



Integrated Urban Riverscape Planning: Spatial Prioritization for Environmental Equity

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Abstract: Natural infrastructure (NI) and nature-based solutions in urban riverscapes can provide a spectrum of environmental, societal, and economic benefits, but widespread implementation of NI strategies remain limited because of their context-dependent nature. Windows of opportunity have opened through legislation and funding to expand NI solutions that address flooding, water quality, air pollution, extreme heat, and environmental equity. System-level approaches may offer these projects a framework that is flexible yet holistic enough to streamline implementation. In fact, a systems approach is essential to realize the potential of NI for equitably achieving these goals, and a critical step includes identification of vulnerabilities (e.g., exposure to environmental harm). The purpose of this study was to support decision makers and managers in prioritizing their urban riverscapes with multiple vulnerabilities: flood risk, water quality, ecosystem function, and environmental inequity. We conducted an urban stream spatial multicriteria decision analysis (MCDA) case study with Charlotte–Mecklenburg Storm Water Services to support equitable and efficient stream reach, floodplain, and watershed planning. Our study assessed the social and ecological characteristics of the system and prioritized vulnerable watersheds and subbasins using a spatial MCDA. We developed an urban stream prioritization framework that could be tailored to complement existing management strategies and also more broadly implemented in other social–ecological systems. DOI: [10.1061/AOMJAH.AOENG-0001](https://doi.org/10.1061/AOMJAH.AOENG-0001). This work is made available under the terms of the Creative Commons Attribution 4.0 International license, <https://creativecommons.org/licenses/by/4.0/>.

Introduction

Surface water managers and organizations face multiple complex challenges in urban riverscapes, particularly flooding, water quality, and associated environmental equity concerns. Natural infrastructure (NI) and nature-based solutions can improve all of these problems while providing greenspace with wildlife habitat and ample social benefits such as recreation, education, and other cultural values (O'Donnell et al. 2020; Skidmore and Wheaton 2022; Whelchel et al. 2018). Moreover, the implementation of the Infrastructure Investment and Jobs Act and similar legislation presents a window of opportunity for expanding NI to address environmental hazards and social justice. Significant funding is increasingly available for generational transformation in the context of a greater awareness of environmental inequities. However, creating resilient urban riverscapes through resources such as the Infrastructure Investment and Jobs Act requires a strategic approach to doing *the right projects, the right way* (ASCE 2022), starting with assessing multiple system vulnerabilities.

The overwhelming scope of urban riverscape problems, possibilities, and priorities is exacerbated by multiple spatial scales (watershed, floodplain, and channel). Unfortunately, spatial mismatches commonly manifest as fragmented stream management approaches and departmental silos, even in municipalities and utilities with relatively

strong programs and planning capacity. At the same time, social injustice (e.g., environmental racism) is often visible through spatial relationships between neighborhood demographics and environmental risks (Pulido 2000; Debbage 2019). Therefore, holistic planning requires practical, straightforward spatial analysis tools that can help a range of stakeholder groups to better understand and prioritize the intertwined complexities of urban streams and watersheds.

Flood risk reduction arguably has been the dominant focus in urban stream systems, probably due to the direct, negative economic impacts of flood events. Floodplain managers and researchers often employ economic cost–benefit analyses to identify priorities and guide projects (ten Veldhuis 2011), and much of applied research has emphasized decision support tools (Habersack et al. 2015; Hammond et al. 2015; Whelchel et al. 2018). Floodplain hydrology and hydraulics encompass multiple spatial scales: the primary focus is a medium valley or floodplain scale, and localized hotspots are handled at the smaller channel or reach scale, but land-use factors and various nature-based solutions to flood risks for many storm events are best understood at the larger landscape or watershed scale (Cohen-Shacham et al. 2019).

Water quality regulation is typically completely separated from floodplain management by organizational structures and missions, despite close coupling via riparian management, and it is more likely to be driven by policies stemming from the Clean Water Act than by the direct economics of environmental risk reduction. Aquatic insects and fish are often used as holistic indicators of overall water quality, and ecological uplift is a frequent objective for stream restoration efforts (Palmer et al. 2014; Smith et al. 2016). Many problems related to water quality are generally tied to non-point source pollution at the largest watershed-scale in urban and agricultural settings (Kaushal et al. 2018; Stets et al. 2020), while medium-scale riparian buffers may be implemented to pretreat stormwater runoff, and monitoring is performed at the reach scale. Conversely, ecological restoration frequently focuses on reach-scale channel geomorphology (Bernhardt et al. 2007), although growing attention has also been given to potential

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Note. This manuscript was submitted on January 9, 2023; approved on September 28, 2023; published online on October 25, 2023. Discussion period open until March 25, 2024; separate discussions must be submitted for individual papers. This paper is part of the *ASCE OPEN: Multidisciplinary Journal of Civil Engineering*, © ASCE, ISSN 04023004(15).

floodplain- and watershed-scale interventions to improve water quality and ultimately aquatic biology (Polvi et al. 2020).

The consequences of flood damage and poor water quality (i.e., pollution) are further compounded by long-standing social inequities. For example, recent studies found increased flood risk among Black, Hispanic, and low-income populations in the southeastern United States (Debbage 2019; Selsor et al. 2023), while others have documented greater exposure to water pollution threats (Davis et al. 2022). At the same time, underserved communities are less likely to have access to greenspace amenities and the positive benefits associated with riverine corridors (Smardon et al. 2018), with neighborhoods at greater risk for gentrification and displacement (Jelks et al. 2021).

In addition to environmental risk assessment and reduction, stream management practices and research have begun to incorporate several key themes: nature-based solutions (including NI), additional cobenefits, shared decision-making, and social equity. For example, *blue-green cities*, Engineering With Nature®, and other similar visions emphasize multiple social–ecological benefits in addition to sustainable flood risk mitigation such as water quality, ecosystem support, and outdoor recreation opportunities (Bridges et al. 2018, 2021; Mant et al. 2020; Sowińska-Swierkosz and Garcia 2021; U.S. Army Corps of Engineers 2022). In this paper, we describe a spatial multicriteria decision analysis (MCDA) that we developed for urban riverscapes. Such an approach is well-suited to addressing complex problems such as watershed and stream prioritization, because it offers a flexible, transparent way for stakeholders to evaluate system vulnerabilities while combining a range of variable inputs across multiple spatial scales, thereby allocating capital resources and/or seeking funding opportunities.

Under the umbrella of shared decision-making, conventional MCDA tools are broadly applied and documented for environmental management (Kiker et al. 2005; Linkov et al. 2011), although they may alternately be called multicriteria evaluation approaches or decision support systems (Renaud et al. 2016; Meerow and Newell 2017). The participatory aspects of MCDA further include collaborative modeling (Evers et al. 2018) and citizen perceptions (Hong and Chang 2020). At the cutting edge of applied research, however, GIS-based prioritization and spatial MCDA are especially relevant for stream and watershed planning for a wide range of benefits, services, and values. Recent urban case studies of green infrastructure (Meerow and Newell 2017) and flood management (Verbrugge et al. 2019) have focused on benefit evaluation (Hoang et al. 2018), spatial planning (Meerow and Newell 2017), site suitability (Verbrugge et al. 2019), and project alternatives (Lim and Lee 2009). To our knowledge, however, past efforts have not targeted urban riverscapes with a multiscale integration of stream functions, flood mitigation, watershed management, and social objectives. While social vulnerability and resilience continue to be popular themes (Meerow and Newell 2017; Evers et al. 2018), we have seen no examples of riverscape spatial prioritization that explicitly tackle measurable environmental inequities. Overlooking social equity when planning for natural and built infrastructure ultimately perpetuates systemic racism and other forms of environmental injustice.

Our primary objective for the current study was to develop a spatial MCDA that includes multiple vulnerabilities (flood risk, water quality, environmental equity, etc.), thereby facilitating system-level prioritization for the *right projects* in urban riverscapes. In addition to identifying system hotspots with overlapping vulnerabilities, we wanted to investigate potential synergies and trade-offs among the various criteria. While this paper focuses on assessing vulnerabilities, we intended to create a practical and transferable framework that could be adapted to support shared decision-making, evaluate local project alternatives, and design sustainable solutions. Using

multiple social metrics, it was our intent to apply an urban stream management strategy that could be flexibly implemented in a variety of environmental equity contexts. Our overarching goal is to provide water managers and urban riverscape communities with useful tools to incorporate multiple planning objectives and prioritize riverscapes to support efficient and equitable benefits and services.

In this paper, we describe the data used for our selected objectives and explain how to apply risk and benefit ratios to develop equity metrics. We summarize the results of the watershed and subbasin MCDA scenarios that we generated and present our overall environmental equity findings. Finally, we explain how riverscape managers can apply and adapt our spatial MCDA approach to support holistic planning efforts.

Methods

Spatial Prioritization Case Study

For our spatial MCDA application, we collaborated with the City of Charlotte and Mecklenburg County in North Carolina (Fig. 1), located in the southeastern piedmont region along the Charlotte megaregion. The western and southern portions of the county drains to the Catawba River Basin and the eastern streams are tributaries to the Yadkin River. The 500-year floodplain excludes the reservoirs along the western boundary (Lake Norman, Lake Wylie). The study focused on the portions of 33 watersheds and their subbasins within the county boundaries. Similar to other municipalities, Charlotte–Mecklenburg Storm Water Services (CMSWS) divides surface water management responsibilities among several main groups, including watershed planning, engineering and flood mitigation, and water quality. Some of the existing CMSWS approaches to prioritization include a watershed-scale water quality matrix (J. Hunt, personal communication, 2022), building-level flood risk assessment/risk reduction (RARR) tool (Charlotte–Mecklenburg Storm Water Services 2020), and reach-scale stream restoration ranking system (SRRS) (Mecklenburg County Storm Water Services 2021), all of which are supported by extensive spatial data. When planning stream improvements, CMSWS often partners with the Mecklenburg County Park and Recreation Department to incorporate greenway trails and other outdoor amenities. Mecklenburg County recently developed an Equity Action Plan, and CMSWS wanted to better understand how they could include social components with their surface water projects and initiatives. In general, our goal was to integrate the established CMSWS components (RARR, SRRS, etc.) while taking steps to identify environmental equity objectives. At the same time, our intent was to develop a generalized approach that could be broadly applied in other urban stream systems.

