Timing and sequencing of infrastructure development are strongly sensitive to climate and land use change as captured by their impacts on utility performance outcomes. This work underscores the need to consider adaptive management system responses and decision-relevant performance measures when determining the impacts of hydrologic change on water availability.

1. Introduction

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

Climate and LULC changes can furthermore have interactive effects (Pielke, 2005). Many papers have discussed the separate impacts of climate or LULC change on runoff and water availability (Christensen et al., 2004; Marquès et al., 2013; Piao et al., 2010; Schewe et al., 2014), but until recently, few studies had investigated water availability impacts of climate and LULC change in combination or in great detail

(Martin et al., 2017; Tong et al., 2012; Tu, 2009). Despite more recent work over the past decade, uncertainty remains as to the relative dominance of climate or LULC factors on streamflow changes (Ye et al., 2013).

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

While reservoir inflows strongly depend on upstream LULC and climatic conditions, water utility operations and regional population pressures also influence the vulnerability of urban areas to water supply shortages (Zeff et al., 2014). When reservoir levels drop, utilities may implement a variety of mitigation strategies. Both short-term decisions, such as use of conservation or usage restrictions (Olmstead et al., 2007; Olmstead & Stavins, 2009) and transfers of water (Characklis et al., 2006; Gorelick et al., 2018; Palmer & Characklis, 2009), and long-term mitigation through infrastructure expansion (Kwakkel et al., 2012; Zeff et al., 2016) can help utilities navigate periods of increased water supply risk. Accounting for decision making across management and investment timescales better represents the capability of utilities to dynamically adapt to changing conditions (Kwakkel et al., 2015); these adaptive policy pathways have emerged as core strategy for flood risk management in the Netherlands (Haasnoot et al., 2013).

Along with ensuring reliable water supply for customers, water utilities must also maintain stable, affordable costs. Balancing the trade-off between service reliability and financial stability requires that utilities track and respond to system conditions other than water availability alone (Zeff & Characklis, 2013). Studies on water availability under climate and LULC change to this point, however, present results that do not capture the broad range of objectives that drive water planning and management decisions, most notably utility-level management responses and their financial implications. For instance, a number of works assess water yield or availability in terms of runoff per capita, ratio of available water to human or environmental demands, or similar indices (Arnell et al., 2011; Arnell & Lloyd-Hughes, 2014; Boithias et al., 2014; Caldwell et al., 2012; Falkenmark, 2013; Gosling & Arnell, 2016; Rijsberman, 2006; Vorosmarty, 2000). Some studies present water availability changes relative to the historic record of streamflow (Kim et al., 2013). Others have approximated utility action in the form of water supply capacity (reservoir) expansion (Lopez-Moreno et al., 2014). While such techniques provide indicators that climatic and LULC changes may impact water supply, they fall short in representing key aspects of reservoir operations and utility decision making, offering an incomplete picture of vulnerability to external stressors or simply equating more (or less) water to better (or worse) outcomes.

This work seeks to move beyond previous analyses of water availability by evaluating hydrologic (i.e., climate and LULC) change at two stages: (1) based on water availability output from ecohydrologic modeling (reservoir inflows) and (2) based on indicators of management system performance at a water utility scale. Our framework can therefore address two main questions not convincingly analyzed by previous work: (1) what are the regional impacts of hydrologic change with and without management system consideration? (2) how can management decision making influence the impacts of hydrologic change? This methodology is applied to a case study within the larger Research Triangle region of central North Carolina (USA), a rapidly growing and urbanizing region where substantial hydrologic and water resource management modeling of current and future conditions has already begun (Gorelick et al., 2018; Herman et al., 2016; Kim et al., 2017; Kirsch et al., 2013; Zeff et al., 2016) but to this point has yet to be consolidated into a coupled modeling framework. In doing so, we show both the relative influences of climate change and LULC

10.1029/2019WR025614

change on water management and that representation of water availability without consideration of utility decision making can obscure important controls on provision of water for human use. While this work is not meant as a comprehensive study over all regions with respect to ecohydrological, climatic, and land use aspects specific to the Research Triangle, we present a generalizable methodology for water supply vulnerability assessment, reproducible across the United States where comparable data is available.

2. Materials and Methods

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

To comprehensively evaluate management and planning outcomes, an exploratory stochastic scenario analysis was used to better account for variability within ecohydrologic modeling projections (Figure 1c). The expanded stochastic analysis is applied to simulation of water utility decision making for three Research Triangle utilities (Cary, Durham, and Orange Water and Sewer Authority [OWASA]), where performance in evaluated based on three operational performance indicators under each hydrologic scenario (Figure 1d) from 2015 to 2060. Water availability is evaluated before (as reservoir inflows) and after (in terms of utility service reliability, conservation implementation frequency, and infrastructure investment indicators) consideration of utility decision making to better understand the interactions between hydrologic change and management actions.

2.1. Regional Characteristics

Our exploratory scenario analysis is tested within the greater Research Triangle region of North Carolina (henceforth Triangle) and its surrounding water supply drainage catchments (Figure 2). Home to over 2 million residents, the Triangle is bracing for rapid population and economic growth over the next half century (Triangle J Council of Governments, 2014) and the accompanying land use changes. Significant increases to urban area are projected for the Triangle, consistent with expectations for the Southeast United States at large (Carter et al., 2018; Wear, 2013), which will alter streamflow patterns as forest cover is reduced. The Triangle falls within the Southeast climate region (Carter et al., 2018) with hot and humid weather in summertime and high-temperature variation in winter. Average annual precipitation across the historical record is 1,124 mm/year, while in the more recent 1990–1999 decade average annual precipitation in the Triangle was 1,167 mm/year with a standard deviation of 142 mm/year. Annual runoff is on average only about 26% of the annual precipitation partially due to high evapotranspiration (ET) from forested land that still dominates the region. Future hydrologic conditions in the region, resulting from climate change, are also highly uncertain. Though predictive skill of precipitation in climate models for the Southeast United States remains low (Seager et al., 2009), the area has experienced increased frequency of extreme flooding and drought events that is expected to worsen (IPCC, 2014a).

Split across two major drainage basins—the Neuse River and Cape Fear River Basins—a number of smaller basins (or catchments) are delineated in this study based on drainage into regional water supply reservoirs (Figure 2, beige). The majority of urbanized area and water demand fall within the service areas of three water utilities in the Triangle—Durham, Cary, and OWASA, with combined 2010 average demands of almost 50 million gallons/day (Triangle J Council of Governments, 2014)—whose water supply is dependent on outflow from watersheds within the larger Neuse and Cape Fear River Basins (Figure 2). The Flat River (USGS 02085500) and Little River (USGS 0208521324) basins drain, respectively, into Durham's Lake Michie and Little River reservoirs within the Neuse River basin. Cane Creek (USGS 02096846) and Morgan Creek (USGS 02097464) basins drain into OWASA's Cane Creek and University Lake reservoirs. The Haw River

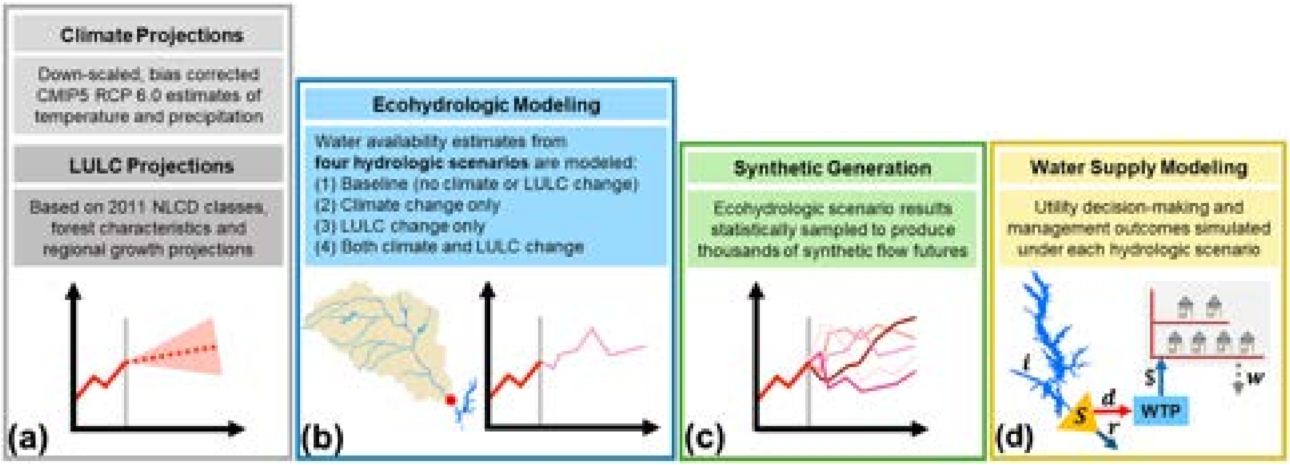

Figure 1. Study modeling framework for assessing water availability under hydrologic change in the Research Triangle. Climate and LULC change projections (a) drive ecohydrologic modeling to simulate water availability under four hydrologic scenarios (b). Water availability estimates are sampled to produce synthetic realizations of future reservoir inflows (c), which drive water supply management modeling for the region to determine utility performance outcomes (d).

