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Water quality impacts of climate change, land use, and population growth in the Chesapeake Bay watershed

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Abstract

The 2010 Chesapeake Bay Total Maximum Daily Load was established for the water quality and ecological restoration of the Chesapeake Bay. In 2017, the latest science, data, and modeling tools were used to develop revised Watershed Implementation Plans (WIPs). In this article, we examine the vulnerability of the Chesapeake Bay watershed to the combined pressures of climate change and growth in population, agricultural intensity, and economic activity for the 60-year period 1995–2055. The results will be used to revise WIPs, as needed, to account for expected increases in loads. Assessing changes relative to 1995 for the years 2025, 2035, 2045, and 2055, mean annual precipitation increases of 3.11%, 4.21%, 5.34%, and 6.91%, respectively, air temperature increases of 1.12, 1.45, 1.84, and 2.12°C, respectively, and potential evapotranspiration increases of 3.36%, 4.43%, 5.54%, and 6.35%, respectively, are projected. Population in the watershed is expected to grow by 3.5 million between 2025 and 2055. Watershed model results show incremental increases in streamflow (2.3%–6.2%), nitrogen (2.6%–10.8%), phosphorus (4.5%–26.7%), and sediment (3.8%–18.8%) loads to the tidal Bay due to climate change. Growth in population, agricultural intensity, development, and economic activity resulted in relatively smaller increases in loads compared to climate change.

KEYWORDS
Chesapeake Bay, climate change, hydrology, water quality, watershed model, TMDL

1 | INTRODUCTION

Estuaries and coastal waters are among the most degraded eutrophic ecosystems worldwide due to anthropogenic pressures related to rapid human population expansion, increased agricultural activities and fertilizer application, changes in land use such as urbanization, decreases in natural lands of forests and wetlands, overexploitation of fishery resources, and climate change (Boesch, 2019; Crain et al., 2009; Lotze et al., 2006). The stressors have resulted in severe water quality degradation and eutrophication-related problems such as hypoxia and harmful algal blooms, ultimately leading to loss of habitat, biodiversity, and associated ecosystem services (Howarth et al., 2011; Rabalais

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Research Impact Statement

We examine the vulnerability of the Chesapeake Bay watershed to the combined pressures of climate change, land use, and population growth. The results will be used to revise Watershed Implementation Plans.

et al., 2010). The Chesapeake Bay, the largest estuary in the continental United States (U.S.), is one of the most studied coastal systems in the world. Negative anthropogenic impacts on the Bay's water quality and overall ecosystem health have been extensively documented (Clune & Capel, 2021; Cooper & Brush, 1991; Kemp et al., 2005; Orth & Moore, 1983). Excess nutrient and sediment inputs resulting from human activities in the surrounding watershed are key drivers of water quality degradation in the Bay.

In 1983, the Chesapeake Bay Program (CBP) partnership was formed to lead the restoration of the Bay ecosystem, bringing together the watershed jurisdictions of Delaware, the District of Columbia, Maryland, New York, Pennsylvania, Virginia, and West Virginia, along with local governments and non-governmental organizations. In 2010, the U.S. Environmental Protection Agency (USEPA), acting with the CBP, established the Chesapeake Bay Total Maximum Daily Load (Bay TMDL) to further the ecological and water quality restoration of the Chesapeake Bay and to maintain and improve the health of streams and rivers and interconnected ecosystems of its watershed (USEPA, 2010a). Under the Bay TMDL, the CBP partners are to develop plans and implement necessary management practices by 2025 to achieve allocated reductions in nitrogen, phosphorus, and sediment loads and ultimately meet water quality standards in the Bay. The 2010 TMDL load reduction targets were developed using a suite of linked models including an airshed, land use, watershed, and estuarine model (Batiuk et al., 2013; Hood et al., 2021; Linker et al., 2013). Different versions of these models have been used over the past four decades together with water quality criteria assessment tools to inform management and support decision-making in the Bay (section 1, Chesapeake Bay Program, 2020). Specifically, these models have been guiding the planning, development, and tracking of management practices that are needed for nutrient and sediment load reductions necessary to achieve living resource-based water quality standards (USEPA, 2010a).

As called for in the 2010 TMDL, in 2017, the CBP conducted a TMDL Midpoint Assessment to review progress toward achieving load reduction goals (USEPA, 2018). As part of the 2017 Midpoint Assessment, the CBP reviewed and updated the inputs and modeling tools to incorporate the latest science, data, and methodology. An updated suite of models was used to revise nutrient and sediment load targets, known as planning targets, in a manner consistent with the 2010 TMDL allocations. The updated planning targets formed the basis for the development of the Phase 3 Watershed Implementation Plans (WIPs; Phase 3 WIPs, Chesapeake Bay Program, 2020). The WIPs are documents that detail the management actions that each jurisdiction plans to take to meet TMDL goals, and the Phase 3 WIPs were designed to account for future population, and land use changes (LUCs). Other nutrient and sediment load reduction plans were developed to account for future climate, and influence of reservoir infill conditions in the Conowingo Reservoir, a hydroelectric facility at the mouth of the Susquehanna River, the Bay's largest tributary. Prior to the infill condition, Conowingo Reservoir was effective at reducing particulate nutrients and sediment loads (Hirsch, 2012; Langland, 2015; Linker et al., 2016; Zhang et al., 2016).

As part of the Midpoint Assessment, an assessment of the risk of climate change on the Chesapeake Bay water quality standards and TMDL achievement was performed for the first time with the objective of quantifying the impacts of several climate-related factors that are expected to influence watershed and estuarine water quality responses. The climate change assessment was for the 30 years between 1995, the end year of the 1993–1995 critical period used for the 2010 Chesapeake TMDL (Linker et al., 2013), and 2025.

Changes in precipitation, air temperature, land use, and population growth are expected to have direct impacts on streamflow and on the amount and timing of sediment and nutrient loads delivered to the tidal Bay (Clune & Capel, 2021). Increases in air and water temperature in the Chesapeake Bay watershed have already been documented in prior studies (Rice & Jastram, 2015; Wagner et al., 2017) and increases in streamflow were also observed, with relatively larger increases in the north as compared to the south regions of the watershed (Fleming et al., 2021; Rice et al., 2017). The amount and intensity of precipitation have also increased in the eastern U.S., with relatively larger increases in the heavy rainfalls defined as events in the top 10 percentile (Groisman et al., 2004; Karl et al., 2009; Karl & Knight, 1998; Melillo et al., 2014). These trends are expected to continue in the future, with the Chesapeake Bay region generally projected to experience further increases in air temperature and precipitation amount and intensity over the next century (Modi et al., 2021; Najjar et al., 2010; Seong & Sridhar, 2017; Wolfe et al., 2008). The largest increases in precipitation are predicted to occur in winter and spring, potentially leading to higher streamflow in those months, whereas greater evapotranspiration and more frequent drought spells may ultimately result in decreased streamflow in summer and fall (Hayhoe et al., 2007; Winter et al., 2020; St. Laurent et al., 2021).

Previous watershed modeling studies conducted in the Chesapeake Bay region generally tend to agree in predicting increases in winter and spring streamflow coupled with decreases in summer streamflow as a result of climate change (Alamdari et al., 2017, 2022; Hawkins, 2015; Neff et al., 2000; Wagena et al., 2018). However, the relative magnitude of the predicted changes varies greatly both among studies and across different climate simulations within the same study, resulting in both negative and positive projected changes in streamflow at the annual scale. Projected changes in nutrient and sediment loads tend to mirror predicted streamflow changes, with the majority of previous studies predicting climate change-driven increases in nutrient and sediment loads in spring and winter and decreases in the summer months (Alamdari et al., 2022; Chang et al., 2001; Lee et al., 2018; Neff et al., 2000).

However, most of these studies were limited to relatively small areas within the Chesapeake Bay watershed. Although recently a few studies have used statistical models to quantify the effect of climate on nitrogen delivery (Alam et al., 2017; Ator et al., 2022; Clune & Capel, 2021), a process-based, watershed-wide quantitative assessment of the potential impacts of climate change on management-relevant nutrient and sediment loads is lacking. The CBP 2017 Midpoint Assessment climate risk analysis filled this gap using the most updated suite of TMDL models to answer the key management question of quantifying the additional level of management effort that is needed by the Bay jurisdictions to offset the adverse impacts of climate change on watershed loads and ensure achievement of TMDL goals (Linker et al., 2023; Shenk, Bhatt, et al. 2021). In this paper, we present results of the watershed modeling component that contributed to answering that question. A comprehensive overview of the implications of these results for the Bay water quality and TMDL target loads can be found in Linker et al. (2023).

The purpose of the research is to evaluate changes relative to the original 2010 TMDL assumptions. Therefore, the time periods associated with the original TMDL set the baseline for evaluation. The TMDL planning targets for nitrogen, phosphorus, and sediment are expressed as the average annual load for 1991–2000 meteorology (defined as the hydrologic period; USEPA, 2010a, Chesapeake Bay TMDL section 6; USEPA, 2010b, Chesapeake Bay TMDL Hydrologic Period Appendix F) that would result in water quality standards being met during the critical period of 1993–1995 (USEPA, 2010a, Chesapeake Bay TMDL section 6; USEPA, 2010b, Chesapeake Bay TMDL Critical Period Appendix G). Here, we present a comprehensive assessment of future changes in climate, land use, and population growth and resulting effects on watershed loads and estuarine dissolved oxygen for the years 2025, 2035, 2045, and 2055 relative to the critical period end year of 1995. Climate-related input changes are incorporated into the 1991–2000 meteorological time series to isolate the relative change due to climate in expressing annual loads. This assessment was made using an extensively reviewed Chesapeake Bay management watershed model and best available data for current and proposed management actions before 2025. Precipitation amount, precipitation intensity, air temperature, and potential evapotranspiration (PET) were the primary climate variables of change. The CBP climate assessment was developed based on 2025 land use conditions and so additional scenarios for LUC and population growth beyond 2025 and up to 2055 were also included in the assessment to assess the impact on water quality of up to 30 years of change. We quantified the influence of these three major drivers of change on watershed responses both individually and jointly to ultimately provide CBP managers and decision makers with critical information necessary to develop strategies for WIPs and to meet TMDL goals in a changing future.

2 | MATERIALS AND METHODS

2.1 | Overview

The objective of assessing the potential water quality impacts of climate change in the Bay watershed was met by (1) performing a synthesis analysis of projected changes in precipitation and air temperature in the Chesapeake Bay watershed that was conducted for a 30-year change between 1995 and 2025, and up to a 60-year change between 1995 and 2055; (2) extrapolating long-term historical trends in county-scale annual precipitation to estimate the 30-year change between 1995 and 2025, and using results from an ensemble of 31 statistically downscaled global circulation models (GCMs) for 2055 projections; (3) developing a blended approach of observations and model projections for 2035 and 2045, where precipitation change was based on the combination of observed trends and the 31-member GCM ensemble; (4) evaluating methods for estimating PET and simulating the effect of increases in ambient carbon dioxide concentrations; (5) quantifying the isolated effects of land use, population growth, and climate change variables on the flow, sediment, and nutrient responses; (6) estimating an integrated water quality response for 2025, 2035, 2045, and 2055; (7) quantifying the level of uncertainty for some of the choices made in the assessment; (8) analyzing model results to understand and explain impacts of climate change risk to the water quality and Bay TMDL; and (9) assessing spatial variability in estimated changes in nitrogen and phosphorus loads in conjunction with the geographic differences in estuarine effectiveness for tidal Bay dissolved oxygen.

The entire effort was guided by the participation and inputs from state, federal, and academic stakeholders as well as by recommendations of the CBP's Modeling Workgroup and Scientific and Technical Advisory Committee (STAC), an independent expert committee that provides scientific and technical guidance to the CBP (Johnson et al., 2016; Pyke et al., 2008, 2012; Shenk, Bennett, et al. 2021).

2.2 | Chesapeake Bay watershed

Chesapeake Bay is the largest of the more than 100 estuaries in the continental U.S. The 11,600 km^2 tidal Bay has a drainage area of 166,389 km^2 with more than 150 major rivers and over 100,000 small streams and creeks in the watershed. The Susquehanna, Potomac, James, Rappahannock, York, Patuxent, Patapsco, Choptank, Chester, Pocomoke, and Nanticoke are the largest rivers discharging into the

Bay. The Appalachian Plateau, Appalachian Mountain, Blue Ridge, Great Valley, Mesozoic Lowland, Piedmont Upland, Piedmont Lowland, and Coastal Plains are the eight physiographic provinces of the watershed (Chesapeake Bay Program, 2020).

As human population has increased in the Chesapeake Bay watershed over the past centuries, land use has changed from primarily undeveloped (forested) to agricultural and developed land (Clune & Capel, 2021). The land use composition of the watershed was 13.2% developed, 20.8% agricultural, and 66.0% natural in 2013 (section 5, Chesapeake Bay Program, 2020). Developed land use includes roads, buildings, turfgrass, construction, and tree canopy over impervious and turfgrass land cover classes. Agricultural land use includes crops, pasture, hay, animal feeding space, and open agricultural space. Natural land cover includes forest, harvested forest, wetlands, open water, and scrub-shrub herbaceous and barren lands that have been minimally disturbed or reclaimed. In 2017, more than 18.2 million people lived in the watershed, an increase of 117% since 1950 (Clune & Capel, 2021). Over a 30-year period between 1982 and 2012, the developed area increased by about 50%, which had considerable impact on the environment and contributed to the degradation of streams and rivers (Claggett et al., 2023).

Excess nutrients and sediment inputs are the major contributors to water quality issues in the Bay such as low dissolved oxygen (Kemp et al., 2005). The major components of the watershed's anthropogenic nutrient sources are, in descending order, agriculture, wastewater, and loads from developed areas (Ator et al., 2020; Shenk & Linker, 2013). Furthermore, the amount of nitrogen fluxes from the watershed is strongly controlled by the amount of freshwater discharge, thereby establishing a strong linkage with climate and changes in precipitation (Howarth et al., 2012).

2.3 | Chesapeake Bay Partnership Phase 6 Watershed Model

The CBP Phase 6 Watershed Model was developed for the 2017 Midpoint Assessment of the Bay TMDL. It draws upon the strengths of multiple models and incorporates improvements in data as well as new science on numerous aspects of the model for supporting management decisions. Some of the significant updates include changes to the overall model structure to integrate multiple models and lines of evidence, incorporation of lag times in the nutrient transport, use of fine-scale estimation of sediment erosion, new science and understanding on the behavior of phosphorus, the representation of the Conowingo Reservoir infill, an expanded and refined simulation of impoundments, new methods for estimating nutrient inputs, high-resolution land cover data, and the characterization of best management practices (Chesapeake Bay Program, 2020; Hood et al., 2021; Kaufman et al., 2021). For brevity, only a general overview of the main features of the Phase 6 Watershed Model is provided, and we refer to the model documentation page for a comprehensive description of the model structure, including a detailed analysis of model performance (Chesapeake Bay Program, 2020).

