Evaluating Changes in Terrestrial Hydrological Components Due to Climate Change in the Chesapeake Bay Watershed

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ABSTRACT

A mesoscale evaluation is performed to determine the impacts of climate change on terrestrial hydrological components and the Net Irrigation Water Requirement (NIWR) throughout the Chesapeake Bay watershed in the mid-Atlantic region of the United States. The Noah-MP land surface model is calibrated and evaluated against the observed datasets of United States Geological Survey (USGS) streamflow gages, actual evapotranspiration from USGS Simplified Surface Energy Balance (SSEBop) Model and soil moisture from Soil Analysis Climate Network (SCAN). Six best performing Global Climate Models (GCM) based on Multivariate Adaptive Constructed Analogs (MACA) scheme are included for two future scenarios (RCP 4.5 and RCP 8.5), to assess the change in water balance components, change in NIWR for two dominant crops (corn and soybeans) and uncertainty in GCM projections. Using these long-term simulations, the flood inundation maps are developed for future scenarios along the Susquehanna River including the City of Harrisburg in Pennsylvania. The HEC-RAS 2D model is calibrated and evaluated against the high-water marks from major historical flood events and the stage-discharge relationship of the available USGS streamgages. Finally, the impacts of climate change are assessed on flood inundation depth and extent by comparing a 30-yr and 100-yr flood event based on the historical and future (scenario-based) peak discharge estimates at the USGS streamgages. Interestingly, flood inundation extent and severity predicted by the model along the Susquehanna River near Harrisburg is expected to rise in the future climate scenarios due to the greater frequency of extreme events increasing total precipitation.
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GENERAL PUBLIC ABSTRACT

Climate change is inevitable due to increased greenhouse gas emissions, with impacts varying in space and time significantly throughout the globe. The impacts are strongly driven by the change in precipitation and temperature which affect the control of the movement of water on the surface of the Earth. These changes in the water cycle require an understanding of hydrological components like streamflow, soil moisture, and evapotranspiration. Development of long-term climate models and computational hydrological models (based on mathematical equations and governed by laws of physics) has helped us in understanding this climate variability in space and time. This study performs a long-term simulation using the datasets from six different climate models to analyze the change in terrestrial hydrological components for the entire Chesapeake Bay watershed in the mid-Atlantic region of the United States. The simulations provide an understanding of the interplay between various land surface processes due to climate change and can help determine future water availability and consumption. To illustrate the usefulness of such long-term simulations, the crop water requirement is quantified for the dominant crops in Chesapeake Bay watershed to project water availability and support the development of mitigation strategies. Flood inundation maps are also developed for a section of Susquehanna River near the City of Harrisburg in south-central Pennsylvania using the streamflow from long-term simulations. The flood inundation depth and extent for major flood events such as Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) are compared along the Susquehanna River, which can aid in managing flood operations, reduce the future flood damages and prioritize the mitigation efforts for endangered communities near the City of Harrisburg.
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Chapter 1: Introduction

With the development at its peak rate, human activities have been solely dependent on the use of fossil fuels leading to the increased concentration of atmospheric carbon dioxide and other greenhouse gases. A strong greenhouse effect causes the warming of the earth’s atmosphere by rising air temperatures and increases the atmospheric water content resulting in the possibility of clouds and precipitation. Increases in CO₂ emissions due to anthropogenic influence has led to significant changes in climatic conditions with a rise of 0.5 °C in global temperature in past decades (IPCC, 2007). One such state-of-the-art framework designed to evaluate and project the climate variability and change is the Coupled Model Inter-comparison Project [CMIP Phase 5; Taylor et al. (2012)]. It includes the long-term simulations from multiple earth system models for historic conditions (1950-2005) and twenty-first century projections (2006-2100). To better understand and evaluate the impacts of climate change on the hydrological cycle, it is important to emphasize the changes in terrestrial hydrological components such as soil moisture, runoff, evapotranspiration, and groundwater storage, which are directly dependent upon the land-atmospheric interactions and land surface processes. Physically-based hydrological models have been popular in the past to evaluate the impacts of climate change on terrestrial hydrological components (Cao et al., 2006).

Najjar et al. (2010) reported that the majority of climate change impacts on Chesapeake Bay watershed are negative and further evaluation is required to implement the mitigation strategies and restore the resilience of the Chesapeake Bay watershed. The impacts of climate change are evident in the hydrological cycle through changes in the water fluxes and energy balance. These alterations in the environment are important and further assessment in terms of the distribution and management of water resources due to climate change is necessary. The irrigation water use is majorly dependent on the crop water requirement and the available effective precipitation which necessitates an assessment of changes in terrestrial hydrological components driven through climate change.
Chapter 2 performs a mesoscale evaluation of the changes in terrestrial hydrological components and Net Irrigation Water Requirement (NIWR) using a physically-based land surface model over the Chesapeake Bay watershed. It uses long term simulations from multiple Global Climate Models (GCM) based on CMIP5 framework that are statistically downscaled and bias-corrected using the Multivariate Adaptive Constructed Analogs (MACA) technique. Two different future scenarios: RCP 4.5 (business as usual) and RCP 8.5 (worst scenario with increased GHG emissions) are considered with simulation periods from 2021-2050 and 2061-2090. Daily crop coefficients for two dominant crops (corn & soybeans) in Chesapeake Bay watershed are derived using the National Oceanic and Atmospheric Administration (NOAA) global reference evapotranspiration and the United States Geological Survey (USGS) actual evapotranspiration estimates. Finally, a water balance approach is used to estimate the change in NIWR for corn and soybeans towards the end of the 21st century. The impact due to the interplay among the projected atmospheric downscaled fields like precipitation and temperature on the terrestrial hydrological components is evaluated and irrigation water requirement for corn and soybeans is estimated which implicates the future agricultural practices in the Chesapeake Bay watershed.

Chapter 3 develops the flood inundation maps for future climate scenarios along Susquehanna River near Harrisburg in Dauphin County in south-central Pennsylvania. It represents an application and usefulness of the climate change analysis performed in Chapter 2. For that purpose, a 2D hydraulic model is calibrated and evaluated using information from major historical floods events like Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) and the available stage-discharge data from USGS streamgage near Harrisburg. The streamflow data for different future climate scenarios (RCP 4.5 and RCP 8.5) are derived from the long-term simulations performed in Chapter 2. A comparison between historic and future 30-yr and 100-yr flood events is performed to observe the changes in the flood inundation due to climate change in future GHG emission-based scenarios.
Chapter 2: Impacts of climate change on terrestrial hydrological components and irrigation water requirement in Chesapeake Bay watershed

2.1. Abstract

This study assesses the impacts of climate change on terrestrial hydrological components and Net Irrigation Water Requirement (NIWR) using a land surface model over the Chesapeake Bay watershed. The Noah-MP land surface model is calibrated and evaluated using the available observed datasets of streamflow for six streamflow gages from United States Geological Survey (USGS), actual evapotranspiration from USGS Simplified Surface Energy Balance (SSEBop) model and soil moisture for five stations from Soil Analysis Climate Network (SCAN). To better understand the impacts of climate change on the hydrological cycle, long term simulations of multiple earth system models from a state-of-art framework, the Coupled Model Inter-comparison Project (CMIP Phase 5), that are statistically downscaled and bias-corrected using Multivariate Adaptive Constructed Analogs (MACA) scheme are used. Precipitation indices are used to identify six best performing models out of the available twenty MACA based Global Climate Models (GCM). Daily crop coefficients (for corn and soybeans) are derived using the National Oceanic and Atmospheric Administration’s global reference evapotranspiration and USGS SSEBop actual evapotranspiration estimates. Finally, the change in terrestrial hydrological components is estimated that indicates an overall increase of 18 % in evapotranspiration and an overall decrease of 5 % in streamflow for the RCP 8.5 scenario towards the end of the 21st century. Using the FAO CROPWAT approach, a decrease of 13 % and 17 % in NIWR is estimated for corn and soybeans respectively, for the RCP 8.5 scenario due to the increase in effective precipitation towards the end of the 21st century. This approach can be applied in agricultural regions and scaled globally to project water availability and design mitigation strategies.

Keywords: Noah-MP, Net Irrigation Water Requirement (NIWR), MACA, Global Climate Models, Climate change
2.2. Introduction

Increases in global CO₂ emissions have led to significant changes in climate conditions (Solomon et al., 2009). The change in precipitation and temperature over the past several decades has substantially impacted environmental sustainability (Solomon et al., 2007). To better understand the impacts of climate change on the hydrological cycle, one such state-of-the-art framework is the Coupled Model Intercomparison Project [CMIP Phase 5; (Taylor et al., 2012)] which is used to evaluate future climate variability and change. It includes long term simulations from multiple earth system models based on the historical conditions and twenty-first century projections based on greenhouse gas (GHG) emissions. Based on past studies, the majority of climate change impacts in the Chesapeake Bay watershed are negative in terms of exacerbating anthropogenic environmental impacts and hence pose a serious challenge to restore the resilience of the Chesapeake Bay watershed (Najjar et al., 2010). Climate projections, although uncertain, suggest an increase in precipitation with changes in annual streamflow, higher in winter and spring (Pyke et al., 2008) and lower in the summer and fall (Wagena et al., 2018). In addition to that, the alteration in biogeochemical cycles due to agricultural management practices has a significant impact on the water quality and quantity in the Chesapeake Bay watershed.

Irrigation has multiple direct and indirect effects on the environment which include changes in the hydrological balance, changes in atmospheric moisture due to increased evaporation (Cook et al., 2011), decreased stream discharge due to reduced groundwater levels (Bredehoeft, 2011), and impacts on water quality via changes in nutrient cycling (Hotes & Pearson, 1977). One of the largest potential changes is the change in crop water requirements due to climate change. Thus, understanding the impacts of climate change on the Net Irrigation Water Requirement (NIWR) is important to assess the distribution and management of water resources. The impact of changes in precipitation and temperature on irrigation water requirements at mesoscale demands further research in areas of developing agriculture and increasing irrigation water use. However, there is limited literature on future net irrigation water requirements and further investigation is necessary to study the impacts of climate change to project water availability and design mitigation strategies. For example, Adams et al. (1990) indicated that the increasing trend of irrigation
water use in the humid regions of the United States can be mitigated by shifting the agriculture to regions projecting higher precipitation in future periods.

Numerous studies have reported the impacts of climate change on NIWR and crop yield using the Global Climate Model (GCM) projections from CMIP5. The use of crop models to estimate the evaporative demand and water balance models to estimate the soil moisture has been the core components of these studies. Islam et al. (2012) assessed the impacts of climate change on corn production in Central Great Plains using climate projections and found a decrease in the NIWR due to shortened growth durations and lower ET demand due to increasing CO2 levels. Kimball & Idso (1983) showed a decrease in maize crop water use due to reduced transpiration at elevated CO2 levels. Huntington et al. (2016) used the ET Demands model to estimate the historical and future NIWR for the western United States and reported an increase in irrigation water requirements in regions with perennial crops. Nkomozepi & Chung (2012) assessed the trend and uncertainty for maize NIWR in Zimbabwe using GCM projections and the CROPWAT model developed by the Land and Water Development Division of Food and Agriculture Organization (FAO). They found an average increase in NIWR ranging from 33% to 99% for the 2020s and 2090s periods, respectively. Recently, Yang et al. (2019) estimated changes in NIWR across the Lower Mississippi Valley using the standard ASCE NIWR formulation and projected an increase of up to 9.2% using the Varied Growing Duration Length [GDL] Scenario and up to 29.4% (Fixed GDL Scenario) under Representative Concentration Pathways (RCP) 8.5. They considered the change of crop cultivars with time maintaining similar growing duration length as fixed GDL whereas the varied GDL was derived using temperature and phenological heat units with no change in crop cultivars.

Given the variability seen in previous studies, and the uncertainty in GCM projections, further evaluation of crop water demands, and the potential changes to the overall water budget in many regions are warranted. This study estimates the changes in NIWR and terrestrial hydrological components due to climate change over rainfed and irrigated croplands in Chesapeake Bay watershed. Six best performing GCM’s are included based on the precipitation indices and two future scenarios (RCP 4.5 and RCP 8.5) are considered. The NIWR is calculated for two dominant crops (corn and soybeans) using the
FAO CROPWAT approach and by considering a fixed growing duration length. The objectives of this study are to quantify the impacts of climate change on terrestrial hydrological components and NIWR due to increased CO₂ levels and discuss uncertainty in GCM projections.

2.3. Data and Methods

2.3.1. Study Area

The Chesapeake Bay watershed occupies 165,760 sq. km. with more than 18 million people residing in the watershed. Five major rivers form the Chesapeake Bay watershed, including the Susquehanna, Potomac, Rappahannock, York, and James.

