Coupling a land surface model with a hydrodynamic model for regional flood risk assessment due to climate change: Application to the Susquehanna River near Harrisburg, Pennsylvania

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Abstract
An increase in heavy precipitation associated with climate change has exacerbated flooding in the Eastern U.S. To assess regional flood risk with changing climatic conditions, we demonstrate the application of a novel hydrologic modeling framework that integrates climate projections with a coupled Noah-MP land surface model and a two-dimensional HEC-RAS hydrodynamic model. We employ this framework along a 41 km reach of the Susquehanna River near Harrisburg, Pennsylvania, where recent flood damages exceeded $2 billion (2011 Irene and Lee floods). Historical and future 30-year and 100-year peak-discharge estimates were compared to assess how flood risk might be altered due to climate change. Results indicate that precipitation increases from climate change do not always lead to increases in flood risk, because interplay of hydrological components in the watershed, which are considered by Noah-MP, largely controls flooding severity. However, climate change is expected to increase the severity of extreme events; if a 50-year flood (the recurrence interval of Tropical Storm Lee) occurred toward the end of the 21st century in the worst-case emission scenario, then flood volume would increase by 40% and flood extent by 15%, due to an increase in soil moisture from a wetter overall climate.

KEYWORDS
climate change, flood depth, flood inundation, flood risk, global climate models, HEC-RAS, land surface model

1 | INTRODUCTION

The impacts of climate change, largely driven by changes in temperature and precipitation, affect ecosystems and human wellbeing (IPCC, 2007). Flooding is of particular concern in large river systems with growing population centers (Jha et al., 2012). In the Eastern U.S., the frequency and magnitude of precipitation events have increased over the past several decades with further increases expected (Groisman et al., 2004). Hayhoe...
et al. (2007) calculated a 10%–15% increase in winter precipitation depth in the Northeast U.S. and no decrease in summer precipitation using nine 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. Positive trends in precipitation and flooding have been observed in the Eastern U.S. for the past century with heavy precipitation days expected to further increase (Karl et al., 2009; Peterson et al., 2013).

The space–time structure of rainfall, antecedent watershed conditions, and the spatial variability of the landscape are the primary controls on flood generation (Le Lay & Saulnier, 2007), and these attributes interact in dynamic and complex ways. These controls are also difficult, expensive, and time-consuming to measure and are, therefore, often assessed using models. Several model structures/applications have been proposed to evaluate the broad impacts of flooding. Some of these models utilize a combination of GCMs and land surface models (LSMs; e.g., Noah-MP [Noah-Multiparameterization; Niu et al., 2011], Soil & Water Assessment Tool [SWAT; Gassman et al., 2007], and variable infiltration capacity [VIC; Liang et al., 1994]) to understand how climate change impacts the timing, frequency, and magnitude of streamflow, with flooding risk and extent inferred (e.g., no hydraulic/hydrodynamic model used; Ali et al., 2019; Huang et al., 2018; Roudier et al., 2016). Other studies have employed a combination of hydraulic/hydrodynamic models (e.g., HEC-RAS) forced by GCMs to evaluate flood characteristics (Kay et al., 2009; Prudhomme et al., 2002). In most of these applications, the hydraulic/hydrodynamic models employ conceptual lumped rainfall–runoff models to provide boundary inputs for the hydraulic model. Unfortunately, it is difficult to capture the coupled effects of rainfall/runoff processes, antecedent watershed conditions, and the spatial variability of the landscape on flooding with either of these modeling paradigms, because the first does not contain the physics or resolution to predict flooding (Dawdy et al., 2012), and the second ignores the effects of watershed/antecedent controls on flood generation (Cea & Fraga, 2018). Coupled models that integrate the relevant controls on climate processes, watershed, and river system are needed to evaluate how flood timing, magnitude, and extent are expected to change in the future.

LSMs are known to accurately estimate the water budget and hydrological partitioning due to coupled water and energy balance than models, such as HEC-HMS, employing a lumped rainfall/runoff model (Hurkmans et al., 2008). Unfortunately, most LSMs lack runoff-routing schemes capable of reconciling flood timing, magnitude, and extent, and therefore, they are sometimes coupled with hydrodynamic models for flood analysis (de Paiva et al., 2013; Rajib et al., 2020; Schumann et al., 2013; Wu et al., 2014). This type of coupling reconciles some of the shortcomings of individual model application to flood assessment by directly linking watershed level and river system controls to more realistically represent the system. Mishra et al. (2018) coupled a lumped rainfall-runoff model (HEC-HMS) with a 2D hydrodynamic FLO-2D model in the Ciliwang River Basin in Jakarta to assess flood risk using climate projections and found an increase in flood inundation of 6%–31%. Shrestha and Lohpaisankrit (2017) combined a physically distributed model (BTOPMC) with 1D HEC-RAS in the Yang River Basin of Thailand and found an increase of 300–325 km² in flood inundation extent for a future 100-year flood. When the added complexity (and uncertainty) of climate change is introduced, where there are many nonlinear interactions among climate, watershed, and river processes, coupled models become critical to evaluate the complex system.