The Phase 6 Watershed Model has two forms—a *dynamic model* that simulates hydrology and water quality at an hourly time step, and a *time-averaged model* that simulates the watershed nitrogen, phosphorus, and sediment response for scenarios of land use and management practices under the average hydrology period of 1991–2000. Nutrient and sediment loads predicted by the time-averaged and dynamic watershed model forms are constrained to match over the long term. During calibration, the dynamic model is used to provide estimates of the hydrologic response to meteorological data and watershed properties. The time-averaged model uses the dynamic watershed model hydrology along with watershed properties and nutrient inputs to predict long-term nutrient outputs to rivers. The dynamic model is then used to calibrate the riverine response to observations.

In management scenario mode, the time-averaged model predicts expected delivery of average annual nitrogen, phosphorus, and sediment loads to the streams and to the Bay for different management scenarios under reference 1991–2000 hydrology conditions and is used as the primary regulatory decision-making model by the seven Partnership jurisdictions in the planning and tracking of the implementation of nutrient and sediment load reduction practices.

The dynamic watershed model is used to translate scenarios developed using the time-averaged model into hourly loads for the estuarine model. For climate change scenarios, the dynamic model is used to estimate hydrologic changes and changes in riverine transport and delivery while the time-averaged model is used to estimate changes in nutrient and sediment loads in response to changes in hydrology and management practices.

The hydrological and sediment transport simulations on land in the dynamic model are based on the Hydrologic Simulation Program—FORTRAN model (HSPF, Bicknell et al., 2001), whereas a new framework called Unit Nutrient Export Curves (UNECs, section 10, Chesapeake Bay Program, 2020) is used for incorporating lag times in nutrient simulation of land uses and to perform a temporal disaggregation of the long-term loads estimated by the time-averaged model.

The dynamic and time-averaged watershed models both have a total of 1990 land-river segments with an average size of approximately 85 km^2. Land-river segments represent the smallest spatial unit simulated by the two models and are the result of the intersection of land segments, which essentially represent administrative counties that fall within the watershed, and river segments, which encompass land draining directly to river reaches explicitly represented in the model. The watershed model inputs include land use, hourly meteorological data, elevation features, fertilizer and manure applications, legume fixation, wastewater discharges (industrial, municipal, and combined sewer overflows [CSOs]), septic systems, atmospheric deposition, animal populations, and other variables necessary to estimate the amount of nutrients and sediment loads delivered to the tidal Bay.

The dynamic watershed model was calibrated at 253 monitoring stations for daily flow, 215 stations for water temperature, 212 stations for dissolved oxygen, 221 stations for nitrate, 216 stations for ammonia, 188 stations for nitrogen, 176 stations for dissolved orthophosphate, 215 stations for phosphorus, and 39 stations for chlorophyll over the 30-year period of 1985–2014 (Chesapeake Bay Program, 2020). A total of 12 statistics (e.g., mean flow, baseflow, winter and summer flow) for each monitoring station were used to calibrate hydrology parameters to distinct aspects of the hydrograph. The level of agreement between the cumulative frequency distributions of observed and simulated paired concentrations was used for the riverine water quality calibration.

Several independent model verifications compared daily observed and simulated concentrations as well as the level of agreement in monthly, annual, and average annual loads estimated at the calibration stations by the U.S. Geological Survey (USGS) through the Weighted Regression on Time, Discharge, and Season (WRTDS) method (Chanat et al., 2016; Hirsch et al., 2010). Geographic efficiencies quantifying the quality of model calibration for explaining the spatial variability in simulated per acre average annual load for sub-watersheds were also calculated, which yielded Nash–Sutcliffe efficiencies (NSE; Nash & Sutcliffe, 1970) of 0.956, 0.974, 0.950, and 0.966 for nitrate, nitrogen, phosphorus, and sediment, respectively. Higher NSE values closer to 1 suggest that the model simulated the spatial variability well.

2.4 | TMDL modeling and climate change

Modeling for the TMDL was based on attainment of water quality standards during a critical period of relatively high flow, 1993–1995 (USEPA, 2010a, Chesapeake Bay TMDL section 6). However, the 1993–1995 period represents an unrealistic long-term climate norm and requires an assumption of stationarity, which is no longer the case under climate change conditions resulting in unrepresented flow conditions. The Partnership recognized the need to revise the 2025 TMDL load targets to account for additional pollutant loads expected due to 2025 climate conditions (Shenk, Bhatt, et al. 2021). The strategy for incorporating the influence of climate change as of 2025 into TMDL planning targets was to examine the changes expected between 1995 and 2025 and apply the predicted 30-year change in climate to the CBP modeling datasets to assess water quality changes. In addition to the year 2025, the Partnership decided to also evaluate future climate scenarios for 2035, 2045, and 2055, thereby representing a change of 40, 50, and 60 years, respectively (Shenk, Bhatt, et al. 2021). The changes are applied using a hydrologic averaging period, 1991–2000, which includes the 1993–1995 critical period and was judged to represent long-term average precipitation, temperature, and meteorology (USEPA, 2010b, Chesapeake Bay TMDL Hydrologic Period Appendix F).

To assist jurisdictions in developing plans to meet TMDL water quality goals, the CBP developed Planning Targets that quantify nutrient and sediment load reduction goals assigned to each jurisdiction. The Planning Target reductions were further divided among 19 state river basins that were identified as the intersection between the eight major river basins within the Bay watershed and the seven Bay jurisdictions of New York, Pennsylvania, West Virginia, Maryland, Delaware, District of Columbia, and Virginia (Linker et al., 2013). This subdivision was based on a set of rules and policy decisions that take into account the fact that more reduction is expected from state river basins with greater impact on estuarine water quality. Jurisdictions used this information to develop plans for implementing management practices that would achieve these nutrient and sediment load reductions. A scenario for the entire Chesapeake Bay watershed which combines these practices is called the WIP Scenario.

Climate change modeling was performed on the WIP Scenario, meaning that all model simulations to quantify the change in watershed flow and loads between the 1991–2000 reference and a future 10-year hydrology assume the implementation of management practices planned by each jurisdiction to achieve the load reductions of 2025 TMDL Planning Targets. This was done by modifying the Phase 3 WIP scenario to precisely match 2025 TMDL Planning Target loads. The end result of this approach was separate planning targets for (a) population growth and LUC between 1995 and 2025 accounted for the Phase 3 WIP, and (b) climate change between 1995 and 2025, allowing greater policy insight into the two different influences.

2.5 | Delta method for future climate scenarios

The purpose of climate change modeling for the CBP is to estimate changes in loads from the 1991 to 2000 baseline, also referred to as the base year 1995 throughout this paper. In this case, it would be inappropriate to use downscaled climate model output directly since that baseline would be different from the 1991–2000 ten-year average CBP hydrology. For the CBP climate analysis, the widely used delta method was chosen, which consists of creating future meteorological time series by applying change factors calculated from a modeled or statistical estimate of the effects of climate change to 1990s historical time series of meteorological data (Anandhi et al., 2011). The use of the delta change method preserves the spatial and temporal relationships that exist between precipitation and other meteorological variables in the observed reference data that were used for model calibration and generates output that is representative of the change in nutrients and sediment loads strictly due to changes in climate. We therefore generated time series of meteorological variables (precipitation, air temperature, and PET) under future climate scenarios by applying monthly delta change factors to the respective 1991–2000 hourly time series.

A method of time disaggregation is needed for the application of monthly delta changes to the reference time series. We applied monthly change in precipitation as multiplicative factors along with a selection of how they varied between intensity deciles while change in monthly air temperature was applied as monthly additive value. Changes in PET were estimated at the daily time scale based on changes in temperature and applied as daily multiplicative factor to hourly PET values.

2.6 | Future climate projections

The CBP's methods for developing climate projections were based on recommendations provided by STAC. In 2016, STAC held a climate-change-focused workshop to provide the CBP with guidance on the development of climate change scenarios for TMDL modeling purposes (Johnson et al., 2016). At the time of the workshop, the years 2025 and 2050 had been selected to assess climate change scenarios. The recommendation of STAC was to use an extrapolation of long-term observed precipitation trends instead of climate model projections to assess expected changes in precipitation for the year 2025, as the uncertainty of the models introduced more variability for this near future than extrapolation of the historical trend. Conversely, for 2050 precipitation estimates, STAC recommended adopting precipitation projections based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) set of GCMs as outlined in the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5 2013). It was also recommended that these models be employed in the assessment of expected temperature changes for both 2025 and 2050, as the model projections of temperature changes are much less variable for both the short term and the long term. Decisions by the CBP's Modeling Workgroup, the technical working group responsible for directing and overseeing CBP modeling activities, affirmed the recommendations of the STAC workshop (Johnson et al., 2016).

After the STAC workshop, the years 2025, 2035, 2045, and 2055 were ultimately selected for climate change assessments. Based on a CBP's Modeling Workgroup decision, we adopted the following hybrid approach to estimate expected changes in precipitation: we estimated changes in 2025 precipitation based on historical observed trends within the watershed while changes in 2055 precipitation were based on the difference in climate model projections for the 30-year periods of 2041–2070 and 1981–2010. For 2035 and 2045, we calculated a weighted average of the trend-based and climate model-based estimated changes in precipitation, where the trend-based estimate was assigned a weight of 2/3 in 2035 and 1/3 in 2045. Expected changes in 2025, 2035, 2045, and 2055 temperatures were extracted from the climate model projections.

2.6.1 | Long-term observed trends in precipitation

We estimated long-term precipitation trends for each land segment (county) in the Watershed Model by performing a linear trend analysis on the Parameter-elevation Relationship on Independent Slope Model (PRISM; Daly et al., 2008) annual precipitation data. The PRISM dataset is a reanalysis product that uses point data measurements at rain gauges and incorporates a conceptual framework to address spatial variability in precipitation due to orographic and other processes. The long-term PRISM monthly dataset (1895–present) is modeled at 30 arc second (approx. 800 m) grid cell resolution but then upscaled to provide monthly total precipitation at 2.5 arc minute (approx. 4-km) grid cell resolution for the conterminous U.S. PRISM data prior to 1981 are based on less extensive observations and do not use NEXRAD data. We used the annual PRISM dataset for the years 1927–2014 (i.e., 88 years) in the linear regression trend analysis. We selected the 88-year period because of overlaps in the availability of historical precipitation data, nearly complete streamflow data at long-term monitoring stations, and the model calibration period. Trend information derived from a short-term (e.g., 30 years) precipitation dataset may be influenced by decadal-scale variations in climate as well as meteorological anomalies, and we verified that the 88-year data were able to overcome such limitations of short-term data, by incrementally increasing the number of years in the estimation of trend. For the regression analysis, we first spatially aggregated gridded PRISM data to each model land segment (county), and then for each segment, a linear trend line was fitted to the annual precipitation data. We extrapolated the county-specific linear trends out to 2025 to estimate county-specific changes in annual precipitation between 1995 (middle of the 1991–2000 reference period) and 2025.

2.6.2 | General circulation model projections

We used 31 GCMs included in what was at the time the most recently completed CMIP5 (Taylor et al., 2012) for the precipitation and air temperature projections (see table 1 in Tian et al., 2023). We retrieved statistically downscaled data for climate models and realizations (i.e., model runs with perturbations of initial conditions) from the "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections" online archive available at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ accessed through the USGS Geo Data Portal at https://cida.usgs.gov/gdp/ (Bureau of Reclamation, 2013; Maurer et al., 2007). We used the same set of models used in the U.S. Climate Resilience Toolkit (CRT; accessed 2016) except for the BNU-ESM model, which was unavailable for download through the USGS Geo Data Portal. We chose the

Bias Correction and Spatial Downscaling (BCSD) statistical downscaling methodology because of its commonality among numerous datasets including the U.S. CRT and the NASA Earth Exchange (NEX) Downscaled Climate Projections (NEX-DCP30), its extensive review in peer-reviewed literature in comparison with other downscaling methodologies (Gutmann et al., 2014; Mizukami et al., 2016), and its relative ease of access and flexibility in choosing models and realizations to be incorporated into analyses. The data included several "model runs" or "realizations" for a few GCMs as noted earlier. It has been shown that the selection of several GCMs as opposed to several "model runs" for a particular GCM provides wider variability that enables an ensemble analysis to capture a broader range of uncertainty in model projections (Pierce et al., 2009). In addition, selecting one realization per model decreases the possibility of biasing the analysis in favor of models with more realizations. Therefore, we used one "model run" member for each of the 31 GCMs in the ensemble analysis.

The statistically downscaled GCM data include greenhouse gas emission scenarios based on representative concentration pathways (RCPs) that describe alternative possible future climates resulting from different assumptions on future socioeconomic and natural conditions. The RCPs (e.g., RCP 2.6, RCP 4.5, RCP 8.5) are defined according to the additional radiative forcing generated by the year 2100 measured in watts per square meter ($W\,m^2$) (IPCC AR5 2013). It has been shown that the spread across RCPs in the near term for a single climate model is typically smaller than the variability between climate models under a single RCP scenario (Kirtman et al., 2013). For both precipitation and temperature, and in both 2025 and 2050, the variability due to model selection is greater than the variability due to emission scenarios (Figures 1 and 2). Nonetheless, we do note that expected median changes in temperature differ substantially across RCPs and a consideration of different RCP scenarios would have allowed us to capture that variability. However, the management community agreed that a "middle of the road" RCP scenario would provide us with the most plausible representation of future challenges in meeting TMDL goals. Accordingly, and due to computational and analysis constraints, we selected the RCP 4.5 scenario whenever using GCMs for precipitation and air temperature projections.

A widely used technique in climate change assessments involving the use of projections from multiple climate models is to combine predictions from a collection of models into an ensemble. This approach increases the sampling of both initial conditions and model properties in the subsequent climate change assessment. Multi-model ensemble means also generally exhibit higher skill, for example, in capturing Atlantic Multi-decadal Variability, as compared to a single-model projection (García-Serrano & Doblas-Reyes, 2012; Kim et al., 2012; Kirtman et al., 2013). To minimize the number of watershed model runs, and to avoid selection of a specific central climate model which may exhibit skewed inter-monthly variability, we selected the ensemble median of the 31 climate models to estimate the central tendency of monthly changes in precipitation and air temperature between the reference period of 1991–2000 and each model's future projection. For each climate change scenario, we calculated a 31-member ensemble median separately for each month to obtain monthly changes in precipitation and temperature at each land segment (county) and applied that change to the reference 1991–2000 precipitation and temperature time series in that land segment as outlined in the section "Delta Method for Future Climate Scenarios." It is important to note here that the Delta Change method largely maintains the interannual variability of the reference period and therefore does not address potential future changes in seasonality or number of days with rainfall. Furthermore, there are limitations associated with the use of only the ensemble median in place of a range of ensemble members. An average or median scenario is not necessarily the most plausible, introducing uncertainty that compounds when run through a hydrologic model (Dahl et al., 2021; Knutti et al., 2010). A range of ensemble members can help scientists, managers, stakeholders, and the public better understand the range of possible future watershed responses. Despite acknowledging these limitations, extensive discussions with the Chesapeake Bay stakeholder and management community during the development phase of these analyses resulted in the decision that the ensemble median would be used for management purposes. Planning targets are expressed as discrete values and therefore adjustments to planning targets must also be expressed as discrete values.