Figure 2-1: Chesapeake Bay watershed with red circles indicating the hydrologic USGS streamgages as indicated in Table 2-1.
More than 100,000 streams, creeks, and rivers drain the Chesapeake Bay watershed with boundaries extending from headwaters of Otsego Lake, near Cooperstown, New York to the Suffolk, Virginia and Atlantic Ocean. Three large rivers - the Susquehanna, Potomac, and the James - collectively drain about 80% of the freshwater through its streams and tributaries. The Susquehanna basin is the largest in the Chesapeake Bay watershed, which lies in the north with a basin area of 71,225 sq. km. The climate of the region is temperate and humid (Source: [https://www.chesapeakebay.net/discover/facts](https://www.chesapeakebay.net/discover/facts)). As per the Chesapeake Bay watershed model (Phase 5.3.2 developed by CBP), 23% of the land is used for agriculture, 6.4% is the developed land and the rest of 69.8% is a forest. With the extent of agricultural activities in the watershed and the ongoing effects of climate change, water use and water quality are major issues that must be evaluated. Figure 2-1 shows the Chesapeake Bay watershed and the USGS gage locations used for this study. The Chesapeake Bay watershed is divided into nine sub-basins corresponding to USGS gages located on the major tributaries (Table 2-1, Source: [https://waterdata.usgs.gov/nwis/rt](https://waterdata.usgs.gov/nwis/rt)).

Table 2-1: USGS streamgages used for calibration of the Noah-MP model.

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>USGS Site</th>
<th>Station Name</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Drainage area (sq. km.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1578310</td>
<td>Susquehanna River at Conowingo, MD</td>
<td>-76.175</td>
<td>39.65733</td>
<td>70189</td>
</tr>
<tr>
<td>2</td>
<td>1491000</td>
<td>Choptank River near Greensboro, MD</td>
<td>-75.7858</td>
<td>38.99719</td>
<td>293</td>
</tr>
<tr>
<td>3</td>
<td>1594440</td>
<td>Patuxent River near Bowie, MD</td>
<td>-76.6937</td>
<td>38.95592</td>
<td>901</td>
</tr>
<tr>
<td>4</td>
<td>1646502</td>
<td>Potomac River (Adjusted) near Washington D.C</td>
<td>-77.1275</td>
<td>38.94956</td>
<td>29940</td>
</tr>
<tr>
<td>5</td>
<td>1668000</td>
<td>Rappahannock River near Fredericksburg, VA</td>
<td>-77.5292</td>
<td>38.30846</td>
<td>4134</td>
</tr>
<tr>
<td>6</td>
<td>1674500</td>
<td>Mattaponi River near Beulahville, VA</td>
<td>-77.163</td>
<td>37.88792</td>
<td>1557</td>
</tr>
<tr>
<td>7</td>
<td>1673000</td>
<td>Pamunkey River near Hanover, VA</td>
<td>-77.3322</td>
<td>37.76764</td>
<td>2800</td>
</tr>
<tr>
<td>8</td>
<td>2035000</td>
<td>James River at Cartersville, VA</td>
<td>-78.0858</td>
<td>37.67098</td>
<td>16206</td>
</tr>
<tr>
<td>9</td>
<td>2041650</td>
<td>Appomattox River at Matoaca, VA</td>
<td>-77.4753</td>
<td>37.22515</td>
<td>3481</td>
</tr>
</tbody>
</table>
2.3.2. Noah-MP model and its configuration

The Noah-MP land surface model, with the multi-parameterization scheme, is an improved version of the baseline Noah land surface model (Ek et al., 2003; Niu et al., 2011). Noah-MP has an interactive vegetation canopy layer to compute canopy and ground surface temperatures with an embedded dynamic vegetation model. The choice of multi-parameterization includes several vegetation models (with an option of dynamic vegetation), radiation transfer, runoff, and groundwater schemes. The soil moisture content and its transition from wet to dry periods are largely affected by the runoff mechanism. The runoff schemes in Noah-MP include the infiltration excess - free drainage runoff (Schaake et al., 1996), a saturation excess based TOPMODEL runoff with an equilibrium water table [(Niu et al., 2005); SIMTOP] and a simple TOPMODEL with groundwater model [(Niu et al., 2007); SIMGM]. In SIMTOP, subsurface runoff is represented as an exponential function of water table depth by using a single coefficient to calculate the maximum subsurface runoff volume. The saturated hydraulic conductivity changes with the soil depth and reduces uncertainty in the total runoff preventing the direct alteration of hydraulic conductivity, which dramatically affects other terrestrial hydrological components like evapotranspiration and soil moisture [(Niu et al., 2005); SIMTOP]. The parameterization options used in this study are shown in Table 2-2.

2.3.3. Model Input Data

Datasets needed to parameterize the model include surface albedo from the Moderate Resolution Imaging Spectrometer (MODIS), the green fraction from MODIS, landuse/landcover from United States Department of Agriculture – National Agricultural Statistics Service (USDA, 2018), leaf area index from MODIS, maximum snow albedo, soil type from State Soil Geographic (STATSGO), and soil temperature from WRF Preprocessing System (WPS) data page managed by UCAR (http://www2.mmm.ucar.edu/wrf/users/download/get_sources_wps_geog.html). These datasets are used to configure the Noah-MP HRLDAS (High-Resolution Land Data Assimilation System) model. The meteorological variables that are used to force Noah-MP include precipitation, mean temperature, specific humidity (2 m), wind speed components (10 m), downward longwave and shortwave radiation, and surface pressure.
Table 2-2: Noah-MP configuration

<table>
<thead>
<tr>
<th>Parametrization for different schemes</th>
<th>Option used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic Vegetation</td>
<td><strong>4</strong> <em>(table LAI and maximum vegetation fraction)</em></td>
</tr>
<tr>
<td>Canopy Stomatal resistance</td>
<td><strong>2</strong> <em>[Jarvis; (Jarvis, 1976)]</em></td>
</tr>
<tr>
<td>Soil Moisture factor for controlling stomatal resistance</td>
<td><strong>1</strong> <em>[Noah; (Chen et al., 1996)]</em></td>
</tr>
<tr>
<td>Runoff and groundwater</td>
<td><strong>2</strong> <em>[TOPMODEL with equilibrium water table; (Niu et al., 2005)]</em></td>
</tr>
<tr>
<td>Surface layer drag coefficient</td>
<td><strong>1</strong> <em>[M-O; (Brutsaert, 1982)]</em></td>
</tr>
<tr>
<td>Supercooled liquid water in frozen soil</td>
<td><strong>1</strong> <em>[No iteration; (Niu &amp; Yang, 2006)]</em></td>
</tr>
<tr>
<td>Frozen soil permeability</td>
<td><strong>1</strong> <em>[linear effects; (Niu &amp; Yang, 2006)]</em></td>
</tr>
<tr>
<td>Radiation transfer</td>
<td><strong>3</strong> <em>[two-stream, gap=1-FVEG; (Niu &amp; Yang, 2004)]</em></td>
</tr>
<tr>
<td>Ground snow surface albedo</td>
<td><strong>2</strong> <em>[CLASS; (Verseghy, 1991)]</em></td>
</tr>
<tr>
<td>Partitioning precipitation into rainfall and snowfall</td>
<td><strong>1</strong> <em>[Jordan; (Jordan, 1991)]</em></td>
</tr>
<tr>
<td>Lower boundary condition of soil temperature</td>
<td><strong>2</strong> <em>(original Noah)</em></td>
</tr>
<tr>
<td>Snow/soil temperature time scheme</td>
<td><strong>1</strong> <em>(semi-implicit)</em></td>
</tr>
<tr>
<td>Surface resistance to evaporation/sublimation</td>
<td><strong>1</strong> <em>[Sakaguchi and Zeng; (Sakaguchi &amp; Zeng, 2009)]</em></td>
</tr>
<tr>
<td>Soil properties</td>
<td><strong>1</strong> <em>(Input dominant soil texture)</em></td>
</tr>
<tr>
<td>Crop model</td>
<td><strong>0</strong> <em>(No crop; default dynamic vegetation)</em></td>
</tr>
</tbody>
</table>

The model is set up at a 4 km spatial resolution with the input data forced at a daily time step. Streamflow routing is performed using a stand-alone routing model (Lohmann et al., 1996), based on a unit-hydrograph method that uses daily surface runoff and baseflow to estimate the streamflow at gauge locations. To do this, flow direction and flow accumulation are determined to develop the routing network and then a convolution-based model, based on the D8 flow direction algorithm, is used to route the streamflow at the USGS gaging stations. The digital elevation model (DEM) is hydrologically conditioned, and available at 3-sec spatial resolution, from the USGS Hydrosheids software (https://www.hydrosheds.org/downloads).
2.3.4. Weather data and selection of GCM’s

Historical reference/training dataset:

The METDATA/gridMET dataset [(Abatzoglou, 2013); gridded meteorological daily dataset] is available over the entire domain of conterminous United States (CONUS) and is a high-resolution gridded meteorological dataset available at 1/24-degree spatial resolution from 1979 to 2010. It is developed by combining the temporally rich data from the North American Land Data Assimilation System Phase 2 (NLDAS 2) (Mitchell, 2004; Xia et al., 2012) and spatially rich data from the Parameter-elevation Regressions on Independent Slopes Model [PRISM; (Daly et al., 2008)]. One of the limitations of METDATA is that the source datasets (NLDAS and PRISM) do not account for evaporative cooling effects from agriculture, which implies that METDATA derived potential evapotranspiration (ET₀) estimates have systematic bias inherited from its source (Abatzoglou, 2013; Huntington et al., 2016). Calibration parameters for Noah-MP particular to Chesapeake Bay watershed are estimated by comparing the output from Noah-MP (forced by METDATA from 1980-2010) with several observed and remotely sensed products, described in section 2.3.6.

Bias correction and statistical downscaling:

In this study, the MACA v2-METDATA version [now known as MACA-M; (Abatzoglou & Brown, 2012); http://thredds.northwestknowledge.net:8080/thredds/reacch_climate_CMIP5_macav2_catalog2.html] is used which is statistically downscaled and bias-corrected with METDATA as a training dataset for the entire CONUS using the constructed analogs (CA) method. MACA v2-METDATA is relevant to this study as it provides a complete set of inputs to Noah-MP including precipitation, minimum and maximum temperature, solar radiation, specific humidity, and wind speed components. The CA method is developed to match the patterns between the synoptic-scale field of Global Climate Models (GCM) and the set of observation patterns (Hidalgo et al., 2008). In simple terms, weather patterns today or in the future corresponds to or exactly replicates the weather pattern following the time of the exact analog in the historical record (van den Dool, 1994; van den Dool et al., 2003). MACA (Multivariate Adaptive Constructed Analogs) uses the same approach except that it uses a multivariate analog search to improve
coherence across downscaled fields. The GCM data are bias-corrected using the quantile mapping approach by spatially interpolating the data to the downscaled grid (Maurer et al., 2010). The epoch adjustment is used to avoid no analogs situations under future climate scenarios by removing the differences between the mean of future time slices and historical time slices on a 21-day moving window and adding or multiplying to the respective downscaled fields. Analogs were constructed from GCM’s by identifying the 30 best predictor patterns as a single field or linear combinations that are matched with a library of observed patterns from METDATA falling within 45 days of the target date. Finally, epoch adjustment and bias correction are again performed to ensure statistical moments between historical observations and GCM’s historical predictions are preserved.

The MACA dataset consists of 20 different GCM’s from the Coupled Model Intercomparison Project 5 [CMIP5; (Taylor et al., 2012)] that includes data from different periods and two future scenarios: historical (1950-2005), and two Representative Concentration Pathways (RCPs): 4.5 (increase in radiation by 4.5 W/m² by 2100), and 8.5 (increase in radiation by 8.5 W/m² by 2100) from 2006 to 2100. For this study, two RCPs, 4.5 and 8.5 are selected, representing business as usual greenhouse gas emissions, and worst-case greenhouse gas emissions, respectively, where each RCP includes historical data (1976-2005) and two future periods, 2021-2050 (near future) and 2061-2090 (distant future).

2.3.5. Selection of GCM’s

To select representative GCMs a series of indices are calculated that compare historical GCM predictions against the METDATA. Precipitation indices including the Annual Maximum Precipitation (AMP), Mean Annual Precipitation (MAP), frequency of precipitation (P-FREQ), and heavy to non-heavy precipitation ratio (H-NH) are calculated for both the statistically downscaled GCMs and the METDATA (Mishra et al., 2014). Annual Maximum Precipitation for each year is the highest magnitude event for each year during the reference period of 1981-2005. Frequency of precipitation is estimated as the number of precipitation events above 99th percentile during the reference period, whereas heavy to non-heavy precipitation ratio is estimated by calculating the ratio of total precipitation due to heavy events (> 99th percentile) and total precipitation due to non-
heavy events (> 1 mm) during the reference period. The top six performing models are selected for use in this study. Table 2-3 shows the relative bias of all GCM for each precipitation index and the best performing models in bold. The six best performing models are identified by ranking each model within each index from least to most biased followed by the sum of ranks. CSIRO-Mk3-6-0 is one of the best performing models that shows the least overall relative bias for all the precipitation indices. Some of the other GCM’s like CCSM4, CNRM-CM5, and HadGEM2-ES365 also indicate good performance when compared with METDATA.

Table 2-3: Relative bias for all precipitation indices for the available 20 MACA-based GCMs. Numbers in bold indicate 6 best performing models. Bias values are with respect to METDATA (1981-2005).