(USGS 02096960) and New Hope River (USGS 02097314) basins drain to Jordan Lake, which is managed by the U.S. Army Corps of Engineers and serves as the primary water supply source for Cary. Urbanized drainage areas of Triangle cities also contribute runoff to Jordan Lake (Figure 2, pink).

Subbasins of the Triangle have distinct land use characteristics that can result in varied hydrological patterns between them (Table 1). Forest and pasture land dominate Durham's Flat River and Little River catchments. The Haw River basin, primarily located west of the heavily populated cities of the Research Triangle, and Cane Creek and Morgan Creek basins are largely undeveloped, covered by forested area, pasture, and some row crops. Land around Jordan Lake (Figure 2; pink) and New Hope Creek catchments is dominated by older urban and rapidly urbanizing areas but otherwise surrounded by forest and residual agricultural land. The Triangle is in a topographical transitional zone between the coastal plain and the Piedmont plateau, having an average slope of 5.6% with geologic settings of fractured crystalline bedrock and rolling hills to the west and a lower-lying Triassic basic dominated by deep sedimentary rock to the east running through Durham. Though a rapidly urbanizing and growing region, forest currently dominates the greater Triangle, primarily consisting of *Carya tomentosa* (*hickory*), *Quercus alba* (*white oak*), *Q. rubra* (*red oak*), *Q. prinus* (*chestnut oak*), *Liriodendron tulipifera* (*tulip tree*), and *Liquidambar styraciflua* (*sweetgum*). About 19% of forested area is evergreen forest with pine plantations (*loblolly pine*).

2.2. Climate and Land Use Projections

2.2.1. CMIP5 Projections

To project climate change across the Triangle, we evaluated both historical regional climate patterns and CMIP5 climate projections (Table 2). Historical climate records were collected by the National Weather Service Cooperative Observation Program (COOP) from stations across North Carolina, providing daily maximum and minimum temperature and daily precipitation from 1940 to 2010. Generally, monthly temperatures decreased slightly during the period of 1940–1975 but show warming from 1980 to present time. Monthly precipitation, by contrast, did not vary significantly year to year in the Triangle but displayed a consistent seasonal pattern of high precipitation in winter (January–March) and summer (July–September) and low precipitation in spring (April–June) and fall (October–December).

The CMIP5 GCM products of monthly average daily temperature and monthly precipitation were provided in a statistically downscaled form at (1/8)° (~12 km) spatial resolution. Downscaling and bias correction were previously done using the bias correction and spatial disaggregation and daily bias correction and constructed analogs techniques (Brekke et al., 2013). CMIP5 projections under RCP 6.0 were used, consistent with LULC change projections by previous studies of central North Carolina (Martin et al., 2017; Wear, 2013). Six GCMs (Table 2) were selected for evaluation and ecohydrologic model application—downscaled products from these GCMs are each available at monthly timescale, from 1950 to 2099 at (1/8)° resolution.

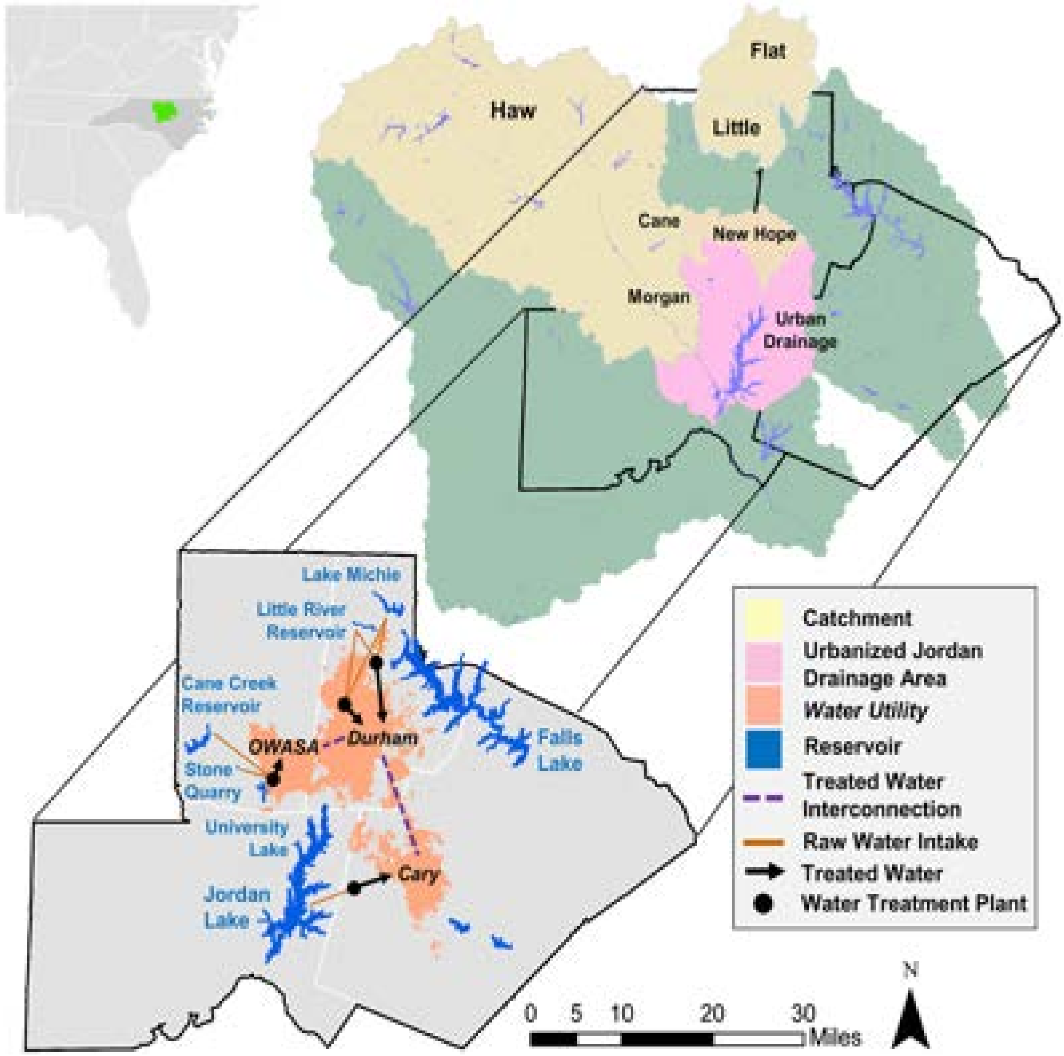

Figure 2. Research Triangle region of the Southeast United States. Six watersheds (beige) contribute inflows to regional reservoirs (blue) along with additional, ungaged runoff from urban basins (pink). Study reservoirs provide water supply to three urban utilities (orange), which may also transfer treated water through existing interconnections (purple, dashed).

Downscaled, daily results were available for the region; however, the available daily data, particularly precipitation, are highly inconsistent with the historical records in terms of seasonality and autocorrelation structures. To prevent these inconsistencies from translating into streamflow prediction and alter hydrologic dynamics in the ecohydrologic models, monthly GCM results combined with historical records were instead used to project future climate that has consistent autocorrelation structure and seasonality of weather.

This set of six GCMs was chosen to provide a diverse assessment of climate futures, spanning the wide range of GCM precipitation and temperature projections for the Triangle. Each GCM has unique seasonal change trajectories for temperature and precipitation (Figure 3). Both GFDL and GISS show large increases in precipitation during spring to fall with moderate increase in winter; GFDL suggests high increases in temperature for all seasons; GISS suggests a relatively muted increase in temperature for all seasons; CCSM shows moderate increase in precipitation in winter and spring; CSIRO projects small precipitation increases in winter and moderated increase in spring and fall; HADG and MIROC project minimal change in summer precipitation. In terms of reservoir recharge, GFDL, GISS, and CCSM show precipitation increase in winter,

Table 1
Regional and Watershed-Level Land Cover Characteristics (2010) for the Research Triangle

Watershed	Catchment drainage area (km^2)	Forest (%)	Pasture/ agriculture (%)	Low-intensity urban (%)	High-intensity urban (%)
Cane Creek	19.7	78.7	17.2	4.0	0.0
Morgan Creek	21.4	75.4	19.4	4.6	0.0
Flat River	385.1	64.4	28.3	6.2	0.7
Little River	202.7	66.8	27.3	5.4	0.1
New Hope Creek	198.9	56.4	5.4	30.5	7.4
Haw River	3359.6	51.5	27.8	15.4	3.5
Regional average		59.5	19.8	15.1	3.2

Note. Primary land cover is forest, followed by roughly equal proportions of pasture and urban land.

which benefits reservoir recharge whereas CSIRO, HADG, and MIROC show little precipitation increase in winter.