With a structured decision-making process, stakeholder groups typically work collaboratively to identify objectives and possible metrics (Bridges et al. 2015). This research was intended to support CMSWS with early planning and outreach initiatives by identifying areas for follow-up with neighborhoods and communities. Through conversations with CMSWS, we elicited baseline criteria and subcriteria for the spatial MCDA, which can be modified later as part of collaborative conversations. For analysis at the watershed and subbasin scales, the main criteria included three *riverscape* criteria (flood regulation, water quality regulation, ecosystem support) as well as amenity access and environmental justice (Table 1). We used a two-part approach to environmental justice by including measures of social vulnerability and historic injustice in a general *landscape* category, complemented by subcriteria in riverscape categories targeting specific aspects of social inequity, such as disproportionate exposure to flood risk or a lack of greenspace access.

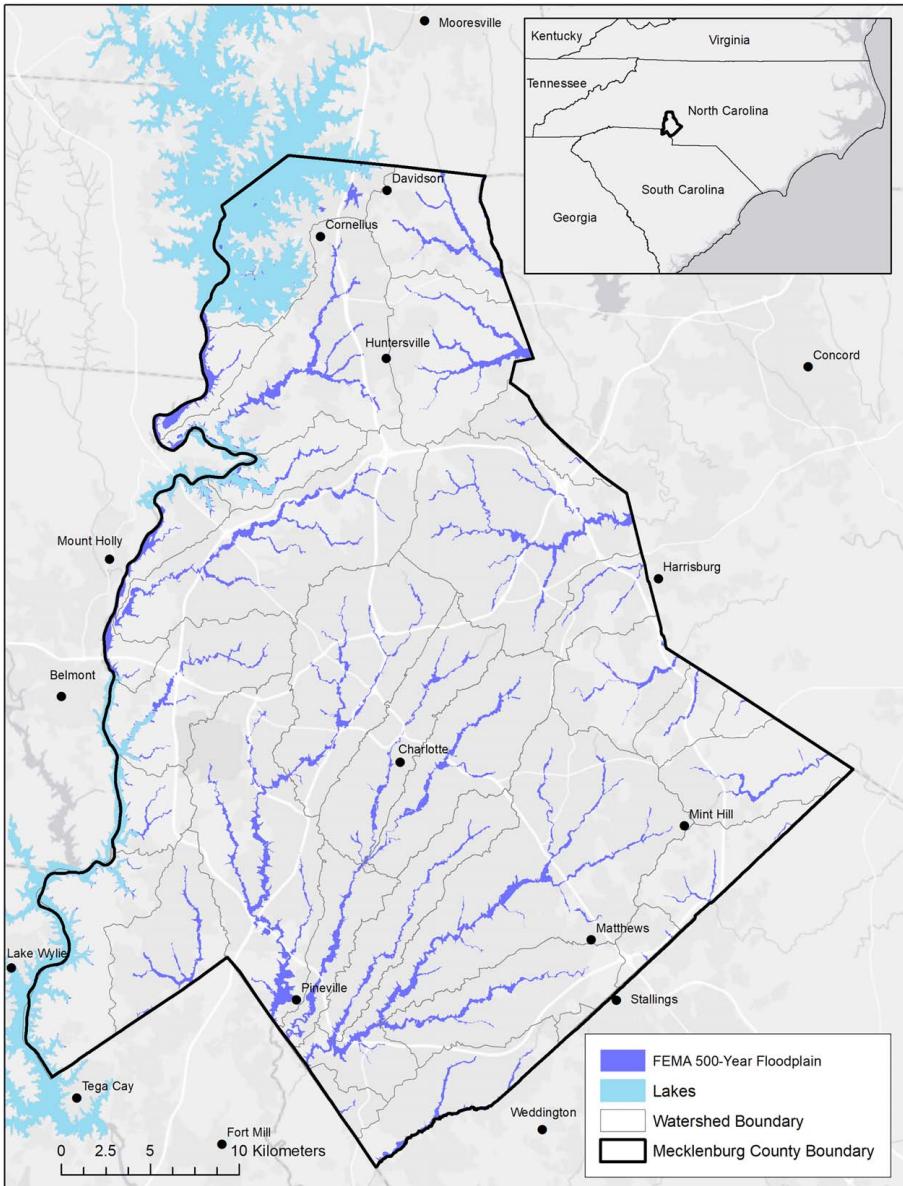


Fig. 1. Mecklenburg County watersheds.

Following prioritization at the large (watershed) and medium (sub-basin) spatial scales, the same objectives may be combined with additional feasibility criteria to evaluate local project alternatives. Preferences from multiple stakeholder groups can be separately elicited and then weighted together, and a trade-off matrix can be used to show the highest rated alternative for each group (Bridges et al. 2015).

Data Acquisition

Flood Risk Data

As part of the flood regulation objective, we prioritized areas based on flood damage risks and hazards to human life—locations with high flood impact and probability, and sensitivity to depth and velocity. We extracted parcels overlapping the 500-year flood hazard zone, and those having buildings with RARR scores, which were based on numerous variables such as water surface and building elevations, flow depth-velocity zones, accessibility and parking, and residential building types (e.g., single- or multifamily). The RARR total risk score is a single value that incorporates multiple flood events (2, 5,

10, 25, 50, 100, and 500 years) to account for major risks that are relatively rare plus lesser risks that occur more often and have potential damage that accumulates over time (ten Veldhuis 2011). All of these GIS layers were obtained from the CMSWS RARR data set.

Water Quality Data

Under the water quality category, the MCDA structure emphasizes streams with watershed impairments based on monitored levels of fecal coliform and turbidity as well as regulatory status. Our data sources included the water quality matrix and 303(d) list, water quality buffers (35–100 ft), and 500-year flood hazard zone shapefiles provided by CMSWS. We used the flood zone and water quality buffers to define the potential exposure of homes and properties to surface water pollution. In determining fecal coliform and turbidity levels, we used supplementary monitoring data for six watersheds (Goose, Rocky River, Clear, McDowell, Clarke, and Gar): we interpreted the average fecal coliform levels as noncompliant or severe in all six watersheds, and the turbidity levels were compliant only in Goose and Car Creek Watersheds.

Table 1. Spatial MCDA priority criteria, subcriteria, and data descriptions

Criteria	Subcriteria	Data description
Riverscape criteria		
Flood regulation	— Flood risk score — Flood risk equity	— RARR building polygons ^a — RARR 500-year flood polygons ^a
Water quality	— Fecal coliform bacteria	— Water quality matrix ^a
Regulation	— Turbidity — Regulatory status	— 303 d list ^a — Water quality buffer polygons ^b
Ecosystem support	— Pollution risk equity — Channel stability and habitat — Riparian buffers	— SRRS scores (polylines) ^a
Landscape criteria		
Amenity access	— Near outdoor recreation — Amenity benefit equity	— Neighborhoods polygons/table ^a
Environmental Justice	— SVI and housing change score — Historic redline areas — Population density	— SVI polygons ^a — Home Owners' Loan Corporation (HOLC) Redlining polygons ^c — Neighborhoods polygons/table ^a
General data		
Various	— Watersheds, subbasins — Parcels — Developed areas — Census blocks, block groups, tracts	— Watershed, subbasin polygons ^a — Parcel polygons ^b — 2019 landcover raster ^d — Population demographics polygons ^b and tables ^e

^aData from Charlotte–Mecklenburg Storm Water Services (J. Hunt, personal communication, 2022).

^bData from Mecklenburg County Open Mapping ([Mecklenburg County n.d.](#)).

^cData from ArcGIS Online ([Univ. of Richmond's Digital Scholarship Lab 2020](#)).

^dData from NLCD ([Dewitz and USGS 2021](#)).

^eData from US Decennial Census and American Community Survey ([U.S. Census Bureau n.d.-a, b](#)). Combinations of various data sets were used to calculate risk and benefit equity layers.

Ecosystem Support Data

We divided ecosystem support into aquatic and riparian subcategories, assigning the highest priorities to streams needing improvements in channel stability and habitat conditions (aquatic ecosystem) as well as buffer vegetation (riparian ecosystem). While the SRRS program includes both desktop and field components, we used only existing desktop data and scores provided by CMSWS. For aquatic ecosystem support, we limited the potential priorities to the SRRS group of reaches recommended for restoration on the basis of stream functions and constructability, which comprised 58% of all stream miles ([Mecklenburg County Storm Water Services 2021](#)). However, we did not make the same distinction for the riparian corridor, because there might be room for improvement with a vegetated buffer, even if the channel itself was deemed unsuitable. While we opted to prioritize areas with poor riparian buffers that need improvement, this particular metric could also be a predictor of potential aquatic ecological uplift, so corridors with high buffer scores could be used alternatively to prioritize opportunities and not just to correct deficiencies.

Amenity Access Data

The amenity access criteria were identified as areas in the landscape with relatively few benefits based on an existing countywide layer for neighborhoods near public outdoor recreation. CMSWS indicated that this data layer was a proximity analysis, with the percentage of housing units within 0.8 km (0.5 mi) of an outdoor public recreation area. Elsewhere, a similar spatial layer could be created by starting with an entire data set of housing units, determining how many are in the 0.8 km (0.5 mi) proximity, and then overlaying the watershed geographies to get the percentages within the watersheds and subbasins. While CMSWS does not have a housing unit layer, the proximity analysis could perhaps be based on a zoning layer, or otherwise use a previously studied approach to green-space access ([Meerow and Newell 2017](#)). The watersheds and subbasins that we used were delineated by CMSWS.

Environmental Justice Data

Under the general environmental justice objective, higher priority areas included those with high social vulnerability as well as historically redlined neighborhoods. As a metric for social vulnerability, the Charlotte Housing Authority uses a neighborhood-level *change score*, and this was supplemented by the standard CDC social vulnerability index (SVI) in portions of Mecklenburg County outside of the city limits. The neighborhood change score identifies areas most vulnerable to gentrification and displacement based on income level and housing changes (sales prices, permit volumes). SVI, on the other hand, incorporates multiple variables from the American Community Survey: socioeconomic and minority status, household type and composition, disability, language, and transportation. While we included population density here, it is also possible to calculate population densities just within flood-prone areas or surface water quality exposure.

Other Data

Additional data used for various subcriteria included the 2019 National Land Cover Dataset (NLCD) ([Dewitz and USGS 2021](#)), stormwater watershed and subbasin polygons, and the 2020 US Decennial Census and American Community Survey (census blocks, block groups, and tracts) ([U.S. Census Bureau n.d.-a, b](#)). Demographic data for race and ethnicity were available at the smallest census block scale, while income (above or below poverty level) was available only from the American Community Survey at the larger census block group scale. The studied populations included 45% White (non-Hispanic), 29% Black (non-Hispanic), 15% Hispanic, 85% non-Hispanic, 10% below poverty level, and 90% above poverty level in Mecklenburg County. Table 1 summarizes the data descriptions and sources for the spatial MCDA criteria and subcriteria. Data availability differed across scales, but reconciliation by aggregating average values for subbasins and watersheds was straightforward using GIS tools. Although water quality monitoring data can be spatially irregular, we assumed

that the same values were applied to an entire watershed, including all of the subbasins. However, the water quality equity metric was based on census block group data, which created spatial heterogeneity when aggregated to subbasin and watershed levels.

