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Repeated Hurricanes Reveal Risks and Opportunities for Social-Ecological Resilience to Flooding and Water Quality Problems

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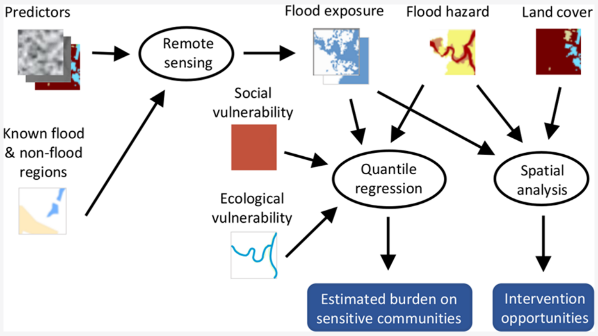

ABSTRACT: Hurricanes that damage lives and property can also impact pollutant sources and trigger poor water quality. Yet, these water quality impacts that affect both human and natural communities are difficult to quantify. We developed an operational remote sensing-based hurricane flood extent mapping method, examined potential water quality implications of two "500-year" hurricanes in 2016 and 2018, and identified options to increase social-ecological resilience in North Carolina. Flooding detected with synthetic aperture radar (>91% accuracy) extended beyond state-mapped hazard zones. Furthermore, the legal floodplain underestimated impacts for communities with higher proportions of older adults, disabilities, unemployment, and mobile homes, as well as for headwater streams with restricted elevation gradients. Pollution sources were repeatedly affected, including ~55% of wastewater treatment plant capacity and swine operations that generate ~500 M tons/y manure. We identified ~4.8 million km^2 for possible forest and wetland conservation and ~1.7 million km^2 for restoration or altered management opportunities. The results suggest that current hazard mapping is inadequate for resilience planning; increased storm frequency and intensity necessitate modification of design standards, land-use policies, and infrastructure operation. Implementation of interventions can be guided by a greater understanding of social-ecological vulnerabilities within hazard and exposure areas.

■ INTRODUCTION

Globally, the most costly natural disasters are attributed to flooding, and the cost of flood events will likely continue to rise due to ongoing climate change and modification of floodplains.[1−3] Substantial resources have been dedicated to delineating flood-prone areas in some regions, yet recent work has revealed that people and property are at greater risk of flooding than previously estimated.[4−6] In addition to higher storm frequency and intensity, which can exceed infrastructure design capacity, development within floodplains has increased risk.[3,7−10]

Unfortunately, flooding disproportionately affects vulnerable human and ecological systems expected to be least equipped to recover.[11−13] While inclusion of social vulnerability in disaster assessment and preparedness is a growing practice, few studies have quantified hazards in relation to ecological vulnerability, though evidence suggests this would improve policy recommendations.[14−16] Recent research emphasizes building resilience, such that communities exposed to future disasters may be buffered from damage, respond and recover more quickly, and achieve better outcomes.[17,18] Quantifying resilience, which varies over space and time, is at the early stages of research and practice.[17,19,20]

Water quality problems during and after floods threaten the health of both humans and aquatic species. Flooding can contaminate drinking water and increase the spread of waterborne diseases.[21,22] Overland flow from agricultural lands can elevate nutrient, chemical, and pesticide concentrations, harming aquatic organisms and degrading the ecosystem.[23−26] Untreated sewage and waste from concentrated animal feeding operations (CAFOs) contain additional biological and chemical elements, including heavy metals, pathogens, and antibiotics.[27] Widespread flooding can also release organic material into waterways, depleting dissolved oxygen that most aquatic organisms need to survive, exacerbating eutrophic conditions and harmful algal blooms, and promoting the spread of invasive species.[28−30] Development of adaptation strategies to reduce flooding and water quality impacts requires understanding the capacity of at-risk people, ecosystems, and water infrastructure to withstand and recover from flooding.

Measuring water quality impacts during large flood events is challenging, but satellite-based remote sensing can provide insight for quantifying potential damage and identifying

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solutions.[11] In 2018, Hurricane Florence caused a variety of water quality problems in North and South Carolina, including wastewater treatment plant (WWTP) and sewer overflows up to 300 km inland, coal ash spills, breaches of CAFO waste lagoons, and numerous fish kills.[31,32] Because many in situ sensors went offline and hazardous conditions precluded manual sample collection, state and federal agencies relied on aerial surveys and anecdotal reporting to assess impacts. Satellite image-based flood extent mapping can aid in estimating the exposure area and the potential reach of water quality impacts. Remote sensing data and geospatial techniques are widely used for tracking of spatial and temporal inundation patterns.[33,34] Radar is particularly suited for mapping storm-induced flooding as it is highly sensitive to the presence of water and can penetrate through clouds and detect water beneath forest and wetland vegetation.[35−38]

Recent hurricanes that repeatedly affected the Carolinas present a timely case study for assessing social-ecological vulnerability across floodplains and highlighting opportunities to improve resilience. Documentation of conditions on the ground by the U.S. Geological Survey (USGS) and the National Oceanographic and Atmospheric Administration (NOAA) following Hurricanes Matthew (October 2016, up to 46 cm rainfall) and Florence (September 2018, up to 89 cm rainfall) and publicly available satellite-based radar enable detection of repeated flood exposure. Affected communities are evaluating options from property buyouts, to infrastructure adaptations and management changes, to watershed-scale nature-based solutions (NBS). Conserving and restoring floodplain forest and wetlands can reduce peak flood stage and reduce economic damage, as well as provide services such as nutrient cycling and water purification, and maintain important plant and wildlife habitats.[36−46] In some cases, NBS can be more cost-effective than hardened infrastructure such as dams and levees.[48]

Our objectives for this study were to (1) map the flood extent from recent hurricanes, (2) investigate the implications of differences between detected flood exposure compared to existing flood hazard maps for assessing impacts to vulnerable human communities and freshwater ecological systems, and (3) identify opportunities to reduce future hurricane-associated water quality problems.