2.6.3 | Precipitation intensity

We compared two methods for assigning monthly changes in precipitation to hourly precipitation events in the 1991–2000 time series. In the first method, the additional monthly precipitation expected under climate change conditions were distributed uniformly across all hourly precipitation events. In the second method, changes in precipitation were distributed unevenly across all daily precipitation events, which were divided by total volume into deciles. The second method aligns well with previous literature estimates of uneven increases in precipitation events in this region, with larger rainfall events increasing more compared to smaller ones (St. Laurent et al., 2021; Winter et al., 2020; Yang et al., 2021). Specifically, the set of hourly precipitation events occurring in a given month throughout the reference 1991–2000 time series was divided into deciles, resulting in 12 total precipitation input datasets. Precipitation events falling in the highest deciles (70%–100%) were then assigned a larger fraction of the overall precipitation change projected for that month. The uneven distribution of increasing precipitation, which served to modify the relative intensities of precipitation events, was based on documented changes in the intensity and frequency of precipitation events in the northeast U.S. over the past century (Gordon et al., 1992; Groisman et al., 2001, 2004; Karl & Knight, 1998). Observed increases in precipitation events documented by Groisman et al. (2004) determined how the total percent change in monthly precipitation were disproportionately assigned across precipitation events. Specifically, the fractions used for dividing precipitation into the 10 deciles were approximately 3%, 3%, 3%, 3%, 3%, 2%, 1%,

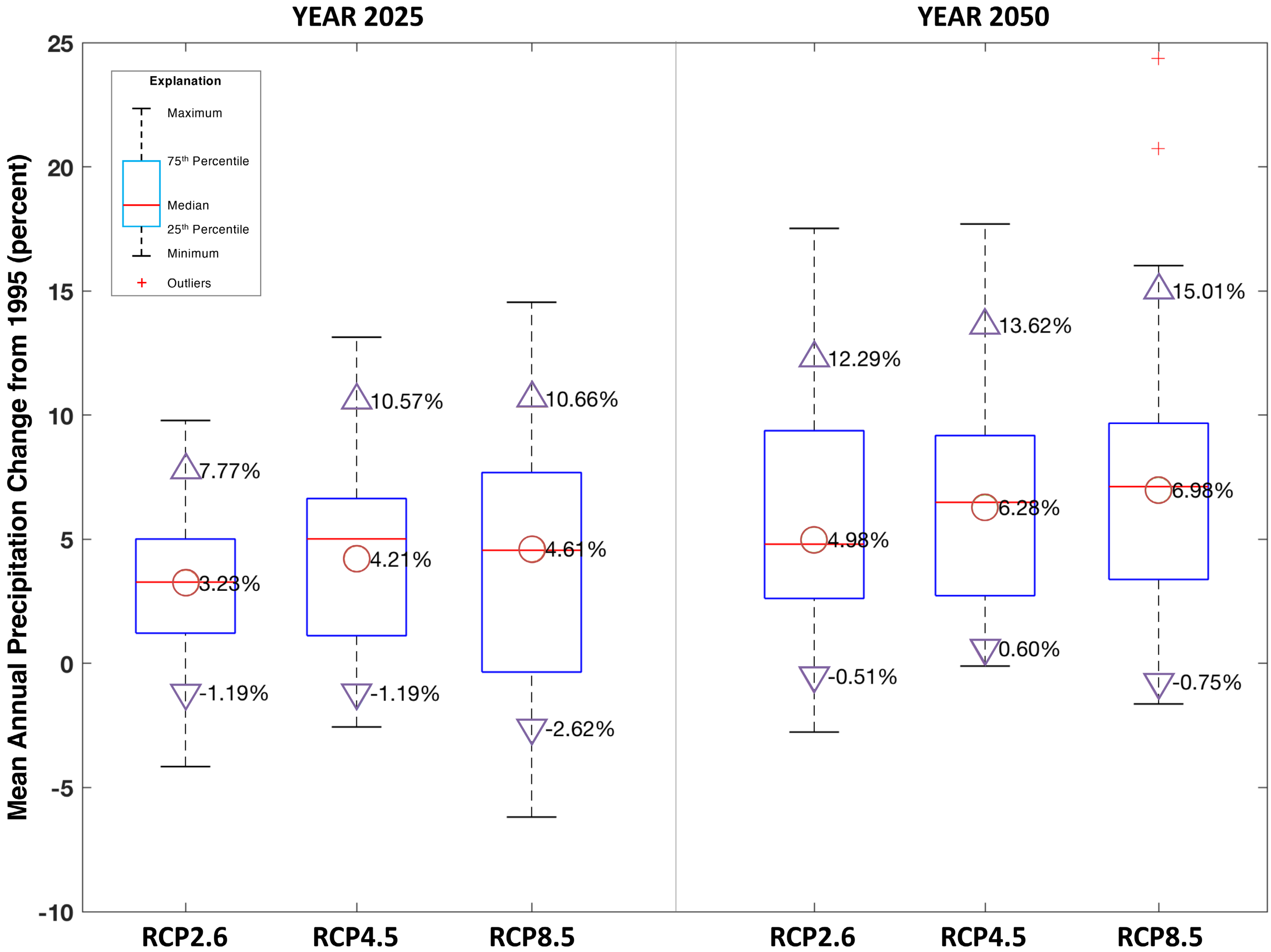

FIGURE 1 Percent change in mean annual precipitation for the Chesapeake Bay Watershed for the years 2025 and 2050 relative to 1995 for three different representative concentration pathway (RCP) emission scenarios. Box plots show variability in the ensemble of 31 global circulation model (GCM) projections that were statistically downscaled using Bias Correction Spatial Disaggregation (BCSD) (Bureau of Reclamation, 2013; Maurer et al., 2007). Ensemble median (circles) and 10th and 90th percentile ranges (triangles) are shown. Ensemble medians are not substantially different across different RCP scenarios and the range of uncertainty bounds (P10–P90) of RCP4.5 mostly captures the range of RCP 2.6 and RCP 8.5.

6%, 12%, and 64%. The larger share of the estimated increase in precipitation volume due to future climate (64%) was assigned to large intensity events in the uppermost decile (90%–100%), and 82% of the volume was assigned to the top 30% rainfall intensity events.

2.6.4 | Ambient carbon dioxide

Previous studies have documented that increases in ambient carbon dioxide concentrations can impact stomatal resistance of plants, thereby leading to changes in the hydrologic response of land uses with a transpiration component (such as forest, crops, etc.) and in the overall watershed water budget by decreasing transpiration (Butcher et al., 2014; USEPA, 2013). We compiled carbon dioxide concentrations predicted under different greenhouse gas emission scenarios from the IPCC's 5th Assessment Report (IPCC AR5 2013). We used carbon dioxide concentrations predicted under the RCP 4.5 scenario of approximately 427, 448, 474, and 498 ppm for 2025, 2035, 2045, and 2055, respectively (IPCC, 2013: annex II, table AII.4.1). This is compared to an average concentration of 363 ppm for the years 1991–2000.

2.6.5 | Potential evapotranspiration

We tested two different methods to estimate PET and its expected changes under future climate: the Hamon equation (Hamon, 1963) and the Hargreaves and Samani (1985) equation. Similar to Hamon PET, Hargreaves–Samani PET requires air temperature as the only meteorological

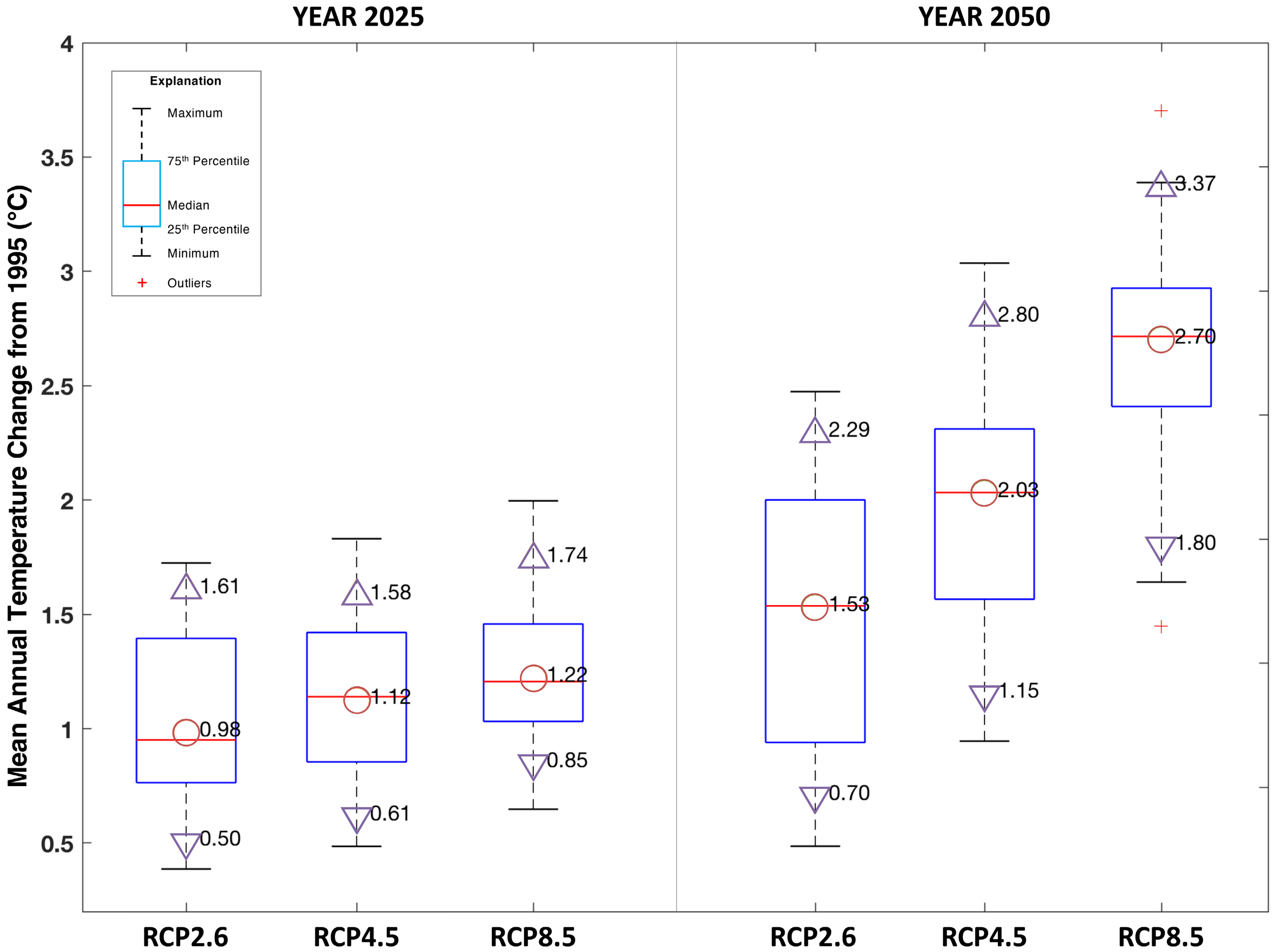

FIGURE 2 Percent change in mean annual temperature for the Chesapeake Bay watershed for the years 2025 and 2050 relative to 1995. Box plots show variability in the ensemble of 31 GCM projections that were statistically downscaled using BCSD (Bureau of Reclamation, 2013; Maurer et al., 2007). Ensemble median (circles) and 10th and 90th percentile (triangles) ranges are shown.

parameter in the estimation of PET, but Hargreaves–Samani uses daily temperature range in the estimation of surface radiation from extra-terrestrial solar radiation. Among methods that require information on air temperature only in estimating PET, Hargreaves–Samani has been shown to estimate changes in PET that closely match those estimated in climate models (Milly & Dunne, 2017).

2.7 | Land use and population growth projections

The CBP high-resolution land use and land cover project provided accurate land use and land cover information for the Chesapeake Bay watershed representing 13 land use and land cover classes at 1-meter spatial resolution (section 5, Chesapeake Bay Program, 2020).

Changes in climate are expected to interact with land use and cover to impact runoff and pollutant loading. Future land use choices have effects on the release of greenhouse gases, climate trends can affect human choices about land cover and land use, and both can be driven by the same societal choices. Climate change may result in a change in the frequency and severity of droughts, heat waves, tropical storms, and other weather hazards which may affect the patterns of development. In addition, farmers will react by planting a different combination of crops more suited to the future weather patterns (Brown et al., 2014; Grimm et al., 2013; Kutta & Hubbart, 2019). We can assume that LUCs in the Chesapeake watershed would have a small effect on the global carbon budget, and the effects of climate change relative to the local economy, regulation, conservation, and other factors are not assessed in this work.

The Chesapeake Bay Land Change Model (CBLCM) was used for estimating future changes in land use and populations served by sewer and septic wastewater treatment technologies associated under different future land use scenarios (i.e., alternative sets of assumptions affecting future urban growth). The model uses county-scale future population and employment trends for quantification of natural and agricultural land conversions in forecasting future mixed, residential, and commercial development across the watershed (Claggett et al., 2023). It accounts for the development of unused or under-utilized developed areas while utilizing population and employment as drivers of future urban growth. For each future scenario, the model produces 101 stochastic Monte Carlo simulations of growth representing equally plausible independent representations of future development patterns. The CBLCM predictions for all simulations were averaged at the land-river segment scale to provide inputs to the watershed model representing the most plausible outcome accounting for spatial uncertainty. Readers are referred to Claggett et al. (2023) for additional details on the model formulation and validation.

Table 1 shows a substantial increase in population over the 30, 40, 50, and 60 years from 1995. However, increases in development are expected to occur at a lower rate—particularly between 2025 and 2055. For example, between 1995 and 2025, both population (including on septic and sewer) and the development footprint are expected to increase by 29%, but between 1995 and 2055, population is expected to increase by 52% whereas the development footprint may only increase by 39%. This is anticipated because of expected “infill and redevelopment,” where development occurs in existing unused or under-utilized developed areas.

2.8 | Atmospheric nitrogen deposition

The CBP Airshed Model, a combination of a regression model of National Atmospheric Deposition Program (NADP) data and a national application of the Community Multiscale Air Quality (CMAQ) Model, predicts changes in deposition of inorganic nitrogen due to changes in emissions (Chesapeake Bay Program, 2020). To assess how atmospheric nitrogen deposition loads may change with changes in rainfall under future climate conditions, we analyzed multiple data sources of atmospheric deposition, including (a) a physically based CMAQ 2050 climate simulation providing monthly estimates of nitrogen deposition loads and rainfall predicted across the Bay watershed for 3 years representing dry (2050), wet (2049), and average (2048) climatic conditions, respectively (Campbell et al., 2019), (b) a dataset of annual wet atmospheric nitrogen deposition estimates generated by the Phase 6 CBP Airshed Model for the years 1985–2014 (section 3, Chesapeake Bay Program, 2020), and (c) observation-based estimates of precipitation amount and precipitation chemistry data for NADP/NTN monitoring stations (National Atmospheric Deposition Program, National Trends Network, 2019). For each of these datasets, we fit linear regressions between estimated percent changes in depositions (wet and dry and separately for ammonium and nitrate) and corresponding percent changes in rainfall at each land segment in the watershed or NADP monitoring station (Shenk, Bhatt, et al. 2021). Wet depositions of nitrate and ammonium showed a positive linear relationship with rainfall while dry depositions showed negligible sensitivity to rainfall (Shenk, Bhatt, et al. 2021). Although the linear regression slopes between percent change in wet deposition and percent change in precipitation showed some variability between land segments (counties), we observed no clear spatial pattern and therefore retained the median of the land segment-specific and NADP station-specific slopes for further analyses.