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

2.2.2. Land Cover Modeling and Projections

Output from a statistical spatial model described by Martin et al. (2017) and Wear (2013) of plausible change across land cover classes at 30-m spatial resolution was used to project future LULC and forest change in the Triangle (Figure 4). We note that these methods provide information on current, and project future, forest ecosystem conditions required for our ecohydrological modeling approach to integrate feedbacks between climate, land cover, ecosystem water use, with surface and subsurface water stores, and fluxes. The methods are designed to balance consistency with climate projections based on emissions/economic scenarios, with local development conditions, trends, and planning at municipal levels. The methods follow Martin et al. (2017) and also incorporate planning projections of development suitability in the Triangle synthesized by the Triangle J Council of Governments (TJCOG) to further condition land use transition probabilities. Methods are described in detail in Martin et al. (2017), though a brief summary is provided here.

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

County-level land use change is projected as a function of regional county-level population growth and socioeconomic projections (household income and agricultural land values) consistent with economic assumptions in the climate model emissions scenarios as described by Wear (2013). Future forest conditions are projected using the U.S. Forest Service Assessment System (US-FAS) (Martin et al., 2017) that provides future forest conditions for every FIA plot based on projected climate, forest age, forest type, and likelihood

10.1029/2019WR025614

Table 2
Selected CMIP5 GCMs

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

Note. Downscaled products of each were used to forecast climate change in the Triangle to 2060.

of harvest. County-level land use projections were refined to a 30-m scale using a spatial allocation model that determined the probability of each pixel converting to a different land use or remaining the same. Changes in forest conditions (e.g., growth and forest type) are derived from the US-FAS projections that are allocated to each plot using plot-level spatial imputations.

Rapid urban development is anticipated to occur in and around the cities of Chapel Hill, Cary, Durham, and Raleigh that constitute the traditional Research Triangle region (right-hand areas in Figures 4a, 4c, and 4d). The expected types of development include intensifying existing urban area (i.e., from low urban density to high urban density), increased sprawl of existing metropolitan areas, and new urbanizing rural areas in the forested hillslopes of the Triangle. Areas outside the traditional Triangle urban areas, such as the Haw River basin feeding Jordan Lake, however, are projected to remain relatively rural. There is minimal future urban development expected in the Haw Basin; outside two population centers of Greensboro (Figure 4, red areas in map area to the left) and Burlington (center red areas in Figures 4a, 4c, and 4d), the basin is expected to maintain its levels of pastureland and forest. Urbanization is expected to occur to greater extents beginning in 2030 based on development projections from each regional municipality, depending on the trajectory of development envisioned (and planned for by regional governments) in currently rural watershed areas. This information was used to condition transition probabilities of land use and the effects of land use transition based on proximal land use, projected at decadal time steps in LULC modeling. However, as an approximation of variability in the effect of urbanization, the specific type of urbanization (e.g., the prevalence of highly vs. moderately impervious surfaces in future development) was varied between land use parameterizations of ecohydrologic models (as described in following sections).

2.3. Ecohydrologic Modeling

2.3.1. Model Selection

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

Both RHESSys and SWAT were applied in this study to suit the level of development and potential land use management in the Triangle water supply catchments and broader Haw River basin. SWAT modeling of hydrologic processes is implemented in hydrologic response units (HRUs) that independently contribute to catchment runoff irrespective of position in the landscape as it is spatially lumped at the subbasin level and does not provide distributed routing (Meng et al., 2018), making SWAT suitable for modeling large basins with spatially well-segregated landscapes (e.g., forested land clearly separated from urban centers

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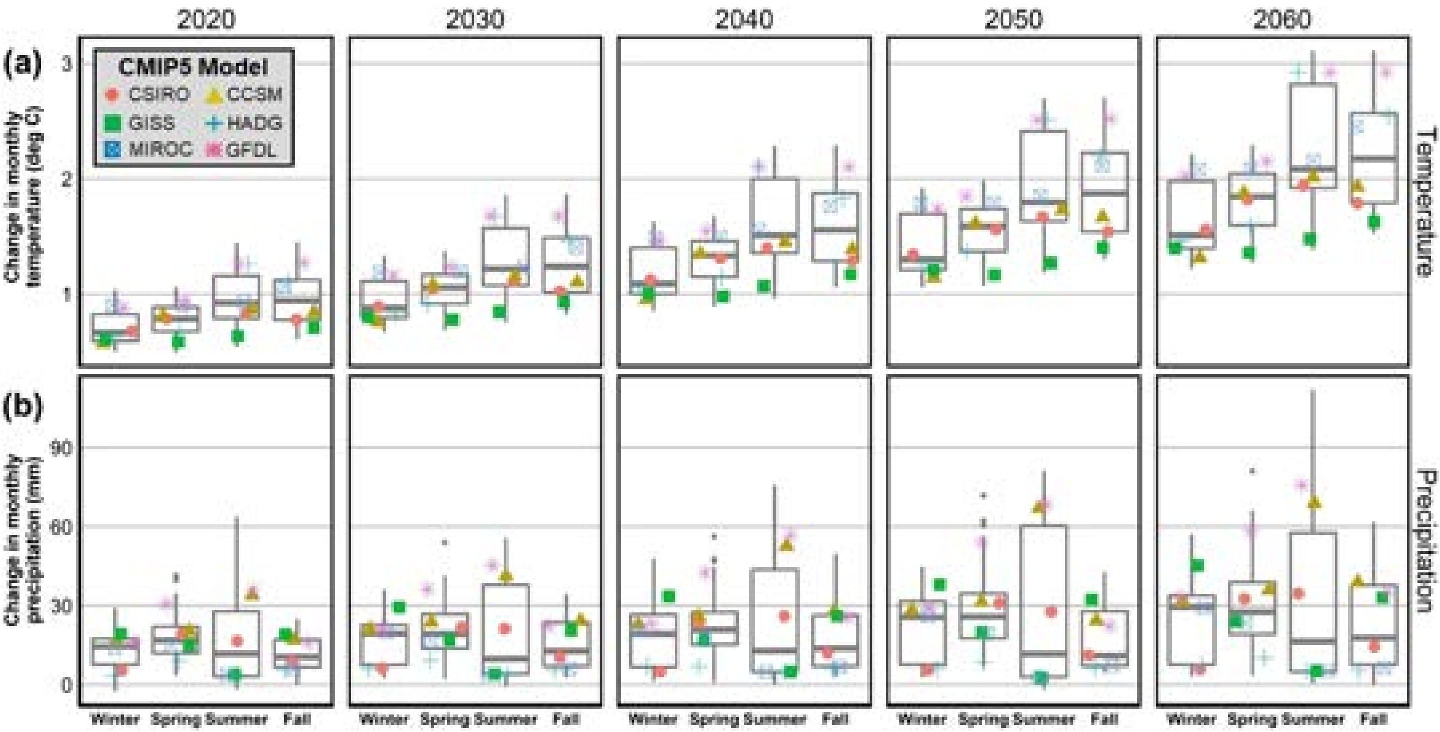

Figure 3. Triangle projections of temperature (a) and precipitation (b) under climate change relative to recent conditions (2000–2010), aggregated seasonally and decadally. Specific results for each of six CMIP5 GCMs overlaid on boxplots.

and agricultural lands) such as the Haw River basin. RHESSys does not use generalized HRUs (as in SWAT) but parameterizes each patch (typically grid cells, but can be multiresolution or nongrid meshes) based on local canopy, soil, land use, and topographic conditions. SWAT HRUs are formed by intersecting soil and land use type with slope classes, though only one slope class was used here as terrain of Triangle basins is relatively flat.

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

RHESSys uses a landscape hierarchical structure over nested patch, hillslope, and watershed scales and operates at high resolution, facilitating the direct representation of detailed urban to rural development on hydrologic and ecosystem processes. Ecohydrologic process components at the patch, hillslope, and catchment scales simulate feedbacks and interaction between climate, atmospheric CO_2, forest composition and structure, and development form to generate runoff, streamflow, groundwater flow, and ET dynamics. As forest conditions are highly variable in space and will vary in time, with forest as the dominant land use, the ecohydrologic components are considered necessary to estimate future response to climate change. These features are particularly important when projecting urban expansion and management in Durham, Chapel Hill, Cary, and their local catchments containing urban, mixed land uses (Figure 4) that are expanding into forested land. As a result, RHESSys was used for more detailed ecohydrologic modeling in all catchments for this work, other than the Haw River basin.