■ MATERIALS AND METHODS

We examined threats posed to water quality and opportunities to improve resilience to future storms in the North Carolina (NC) Piedmont and Coastal Plain. We defined flood hazard areas using state-mapped flood hazard and estimated exposure to flooding with satellite remote sensing methods. To assess water quality implications of hazard and exposure, we conducted a spatial overlay analysis considering social and ecological assets, as well as sources of water quality contaminants. To aid relief and recovery efforts, we examined the distribution of hazard and exposure in the context of social vulnerability and freshwater ecological vulnerability. Finally, we identified locations where interventions could be implemented. Although resilience and vulnerability may not be direct opposites, they are related.[18] We reasoned that an intervention that can reduce impacts to sensitive human and natural systems should result in higher resilience and better long-term outcomes following a flood event. Remote sensing and spatial analysis were completed using Google Earth Engine (GEE).[49] Flood extent classification algorithm tuning and statistical analyses were completed in the R programming environment.[50]

Study Area. This study focused on NC watersheds that drain to the Atlantic Ocean, mainly in the Piedmont and Coastal Plain regions (Figure 1). Elevations across the Piedmont plateau east of the Southern Appalachian mountains range from 450 to 100 m, transitioning to the Coastal Plain with sandy soils extending to the coastline (Figure 1A). The region is characterized by a humid subtropical climate, with average temperatures ranging from −1 °C during the winter to 31.7 °C in the summer. Snow is rare below the mountains, with most precipitation falling as rain in the Piedmont (112−122 cm/y) and Coastal Plain (112−142 cm/y) regions. NC has repeatedly been affected by hurricanes, especially during late summer and early fall. Historically used for agriculture and

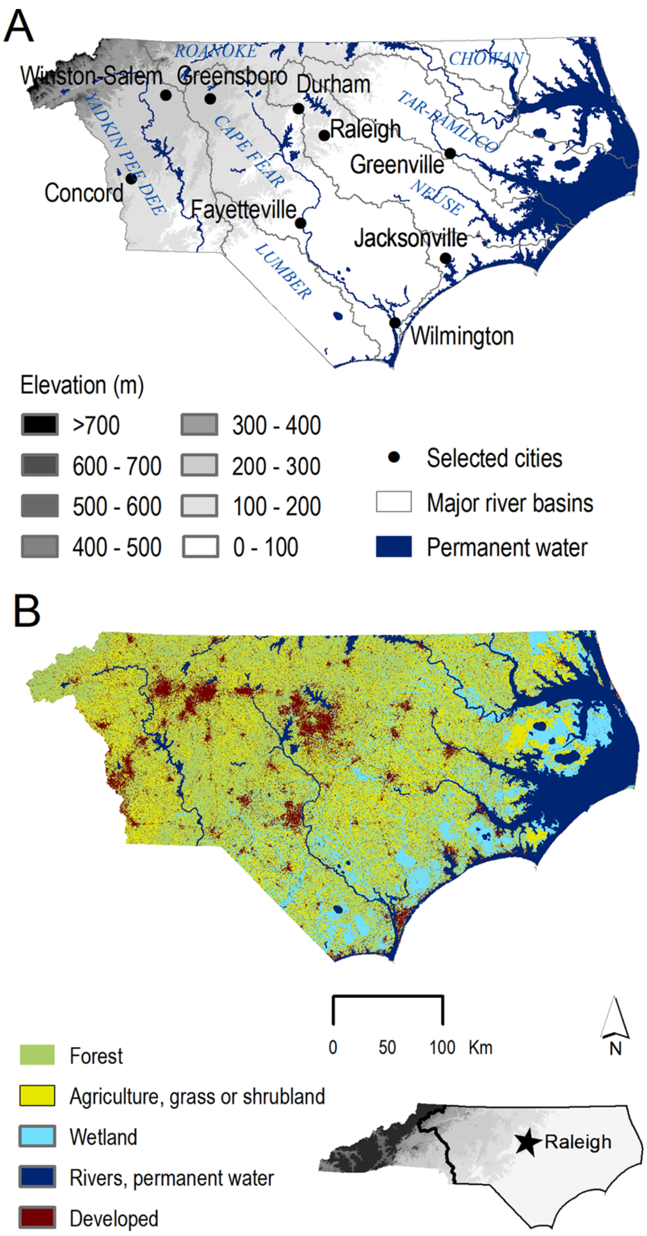

Figure 1. Study area in North Carolina showing topography and the major river basins draining to the Atlantic Ocean (A), as well as 2011 landcover (B) in the coastal plain and piedmont regions.

forestry, the landscape has undergone rapid urban and suburban development in recent decades (Figure 1B). However, substantial riparian forests remain along rivers, as well as extensive swamps and wetlands. These habitats support high biodiversity, including providing spawning areas for diadramous fish populations and species of concern such as the Atlantic sturgeon.[47]