By suggestion of the CBP Modeling Workgroup, we then calculated the rounded average of the median slopes obtained from the three different data sources and used that as the sensitivity of wet depositions to future changes in rainfall. The sensitivities for wet nitrate and wet ammonium depositions were 0.8 and 1.0, respectively, and we used these sensitivities to adjust the reference 1991–2000 time series of wet deposition to the watershed and estuarine open waters to account for the effect of changes in precipitation expected under future climate scenarios (Table 2). Although nitrogen deposition in the Chesapeake Bay region has been decreasing since the 1980s and that trend is estimated to continue though at a slower rate (Burns et al., 2021), the data shown here are based on future emissions of 2025 and 2030.

TABLE 1 Historical and future decadal projections of (a) population on private septic systems and public sewer service areas from the Chesapeake Bay Land Change Model (CBLCM), (b) estimates of historical land use acres for major land cover classes developed by the Chesapeake Bay Program high-resolution land cover project, and (c) future estimates of land use acres from the CBLCM (Claggett et al., 2023). Data in square brackets show the percent change in data for any given time-period as compared to 1995.

Year	Population on septic (in millions)	Population on sewer (in millions)	Crop (millions of acres)	Pasture (millions of acres)	Natural (millions of acres)	Developed (millions of acres)
1985	2.53 [−12.5%]	10.95 [−09.1%]	4.54 [+6.8%]	5.12 [+06.1%]	27.37 [+0.7%]	3.55 [−17.8%]
1995	**2.90 [+00.0%]**	**12.05 [+00.0%]**	**4.25 [+0.0%]**	**4.82 [+00.0%]**	**27.18 [+0.0%]**	**4.32 [+00.0%]**
2005	3.25 [+12.2%]	13.27 [+10.1%]	3.94 [−7.3%]	4.82 [−00.1%]	26.87 [−1.1%]	4.94 [+14.5%]
2015	3.54 [+22.3%]	15.03 [+24.7%]	4.04 [−5.1%]	4.35 [−09.9%]	26.79 [−1.4%]	5.40 [+25.2%]
2025	3.66 [+26.2%]	15.66 [+29.9%]	4.03 [−5.2%]	4.21 [−12.7%]	26.76 [−1.5%]	5.57 [+29.0%]
2035	3.84 [+32.5%]	16.66 [+38.2%]	4.01 [−5.6%]	4.18 [−13.4%]	26.68 [−1.8%]	5.71 [+32.2%]
2045	4.01 [+38.5%]	17.59 [+45.9%]	3.98 [−6.3%]	4.14 [−14.1%]	26.60 [−2.1%]	5.84 [+35.4%]
2055	4.19 [+44.7%]	18.59 [+54.2%]	3.96 [−6.9%]	4.11 [−14.8%]	26.52 [−2.4%]	5.98 [+38.6%]

TABLE 2 Estimated atmospheric nitrogen deposition (millions on pounds of nitrogen) to the watershed and tidal waters of the Bay under different climate projections and nitrogen emission scenarios.

Climate scenario	Nitrogen emission scenario	Atmospheric N-deposition (Mlb/y)	
		Watershed	Tidal waters
1995 Climate	2025 Emission	280.82	15.60
2025 Climate	2025 Emission	284.36	15.85
2035 Climate	2030 Emission	271.28	15.08
2045 Climate	2030 Emission	272.20	15.14
2055 Climate	2030 Emission	273.54	15.23

2.9 | Other included effects

The Chesapeake watershed has a total of 64 communities with combined sewer systems. The amount of flow generated during rainfall events that are larger than the treatment plant capacity is discharged directly to the receiving water body. The CSOs for the 64 facilities are estimated based on a fusion of monitored data and regression models with daily precipitation inputs (Chesapeake Bay Program, 2020; Shenk, Bhatt, et al. 2021). For future climate scenarios, CSO data were adjusted based on expected changes in rainfall events.

2.10 | Other excluded effects

A number of factors that are expected to change were not included either because not enough information was available or their effects were estimated to be small. These factors included changes in farmers' response to agricultural practices and nutrient inputs, groundwater lag, land to water delivery factors, stream delivery factors, resilience and effectiveness of management practices, phosphorus runoff from developed land uses, and changes in surface water withdrawals for water supply and agriculture. Readers should refer to Linker et al. (2023) for additional detail.

2.11 | Watershed response to climate change

We provide a broad overview of the methods adopted to simulate the watershed hydrology and water quality response under climate change scenarios, and we refer the reader to Shenk, Bhatt, et al. (2021) for a more detailed account on the implemented methods. Figure 3 contrasts the operation and dataflow of a model run for a management scenario that uses a fixed average hydrology with a climate change scenario. For climate change simulations, we ran the dynamic watershed model with projected precipitation and meteorology inputs to predict changes in hydrology and sediment runoff from land uses. These changes were then used in the time-averaged model, along with additional methods developed using multiple lines of evidence and outlined below, to predict changes in nitrogen and phosphorus delivery from land uses to large rivers. The dynamic watershed model was then used to temporally disaggregate the predicted time-averaged edge of stream water quality response of land uses, simulate the climate-induced changes in riverine transport with changes in hydrology and water temperature, and ultimately generate loads for the estuarine model.

2.11.1 | Hydrologic response

We simulated the impact of climate change-modified variables (precipitation amount and intensity, air temperature, PET, and carbon dioxide) on the watershed hydrologic response using the HSPF PWATER, IWATER, SNOW, and HYDR modules (Bicknell et al., 2001). Changes in air temperature inputs influence snow hydrology by introducing changes in the amount of snow and energy balance for the snowpack, while changes in PET and adjustments for carbon dioxide levels influence transpiration calculations, subsequently impacting the simulated water budget.

2.11.2 | Sediment transport

We simulated the impact of climate change on sediment delivery using the HSPF SEDMNT, SOLIDS, and SEDTRN modules (Bicknell et al., 2001). HSPF uses a process-based approach for the production and removal of sediment from land uses and sediment erosion from land surfaces is

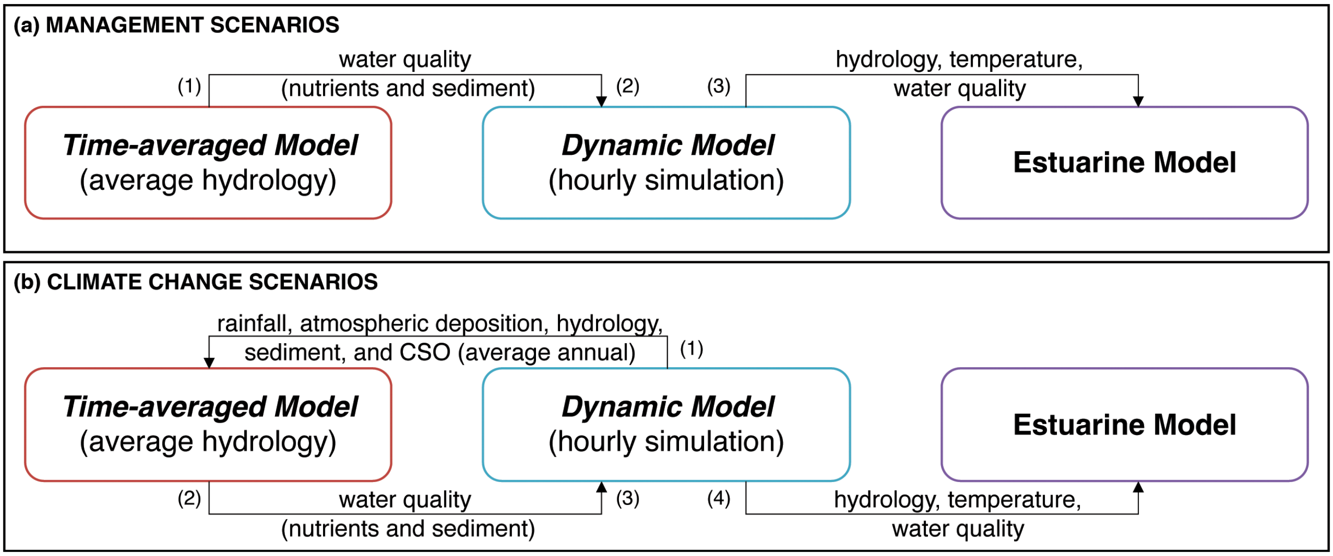

FIGURE 3 Schematic flowchart diagram showing the dataflow and procedures linking Phase 6 time-averaged and dynamic watershed and estuarine modeling systems. (a) Management scenarios are based on average hydrology where the changes in nutrient and sediment delivery are estimated by the time-averaged model (1), and the dynamic watershed model performs an hourly temporal disaggregation (2) for providing inputs to the estuarine model (3). (b) In contrast, for climate change scenarios, changes in hydrology and sediment yield are simulated in the dynamic model, which are then along with changes in atmospheric deposition and combined sewer overflows (CSOs) are used as inputs to the time-averaged watershed model (1). Time-averaged model estimated change in edge-of-stream response (2) is used in the dynamic watershed model in further water quality simulation (3) for providing inputs to the estuarine model (4) (Chesapeake Bay Program, 2020).

directly impacted by changes in precipitation amount and intensity due to climate change. Settling and scour in rivers are simulated in response to changes in magnitude and timing of streamflow and upstream sediment loads.

2.11.3 | Nitrogen simulation

We incorporated information from multiple lines of evidence in the time-averaged watershed model to estimate change in edge of stream nitrogen load for land uses in response to change in hydrology due to climate change. Specifically, we looked at the relationship between percent changes in flow and corresponding percent changes in nitrogen delivery by analyzing monitoring data in the Bay watershed as well as data from climate change watershed modeling studies reported in peer-reviewed literature (Shenk, Bhatt, et al. 2021). Our analysis showed a 1:1 relationship for the sensitivity of nitrogen loads to climate-related changes in flow (Shenk, Bhatt, et al. 2021) could be applied for individual land uses. Changes in nitrogen due to LUC are based on differences in loading rates between land uses. We also incorporated a combined nitrogen speciation response for the land and instream processes using an empirical model that quantifies changes in the nitrate-to-total nitrogen ratio as a function of changes in hydrology in the Chesapeake Bay watershed (Bertani et al., 2022). Nitrogen biochemical processes in rivers are simulated by HSPF and changes in scour of organic material were estimated as a function of sediment scour.

2.11.4 | Phosphorus simulation

Phosphorus transport from agricultural and natural land uses is simulated in the time-averaged model as a function of changes in precipitation, stormflow, sediment transport, soil phosphorus concentration, and water extractable phosphorus inputs. Under climate change scenarios, stormflow and sediment transport are modified in the HSPF simulation as a result of changes in precipitation and air temperature. The time-averaged model receives the modified stormflow and sediment transport and estimates the expected changes in phosphorus transport by applying sensitivity coefficients that were established based on results from the Annual Phosphorus Loss Estimator (APLE) model (Chesapeake Bay Program, 2020; Vadas, 2014). We also calculated future soil phosphorus concentrations expected with changes in precipitation stormflow, and sediment delivery using sensitivities developed from APLE model results (Shenk, Bhatt, et al. 2021). Finally, we incorporated a 1:1 percent change in phosphorus delivery to streams from developed land uses as a result of a given percent change in flow. This sensitivity was established based on a literature review of small-scale studies that have simulated flow and phosphorus loads under climate change scenarios in predominantly developed watersheds and an empirical analysis of data from the National Stormwater Quality Database (Shenk, Bhatt, et al. 2021). Changes in phosphorus due to LUC are based on differences in loading rates between land uses.

3 | RESULTS

3.1 | Synthesis of climate change projections

Changes in precipitation for 2025, 2035, 2045, and 2055 were developed using long-term precipitation trends and an ensemble of statistically downscaled GCMs. The trend and GCM projections were reconciled using a weighted average approach, where the weight assigned to the trend varied linearly from 1 to 0 between 2025 and 2050, and the weight assigned to the GCM projections varied linearly from 0 to 1 between 2025 and 2050. The increase in mean annual precipitation for the Chesapeake Bay watershed in 2025, 2035, 2045, and 2055 was estimated as 3.11%, 4.21%, 5.34%, and 6.91%, respectively, as compared to 1995 (Figure 4).

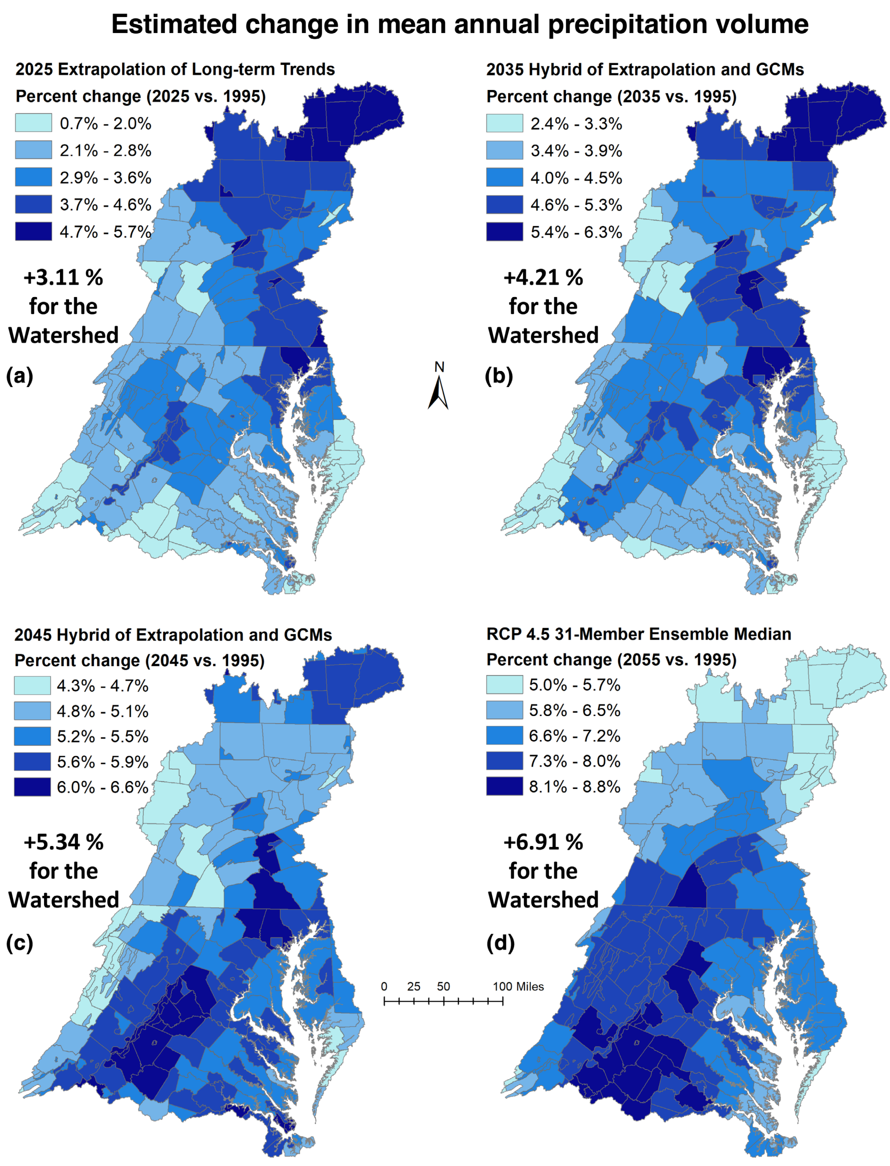

FIGURE 4 Estimated percent change in mean annual precipitation for the land segments (counties) in the Chesapeake Bay watershed for 2025 (a; top-left), 2035 (b; top-right), 2045 (c; bottom-left), and 2055 (d; bottom-right) climate change scenarios as compared to 1995. The changes in precipitation are based on a combination of extrapolation of long-term trends and a 31-member ensemble median of downscaled Global Climate Models (Bureau of Reclamation, 2013; Maurer et al., 2007) for the RCP 4.5 scenarios.