Environmental Equity Metrics

Spatial prioritization approaches that incorporate social objectives typically use some type of demographic-based SVI (Meerow and Newell 2017), and environmental justice is especially important for the vulnerable communities identified by SVI. Environmental equity, on the other hand, relates to the distribution of risks and benefits, and metrics involve both social vulnerability (e.g., race, ethnicity, income) and either exposure or access, respectively. This is because environmental hazards to human health and well-being (e.g., flood damage, water pollution) also involve exposure, just as environmental benefits (e.g., greenway trails, outdoor education) require access opportunities. For example, a poor neighborhood is socially vulnerable in a general sense, whereas a poor neighborhood in a low-lying area floodplain area is both socially vulnerable and at risk of exposure to flooding.

Our approach to environmental equity built upon prior methods of analyzing inequitable flooding in the Charlotte megaregion (Debbage 2019). Starting with Mecklenburg County parcels and the 2019 NLCD, we selected parcels only where all or the majority of them were in the developed range between open space and high-density areas (NLCD classes 21–24). While the landcover raster was used to identify developed parcels (and can be easily accessed for other locations), there might be more precise ways to filter out parcels that are undeveloped open spaces or otherwise vacant.

For a baseline flood scenario, we then identified developed parcels overlapping the 500-year flood hazard zone. We opted to use a parcel-based approach to area calculations following Selsor et al. (2023) rather than raster coverage within each census block used in an earlier study (Debbage 2019), because parcels provide more accurate spatial resolution. In the GIS attribute table for parcels, we added fields to include census block group number as well as selection categories (developed, 500-year flood, water quality exposure, etc.), with 1 (yes) or 0 (no). Using the Summary Statistics tool (ArcMap v. 10.5), we calculated the area sum and exposure risk factor for each census block group ($N=624$) as shown here:

$$\text{Risk factor} = \frac{\sum \text{At-risk developed parcel area}}{\sum \text{Developed parcel area}} \quad (1)$$

We then estimated the number of exposed individuals in each category by multiplying the risk factor with the group populations from the census block group demographic data (Non-Hispanic Black, non-Hispanic White, Hispanic, Non-Hispanic, Below Poverty, and Above Poverty). The total number of individuals for each category was summed together for a larger spatial unit, typically the census tract. However, we also assigned each census block group to a subbasin and watershed based on the centroid of the census block group, thereby creating *demographic watersheds* as an alternative to conventional topographic delineation. The overall topographic and demographic watersheds were similar but not identical, and we would not recommend using the latter for hydrologic calculations. However, these demographic boundaries enabled us to directly compute categorical populations and risks without needing to apply weighting based on spatial areas and variable population densities. As with prior flood inequity studies (Debbage 2019; Selsor et al. 2023), we calculated risk ratios as

follows:

$$\text{Race risk ratio} = \frac{\left(\frac{\text{At-risk non-Hispanic Black}}{\text{Total non-Hispanic Black}} \right)}{\left(\frac{\text{At-risk non-Hispanic White}}{\text{Total non-Hispanic White}} \right)} \quad (2)$$

$$\text{Ethnicity risk ratio} = \frac{\left(\frac{\text{At-risk Hispanic}}{\text{Total Hispanic}} \right)}{\left(\frac{\text{At-risk non-Hispanic}}{\text{Total non-Hispanic}} \right)} \quad (3)$$

$$\text{Poverty risk ratio} = \frac{\left(\frac{\text{At-risk Below Poverty}}{\text{Total Below Poverty}} \right)}{\left(\frac{\text{At-risk Above Poverty}}{\text{Total Above Poverty}} \right)} \quad (4)$$

A risk ratio greater than 1 indicates environmental inequity, such as a predominantly Black community with a disproportionately high exposure to flood hazards. Approximately one-third of the developed and flooded parcels also had RARR scores greater than zero, which we used for a separate flood scenario based on an established CMSWS flood mitigation strategy. We used the RARR scenario for the MCDA, but the baseline 500-year scenario could easily be implemented elsewhere. We used a similar risk calculation method for water quality equity. To approximate exposure to surface water pollution (e.g., fecal coliform bacteria), we combined the 500-year flood zone with the stormwater buffers, which ranged in width between 35 and 100 ft, thereby including the smaller streams that also convey polluted water. Fig. 2 illustrates the different delineation methods used for environmental risk exposure. Risk factors were based on developed parcels: (1) with building flood risk assessment/risk reduction (RARR) scores greater than one; (2) overlapping the 500-year flood zone; and (3) overlapping the water quality zone (combined stormwater quality buffers and 500-year flood zone).

We calculated benefit ratios for amenity access in a similar fashion, except that the data for population near public outdoor recreation had its own neighborhood spatial units ($N=464$), and we did not use parcel areas or the NLCD raster. The equation for a benefit ratio looks nearly identical to a risk ratio, like the following example:

$$\text{Poverty benefit ratio} = \frac{\left(\frac{\text{Below Poverty with access}}{\text{Total Below Poverty}} \right)}{\left(\frac{\text{Above Poverty with access}}{\text{Total Above Poverty}} \right)} \quad (5)$$

However, opposite from risk ratios, a benefit ratio less than 1 indicates social inequity, such as a low-income neighborhood with less access to public parks. For each scenario, after summing up the at-risk and total populations for the demographic groups at the tract, subbasin, and watershed scales, we obtained risk ratios using R statistical software. While the ratios can be calculated easily using a spreadsheet or GIS attribute table, the fmsb package in R also provided *p*-values to describe statistical significance (<0.05). However, the *p*-values were not used for spatial MCDA prioritization purposes.

Following the method of Selsor et al. (2023) to create a single combined equity metric for each spatial unit (census tract, watershed, subbasin), we first reassigned values of 1 for all risk ratios less than 1 and benefit ratios greater than 1 (i.e., no inequity) and then added together the ratios for race, ethnicity, and income level. For example, the poverty benefit ratio [Eq. (5)] was rolled together with the race and ethnicity benefit ratios to generate the overall *amenity equity*

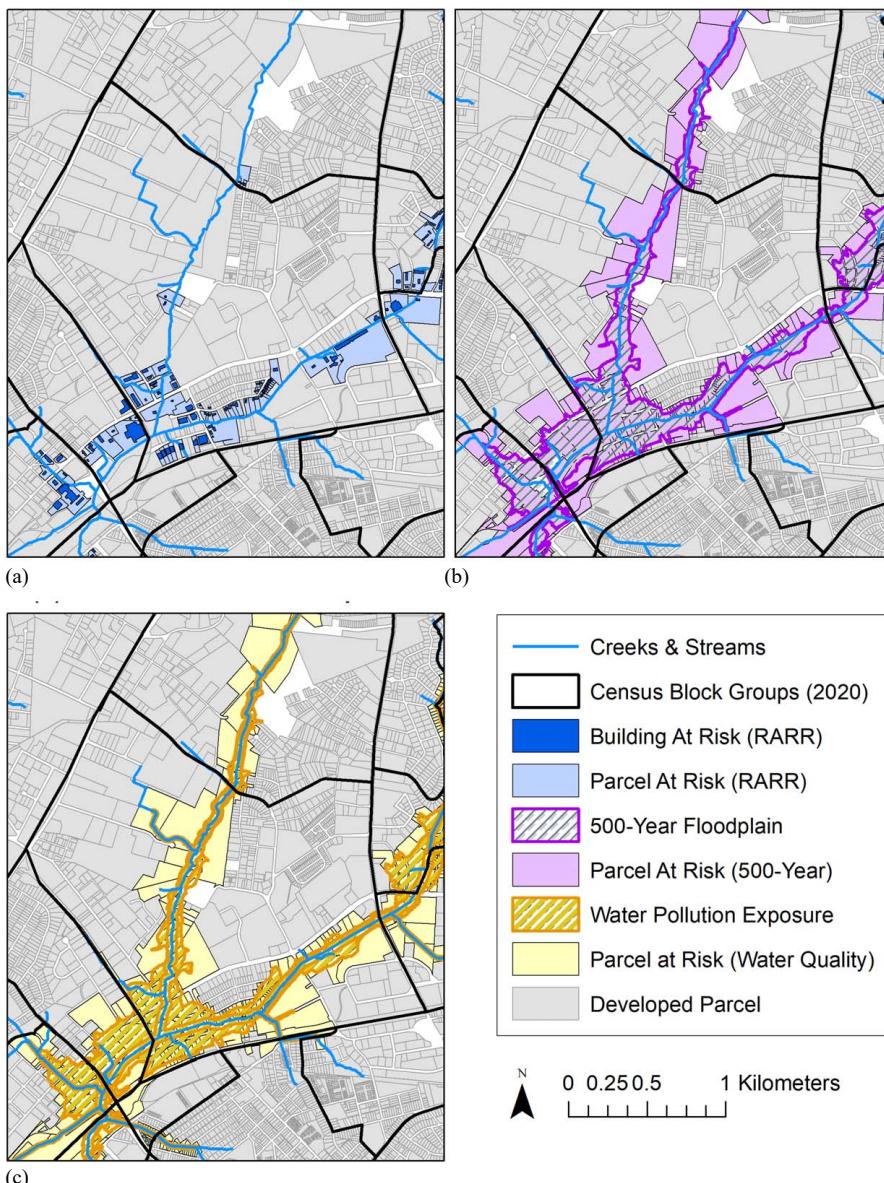


Fig. 2. Examples of three different environmental risk exposure areas used for calculating risk ratios and social equity priorities: (a) building flood risk; (b) 500-year flood extent; and (c) surface water pollution exposure.

scores. In addition to calculating risk ratios for the Mecklenburg County census tracts ($N=305$), we assigned each census block group to both a watershed ($N=33$) and a subbasin ($N=113$) and calculated equity at the larger scales to better support spatial prioritization. Nine subbasins, all located at the county boundaries, did not contain centroids of any census block groups and therefore received the lowest priority for the various equity subcriteria.