<table>
<thead>
<tr>
<th>Global Climate Models</th>
<th>AMP (%)</th>
<th>MAP (%)</th>
<th>P-FREQ (events/year)</th>
<th>H-NH (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>bcc_csm1_1</td>
<td>8.09</td>
<td>0.30</td>
<td>-0.033</td>
<td>5.88</td>
</tr>
<tr>
<td>bcc_csm1_1_m</td>
<td>19.05</td>
<td>6.60</td>
<td>-0.058</td>
<td>6.96</td>
</tr>
<tr>
<td>BNU_ESM</td>
<td>12.96</td>
<td>3.59</td>
<td>-0.079</td>
<td>2.45</td>
</tr>
<tr>
<td>CanESM2</td>
<td>5.22</td>
<td>3.13</td>
<td>-0.056</td>
<td>-2.09</td>
</tr>
<tr>
<td>CCSM4</td>
<td>6.47</td>
<td>0.15</td>
<td>-0.046</td>
<td>2.81</td>
</tr>
<tr>
<td>CNRM_CM5</td>
<td>6.38</td>
<td>1.21</td>
<td>-0.084</td>
<td>-0.62</td>
</tr>
<tr>
<td>CSIRO_Mk3_6_0</td>
<td>1.03</td>
<td>-0.52</td>
<td>-0.038</td>
<td>-0.99</td>
</tr>
<tr>
<td>GFDL_ESM2G</td>
<td>10.89</td>
<td>1.92</td>
<td>-0.082</td>
<td>4.48</td>
</tr>
<tr>
<td>GFDL_ESM2M</td>
<td>12.52</td>
<td>2.40</td>
<td>-0.084</td>
<td>2.32</td>
</tr>
<tr>
<td>HadGEM2_CC365</td>
<td>6.35</td>
<td>0.82</td>
<td>-0.083</td>
<td>1.24</td>
</tr>
<tr>
<td>HadGEM2_ES365</td>
<td>5.06</td>
<td>0.98</td>
<td>-0.062</td>
<td>-1.32</td>
</tr>
<tr>
<td>Inmcm4</td>
<td>11.03</td>
<td>2.21</td>
<td>-0.091</td>
<td>2.69</td>
</tr>
<tr>
<td>IPSL_CM5A_LR</td>
<td>6.72</td>
<td>2.34</td>
<td>-0.030</td>
<td>1.98</td>
</tr>
<tr>
<td>IPSL_CM5A_MR</td>
<td>8.30</td>
<td>1.21</td>
<td>-0.087</td>
<td>1.21</td>
</tr>
<tr>
<td>IPSL_CM5B_LR</td>
<td>7.45</td>
<td>0.86</td>
<td>-0.082</td>
<td>-1.75</td>
</tr>
<tr>
<td>MIROC5</td>
<td>9.82</td>
<td>1.36</td>
<td>-0.047</td>
<td>5.54</td>
</tr>
<tr>
<td>MIROC_ESM</td>
<td>9.06</td>
<td>1.48</td>
<td>-0.085</td>
<td>-0.86</td>
</tr>
<tr>
<td>MIROC_ESM_CHEM</td>
<td>13.94</td>
<td>0.89</td>
<td>-0.085</td>
<td>4.43</td>
</tr>
<tr>
<td>MRI_CGCM3</td>
<td>15.10</td>
<td>2.98</td>
<td>-0.080</td>
<td>3.60</td>
</tr>
<tr>
<td>NorESM1_M</td>
<td>12.35</td>
<td>3.65</td>
<td>-0.076</td>
<td>0.20</td>
</tr>
</tbody>
</table>
Three out of the six GCM’s (CCSM4, CSIRO-Mk3-6-0, IPSL-CM5A-LR) chosen are similar to the work of Maloney et al. (2014) and Sheffield et al. (2013) that ranked and analyzed the GCMs based on the bias with the observed precipitation and air temperature and which was later adapted by Wagena & Easton (2018) to study the impacts of climate change on agricultural conservation practices in Susquehanna River Basin in Chesapeake Bay watershed. There is no significant difference observed between the spatial plots of precipitation indices like AMP and MAP as the statistical moments of GCM’s are preserved during the downscaling and bias correction. Precipitation indices related to extreme events like P-FREQ and H-NH show a significant difference in the spatial patterns among the different GCM’s when compared to METDATA providing further confidence in identifying the best performing GCM’s. Spatial plots indicating the different precipitation indices and their relative bias with respect to METDATA for six best performing GCMs are included in Appendix A (Figure A-1 and Figure A-2 respectively). Although the GCM’s used are statistically downscaled and bias-corrected, the inter-model variation introduces uncertainty in future projections. To reduce the range of uncertainty, six best performing GCMs are selected based on the precipitation indices with respect to the baseline METDATA. The importance of temperature is excluded from the selection of GCMs as they have a narrow range of uncertainty among the models with all of them showing a consistently increasing trend in future climate scenarios.

2.3.6. Calibration and Evaluation of Noah-MP

Noah-MP is calibrated for the water balance components including streamflow, evapotranspiration, and soil moisture. Monthly streamflow is calibrated for each of the nine stations (Table 2-1) in CBW with the USGS streamflow measurements from 1995-2001 and evaluated from 2002-2008 to ensure good model performance. Two evaluation metrics are used, the Nash Sutcliffe Efficiency (NSE) and the coefficient of determination ($R^2$) to evaluate model performance. NSE usually ranges from $-\infty$ to +1, where positive values (NSE>0) indicate better model predictions and negative values indicate low accuracy model predictions. NSE greater than 0.6 indicates quality predictions and acts as a threshold for good model performance. NSE at each gaging station depends on the input forcing data, static model data, and model parametrization. The Theil-Sen slope estimator
is used to estimate the trend and slope for each of the terrestrial hydrological components in the future periods relative to the baseline scenario. This non-parametric technique chooses the median slope among the lines generated through pairs of two-dimensional sample points and computes trends insensitive to the outliers. The model was calibrated and run on the Computational Information Systems Laboratory (CISL, UCAR/NCAR) supercomputing facilities. For better model performance, Noah-MP (forced by METDATA) is calibrated and evaluated using available observed and derived products. A manual sub-basin calibration is performed using a combination of literature values and expert judgment for the nine sub-basins (in Table 2-1) as described in Table 2-4. Some parameters are distributed throughout the study area and some are multiplier values rather than the replacement values. The topographic mean in the SIMTOP runoff routine affects the partitioning of total excess moisture into surface runoff and baseflow and varies for each sub-basin.

Table 2-4: Calibration parameters for Noah-MP. The numbers in bold indicate multiplier values and the rest are replacement values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Units</th>
<th>Distributed</th>
<th>Min</th>
<th>Max</th>
<th>Actual value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMCMAX (SOILPARM.TBL)</td>
<td>Soil porosity</td>
<td>m³ m⁻³</td>
<td>Yes</td>
<td>0.7</td>
<td>1.2</td>
<td>0.7</td>
</tr>
<tr>
<td>DKSAT (SOILPARM.TBL)</td>
<td>Saturated soil hydraulic conductivity</td>
<td>m s⁻¹</td>
<td>Yes</td>
<td>0.001</td>
<td>1.5</td>
<td>0.01</td>
</tr>
<tr>
<td>BEXP (SOILPARM.TBL)</td>
<td>Pore size distribution index</td>
<td>-</td>
<td>Yes</td>
<td>0.5</td>
<td>1.25</td>
<td>0.6</td>
</tr>
<tr>
<td>TIMEAN (setup file)</td>
<td>Mean Topographic index</td>
<td>-</td>
<td>Yes (manually integrated)</td>
<td>7.5</td>
<td>12</td>
<td>Basin-dependent</td>
</tr>
<tr>
<td>RS (MPTABLE.TBL)</td>
<td>Minimum stomatal resistance</td>
<td>s m⁻¹</td>
<td>Yes</td>
<td>0.2</td>
<td>1.2</td>
<td>0.2</td>
</tr>
<tr>
<td>FFF (source code)</td>
<td>Runoff decay factor</td>
<td>m⁻¹</td>
<td>No</td>
<td>1</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>RSBMX (source code)</td>
<td>Baseflow coefficient</td>
<td>mm s⁻¹</td>
<td>No</td>
<td>0.5</td>
<td>8</td>
<td>3</td>
</tr>
</tbody>
</table>

Noah-MP by default has a single value for topographic index throughout the domain but by manually configuring an additional layer of the topographic index into setup
file and code, the topographic index mean for each sub-basin is delineated. The topographic index mean is further calibrated for each sub-basin based on the water balance components. Streamflow is calibrated by adjusting parameters like runoff decay factor (FFF), baseflow coefficient (RSBMX), topographic index (TIMEAN), saturated hydraulic conductivity (DKSAT), and maximum soil moisture level (SMCMAX). ET is calibrated by adjusting the vegetation parameters including stomatal resistance (RS), and soil parameters including pore size distribution index (BEXP). For ET, model predictions are compared to the remotely sensed USGS SSEBop dataset from 2002-2008 (Senay et al., 2013). SSEBop method is based on the Simplified Surface Energy balance model that estimates ET using predefined boundary conditions between hot and cold reference values for each grid. SCAN [Soil Climate Analysis Network; (Schaefer et al., 2007)] station data led by the United States Department of Agriculture (USDA)/National Resources Conservation Service (NRCS) are used for calibrating the soil moisture of the top 10 cm layer. Five stations throughout the CBW are used to evaluate model performance from 2002-2008 using the coefficient of determination ($R^2$) and Root Mean Squared Error (RMSE). Soil moisture is calibrated using a combination of calibration parameters of ET and streamflow that includes the maximum soil moisture (SMCMAX) and pore size distribution index (BEXP).

2.3.7. Crop types and growing season

In this study, the USDA 2018 cropland data layer (CDL) with a 30 m spatial resolution is used which has multiple agricultural and non-agricultural land cover classes. The classes from CDL are reassigned to the MODIS Noah International Biosphere-Geosphere Programme (IGBP) scheme [21 classes; (Strahler et al., 1999)] by grouping them as agricultural or non-agricultural classes. The CB watershed has two dominant crop types (corn & soybeans) which are predominantly located on the Delmarva Peninsula (East coast of Maryland, Delaware, and Virginia) and in York and Lancaster County in Pennsylvania. As per the statistics from USDA, the CB watershed contains 1.25 million hectares of corn and 0.78 million hectares of soybeans. The CDL is resampled to the model’s spatial resolution using a maximum likelihood method of 30 m pixels in each 4 km grid cell. At 4 km model resolution, the maximum agricultural area derived is
approximately 55% for both corn and soybeans of the actual USDA acreage. The decrease in the crop acreage is because the 4 km grid cells in Noah-MP landcover are aggregated based on the neighboring algorithm. This decrease in acreage can be resolved by increasing the spatial resolution of the land surface model but this study estimates the NIWR which is strongly dependent on the overall climatic conditions.

Based on the USDA (2010), the typical planting and harvesting dates are obtained for both corn and soybeans (Table 2-5 and Table 2-6). From the estimated daily crop coefficients (as described in section 2.3.8) and the planting and harvesting dates, the initial crop growth stage, the crop development stage, the mid growth stage, and the harvest period are defined for both crops. The dates were in a similar range for all the states for both corn and soybeans, which allowed us to develop a single crop coefficient curve for each crop over the entire CB watershed.

Table 2-5: Planting and harvesting dates for corn in the states constituting Chesapeake Bay watershed (USDA-NASS, 2010).

<table>
<thead>
<tr>
<th>State</th>
<th>Planting dates</th>
<th>Harvesting dates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>\textit{Begin}</td>
<td>\textit{Most Active}</td>
</tr>
<tr>
<td>Delaware</td>
<td>Apr 12</td>
<td>Apr 30-May 16</td>
</tr>
<tr>
<td>Maryland</td>
<td>Apr 20</td>
<td>Apr 30-May 20</td>
</tr>
<tr>
<td>Virginia</td>
<td>Apr 5</td>
<td>Apr 11-May 20</td>
</tr>
</tbody>
</table>

Table 2-6: Planting and harvesting dates for soybeans in the states constituting Chesapeake Bay watershed (USDA-NASS, 2010).

<table>
<thead>
<tr>
<th>State</th>
<th>Planting dates</th>
<th>Harvesting dates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>\textit{Begin}</td>
<td>\textit{Most Active}</td>
</tr>
<tr>
<td>Maryland</td>
<td>May 11</td>
<td>May 28-Jun 26</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>May 10</td>
<td>May 20-Jun 10</td>
</tr>
<tr>
<td>Virginia</td>
<td>May 5</td>
<td>May 15-Jul 3</td>
</tr>
</tbody>
</table>
A fixed growth duration is considered for both the crops instead of the varying growth duration calculated using GDD (Growing Degree Days). The varying growth duration is driven by both climatic changes as well as technological advancement in agronometrics which necessitates the use of crop models to generate various scenarios based on historical records of management practices. Considering either of the univariate scenarios (in case of varying growth duration) to derive the change in growing duration length might mislead the estimates of crop NIWR (Sacks & Kucharik, 2011). It should also be noted that the underestimation or overestimation of the growing duration length for future periods can lead to incorrect NIWR estimates. In this study, the change in crop cultivars with time is considered by keeping the growing duration length similar in historical and future periods.