Air temperature changes for 2025, 2035, 2045, and 2055 were obtained from an ensemble of statistically downscaled GCMs. As per the 31-member ensemble median for the RCP 4.5 scenario, the increase in mean annual air temperature for the Chesapeake Bay watershed in 2025, 2035, 2045, and 2055 was estimated as 1.12, 1.45, 1.84, and 2.12°C, respectively.

Changes in PET for 2025, 2035, 2045, and 2055 were estimated using the Hargreaves and Samani (1985) method and the 31-member ensemble median air temperature changes predicted by the statistically downscaled GCMs under the RCP 4.5 scenario. The increase in mean annual PET for the Chesapeake Bay watershed for 2025, 2035, 2045, and 2055 was 3.36%, 4.43%, 5.54%, and 6.35%, respectively (Figure 5). An elevation gradient in PET change is apparent for all future climate scenarios, that is, increases in air temperature (and PET) are relatively lower at lower elevations.

3.2 | Climate change sensitivities

Watershed model runs were made for evaluating the relative impacts of climate change variables such as precipitation amount, precipitation intensity, air temperature, PET, and carbon dioxide. Analysis and understanding of these model results were useful in communicating their impacts on the watershed response and the risks to the Bay TMDL.

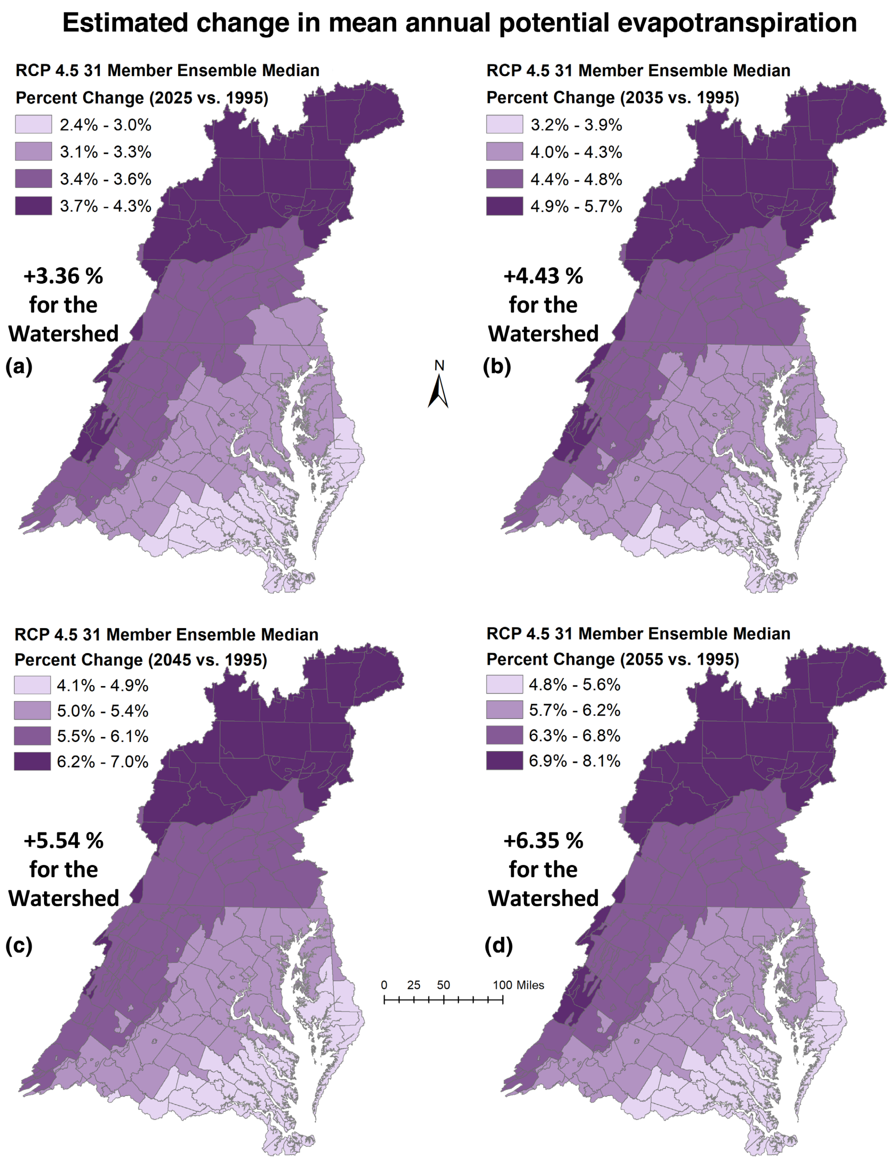

FIGURE 5 Estimated percent change in mean annual potential evapotranspiration (PET) for the land segments (counties) in the Chesapeake Bay watershed for 2025 (a; top-left), 2035 (b; top-right), 2045 (c; bottom-left) and 2055 (d; bottom-right) climate scenarios as compared to 1995. The changes in PET with respect to 1995 are based on the Hargreaves and Samani (1985) method and the 31-member ensemble median temperature change predicted by downscaled Global Climate Models (Bureau of Reclamation, 2013; Maurer et al., 2007) for the RCP 4.5 scenario.

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3.2.1 | Precipitation intensity

In addition to the use of observed trends for distributing monthly precipitation change preferentially into higher intensity deciles, we developed a scenario with "no trend" where monthly volume changes were equally distributed among the intensity deciles. For the same amount of change in precipitation, the simulated average annual flow was similar across the two scenarios (the scenario with "observed trends" exhibited slightly higher, less than 0.5% additional flow than the "no trend" scenario for 2025) suggesting the choice of how precipitation amount was distributed into hourly events did not substantially affect the average annual streamflow response. However, simulated water quality results for the watershed showed that the choice was somewhat important for average annual nitrogen delivery (difference of less than 1.5%) and was substantial for average annual sediment and phosphorus responses (difference of about 5%).

3.2.2 | Potential evapotranspiration

The choice of the method used to estimate changes in PET had a substantial impact on the model responses for streamflow, nitrogen, phosphorus, and suspended sediment delivery. The delta change estimated by Hamon (+6.7% and +12.2% for 2025 and 2050, respectively) was considerably higher than that estimated by Hargreaves–Samani (+3.4% and +6.0% for 2025 and 2050, respectively). This is consistent with the analysis of different PET methods in Milly and Dunne (2017), which demonstrated that the Hamon method overestimated the impact of temperature change on the PET as compared to other methods, including Penman–Monteith (Allen et al., 1998). As a result, changes in flow and nutrient load delivery predicted by the model for 2025 conditions also differed when using the two methods to estimate PET, with the Hargreaves–Samani resulting in a +2.3%, +2.4%, +3.1%, and +3.3% increase and the Hamon method resulting in a −0.5%, −0.6%, −1.4%, and −1.3% decrease in streamflow, nitrogen, phosphorus, and sediment delivery, respectively. The Hargreaves–Samani method was ultimately used in the assessment because of similar estimated change as compared to Penman–Monteith PET (Bureau of Reclamation, 2013), along with guidance provided by CBP STAC, and the recommendation of the CBP Modeling Workgroup.

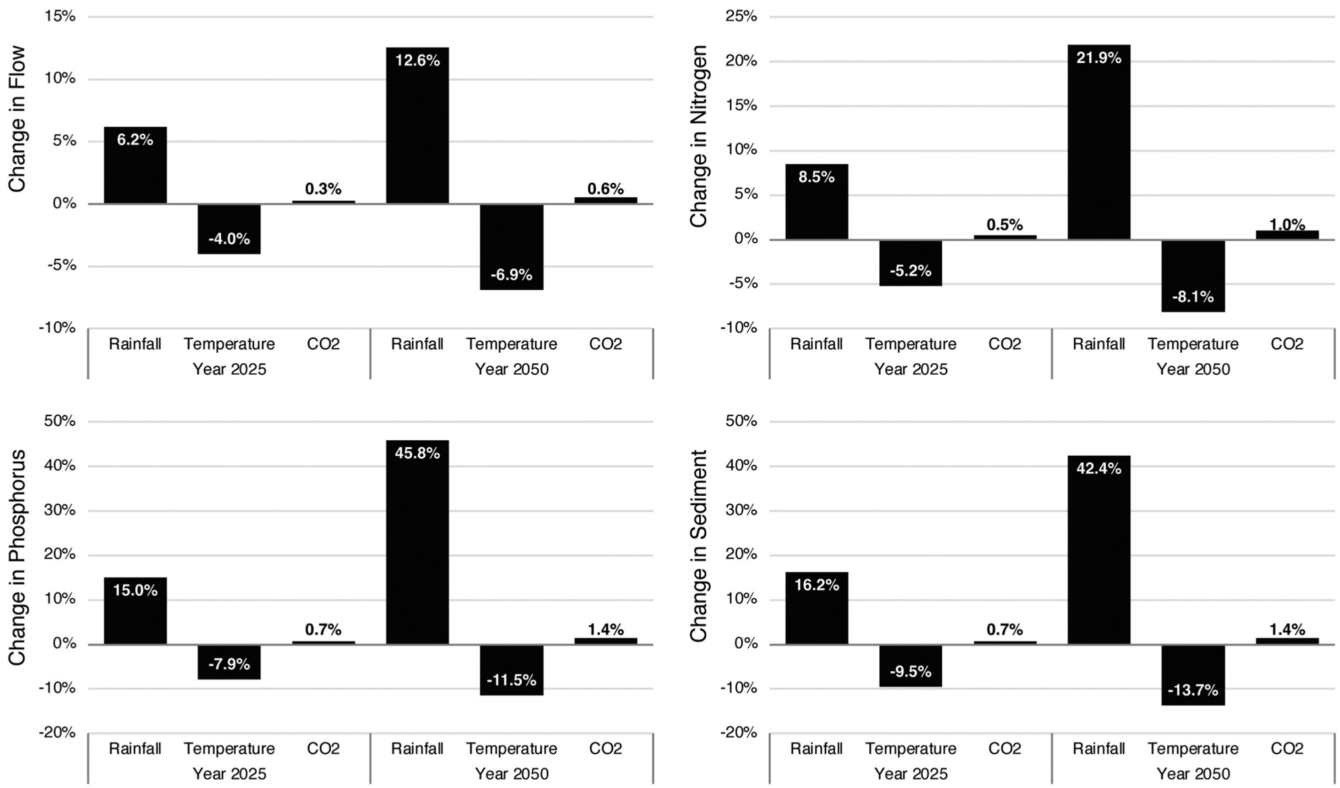

FIGURE 6 Relative impact of projected changes in precipitation, temperature, and carbon dioxide levels analyzed as sensitivity scenarios for the years 2025 and 2050 as change from 1995. Precipitation and to a lesser extent air temperature was the dominant driver for the changes in average annual delivery of flow, nutrients, and sediment, whereas carbon dioxide had minimal impact. Trends in rainfall intensity were included in our application of the delta method in preferential allocation of precipitation to higher intensity events.

3.2.3 | Precipitation, temperature, and carbon dioxide

These three climate change drivers were separately analyzed as sensitivity scenarios. They provided a better understanding of the watershed hydrology and water quality response by quantifying the relative impact of these climatic drivers on the simulated changes in flow, nutrients, and sediment transport and load delivered to the tidal Bay. Model results showed that changes in precipitation were the dominant driver of changes resulting in increased delivery of average annual streamflow, nutrients, and sediment loads (Figure 6). Changes in air temperature and PET resulted in a decreased delivery of loads and were a close second in terms of their relative importance. The impact of elevated carbon dioxide levels was relatively minor, resulting in slight increases in delivery. In general, the relative impacts were an increasingly greater magnitude of change in streamflow and nitrogen. Phosphorus and sediment loads had the greatest impact.

3.3 | Change in watershed delivery

Two types of scenarios were evaluated in this work: (a) climate change-only scenarios and (b) climate change, population growth, and land use scenarios. Results for these two types of scenarios are presented in Figure 7, where the sum of the changes in the Agriculture (AGR), Developed (DEV), Natural (NAT), and Stream (STR) source categories represent the overall expected changes in flow and loads under climate change-only scenarios. For the climate change, population growth, and land use scenarios, the additional change due to the LUC category represents the expected changes in flow and loads.