The purpose of this study is to demonstrate how a hydrological modeling framework, coupling a LSM (Noah-MP) with a hydrodynamic model (2D HEC-RAS), can be used to directly assess regional flood inundation due to climate change. We demonstrate this model coupling with an application to the Susquehanna River in Harrisburg, Pennsylvania, by evaluating the changes in flood inundation depth and extent between historical and future 30-year and 100-year flood events. This is one of the most flood-prone river systems in the Eastern U.S. and is at risk from the compounding effects of climate change and increasing population growth along the flood-prone river corridor (SRBC, 2008). The Noah-MP LSM has been widely used for evaluating spatiotemporal patterns of runoff (Cai et al., 2014; Liang et al., 2019) and is used for streamflow predictions in the National Water Model (Maidment, 2017). The 2D HEC-RAS hydrodynamic model is considered to be advantageous for simulating overbank flooding and has been successfully applied in past flood inundation studies (Pathirana et al., 2011; Poretti & De Amicis, 2011; Quiroga et al., 2016).

2 | DATA AND METHODS

2.1 | Study area

There have been 14 major floods since 1810 along the Susquehanna River that has impacted the City of Harrisburg, Pennsylvania. Tropical Storm Agnes in 1972 (a historical 200-year flood) and Tropical Storm Lee in 2011 (a historical 50-year flood) have led to economic
losses measured in the billions and affected communities throughout the region (SFFWS, 2020). Harrisburg is located in south-central Pennsylvania with an estimated population of 50,000. The city sits along the Susquehanna River, which extends from its headwaters in Otsego Lake, near Cooperstown, New York, to the head of the Chesapeake Bay. The study reach is the same 41 km as studied by Roland et al. (2014) of the Susquehanna River that extends just below its confluence with the Juniata River at Clarks Ferry Bridge and ends upstream of Hill Island above its confluence with Swatara Creek (Figure 1 and Figure S1). USGS streamgage 01570500 lies on the east bank of City Island (Figure 1) with a drainage area of 62,419 km² and a gage datum of 88.18 m above NAVD 88 (U.S. Geological Survey, 2016a). Throughout the study reach, there are three interstate bridges, three smaller road crossings, and two railroad crossings along with a levee protecting Harrisburg International Airport (Table S1). Multiple creeks drain into the Susquehanna within the 41-km reach, but are not substantial enough to greatly affect the flow along the study reach.

2.2 | Land surface model

2.2.1 | Noah-MP and downscaling GCMs

Multivariate adaptive constructed analogs (MACA)-based GCM datasets from the Coupled Model Intercomparison Project (CMIP Phase 5) that are statistically downscaled and bias-corrected with METDATA (Abatzoglou, 2013) as a training dataset were used in this analysis (Abatzoglou & Brown, 2012). Two different future climate change scenarios based on representative concentration pathways (RCPs) were used in this analysis: RCP 4.5 (business as usual greenhouse gas emissions) and RCP 8.5 (worst-case greenhouse gas emissions). The meteorological forcing from the best performing GCM...
ranked using precipitation indices was used as an input to a 4-km resolution Noah-MP LSM (Ek et al., 2003; Niu et al., 2011) for the entire Chesapeake Bay watershed to estimate the water balance components, such as evapotranspiration, surface runoff, baseflow, and soil moisture, and energy fluxes, such as latent heat flux, ground heat flux, and sensible heat flux. The water balance components of surface runoff and baseflow were fed to a convolution-based routing model (Lohmann et al., 1996) to predict river discharges at desired locations in the watershed. Further details about the dataset and LSM calibration and validation are discussed in Modi et al. (2021).

2.2.2 | Streamflow data

Historical peak discharges for 30-year and 100-year events were obtained from annual exceedance probability (AEP) estimates from FEMA Flood Insurance Studies (Federal Emergency Management Agency, 2012). We identified 11-day hydrographs corresponding to these events from the USGS streamgage record: September 14–24, 2004 (historical 30-year flood event) and June 19–29, 1972 (historical 200-year flood event), respectively (Figure S2).

The majority of floods along the Susquehanna River have resulted from events, such as tropical storms, hurricanes, and ice jams, which are difficult to predict even with short-term operational forecasting and are poorly captured by MACA based GCM datasets (Ranson et al., 2016). However, GCMs are suitable for estimating the long-term impacts of climate change on processes controlling the water and energy fluxes in a basin, which impact flooding (Collins et al., 2013). Therefore, we use the LSM forced with projections from the GCMs to determine the long-term changes in watershed conditions, including streamflow and peak discharge. The streamflow data from GCM-LSM coupling were used to predict the future 30-year and 100-year flood event for two 30-year periods (RCP 4.5 [2020–2050; 2060–2090] and RCP 8.5 [2020–2050; 2060–2090]). Flood volume (average state) was extracted from future hydrographs 5 days before and after the peak event (total volume over 11 days, based on analysis of historical flood hydrographs [Figure S2]). Peak discharge (point estimate) was not extracted because of its higher uncertainty compared with flood volume in GCM projections. It should be noted that the flood volumes for the 100-year flood events were extrapolated from 30-year GCM periods, and there was no actual storm corresponding to such events in the GCM record.