A variety of water quality concerns exist in the study area.[51] Numerous hazardous waste sites, such as defunct coal ash ponds, occur across NC. Point sources of nutrients and other effluents are ubiquitous, including industrial dischargers, WWTPs, and postconstruction stormwater management systems permitted under the National Pollutant Discharge Elimination System (NPDES). NC is nationally ranked second for swine production and third for poultry production, with one of the highest densities of CAFOs in the US. CAFOs can be a point source (via discharges from manure lagoons) and a nonpoint source (via land application of manure).[52,53] Swine CAFOs typically use liquid waste management regulated by a statewide general permit under NPDES, which designate crops where manure can be applied at agronomic rates, among other parameters.[54] Poultry facilities mainly operate with dry waste and are not regulated by NPDES in NC.[53,55] A recent analysis found that nonpoint sources, including fields where manure is applied, may contribute 35% of pollutants in the Cape Fear River under normal flow conditions.[56]

Defining Flood Hazard and Exposure. *Mapped Flood Hazard Zones.* We considered three levels of flood hazard mapped by the NC Division of Emergency Management Services, including the 0.2% annual exceedance probability (AEP) zone (500-year floodplain), the 1% AEP zone (100-year floodplain), and the floodway, which floods frequently and includes levees and channels intended to protect adjacent land. These categories correspond to distinct legal requirements and land use planning restrictions under the National Flood Insurance Program; in particular, insurance for structures is not always required beyond the 1% AEP zone, depending on local regulations.[57] We considered areas mapped as "future 1% AEP" to be part of the 1% AEP zone, as these locations are likely to flood when development shown on zoning and land use planning maps is realized.[58]

Estimating Hurricane Flood Exposure Using Remote Sensing. To represent flood exposure, we delineated flood extent following Hurricanes Matthew and Florence. We used a supervised random forest classification approach incorporating pre- and poststorm 10-m radar imagery (Tables S1 and S2).[59−62] Random forest is a nonparametric machine learning algorithm that is widely applied in remote sensing and classification problems across disciplines, including social science, economics, ecology, and even previous studies of flood hazard.[6,59,63−65] Combining bootstrap aggregation and random feature selection, random forest constructs many independent decision trees with controlled variance and corrects for overfitting. Random forest can handle large, multidimensional data sets, including both categorical and continuous covariates, and is robust to multicollinearity.[59,62,66] We reasoned that regions where repeated flooding was detected would represent higher intensity exposure. For model training and validation, we compiled confirmed flooded and nonflooded location data for each event, consisting of high water marks verified in the field and randomly selected pixels within flooded and nonflooded regions delineated from NOAA high resolution aerial photography acquired following each hurricane (Tables S1 and S2).[67−69] Final random forest models included the following covariates: pre- and poststorm Sentinel-1 C-Band radar vertical and cross-polarizations, vertical/cross-polarization ratio, elevation, height-above-nearest-drainage (100 upstream cell threshold), geomorphological features, 1000-year pluvial and defended floodplains, and the percent tree cover and impervious cover mapped by the National Land Cover Database.[70−74]

Assessing Impacts to Vulnerable Communities within and beyond Mapped Hazard Zones. To gain insight into how flood hazard and exposure affected vulnerable human communities and freshwater systems, we used quantile regression. Quantile regression has been previously applied in studies of hazards and social vulnerability; this approach accounts for differences in the effect of a factor that are not captured by changes in the average of the distribution of the response variable.[75,76] We explored how the effect of hazard and exposure varied across the distribution of socio-economic indicators within census tracts and indicators of ecological vulnerability within hydrological unit code (HUC) 12 watersheds. For each indicator, we estimated separate regressions for the relationship between hazard zones or detected flooding and the median (0.5 quantile), the lowest (0.1) conditional quantile, and the highest (0.9) conditional quantile subsets of census tracts or watersheds.

Socio-economic Vulnerability. To represent socio-economic vulnerability, we used the Center for Disease Control's Social Vulnerability Index (SVI), which ranks census tracts in each state and the District of Columbia according to 15 indicator variables expected to predict the ability of communities to respond during a natural disaster and recover after it has passed.[77] These variables are derived from the 5-year American Community Survey (ACS) data set, centered on the year 2016, which supplements the decennial census to provide detailed measurements for a subset of households within each census tract. The normalized indicators fall into four themes: (1) socioeconomic status, (2) household composition and disability, (3) minority status and language, and (4) housing and transportation. The overall SVI score is computed by summing scores within each theme and then summing the scores across all themes.

Ecological Vulnerability. To represent the ecological vulnerability of freshwater systems, we used an existing resilience assessment completed for ∼70% of the stream miles in NC.[78,79] The aim of this effort was to identify places that "...will continue to sustain high levels of biodiversity and ecosystem function" in the future, despite climate and species composition changes.[78] The assessment normalized 12 underlying indicators, including physical parameters (e.g., number of temperature classes) and ecological condition metrics (e.g., proportion of development in the watershed), which were summed to produce an overall resilience score. Low resilience streams can conversely be viewed as vulnerable, and several of the parameters have direct implications for flooding. For consistency in the direction of our analysis of human and ecological systems, we inverted overall freshwater resilience and the underlying indicators to equate to vulnerability. We then aggregated these data to the scale of HUC 12 watersheds to consider how spatial patterns of flood hazard and detected flooding affect the landscape that contributes to the flow and water quality of the stream network. For each HUC 12 watershed we generated a weighted vulnerability score using the proportional length of all scored stream segments that the watershed contained.

Assessing Potential Exposure of Key Assets and Sources of Water Quality Contaminants. To assess how flood hazard and exposure affected human and ecological assets and potential sources of water quality contaminants, we conducted an overlay analysis within flood hazard and flood exposure zones. To account for uncertainty for sites with only fixed-point locations (e.g., water supply wells, CAFOs), we defined the level of hazard or flood exposure as the zone comprising the majority of pixels within a 60-m radius around each point.