Weighting and Prioritization

The basic procedure was to develop scores for all of the subcriteria at the watershed and subbasin scales, convert to a common priority scale (e.g., 0 to 1), and then apply weighted averages to calculate combined criteria and overall scores. For the purposes of this study, we assigned equal weights to all subcriteria to calculate the overall priority scores for the criteria, and then we assigned equal weights to all of the criteria to calculate the combined priority score. It is possible to use a Weighted Sum tool in ArcMap, but compiling the data in a spreadsheet with inputs for variable weights

is more user-friendly for stakeholders (Fig. 3). The combined criteria and overall MCDA priority scores are automatically calculated for watersheds and subbasins.

Flood Risk Priorities

For the flood regulation objective, we used the Summary Statistics tool to find the mean RARR score for each watershed and subbasin and then normalized based on the highest average value to assign a score between 0 and 1, so that 1 was the highest priority. We calculated overall flood risk equities for both spatial scales using the procedures described previously and then reclassified to the common priority scale. Other possible variations could include a different RARR cutoff score, filter method for developed parcels, or simplification based on a 500-year overlap. Although we computed watershed and subbasin risk ratios for the baseline 500-year flood scenario, they were not used in the spatial MCDA calculations. Fig. 4 shows the numerical distributions of watershed scores. Priorities were calculated based on MCDA spreadsheet input data and then weighted to calculate combined criteria and overall total

Fig. 3. Urban stream MCDA spreadsheet user interface enables variable weights for criteria and subcriteria.

scores. Average flood risk (RARR Scores) and flood risk equity (RARR Equity) were heavily skewed toward the low end of the priority range with outliers in the upper tails. Fig. 5(a) depicts the spatial distributions of subbasin flood regulation priorities.

Water Quality Priorities

In the water quality category, the fecal coliform conditions (and categorical priority scores) were either noncompliant ($=0.5$) or very bad ($=1.0$) for all 23 monitored watersheds, although only 6 watersheds were listed with a fecal total maximum daily load (TMDL), so the highest combined priority ($=1.0$) was a listed watershed with very bad conditions. None of the watersheds with the worst turbidity levels also had a regulatory status, so the highest combined priority scores ($=0.75$) for turbidity were found in watersheds with noncompliant conditions ($=0.5$) and also a turbidity TMDL or 303(d) listed ($=1.0$). The water quality regulatory subcriteria also included a stand-alone priority score for 303(d) listed watersheds for any reason. To calculate pollution risk equity, we used exposure to noncompliant or very bad fecal conditions for all developed parcels overlapping the 500-year flood zone or streamside water quality buffers. The ranges of water quality subcriteria scores are shown in Fig. 4. Water quality equity (WQ Equity) was heavily

skewed toward the low end of the priority range with outliers in the upper tails. No watersheds had a turbidity priority equal to 1, which would have required a severe level plus a turbidity TMDL or 303 d listed status. The 303 d listed priorities for any reason were either 0 (not listed) or 1 (listed). Because the original water quality data were at the larger watershed scale, equity accounted for the only differences between subbasins in any single watershed [Fig. 5(b)]. Most of the water quality subcriteria (fecal coliform, turbidity, 303 d listed) were characteristics inherited from the parent watershed, so water pollution exposure equity accounted for the only combined differences at the subbasin scale within a given watershed. Although pollution exposure may also be linked to subsurface utilities (Alves et al. 2021), our spatial MCDA focused on surface water environmental hazards.

Ecosystem Support Priorities

Under the ecosystem support category, we converted the polyline shapefile with SRRS scores to raster format and used the Zonal Statistics as Table tool to find the mean scores for each watershed and subbasin. Because higher SARR condition scores in the existing channel and riparian buffer corresponded to lower restoration priority, we inverted the scores as well as normalizing them from 0 to 1.

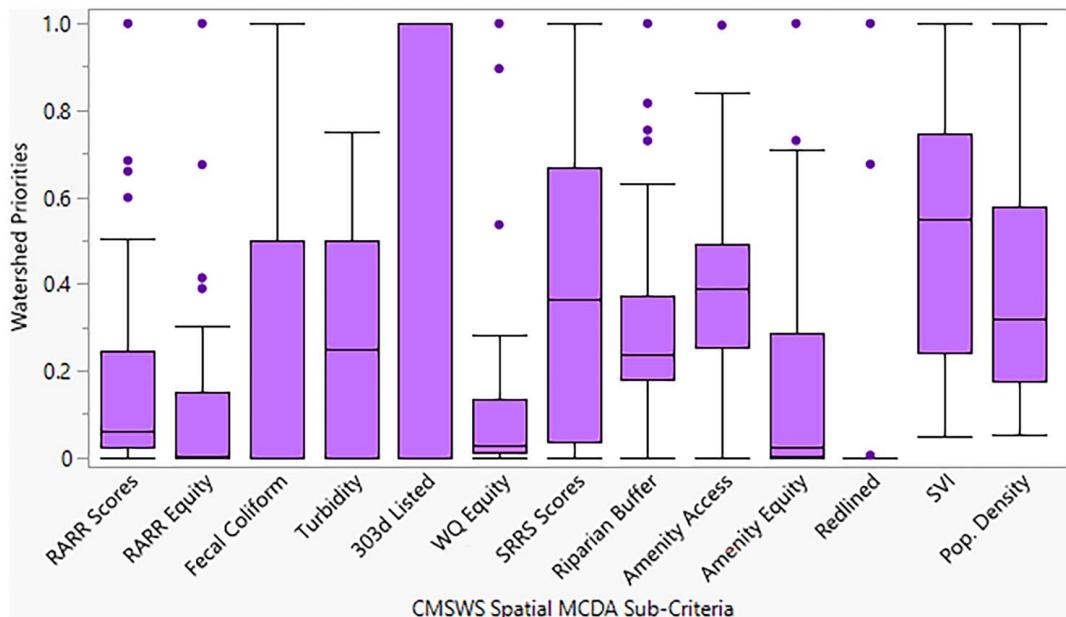


Fig. 4. Distributions of watershed subcriteria priority scores in all five categories.

The ecological watershed subcriteria score distributions are provided in Fig. 4, and combined subbasin priorities are shown in Fig. 5(c). In Fig. 4, ecosystem restoration priority scores based on channel stability and habitat (SRRS Scores) were normally distributed, while riparian vegetation (Riparian Buffer) was skewed toward higher priorities with only a couple low-scoring outliers. Alternative ecological protocols such as the Stream Function Assessment Method for Oregon (Nadeau et al. 2018) may include similar desktop analyses (e.g., aerial imagery).

Amenity Access Priorities

For characterizing access to amenities, we converted the neighborhood polygons to raster format, used the Zonal Statistics as Table tool for watersheds and subbasins to find the mean proportion near public outdoor education, inverted the values, and then reclassified them to the common priority scale. The benefit equity for amenity access was calculated and prioritized similar to that done for the flood and pollution risk ratios, except that inequity was characterized by disproportionately lower access to benefits rather than

a greater exposure to risk. The numerical and spatial distributions of watershed subcriteria and overall subbasin priorities related to amenity access are shown in Figs. 4 and 5(d), respectively. In Fig. 4, access to public outdoor recreation (Amenity Access) was normally distributed, while amenity access equity (Amenity Equity) was heavily skewed toward the low end of the priority range with outliers in the upper tails.

Environmental Justice Priorities

Under the general environmental justice category, we converted the population densities, SVI polygons, and redline areas to raster format, used the Zonal Statistics as Table tool, and then normalized the subcriteria priorities to a maximum score of 1. As indicated in Fig. 4, no watersheds had an average SVI score or a population density of 0. While the SVI and population density exhibited normally distributed values and corresponding priorities across the subbasins and watersheds (Fig. 4), redlining was much more isolated, being limited mostly to the Upper Little Sugar and Irwin watersheds. The overall subbasin environmental justice priorities are

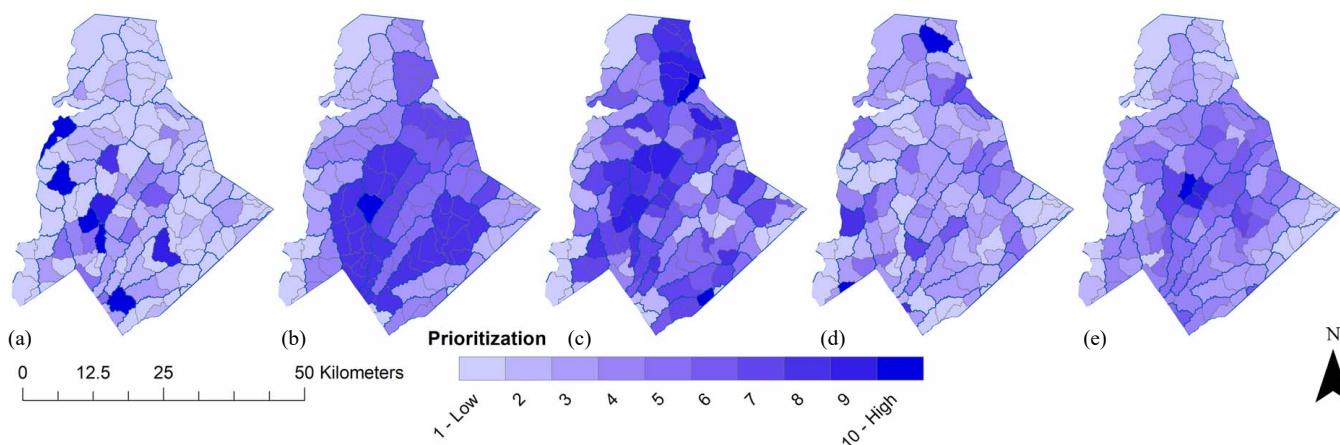


Fig. 5. Subbasin combined criteria scores for (a) flood regulation; (b) water quality regulation; (c) ecosystem support; (d) amenity access; and (e) environmental justice.

depicted in Fig. 5(e). Although we included population density as one of the environmental justice subcriteria, it would also be possible to combine this metric with the other categories to reflect the relatively great or less numbers of those who stand to benefit from flood protection, ecosystem rehabilitation, access to outdoor recreation, and so on.