Future hydrograph volume from the GCM-LSM model coupling for two 30-year periods was used to develop the future 30-year and 100-year flood events by scaling them to the historical 11-day hydrographs. Scaling was achieved by uniformly changing the ordinates of the historical 30-year and 100-year hydrographs until the total volume conveyed by that hydrograph was equal to the future flood volume. The assumption is that the shape of the future hydrographs would be consistent with historical hydrographs, and it is the change in the hydrograph volume that intensifies the future flood risk and reflects the impact of climate change. This method ensured that the hydrograph shape, flood volumes, and peak discharges were consistent across the historical 2021–2050 and 2061–2090 time periods for a given recurrence interval event, but created some issues when trying to directly compare future peak discharge estimates between the 30-year and 100-year events as described in Section 3.3.

2.3 | Hydrodynamic model

2.3.1 | 2D HEC-RAS

Flood inundation was predicted using 2D HEC-RAS (v5.0.7), developed by the U.S. Army Corps of Engineers (USACE, 2016), with unsteady flow and the diffusive wave equations to simulate flood inundation depth and extent (Figure 1).

2.3.2 | Input data and model configuration

The terrain for the 2D HEC-RAS model was developed using a combination of a 3 m lidar digital elevation model (DEM; U.S. Geological Survey, 2016b) and cross-sections along the study reach. Channel cross-sections from Roland et al. (2014) were used to interpolate 2D bathymetry. This included a total of 123 cross-sections from USGS discharge measurements, the Pennsylvania Department of Transportation bridge plans (PennDOT), and an HEC-2 model from earlier flood-inundation studies by FEMA. The data from the lidar DEM and channel cross-sections were combined to generate a representative terrain for the study reach using the interpolation algorithms in 2D HEC-RAS (USACE, 2016). Artifacts that developed around islands, due to the interpolation of river bathymetry from the channel cross-sections, were reduced using island polygons from the National Hydrography Dataset where we kept the original lidar DEM topography. This allowed us to only interpolate across the wetted channel and not across islands. For this correction around islands, we connected the island lidar DEM topography to the cross-section interpolated bathymetry using the nearest neighborhood interpolation method.
The model used an unstructured mesh of polygons (with three to eight sides) with nominal cell spacing of 50 m corresponding to roughly five to six cells across the width of the channel (Figure S1). The cell spacing was set considering the fact that 2D HEC-RAS uses a sub-grid model (via hydraulic attribute tables) that incorporates the full resolution of the underlying terrain (USACE, 2016). The ability for this model to capture inundation of small-scale features using a large cell spacing was explicitly highlighted in Czuba et al. (2019), where they validated model predictions against an aerial photograph showing a range of scales of floodplain channels, some much smaller than the grid spacing.

The upstream boundary condition was set as an inflow hydrograph from the USGS streamgage with an energy slope, calculated as the longitudinal slope of the channel from a lidar DEM, of 0.00046 m/m. The downstream boundary condition was set as normal depth with friction slope equal to the energy slope from the upstream boundary condition. Seven break lines were added along high ground to prevent water from inundating the floodplain before overtopping high ground.

Manning’s $n$ values based on the National Land Cover Database (NLCD; Yang et al., 2018), were initially assigned using the table developed by the National Resources Conservation Service (NRCS-Kansas, 2016). These $n$ values were changed as part of model calibration, described in Section 2.4. Parameters describing hydraulic structures were acquired from Roland et al. (2014), which included the position and design of bridges, levees, and dams (see Table S1). In this application, bridges were accounted for by introducing break lines and increasing the Manning’s $n$ values for the cells containing bridges. This simple workaround was implemented to tackle the inability of adding bridge structures in version 5.0.7 of 2D HEC-RAS. The levee in the domain was modeled as a 2D area connection with a weir structure and crest elevation of 94.58 m (based on data from Roland et al., 2014). The time step was controlled using the Courant condition that ensures model stability during rapid changes in flow and velocity (USACE, 2016). The Courant number was set to 1 with adaptive time steps up to 5 min. The horizontal coordinate system for the entire study was North American Datum 1983 Universal Transverse Mercator (UTM) Zone 18 and the vertical datum was NAVD 88 (meters).

### 2.4 Model calibration and evaluation

The USGS streamgage provides discharge and stage at 30-min intervals from 1890 to present, which have been used to calibrate and evaluate 2D HEC-RAS model performance. We also used results from past studies, including Roland et al. (2014), who developed flood-inundation maps and flood-depth grids using a 1D HEC-RAS model at selected water levels (stages of 3.4–11.3 m at the USGS streamgage) for our same study reach. Roland et al. (2014) also developed longitudinal flood profiles and compiled observed high-water marks for Tropical Storm Agnes (1972) and Lee (2011), which we used to benchmark our model predictions.