We first examined how spatial patterns of flood hazard and exposure affected human and natural community assets. To evaluate effects on human communities, we examined municipal boundaries and census tracts[80,81] as well as affected population based on decennial census records. To examine the risks to drinking water, we assessed surface water intakes and public groundwater supply wells.[51] To evaluate effects on natural communities, we examined the highest value fish habitat mapped by the NC Natural Heritage Program.[82] We did not use records for individual aquatic species given known limitations including numerous distinct observers, bias in survey methods, and effort.[83]

We also considered how flood hazard and exposure affected potential water quality contaminant sources, including hazardous waste sites, industrial dischargers, WWTPs, municipal stormwater infrastructure, and CAFOs. Although poultry CAFO locations are not publicly available, their recent dramatic expansion throughout NC prompted nonprofit organizations to map these facilities using aerial imagery and ground truthing.[55] Before inclusion of CAFO data in this study, we examined a 10% random sample of both swine and poultry CAFOs to verify that animal barns were present within 1 km of the registered location using Google Earth imagery from the past 5 years. While NC swine manure application records are not publicly available, data from other regions suggest that the majority of liquid manure is applied within ∼5 km from CAFO facilities within the same watershed, due to high transportation costs.[84] We therefore considered croplands within 5 km of mapped swine CAFOs as a potential source of nutrients from manure land applications.[85]

Identifying Opportunities for Watershed-Scale Buyouts and Nature-Based Solutions. To provide a portfolio of interventions in the region, we identified land within flood hazard and exposure areas where buyouts or NBS could be implemented based on current land cover.[85] We considered existing urban areas as high priorities for buyouts, while forests and wetlands lacking formal protection would represent conservation opportunities. Other unprotected open space, predominantly agricultural lands, could be sites for floodplain forest and wetland restoration. Alternatively, easements or incentive-based land management modifications could permit continued agricultural production.

■ RESULTS AND DISCUSSION

Comparison of Flood Hazard Zones and Detected Flood Exposure Areas. Final random forest models detected hurricane flooding with >91% accuracy across the Piedmont and Coastal Plain regions of NC (Table S3). Although a substantial portion of the study area falls within state-mapped flood hazard zones (Figure 2A), hurricane flooding was detected beyond these boundaries (Figure 2B). Despite distinct storm tracks and local rainfall intensities, >18 million km^2 was impacted by both Hurricanes Matthew and Florence (84.40% of the 1% AEP zone). Flooding from Hurricane Matthew was nearly equivalent to the extent of the 1% AEP zone, while flooding from Hurricane Florence exceeded the 1% AEP zone by 22.70% and the 0.02% AEP zone by 15.10%. Florence caused more extensive flooding in southeastern NC, particularly in the Cape Fear and Lumber basins.

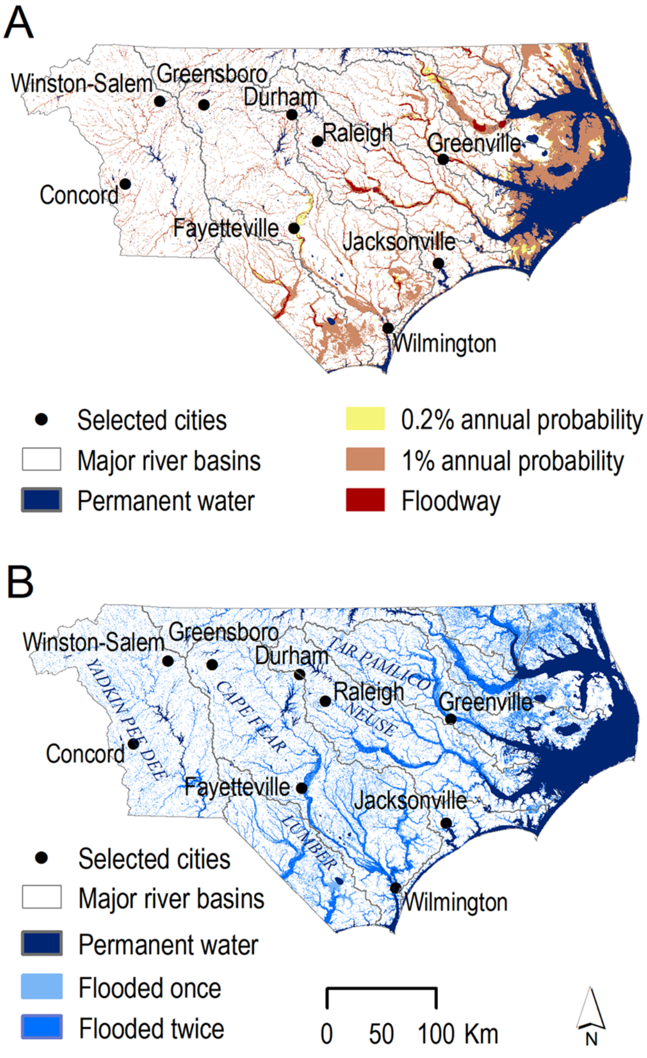

Figure 2. Flood hazard zones mapped by the state of North Carolina (A) and remotely sensed flooding detected from Hurricane Matthew in 2016 and Hurricane Florence in 2018 (B) across the study area.

Our models likely underestimated the true maximum flood extent. Flooding detected from a given image is based on conditions when the satellite overpass occurred. Therefore, our flood extent maps may not capture storm surge on the coast or peak flooding for all rivers—most river gages registered crests within 4 days of Hurricane Florence's landfall, yet portions of the Northeast Cape Fear River crested 9 days later. Differences in flood extent patterns for the two hurricanes are attributable to the geographic distribution of rainfall intensities and durations, not to stochastic variability in flooding from a given storm event. The storm tracks and landfall locations for these two hurricanes were similar, but other areas of the state have previously been affected by hurricanes. Our maps measuring exposure from Hurricanes Matthew and Florence are not intended to replace Federal Emergency Management

Agency (FEMA) hazard mapping, which considers a longer time span of historical flood events.