MCDA Scenarios

The watershed distributions of subcriteria scores are shown in Fig. 4, in many cases exhibiting highly skewed trends, which is also evident at the subbasin scale. For example, the priority of median flood risk assessment (RARR score) was quite low compared with that of the water quality, ecosystem support, amenity access, and general environmental justice metrics. Likewise, all of the equity priority scores had skewed distributions with low median scores and a handful of outliers at the upper end of the range, the hotspots for environmental inequity. We organized the subcriteria scores for both watersheds and subbasins in a spreadsheet (Fig. 4) as the primary spatial MCDA user interface with variable weights. Eliciting weights from CMSWS would typically be the next step for full implementation of the urban riverscape MCDA. For the purposes of this study, however, we assigned equal weights to all subcriteria to calculate the overall priority scores for the various criteria (Fig. 5), and we used the spreadsheet to explore two spatial MCDA scenarios:

1. Combined MCDA—we assigned equal weights to all five of the criteria to calculate the combined priority score.
2. Riverscape MCDA—we used only flood and water quality regulation and ecosystem support, the main criteria most physically linked to arterial waterways and their contributing watersheds, as well as the associated environmental hazards and benefits.

In addition to reviewing the watershed and subbasin priorities resulting from the two MCDA scenarios, we investigated trade-offs and synergies by performing Pearson's bivariate correlations to test the criteria and subcriteria priority scores for possible relationships.

Results

Spatial Prioritization

We found that inclusion of the landscape criteria (amenity and environmental justice) in the Combined MCDA substantially altered the spatial prioritization compared with the Riverscape MCDA based only on flood regulation, water quality, and ecosystem support, but the differences were evident only at the subbasin scale [Figs. 6(c and d)]. The subset of criteria used for the Riverscape MCDA scenarios most closely align with the primary management goals elicited from our CMSWS collaborators as well as potential landscape-scale interventions and natural infrastructure strategies. For the watershed scenario including both riverscape and landscape criteria, Lower Little Sugar and Irwin had the highest combinations of priority scores [Figs. 6(a) and 7], with Upper Little Sugar and Sugar closely tied for third place—spatially, these watersheds are directly adjacent to one another. The water quality, ecosystem support, and amenity access overall criteria scores were comparable among the top few watersheds, but Upper Little Sugar had the highest environmental justice metrics (social vulnerability, population density, historic redlining), whereas Sugar exhibited the highest average flood risk (RARR scores). The highest priorities for the Riverscape MCDA scenario [Figs. 6(b) and 7] again included Lower Little Sugar, Sugar, and

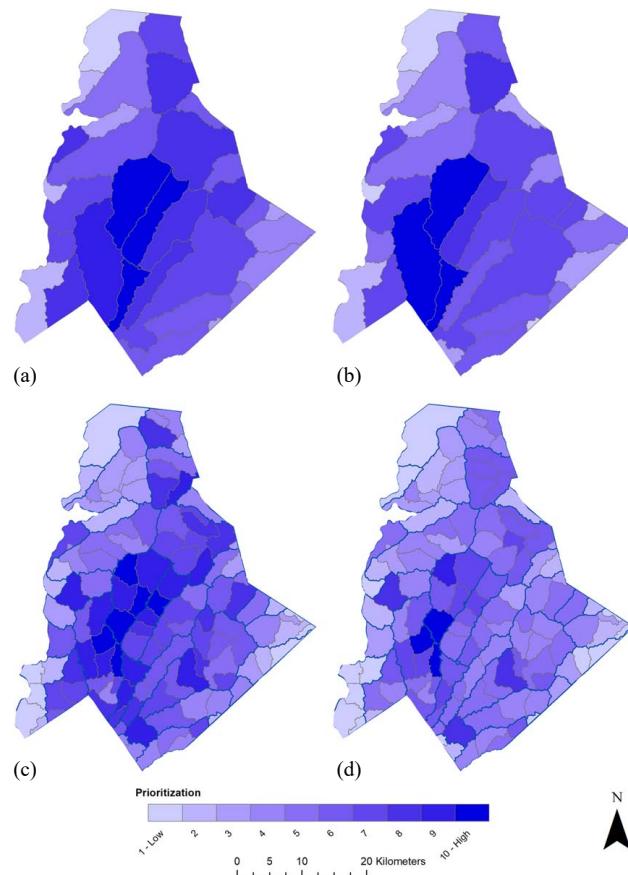


Fig. 6. Spatial MCDA results for watershed and subbasin scenarios: (a) watershed-combined MCDA; (b) watershed riverscape MCDA; (c) subbasin combined MCDA; (d) subbasin riverscape MCDA; (a and c) combine all five criteria shown in Fig. 5; and (b and d) combine only flooding [Fig. 5(a)], water quality [Fig. 5(b)], and ecosystem support [Fig. 5(c)], which are most directly linked to arterial waterways.

Irwin watersheds. Not surprisingly, Upper Little Sugar dropped in priority without the general environmental justice criteria. However, the Riverscape MCDA scenario still incorporated context-specific environmental risk equity. With side-by-side comparisons of the two priority results, we found similar watershed priorities between the two scenarios (Fig. 7). Lower Little Sugar scored highest for both scenarios, and the other watersheds with the highest priorities include Irwin, Sugar, and Upper Little Sugar. The Riverscape MCDA watershed priorities for Lake Norman and Twelve Mile were zero, because they had no developed parcels with environmental risk exposure (Fig. 2) or stream reaches with SRRS scores.

The subbasin prioritization highlighted the spatial hotspots combining social–ecological system vulnerabilities and deficiencies across multiple dimensions. We found a distinct contrast between the subbasin priorities for the two MCDA scenarios [Figs. 6(c and d) and 8], although subbasin hotspots are evident with both scenarios. For the combined scenario based on all five criteria, subbasins within the same watershed showed a degree of spatial similarity [Fig. 6(c)], and there were many more high-priority areas, which were probably due to the inclusion of landscape-based amenity access [Fig. 5(d)] and environmental justice [Fig. 5(e)]. In contrast, the riverscape scenario generated a distinct spatial pattern of isolated hotspots [Fig. 6(d)], a splotchy

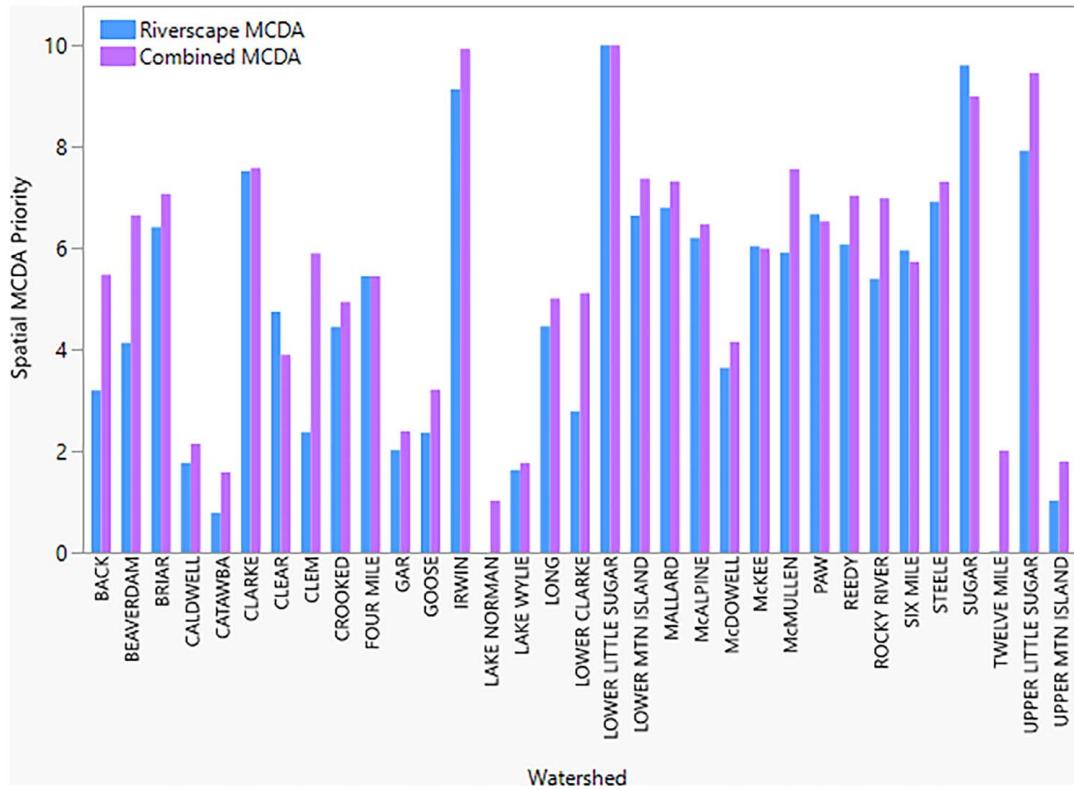


Fig. 7. Watershed priority scores for two MCDA scenarios.

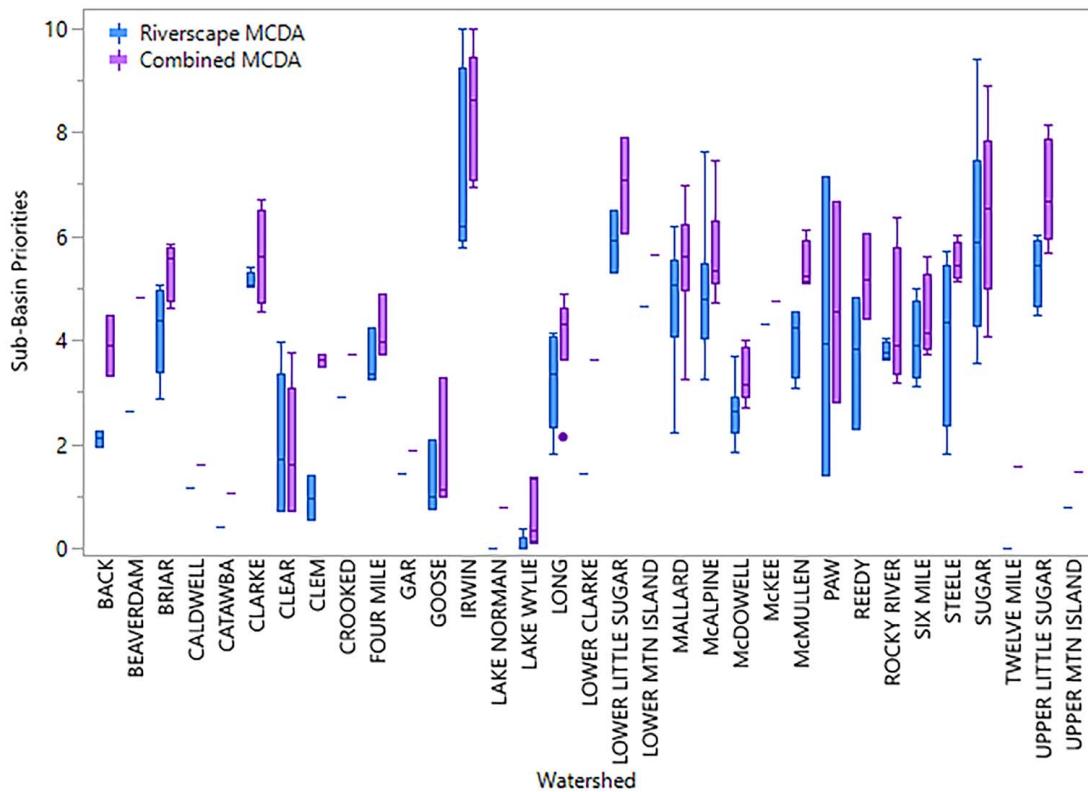


Fig. 8. Distributions of subbasin priorities for two MCDA scenarios within each watershed.

appearance corresponding to just a few outliers with the highest priority scores. These results make sense, given that the additional criteria (amenity access, environmental justice) used in the first scenario are distributed across the entire landscape rather

than only in the arterial waterways. In Fig. 8, the Combined MCDA scenario including both riverscape and landscape criteria often generated higher mean values of basin priorities compared with the Riverscape MCDA.