The 2D HEC-RAS model was calibrated using the stage–discharge relationship from the USGS streamgage by estimating relative root mean square error (RRMSE) where RRMSE < 10% indicates excellent model performance (Despotovic et al., 2016). Model calibration used hydrographs for peak discharge events in water years 2008–2013 to build the stage–discharge relationship and 2014–2019 for model validation. The objective function for calibration was RRMSE and was performed using trial and error by adjusting Manning’s $n$. It should be noted that the calibration was only carried out for the open-water computational cells using the USGS stage–discharge relationship. The Manning’s $n$ values for bridge computational cells were then calibrated at the location of bridges using water-surface elevation (WSE) longitudinal profiles from the 1D HEC-RAS model (Roland et al., 2014). The calibration for bridges was performed independently using the trial-and-error approximation.

Following calibration of the 2D HEC-RAS model, the model was further evaluated in comparison with post-flood high-water marks at river cross-sections and longitudinal WSE flood profiles from the 1D HEC-RAS model (Roland et al., 2014) for both Tropical Storm Agnes (Page & Shaw, 1973) and Lee (Roland et al., 2014). Roland et al.’s (2014) 1D HEC-RAS model was developed using the cross-sections and engineered structures (see Section 2.3.2) and was calibrated with USGS streamgage data and high-water marks of major flood events including Tropical Storm Agnes and Lee. However, several modifications were made by Roland et al. (2014) in the 1D HEC-RAS model for the simulation of the Tropical Storm Agnes (1972) flood, which included adding Walnut Bridge that collapsed during a 1996 flood, a different location of the USGS streamgage, and removal of the airport levee. Similar changes were also made in this application for the simulation of the Agnes flood event in the 2D HEC-RAS model. Flood depths from the 2D HEC-RAS model were compared with the flood depth grids available from Roland et al. (2014) to assess the spatial variability in the estimates of flooded areas for Tropical Storm Lee.

Finally, data from Page and Shaw (1973), who developed a flood inundation map for the flood of June 1972 (Tropical Storm Agnes) in Harrisburg, PA, were used to
further evaluate the model predictions of flood inundation. Page and Shaw (1973) estimated the flood depth and areal extent along a 32 km reach of the Susquehanna from Marysville to Falmouth, PA, and constructed a WSE profile along the reach from the surveys of post-flood high-water marks.

3 | RESULTS AND DISCUSSION

3.1 | Model calibration and evaluation

3.1.1 | Stage–discharge curves

We calibrated the 2D HEC-RAS model by comparing the stage–discharge relationships at the USGS streamgage, as shown in Figure 2a. It includes peak streamflow events during 2008–2013 ranging from 3850 m$^3$/s in 2012 to 16,700 m$^3$/s in 2011, which was from Tropical Storm Lee (Table 1). Flows below a threshold of 2500 m$^3$/s had greater error when compared with the higher flow events, because we were not able to vary roughness with stage in the 2D HEC-RAS model, which was calibrated for fidelity at high flows and, therefore, did not perform as well at low flows. In addition, Manning’s roughness was varied based on the NLCD classification, and similar roughness values were assigned throughout the channel, reducing the complexity of the riverbed roughness but increasing uncertainty in predicted flows. The final calibrated Manning’s $n$ value used for open-water computational cells ranged from 0.0275 to 0.0295 depending on the magnitude of the flow, whereas it varied from 0.020 to 0.060 for bridge cells. The higher RRMSE of 9.7% for flows <4000 m$^3$/s compared with 4.6% for flows >7000 m$^3$/s during 2008–2013 indicates the errors at different flow magnitudes along the study reach, as shown.

![Stage–discharge curve](https://example.com/fig2.png)

**FIGURE 2** Stage–discharge curve at USGS streamgage 01570500 for (a) calibration period (2008–2013) and (b) evaluation period (2014–2019); RRMSE = relative root mean square error, L = low (<4000 m$^3$/s), M = medium (4000–7000 m$^3$/s), and H = high (>7000 m$^3$/s)
in Figure 2a. The model evaluation was performed for peak streamflow events during 2014–2019 (events described in Table 1), and an RRMSE of 5.3% for <4000 m$^3$/s and 4.1% for >7000 m$^3$/s was calculated, indicating good model performance (Despotovic et al., 2016; Figure 2b).

3.1.2 Longitudinal flood profile and high-water marks

We compared the simulated WSEs for peak streamflow events in each water year during 2008–2019 against the observed WSE from the USGS streamgage (Table 1). The difference ranged from 0.01 to 0.08 m, indicating that the 2D HEC-RAS model performed well for most of the peak streamflow events. A similar comparison of WSE was made in Roland et al. (2014) during 1996–2010 at USGS streamgage 01570500, and the difference ranged from /C0 to 0.03 m, similar in magnitude. The WSE along the study reach for Tropical Storm Lee (2011) was extracted from the 1D HEC-RAS model from the event with a peak flood stage of 7.6 m at the USGS streamgage. Figure 3a shows a comparison of the simulated WSE from 2D HEC-RAS along the reach with the extracted WSE from the 1D HEC-RAS model. The absolute error between 2D HEC-RAS and 1D HEC-RAS ranged from /C0 to 0.3 m where the maximum error was at the locations of bridges along the reach (Figure 3a), 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 (Figure 3a). These differences in WSEs were also attributed to how bridge energy-losses/roughness were incorporated into each model and to the interpolation of river bathymetry from cross-sections in the upstream section of the reach. These interpolation errors were introduced due to the presence of islands and the linear interpolation of river bathymetry between consecutive cross sections.