Social Vulnerability Across Flood Hazard and Exposure Areas. Quantile regression revealed that the overall SVI within census tracts was not clearly associated with all levels of state-mapped flood hazard and remotely sensed exposure. For the highest quantile, the relationship was only significant for the mapped floodway (R^2 = 0.31) (Figure 3A, Table S4). Stronger associations were identified for variables underlying the SVI (Table S4). State-mapped flood hazard and flood exposure were both positively associated with the proportion of unemployment, disability, and mobile home structures—yet the magnitude of the effect of remotely sensed flood exposure was greater than for the mapped hazard zones. Flood hazard and exposure were both negatively associated with the proportion of limited English-speaking households, the proportion of multiunit structures, and crowding. We also identified some key differences across hazard and exposure levels. While state-mapped flood hazard was strongly associated with the proportion of young children at the census tract level, remotely sensed flood exposure was associated with the proportion of older adults. Flood hazard was strongly associated with limited vehicle access, while no significant relationship was identified for flood exposure. Only the state-mapped floodway was significantly associated with poverty and minority population within census tracts, and surprisingly, no significant associations were identified for per-capita income or education.

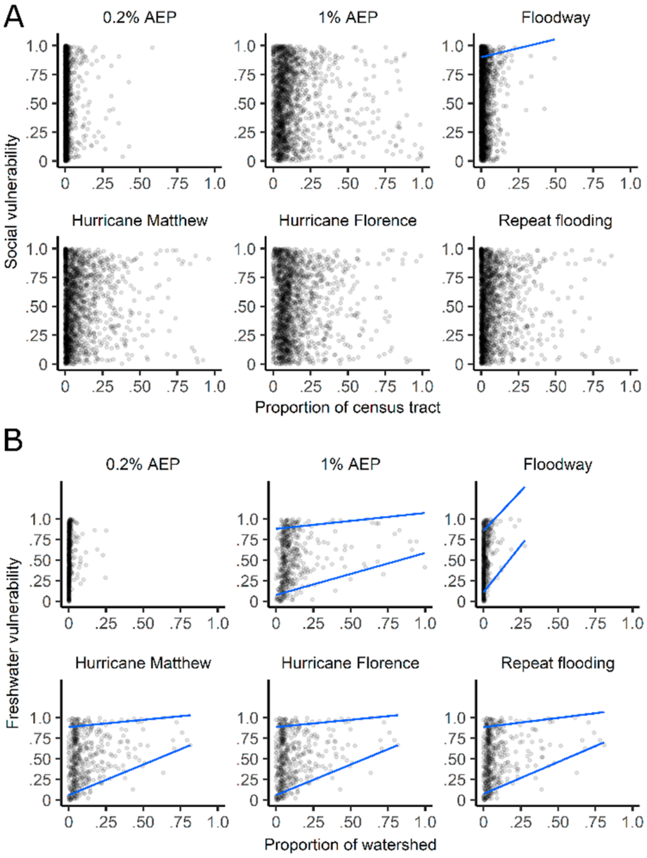

Figure 3. Relationship between flooding and vulnerability assessed with quantile regression: (A) flooding within census tracts and overall social vulnerability and (B) flooding within HUC 12 watersheds contributing to headwater streams and overall freshwater ecological vulnerability. Relationships between indices of vulnerability and levels of mapped flood hazard (top panels) and remotely sensed flood exposure (bottom panels) are shown, with regression lines for the 0.1 and 0.9 quantiles of data, if significant ($p < 0.05$).

The lack of apparent relationship between flood hazard and exposure and some socioeconomic vulnerability indicators may be explained by several factors. Social and economic indicators vary across the landscape; for example, inland counties in eastern NC rely heavily on agriculture, while coastal communities are often supported by additional fishing and tourism industries and have higher per capita income.[81] Some flood-prone properties are more expensive because they offer scenic views and access to water features or shorelines.[86] Furthermore, SVI data does not measure social vulnerability indicators with uniform precision. Although the five-year ACS data used as the basis of the SVI is the most recent source of the socioeconomic information needed for this study, data collected for a subset of households may be subject to higher margins of error for small sample sizes.[81]

Ecological Vulnerability Across Flood Hazard and Exposure Areas. Flood hazard and remotely sensed flood exposure at the scale of contributing watersheds were strongly associated with vulnerability of stream and river networks. For watersheds contributing to headwater streams, the relationship between flood exposure and overall vulnerability was significant for the floodway, the 1% AEP zone, both Hurricanes Matthew and Florence, and repeatedly flooded areas (Figure 3B, Table S5)—the magnitude of the effect was stronger for repeatedly flooded areas compared to the state-mapped 1% AEP zone. Flood exposure and hazard had a strong positive association with limited elevation range yet a strong negative association with narrow range of temperature classes in freshwater networks.

For watersheds contributing to larger streams and rivers, no significant relationship was identified between state-mapped AEP flood hazard and the highest quantile of overall freshwater vulnerability (Table S6). Remotely sensed flood exposure was significantly positively related to vulnerability for the lowest quantile yet negatively associated with vulnerability for the highest quantile, indicating that the effect diminished with increasing vulnerability. Flood exposure had a greater magnitude of effect than the 1% AEP zone for the elevation range, while the 1% AEP had a greater magnitude of effect than detected flooding for dam storage. For higher vulnerability streams and rivers, negative associations between hazard and exposure at the watershed scale were identified for most variables underlying the overall freshwater vulnerability index.