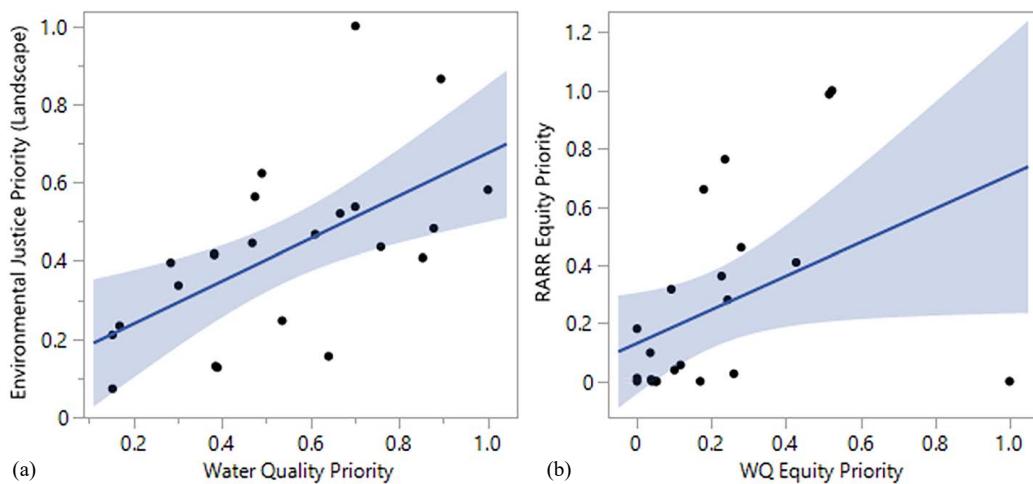


Fig. 9. Statistical relationships among criteria and subcriteria at the watershed scale: (a) environmental justice versus water quality; and (b) RARR equity versus water quality equity.

System-Level Synergies

A part of the purpose of a spatial MCDA is to help stakeholders leverage potential synergies among multiple objectives. An individual watershed or subbasin with a much higher overall priority score compared with others has greater combined effects from its constituent criteria. For example, the Lower Little Sugar watershed rose to the top of both MCDA scenarios (Fig. 7) with upper quartile scores for flood risk, water quality, ecosystem support, and environmental justice criteria (Fig. 4).

When we looked for positive or negative correlations between criteria across all watersheds, we found little statistical power to support conclusions about system-wide synergies or trade-offs. However, for watersheds with monitoring data, we did find evidence of a positive correlation ($0.60, p = 0.0027$) between the overall water quality and general environmental justice criteria [Fig. 9(a)]. This result intrigued us, especially because none of the water quality equity subcriteria scores (race, ethnicity, income, combination) were correlated with any of the environmental justice subcriteria. However, the lack of relationship between the equity scores and the general environmental justice criteria underscores the value of including both types of metrics and not just social vulnerability. The broader metrics are still valuable for capturing neighborhood characteristics beyond environmental risk exposure because neighborhoods may not spatially correspond to topographically delineated watersheds and subbasins.

When we analyzed the subcriteria, we also found a positive correlation between the equity scores for flood risk (RARR) and water pollution exposure at both subbasin ($0.63, p < 0.0001$) and watershed scales ($0.51, p = 0.0022$), as shown in Fig. 9(b). The environmental risk equity relationship makes sense, given the similar methods we used to develop the two metrics, with the only difference being the extent of exposure. This correlation might also have contributed to the pattern of subbasin priority outliers visible in Figs. 6(d) and 8 if there was an amplifying effect by including separate flood and water pollution risk ratios in the waterway-focused MCDA scenario.

Environmental Equity

The environmental equity aspect of our study produced several important results and applications. First, we found that spatial trends in flood inequity were in agreement with previous findings about the areas in Charlotte with socioeconomic disparities, and the

magnitudes of risk ratios above 1, despite the differences in how we defined flood exposure and aggregated risk areas using parcels. For example, Debbage (2019) found that the Lansdowne neighborhood (Census Tract 37119002004) had some of the highest risk ratios that were statistically significant, the worst being 3.28 for the Non-Hispanic Black population, and we found that the corresponding RARR and 500-year flood risk ratios were both 3.40 ($p < 0.0001$) for the same tract. However, the spatial resolution of the analysis matters, because Debbage (2018) found only one significant risk ratio (below poverty versus above poverty) for Mecklenburg County as a unified whole. Like Debbage, however, we found a different story when zooming into the census tract level for equity comparisons by demographic groups (Fig. 10). The Hispanic, Non-Hispanic Black, and Below Poverty demographic categories all had more census tracts with inequitable risk ratios (>1) for both flood scenarios. While the presence of any risk ratio greater than 1 shows that there are equity concerns that need to be addressed, the number of tracts with statistically significant risk scores greater than 1 exceeded that with risk scores less than 1, suggesting overall inequities across race, ethnicity, and income level. In contrast, among subbasins with statistically significant risk ratios, only the poverty category continued to show a negative disparity, and the larger watershed scale altogether erased this tendency through overall aggregation.

In addition to confirming overall trends in flood risk, we were able to take a step toward operationalizing flood risk equity through spatial prioritization. For starters, we combined multiple minority and income categories (Hispanic, Non-Hispanic Black, Below Poverty) to create a single equity score for each subbasin and watershed, thereby including intersectionality of these socially vulnerable classes (e.g., low-income Black and Hispanic people). Leveraging multiple spatial scales was also useful when characterizing the distributions of environmental risks and benefits. Even if risk ratios at the large county scale failed to demonstrate overall inequities, the medium and small spatial scales enabled us to determine which watersheds, subbasins, and tracts were the areas of greatest concern. Therefore, we applied the environmental equity scores as part of the criteria for a spatial MCDA.

Moreover, we found that the environmental equity techniques were both relatively simple and flexible enough for a range of practical applications. For example, we were able to use the 500-year flood zone as a proxy for flood risk similar to previous work (Debbage 2019), and the same basic technique worked with alternative

definitions of environmental risk (e.g., surface water pollution exposure) and a specialized approach that incorporated risk frequency and probability (i.e., RARR scores). Access to environmental benefits (i.e., public outdoor recreation) was also readily incorporated in a comparable fashion through the use of benefit ratios. Furthermore, it was relatively straightforward to estimate risk and benefit factors (i.e., exposure and access), combine them with census data, and then perform risk and benefit ratio calculations with tools widely used by municipalities and utilities (GIS, spreadsheets).

Discussion

The urban stream spatial MCDA that we developed through collaboration with CMSWS provides a flexible approach to identifying social–ecological system vulnerabilities, prioritizing streams and watersheds for future interventions, and working across departments to meet multiple management objectives. Rather than responding to isolated environmental hazards and challenges in a piecemeal fashion, our spatial MCDA facilitates more holistic system–level planning for investments that will best support sustainable cities for generations to come.

Facing Challenges

Properties and people suffering from flood damage, underfunctioning stream reaches that fail to support aquatic life, and impaired watersheds that fall short of regulatory goals are just the tip of the urban riverscape iceberg encountered by organizations and stakeholders. Our spatial MCDA incorporates all of these specific concerns in an approach that further addresses some of the underlying challenges and system drivers. For example, these problems involve multiple spatial scales with variable degrees of interaction, and our MCDA approach includes both the large (watershed) and the medium (subbasin) landscape context, with

further potential to modify metrics for evaluating local project alternatives while sharing the same overarching criteria. The sheer scope of responsibilities held by stream and watershed managers has led to a natural division of labor, which can function as a barrier. Our spatial MCDA bridges departmental boundaries and includes input from CMSWS individuals tasked with multiple missions, which is reflected in the range of criteria and incorporation of various established management tools (i.e., RARR, SRSS, Water Quality Matrix). Engineers and scientific specialists might also struggle with questions related to human dimensions outside of their technical expertise, such as how to incorporate social equity in a meaningful way. For example, this study agreed with previous findings of flood inequity in the Charlotte metropolitan area (Debbage 2019) with regard to locations and magnitudes of socioeconomic disparities, which is most evident at smaller spatial scales. Our dual approach to environmental equity in the urban stream spatial MCDA uses widely recognized metrics of social vulnerability in tandem with equitable distributions of specific environmental risks and benefits, similar to prior spatial planning for green infrastructure (Meerow and Newell 2017). Finally, the spreadsheet serving as the user interface for the spatial MCDA helps address the inherent challenge of multiobjective prioritization in a transparent and flexible fashion through weighted criteria and subcriteria that can be easily modified by multiple stakeholder groups to explore alternative riverscape scenarios.