The simulated WSE was also compared with the surveyed high-water marks from Tropical Storm Lee (2011) by Roland et al. (2014) and collected by The Harrisburg Authority (Table 2). The differences between the predicted WSEs and the high-water marks ranged from /C0 to 0.2 m (Table 2). Most of the high-water marks were collected in the vicinity of the bridges that caused the error to be slightly greater when compared against the results from 1D HEC-RAS. The simulation of water-surface profiles around structures like bridges, buildings, or trees is complicated and is inadequately captured by the present 2D HEC-RAS model. The dynamic and unsteady behavior around such structures due to turbulent flow can be captured using three-dimensional computational fluid dynamics models or at the very least including more detailed information on the energy losses around bridge structures that is available in 1D HEC-RAS, for instance. However, this study does not aim to compare the 1D and 2D HEC-RAS models, as they both have their respective limitations. We simply employ the 1D HEC-RAS model as a point of comparison with the 2D HEC-RAS model.

The simulated WSE from the 2D model was also compared with the flood profile from Page and Shaw (1973), which was extracted from the 1D HEC-RAS model at a flood stage of 10 m. The Manning’s $n$ value for the open

| Water year | Date             | USGS 01570500 flow (m$^3$/s) | USGS 01570500 WSE (m) | 2D HEC-RAS WSE (m) | WSE difference (m) |
|------------|------------------|-----------------------------|----------------------|--------------------|--------------------|
| 2008       | March 6, 2008    | 9061                        | 5.3                  | 5.32               | 0.02               |
| 2009       | March 11, 2009   | 4021                        | 3.11                 | 3.13               | 0.02               |
| 2010       | January 27, 2010 | 8580                        | 5.11                 | 5.14               | 0.03               |
| 2011       | September 9, 2011| 16,707                      | 7.67                 | 7.7                | 0.03               |
| 2012       | December 9, 2011 | 3851                        | 3.03                 | 3.04               | 0.01               |
| 2013       | February 1, 2013 | 5663                        | 3.88                 | 3.95               | 0.07               |
| 2014       | May 18, 2014     | 5182                        | 3.66                 | 3.74               | 0.08               |
| 2015       | April 12, 2015   | 4984                        | 3.56                 | 3.64               | 0.08               |
| 2016       | February 27, 2016| 4474                        | 3.33                 | 3.4                | 0.07               |
| 2017       | April 8, 2017    | 5097                        | 3.62                 | 3.7                | 0.08               |
| 2018       | July 26, 2018    | 9005                        | 5.28                 | 5.3                | 0.02               |
| 2019       | December 23, 2018| 5550                        | 3.83                 | 3.91               | 0.08               |
channel was slightly reduced for the simulation of the 1972 flood event due to its exceptional flow volume (28,900 m³/s) and assignment of a single Manning’s n value for the entire reach as part of the calibration. This reduction in Manning’s roughness (from 0.0295 [calibrated value] to 0.0275) was carried out only for the simulation of Tropical Storm Agnes due to the availability of post-flood high-water marks and was unchanged for other simulated flood events (historical and future) in this study due to the shape of future hydrographs being unknown. The absolute error between 2D and 1D HEC-RAS WSE for Tropical Storm Agnes ranged from −1.5 to 1.25 m with

**FIGURE 3** (a) 2D HEC-RAS simulated longitudinal flood profiles along the study reach of the 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 1D HEC-RAS (Roland et al., 2014) with the absolute error shown at the top. The vertical labels in black indicate the structures from Table 1. (b) Difference in water-surface elevation (WSE) for Tropical Storm Lee (discharge: 16,700 m³/s) between 1D HEC-RAS (Roland et al., 2014) and 2D HEC-RAS model. Positive values indicate the 2D model predicted higher WSE than the 1D model.
higher uncertainty due to the pronounced effect of bridges at higher flows (Figure 3a). Table 2 indicates the differences in simulated WSE (for 2D and 1D HEC-RAS) with the observed high-water marks from Tropical Storm Agnes documented by Page and Shaw (1973). The difference in WSEs ranged from $0.5$ to $0.5$ m, which was again slightly higher when compared with the differences with 1D HEC-RAS simulations (Table 2).

### 3.2 Flood inundation (Tropical Storm Lee)

We used the 2D HEC-RAS model to simulate the WSE for Tropical Storm Lee and compared it with the flood inundation maps prepared by Roland et al. (2014). Figure 3b shows the difference in WSE for Tropical Storm Lee between the 1D and 2D HEC-RAS models for the entire reach. The 2D HEC-RAS model agreed well in most sections of the reach with differences ranging between $-1$ and $1$ m. The maximum difference ($-2$ m) was observed near Marysville due to an artifact in the 1D HEC-RAS DEM where it was $10$ m higher than the lidar DEM used in 2D HEC-RAS (purple triangular artifact near Marysville in Figure 3). The WSE differences in other sections of the reach (just above the downstream boundary) and floodplain regions were attributed mainly to the interpolation of river bathymetry from channel cross-sections and different lidar datasets. These differences are also evident as the flood depth estimates from Roland et al. (2014) were made with respect to bare earth DEMs, and not river bathymetry (see discussion on lidar datasets in the Supplementary Material). Another major difference between the models was that backwater at bridge constrictions was not considered in the 2D model (beyond higher roughness locally), whereas in the 1D model, WSEs were mapped independently at four locations where backwater flooding was occurring and was rendered as a water-surface triangulated irregular network (TIN) that was incorporated into the final 1D-generated WSE grid (Roland et al., 2014). Flood depth grids for Tropical Storm Lee from 2D HEC-RAS and 1D HEC-RAS are shown and further discussed in the Supplementary material (Figure S3).