The strong association between flooding and overall freshwater vulnerability is unsurprising, given that many of the underlying vulnerability indicators are geomorphic factors that contribute to flooding. The weaker relationship for larger streams and rivers also follows expectations. Headwaters are more variable and more directly affected by smaller catchments, while watersheds contributing to larger stream and river networks are influenced by upstream reaches and the areas they drain.

Affected Human and Natural Communities and Contaminant Sources. Both human and natural assets in NC were subject to substantial flood exposure from Hurricanes Matthew and Florence (Table 1). Out of 433 municipalities in the study area, some portion of 380 municipal boundaries (>87%) experienced flooding in both Hurricanes Matthew and Florence. Census tracts affected by both storms contain >7

Table 1. Mapped Flood Hazard and Detected Flooding Affecting Key Socio-ecological Assets and Potential Sources of Water Quality Contaminants in the Study Area[a]

		flood hazard zones			detected flooding		
	total	0.2% AEP	1% AEP	floodway	Hurricane Matthew	Hurricane Florence	repeat flooding
watersheds	1,374	880	1,355	713	1,345	1,345	1,338
		64.05%	*98.62%*	*51.89%*	*97.89%*	*97.89%*	*97.38%*
watershed area (km^2)	113,698	72,331	112,112	58,665	111,201	111,201	110,472
		63.62%	*98.60%*	*51.60%*	*97.80%*	*97.80%*	*97.16%*
census tracts	1,629	1,261	1,566	1,278	1,539	1,612	1,517
		77.41%	*96.13%*	*78.45%*	*94.48%*	*98.96%*	*93.12%*
estimated population	7,565,948	5,992,791	7,353,120	6,208,932	7,239,924	7,491,073	7,171,901
		79.21%	*97.19%*	*82.06%*	*95.69%*	*99.01%*	*94.79%*
municipalities	433	266	356	220	408	431	380
		61.43%	*82.22%*	*50.81%*	*94.23%*	*99.54%*	*87.76%*
fish habitat (km^2)	732,991	4,521	615,383	18,292	592,562	610,377	571,474
		0.62%	*83.96%*	*2.50%*	*80.84%*	*83.27%*	*77.96%*
surface water intakes[b]	141	0	122	57	121	129	118
		0.00%	*86.52%*	*40.43%*	*85.82%*	*91.49%*	*83.69%*
public water supply wells[b]	5,622	115	427	55	266	370	206
		2.05%	*7.60%*	*0.98%*	*4.73%*	*6.58%*	*3.66%*
well yield[b] (gal/min)	743,718	27,306	73,995	6,630	41,402	60,805	28,636
		3.67%	*9.95%*	*0.89%*	*5.57%*	*8.18%*	*3.85%*
hazardous sites[b]	1,831	20	81	8	56	97	40
		1.09%	*4.42%*	*0.44%*	*3.06%*	*5.30%*	*2.18%*
permitted industrial dischargers[b]	3,913	80	504	108	466	527	339
		2.04%	*12.88%*	*2.76%*	*11.91%*	*13.47%*	*8.66%*
permitted wastewater treatment plants[b]	733	10	310	96	239	299	218
		1.36%	*42.29%*	*13.10%*	*32.61%*	*40.79%*	*29.74%*
wastewater treatment as built flow[b] (gal/day)	1,345,994,400	5,290,000	803,531,800	525,608,000	763,012,800	856,808,800	733,421,800
		0.39%	*59.70%*	*39.05%*	*56.69%*	*63.66%*	*54.49%*
Permitted urban stormwater[b]	14,817	669	4,236	590	2,306	2,712	1,938
		4.52%	*28.59%*	*3.98%*	*15.56%*	*18.30%*	*13.08%*
swine CAFOs[b]	2,022	9	52	4	199	190	91
		0.45%	*2.57%*	*0.20%*	*9.84%*	*9.40%*	*4.50%*
swine lagoons[b]	3,123	17	78	4	303	287	125
		0.54%	*2.50%*	*0.13%*	*9.70%*	*9.19%*	*4.00%*
swine animals[b]	9,223,385	25,076	214,742	12,320	1,059,766	835,899	412,056
		0.27%	*2.33%*	*0.13%*	*11.49%*	*9.06%*	*4.47%*
swine manure[b] (gal/y)	8,988,086,427	26,532,528	183,782,696	11,420,640	1,193,613,546	920,014,434	496,466,620
		0.30%	*2.04%*	*0.13%*	*13.28%*	*10.24%*	*5.52%*
agriculture 5 km from swine CAFOs (km^2)	224,884	1,192	5,594	237	26,171	16,813	6,676
		0.53%	*2.49%*	*0.11%*	*11.64%*	*7.48%*	*2.97%*
poultry CAFOs[b]	3,543	19	35	2	113	112	36
		0.54%	*0.99%*	*0.06%*	*3.19%*	*3.16%*	*1.02%*
poultry barns[b]	13,102	105	142	11	497	441	146
		0.80%	*1.08%*	*0.08%*	*3.79%*	*3.37%*	*1.11%*
poultry animals[b]	190,592,530	1,509,067	2,291,989	195,684	6,405,818	7,422,510	2,172,184
		0.79%	*1.20%*	*0.10%*	*3.36%*	*3.89%*	*1.14%*
poultry manure (tons/y)	1,890,074	16,660	22,824	1,477	75,290	68,545	23,181
		0.88%	*1.21%*	*0.08%*	*3.98%*	*3.63%*	*1.23%*

[a] Fixed point infrastructure was considered to be at-risk if the majority of a 60 m radius around a site's geographic position fell into that zone or had detected flooding. Units represent the number and percentage of locations in the study area for the target of interest, unless otherwise noted. [b] Fixed point locations.

million residents (~70% of NC's population). Nearly 80% of state-designated important in-stream fish habitat was affected by repeated flooding.