2.3.8. Current and Future Net Irrigation Water Requirement (NIWR)

The Net Irrigation Water Requirement is calculated using the FAO CROPWAT approach from Smith (1992). NIWR is determined as the difference between crop evapotranspiration ($ET_C$) and effective rainfall ($P_{eff}$).

\[
NIWR = ET_C - P_{eff}
\]

\[
ET_C = PET * K_C * B_C * C_D
\]

\[
P_{eff} = P - TR - \Delta S
\]

Where $P_{eff}$ is the effective rainfall (mm/day), $ET_C$ is the crop evapotranspiration (mm/day), $PET$ is the potential evapotranspiration (mm/day), $K_C$ is the 10-day mean daily crop coefficient, $B_C$ is the monthly bias correction factor, $P$ is the total precipitation (mm/day), $TR$ is the total runoff including surface runoff and baseflow (mm/day), $C_D$ is the carbon dioxide ($CO_2$) correction factor and $\Delta S$ is the change in soil moisture (mm/day). In this study, the NIWR is calculated using the crop IWR equation (Equation 1) where the components (used in equations 2 & 3) are calculated using from Noah-MP that can be
scaled globally and applied in developing agricultural regions. $P_{\text{eff}}$ is estimated using the water fluxes from the Noah-MP land surface model that includes surface runoff, baseflow, and change in soil moisture. However, the uncertainty in $P_{\text{eff}}$ due to the underestimation of the acreage is not considered in this study as it might not have a huge impact on the overall mean NIWR estimates from CB watershed. PET is calculated from the energy fluxes of Noah-MP that use the Penman-Monteith equation with inputs as precipitation, air temperature, relative humidity, wind speed, air pressure, and incoming radiation.

Daily crop coefficients are determined by calculating the ratio of NOAA global reference evapotranspiration ($ET_0$) and USGS SSEBop actual ET. The $ET_0$ estimations are based on Global Data Assimilation System (GDAS) drivers from (Senay et al., 2008), who used ASCE’s standard Penman-Monteith formulation to derive $ET_0$ estimates using Modern-Era Retrospective Analysis for Research and Application (MERRA2) Reanalysis product. The ratio is estimated from 2000-2017 and is averaged over the years (2000-2017) to get a daily crop coefficient. To reduce the uncertainty due to precipitation variability, a 10-day moving mean is used.

Monthly bias correction factors are calculated by taking the ratio of METDATA derived $ET_0$ estimates (from Noah-MP) and NOAA reference evapotranspiration from 2000-2017 and are multiplied with projections from GCM’s $ET_0$ estimates (Huntington et al., 2016). Using the ET Demands approach of instating the potential effects of rising CO$_2$ in future periods, the stomatal conductance sensitivity functions developed by Kruijt et al. (2008) for C$_3$ and C$_4$ crops are used. As suggested by Huntington et al. (2016), the CO$_2$ correction factors for the respective C$_3$ (soybeans) and C$_4$ (corn) crops are used at daily time steps for both RCP 4.5 and RCP 8.5. These accounts for the impacts of rising CO$_2$ on stomatal aperture, transpiration, and crop production processes. The impacts of carbon dioxide levels in future scenarios are accounted for by using the carbon dioxide correction factors that correct for transpiration in future periods.

The stomatal conductance is suppressed by elevated CO$_2$ levels thereby decreasing the water loss and hence the evaporative demand. The impacts of CO$_2$ levels on evapotranspiration are not well understood and needs further research. However, field
experiments have reported suppression of stomatal leaf conductance due to elevated CO$_2$ levels (Medlyn et al., 2001; Ainsworth & Rogers, 2007) which has been accounted for through the use of carbon dioxide correction factor.

2.4. Results and Discussion

2.4.1. Model performance evaluation

Figure 2-2 shows the calibration (left; 1995-2001) and evaluation (right; 2002-2008) of streamflow for the Noah-MP model. All stations except Choptank have NSE values and $R^2$ greater than 0.6 for both calibration and evaluation periods signifying good model performance over the entire CB watershed. The Choptank is dominated by groundwater flow due to the presence of shallow unconfined aquifers and short groundwater recharging paths (Sun et al., 2017). The streamflow is highly sensitive to the partitioning of input precipitation and soil parameters such as saturated hydraulic conductivity. The SIMTOP runoff scheme used in this study is governed by the topographic index of the respective sub-basin, runoff decay factors, and the baseflow coefficient, which differ substantially between the majority of the basin and the coastal plain Choptank.

Figure 2-3 shows the difference between the model predicted ET and actual ET from the USGS. ET is underestimated by 10-15 % in the Coastal plain region and over predicted by 40 % in the urban areas, which can be attributed to a simple urban scheme used in the study that does not provide reliable estimates of ET. ET is obtained as a sum of three components in Noah-MP that constitutes evaporation of canopy intercepted water ($E_{\text{CAN}}$), transpiration ($E_{\text{TRAN}}$), and soil surface evaporation ($E_{\text{DIR}}$). $E_{\text{CAN}}$ and $E_{\text{TRAN}}$ are dominated by the forest regions whereas croplands have higher direct soil surface evaporation ($E_{\text{DIR}}$). Figure 2-4 shows the comparison between the modeled soil moisture (top 10 cm layer) and the observed SCAN soil moisture for five locations with the $R^2$ and RMSE. The left panels show a temporal series of soil moisture from 2002-2008 whereas the middle panels display the seasonal climatological cycle from 2002-2008 and the right panel shows the sites georeferenced in the study area.
Figure 2-2: Monthly calibration (left to the dotted line; 1995-2001) and evaluation (right to the dotted line; 2002-2008) of streamflow with USGS streamflow gage data for nine stations in Table 2-1. Note the different scales for Y-axis (streamflow).
Figure 2-3: a) shows annual actual evapotranspiration from Noah-MP model (2002-2008), b) shows annual actual evapotranspiration from USGS SSEBop model (2002-2008) and c) shows relative bias between b) and a) [(a-b)/b] *100].

As indicated in the table from Figure 2-4, all model predictions show $R^2 > 0.6$ and RMSE $< 0.1$. The time-series data shows that the model tends to have a much more damped response than observed. The top 10 cm soil moisture layer is highly sensitive to the seasonality of precipitation and its partitioning. Indeed, Cai et al. (2014) showed similar soil moisture predictions in the Northeast region, a damped response to drying and wetting conditions. However, Yang et al. (2011), Cai et al. (2014), and Zhuo et al. (2019) all showed much better model predictions of soil moisture when conditions were less variable. The uncertainty in model output is also introduced due to underlying assumptions of the Noah-MP land surface models for different parametrization schemes. The use of different combinations of multi-parameterization schemes can lead to multiple model ensembles which can be used to derive the range of model uncertainty.
Figure 2-4: Temporal series of soil moisture (left; 2002-2008) and the seasonal climatological cycle of soil moisture (right; 2002-2008) at five locations – a) Mahantango Creek, PA; b) Rock Springs, PA; c) N Piedmont Arec, VA d) Powder Mill, MD, and e) Shenandoah, VA. The statistics are displayed in the table on the bottom right.
2.4.2. Changes in Terrestrial Hydrologic Variables

Figure 2-5 (a-c) shows the average monthly change and inter-model variation in the precipitation (%), 2 m air temperature [K], and evapotranspiration (%) respectively across the six selected GCMs. Figure 2-5 (a) depicts the monthly precipitation change and inter-model variation. Precipitation increases by 9 % and 10 % in RCP 4.5 and RCP 8.5 scenarios in the 2061-2090 period as compared to the historical period (1976-2005). Interestingly, a consistent increase of 7.5 % in precipitation is observed across all models for RCP 4.5 in the 2021-2050 period whereas there is greater uncertainty of ±20 mm/month among the RCP 8.5 model scenarios with an overall mean change of 6 % in the 2021-2050 period. A larger mean difference is observed during the winter and spring seasons while greater variation is observed during the summer and fall seasons for both RCP 4.5 and RCP 8.5. Likewise, a lower inter-model variation of ±5 mm/month is observed during the historical period for the winter and spring seasons as compared to the higher inter-model variation during the future period for the summer and fall seasons. From the spatial plots of precipitation in Appendix B (Figure B-1), a consistent increase is observed in the Appalachian Plateau and Valley region across all GCM’s and scenarios. However, a decrease in overall mean precipitation in the RCP 8.5 scenario during the 2021-2050 period is due to a decrease in precipitation in Pennsylvania and the lower portion of the Chesapeake Bay watershed.

As shown in Figure 2-5 (b), an overall increase of 2.8 K and 4.5 K is observed in RCP 4.5 and RCP 8.5 scenarios respectively for the 2061-2090 period. Similar to precipitation, higher inter-model variation ±2 K is seen during the summer and fall for the RCP 8.5 scenario for the 2061-2090 period. Based on the spatial plots of air temperature in Appendix B (Figure B-1), the change is uniform throughout the Chesapeake Bay watershed. Evapotranspiration is sensitive to both temperature and precipitation, and therefore climate change results in an increase of 12 % and 18 % on average in RCP 4.5 and RCP 8.5 scenarios for the 2061-2090 period [Figure 2-5 (c)]. A substantial change of 9 % is observed for the 2021-2050 period for both RCP 4.5 and RCP 8.5 scenarios.
Figure 2-5: Box plots (a-c) representing the climatological monthly uncertainty and change for historical and future scenarios for precipitation, 2m air temperature, and evapotranspiration respectively for six GCM. The values in box brackets indicate an overall change with respect to the mean of historical data from 1976-2005 and ‘x’ denotes the mean.
Figure 2-6: shows the annual change (mean and one standard deviation as ribbon) for historical and future scenarios. The change is with respect to the mean of historical data from 1976-2005. The values colored indicate the Sen’s slope for the respective scenarios. The units for SS are mm/yr, K/yr, and mm/yr for d-f respectively.
The change in evapotranspiration is also affected by the selection of runoff scheme and calibration parameters for soil and vegetation in the model. Figure 2-6 (a-c) represents the annual change relative to the historical mean from 1976-2005 along with the Sen’s slope (Theil-Sen's estimator) for each scenario across the six GCM’s. Figure 2-6 (a) illustrates the increasing trends for all precipitation scenarios except for RCP 4.5 that indicates the decreasing trend towards the end period with a Sen’s slope value of -0.99. Figure 2-6 (b) shows a consistent increase in temperature for both RCP 4.5 and RCP 8.5 with a similar Sen’s slope of 0.06 for the 2021-2050 and 2061-2090. However, a plateau in precipitation is observed in the RCP 4.5 scenario towards the end period with a non-significant Sen’s slope. The change in evapotranspiration Figure 2-6 (c) depends on the change in precipitation and temperature that can be observed in Figure 2-6, where the decrease in precipitation (SS: -0.99) and constant Sen’s slope for temperature (0.01) in RCP 4.5 scenario lead to a uniform change in evapotranspiration (SS: 0.02) for the 2061-2090 period.

Figure 2-7 (a) shows the mean annual soil moisture averaged across all GCM’s for the historical period (1976-2005). Figure 2-7 (b-e) depicts the change in soil moisture for RCP 4.5 (2021-2050 and 2061-2090) and RCP 8.5 (2021-2050 and 2061-2090) scenarios respectively. A decrease in soil moisture is observed throughout the Chesapeake Bay watershed with a maximum decrease of 5 % on the Delmarva Peninsula. Based on the box plots of soil moisture in Figure 2-7 (g), an overall decrease of 1 % and 3.5 % is observed in RCP 4.5 and RCP 8.5 scenarios respectively for the 2061-2090 period. The change remains uniform for RCP 4.5 and RCP 8.5 for both the 2021-2050 and 2061-2090 periods, respectively with Sen’s slope of 0.02 and -0.003 as shown in Figure 2-7 (f). The soil moisture decreases at a constant rate of 0.07 and 0.09 for RCP 4.5 and RCP 8.5 for the 2021-2050 and 2061-2090 periods, respectively. Figure 2-8 (a-i) shows the monthly uncertainty and change in streamflow for nine stations (Table 2-1) in historical and future scenarios. Most of the stations indicate a decrease in streamflow in summer whereas an increase in streamflow in winter for both future scenarios in 2061-2090.
Figure 2-7: Spatial plots representing soil moisture (kg kg\(^{-1}\)) in the historical period (1976-2005) [a]. b-e represents a change in soil moisture (%) for RCP 4.5 (2021-2050; 2061-2090) and RCP 8.5 (2021-2050; 2061-2090) scenarios respectively. f shows the annual change (mean and standard deviation as ribbon) in soil moisture. The values in panel f show the Sen’s slope for the respective scenarios. The unit for SS is kg kg\(^{1}\)/yr.
28 Figure 2-8: Box plots (a-i) representing the climatological monthly uncertainty and change for historical and future scenarios for streamflow at nine stations (Table 2-1) for six GCM’s. The values in box brackets indicate an overall change with respect to the mean of the historical data from 1976-2005 and ‘x’ denotes the mean.
Interestingly, an overall increase of 2 % in streamflow is observed in the RCP 4.5 scenario for 2021-2050 while an overall decrease of 5 % in streamflow is observed in the RCP 8.5 scenario for 2061-2090. Higher uncertainty and change are observed from February to April especially for the Susquehanna basin that shows a decrease of 30 % in streamflow in the RCP 8.5 scenario (2061-2090) as compared to the historical period (1976-2005). Hawkins (2015) used CMIP3 and CMIP5 climate projections to simulate the changes in streamflow and hydrological cycle in Chesapeake Bay watershed and concluded an overall increase of 1.9 % to 5.4 % in annual air temperature, an increase between 5.2 % and 15.2 % in annual total precipitation and a decrease of up to 5.1 % in annual runoff in 2080-2099 which conforms with the results from this study.