### Table 2

Comparison of water-surface elevations (WSE) from surveyed high-water marks for Tropical Storm Lee (2011; collected by Roland et al., 2014 and The Harrisburg Authority) and Tropical Storm Agnes (1972; collected by Page & Shaw, 1973) to model simulation results for the 1D (Roland et al., 2014) and 2D HEC-RAS model (present study)

| River mile | High-water mark elevation (m) | Modeled WSE 1D (m) | WSE difference 1D (m) | Modeled WSE 2D (m) | WSE difference 2D (m) |
|------------|------------------------------|--------------------|-----------------------|--------------------|-----------------------|
| **Tropical Storm Lee (2011)** |
| 75.82      | 99.3                         | 99.4               | 0.1                   | 99.1               | −0.2                  |
| 74.99      | 98.1                         | 98.6               | 0.4                   | 98.3               | 0.2                   |
| 72.84      | 97.3                         | 97.2               | −0.1                  | 97.2               | −0.1                  |
| 69.95      | 96.6                         | 96.4               | −0.2                  | 96.2               | −0.3                  |
| 69.03      | 96.0                         | 95.8               | −0.2                  | 95.7               | −0.2                  |
| 66.43      | 94.1                         | 94.1               | 0.0                   | 94.3               | 0.1                   |
| **Tropical Storm Agnes (1972)** |
| 83.47      | 109.5                        | 109.7              | 0.2                   | 109.0              | −0.5                  |
| 77.91      | 102.8                        | 102.8              | 0.0                   | 103.0              | 0.2                   |
| 75.13      | 101.0                        | 100.7              | −0.3                  | 101.1              | 0.1                   |
| 74.57      | 100.7                        | 100.3              | −0.3                  | 100.5              | −0.2                  |
| 71.14      | 99.3                         | 99.5               | 0.1                   | 99.1               | −0.2                  |
| 70.01      | 99.3                         | 107.5              | −0.1                  | 98.8               | −0.5                  |
| 69.67      | 99.1                         | 99.0               | −0.2                  | 98.6               | −0.5                  |
| 69.33      | 98.6                         | 98.6               | 0.0                   | 98.4               | −0.2                  |
| 68.77      | 98.1                         | 97.9               | −0.2                  | 98.1               | 0.0                   |
| 67.58      | 96.9                         | 96.8               | −0.1                  | 97.2               | 0.3                   |
| 66.8       | 96.3                         | 96.5               | 0.2                   | 96.8               | 0.5                   |
| 65.43      | 95.6                         | 95.1               | −0.5                  | 95.7               | 0.2                   |
3.3 Impacts of climate change on flood inundation

A comparison of flood inundation depth and extent for a historical and future 30-year and 100-year flood event was performed using the 2D HEC-RAS model. Table 3 shows the peak discharge for historical and future hydrographs for both RCP 4.5 and RCP 8.5 scenarios at the USGS streamgage indicating the maximum peak discharge of 23,000 and 31,000 m³/s for a 30-year and 100-year flood event in the RCP 8.5 scenario for the 2061–2090 period. The three-day mean precipitation for the RCP 8.5 scenario indicates an increase in multi-day precipitation events causing higher river discharge as compared with RCP 4.5 (Table 3).

An overall increase in precipitation was observed in the Chesapeake Bay watershed, due primarily to a greater frequency of extreme events, resulting in greater total precipitation (Modi et al., 2021; Myhre et al., 2019). The predicted peak discharges for an 11-day flood hydrograph are shown in Table 3 from the best performing GCM (CSIRO-Mk3-6-0) for RCP 4.5 and RCP 8.5, selected based on the analysis performed in Modi et al. (2021). The 100-year peak discharges for RCP 4.5 (2061–2090) and RCP 8.5 (2021–2050) were lower than the historical peak discharge, because the projected increase in precipitation and temperature (Modi et al., 2021) resulted in a greater partitioning of precipitation into evapotranspiration and soil moisture than runoff and river discharge. In the RCP 8.5 scenario (2021–2050), the scaling of hydrographs led to a higher peak discharge for a 30-year flood as compared with a 100-year flood, contrary to its respective hydrologic volumes (Table 3). This phenomenon relates to the historical hydrographs used for scaling (Figure S2), where the future hydrograph ordinates are based on the weighted distribution of future flood volume and are dependent on the shape of the historical flood event. This illustrates the drawbacks in the scaling of hydrographs, mentioned earlier in Section 2.2.2, where