Our analysis provides the first assessment of the potential implications of recent hurricanes for water quality across broad areas of NC (Table 1). At least 118 municipal surface water intakes and 206 public water supply wells (3.6% of the public water well yield) are in repeatedly flooded areas. Additionally, 40 hazardous waste sites, 339 permitted industrial dischargers, and 218 WWTPs (55% of the total treatment capacity) were likely compromised. Most swine CAFOs are located outside of the 1% AEP zone, as required by NC's general permit. However, within the repeatedly flooded area we identified 91 swine CAFOs with 125 waste lagoons, which produce ~500 million gallons of liquid manure per year, as well as almost 6,700 km^2 of agricultural land where manure is likely regularly applied. We also identified 36 poultry CAFOs in repeatedly flooded areas which produce >23,000 tons of dry litter per year. Many contaminant sources are subject to setbacks from streams or not permitted within the 1% AEP zone; however, current siting restrictions may not go far enough.

To illustrate the potential for water contamination due to flooding outside the 1% AEP zone, we use the example of nutrient sources subject to distinct regulatory limitations, including WWTPs (NPDES permitted point-source), swine CAFOs (NPDES permitted point-source, or nonpoint source), and poultry CAFOs (nonpoint source) (Figure 4). Outside the 1% AEP zone, potential loads from WWTP where hurricane flooding was detected are of greater concern for Piedmont and coastal watersheds, with lower potential loads in the mid-Coastal Plain. Potential loads from swine CAFOs are greater for the mid-Coastal Plain region, particularly for the Cape Fear Basin, but also the Neuse, Lumber, and Chowan. Similarly, potential loads from poultry CAFOs outside the 1% AEP zone are a concern for the mid-Coastal Plain, particularly the Cape Fear, Chowan, and Neuse Basins.

Although we rigorously identified potential exposure of contaminant sources, we cannot definitively confirm that releases occurred. Nor do our methods estimate the level of damage that may have resulted, which depends on actual pollutant concentrations. To conclusively demonstrate that water quality impacts occurred due to the flooding we detected, additional information would be required. Data availability also limited our ability to quantify some potential impacts. For example, ~26% of NC's population relies on privately owned and maintained shallow groundwater wells as their primary source of drinking water, yet reliable location information for these wells was not available.[87] Private wells are more vulnerable to contamination than municipal wells, which are subject to different construction standards, regular maintenance, and testing.[88]

Opportunities for Watershed-Scale Buyouts and Nature-Based Solutions. Within lands lacking formal protection, we identified extensive regions where buyouts or NBS could be implemented (Table 2). Working land restoration, easements, or incentive-based management changes represent the greatest extent of potential interventions, followed by forest management and protection, wetland conservation, and finally buyouts of existing development. However, within repeatedly flooded areas, conservation of wetlands that currently lack protection represents the largest opportunity in terms of spatial area—losing the flood storage and water purification services they provide could increase risk for communities downstream under future storms.

While planning and land management have emphasized the use of hardened infrastructure to protect against riverine flooding, these defenses may increase vulnerability and exposure.[89] Although the costs of NBS have not been thoroughly compared to hardened flood control structures, economic optimization can substantially reduce the cost and change the direction of a cost-benefit analysis for such projects.[48] Accounting for the value of water purification and other services would increase the net benefit. Similarly, buyouts or adaptation measures to increase the permeability of existing development or reduce distribution of contaminants during flood events could improve water quality, but further study of these trade-offs is needed. Interventions that enhance floodplain function can also be coupled with changes to infrastructure siting, design, and operations.