### 2.4.3. Current and Future Net Irrigation Water Requirement

As described in section 2.3.8, the daily crop coefficient is calculated using the ratio of PET from NOAA and actual ET from USGS SSEBop. The estimated ratios are averaged over the crop growth periods described in Table 2-5 (corn) and Table 2-6 (soybeans) to derive the crop coefficients (Figure 2-9). Figure 2-10 illustrates the daily crop coefficient curve for corn and soybeans with a 10-day moving mean. The corn [Figure 2-10 (a)] and soybeans [Figure 2-10 (b)] have similar $K_C$ patterns but with different planting and harvesting dates. These $K_C$ values are similar to the values determined by Allen et al. (1998), who found average $K_{C[MID]}$ values of 1.15 for corn, and 1.20 for soybeans.

The NIWR is calculated for both corn and soybeans by using the daily crop coefficient, effective rainfall, and potential evapotranspiration from the MACA based GCMs (equation 1). An overall decrease is observed in NIWR for both corn and soybeans dominated pixels. For the 2061-2090 period, an overall decrease of 4 % and 13 % in NIWR for corn is observed, which is consistent with the decrease in the Sen’s slope of - 4 and - 19, under the RCP 4.5 and RCP 8.5 scenarios, respectively [Figure 2-11 (a-b)]. A similar trend is observed for soybeans indicating an overall decrease in NIWR of 6 % and 17 % in RCP 4.5 and RCP 8.5 scenarios for the 2061-2090 period, respectively [Figure 2-11 (c)]. The NIWR ranges from 50 mm/month during the initial crop growth phase to 100 mm/month during the peak crop growth phase.
**Figure 2-9:** Crop coefficients representing the average over Initial (a-b); Development (c-d); Middle (e-f) and Harvesting (g-h) period for corn and soybeans respectively.

**Figure 2-10:** Daily crop coefficient for corn and soybeans respectively with a 10-day moving mean representing crop growth stages along with Julian day.
Figure 2-11: Annual change (mean and one standard deviation, shading) in NIWR for corn and soybeans respectively (a and c). The in panels a and c indicate the Sen’s slope for the respective scenarios. Boxplots (b and d) represent the monthly change and inter-model variation for crops and soybeans respectively. The values in box brackets indicate the change relative to historical data (1976-2005). The SS unit for NIWR is m³/ha/yr.

As shown in Figure 2-12, the NIWR for both crops decreases due to an increase in the effective precipitation in RCP 4.5 and RCP 8.5 scenarios. The change in NIWR is sensitive to the change in total runoff whereas the change in soil moisture does not appear to impact the NIWR substantially. The overall precipitation tends to increase leading to a decrease in NIWR, however, a concomitant increase in temperature, which increases ET, results in very little net change to soil moisture. The change in NIWR is observed during the initial growing period where an increase in precipitation leads to higher crop evapotranspiration in the future periods. Total runoff also decreases during the middle and development growing periods due to increased crop evapotranspiration. Differences between the model spatial resolution and cropland data layer lead to the underestimation of irrigation water requirements. However, a weighted average of the number of cropland pixels (250 m) in each 4 km model grid leads to a better representation of the agricultural area in this study.
Figure 2-12: Different water balance components illustrating the estimation of NIWR (Equation 1). The top and bottom plots represent corn and soybeans respectively for historical (a) and future scenarios (b-e).

2.5. Conclusion

A mesoscale evaluation of terrestrial hydrologic components and how those components impact the NIWR due to climate change in the Chesapeake Bay watershed is conducted. NIWR is an important tool in understanding future water availability and developing mitigation strategies. The Noah-MP has been used to assess the change in the terrestrial hydrological components in future RCP scenarios relative to the historical period. Through the use of available evapotranspiration products, daily crop coefficients for corn and soybeans are generated. The impacts of carbon dioxide levels on crop coefficients in future scenarios are accounted for by using the CO$_2$ correction factor considering the soybeans as C$_3$ and corn as C$_4$ crops. FAO CROPWAT approach is then
used to calculate the NIWR for the pixels dominating corn and soybeans. The results suggest an increase in precipitation and temperature over the entire Chesapeake Bay watershed for both RCP 4.5 and RCP 8.5 scenarios in future periods, resulting in an overall increase of 18 % in evapotranspiration and an overall decrease of 5 % in streamflow for the 2061-2090 period for the RCP 8.5 scenario. The increase in effective precipitation due to increased rainfall accompanied by a concomitant increase in temperature leads to a decrease of 13 % and 17 % in NIWR for corn and soybeans respectively in the RCP 8.5 scenario for 2061-2090. Future studies can focus on using high spatial resolution models to account for maximum acreage of croplands and estimate the water balance components accurately. Improved gridded evapotranspiration products can help accurately derive the daily crop coefficients for different crops on a grid-by-grid basis, refining the NIWR estimates.
Chapter 3: Impacts of climate change on flood inundation along Susquehanna River near Harrisburg, Pennsylvania

3.1. Abstract

Several flooding events over the last several decades have led to extensive damages in the communities along the Susquehanna River. One such flood-prone region is the City of Harrisburg in Pennsylvania, where the damages during the 1972 flood from storm Agnes and 2011 flood from storms Irene and Lee were severe, with over $2 billion damage to infrastructure. With changing climatic conditions, it is important to assess the flood risk and the associated uncertainty of flood events in flood-prone regions along the Susquehanna River. The impact of climate change on flood inundation depth and extent is evaluated using a 2D HEC-RAS model along a 41 km long reach in Susquehanna River including the area of Harrisburg, Pennsylvania. To calibrate and evaluate the model, simulations of peak streamflow events in each water year from 2008 to 2019 are compared against the available USGS streamgage data (01570500) at Harrisburg, PA. To ensure adequate model performance, the simulated water-surface elevations from the major flood events are evaluated with the observed high-water marks and flood profiles available in the literature. The streamflow data for different future scenarios are derived from a hydrologic land surface model that is forced by the long-term simulations from the MACA-based Global Climate Models (GCM) dataset. Finally, the flood inundation depth and extent of the 30-yr and 100-yr flood events are compared based on the historic and future (scenario-based) annual peak-discharge estimates at USGS streamgage. These flood inundation maps show how the long-term change in precipitation and temperature can impact the flood potential in the Harrisburg, PA region. These maps are useful for flood management operations and prioritizing mitigation efforts.

Keywords: HEC-RAS, flood inundation, climate change, water-surface elevation, flood depth, Global Climate Models (GCM)
3.2. Introduction

The impacts of climate change are strongly driven through the change in temperature and precipitation that affects ecosystems, agriculture, human wellbeing in the form of climate hazards (IPCC, 2007). The frequency of heavy precipitation events has increased over the past several decades in the U.S. Northeast with further increases expected (Groisman et al., 2004). Hayhoe et al. (2007) calculated a 10-15 % increase in winter precipitation depth in the U.S. Northeast and no decrease in summer precipitation using 9 Global Climate Models (GCMs). Najjar et al. (2009) also projected an increase of 7-15 % in winter and spring precipitation throughout the mid-Atlantic region using a multi-model ensemble of GCMs. This increase in precipitation is accompanied by the risk of severe flooding in major rivers that include the Penobscot, Connecticut, Hudson, Delaware, and Susquehanna. Extreme precipitation has a major impact on streamflow and is one of the key factors responsible for riverine and urban flash floods.

Increasing global population and development in river corridors have increased susceptibility to flooding. As reported by the Susquehanna River Basin Commission (SRBC), the Susquehanna is one of the most flood-prone basins in the Chesapeake Bay watershed and the mid-Atlantic region of the United States. The National Weather Service (NWS) has dedicated forecasting services to predict floods and issue warnings to regions at risk of harm to humans and property. According to the information provided by the Susquehanna Flood Forecast and Warning System (SFFWS), there have been fourteen major floods since 1810. Tropical Storm Agnes in 1972 was the largest flood of all time in the Susquehanna River that claimed around seventy-two lives and resulted in an estimated $2.8 billion in damages. Recently, the Susquehanna River was hit by the Tropical Storm Lee in 2011 that flooded the lowland areas along the floodplain. The majority of the floods have affected the communities along the Susquehanna mainstem and the City of Harrisburg in Dauphin County, Pennsylvania has been one of the most severely affected regions. During the Tropical Storm Agnes in 1972, the river stage height rose to 10 m (above NAVD 88 datum) at the United States Geological Survey (USGS) streamgage station 01570500, completely inundating Paxton Creek and the City Island communities. The frequency of floods and development of the Harrisburg area into floodplains occupying the flood-prone
areas like Paxton Creek's lowland (Socolow, 1972) has exacerbated the problem. With changing climate conditions, it is important to prepare for and mitigate the impact of flooding events which can take place due to tropical storms, extreme precipitation, snowmelt, dam breaches, and tsunamis (coastal floods).

Page & Shaw (1973) developed a flood inundation map for the flood of June 1972 in Harrisburg, PA. They mapped the areal extent of the flooding along a 32 km. reach of the Susquehanna mainstem from Marysville, PA to Falmouth, PA which includes the Harrisburg area. They also constructed the water-surface profile along the reach from the surveys of post-flood high-water marks. These maps were developed by USGS in collaboration with the Pennsylvania Department of Environmental Resources, the Susquehanna River Basin Commission (SRBC), and the U.S. Army Corps of Engineers (USACE), and can be used to estimate the flood depth in areas away from the river channel. Roland et al. (2014) developed the digitized flood inundation maps using HEC-RAS 1D model (now HECR1D) at selected water levels (3.4 m to 11.3 m above NAVD 88) for a 40 km reach of the Susquehanna River near Harrisburg, Pennsylvania with its upstream end at the confluence of the Juniata River and its downstream extending just below the Swatara Creek. They developed the longitudinal flood profiles and acquired observed high-water marks for the Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) and simulated the flood depth grids over the channel and inundated areas near Harrisburg, PA for river stage height from 3.4 m to 11.3 m (at 0.3 m intervals above NAVD 88) at USGS streamgage. Data for cross-sections, bridges, and levees are also acquired from Roland et al. (2014) for a better configuration of the hydraulic model and to ensure adequate model performance in this study.

Numerical models are increasingly used to perform floodplain mapping and they typically use 1D, 2D, or coupled 1D-2D modeling approaches. The 1D model is generally considered advantageous for river channel flow as it requires the topographic data only at the cross-sections of interest, which results in less computational resources needed, whereas the 2D model is advantageous for floodplain mapping as it can quantify overbank flooding and has been successfully applied in past studies of flood mapping (Pathirana et al., 2011; Poretti & De Amicis, 2011; Quiroga et al., 2016). There are certain drawbacks
of 2D modeling that includes higher computational times and the requirement of continuous river bathymetry data. Due to the limitation of LiDAR sensors in penetrating water depth at higher flows and velocities, the bathymetry of rivers is represented with shallower depths in LiDAR-based DEM. For 2D modeling, the LiDAR-based river terrain is often interpolated using the available cross-section data which are necessary to capture features of large rivers but bring additional effort, uncertainty, and the potential of increased errors (Costabile & Macchione, 2015). The 1D/2D coupling approaches take advantage of both 1D and 2D models with the channel flow considered as a 1D model whereas the overbank flow is represented by a 2D model. Consequently, model performance is dependent on the coupling technique as the boundary conditions are linked and can introduce continuity errors due to limitations of either model (Betsholtz & Nordlöf, 2017).

The objective of this study is to predict and assess the projected changes in flood inundation depth and extent due to climate change at Harrisburg, PA using the HEC-RAS 2D model. The model is calibrated and evaluated using the USGS streamgage data and elevation profiles from the major historical floods and past studies (Roland et al., 2014). The daily discharge data for 30-yr and 100-yr flood events are extrapolated from the hydrologic land surface model for different future scenarios at the streamgage location near Harrisburg, PA. The flood inundation depth and extent for the 30-yr and 100-yr flood events at the USGS streamgage are compared based on the historical and future conditions throughout the study reach along the Susquehanna River.

3.3. Data and Methods

3.3.1. Study Area

The City of Harrisburg is located in Dauphin County in south-central Pennsylvania with a total area of around 30 km² and an estimated population of 50,000. The study reach is a 41 km section along the Susquehanna River which extends from headwaters of Otsego Lake, near Cooperstown, New York to the Suffolk, Virginia, and Atlantic Ocean (Source: https://www.chesapeakebay.net/discover/facts). The study reach extends from the confluence of Juniata River and Susquehanna’s main stem following the Clarks Ferry
Bridge and ends before the Hill Island near the mouth of Swatara Creek. A USGS streamgage 01570500 lies on the east bank of City Island, 18 m downstream from Market Street Bridge (Figure 3-1) with a drainage area of 62,419 km² and gage datum of 88.18 m above NAVD 88 (Source: https://nwis.waterdata.usgs.gov/nwis/nwismap/?site_no=01570500&agency_cd=USGS). The upstream and downstream boundary conditions are indicated in Figure 3-1 with the direction of flow shown by an arrow. Throughout the study reach, there are three interstate bridges, three smaller road crossings, and two railroad crossings along with a levee for the protection of Harrisburg International Airport (Table 3-1). Multiple creeks drain into the Susquehanna main stem within the 41-km reach including the Sherman, Stony, Fishing, Conodoguinet, and Yellow Breeches.