| Recurrence interval (year) | USGS 01570500 | RCP 4.5 (2021–2050) | RCP 8.5 (2021–2050) | RCP 4.5 (2061–2090) | RCP 8.5 (2061–2090) |
|--------------------------|----------------|---------------------|---------------------|---------------------|---------------------|
| Three-day mean precipitation (mm) | | | | | |
| 30 | [1,9,100] | [3,15,97] | [9,42,104] | [1,18,101] | [7,76,93] |
| Three-day storm total (mm) | | | | | |
| 30 | 110 | 115 | 155 | 120 | 176 |
| Relative change in three-day storm total (%) | | | | | |
| 30 | 4 | 29 | 8 | 38 |
| Relative change in flood volume (%) | | | | | |
| 30 | 6 | 10 | 5 | 50 |
| 100 | 6 | –16 | –4 | 57 |
| Peak discharge (m³/s) | | | | | |
| 30 | 15,400 | 16,300 | 16,900 | 16,200 | 23,000 |
| 100 | 19,800 | 21,000 | 16,700 | 19,000 | 31,000 |
| Relative change in peak discharge (%) | | | | | |
| 30 | 6 | 9 | 5 | 33 |
| 100 | 6 | –19 | –4 | 36 |
| Relative change in flood extent (%) | | | | | |
| 30 | 3 | 5 | 2 | 18 |
| 100 | 4 | –9 | –3 | 18 |
| Relative change in maximum flood depth for floodplains only (%) | | | | | |
| 30 | 4 | 6 | 3 | 26 |
| 100 | 3 | –9 | –2 | 28 |

Notes: Three-day mean and storm total precipitation (relative change) with peak occurring on third day is shown for 30-year return period storms. Peak discharge for the historical and future 30-year and 100-year flood events at USGS streamgage 01570500 for both RCP 4.5 and RCP 8.5 scenarios. Relative change in flood volume (%) is calculated with reference to the USGS gage historical streamflow and extent (%) and maximum depth (floodplains only [%]) is calculated with reference to 2D HEC-RAS simulated historical inundation (Figure 4 for 30-year and Figure 5 for 100-year).
comparisons are most appropriate only among historical and future flood events with similar recurrence intervals for this study. These estimates of peak discharges highlight the importance of assessing the mesoscale hydrological processes using LSMs, as these processes significantly affect river discharge and flood impacts.

**FIGURE 4** Flood inundation map for (a) historical 30-year flood event (discharge: 15,400 m$^3$/s) and (b) future RCP85 (2061–2090) 30-year flood event (discharge: 23,000 m$^3$/s) at the USGS streamgage generated using the calibrated 2D HEC-RAS model.
Further details on the hydrological analysis explaining the impacts of climate change on terrestrial hydrologic components in the Chesapeake Bay watershed can be found in Modi et al. (2021).

The flood inundation extent and depth predicted by the 2D HEC-RAS model along the Susquehanna River near Harrisburg are expected to increase, particularly in RCP 8.5 (2061–2090), primarily due to an overall increase in antecedent soil moisture (Modi et al., 2021), resulting from greater total precipitation (Table 3). Figure 4a,b shows the flood inundation depth and extent for the historical and future (RCP 8.5) 30-year flood event, respectively. The maximum flood depth observed for the historical 30-year flood event was less than 6.5 m, whereas the flood depth in the RCP 8.5 scenario was above 6.5 m in most sections of the reach inundating the overbank areas. Figure 5a,b shows the flood inundation and extent for the historical and future (RCP 8.5) 100-year flood event, respectively. Higher flood depths between 4 and 6.5 m were simulated throughout the river for the historical 100-year flood event, and the future flood event exceeded 6.5 m in major parts of the reach with a maximum depth of 8.5 m. The flood inundation due to the historical 100-year 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 above 2.5 m high (Figure 5a), whereas for the future 100-year flood event, the flood depth completely submerged all the islands, low-lying areas of Paxton Creek, Harrisburg International Airport, overbank areas that include N. Front Street, South Cameron Street, and New Market along the reach with flood depths between 2 and 2.5 m high (Figure 5b). Based on the rating curve developed for the USGS streamgage by Roland et al. (2014), the historical and the future (RCP 8.5) 100-year flood event can be categorized as NWS flood category major flood stage (8.5 m) and record flood stage (10.3 m), respectively. The future 100-year flood event had a slightly higher flood magnitude of 31,000 m$^3$/s (stage: 10.3 m) as compared with Tropical Storm Agnes (1972), which has a peak of record at the USGS streamgage with a flood magnitude of 28,890 m$^3$/s (stage: 10.1 m). Figure S4a,b shows the difference in WSE for 30-year and 100-year flood event between the future and historical scenario indicating the regions with higher flood risk and is further discussed in the Supplementary Material.