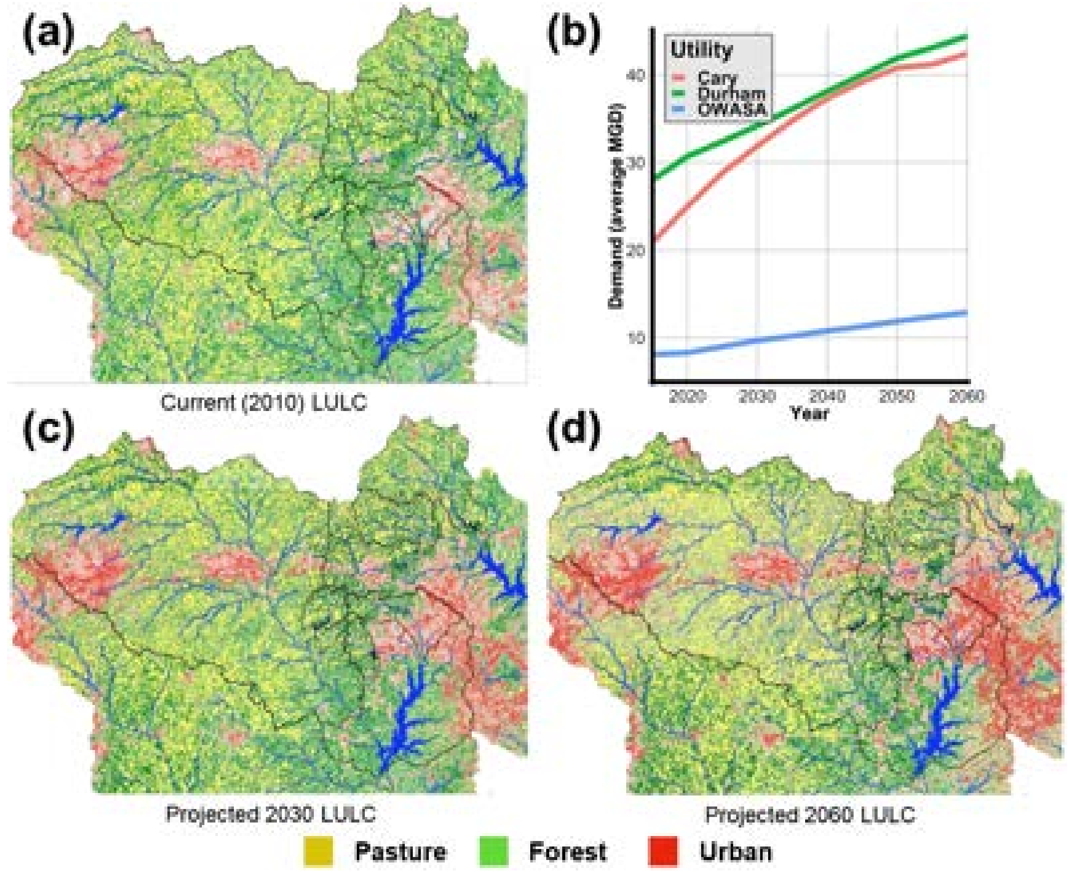

Figure 4. Land use for current (a) and projected (c, d) decades across the Triangle and corresponding regional water demand growth projections (b). A reduction of dense forested area in future decades is observed due to continued urban growth.

More details on RHESSys and SWAT model development for this study can be found in sections 2.3.2 and 2.3.3 and in Texts S1 and S2 of the supporting information. Previous comparisons of SWAT and RHESSys streamflow simulations in the Flat River (one of Durham's water supply watersheds) over the gauge record (since 1926) showed comparable results, and comparison of projected SWAT and RHESSys streamflow from 2020–2060 showed good agreement with the exception of a very wet period around 2040 (Kim et al., 2008).

2.3.2. Model Calibration and Bias Correction

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

To capture the lengthy historical record of reservoir inflows, long-period simulations of calibrated RHESSys and SWAT models were additionally performed. Modeled reservoir inflows were compared to empirical estimates of historical reservoir inflows at USGS gage sites in the region from 1930–2011 for bias correction (HydroLogics, 2011; Kirsch et al., 2013). These empirical estimates of unimpaired reservoir inflows were previously adjusted to remove effects of reservoir operations and consumptive withdrawals (i.e., municipal, industrial, and agricultural demands) as well as gage location (if a gage is not located immediately upstream of a reservoir, additional inflow is added to account for runoff into the reservoir below the gage) (HydroLogics, 2011). Additional bias correction using these products was done to be consistent with Triangle utilities who make use of this reservoir inflow product for planning purposes and therefore ensure consistent inflow prediction from ecohydrologic models for input to water supply management modeling; more details on bias correction and validation are available in Text S2.

2.3.3. Ecohydrologic Model Simulation

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

2.4. Water Availability Scenarios

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

It should be noted that the scenario analysis described in this section (section 2.4) is separate from the simulations described as being produced by ecohydrologic modeling in section 2.3. The projections of climate and land use previously developed to drive ecohydrologic modeling ("multiple model parameterizations" referred to in section 2.3.3) are not the same as the hydrologic scenarios defined here. Each scenario, as detailed in the remainder of sections 2 and 3, consists of multiple ecohydrologic model simulations, each simulation a different parameterization of the ecohydrologic model under a different CMIP5 and/or LULC trend.

2.5. Synthetic Hydrology Development

Each ecohydrologic projection of water availability, just as the historic record itself, represents a single realization of stochastic environmental processes. Constrained by computational intensity of ecohydrologic modeling, evaluation of management decision making and outcomes under only a handful of ecohydrologic model simulations cannot effectively locate robust management strategies. However, use of stochastic, or "synthetic," generation of hydrology has been widely applied in the field of water

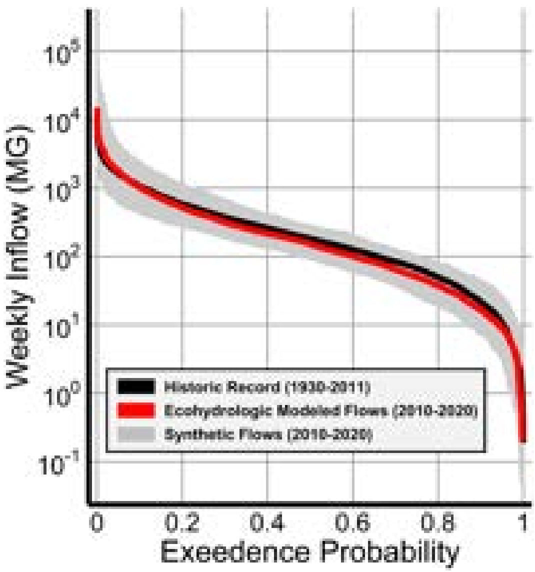

Figure 5. Example comparison of historic Durham reservoir inflows from the Little River (black) to ecohydrologically modeled (red) and synthetic, stochastic (gray) products. Modeled results from 2010–2020 based on stationary (historic) hydrologic conditions.

resources management to resolve issues of limited data availability and for evaluation of management strategies (Borgomeo et al., 2015; Hao & Singh, 2016; Herman et al., 2016; Kirsch et al., 2013; Nowak et al., 2010; Quinn et al., 2017). Synthetic generation is especially valuable for questions of system performance, where evaluation under the historical record alone can produce an inaccurate representation of outcomes, even under stationary hydrologic conditions, and overestimations in the robustness or viability of tested management actions (Loucks & van Beek, 2017; Vogel & Stedinger, 1988).

To capture a more comprehensive range of hydrologic variability, ecohydrologic model simulations of water availability (reservoir inflows) were statistically sampled to generate thousands of stochastic reservoir inflow time series (realizations). Generating synthetic hydrology allows for a more robust identification of effective management strategies, subjecting water supply management decision making (described in the following section) to a wider array of extreme high and low flow conditions than is possible from ecohydrologic modeling products alone (Figure 5).

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

Another reason to employ synthetic generation is to evaluate impacts of hydrologic nonstationarity (Herman et al., 2016), such as changes due to climate or LULC change. This work built upon an existing streamflow generator for stationary hydrology (Giuliani et al., 2017; Quinn et al., 2017), sampling from decadally shifting ecohydrologic modeling outputs to generate transient reservoir inflow and lake net evaporation records, correlated across multiple Triangle sites, at a monthly time step through Cholesky decomposition (Kirsch et al., 2013), and disaggregated using a k-nearest neighbor method (Nowak et al., 2010) to a weekly time step for water supply modeling. Due to the nonstationary nature of ecohydrologic outputs under climate and land use change, sampling was done decadally to capture shifting statistical properties of ecohydrologically simulated records and 10-year synthetic realizations were combined to produce complete stochastic time series futures. More detailed description of generator construction and validation can be found in Text S3. For each hydrologic scenario described in the previous section, 1,000 synthetic futures of inflow and net evaporation from 2010 to 2060, the planning period for regional water utilities, were generated for each regional reservoir.

2.6. Water Supply Management Modeling

2.6.1. Modeling Framework

A comprehensive analysis of water availability and the impact of future hydrologic change on urban water supply is incomplete without consideration of water utility controls on water management. Given ecohydrologic modeling output of reservoir inflows to three major Triangle utilities—Cary (Jordan Lake), Durham (Little River Reservoir and Lake Michie), and OWASA (Cane Creek Reservoir, University Lake, and Stone Quarry)—this work simulates weekly utility decision making from 2015 to 2060 (consistent with previous work by Zeff et al., 2016 in the Triangle) under each climate and LULC scenario in order to assess the impact of change on utility performance indicators (outcomes). Monte Carlo model simulations for each evaluation of the water supply model simulate weekly decision making under 1,000 separate synthetic hydrologic futures (synthetic development described in previous section and Text S3).