Finding Opportunities

With our urban stream spatial MCDA, we wanted to help CMSWS identify areas in Mecklenburg County with opportunities to realize multiple potential benefits. In contrast to a green infrastructure study in Detroit (Meerow and Newell 2017), we found little evidence for synergies or trade-offs across criteria, perhaps because we were focused on riverscapes with different environmental risks and benefits. Although different weightings may result in

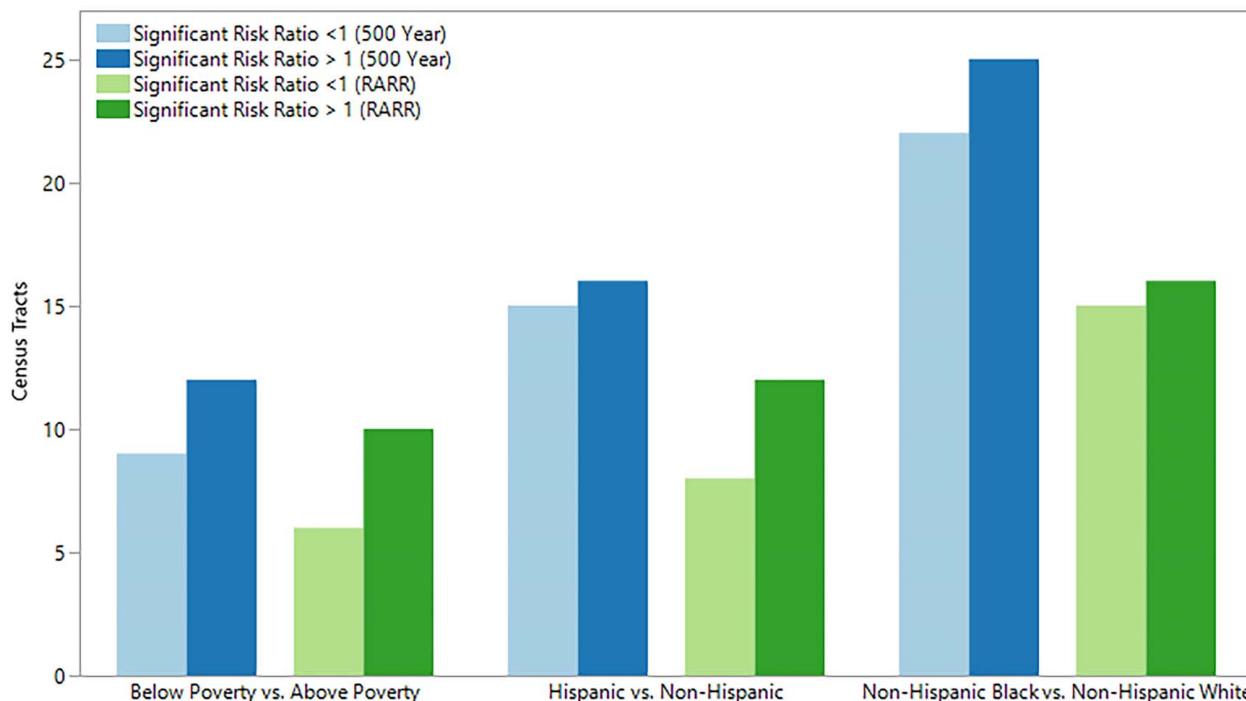


Fig. 10. Frequencies of census tract risk ratios with significant *p*-values greater and less than 1 for the studied socioeconomic groups and two different metrics of flood risk exposure: developed parcels with nonzero RARR scores (building level) and overlapping the 500-year flood hazard zone.

different prioritizations (Meerow and Newell 2017), our case study did highlight specific watersheds and subbasins as promising locations for addressing multiple objectives. Similarly, the inclusion of alternative or additional metrics, or even the normalization of the metrics, may lead to different spatial priorities.

Identifying hotspots on the basis of more environmental risks, coupled with fewer existing benefits, was the primary task of our MCDA approach, but we envision a complementary spatial prioritization with benefits-related subcriteria such as future greenway trails, adopted streams, outdoor education, and other social connectivity. Furthermore, specific natural infrastructure solutions, such as those for flood mitigation, involve different types of spatial criteria (Hovis et al. 2021). If stream renovation (restoration, revitalization, naturalization, etc.) priorities feature ecological uplift, then upgrading urban aquatic and riparian ecosystems from poor to fair may involve the use of success indicators that are different from indicators such as improvement from fair to good. For example, a poorly vegetated stream buffer zone presents a potential opportunity to enhance riparian conditions and support terrestrial wildlife, but connectivity to a high-quality forested stream reach may increase the likelihood of restoration success for fish and aquatic insects. In short, what makes for a *good opportunity* for environmental benefits and co-benefits is highly context specific, so it may be most appropriate to conduct separate analyses at the subbasin, floodplain, and/or stream reach scales rather than lumping opportunities together with social–ecological system vulnerabilities and deficiencies. Feasibility criteria could also be incorporated to reflect constraints faced by managers, such as Clean Water Act compliance, water capture potential across the landscape, or available acreage for project development.

The inclusion of environmental equity in our case study corresponds to particularly valuable opportunities, providing a potential starting point for water managers struggling to incorporate social components. We demonstrated how to include social vulnerability and advance environmental equity with our spatial MCDA. Moreover, our approach is intended to be a collaborative decision support tool for community inclusion and diverse stakeholder groups. That being said, when adding new subcriteria with priority scores based on potential opportunities (e.g., specific NI solutions, alignment with other planned improvements, etc.), it will be especially important to review potential trade-offs with environmental equity criteria, such as risks associated with neighborhood displacement and gentrification (neighborhood change score). We are concerned about the potential for *win–win–win* scenarios based on some combination of *good opportunities* or a resilience narrative that inadvertently reinforces existing systemic injustices caused by unacknowledged social trade-offs (Eakin et al. 2017; Béné et al. 2018). However, the potential alignment that we found between the overall water quality and environmental justice criteria is a promising avenue for further study and action.

Flexible Applications

Working together with CMSWS on the urban stream MCDA case study demonstrated one practical application of our approach. However, our larger intent was to create a multifunctional spatial prioritization framework to support the larger body of managers, practitioners, and communities tackling urban riverscape challenges. Integrating existing management tools and strategies such as those used by CMSWS (RARR, SRRS) showed how the general approach could be tailored for specific organizations and departments. However, the spatial MCDA could easily transfer to other municipalities with alternative methods for

characterizing flood risk, channel stability, water quality, and so on. For example, floodplain managers could apply our spatial MCDA in tandem with probabilistic mapping (Stephens and Bledsoe 2020) or frequency-based risk equity (Selsor et al. 2023), and use different methods for determining which parcels are developed and are at risk. Environmental scientists could evaluate and prioritize stream restoration using ecological potential based on the ratio of existing to predicted biotic scores (Paul and Allen 2022). Subcriteria related to fecal coliform and water quality could incorporate spatial data about basement backups (Alves et al. 2021). Census data, the CDC version of SVI, and historic redlining maps are readily available in the United States to support environmental equity objectives, and our methods for delineating *demographic watersheds* and calculating environmental risk and benefit ratios are highly adaptable. The spatial MCDA used software tools that are already familiar to technical specialists in our target audience, and GIS can be coupled with story maps to present information to the wider group of stakeholders (Meerow and Newell 2017; EPA 2020).

Conclusions

The spatial MCDA that we developed for urban watersheds and streams was used in collaboration with CMSWS for preliminary planning to meet multiple priorities: flood risk, water quality, aquatic ecosystems, amenity access, and environmental equity. Our environmental equity methods and findings can help the City of Charlotte and Mecklenburg county to advance social justice by expanding the scope from vulnerability to the distributions of environmental risks and benefits, keeping in mind that inclusion of landscape criteria such as access to amenities and general environmental justice (SVI, historic redlining, population density) can substantially shift the perspective. The spatial analysis revealed synergies and identified hotspots to begin conversations with neighborhoods and communities as part of structured decision-making: problem definitions, knowledge coproduction, and opportunity identification leading to community-based solutions. At the same time, the practical transferability of our spatial MCDA supports broader applications in other social–ecological systems and urban riverscapes, and can be used to operationalize equity in infrastructure decisions.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This work was supported by the US Army Corps of Engineers Engineering With Nature Initiative through Cooperative Ecosystem Studies Unit Agreement W912HZ-20-2-0031; the National Science Foundation (NSF) Sustainability Research Network (SRN) Cooperative Agreement 1444758, Urban Water Innovation Network (U-WIN): Transitioning Toward Sustainable Urban Water Systems; and the NSF Non-Academic Research Internships for Graduate Students (INTERN) Supplemental Funding (Proposal ID—2001796). We thank Haley Selsor for constructive comments on the manuscript and assistance with the fmsb package in R, and Kevin Samples for GIS support. We gratefully acknowledge the

collaboration of Charlotte-Mecklenburg Storm Water Services, including the individuals who originally collected and subsequently compiled the data utilized in this study.

References

Alves, P. B. R., S. Djordjević, and A. A. Javadi. 2021. "An integrated socio-environmental framework for mapping hazard-specific vulnerability and exposure in urban areas." *Urban Water J.* 18 (7): 530–543. <https://doi.org/10.1080/1573062X.2021.1913505>.

ASCE. 2022. "ASCE's roadmap to sustainable development: Four priorities for change." Accessed September 30, 2022. <https://www.asce.org/communities/institutes-and-technical-groups/sustainability/sustainability-roadmap>.

Béné, C., L. Mehta, G. McGranahan, T. Cannon, J. Gupte, and T. Tanner. 2018. "Resilience as a policy narrative: Potentials and limits in the context of urban planning." *Clim. Dev.* 10 (2): 116–133. <https://doi.org/10.1080/17565529.2017.1301868>.

Bernhardt, E. S., et al. 2007. "Restoring rivers one reach at a time: Results from a survey of U.S. river restoration practitioners." *Restor. Ecol.* 15 (3): 482–493. <https://doi.org/10.1111/j.1526-100X.2007.00244.x>.

Bridges, T. S., E. M. Bourne, J. K. King, H. K. Kuzmitski, E. B. Moynihan, and B. C. Suedel. 2018. *Engineering with nature: An atlas*. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Bridges, T. S., E. Bourne, B. Suedel, E. Moynihan, and J. King. 2021. *Engineering with nature: An atlas, volume 2*. Vicksburg, MS: U.S. Army Engineer Research and Development Center.

Bridges, T. S., et al. 2015. *Use of natural and nature-based features (NNBF) for coastal resilience*. Vicksburg, MS: U.S. Army Corps of Engineers Engineer Research Development Center.

Charlotte-Mecklenburg Storm Water Services. 2020. *RARR user guide update user guide update: Risk assessment/risk reduction tool*. Charlotte, NC: Charlotte-Mecklenburg Storm Water Services.

Cohen-Shacham, E., et al. 2019. "Core principles for successfully implementing and upscaling Nature-based Solutions." *Environ. Sci. Policy* 98: 20–29. <https://doi.org/10.1016/j.envsci.2019.04.014>.

Davis, L. J., R. Milligan, C. E. Stauber, N. O. Jelks, L. Casanova, and S. H. Ledford. 2022. "Environmental injustice and *Escherichia coli* in urban streams: Potential for community-led response." *WIREs Water* 9: e1583. <https://doi.org/10.1002/wat2.1583>.