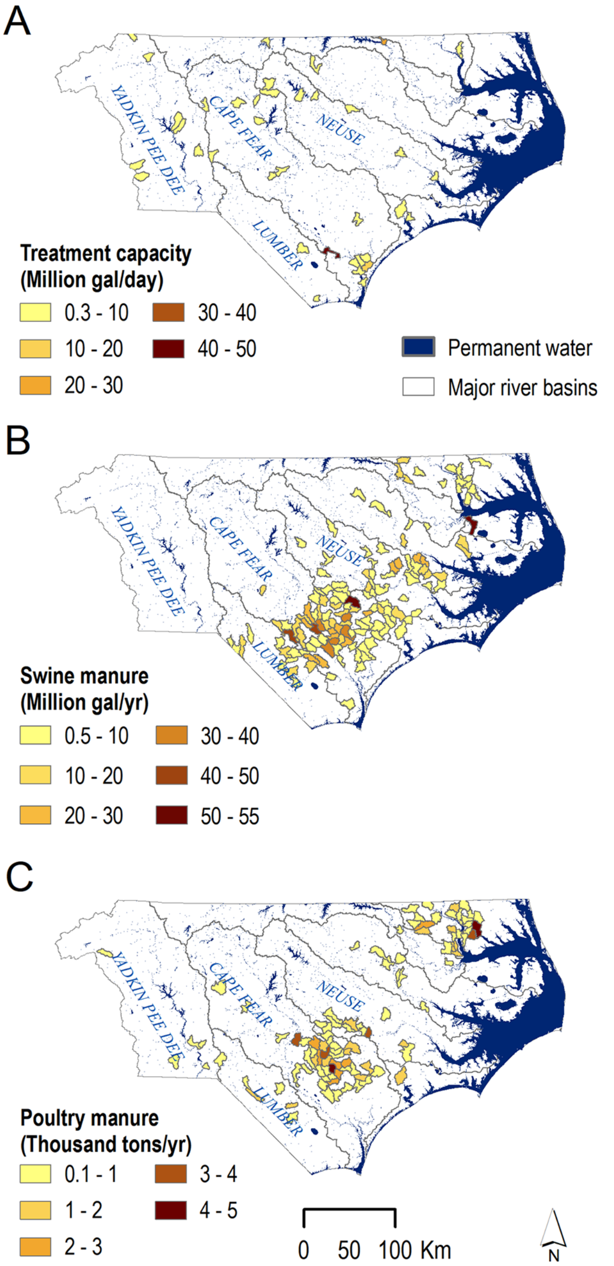

Figure 4. Nutrient pollution sources beyond the 1% annual exceedance probability flood hazard zone were affected by Hurricanes Florence and Matthew, including (A) permitted wastewater treatment plants, (B) permitted swine CAFOs, and (C) poultry CAFOs not regulated by NPDES. Manure volume was estimated from the number of animals and standard production rates.

Implications for Floodplain Planning and Management in a Changing World. This study presents a timely investigation into the impacts of hurricane-induced flooding and opportunities to increase social and ecological resilience across floodplains. Results suggest that state-mapped flood hazard zones not only underpredict the extent of hurricane-induced flood exposure but also systematically underpredict burdens on vulnerable human populations and freshwater ecosystems. In light of these findings, the use of the "100-year" floodplain as a basis for insurance, siting restrictions, and infrastructure design standards needs to be revisited.

Table 2. Extent of Nature-Based Intervention Opportunities (km^2) in the Study Area on Lands Currently Lacking Formal Protection that Fall within Mapped Flood Hazard Zones and Regions where Flooding Was Detected during Recent Hurricanes[a]

		flood hazard zones			detected flooding		
intervention	total	0.2% annual probability	1% annual probability	floodway	Hurricane Matthew	Hurricane Florence	repeat flooding
buyouts	9,565,819	169,574	637,644	52,046	460,712	750,681	327,168
		1.77%	*6.67%*	*0.54%*	*4.82%*	*7.85%*	*3.42%*
forest conservation	31,014,258	183,633	2,238,435	239,104	1,349,269	3,561,312	1,223,450
		0.59%	*7.22%*	*0.77%*	*4.35%*	*11.48%*	*3.94%*
wetland conservation	15,873,488	361,641	7,192,684	792,785	3,734,115	6,465,052	3,573,740
		2.28%	*45.31%*	*4.99%*	*23.52%*	*40.73%*	*22.51%*
restoration or easements	31,071,639	558,356	2,490,258	141,159	4,329,573	3,499,065	1,733,667
		1.80%	*8.01%*	*0.45%*	*13.93%*	*11.26%*	*5.58%*

[a] Landcover data were recategorized to identify potential buyouts of developed land, forests, and wetlands that could be acquired for preservation and other undeveloped land where restoration or easements could be implemented.

The flood extent mapping methods we developed provide a vital tool for future disaster planning, response, and recovery efforts. This approach could be integrated by FEMA, state, and local emergency managers to update hazard projections. Following future storms, as soon as radar imagery and high water marks are available, our calibrated model can be leveraged for rapid mapping of inland flooding to help direct resources where they are most needed. Ongoing mapping of storm-induced flooding can help to refine understanding of how hazards are changing and how impacts affect sensitive communities over time.[17] The knowledge generated can inform better disaster preparedness and formulation of new standards and policies to protect people and ecosystems.

Appropriate solutions must be tailored to the needs and constraints of a given locale; rebuilding NC after Hurricanes Matthew and Florence presents a different case than efforts to rebuild Manhattan after Hurricane Sandy. For small, unincorporated communities that rely on agriculture as their main economic driver, buyouts and NBS merit consideration as potentially cost-effective options. Many rural communities lack centralized planning and engineering, necessitating a larger-scale cost-benefit analysis and coordination by state or regional governments. The intervention opportunities we identified at broad scales can be further evaluated in the future; working with USGS, we will use a Soil and Water Assessment Tool model to estimate water storage and nutrient loads that would result from specific interventions, under conditions ranging from droughts to floods.[90] Because burdens on vulnerable communities may not be detected using measures of overall vulnerability, locally relevant social and ecological indicators should be considered when allocating disaster response resources and prioritizing where and how to implement interventions.

Given societal and climatic changes, assessments such as those we presented here will be crucial to meet these challenges. Urbanization and industrialized agriculture are expanding their footprint to meet the needs of a growing population demanding a more protein-rich diet. This rapid land use change is occurring within a regulatory system that does not adequately offset impacts for flood risk and water quality. More frequent hurricanes and increasing rain intensity will likely magnify the co-occurrence of flooding and water quality problems in more places in the future, necessitating mitigation strategies. While this study focused on water quality, the approach we demonstrated can be readily translated to address other questions (e.g., transportation accessibility) and support policies aimed at resilience in other flood prone regions.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.9b07815.

Additional information regarding remote sensing methods (data sources, model tuning and validation) and complete results of quantile regression analysis (PDF)

Data (inputs and map products) and code for flood extent mapping and identification of opportunities where interventions could be sited to address flooding and water quality issues (ZIP)

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Author Contributions

All authors participated in designing the research and contributed to writing the manuscript. D.S.-S. conducted flood extent mapping, data compilation, and analysis. All authors have given approval to the final version of the manuscript.

Notes

The authors declare no competing financial interest.

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