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

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

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

2.6.2. Utility Performance Metrics

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

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

$$\min f_{Rel} = \max_{U}\left[\frac{\max_{Y}\left(\sum_{r} F_{r,u,y}\right)}{N_r}\right] \tag{1}$$

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

$$\min f_{Rest} = \max_{U}\left[\sum_{r}\frac{\sum_{y} R_{r,u,y}}{N_r N_y}\right] \tag{2}$$

Conservation programs by a water utility can reduce water use during drought but result in reduced revenues (financial risk), introducing revenue volatility and jeopardize a water utility's financial stability (Hughes & Leurig, 2013). Utilities consistently facing financial hardship also run the risk of credit downgrades; future infrastructure maintenance or expansion then become more expensive as interest rates on bonds increase, in turn leading to increased rates for customers. Similarly, utilities are interested in minimizing the infrastructure investment costs necessary to sustainably meet long-term demand, avoiding the rate increases accompanying a large debt burden. An indicator of regional infrastructure investment f_{Cost} is calculated to measure average realization present-value infrastructure costs across a model evaluation (equation (3)). Debt service payments $DS_{r,u,y}$ on infrastructure bonds made in each year y of each realization r for each utility u are discounted in time at a discount rate d of 5% (implying that deferred infrastructure investment, and reduced present-value cost, is preferable in terms of system performance) and summed across time. Calculation of the cost indicator for a model evaluation of discounted debt service payments is done by averaging total discounted debt service of each realization, which is summed across each entire realization rather than each year (whereas the previous two performance metrics rely on annual measures).

$$\min f_{Cost} = \max_{U}\left[\sum_{r}\frac{\sum_{y}\frac{DS_{r,u,y}}{(1+d)^{y-1}}}{N_r}\right] \tag{3}$$

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

2.6.3. Infrastructure Development Pathways

In line with Triangle utility goals of maintaining high reliability and low restriction use frequency two well-behaved solutions—two contrasting water supply model parameter sets, chosen from a Pareto-approximate set of solutions for the Triangle utilities originally optimized by Zeff et al. (2016)—were selected that maintain reliability greater than 96% (failure 1 in 25 years on aggregate) and restriction frequency less than 20% (1 in 5 years on average) under baseline (Scenario 1) conditions.

The two solutions, or "development pathways," were based on operational designs outlined in planning studies by regional utilities (Triangle J Council of Governments, 2014). A development pathway can be thought of as one infrastructure development sequence, which, combined with short-term drought mitigation options available to each utility, represents a single parameterization of the water utility decision-making model (one "state of the world"). While a single pathway is constituted of available infrastructure options in a given evaluation of the water supply model, sequencing of infrastructure options in each realization is dynamic. Utilities may trigger infrastructure construction when ROF rises above a predefined trigger

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level; because ROF is recalculated weekly as conditions change, infrastructure investment is adaptive to hydrologic change through its dependence on ROF for implementation.

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

3. Results

The following text and figures describe regional water availability under each of four modeled hydrologic scenarios—(1) future hydrology consistent with present-day climate and land use conditions; (2) climate change in line with IPCC RCP 6.0 projections; (3) LULC change, largely continued urbanization of the region (and forest ecosystem change); and (4) combined effects of climate and LULC change—through measures of inflow to Triangle reservoirs as well as utility performance indicators of supply reliability, conservation (use restriction) frequency, and infrastructure cost. Figure 6 highlights the differences in streamflow to regional reservoirs under each hydrologic scenario and across time. Figure 7 visualizes performance indicators for each Triangle utility and the overall region under all hydrologic scenarios, exploring indicator performance trade-offs and impacts of infrastructure development across two select development pathways. Figure 8 details an example of time-evolving risk and infrastructure decision making for one regional utility.

3.1. Raw Water Availability

A common water availability metric of use is streamflow, or reservoir inflow. Figure 6 shows 52-week (1-year) moving sum Triangle reservoir inflows for each utility of the study, both before and after 2030. This temporal division at 2030 is useful for this region as more significant development of the contributing water supply watersheds is projected to begin at or after this date, with prior development concentrating in areas that do not drain into the water supply reservoirs considered in this analysis. Inflows to each utility are quantified for drought events of low probability—return periods of 5 years or longer—and differentiated by hydrologic scenario. The intention of Figure 6 is to visualize how water availability is quantified as a direct output from ecohydrologic modeling, before any consideration of management.

3.1.1. Hydrologic Change Influence on Reservoir Inflows

Climate (Figure 6, blue) and LULC change (Figure 6, red) result in an increase to water availability during drought across all utilities before and after 2030 with the exception of pre-2030 Durham. The effects of climate and LULC hydrologic change were additive, with largest increases to water availability seen when both effects were modeled in tandem (Figure 6, green). One exception to inflow increases can be seen for Durham under LULC alone before 2030 (Figure 6b(1)); flows under LULC change in this case were similar to flows under baseline conditions (Figure 6, black) or slightly reduced on average for low-flow return periods. Durham water supply catchments are more rural, without significant development envisioned before 2030. Variability of inflows, demonstrated by the width of boxplots in Figure 6, tended to increase under hydrologic change relative to baseline conditions. Climate change generally displayed wider variability in inflows than LULC change. The combination of climate and LULC change effects caused the widest ranges in reservoir inflow availability (Figure 6, green). With respect to reservoir inflows, results here indicate that both climate and LULC change could reduce the probability of low-flow, drought events across the Triangle.

3.1.2. Differences of Inflow Across Space and Time

The impacts of climate and LULC change on drought flow severity varied between utility and between early (pre-2030) and late (2031–2060) time periods. The impacts of hydrologic change manifest more heavily after 2030 (Figure 6(2)) than before (Figure 6(1)). The largest absolute increases to inflows relative to baseline conditions due to either climate or LULC change were seen in Cary (Figure 6c), while largest percentage increases were seen in Durham (Figure 6b). Before 2030, climate change increases Durham inflows while

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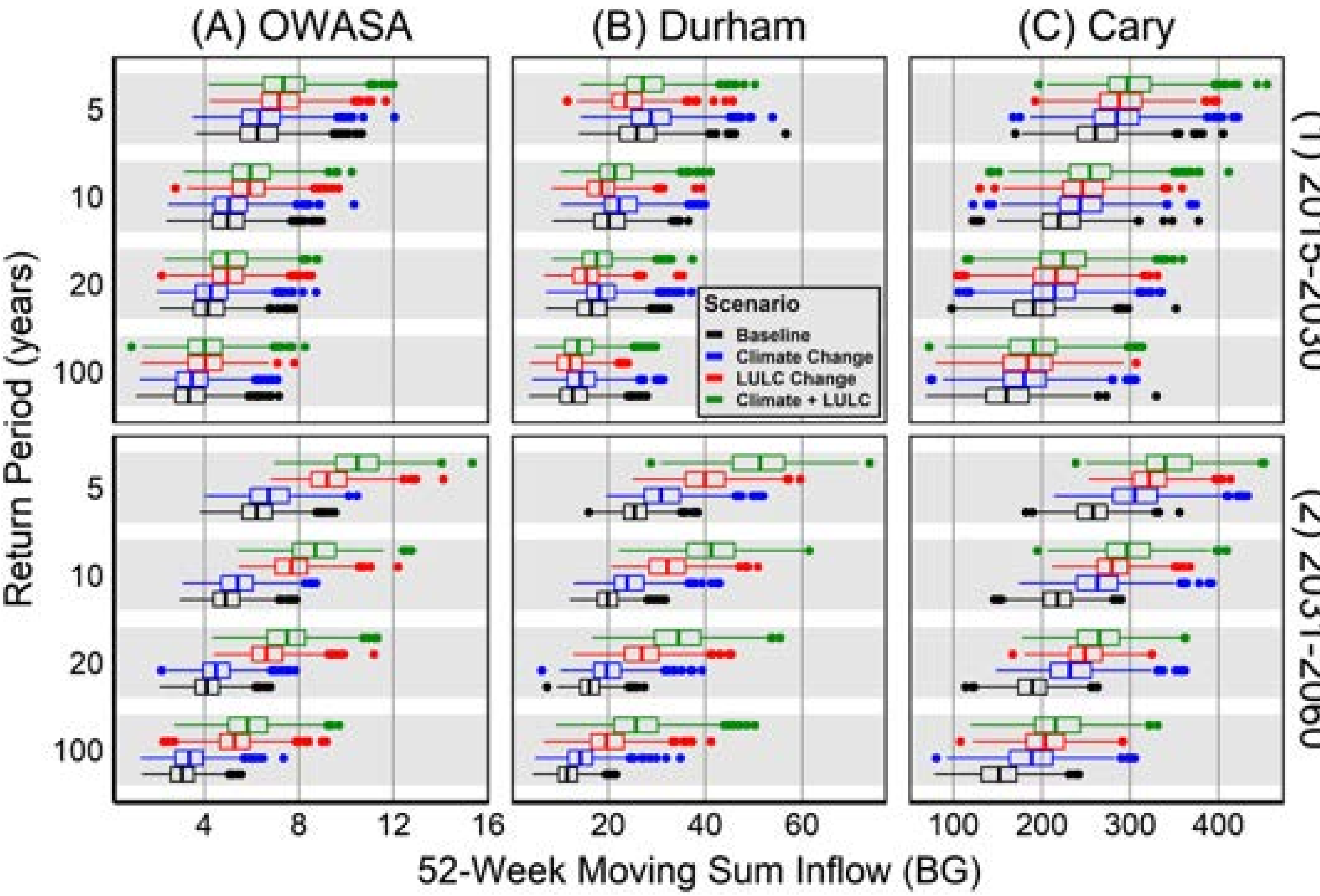

Figure 6. (a–c) The 52-week (1-year) moving sum of reservoir inflows for low-flow return periods, given for Triangle utilities (panel columns) before and after 2030 (panel rows) under each hydrologic scenario (colors). Box plot ranges show the distribution of flows for each return period across 1,000 synthetic hydrologic realizations. Both climate (blue) and LULC change (red) increase reservoir inflows and act additively in combination (green). Inflows after 2030 (bottom row of panels) are greater under hydrologic change than before 2030 (top row).