Debbage, N. 2019. "Multiscalar spatial analysis of urban flood risk and environmental justice in the Charlanta megaregion, USA." *Anthropocene* 28: 100226. <https://doi.org/10.1016/j.ancene.2019.100226>.

Debbage, N. A. 2018. *Urban flooding vulnerability: A multifaceted comparative assessment of the Charlanta megaregion*. Athens, GA: Univ. of Georgia.

Dewitz, J., and USGS. 2021. "National Land Cover Database (NLCD) 2019 Products (ver. 2.0, June 2021): U.S. Geological Survey data release." Accessed April 12, 2022. <https://www.sciencebase.gov/catalog/item/5f21cef582cef313ed940043>.

Eakin, H., L. A. Bojórquez-Tapia, M. A. Janssen, M. Georgescu, D. Manuel-Navarrete, E. R. Vivoni, A. E. Escalante, A. Baeza-Castro, M. Mazari-Hiriart, and A. M. Lerner. 2017. "Urban resilience efforts must consider social and political forces." *Proc. Natl. Acad. Sci. USA* 114 (2): 186–189. <https://doi.org/10.1073/pnas.1620081114>.

EPA (Environmental Protection Agency). 2020. "Proctor creek watershed story map: The intersection of green infrastructure and health." Accessed February 2, 2022. https://www.epa.gov/sites/default/files/2020-09/documents/proctor_creek_story_map_fact_sheet_sep2020.pdf.

Evers, M., A. Almoradie, and M. M. de Brito. 2018. "Enhancing flood resilience through collaborative modelling and multi-criteria decision analysis (MCDA)." *Urban disaster resilience and securities: Addressing risks in societies*. <https://doi.org/10.1007/978-3-319-68606-14>.

Habersack, H., B. Schober, and C. Hauer. 2015. "Floodplain evaluation matrix (FEM): An interdisciplinary method for evaluating river floodplains in the context of integrated flood risk management." *Nat. Hazards* 75 (1): 5–32. <https://doi.org/10.1007/s11069-013-0842-4>.

Hammond, M. J., A. S. Chen, S. Djordjević, D. Butler, and O. Mark. 2015. "Urban flood impact assessment: A state-of-the-art review." *Urban Water J.* 12 (1): 14–29. <https://doi.org/10.1080/1573062X.2013.857421>.

Hoang, L., R. A. Fenner, and M. Skenderian. 2018. "A conceptual approach for evaluating the multiple benefits of urban flood management practices." *J. Flood Risk Manage.* 11: S943–S959. <https://doi.org/10.1111/JFR3.12267>.

Hong, C.-Y., and H. Chang. 2020. "Residents' perception of flood risk and urban stream restoration using multi-criteria decision analysis." *River Res. Appl.* 36 (10): 2078–2088. <https://doi.org/10.1002/rra.3728>.

Hovis, M., et al. 2021. "Natural infrastructure practices as potential flood storage and reduction for farms and rural communities in the North Carolina coastal plain." *Sustainability* 13 (16): 9309. <https://doi.org/10.3390/SU13169309>.

Jelks, N. O., V. Jennings, and A. Rigolon. 2021. "Green gentrification and health: A scoping review." *Int. J. Environ. Res. Public Health* 18 (3): 907. <https://doi.org/10.3390/IJERPH18030907>.

Kaushal, S. S., et al. 2018. "Watershed 'chemical cocktails': Forming novel elemental combinations in Anthropocene fresh waters." *Biogeochemistry* 141 (3): 281–305. <https://doi.org/10.1007/s10533-018-0502-6>.

Kiker, G. A., T. S. Bridges, A. Varghese, T. P. Seager, and I. Linkov. 2005. "Application of multicriteria decision analysis in environmental decision making." *Integr. Environ. Assess. Manage.* 1 (2): 95–108. https://doi.org/10.1897/IEAM_2004a-015.1.

Lim, K.-S., and D.-R. Lee. 2009. "The spatial MCDA approach for evaluating flood damage reduction alternatives." *KSCE J. Civ. Eng.* 13 (5): 359–369. <https://doi.org/10.1007/s12205-009-0359-2>.

Linkov, I., P. Welle, D. Loney, A. Tkachuk, L. Canis, J. B. Kim, and T. Bridges. 2011. "Use of multicriteria decision analysis to support weight of evidence evaluation." *Risk Anal.* 31 (8): 1211–1225. <https://doi.org/10.1111/J.1539-6924.2011.01585.X>.

Mant, J., C. R. Thorne, J. Burch, and M. Naura. 2020. "Restoration of urban streams to create blue–green infrastructure." In *Blue–green cities*, edited by C. R. Thorne, 77–97. London: ICE.

Mecklenburg County. n.d. "Open mapping: Mecklenburg county GIS, North Carolina." Accessed April 12, 2022. <https://maps.mecknc.gov/openmapping/>.

Mecklenburg County Storm Water Services. 2021. *Stream restoration ranking system (SRRS): SRRS administrative and desktop score procedure manual*. Charlotte, NC: Charlotte-Mecklenburg Storm Water Services.

Meerow, S., and J. P. Newell. 2017. "Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit." *Landscape Urban Plann.* 159: 62–75. <https://doi.org/10.1016/j.landurbplan.2016.10.005>.

Nadeau, T., D. M. Hicks, C. Trowbridge, N. Maness, R. Coulombe, and N. Czarnomski. 2018. *Stream function assessment method for Oregon*. Salem, OR: Oregon Department of State Lands.

O'Donnell, E., et al. 2020. "The blue–green path to urban flood resilience." *Blue-Green Systems* 2 (1): 28–45. <https://doi.org/10.2166/bgs.2019.199>.

Palmer, M. A., K. L. Hondula, and B. J. Koch. 2014. "Ecological restoration of streams and rivers: Shifting strategies and shifting goals." *Annu. Rev. Ecol. Evol. Syst.* 45 (1): 247–269. <https://doi.org/10.1146/annurev-ecolsys-120213-091935>.

Paul, M., and D. Allen. 2022. *Biological condition in NC urban streams phase III: Development of a web application*. Research Triangle Park, NC: North Carolina Water Resources Research Institute.

Polvi, L. E., L. Lind, H. Persson, A. Miranda-Melo, F. Pilotto, X. Su, and C. Nilsson. 2020. "Facets and scales in river restoration: Nestedness and interdependence of hydrological, geomorphic, ecological, and biogeochemical processes." *J. Environ. Manage.* 265: 110288. <https://doi.org/10.1016/j.jenvman.2020.110288>.

Pulido, L. 2000. "Rethinking environmental racism: White privilege and urban development in southern California." *Ann. Assoc. Am. Geogr.* 90 (1): 12–40. <https://doi.org/10.1111/0004-5608.00182>.

Renaud, F. G., K. Sudmeier-Rieux, M. Estrella, and U. Nehren. 2016. "Ecosystem-based disaster risk reduction and adaptation in practice."

In *Advances in natural and technological hazards research*, 1–598. Cham, Switzerland: Springer International Publishing AG.

Selsor, H., B. P. Bledsoe, and R. Lammers. 2023. “Recognizing flood exposure inequities across flood frequencies.” *Anthropocene* 42: 100371. <https://doi.org/10.1016/J.ANCENE.2023.100371>.

Skidmore, P., and J. M. Wheaton. 2022. “Riverscapes as natural infrastructure: Meeting challenges of climate adaptation and ecosystem restoration.” *Anthropocene* 38: 100334. <https://doi.org/10.1016/j.ancene.2022.100334>.

Smardon, R., S. Moran, and A. K. Baptiste. 2018. *Revitalizing urban waterway communities: Streams of environmental justice*. New York: Routledge.

Smith, R. F., et al. 2016. “Urban stream renovation: Incorporating societal objectives to achieve ecological improvements.” *Freshwater Sci.* 35 (1): 364–379. <https://doi.org/10.1086/685096>.

Sowińska-Świerkosz, B., and J. García. 2021. “A new evaluation framework for nature-based solutions (NBS) projects based on the application of performance questions and indicators approach.” *Sci. Total Environ.* 787: 147615. <https://doi.org/10.1016/j.scitotenv.2021.147615>.

Stephens, T. A., and B. P. Bledsoe. 2020. “Probabilistic mapping of flood hazards: Depicting uncertainty in streamflow, land use, and geomorphic adjustment.” *Anthropocene* 29: 100231. <https://doi.org/10.1016/j.ancene.2019.100231>.

Stets, E. G., L. A. Sprague, G. P. Oelsner, H. M. Johnson, J. C. Murphy, K. Ryberg, A. V. Vecchia, R. E. Zuellig, J. A. Falcone, and M. L. Riskin. 2020. “Landscape drivers of dynamic change in water quality of U.S. rivers.” *Environ. Sci. Technol.* 54: 4336–4343. <https://doi.org/10.1021/acs.est.9b05344>.

Univ. of Richmond’s Digital Scholarship Lab. 2020. “Home Owners’ Loan Corporation (HOLC) neighborhood redlining grade.” *Esri*. Accessed April 12, 2022. <https://www.arcgis.com/home/item.html?id=ef0f926eb1b146d082c38cc35b53c947>.

U.S. Army Corps of Engineers. 2022. “Engineering with nature.” Accessed September 20, 2022. <https://ewn.erdc.dren.mil/>.

U.S. Census Bureau. n.d.-a. “American community survey data.” Accessed September 9, 2022. <https://www.census.gov/programs-surveys/acs/data.html>.

U.S. Census Bureau. n.d.-b. “2020 US Decennial Census.” Accessed September 9, 2022. <https://www.census.gov/programs-surveys/decennial-census/decade/2020/2020-census-results.html>.

ten Veldhuis, J. A. E. 2011. “How the choice of flood damage metrics influences urban flood risk assessment.” *J. Flood Risk Manage.* 4 (4): 281–287. <https://doi.org/10.1111/j.1753-318X.2011.01112.x>.

Vercruyse, K., D. A. Dawson, V. Glenis, R. Bertsch, N. Wright, and C. Kilsby. 2019. “Developing spatial prioritization criteria for integrated urban flood management based on a source-to-impact flood analysis.” *J. Hydrol.* 578: 124038. <https://doi.org/10.1016/j.jhydrol.2019.124038>.

Whelchel, A. W., B. G. Reguero, B. van Wesenbeeck, and F. G. Renaud. 2018. “Advancing disaster risk reduction through the integration of science, design, and policy into eco-engineering and several global resource management processes.” *Int. J. Disaster Risk Reduct.* 32: 29–41. <https://doi.org/10.1016/j.ijdrr.2018.02.030>.