Table 3-1: Structures along the study reach included in the HEC-RAS 2D model [adapted from Roland et al. (2014)]. The numbers in brackets correspond to Figure 3-1.

<table>
<thead>
<tr>
<th>River Mile</th>
<th>Structure Name</th>
<th>Description</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>75.15 [1]</td>
<td>Rockville Bridge</td>
<td>Stone arch bridge</td>
<td>USGS field reconnaissance and FEMA HEC-2 model</td>
</tr>
<tr>
<td>73.65 [2]</td>
<td>Interstate Highway 81</td>
<td>Elevated Bridge</td>
<td>PennDOT Plans S-8786 (dated 1968)</td>
</tr>
<tr>
<td>69.14 [6]</td>
<td>Penn Central Railroad</td>
<td>Stone arch bridge</td>
<td>USGS field reconnaissance and FEMA HEC-2 model</td>
</tr>
<tr>
<td>68.94 [7]</td>
<td>Reading Railroad</td>
<td>Stone arch bridge</td>
<td>USGS field reconnaissance and FEMA HEC-2 model</td>
</tr>
<tr>
<td>68.69 [8]</td>
<td>Dock Street Dam</td>
<td>In-channel dam</td>
<td>FEMA HEC-2 model</td>
</tr>
<tr>
<td>68.65 [9]</td>
<td>Interstate Highway 83</td>
<td>Concrete bridge</td>
<td>PennDOT Plans S-12130 (dated 1979) and USGS field reconnaissance</td>
</tr>
<tr>
<td>63.75 [10]</td>
<td>Interstate Highway 76 (PA Turnpike)</td>
<td>Concrete bridge</td>
<td>PennDOT Plans A-00118748 (dated 2007)</td>
</tr>
<tr>
<td>62.41-60.49 [11]</td>
<td>Airport Levee</td>
<td>Privately owned levee at airport built in 1956 at a top elevation of 94.6 m</td>
<td>Harrisburg International Airport engineer (March 2012)</td>
</tr>
</tbody>
</table>
Figure 3-1: Study reach near the City of Harrisburg, Pennsylvania along the Susquehanna River.
3.3.2. **HEC-RAS model and its configuration**

The flood inundation mapping is simulated using the HEC-RAS (v5.0.7) model developed by the U.S. Army Corps of Engineers (USACE, 2016). HEC-RAS is used to perform standalone 1D/2D steady and unsteady flow modeling as well as coupled 1D/2D flow modeling. The 2D modeling solves the Saint-Venant Equations or Diffusive Wave equations and calculates the water-surface profiles of the flow. This study uses an HEC-RAS 2D unsteady flow model to simulate the flood inundation depth and extent at Harrisburg, PA due to major flood events in Susquehanna River. The 2D model is configured by developing 2D flow areas throughout the entire reach and in the flood-prone areas, derived from the past flood events. To do this, a 2D computational mesh is developed for the domain that links the hydraulic structures and boundary conditions with the 2D flow areas. An unstructured mesh is implemented that contains polygons with a minimum of 3 sides and a maximum of 8 sides. The spatial resolution of the computational mesh is approximated by taking the ratio of the area of the channel and the length of the reach, approximately 50 x 50 m. This computational cell size is relatively larger as compared to the spatial resolution of the LiDAR-based (Light Detection and Ranging) 3 m Digital Elevation Model (DEM). HEC-RAS computes a detailed hydraulic table for each 2D computational cells based on the underlying terrain by developing the relationships between elevation and hydraulic properties (wetted perimeter, area, roughness) for each computational cell. In this application, the 2D diffusion wave equations are used due to lower computational requirements and greater model stability as compared to the Saint-Venant equations.

The study domain contains upstream and downstream boundary conditions (Figure 3-1). The upstream boundary condition is configured as an inflow hydrograph from USGS streamgage and is located at the confluence of Juanita River and Susquehanna River. Along with the inflow hydrograph at the upstream boundary condition, an energy slope is necessary and is calculated as the longitudinal slope of the channel from LiDAR-based terrain, estimated to be 0.00046 m/m. The downstream boundary condition is located near the Hill island and is assigned as a normal depth boundary condition where friction slope is assumed equal to the energy slope from the upstream boundary condition.
The time step is controlled using the Courant condition that ensures model stability during rapid changes in flow and velocity. The Courant number for diffusion wave equation is given by:

\[ C = \frac{V \Delta T}{\Delta X} \]  

(1)

Where C is the Courant number, V is the flood wave velocity (m/s), \( \Delta T \) is the computational time step (sec) and \( \Delta X \) is the computational cell size (m). Due to rapid changes in the flow in the Susquehanna River during the flood events, the Courant number is set to 1 with an adaptive time step of 5 minutes. A spatially varying map of Manning’s roughness values is developed for the study domain based on the land use classification with further details provided in section 3.3.3. The horizontal coordinate system for the entire study is North American Datum 1983 UTM Zone 18 and the vertical datum is NAVD 88 (meters).

3.3.3. Input Data

The terrain for the HEC-RAS 2D model is developed using a combination of LiDAR-based DEM and cross-sections along the study reach. The LiDAR-based DEM is acquired from the 3D Elevation Program (3DEP) products at 1/9 arc-second from USGS National Download Viewer (https://viewer.nationalmap.gov/basic/). These DEM products are developed from the LiDAR point source cloud as part of the 3DEP. One of the drawbacks to the LiDAR-based DEM is the representation of the river bathymetry due to the inability of the infrared sensors to penetrate water. Due to higher depth and velocities in the Susquehanna River, the river bathymetry from the LiDAR-based DEM was shallower and not representative of the actual bathymetry based on the river stage comparison at the USGS streamgage 01570500. To overcome this limitation, the river bathymetry is interpolated from the channel cross-sections of the study performed by USGS (Roland et al., 2014). A total of 123 cross-sections were developed along a similar river section using data from various USGS bathymetry projects, Pennsylvania Department of Transportation (PennDOT) bridge plans, and the HEC-2 model from the appropriate
flood inundation studies by Federal Emergency Management Agency (FEMA). The data from LiDAR DEM and channel cross-section are combined to generate a representative terrain for the study reach using GIS applications. The artifacts developed around the islands in the study reach, due to the interpolation of river bathymetry from the channel cross-sections are reduced using the channel polygons from the National Hydrography Dataset (NHD) and the available LiDAR-based DEM by masking the islands and lowering the artifacts to match the river bathymetry.

Each floodplain 2D cell is assigned to a single Manning’s n value based on the land use classification. The land use data is acquired from the National Land Cover Database (Yang et al., 2018). The Manning’s n values for various land cover are assigned using the table developed by National Resources Conservation Service (NRCS; https://www.wcc.nrcs.usda.gov/ftpref/wntsc/H&H/HecRAS/NEDC/lectures/docs/Manning%92s n-values for Kansas Dam Breach Analyses - Adopted 071216.pdf).

Parameters describing hydraulic structures including bridges are acquired from Roland et al. (2014) and it includes the positioning and design of bridges, levees, and dams as described in Table 3-1. In this application, bridges are accounted for by introducing break lines and increasing the Manning’s n values for the cells with the bridges. The levee in the domain is modeled as a 2D area connection with a structure type of weir and a top elevation of 94.58 m (based on the data from Roland et al. (2014).

3.3.4. Streamflow data

The boundary condition at the upstream section of the reach is assigned as an inflow hydrograph from USGS gage 01570500 data as the creeks between the upstream boundary condition and the streamgage drain relatively lower amount of water compared to the drainage area of the Susquehanna River. The computational cells are aligned with the 1D upstream boundary conditions through the cell face points. The USGS streamgage provides discharge (in ft$^3$/s) and stage (ft) data at 30-minute intervals from 1890 to present. These data have been used to calibrate and evaluate the model performance, with details described in section 3.3.5.
Two different future climate change scenarios are used in this analysis: RCP 4.5 (business as usual greenhouse gas emissions) and RCP 8.5 (worst-case greenhouse gas emissions). MACA-based GCM datasets are used from the state-of-the-art framework: Coupled Model Intercomparison Project (CMIP Phase 5) and the meteorological forcing from the best performing GCM is used as an input to the Noah-MP land surface model to estimate the water balance components and energy fluxes. These water balance components are fed to the convolution-based routing model to extract streamflow at desired locations in Chesapeake Bay watershed. Two time periods for each scenario are considered: RCP 4.5 (2020-2050; 2060-2090) and RCP 8.5 (2020-2050; 2060-2090). The land surface model calibration and performance are discussed above in section 2.4.1. The evaluation from GCM is more focused on evaluating the quantitative change rather than capturing qualitative patterns in future climate scenarios. For example, the hydrologic volume of the future streamflow hydrographs can provide a better understanding of the changes in the future rather than relying on the shape of the flow hydrograph which in general has higher uncertainties. Noting this behavior, the changes in the hydrologic volume for 30-yr and 100-yr flood events are estimated for future periods which are extrapolated from the two 30-yr periods [RCP 4.5 (2020-2050; 2060-2090) and RCP 8.5 (2020-2050; 2060-2090)]. In simple terms, the 30-yr and 100-yr flood events from each of these periods are developed by converting the flow hydrograph at the USGS streamgage for different climate scenarios to the historic 30-yr and 100-yr flood events through conservation of hydrograph volume. This preserves the shape of the flow hydrograph based on the historical conditions but reflects the hydrograph volume from future climate scenarios into historic flow hydrographs by changing the peak discharge.

3.3.5. Calibration and model evaluation

The presence of the USGS 01570500 streamgage in the study reach provides qualitative streamflow and stage data at the 30-minute interval for calibration of the HEC-RAS 2D model. This includes the data for major flood events such as Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) and peak discharges in each water year providing a long-term rating curve for calibration and evaluation of HEC-RAS 2D model. The primary
calibration for the HEC-RAS 2D model is performed using the relationship between discharge and stage from the USGS 01570500. The peak discharge events for each water year are derived from 2008-2013 for the model calibration and 2014-2019 for model evaluation.

As part of the calibration, Manning’s n is considered as an important parameter towards the model calibration. The horizontal Manning’s n values over the 2D flow area are assigned based on the NLCD land use (as described in section 3.3.3). The calibration is carried out for the open-water computational cells that are responsible for the energy loss throughout the reach. The Manning’s n roughness for the open channel is parameterized initially with a value of 0.04 which causes high water-surface elevations initially at most cross-sections. The final Manning’s value used for open-water computational cells is in the range of 0.0275 to 0.0295 depending on the magnitude of the flow and a similar value is assigned to all open-water computational cells. The change in roughness values for the other land-use types will be considered in future studies. The bridges in the 2D model are implemented by increasing the Manning’s n roughness for the cells that occupy bridges. Based on the comparison of the longitudinal profiles from the HECR1D model, the manning’s roughness is calibrated for different manmade structures with calibration values ranging from 0.02 to 0.06. The advantage of using the 2D model is it accurately represents the Manning’s n for each computational cell based on the land use.

Following calibration, the post-flood high-water marks are compared at river cross-sections available for the Tropical Storm Agnes (Page & Shaw, 1973) and Tropical Storm Lee (Roland et al., 2014). To be confident about the HEC-RAS 2D model and its configuration, the longitudinal flood profile based on the water-surface elevation from the 2D model is compared with the flood profiles from the HECR1D model for both flood events for entire study reach. Roland et al. (2014) developed the flood profiles at stages from 3.4 m to 11.3 m and corresponding discharge from 4520 m$^3$/s to 36100 m$^3$/s at USGS streamgage 01570500 and found an elevation difference ranging from -0.09 m to 0.03 m between the modeled and observed USGS stage data. The HECR1D model is developed using the cross-sections and man-made structures (described in section 3.3.3) and is calibrated with USGS 01570500 streamgage data and high-water marks of major flood
events including the Tropical Storm Agnes and Tropical Storm Lee. However, it is important to note that a few modifications were made by Roland et al. (2014) in the HECR1D model for the simulation of Tropical Storm Agnes flood, which included consideration of the Walnut Bridge that collapsed during the 1996 flood, different location of USGS gage and removal of the airport levee. Similar changes are also made in this application for the simulation of the Agnes flood event in the HEC-RAS 2D model.

A final comparison is made between the flood depth grids available from Roland et al. (2014) and the HEC-RAS 2D model to assess the spatial variability in the channels, floodplain, and inundated areas. The flood depth grids are available for multiple gage heights (3.4 m to 11.3 m) at USGS streamgage 01570500 and are available through USGS Flood Inundation Mapper (https://wimcloud.usgs.gov/apps/FIM/FloodInundationMapper.html - app=dc6c&7b57-selectedIndex=2&f40b-selectedIndex=0&7234-selectedIndex=0). This study compares the flood depth grids for the Tropical Storm Lee (2011) over the entire reach and nearby inundated areas. On visually comparing the inundated and non-inundated areas of the simulations from the HEC-RAS 2D model with the available flood depth grid for Tropical Storm Lee from Roland et al. (2014), seven break lines are introduced along the study reach at high grounds to prevent the inundation over non-flooded areas. This prevents the water leakage from the channel and tributaries to the floodplain and tightens the 2D flow area causing the inundation to occur only through overtopping of high grounds.