For a 30-year flood event in the RCP 4.5 scenario (2020–2050), precipitation is projected to increase by 4%, leading to an increase in flood volume of 6% and a peak discharge of 6%, which further translates to a 3% and 4% increase in flood extent and maximum depth over the floodplain, respectively (Table 3). Whereas for the same scenario in 2061–2090, the precipitation is projected to increase by 8%, leading to an increase in flood volume of 5% and in peak discharge of 5%, which translates to only a 2% and 3% increase in flood extent and maximum depth over the floodplain, respectively. This demonstrates that even though precipitation is projected to be higher in 2061–2090 than in 2021–2050, the increase in peak discharge, flood volume, flood extent, and maximum flood depth may be less. The interplay among soil moisture, evapotranspiration, temperature, and precipitation is responsible for the changes in effective rainfall and runoff volume/river discharge, which underscores the importance of considering the water and energy balance in translating future changes in precipitation to river discharges and flood extent. Studies that employ lumped/conceptual rainfall-runoff models cannot capture the dynamic processes that interact to control flood impacts.

For a 100-year flood event, in the RCP 8.5 scenario (2021–2050), flood volumes are projected to decrease by 16%, leading to a decrease in a peak discharge of 19%, which further translates to a 9% decrease in flood extent and maximum depth over the floodplain, respectively. Whereas for the same scenario in 2061–2090, flood volumes are projected to increase by 57%, leading to an increase in a peak discharge of 36%, which further translates to an 18% and 28% increase in flood extent and maximum depth over the floodplain, respectively. These results also indicate that if a storm similar to the recurrence interval of Tropical Storm Lee occurs in the future, substantial increases in flood magnitude and severity are likely. For instance, should a storm like Lee (historical 50-year flood) occur in the 2061–2090 period for the RCP 8.5 scenario, the model indicates an increase of 40% in the flood volume, which translates to an increase of 15% and 20% in flood extent and maximum depth (over the floodplain), respectively.

This study uses the Noah-MP LSM coupled with 2D HEC-RAS to estimate the future flood risk using GCMs data. One of the important findings of this study highlights that an increase in precipitation in future climate scenarios may not translate to an increase in flood risk underscoring the importance of land surface modeling for flood analysis. This would not have been the case with conceptual rainfall-runoff models, as they lack coupled water and energy balance simulations affecting the hydrological partitioning and, hence, the streamflow estimates (Hurkmans et al., 2008). Uncertainties in model structure and input data are inevitable and, hence, remain as one of the drawbacks to this study. The hydrograph scaling employs a weighted distribution of future flood volume playing a crucial role in extracting the flood risk information from GCMs. However, the assumption of consistent hydrograph shape limits the ability to
compare across different recurrence interval flood events in historical and future climate scenarios. Given the underlying potential of this integrated modeling framework, it can be extended further to predict future flood risk in flood-prone regions. Information like this can be useful to develop long-term strategies and policies.

**FIGURE 5** Flood inundation map for (a) historical 100-year flood event (discharge: 19,800 m$^3$/s) and (b) future RCP85 (2061–2090) 100-year flood event (discharge: 31,000 m$^3$/s) at the USGS streamgage generated using the calibrated 2D HEC-RAS model.
that minimize risk and facilitate development in the face of threats due to climate change.

4  |  SUMMARY

A hydrological modeling framework integrating climate projections with a coupled LSM and hydrodynamic model was developed to investigate the impacts of climate change on flood risk along the Susquehanna River near Harrisburg, PA. The framework was employed for a 41 km reach starting at the confluence of Juniata River and ending before Hill Island near Swatara Creek. The 2D HEC-RAS model was calibrated and evaluated using the stage-discharge relationship of a USGS streamgage and was verified for post-flood high water marks from Tropical Storm Agnes (1972) and Tropical Storm Lee (2011) and water-surface elevation profiles from a 1D HEC-RAS model developed by the USGS. The historical 30-year and 100-year flood hydrographs were extrapolated based on FEMA AEP estimates at the USGS streamgage, and future hydrograph volumes were derived from the best-performing MACA-based GCM forced through the calibrated Noah-MP LSM for two scenarios and two future periods (RCP 4.5 [2020–2050; 2060–2090] and RCP 8.5 [2020–2050; 2060–2090]). The future hydrographs for each scenario were scaled to historical 30-year and 100-year flood hydrographs based on the future hydrograph volume assuming that they have similar hydrograph shapes. The historical and future flood hydrographs were simulated with a 2D HEC-RAS model to assess the changes in flood inundation depth and extent due to climate change. This study shows that an increase in precipitation may not translate to an increase in flood risk for future climate scenarios. Hence, instead of considering precipitation as the only driving factor to predict future flood risk, incorporating LSMS to translate and extract more information from climate model data can provide insight into future flooding risk. We also conclude that a higher flood severity and risk are expected near Harrisburg, PA toward the end of the 21st century under the RCP 8.5 scenario due to an increase in river discharge, resulting from increased total precipitation and wetter antecedent soil moisture conditions. This study develops future flood inundation maps for the Harrisburg region that depicts an increase of up to 18% in flood extent corresponding to an increase of up to 28% in maximum flood depth over the floodplain for future climate scenarios as compared with the historical observations. For instance, a storm similar to the recurrence interval of Tropical Storm Lee that occurs in the future would result in an increase of 15% and 20% in flood extent and maximum flood depth over the floodplain, respectively.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

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

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