LULC change maintains or reduces flows relative to baseline conditions (Figure 6b(1)). LULC change increased OWASA inflows to a much larger degree than climate change across both time periods (Figure 6a).

3.2. Utility Operational Impacts of Hydrologic Changes

Measuring utility performance under hydrologic change through reservoir water availability alone does not capture additional factors, such as demand growth or financial risk, controlling management outcomes. Figure 7 summarizes utility performance according to indicators of reliability (measured as storage failure frequency; Figure 7, left axis of each panel), restriction use frequency (center axis of each panel), and infrastructure investment (right axis) for each utility (and the total region) under two contrasting development pathways. Each panel of Figure 7 is a separate parallel axis plot; each panel contains multiple lines across all three performance indicators. One line represents an evaluation of the water supply model and its performance for each indicator. To compare the performance of an evaluation against another, observe their relative locations on the plot—if one line crosses a vertical indicator axis at a lower point than another line, the former model evaluation has performed better than the latter based on that indicator (an ideal evaluation of the model would result in a horizontal line across the bottom of the plot).

Eight separate model evaluations (two development pathways by four hydrologic scenarios) are shown in Figure 7; each evaluation's indicator outcomes are given for every utility (Figure 7, rows) and for the region as a whole. Differences between indicator values of separate model evaluations (lines) are absolute changes

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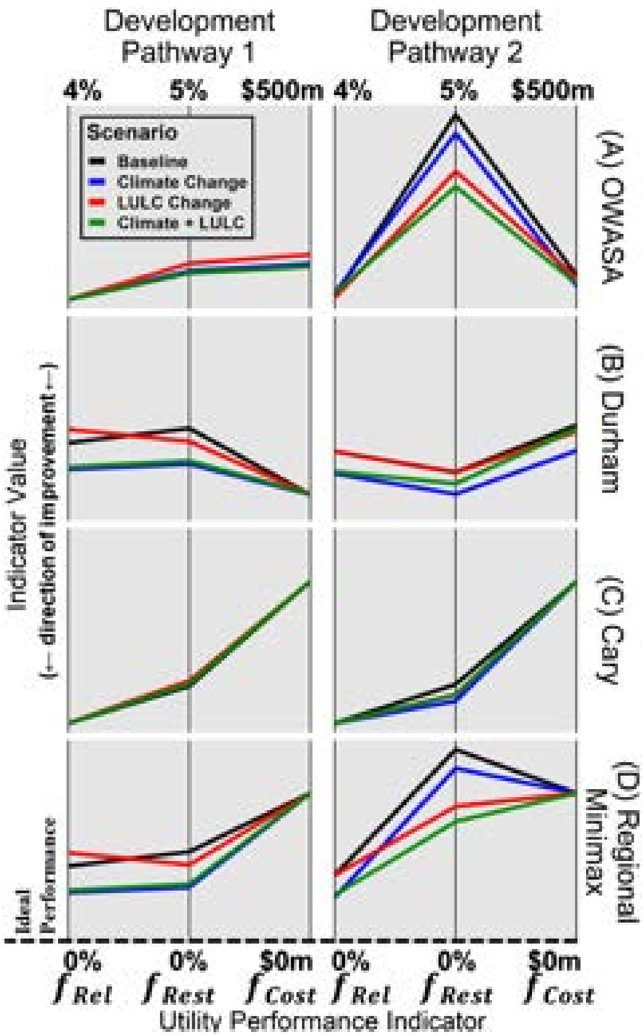

Figure 7. (a–d) Panels of parallel axis plots showing modeled outcomes based on three regional utility performance indicators. Model evaluations under tested hydrologic scenarios (colors) are given for each regional utility and the overall region (rows) for two contrasting development pathways (columns). Each line represents one model evaluation's performance across each indicator.

in indicator value. Reliability indicator values on Figure 7 range from 0% (an ideal level of no failures) to 4% (1 in 25 years experiences storage failure); restriction frequency ranges from 0% (ideal, no restriction use) to 5% (1 in 20 years implemented conservation); infrastructure investment range in Figure 7 ranges from $0 (ideal, no infrastructure spending triggered) to $500 million (discounted total over the 2015–2060 year period). In comparison to Figure 6, Figure 7 is intended to demonstrate by contrast the complex nature of utility vulnerability to hydrologic change when considering performance based on management objectives, rather than reservoir inflow and water availability alone.

3.2.1. Comparing Reservoir Inflow and Utility Performance Indicators

While reservoir inflows increase regionally as a result of climate and/or LULC change, the effect of hydrologic change on utility performance indicators was not as direct. In some cases, trends of increased reservoir inflows seen in Figure 6 under each hydrologic scenario were reflected in management indicators—OWASA restriction frequency under Development Pathway 2 (Figure 7a(2), center axis) is an example of this. In other cases, inflow increases did not result in improved management outcomes; Durham reliability under Development Pathway 1 degraded under LULC change relative to baseline conditions (Figure 7b(1), left axis, red). In other cases, hydrologic change had marginal influence on management objectives—Cary experienced little change in indicator value due to hydrologic change, and infrastructure investment indicators across all utilities were relatively inelastic to hydrologic change. Climate change was generally more influential than LULC change in improving indicator values relative to baseline (Figure 7d(1)) despite often contributing less reservoir inflow (Figure 6), though the opposite was true in some cases (Figure 7a(2)).

3.2.2. Differences Between Utility Outcomes

Indicator performance varied widely between utilities. OWASA and Cary, already with very reliable performance levels under baseline conditions, did not see substantial improvement in reliability due to hydrologic change (Figures 7a and 7c, left axes). Durham, on the other hand, consistently saw reliability improvement as a result of climate change, but not LULC change (Figure 7b). Infrastructure investment indicator values for Cary were unaffected by hydrologic change; Cary expands water treatment capacity based on demand growth targets that occur soon after 2015, which hydrologic change does not impact. Durham saw varied impact of hydrologic change on infrastructure investment, which was also dependent on the development pathway (more detail in next subsection). Climate change and combined climate and LULC change impacts infrastructure investment improvement for OWASA more-so than LULC change, as they were for restriction use frequency in Durham.

3.2.3. Differences Between Development Pathway Outcomes

How utility performance indicators responded to hydrologic change was also dependent on the development pathway followed. Under Pathway 1 (Figure 7, left panels), infrastructure development opportunities are more extensive for OWASA but restricted for Durham—the opposite is true for those utilities in Pathway 2 (Figure 7, right panels). Pathway 1 prioritizes the option for Durham and OWASA to jointly develop water withdrawal and treatment infrastructure on Jordan Lake, followed by additional, independent options such as implementation of reclaimed water reuse for Durham or University Lake expansion for OWASA. Under Pathway 2, Jordan Lake development is still prioritized, though OWASA is now allotted a larger treatment (and financing) allocation in the Jordan Lake development than allocated in Pathway 1, and the opposite is true for Durham. In both pathways, Cary has the singular option to expand its Jordan Lake water treatment