3.4. Results and Discussions

3.4.1. Model Calibration and Evaluation

Stage-Discharge Curves

The HEC-RAS 2D model is calibrated by comparing the stage-discharge relationships at the USGS streamgage 01570500 as shown in Figure 3-2 (a). It includes peak streamflow events (Table 3-2) from 2008 to 2013 ranging from a discharge of 3850 m³/s in 2012 to 16700 m³/s in 2011 (Tropical Storm Lee). The lower flows below a threshold of 2500 m³/s have higher uncertainty and error when compared to the larger flow events. This behavior is attributed to the sensitivity of Manning’s roughness over the channel. One of the limitations of the 2D model is the lack of varying vertical roughness
in channels which is majorly responsible for the recession of the low flows. It should also be considered that the horizontal Manning’s roughness is varied based on the NLCD land use classification and similar roughness values are assigned throughout the channel which reduces the complexity of the river terrain causing uncertainty in the predicted flows. The higher RRMSE of 9.7 % for lower flows (<4000 m³/s) whereas 4.6 % for higher flows (>7000 m³/s) during 2008-2013 indicates the errors at different flow magnitudes along the study reach as shown in Figure 3-2 (a). The model evaluation is performed for peak streamflow events from 2014 to 2019 (Table 3-2) and an RRMSE of 5.3 % for low flows and 4.1 % for high flows is estimated [Figure 3-2 (b)] indicating good model performance.

Figure 3-2: Stage-Discharge relation at USGS streamgage 01570500 for a) calibration period (2008-2013) and b) evaluation period (2014-2019).
Table 3-2: Water-surface elevations at USGS streamgage 01570500 and simulated water-surface elevation profiles for peak flows in each water year from 2008 to 2019.

<table>
<thead>
<tr>
<th>Water year</th>
<th>Date</th>
<th>USGS 01570500 flow (m³/s)</th>
<th>USGS 01570500 WSE (m)</th>
<th>HECR2D WSE (m)</th>
<th>WSE Difference (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>3/6/2008</td>
<td>9061</td>
<td>5.3</td>
<td>5.32</td>
<td>0.02</td>
</tr>
<tr>
<td>2009</td>
<td>3/11/2009</td>
<td>4021</td>
<td>3.11</td>
<td>3.13</td>
<td>0.02</td>
</tr>
<tr>
<td>2010</td>
<td>1/27/2010</td>
<td>8580</td>
<td>5.11</td>
<td>5.14</td>
<td>0.03</td>
</tr>
<tr>
<td>2011</td>
<td>9/9/2011</td>
<td>16707</td>
<td>7.67</td>
<td>7.7</td>
<td>0.03</td>
</tr>
<tr>
<td>2012</td>
<td>12/9/2011</td>
<td>3851</td>
<td>3.03</td>
<td>3.04</td>
<td>0.01</td>
</tr>
<tr>
<td>2013</td>
<td>2/1/2013</td>
<td>5663</td>
<td>3.88</td>
<td>3.95</td>
<td>0.07</td>
</tr>
<tr>
<td>2014</td>
<td>5/18/2014</td>
<td>5182</td>
<td>3.66</td>
<td>3.74</td>
<td>0.08</td>
</tr>
<tr>
<td>2015</td>
<td>4/12/2015</td>
<td>4984</td>
<td>3.56</td>
<td>3.64</td>
<td>0.08</td>
</tr>
<tr>
<td>2016</td>
<td>2/27/2016</td>
<td>4474</td>
<td>3.33</td>
<td>3.4</td>
<td>0.07</td>
</tr>
<tr>
<td>2017</td>
<td>4/8/2017</td>
<td>5097</td>
<td>3.62</td>
<td>3.7</td>
<td>0.08</td>
</tr>
<tr>
<td>2018</td>
<td>7/26/2018</td>
<td>9005</td>
<td>5.28</td>
<td>5.3</td>
<td>0.02</td>
</tr>
<tr>
<td>2019</td>
<td>12/23/2018</td>
<td>5550</td>
<td>3.83</td>
<td>3.91</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Longitudinal Flood profile and High-water marks

A comparison of the simulated water-surface elevations (WSE) for peak streamflow events in each water year from 2008 to 2019 with observed WSE from USGS streamgage 01570500 is shown in Table 3-2. The difference ranges from 0.01 m to 0.08 m and it signifies that the HEC-RAS 2D model performs well for most of the peak streamflow events. A similar comparison of WSE is made in Roland et al. (2014) from 1996 to 2010 at USGS streamgage 01570500 and the difference ranges from -0.07 m to 0.03 m. WSE profile along the study reach for Tropical Storm Lee (2011) is derived from the HECR1D model that had the peak flood stage of 7.6 m at USGS streamgage 01570500. Figure 3-3 shows a comparison of simulated WSE from HECR2D along the river miles with derived WSE from the HECR1D model. The error ranges from -0.5 to 0.3 m where the maximum error is due to the presence of bridges along the reach. Due to the limitations of HECR2D, the bridges have been simulated as regions with higher Manning’s n for modeling purposes. This increases the uncertainty of the WSE especially around the bridges like Rockville Bridge (river mile 75.15) and the cluster of bridges [Harvey Taylor Bridge, Market Street Bridge, Interstate 83 (John Memorial Bridge)] from river mile 68.65 to 70.14. The errors in WSE can also be attributed to the interpolation of river bathymetry from cross-sections which can be observed in the upstream section of the reach. The simulated WSE is also
compared with the surveyed high-water marks from the Tropical Storm Lee (2011) which were obtained by Roland et al. (2014) and collected by The Harrisburg Authority (Table 3-3). The quality of the high-water marks is not documented but they can be used for calibration and evaluation purposes. The differences with the high-water marks ranged from -0.3 m to 0.2 m. Most of the high-water marks are collected in the vicinity of the bridges that cause the error to be slightly higher when compared against the results from HECR1D.

Table 3-3: Water-surface elevations compared to the surveyed high-water marks and the HECR1D model (Roland et al., 2014) for Tropical Storm Lee (2011). The WSE differences are with respect to the high-water marks.

<table>
<thead>
<tr>
<th>River Mile</th>
<th>High-water mark elevation (m)</th>
<th>Modeled WSE 1D (m)</th>
<th>WSE difference 1D (m)</th>
<th>Modeled WSE 2D (m)</th>
<th>WSE difference 2D (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>75.82</td>
<td>99.3</td>
<td>99.4</td>
<td>0.1</td>
<td>99.1</td>
<td>-0.2</td>
</tr>
<tr>
<td>74.99</td>
<td>98.1</td>
<td>98.6</td>
<td>0.4</td>
<td>98.3</td>
<td>0.2</td>
</tr>
<tr>
<td>72.84</td>
<td>97.3</td>
<td>97.2</td>
<td>-0.1</td>
<td>97.2</td>
<td>-0.1</td>
</tr>
<tr>
<td>69.95</td>
<td>96.6</td>
<td>96.4</td>
<td>-0.2</td>
<td>96.2</td>
<td>-0.3</td>
</tr>
<tr>
<td>69.03</td>
<td>96.0</td>
<td>95.8</td>
<td>-0.2</td>
<td>95.7</td>
<td>-0.2</td>
</tr>
<tr>
<td>66.43</td>
<td>94.1</td>
<td>94.1</td>
<td>0.0</td>
<td>94.3</td>
<td>0.1</td>
</tr>
</tbody>
</table>

The simulated WSE from the 2D model is also compared with the flood profile of the Tropical Storm Agnes (1972) which is derived from the HECR1D model with a flood stage of 10 m. The Manning’s n value for the open channel was slightly tuned for the simulation of the 1972 flood event due to its exceptional flow volume (28,900 m³/s) and a single manning’s value assigned for entire reach as part of the calibration. The error ranges from -1.5 m to 1.25 m with higher uncertainty in the stage due to the pronounced effect of bridges at higher flows. The assigning of a single manning’s roughness value to an entire reach can be resolved by breaking and assigning the roughness value to the reach in smaller sections or by developing a flow-roughness relation for 2D modeling. Table 3-4 indicates the differences in simulated WSE with the observed high-water marks of Tropical Storm Agnes developed by Page and Shaw (1973) and the HECR1D simulated water-surface elevations. The error ranges from -0.5 m to 0.3 m which is again slightly higher when compared to the HECR1D simulations.
Figure 3-3: Longitudinal flood profile along the domain reach in Susquehanna River for Tropical Storm Agnes (1972; Stage: 10 m) and Tropical Storm Lee (2011; Stage: 7.6 m) compared with the water-surface elevation profiles from HECR1D (Roland et al., 2014) with the absolute error shown in the top. The vertical labels in black indicate the structures from Table 3-1.
Table 3-4: Water-surface elevations compared to the surveyed high-water marks (Page and Shaw, 1973) and the HECR1D model (Roland et al., 2014) for Tropical Storm Agnes (1972). The WSE differences are with respect to the high-water marks.

<table>
<thead>
<tr>
<th>River Mile</th>
<th>High water mark elevation (m)</th>
<th>Modeled WSE 1D (m)</th>
<th>WSE difference 1D (m)</th>
<th>Modeled WSE 2D (m)</th>
<th>WSE difference 2D (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>83.47</td>
<td>109.5</td>
<td>109.7</td>
<td>0.2</td>
<td>109.0</td>
<td>-0.5</td>
</tr>
<tr>
<td>77.91</td>
<td>102.8</td>
<td>102.8</td>
<td>0.0</td>
<td>103.0</td>
<td>0.2</td>
</tr>
<tr>
<td>75.13</td>
<td>101.0</td>
<td>100.7</td>
<td>-0.3</td>
<td>101.1</td>
<td>0.1</td>
</tr>
<tr>
<td>74.57</td>
<td>100.7</td>
<td>100.3</td>
<td>-0.3</td>
<td>100.5</td>
<td>-0.2</td>
</tr>
<tr>
<td>71.14</td>
<td>99.3</td>
<td>99.5</td>
<td>0.1</td>
<td>99.1</td>
<td>-0.2</td>
</tr>
<tr>
<td>70.01</td>
<td>99.3</td>
<td>107.5</td>
<td>-0.1</td>
<td>98.8</td>
<td>-0.5</td>
</tr>
<tr>
<td>69.67</td>
<td>99.1</td>
<td>99.0</td>
<td>-0.2</td>
<td>98.6</td>
<td>-0.5</td>
</tr>
<tr>
<td>69.33</td>
<td>98.6</td>
<td>98.6</td>
<td>0.0</td>
<td>98.4</td>
<td>-0.2</td>
</tr>
<tr>
<td>68.77</td>
<td>98.1</td>
<td>97.9</td>
<td>-0.2</td>
<td>98.1</td>
<td>0.0</td>
</tr>
<tr>
<td>67.58</td>
<td>96.9</td>
<td>96.8</td>
<td>-0.1</td>
<td>97.2</td>
<td>0.3</td>
</tr>
<tr>
<td>66.8</td>
<td>96.3</td>
<td>96.5</td>
<td>0.2</td>
<td>96.8</td>
<td>0.5</td>
</tr>
<tr>
<td>65.43</td>
<td>95.6</td>
<td>95.1</td>
<td>-0.5</td>
<td>95.7</td>
<td>0.2</td>
</tr>
</tbody>
</table>

3.4.2. Flood inundation depth and extent (Tropical Storm Lee)

The flood depth grids are generated using the water-surface elevations and the LiDAR-based DEM (from 3DEP) used in this study. Using the calibrated HEC-RAS 2D model, the simulated water-surface elevations for the Tropical Storm Lee are compared with the depth and extent of the flood inundation maps prepared by Roland et al. (2014). The flood depth grids from Roland et al. (2014) are calculated using WSE from HECR1D and PAMAP DEM which is managed by The Pennsylvania Department of Conservation and Natural Resources, Bureau of Topographic and Geological Survey (PAMAP, 2006). The depth estimates from Roland et al. (2014) are with respect to bare earth DEM which does not represent the river bathymetry and is a flat-water-surface at a shallower depth. The workaround to flood depth from HECR2D model is through reconditioning of DEM by adding the difference between the actual river bathymetry and the gage datum at the USGS streamgage 01570500. This reduces the terrain elevation throughout the channel and creates a reference surface similar to the flat-water surface from PAMAP. This step is essential as the DEM dataset used by Roland et al. (2014) is different than the DEM used in this study. The difference between the simulated WSE and the reconditioned DEM is then considered as the flood depth which is compared with the HECR1D depth estimates.
Figure 3-4: Flood inundation map for Tropical Storm Lee (Discharge: 16,700 m³/s) representing the flood depth and extent for the study reach from the HEC-RAS 2D model.
Figure 3-5: Flood inundation map for Tropical Storm Lee (Discharge: 16,700 m$^3$/s) representing the flood depth and extent for the study reach from USGS developed HEC-RAS 1D model (Roland et al., 2014).
Figure 3-6: Flood inundation map for Tropical Storm Lee representing the difference in the flood depth for the study reach between HEC-RAS 2D and HEC-RAS 1D (Roland et al., 2014).
Figure 3-4 shows the flood depth grids from the HEC-RAS 2D model throughout the entire reach with a maximum depth of 9 m in some regions for Tropical Storm Lee. Figure 3-5 shows the flood depth grid for Tropical storm Lee (with a stage of 7.6 m at the USGS streamgage 01570500) from the HECR1D model. Figure 3-4 & Figure 3-5 show similar flood inundation in the Paxton creek and lowland areas in its vicinity with most of the islands including the City Island entirely submerged and overbank flow extended to the South Front Street.