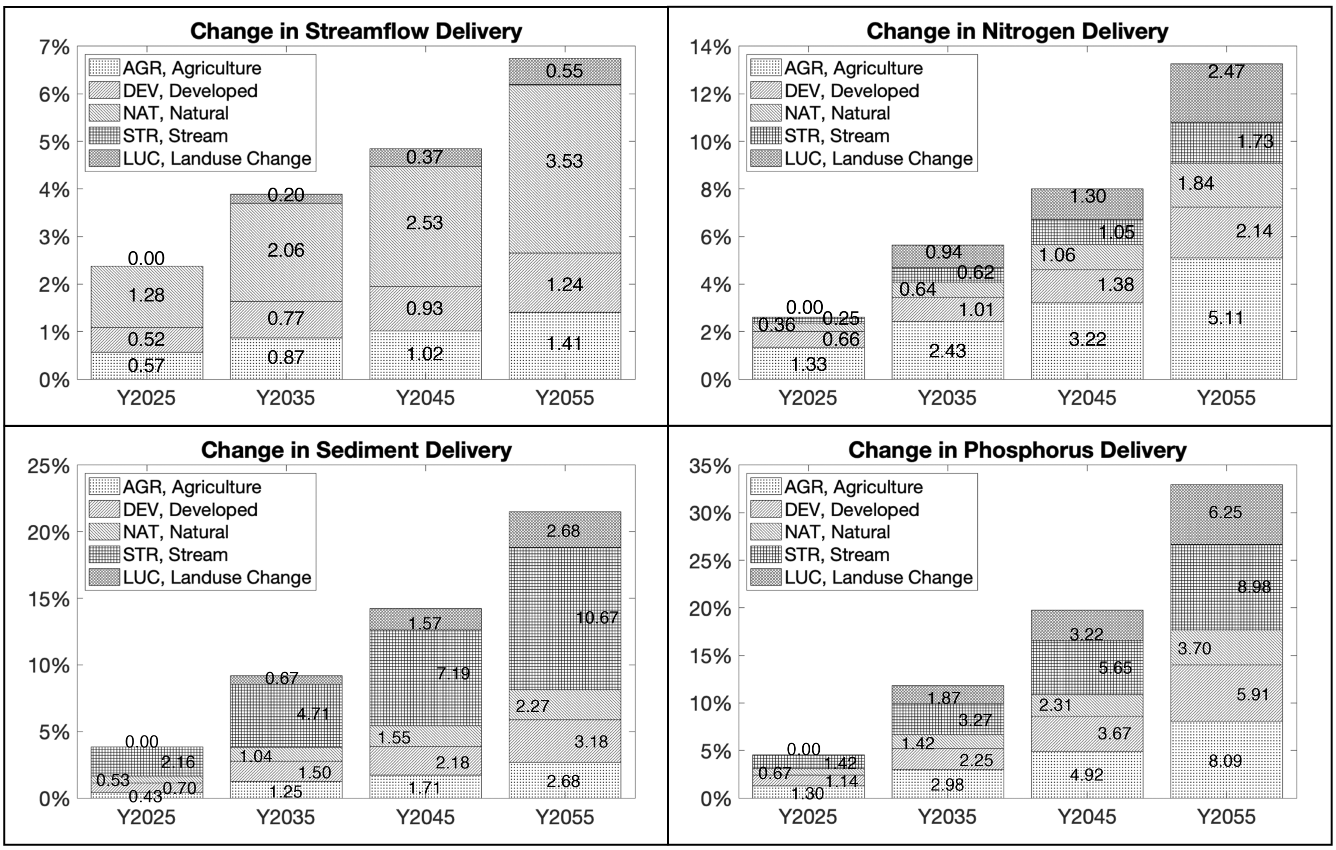

FIGURE 7 Simulated changes in the delivery of streamflow, nutrients, and sediment loads to the Chesapeake Bay for 2025, 2035, 2045, and 2055 climate change, population growth, and land use change (LUC) scenarios. Plots show change in flow and loads due to climate change from AGR, Agriculture (dots), DEV, Developed (upward stripes), NAT, Natural (downward stripes), STR, Streams (grid), and LUC is the compounded effect of population growth, land use, and climate change (diamond grid).

3.3.1 | Climate change only

The combined impact of precipitation, temperature, and carbon dioxide was estimated for 2025, 2035, 2045, and 2055 using the same underlying land use and management conditions. Estimated changes in average annual flow, nitrogen, phosphorus, and sediment show continual increase in delivery to the Bay through all four periods (Figure 7). These results show that with projected increases in precipitation and air temperature, where these two climatic factors generally counteract one another in terms of their net impact on streamflow and water quality responses, the precipitation was dominant during these periods, adversely impacting the water quality response (Figure 6).

3.3.2 | Climate change, population growth, and land use

Population growth and LUC were incorporated in the future scenarios for 2035, 2045, and 2055 to simulate the cumulative effect of all major future change components considered in this effort. In contrast to climate change components included in 2025, 2035, 2045, and 2055 scenarios that capture changes of 30, 40, 50, and 60 years from 1995, the population and LUC components in these scenarios represent changes of 0, 10, 20, and 30 years from 2025. Future LUC resulted in increased delivery of flow, sediment, nitrogen, and phosphorus (Figure 7). The 30-year projection of population growth and LUC impact between 2025 and 2055 exhibited a similar impact on total nitrogen and phosphorus load delivery (+2.47% and +6.25%, respectively) as the impact due to 30 years of climate change between 1995 and 2025 (+2.60% and +4.53%, respectively, estimated as the sum of percent changes in Agriculture, Developed, Natural, and Stream sources in Figure 7). The impact of LUC on streamflow and sediment load delivery (+0.55% and +2.68%, respectively) was relatively smaller as compared to those due to climate (+2.37% and 3.82%, respectively).

3.3.3 | Implications for major source sectors

Model results showed that the largest portion of the increase in absolute flow, nitrogen, and phosphorus loads with future climate is estimated to be from agricultural land followed by developed (Figure 7). However, this analysis of total load includes the total acres as well as per acre load generated by the source sectors. Therefore, to supplement the estimated change in loads from major source sectors, we also analyzed the model outputs to estimate the impact of climate individually on the source sector per acre loads (Figure 8). Results show that changes in streamflow and per acre nitrogen load from all major sectors are equally vulnerable to future climate. However, changes in per acre sediment and phosphorus loads from the agricultural sector are substantially more vulnerable as compared to developed, whereas the natural sector shows the lowest degree of vulnerability.

Figures 7 and 8 show variability in the impact of climate change between different source sectors. They provide a generalized assessment of the spatially aggregated effect of climate change on the source sectors, but the effect of climate change also varies spatially due to relative differences in climate, riverine response, and composition of land uses. Table 3 provides a summary of the estimated changes in streamflow and loads due to future climate aggregated in space and time for the seven jurisdictions.

4 | DISCUSSION

The Chesapeake Bay is vulnerable to climate change impacts along with socioeconomic factors that influence LUC and growth including population, animal, crops, and housing density. To recognize and address the challenges presented by climate change, the CBP Partnership has committed to evaluating the effects of climate and LUC on the Chesapeake Bay TMDL (Shenk, Bhatt, et al. 2021). Modeling studies and analyses are important tools for assessing the estimated effects of different components of change, and for providing science-based information to stakeholders and managers so they can understand, anticipate, and prepare for possible impacts by including them in the decision-making process. Ultimately, the process of assessing future climate risk to the Chesapeake watershed and tidal waters will be an iterative process of reassessment over periods of about a decade reflecting improvements in the science, analysis tools, and modeling of climate and watershed processes.

We analyzed the watershed hydrology and water quality response to provide and communicate the results using functions of changes in freshwater and sediment loads for better understanding and generalization of watershed model results for future climate conditions. Figures 9 and 10 show the response of nitrogen and phosphorus constituents, respectively, as a function of driver variables such as freshwater and sediment. The total nitrogen load delivery to the Bay is expected to increase nonlinearly with increases in freshwater flow. The nitrate load delivery increased linearly with increases in freshwater flow, while organic nitrogen responded nonlinearly to changes in freshwater flow but almost linearly to changes in sediment loads. Analysis of phosphorus response shows that the phosphorus delivery

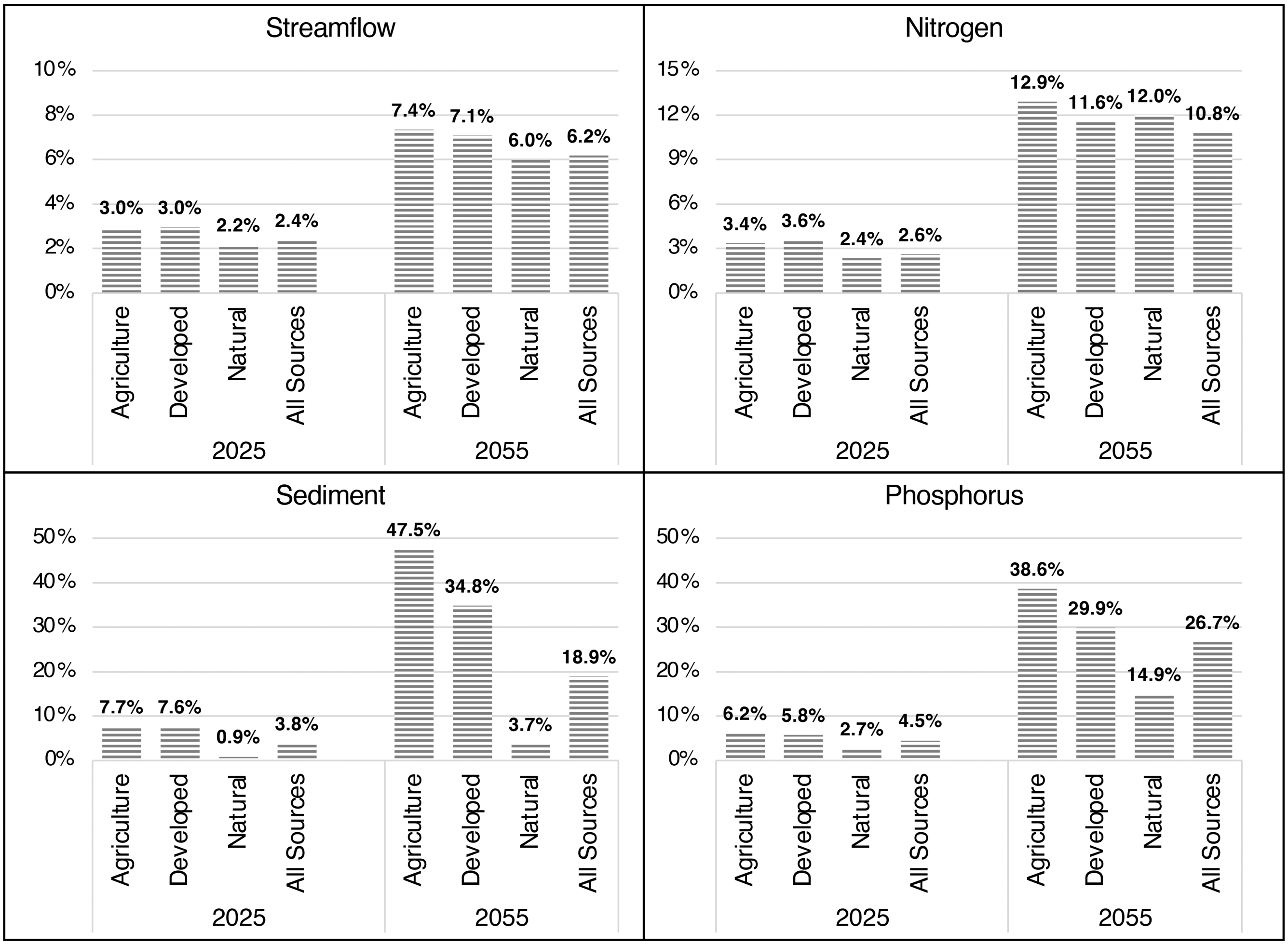

FIGURE 8 Simulated percent changes in the load per unit acre delivery to the Bay of streamflow, nutrients, and sediment for major source sectors in the Chesapeake Bay watershed for 2025 and 2055 climate change only scenarios. All sources include wastewater, septic, and stream bed and bank loads in addition to loads from Agricultural, Developed and Natural source sectors.

increased nonlinearly with changes in freshwater and the response was steeper as compared to that of nitrogen. Dissolved inorganic phosphorus increased nonlinearly with changes in freshwater, whereas both particulate inorganic phosphorus and organic phosphorus increased almost linearly with changes in sediment delivery. The results show an increasing decadal trend of as much as 1% in streamflow, 1.8% in total nitrogen, 4.4% in total phosphorus, and 3.1% in sediment loads delivered from the watershed to the Bay that can be entirely attributed to the influence of climate change.

4.1 | Nutrient speciation

Model results for future climate scenarios show increasing trends in nitrogen and phosphorus delivery to the Bay. However, the amount of increase differs across nutrient species (Figure 11). Organic nitrogen is less bioavailable as compared to nitrate, and particulate inorganic phosphorus and organic phosphorus are less bioavailable as compared to dissolved inorganic phosphorus. Therefore, the degree of change in nutrient species with different levels of bioavailability has meaningful implications for the expected estuarine water quality response. Figure 11a,b shows that much of the increase in nitrogen and phosphorus load is expected to occur in organic and particulate forms as compared to dissolved inorganic nutrients. Although both total nitrogen and nitrate deliveries are expected to increase, the fraction of nitrate in total nitrogen is expected to decrease with increasing freshwater delivery to the Bay (Figure 11c; see Bertani et al., 2022 for comprehensive details). Hence, increases in total nitrogen and total phosphorus with relatively greater increases in the delivery of less bioavailable nutrient species due to climate change will have a relatively lesser adverse impact on the Bay water quality.

TABLE 3 Estimated change in streamflow, total nitrogen (TN), total phosphorus (TP), and suspended sediment for the jurisdictions for 2025, 2035, 2045, and 2055 climate reflecting the effects of 30, 40, 50, and 60 years of climate change compared to 1995. Model results highlight geographic differences in the impact of climate change resulting from differences in climate, geographic setting, and land use.

Jurisdiction	Y2025	Y2035	Y2045	Y2055
Streamflow to the Bay				
DC	0.59%	0.83%	1.06%	1.53%
DE	0.99%	2.46%	3.79%	7.10%
MD	2.62%	4.00%	4.71%	7.32%
NY	4.98%	5.97%	4.49%	4.16%
PA	2.30%	3.67%	3.70%	5.19%
VA	1.73%	3.12%	5.58%	7.92%
WV	0.76%	2.00%	4.27%	6.13%
Nitrogen to the Bay				
DC	0.26%	0.24%	0.34%	0.53%
DE	0.77%	1.77%	3.08%	6.20%
MD	2.32%	3.48%	4.57%	7.76%
NY	6.94%	11.07%	7.99%	7.14%
PA	2.62%	4.78%	5.14%	8.00%
VA	2.81%	5.00%	9.56%	15.69%
WV	−0.52%	3.35%	11.57%	22.94%
Phosphorus to the Bay				
DC	0.55%	0.82%	1.13%	1.67%
DE	3.10%	6.24%	8.35%	13.42%
MD	2.88%	5.55%	7.87%	13.10%
NY	7.52%	13.83%	10.78%	10.52%
PA	3.05%	8.11%	8.69%	12.96%
VA	5.73%	11.49%	22.72%	37.27%
WV	1.98%	10.68%	25.40%	47.06%
Sediment to the Bay				
DC	4.43%	6.53%	8.94%	12.87%
DE	10.02%	18.37%	24.97%	40.17%
MD	1.69%	3.54%	5.07%	8.00%
NY	15.46%	30.92%	25.09%	23.97%
PA	7.30%	18.60%	18.37%	24.38%
VA	4.27%	8.66%	16.57%	25.59%
WV	3.49%	14.95%	32.71%	54.70%

4.2 | Change in riverine nutrient and sediment delivery

Mass balance analyses showed that both land and riverine processes contribute to changes in nitrogen and phosphorus deliveries (Figure 12). Nutrient load delivery to streams (edge of stream) increased with increases in flow and sediment loads. As shown in Figure 12 for the Susquehanna and Potomac Rivers, greater increases in higher daily flow quantiles impacted mobilization and transport of sediment and nutrients, especially in particulate forms, leading to an overall decrease in net trapping in the rivers, or higher nutrient delivery. This response arises from the same hydrologic forcing that increases sediment competency, and therefore the mobilization of particulate inorganic phosphorus and particulate organic phosphorus and nitrogen associated with sediment. The increased nutrient delivery from the watershed with future climate scenarios is reflected in the increasingly higher stream to Bay delivery factors, defined as the ratio of total outputs to total inputs, for total nitrogen, total phosphorus, and suspended sediment (Figure 12).