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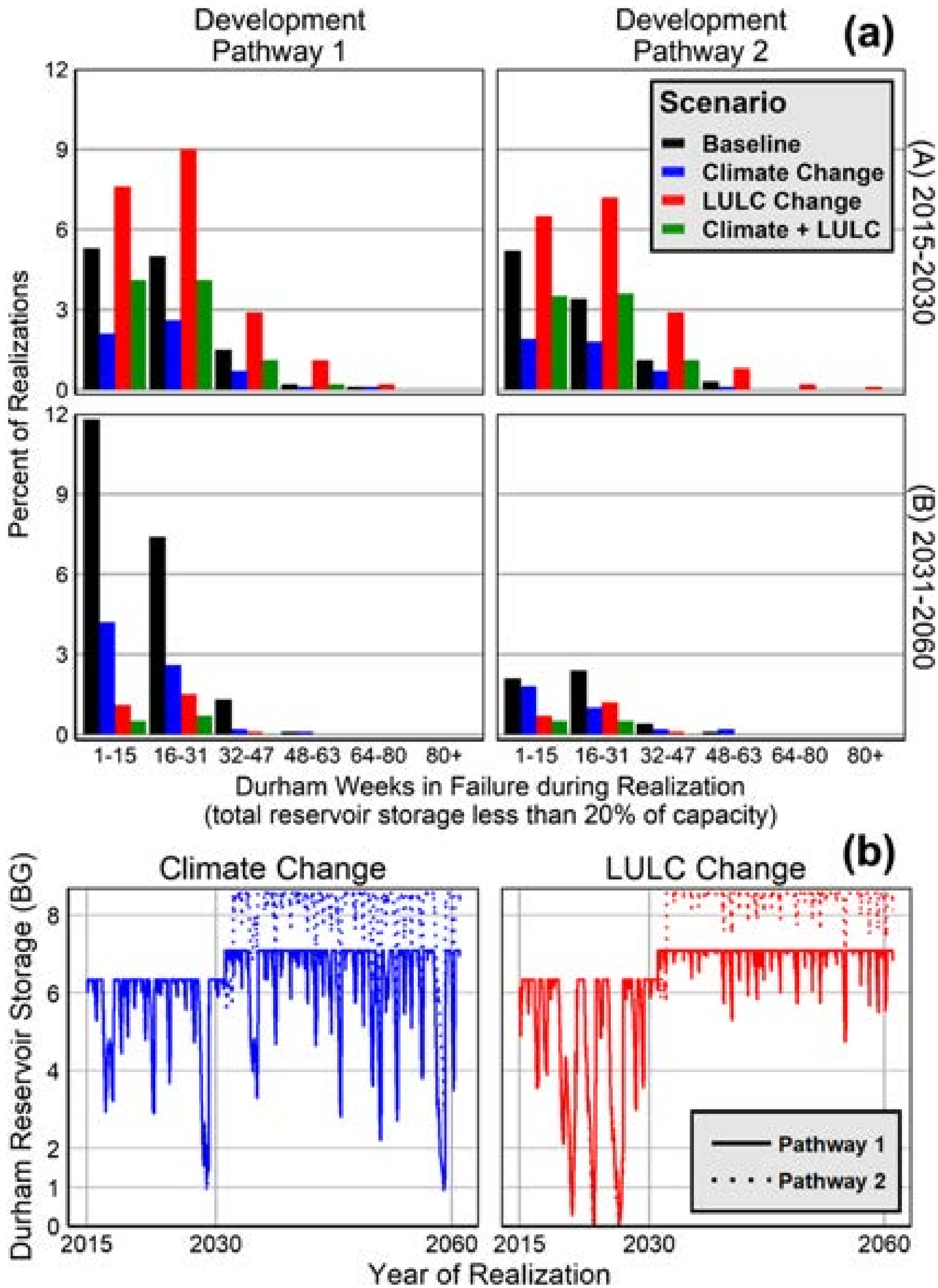

Figure 8. (a) Histograms of Durham weekly storage failure frequency across 1,000 synthetic hydrologic realizations, differentiated by hydrologic scenario (color), development pathway (column), and time period (row). Each panel shows the percent of all realizations that see a given range of storage failure. (b) Time series examples of Durham reservoir storage for a single realization under climate (left panel) and LULC (right panel) change for each of the two development pathways modeled (line type). Discontinuity around 2032–2033 due to infrastructure development.

plant. Both prioritization order and permitting period, the number of years from 2015 that must elapse before a project can be built, factored into the relative availability and implementation of infrastructure in either Pathway 1 or Pathway 2. A full list of potential infrastructure development options and their implementation constraints for Triangle utilities is provided in Table 1 of Zeff et al. (2016).

Risk tolerance levels (ROF trigger levels for infrastructure development and restriction use) also differed between pathways. OWASA's short-term risk tolerance in Pathway 1 is much greater (ROF trigger for restriction use is higher) than in Pathway 2, leading to a more substantial influence of hydrologic changes on the restriction use indicator in Pathway 2 (with a low ROF trigger level, restriction use is more frequent and sensitive to mild or moderate droughts). Under Pathway 1, LULC change also results in a degradation in Durham reliability relative to baseline conditions, while Pathway 2 showed no reduction in reliability due to LULC change (Figure 7b, red, left axis). Because the development pathways shown here represent two different sets of decision-making “rules” for utilities, our results demonstrate that utility actions can influence management outcomes and provide considerably control over hydrologic change impacts on water resource systems.

When more infrastructure development options were available, more variability in the infrastructure investment indicator also occurred. In Pathway 1, hydrologic change did not impact infrastructure investment indicator levels for Durham, while they are affected in Pathway 2 (Figure 7b(2)), especially by climate change. LULC change increased infrastructure investment relative to baseline for OWASA under Pathway 1 (Figure 7a(1), red) but led to a slight reduction in investment under Pathway 2.

3.3. Durham Hydrologic Change Impacts

To explore the mechanisms driving utility performance outcomes under hydrologic change, we present detailed results for Durham under both tested development pathways in Figure 8. The four panels of Figure 8a show weekly storage failure frequency histograms for Durham reservoirs across 1,000 hydrologic realizations tested under each hydrologic scenario. These results are given for both development pathways (panel columns) before and after 2030 (panel rows). The two panels of Figure 8b give time series examples of two realizations of weekly Durham reservoir storage from 2015–2060 under either climate (left panel) or LULC (right panel) change and following both development pathways (line type). While Figures 6 and 7 visualize simulation-scale vulnerability at a regional level, Figure 8 provides realization-level details to reveal the interplay between individual realizations of hydrologic change and their impact on water availability when infrastructure and management are considered.

3.3.1. Storage Failure Frequency Under Baseline Conditions

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

3.3.2. Failure Frequency Under Hydrologic Change

The same behavior of failure frequency exhibited under baseline conditions is also observed under the climate change scenario to a lesser degree (Figure 8a, blue). Failure frequency for Durham under the LULC change scenario is greater than baseline conditions before 2030 (Figure 8a(A), red compared to black), and failures with combined LULC and climate change are greater than those under just climate change before 2030 (Figure 8a(A), green compared to blue). This behavior as a result of LULC change is linked to trends in reservoir inflows to Durham before 2030 (Figure 6a(B)(1), red). Drought event flows under LULC change were found to be approximately equal to, or slightly lower than, baseline flows on average while also exhibiting extreme values beyond those observed under baseline conditions for some return periods. The change to extreme flow event frequency, as well as small changes in average drought flows, had heavy influence on failure rates for Durham under LULC change before 2030. After 2030, however, hydrologic scenarios with LULC change (Figure 8a(B), red and green histograms) show failure rates lower than those observed under baseline or climate change conditions for both development pathways.

3.3.3. Influence of Short-Term Drought Mitigation

Both short- and long-term utility decision making, as well as hydrologic change, had influence over Durham's susceptibility to storage failure. Based on regional infrastructure planning, Durham has limited ability to expand storage or treatment capacity infrastructure until at least 2030 in either development pathway. As a result, differences in failure frequency between pathways before 2030 (Figure 8a(A)) are primarily due to hydrologic change and short-term drought mitigation actions (i.e., use restrictions) only. Short-term mitigation is carried out when ROF levels for Durham reach a fixed trigger level, which is higher (less risk averse) for development Pathway 1 than for Pathway 2 (higher risk aversion). Because of differences in utility decision making related to drought mitigation, failure frequency for Durham before 2030 is reduced under Pathway 2 (Figure 8a(A)(2)) more than under Pathway 1 (Figure 8a(A)(1)) for all hydrologic scenarios. Mitigation is also more effective at reducing failure rate in baseline (black) and LULC change (red) scenarios before 2030 in Durham, as neither scenario sees increases to reservoir inflows in this time period relative to scenarios under climate change.

3.3.4. Relative Influences of Infrastructure Investment and Hydrologic Change

After 2027, infrastructure development is available for Durham (Figure 8b), greatly reducing the frequency of storage failure after 2030 in most cases (Figure 8a(B)). However, under Development Pathway 1, baseline and climate change scenarios see either a continuation or increase of failure frequency after 2030 relative to before 2030 (Figure 8a(1), blue and black). At the same time, both hydrologic scenarios including LULC change (Figure 8a(1), red and green) see substantial reductions in failure frequency after 2030 in Pathway 1. These different outcomes are a result of two concurrent causes: (1) urbanization in the Durham reservoir catchments that ramps up after 2030 and (2) expansion of water supply infrastructure. Under baseline and climate change only scenarios, no LULC change resulting from urbanization occurs to further increase water availability to reservoirs after 2030. With LULC change effects, the remaining two hydrologic scenarios utilize excess urban (and exburban) runoff to reduce storage failure frequency from 2030–2060.

The level to which infrastructure is expanded can be as consequential as hydrologic change. Under baseline and climate change conditions, Development Pathway 1 is less effective than Pathway 2 at reducing storage failure frequency (Figure 8a(B), black and blue). Without additional reservoir inflow from LULC change, the major differences in failure frequency are due to the differing degrees of infrastructure expansion. An example of this behavior is given for one realization of Durham reservoir storage under the climate change scenario for both development pathways (Figure 8b, left panel). Development Pathway 2 (Figure 8b, dotted line) sees Durham opt to expand reservoir capacity after 2030 to a greater degree than Pathway 1 (Figure 8b, solid line). Because climate change does not increase reservoir inflows as substantially as LULC change, demand growth outpaces long-run water availability increases due to climate change. The additional reservoir capacity available in Pathway 2 insulates Durham from storage failures that Pathway 1 experiences (Figure 8b, left panel—difference between solid and dotted lines of 2058 drought event). The same drop in failure frequency due to additional storage capacity in Pathway 2 is also observed for baseline hydrologic conditions.