Figure 3-6 shows the difference in flood depth between the HECR1D and HEC-RAS 2D model for the entire reach. The HEC-RAS 2D model performs well in depicting the flood extent as the error ranges from -0.5 m to 0.5 m in most sections of the reach. The flood depth difference above 1 m is caused due to multiple sources of uncertainty. The interpolation of river bathymetry from the cross-sections into the LiDAR-based DEM introduces uncertainty due to the artifacts generated around islands in the flood depth. The dark purple regions in Figure 3-6 near City Island is the overestimation of flood depth due to the interpolation of the river bathymetry from cross-sections. The errors in the inundated areas are in the range of -0.5 m to 0.5 m which is due to lack of urban structures (buildings, overhead bridges) and calibration of Manning’s roughness for other land-use types. Flood propagation and inundation are affected by the presence of densely spaced buildings which can be placed as a cluster of blocks by reconditioning the DEM. The effects due to backwater flooding are also not considered in this study as compared to the HECR1D model.

3.4.3. Impacts of climate change on flood inundation depth and extent

A comparison of flood inundation depth and extent for a historic and future 30-yr and 100-yr flood event is performed using the HEC-RAS 2D model. Table 3-5 shows the peak volumes for historic and future hydrographs for both RCP 4.5 and RCP 8.5 scenario at the USGS streamgage 01570500 indicating the maximum peak discharge of 23,000 m$^3$/s and 31,000 m$^3$/s for a 30-yr and 100-yr flood event in the RCP 8.5 scenario from 2061 to 2090.
Table 3-5: Peak discharge for historic and future 30-yr and 100-yr flood event at USGS streamgage 01570500 for both RCP 4.5 and RCP 8.5 scenario.

<table>
<thead>
<tr>
<th>Recurrence Interval (year)</th>
<th>Peak discharge (m$^3$/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>USGS 01570500</td>
</tr>
<tr>
<td>30</td>
<td>15,400</td>
</tr>
<tr>
<td>100</td>
<td>19,800</td>
</tr>
</tbody>
</table>

The results from Figure 2-8 in Modi (2020) suggest a decrease in streamflow in the Susquehanna basin for future climate scenarios but the major floods in the Susquehanna basin in the past have occurred due to events such as tropical storms and ice jams and are difficult to predict from the MACA based GCM datasets. However, simulations from these earth systems models are considered suitable for estimating the long-term impact of climate change on the overall water balance. As discussed in Modi (2020), an overall increase in precipitation is observed in Chesapeake Bay watershed, with a greater frequency of extreme events resulting in the higher total precipitation (Myhre et al., 2019). The predicted hydrograph volumes shown in Table 3-5 are estimated using the Noah-MP land surface model from the best performing GCM (CSIRO-Mk3-6-0) for two future scenarios as discussed in Modi (2020).

Figure 3-7 & Figure 3-8 show the flood inundation depth and extent for the historic and future (RCP 8.5) 30-yr flood event respectively at USGS 01570500 for the study reach. The flood inundation extent and severity predicted by the HEC-RAS 2D model along the Susquehanna River near Harrisburg is expected to rise, primarily due to an overall increase in precipitation increasing the soil moisture. The maximum flood depth observed for the historic 30-yr flood event is less than 6.5 m whereas the flood depth in the RCP 8.5 scenario is above 7.5 m in most sections of the reach inundating the overbank areas. Based on the rating curve developed for the USGS streamgage 01570500 by Roland et al. (2014), the historic 30-yr flood event can be categorized as moderate flood stage (7 m) with extensive flooding in the low-lying areas of Paxton Creek and its vicinity whereas for the future (RCP 8.5) 30-yr event can be categorized as major flood stage (9 m) completely inundating structures in the low-lying areas in Paxton Creek and flooding the Harrisburg International Airport.
Figure 3-7: Flood inundation map of a historic 30-yr flood event at USGS streamgage 01570500 (Discharge: 15,400 m$^3$/s) generated using the calibrated HEC-RAS 2D model.
Figure 3-8: Flood inundation map of a future 30-yr flood event for the RCP 8.5 scenario (2061-2090) at USGS streamgage 01570500 (Discharge: 23,000 m$^3$/s) generated using the calibrated HEC-RAS 2D model.
Figure 3-9: Flood inundation map of a historic 100-yr flood event at USGS streamgage 01570500 (Discharge: 19,800 m$^3$/s) generated using the calibrated HEC-RAS 2D model.
Figure 3-10: Flood inundation map of a future 100-yr flood event for the RCP 8.5 scenario (2061-2090) at USGS streamgage 01570500 (Discharge: 31,000 m³/s) generated using the calibrated HEC-RAS 2D model.
Figure 3-9 & Figure 3-10 also show a similar trend for the historic and future (RCP 8.5) 100-yr flood event respectively. Higher flood depth above 8 m is observed throughout the stream for the historic 100-yr flood event and the future flood event exceeds 9 m in major parts of the reach. The flood inundation due to historical 100-yr flood event has a drastic impact on the urbanized regions in Harrisburg near Paxton Creek and downstream of Interstate-76 near the Harrisburg International Airport with flood depths 1.5 m high, whereas for the future 100-yr flood event the flood depth completely submerges all the islands, low-lying areas of Paxton Creek, Harrisburg International Airport, overbank areas that include N. Front Street, N. 2nd Street, and New Market along the reach. Based on the rating curve developed for the USGS streamgage 01570500 by Roland et al. (2014), the historic and the future (RCP 8.5) 100-yr flood event can be categorized as major flood stage (8.5 m) and record flood stage (10.3 m) respectively. The future 100-yr flood event has a slightly higher flood magnitude of 31,000 m³/s (Stage: 10.3 m) as compared to Tropical Storm Agnes (1972) which has a peak of record at USGS 01570500 with flood magnitude of 28,890 m³/s (Stage: 10.1 m).

3.5. Conclusions

The change in flood inundation depth and extent is analyzed due to the impacts of climate change in the Susquehanna River near Harrisburg, PA. The hydraulic model HEC-RAS is configured with 2D flow areas to perform floodplain mapping for a 41 km reach starting at the confluence of Juniata River and ending before the Hill Island near Swatara Creek. The model is calibrated using the stage-discharge relation of the USGS streamgage and is verified for post-flood high water marks from Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) and water-surface elevation profiles from HEC-RAS 1D model developed by USGS. To study the impacts of climate change, the 30-yr and 100-yr flood events are extrapolated and acquired from the historical conditions of USGS streamgage. The future streamflow data are generated from the best performing MACA-based GCM forced through the calibrated Noah-MP land surface model for two scenarios and four periods [RCP 4.5 (2020-2050; 2060-2090) and RCP 8.5 (2020-2050; 2060-2090)]. The 30-yr and 100-yr flood events are extracted from the future streamflow data for each scenario
and are reshaped to historical 30-yr and 100-yr flood events based on the future hydrograph volume. An increase in flood magnitude is observed in all future scenarios due to the greater frequency of extreme precipitation events in both 30-yr and 100-yr floods as compared to the historical period. This study develops the flood inundation maps for the Harrisburg region stating an increase in flood inundation extent and depth in the future climate scenarios as compared to the historical conditions.
Chapter 4: Conclusions

Change in the terrestrial hydrological components due to climate change is an important assessment towards understanding the future supply-demand relationship. The change in the NIWR can guide us in the direction of future water availability and irrigation needs. A mesoscale evaluation using the Noah-MP land surface model and MACA based Global Climate Model datasets is carried out over the Chesapeake Bay watershed. A successful calibration of the land surface model followed by the long-term assessment of terrestrial hydrological components such as evapotranspiration, runoff, and soil moisture are performed for two future climate scenarios RCP 4.5 and RCP 8.5. An increase in precipitation and temperature over the entire Chesapeake Bay watershed is observed for both RCP 4.5 and RCP 8.5 scenarios, with an overall increase of 18% in evapotranspiration and a decrease of 5% in streamflow for RCP 8.5 scenario from 2061-2090. An increase in the effective precipitation leads to an overall decrease of 13% and 17% in NIWR for corn and soybeans respectively in RCP 8.5 scenarios at the end of the 21st century. The NIWR projections can be an important tool in assessing future irrigation needs and developing mitigation strategies by shifting agriculture in evolving agricultural regions with increased precipitation from water-scarce regions.

The simulations and the analysis of the terrestrial hydrological components from Modi (2020) are certainly useful in evaluating the credibility of the Global Climate Models, drought prediction, projecting the availability and consumption of water in water-scarce regions, alteration in biogeochemical cycles and many other climate change-based applications. One such potential application of climate change studies is mapping the change in the flood inundation through the coupling of Global Climate Models, a land surface model, and a hydraulic model. An HEC-RAS 2D model is set up to evaluate the impact of climate change in the flood inundation extent and depth along the Susquehanna River near Harrisburg in Dauphin County in south-central Pennsylvania. The model is calibrated using the stage-discharge relation at the available USGS streamgage (01570500) and water-surface elevation profiles from the major historical flood events like Tropical Storm Agnes (1972) and Tropical Storm Lee (2011). To study the impacts of climate change, the historic and future 30-yr and 100-yr flood events are compared at the USGS
streamgage. The projected 30-yr and 100-yr flood events are derived from the future hydrograph volume in different climate scenarios and reshaped to the historic flow hydrographs. Two major questions are acknowledged throughout the entire analysis. The first question addresses how the future climate change affects the mesoscale land surface processes and agricultural practices in Chesapeake Bay watershed. The second question is focused on understanding how the change in extreme precipitation events affect climate hazards like floods and to what extent they pose risk to the communities severely affected in the past due to major historical flood events. The results indicate an overall increase in precipitation and a decrease in streamflow that can be explained by rising temperature and the associated evapotranspiration which plays a major role in the hydrological cycle for Chesapeake Bay watershed. However, the study develops the flood inundation maps for future climate scenarios that signifies that the flood inundation extent and severity predicted by the model along the Susquehanna River near Harrisburg is expected to rise, primarily due to the greater frequency of extreme events resulting in higher total precipitation.

These results indicate the impacts of climate change in Chesapeake Bay watershed with a focus on alterations in the hydrologic cycle and extreme events. Future research shall focus on improving the water-balance components from hydrological models by using the higher resolution meteorological datasets. The increase in spatial resolution will provide improved and discrete estimates of NIWR over the watershed. Models such as CROPWAT account for irrigation practices and crop performance to estimate the irrigation water depth. A further comparison between the simulated irrigation depth from CROPWAT and NIWR from land surface models is needed to evaluate the uncertainty in the current approach. Improved gridded evapotranspiration products can help accurately derive the daily crop coefficients for different crops on a grid-by-grid basis and refine the NIWR estimates. The simulated streamflow can be further improved by using the advanced routing algorithms that account for channel geometry and spatially varying roughness coefficients.
References


Modi, P. (2020). *Evaluating changes in terrestrial hydrological components due to climate change in the Chesapeake Bay watershed*. Virginia Polytechnic Institute and State University, Masters Thesis.


Appendix

Appendix A. Selection of GCM using precipitation indices

Four precipitation indices are estimated to select the six best performing GCM which includes the Annual Maximum Precipitation (AMP), Mean Annual Precipitation (MAP), Number of precipitation events greater than 99th percentile of the total number of rainy days (>1 mm) (P-FREQ), ratio of sum of heavy (greater than 99th percentile) to sum of non-heavy precipitation events (>1 mm) (H-NH). The comparison between the six GCM with respect to METDATA (1981-2005) is shown in Figure A-1 and the corresponding bias for each of the indices and GCM’s is shown in Figure A-2.
Figure A-1. Spatial plots representing precipitation indices: Annual Maximum Precipitation (AMP) [a-g], Mean Annual Precipitation (MAP) [h-n], Number of precipitation events greater than 99th percentile of the total number of rainy days (>1 mm) (P-FREQ) [o-u], ratio of sum of heavy (greater than 99th percentile) to sum of non-heavy precipitation events (>1 mm) (H-NH) [v-ab] for METDATA and six best performing GCM’s.
Figure A-2. Spatial plots representing bias from precipitation indices: Annual Maximum Precipitation (AMP) [a-g], Mean Annual Precipitation (MAP) [h-n], Number of precipitation events greater than 99th percentile of the total number of rainy days (>1 mm) (P-FREQ) [o-u], ratio of sum of heavy (greater than 99th percentile) to sum of non-heavy precipitation events (>1 mm) (H-NH) [v-ab] for METDATA and six best performing GCM’s.
Appendix B. Spatial plots for precipitation and air temperature

Figure B-1 shows mean annual precipitation and air temperature for the historical period (1981-2005) and corresponding bias in each scenario (RCP 4.5 and RCP 8.5) for two time periods: 2021-2050 and 2061-2090 with respect to the historical period across six GCM’s.
Figure B-1. Spatial plots (a) and (f) representing precipitation and air temperature in the historical period (1976-2005) respectively. (b-e) represents a change in precipitation for RCP 4.5 (2021-2050; 2061-2090) and RCP 8.5 (2021-2050; 2061-2090) scenarios respectively whereas (g-j) represents for air temperature.
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