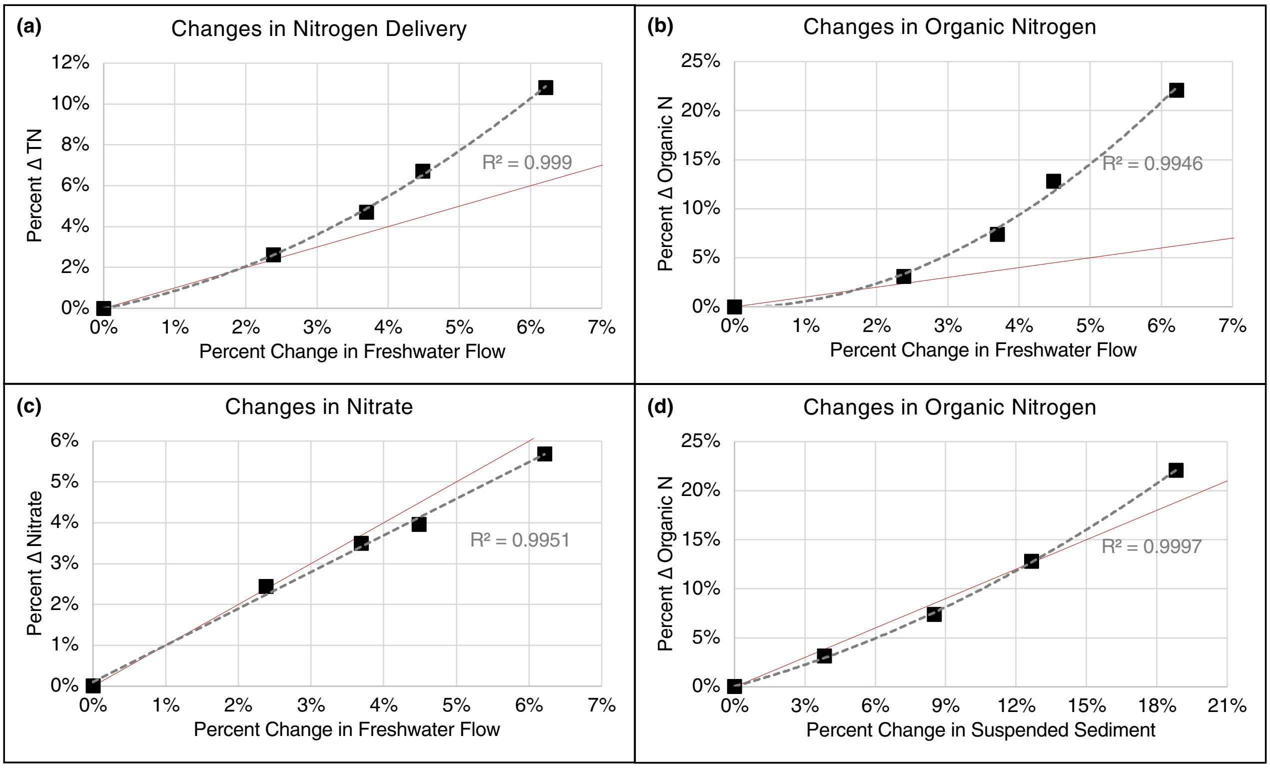

FIGURE 9 Average annual change in nitrogen delivery with changes in freshwater flow and sediment load delivery to the Bay. (a) TN and (b) organic nitrogen, Organic N loads increase nonlinearly with increases in freshwater flow. (c) Nitrate and (d) organic nitrogen increase almost linearly with increases in delivery of freshwater flow and sediment load, respectively. Red lines represent a 1:1 relationship.

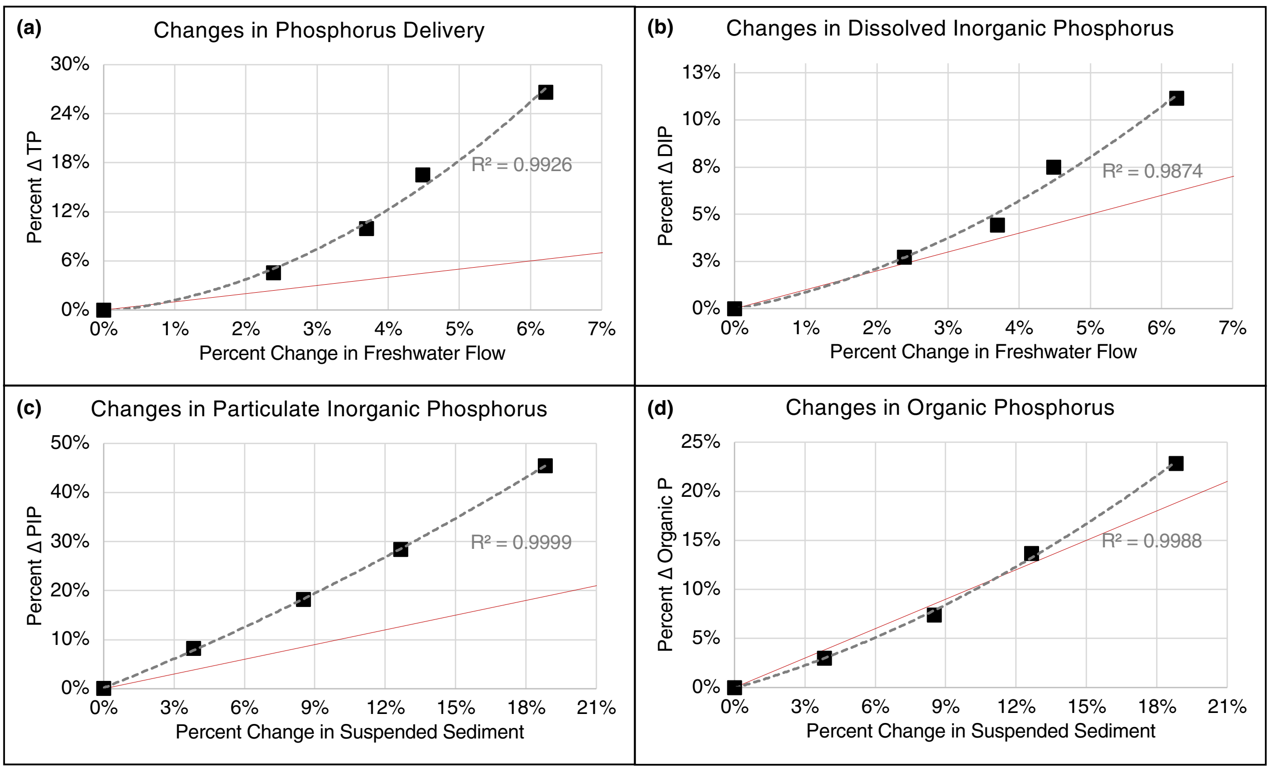

FIGURE 10 Average annual changes in phosphorus delivery with changes in freshwater flow and sediment load delivery to the Bay. (a) TP and (b) dissolved inorganic phosphorus, DIP loads increase nonlinearly with increases in freshwater flow. (c) Particulate inorganic phosphorus, PIP and (d) organic phosphorus, Organic P increase linearly with increases in sediment load delivery. Red lines represent a 1:1 relationship.

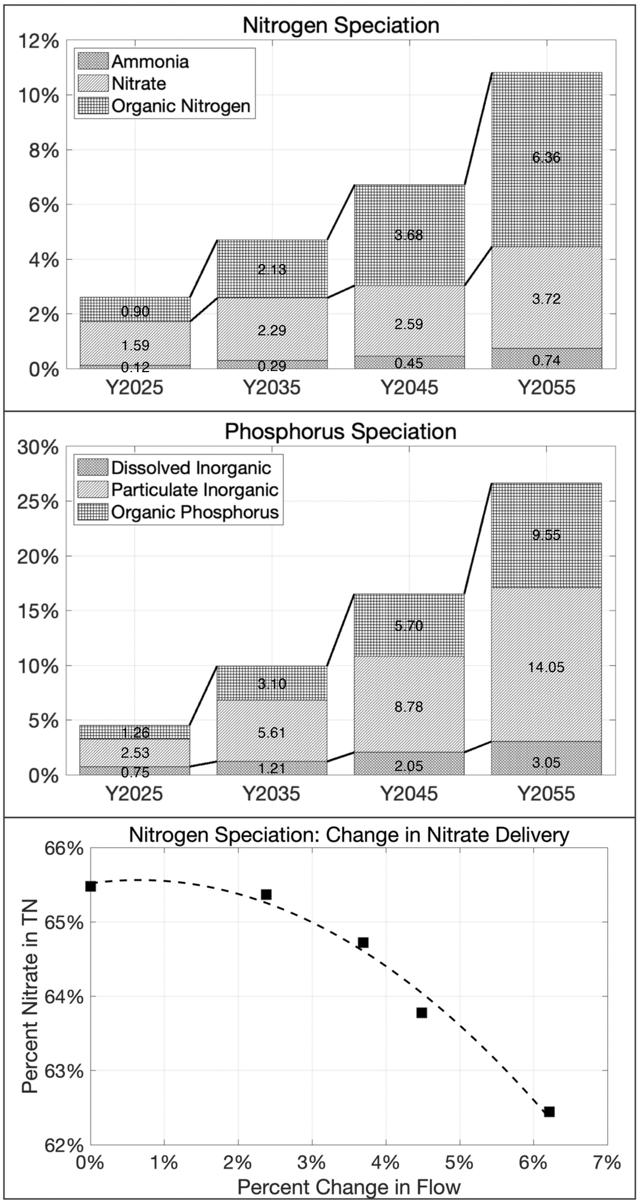

FIGURE 11 Changes in nitrogen and phosphorus speciation with climate change. Majority of the increases in nitrogen and phosphorus load deliveries to the Bay are expected to occur in (a) particulate nitrogen and (b) particulate phosphorus forms. (c) Fraction of nitrate in TN load delivery to the Bay decreases with increasing freshwater flow, thereby dampening the adverse water quality impacts.

Increase in precipitation amount and intensity contributes to increases in streamflow, whereas increasing air temperature and evapotranspiration act to decrease streamflow. The interaction of these two drivers spatially with respect to their magnitudes and timing is expected to be an important factor causing variability in event-scale streamflow response. Figure 13a shows average monthly change in streamflow for the nine largest rivers (Susquehanna, Potomac, James, Rappahannock, York, Patuxent, Patapsco, and Choptank) that discharge into the Bay. Although there is variability in monthly response resulting from spatial variability in climate, the winter and fall seasons generate increasingly higher streamflow, whereas changes during spring and summer months are less well defined. The aggregate response for the nine major rivers is heavily influenced by the changes in the Susquehanna River. Figure 13b shows the magnitude of the future winter peak flow for the Susquehanna River is increasing as compared to that of 1995 due to less snow and more rainfall, whereas future spring peak flows are decreasing due to decrease in snow accumulation because of less snowfall and early melt with higher temperature. This is corroborated by the substantial expected decreases in future snowfall amounts as compared to 1995 shown in Figure 13c that inherently changes the storage and antecedent conditions of the watershed as well as its response. Change in Susquehanna River basin's snow hydrology is more pronounced as compared to that of the other major river basins because of its spatial coverage of the northern portion of the watershed. Overall, such underlying seasonal changes as well as shifts in event-scale streamflow responses have an equally important role if not more as compared to that of

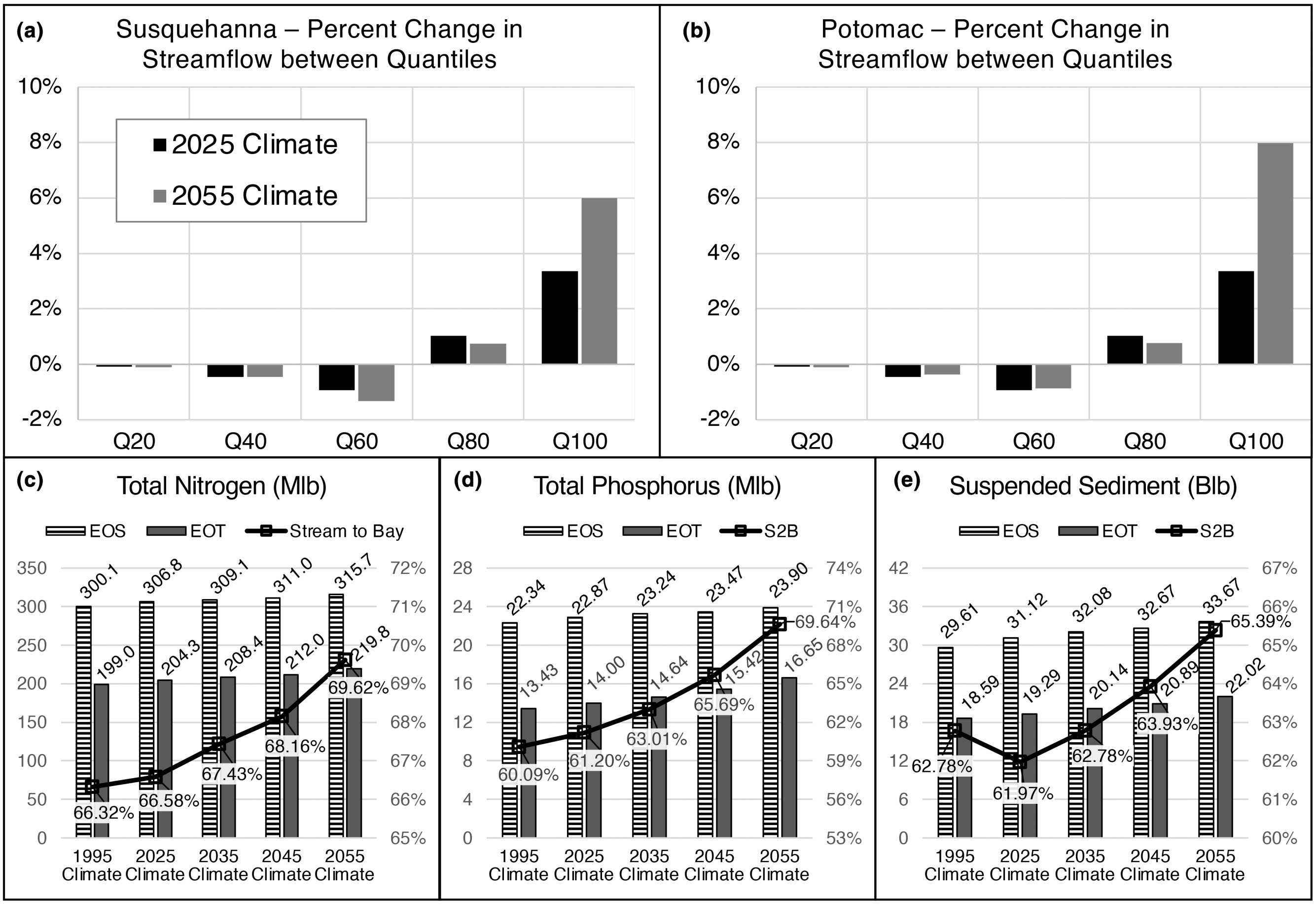

FIGURE 12 Greater increases in higher streamflow quantiles (top 20 percentile) for the (a) Susquehanna and (b) Potomac, the two largest rivers of the Chesapeake Bay watershed. Delivery of (c) TN, (d) TP, and (e) suspended sediment (units in millions or billions of pounds) to the streams (EOS or edge of stream) and to the Bay (EOT or edge of tide) for 1995, 2025, 2035, 2045, and 2055 climate change scenarios and corresponding riverine delivery (S2B or Stream to Bay) factors for the entire Chesapeake Bay watershed including all major river basins and tidal watershed are shown. Title for the figure panels shows values on *Y*-axis. Increasingly higher riverine delivery factors reflect a decrease in net trapping in the rivers because of increased high flows under climate change scenarios.

increasing precipitation amount and intensity on the fate and transport of nutrients and sediments, leading to increasingly higher mobilization and delivery during larger and more frequent streamflow events.