3.3.5. LULC urbanization Timing Effects on Failure Frequency

Timing of urbanization in Durham catchments has a different impact on failure frequency. Between Development Pathways 1 and 2, Durham failure frequency is effectively unchanged after 2030 if LULC change occurs (Figure 8a(B), red and green) despite differences in infrastructure investment noted in the previous paragraph. Urbanization begins to drive reservoir inflow increases after 2030 when additional development occurs in Durham catchments, a later shift than seen in Cary or OWASA. This additional inflow provides Durham enough water (relative to baseline conditions) to offset future demand growth. However, the abrupt change to LULC combined with a reliance on ROF (calculated based on a moving window of past hydrologic conditions) to trigger infrastructure development means that Durham is slow to adapt to this hydrologic regime shift. As a result, no matter to what degree water supply infrastructure is expanded after 2030, LULC change drives late-term reduction in failure frequency (Figure 8b, right panel). While baseline and climate change scenarios depend on more infrastructure investment to reduce supply failure, LULC change improves supply reliability irrespective of the level of infrastructure expansion.

10.1029/2019WR025614

4. Discussion

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

4.1. Ecohydrologic Drivers of Water Availability

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

Under climate change, an increase in precipitation during the dormant season relative to baseline (hydrologically stationary) conditions results in increased reservoir recharge. During the growing season increase in flows is not as evident, possibly due to increased summer and fall temperatures that extend the growth period for vegetation, increasing ET in early spring and late fall. Under LULC change, runoff increases over urbanizing areas in the Triangle (area surrounding Jordan Lake, including Durham catchments) but does so to a smaller degree over the larger Haw River Basin that is projected to remain heavily forested (Figure 6c, difference before and after 2030). Where forest land cover is converted to urban developed area, leaf area index is reduced and runoff significantly increases due to a drop in ET. The magnitude of this effect is dependent upon the type of urban development; whether development is dense (sprawling) or more (less) intensive, which varied between LULC projections, can influence the effect of urbanization on reservoir inflow. In this work, LULC change through urbanization increases runoff through a decrease in ET and increased impervious surface, while climate change increases runoff through increased precipitation in the Triangle.

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

Though climate change may be a strong driver of change to streamflows, climate effects and LULC effects are not necessarily additive in terms of their joint effects on water availability (i.e., Figure 6 distributions). In our study region, runoff generation is primarily controlled by precipitation, water consumption by forest (i.e., ET) and the type of urban development that occurs. Most of the denser new development in the Triangle is outside of the drainage areas to the regional reservoirs, and small amounts of LULC change in Triangle catchments are dominated by the simulated effects of climate change and in places can offset climate change effects. However, should deforestation (i.e., LULC change) become more prevalent, as is expected after 2030, LULC change can have strong effects on return flows, yielding streamflow signals that are different than those from climate change as ET patterns change. Climate change widens the variation of return flows, but LULC change increases flow while also decreasing its variation. When both effects occur in tandem our results indicate an increase in overall flow with wider variation, but not in a linear additive sense. This nonlinear behavior can be strongly influenced by specific types of LULC development that, in cases, offset some effects of climate change. As an example, increased growing season length and temperature due to climate change can increase annual ET, but be offset by impervious surface runoff and increased soil and groundwater recharge in open areas, supporting higher baseflows.

10.1029/2019WR025614

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

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

4.2. Hydrologic Impacts on Utility Performance

Generally, when more water was available to reservoirs through hydrologic change, reliability improves and restriction usage falls. However, indicator performance varied widely between utilities. Drawing water from the largest reservoir in the Triangle, Jordan Lake, Cary indicator performance was relatively unaffected by hydrologic change or shifts in reservoir inflows (Figure 7c). With moderate demand growth expected over the 45-year modeling period and ample water storage and treatment capacity under baseline conditions, increases in water availability were inconsequential to Cary. Durham and OWASA, by contrast, showed wider ranges of performance outcomes due to hydrologic change (Figures 7a and 7b). Interestingly, LULC change alone (red) led to cases of worse indicator performance for both Durham and OWASA than model evaluations with climate change (blue and green) despite being an overall larger hydrologic contributor to increased water availability. For Durham, performance outcomes were degraded by LULC change scenarios because substantial increases in runoff due to LULC change in the water supply drainage areas do not accelerate until 2030 (Figure 6b).

Similarly, OWASA saw performance indicators negatively impacted by LULC change, but to a lesser degree than Durham (Figure 7a(1)). OWASA indicator degradation relative to baseline results was also primarily driven by early-term water availability (Figure 6a(1)); OWASA's baseline indicators of restriction use and infrastructure investment under Development Pathway 1 were already well performing (Figure 7a(1), black), and small changes to reservoir inflow persistence from LULC change without substantial increase in drought flows during 2015–2030 drove slight increases in restriction use frequency and heightened ROF, driving small increases to infrastructure investment (Figure 7a(1), red). An increase in impervious surface cover as a result of LULC change can lead to increased “flashiness” of runoff from lands that are highly impervious; larger amounts of runoff are likely immediately following precipitation events, but these events are followed by periods of reduced runoff. Large events may also not be completely retained as reservoir storage if inflows are too great over a short period of time and must be spilled out of the reservoir. Reduced consistency of base flow into reservoirs can exacerbate drought, resulting in lower rates of reliability even compared to baseline conditions in some cases.

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

4.3. Influence of Utility Decision Making on Performance Outcomes

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

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

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

4.4. Additional Considerations

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

10.1029/2019WR025614

With respect to this analysis of water scarcity, however, the impact of flooding is muted in surface water-dependent systems of reservoirs like those in the Triangle that cannot hold more water than their capacity allows. From a water supply modeling standpoint, and the standpoint of concerns over water scarcity, whether a reservoir receives enough inflow to fill to its capacity or a much greater volume of inflow, with most of it passing immediately downstream via spill structures, is largely irrelevant as both provide for the same volume of available water supply. That said, high-flow flooding events and storm water pollution in reservoirs like Jordan Lake, which is operated by the U.S. Army Corps of Engineers to manage water quality and flooding along with water supply, are areas of concern for future work in water resources management.

An increase in water availability does not automatically alleviate all regional worries of future water scarcity under hydrologic change. Both climate and LULC change may affect the variability of water availability, changing the frequency of both drought and flooding as well as the persistence of wet and dry conditions. One week of heavy rain followed by 4 weeks of dry weather may produce the same amount of reservoir inflow as five weeks of steady, less extreme precipitation, but a "flashy" hydrologic regime would create difficult operating conditions for a utility trying to balance flood risk and water supply reliability when holding or releasing inflows.

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

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

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

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

5. Conclusions

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

Acknowledgments
The authors would like to mention and to thank the National Science Foundation for funding this work (Water Sustainability and Climate Program, Award 1360442). We would also like to thank Orange County Water and Sewer Authority, Town of Cary Water Resources Department, City of Durham Department of Water Management, and other Research Triangle water utilities for their advisory roles on this work through the Triangle Water Supply Partnership. The Triangle J Council of Governments (TJCOG), specifically John Hodges, also provided regional growth forecasts and important insight into development in the region. This work reflects views of the authors and not necessarily views or policy of the NSF. Code used for synthetic generation is available on GitHub (https://github.com/degorelick/TransientGenerator). Code used for water supply management modeling is available on GitHub (https://github.com/bernardoct/WaterPaths/tree/ThreeUtilityModel). Data produced by or used to drive ecohydrologic modeling, synthetic streamflow generation, and water supply management modeling can be found online (https://www.hydroshare.org/resource/f7614f0b1c784584af3cd4cdd7675a5a/), and additional code and information about data sources or models used for climate, land use, and ecohydrologic modeling can be found at a number of sources given below. Generally, we provide useful links to the data sources and avoid redistributing the data that are already public available and maintained by federal/state agents. (1) The 30-m elevation: this is available for general public via U.S. Geological Survey (USGS) web service (https://viewer.nationalmap.gov/basic/). (2) USGS certified streamlines (National Hydrography Dataset and NHDPlus) and catchment/subbasin boundaries are also available online (https://viewer.nationalmap.gov/basic/). (3) USGS gaging stations and streamflow records are available at the website (https://maps.waterdata.usgs.gov/mapper/index.html). In this study, we gathered daily time of streamflow from the follow gages: 0208521324 (Little River), 02085500 (Flat River), 02096846 (Cane Creek), 02097464 (Morgan Creek), 02096960 (Haw River), and 02097314 (New Hope Creek). (4) Road network (National Transportation Dataset) (https://viewer.nationalmap.gov/basic/). (5) The 2006 and 2011 thirty-meter National Land Cover Data (NLCD) are maintained by Multi-Resolution Land Characteristics Consortium and available for public

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