4.3 | Spatial variability in load and impact on the bay

Watershed model estimated changes in nutrient and sediment load to streams and to the Bay were analyzed along with nutrient effectiveness estimated by the estuarine water quality model to develop a generalized assessment of probable impact of climate change on the Bay water quality due to spatial variability in estimated changes in watershed nitrogen and phosphorus loads. Prior studies have documented the methods for the calculation of estuarine effectiveness for total nitrogen (Estuarine TN effectiveness) and total phosphorus (Estuarine TP effectiveness) (USEPA, 2010b, Allocation Methodology to Relate Relative Impact to Needed Controls, Appendix K; Linker et al., 2013). The effectiveness data quantify the estimated change in Bay dissolved oxygen (DO) concentration per unit change in watershed nitrogen and phosphorus delivery and vary geographically around the Bay to capture the influence of differences in location, timing, and bioavailability of loads.

Figure 14 shows an assessment of changes in DO concentrations attributed to changes in nitrogen and phosphorus delivery due to 2025, 2035, 2045, and 2055 climate change since 1995. The change in DO concentration was calculated by multiplying spatially variable change in nutrient loads and estuarine TN and TP effectiveness factors (Figure 14). Results show that climate change in the watershed will impact the Bay water quality resulting in increased hypoxia. The DO concentration is expected to decline as a result of increases in both nitrogen and phosphorus loads. Figure 14 also shows that both the net effect and rate of changes in DO are greater for nitrogen than for phosphorus. Figure 15 provides similar information for the impact of 30-year climate change captured in the 2025 scenario but has been normalized by the

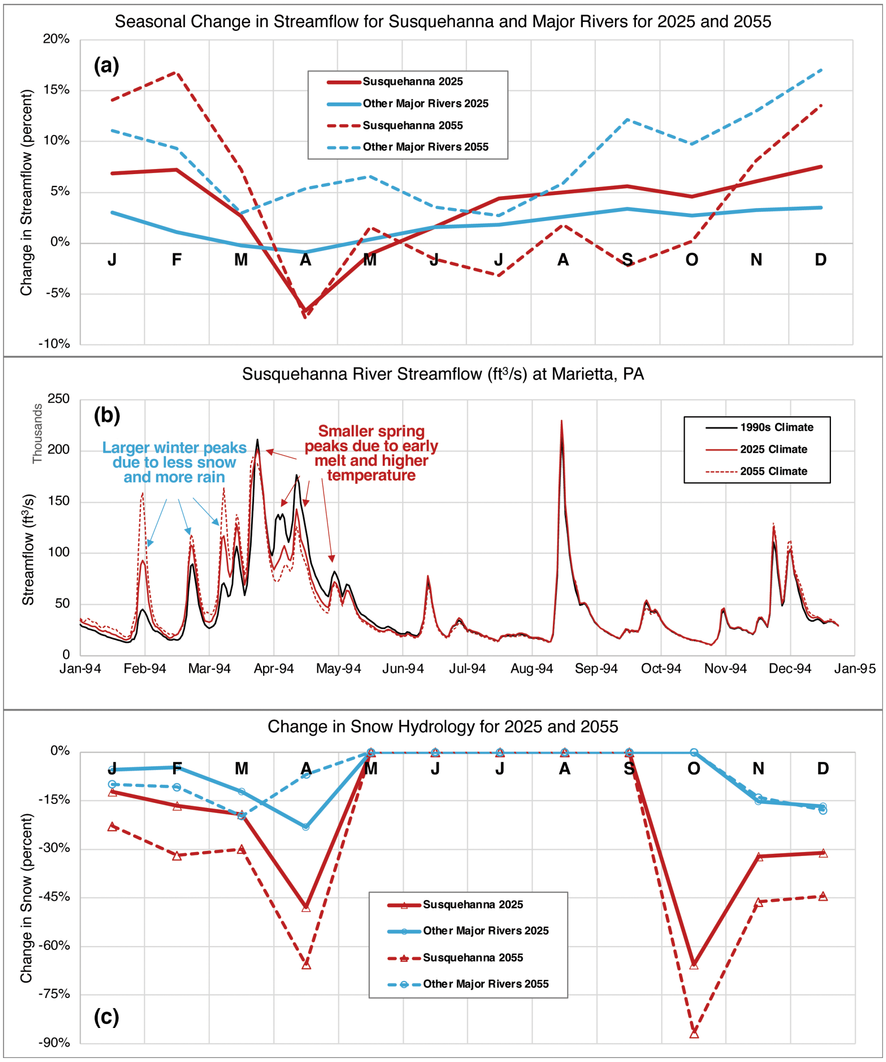

FIGURE 13 Simulated changes in seasonal streamflow and underlying event scale changes that increase riverine nutrient delivery, or an overall decrease in net trapping in the rivers. (a) estimated change in average monthly streamflow for the nine major river basins due to 30–60 years of climate change. (b) A sample of event scale responses over 1-year period for the Susquehanna River show temporal differences in streamflow response (i.e., larger peaks during January–March and smaller peaks during March–May) due to changes in antecedent condition. (c) A substantial decrease in snow volume is estimated during winter months.

area to highlight the spatial variability of climate change impacts. We refer readers to Linker et al. (2023) for climate change assessment that uses linked simulations of both watershed and estuarine water quality responses.

4.4 | Sources of uncertainties

Although we recognize the importance and utility of a comprehensive uncertainty estimation, a formal assessment was not performed. This is mostly because of the complexity of the linked modeling systems and extensive list of sources that may contribute to uncertainty due to a number of choices and assumptions involved in the use of models and data generated by them in this assessment. Major sources of uncertainty include uncertainty due to structure and formulation of climate models, LUC model, airshed model, watershed model as well as estimation of model parameters and initial condition of the model state variables. The CBP considered a wide array of effects and made decisions to include those processes that were both well understood and judged to have a substantial effect on water quality standards. Nevertheless, some processes left out of the analysis could be important but were without sufficient data and understanding for inclusion in the analyses presented here. Several different choices can be made when it comes to data sources, methods, and approaches used to perform climate change modeling to assess water quality impacts. They include choices for (a) spatial downscaling of future climate projections; (b) method for incorporation

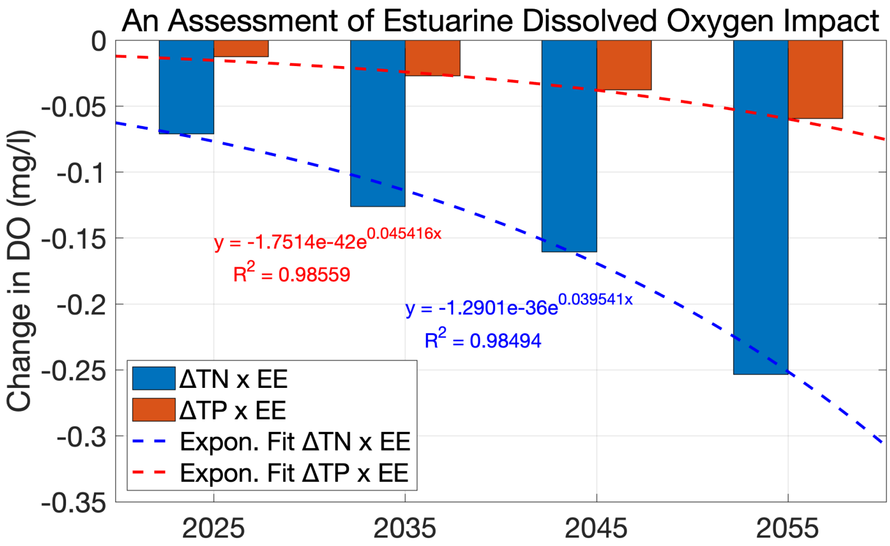

FIGURE 14 A generalized assessment of change in estuarine dissolved oxygen (DO) response shows an increasingly adverse impact of climate change induced increases in TN (ΔTN) and TP (ΔTP) delivery to the Bay. Change in DO concentration was calculated by multiplying spatially variable changes in nutrient loads and estuarine effectiveness (EE; Linker et al., 2013), which quantifies geographic variability in the effect of change in delivery of nitrogen and phosphorus load on change in Bay DO concentration.

of future climate (e.g., Delta Method that was used here); (c) selection of baseline meteorological pattern to which the delta change is applied; (d) temporal disaggregation of the delta change from monthly to hourly time steps; (e) estimation of change in PET; (f) method for estimating changes in load from land uses; (g) assumption for the watershed processes contributing to land to water delivery, instream water quality response, and changes in streambank erosion and floodplain deposition; and (h) performance and/or failure of about 200 or so management practices that are used in the model under a different climate regime, as well as the performance of wastewater facilities and CSOs. There are also data such as surface water withdrawals for public water supply and agriculture for which reliable information on future projection is not available. This list of sources of uncertainty, which we acknowledge is not a complete one, is provided here to highlight the complexity of a comprehensive uncertainty estimation.

5 | SUMMARY

The climate change assessment undertaken for the Midpoint Assessment of the Chesapeake Bay TMDL using the Phase 6 Watershed Model relied heavily upon recommendations and guidance provided by CBP STAC workshops (Johnson et al., 2016; Pyke et al., 2008, 2012; Shenk, Bennett, et al. 2021) and the CBP's Climate Resiliency Workgroup as well as previous modeling studies of climate change in the Chesapeake region. It was developed by the Partnership in a stakeholder-driven setting by leveraging expertise, reviews, and feedback of scientific subject matter experts, academic researchers, model practitioners, and managers involved in climate change research and watershed restoration efforts from different jurisdictions and source sectors. Changes in watershed nutrient and sediment load delivery to the Bay were estimated for 2025, 2035, 2045, and 2055 climate projections, representing a change of 30, 40, 50, and 60-years as compared to the 1993–1995 Chesapeake Bay TMDL critical period and 1991–2000 average hydrology period.

The CBP examined the estimated future climate risks to the Bay TMDL based on 2035–2055 climate scenarios for information and planning purposes but used the 2025 climate scenario to quantify additional levels of management efforts needed to offset water quality impacts. Linker et al. (2023) provide details on how watershed model results were used in conjunction with the estuarine water quality model in a comprehensive, integrated assessment of climate change impacts on Bay TMDL and how the Partnership used them in developing and adopting a quantitative load reduction target for the Bay jurisdictions.

There were several knowledge gaps that were not addressed in this climate change assessment, for example, potential changes in the performance of management practices, resiliency, or considerations for structural failure under climatic extremes. Future adaptations of social and agricultural practices, and changes in phenology and irrigation were also not included.

Although the analysis of climate change modeling presented in this paper represents the current best estimates based on available data and modeling resources, it is anticipated that the CBP will reassess the TMDL progress relative to climate change and other factors going forward in an iterative process. Such efforts will be based on refined inputs and method updates for the representation and estimation of watershed hydrology and water quality processes along with the next generation of land use, airshed, watershed, and estuarine modeling tools.

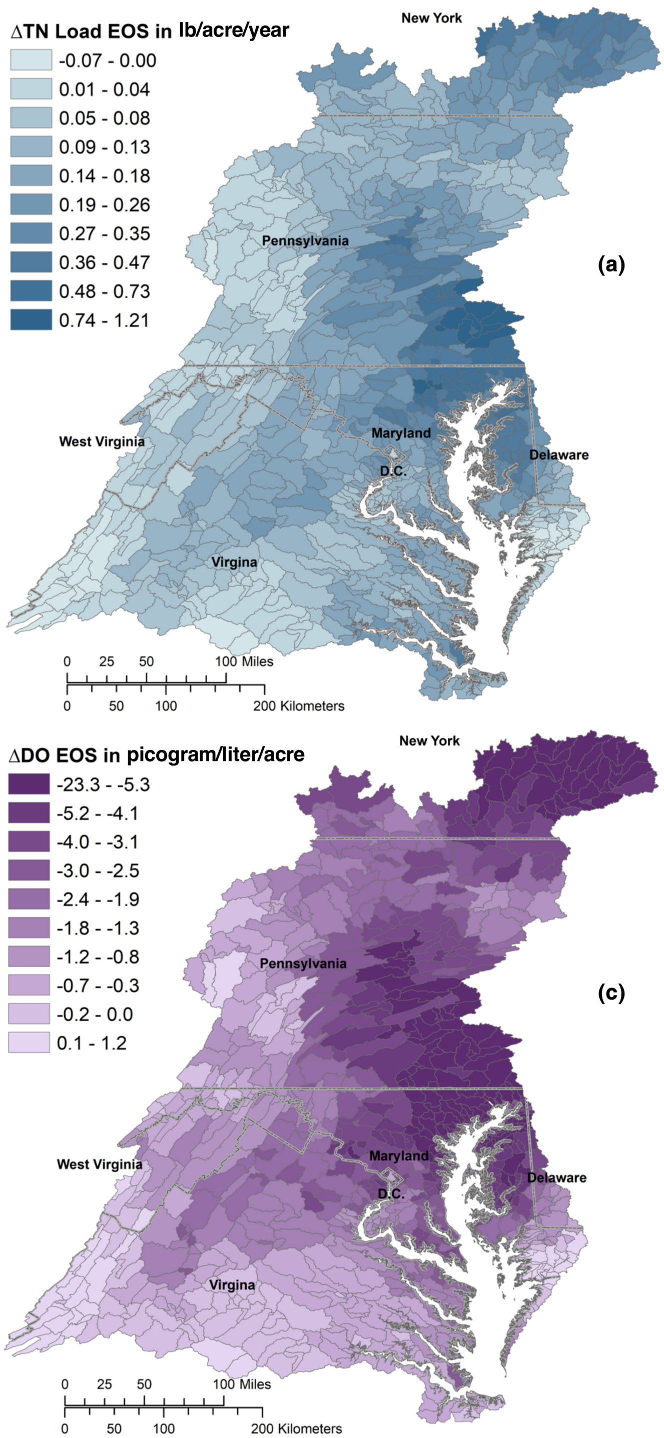

FIGURE 15 Changes in nutrient delivery and estimated change in DO (ΔDO) of the Bay due to 30-years of climate change assessed in the 2025 scenario. Average change in EOS delivery of (a) TN (ΔTN), and (b) TP (ΔTP) loads. Spatial variability in the estimated impact of watershed response on the Bay water quality expressed as change in DO concentration, which was calculated by multiplying (c) EOS and (d) EOT change in nitrogen (ΔTN) and phosphorus (ΔTP) loads and EE (change in DO with ΔTN or ΔTP; Linker et al., 2013) for the sub-watersheds.

AUTHOR CONTRIBUTIONS

Gopal Bhatt: Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Lewis Linker:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Gary Shenk:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Isabella Bertani:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing

– review and editing. **Richard Tian:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Jessica Rigelman:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Kyle Hinson:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing. **Peter Claggett:** Conceptualization; data curation; formal analysis; investigation; methodology; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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